Demand Shocks and Productivity: Evidence from a Natural Experiment

PRELIMINARY DRAFT

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Abstract
Does demand have productive consequences? While theoretical work predicts that one should find productivity implications of demand, there is little direct evidence on this question. The Energy Policy Act of 2005 mandated a 3.5 billion gallon increase in the ethanol content of gasoline. In turn, this created a large, exogenous increase in demand for corn, the primary ingredient used to produce ethanol. We leverage this natural experiment using county-level data for corn and soybean producers located in the U.S. Corn Belt to investigate the demand-productivity nexus. Consistent with theoretical predictions, the demand shock caused a 26% increase in the treatment group's productivity. This effect is robust to a battery of robustness tests and cannot be explained by alternative forces such as product substitutability. The results are quantitatively similar when we use an alternative demand shock – Coca-Cola and Pepsi's switch from a sugar cane-based sweetener to high fructose corn syrup in 1985 – confirming external validity. We find evidence that the productivity gains were attributable to improvements in capacity utilization and large investments in an important factor of production, fertilizer. In contrast to Syverson (2004) we document a direct causal link between the demand environment and firm productivity.

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1. Introduction

Productivity is typically viewed as a supply-side concept. But allowing an explicit role for demand-side influences adds a realistic richness to our understanding of producers' fates: all firms need buyers.

Although demand is intrinsic to the process of production in most economic theories, it tends not to have any directly productive role. A permanent positive demand shock reduces the uncertainty surrounding the future level of demand, makes available new revenues, and raises the expected returns to investment, all of which might be expected to encourage firms to invest to raise their productivity. Theoretical work suggests that changes in the demand environment, as measured by market size, lead firms to innovate. Chaney and Ossa (2012) for example open the black box of the production function and allow for a production chain in which a range of tasks are carried out by specialized production teams. An increase in market size is predicted to lead to deeper division of labor among these teams which causes an increase in firm productivity. The novel setup in Desmet and Parente (2010) contains the key theoretical prediction that the productivity gains associated with larger markets are the result of innovations by established firms. In that model larger markets support a greater variety of goods, resulting in a more crowded product space. This raises the price elasticity of demand and lowers mark-ups leading firms to become bigger (in terms of output) to break even. Using a standard model of process and product innovation they predict that this facilitates productivity upgrading as larger firms can amortize fixed R&D costs over more units of output.

The inherent difficulties associated with measuring demand pose a challenge to empirical modelling of the demand-productivity nexus. In this paper we deal with these problems by leveraging a natural experiment. Amid a backdrop of rising oil prices and concerns surrounding the future security of foreign energy sources, the Energy Policy Act of 2005 (EPA) was passed by the U.S. government in an attempt to to safeguard national energy independence and security. At heart the EPA was designed to make the country less reliant on foreign oil suppliers by offering tax breaks and incentives to stimulate domestic energy production. A notable aspect of the legislation was that it mandated the ethanol content of gasoline should rise from 4 billion gallons in 2006 to 7.5 billion in 2012. The subsequent Energy Independence and Security Act of 2007 (EISA) set yet higher targets. In order that these goals were met, ethanol manufacturers were paid a subsidy worth 51 cents per blended gallon of gasoline through the Volumetric Ethanol Excise Tax Credit (VEETC).

As a result of the legislation, from 2005 onwards demand for corn - the primary ingredient in the manufacture of U.S. ethanol - was substantially higher than previously. Corn producers therefore experienced a large, exogenous increase in demand for their output. Moreover, the demand shock was additive and did not lead to displacement of other sources of corn demand.

Exploiting county-level data on physical output per acre for 12 mid-western states that make-up the Corn Belt, we investigate how productivity responded to the demand shock. In parts of the paper we contrast the fortunes of corn producers with soybean producers that did not experience a change in demand. Using a difference-in-difference (DD) estimation strategy, we find the demand shock caused a 4.8% increase in productivity within the treatment group. This result is robust to the use of other control groups such as wheat and barley, and cannot be explained by alternative factors such as product substitutability. Adoption of other econometric tools does not change our findings. Motivated by the decline in soybean firms observed between the 2002 and 2007 U.S. Economic Census, we experiment with an instrumental variable methodology that allows us to overcome possible downward bias in the implied counterfactual. Here we leverage variation in the location of ethanol production plants across both time and space to identify the effect of demand on productivity. Using this approach we estimate that productivity increased by 10.8% because of the demand shock. We also present evidence of productivity increases following a different demand shock, the switch by Coca-Cola and Pepsi from a sugar cane based glucose sweetener to high fructose corn syrup in 1985, indicating that our results are externally valid.

The findings are consistent with the view that changes in the demand environment cause firms to make productivity enhancing investments. This behavior is consistent with theoretical predictions that at high levels of output marginal costs become more important relative to fixed costs (Desmet and Parente, 2010; Chaney and Ossa, 2012). When confronted by higher demand, firms find it optimal to invest in productivity.

In order to hone in on the mechanism underpinning our headline figures, we also study the types of investment, and the type of firms that undertook them. While the productivity increases are a general finding, the data reveal that it was less efficient corn producers that raised productivity the most and that they achieved this through imitation of the production process used by frontier firms. In particular, laggards greatly increased the amount of fertilizer used per acre.

Our paper is related to a new line of research that has recently opened, that expands the sources of heterogeneity between firms to include both technological and demand-based factors, with each following separate and sometimes independent stochastic processes. Key references on this line of research include Das et al. (2007), Eslava et al. (2008), Foster et al. (2008), Kee and Krishna (2008) and De Loecker (2011). Idiosyncratic demand shocks have been shown to exert a key influence on some aspects of firm performance such as survival and growth (Foster et al., 2008, 2012; Pozzi and Schivardi, 2012). Reinforcing the view that demand is important, Foster et al. (2008) find demand shocks to be the primary determinant of survival among U.S. manufacturing firms.

Our paper is also related to the pioneering work by Syverson (2004) who examined the effect of market size on selection and productivity in the ready-mix concrete industry. The key prediction of his theory is that in large markets consumers have greater choice over who they buy from. Because there is greater product substitutability in large markets less efficient firms find it harder to retain market share leading to truncation of the productivity distribution. Syverson finds evidence consistent with the models predictions of higher average productivity and lower productivity dispersion in large markets. A similar result can be found in the dynamic stochastic model of an imperfectly competitive industry by Asplund and Nocke (2006).

The key distinction between those papers and ours is that in Syverson (2004) and Asplund and Nocke (2006) productivity remains fixed over the firm's lifetime. Increases in average industry productivity due to changes in market size accrue through reallocations of market share from the least to most efficient firms. In our setup changes in market size (demand) cause firms to invest in raising productivity and resemble the productivity improvements that firms undertake in response to an increase in the competitive environment (Schmitz, 2005; Matsa, 2011). The closest empirical papers to ours are those by Lileeva and Trefler (2010) and Bustos (2011). Those papers show that firms that were induced to export because of trade liberalization undertook process and product innovation to increase labor productivity. However, clean identification of the productivity effects of demand through the lens of trade liberalization is complicated by the simultaneous changes in competition following entry by foreign firms into the domestic marketplace.

Our paper is organized as follows. In the next section we outline the theory underlying our empirical work. We outline the details of the natural experiment in Section 3. Section 4 contains a description of the data set. The research design is outlined in Section 5. Our main empirical findings are provided and discussed in Section 6 and robustness tests are reported in the following section. In Section 8 we investigate what type of investments firms used to raise productivity. Finally conclusions are drawn in Section 9.

2. Theoretical Framework

We start by providing a simple theoretical framework to motivate our analysis and help interpret our results. The framework is based on some recent contributions to the literature that fit well with our empirical framework. We focus on one key issue. Specifically, we want to identify the mechanism through which demand shocks motivate firms to make productivity enhancing investments, so as to guide our empirical modelling.

Chaney and Ossa (2012) develop a simple general equilibrium model that opens the black box of the production process. Firms are faced with a trade-off between paying fixed investment costs and marginal costs. An increase in demand in the model, as captured by an increase in the number of consumers, implies that each consumer gets less of a given quantity of output which increases demand elasticities and reduces mark-ups. Firms therefore chare lower prices but produce more output. At high levels of output marginal costs become more important relative to fixed costs leading firms to invest in order to raise productivity. Firms can therefore better amortize the fixed costs of investment by spreading these costs over a greater quantity of output.

In the model proposed by Chaney and Ossa (2012) these productivity gains are manifested through a deeper division of labor which allows teams to focus on tasks that lie closer to their core competences. While we do not view this mechanism as being relevant in the context of our paper, we view the model's broader predictions as being highly applicable.

3. Data

We explore the demand-productivity links using county-level information for producers of corn using data from the National Agricultural Statistics Service (NASS). The NASS collects information on the average productivity of crop production by farms within each US county on an annual basis. Our sample period begins in 2000 and ends in 2010 following the expiry of the VEETC on 31 December. Given the concentration of corn production we restrict the sample to include only counties located in the 12 mid-western states that make up the Corn Belt.[1] This region accounts for 88% of national corn.

[INSERT FIGURE 1]

In parts of the paper we contrast the evolution of corn yields with those for soybeans. Corn and soybeans are the two largest planted cash crops in the US, accounting for 26% and 23% of total field crop acres planted during the period 2000-2010 respectively.[2] By comparison, the next most commonly planted crops are wheat (18%), cotton (8%) and sorghum (2%). While there is only one variety of soybeans (yellow), we focus on field corn (yellow-kernelled) rather than sweet corn as field corn is used in ethanol production whereas sweet corn is not.[3] The choice of soybeans as a control group is motivated by a number of factors. As shown in Figure 1 both crops are grown intensively throughout the mid-west, together the 12 mid-western states account for 81% of national soybean production. They also share similar planting (spring/late spring) and harvest (fall) seasons with corn meaning that any productivity differences are unlikely to be explained either by locational or climatic factors. Finally, the similar machinery (combines, trailers, seeders and tractors) is used to plant and harvest both crops.

The unit of observation in the sample is the county within which two products, corn and soybeans, are produced.[4] We therefore know about the average productivity of corn and soybean farms within each county.[5] For both crops productivity is measured in physical units: yield (productivity) is the average number of bushels produced per planted acre. As discussed in Foster et al. (2008, 2012), Katayama et al. (2003) and De Loecker (2011) an attractive property of using physical output data to measure productivity is that this provides researchers with superior insights into technological efficiency that would not be possible with traditional revenue-based TFP estimates.[6] In the context of this paper, this is

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[1]The states are Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota and Wisconsin.

[2] Source: author's calculations from NASS.

[3] The above figures do not include sweet corn. When we refer to corn this means yellow-kernelled (field corn).

[4] A minority of counties do not have productivity data for corn, soybeans or both products because no production takes place. This is particularly evident in more northern areas such as the Upper Peninsula of Michigan which is unsuited to growing corn.

[5] That is, we do not have firm-level data. Rather our data represents an average of the firms within each county-industry-year.

[6]Micro data sets invariably provide information on firm sales which, in the absence of firm-level price information, are deflated using industry price indices. Semi-parametric methods such as those outlined in Levinsohn and Petrin (2003) and Olley and Pakes (1996) are then applied to the data to calculate productivity.

particularly important: prices may reflect idiosyncratic demand shifts meaning that firms (county-industries) which appear to be highly productive may not necessarily be particularly efficient.[7] Crop yield overcome the problems associated with these measurement issues. Moreover, we use homogenous products in which there is little quality variation; field corn and soybeans are much the same regardless of the production location. This has the attractive property that physical productivity measures are more meaningful when quality variation is minimal (Foster et al., 2008). To remove any outliers from the data we winsorize the crop yields for each industry separately at the 1st and 99th percentiles.[8]

[INSERT TABLE 1]

In the empirical section we control for a host of potential confounding factors that might explain productivity. One important factor is likely to be the number of operating firms as this affects both the degree of competition (Schmitz, 2005) and product substitutability (Syverson, 2004). We take data on the number of firms per capita operating within each 5-digit NAICS industry in each county from the NASS. This data is collected as part of the U.S. Census for years ending in '2' and '7'. We therefore have data for the corn (NAICS 11115) and soybean (NAICS 11111) industries for the years 2002 and 2007. In the empirical analysis we apply the figures for 2002 across the years 2000 to 2004 and the data for 2007 to the period 2005-2010. Given the reporting dates lie roughly in the middle of each period, it seems reasonable that the data are representative of conditions in the two industries during each period.

From this there is evidence of either retrenchment or consolidation within the soybean sector where the number of firms per county falls from 104 in 2002 to 61 in 2007. In part this may reflect farmers switching to corn production although according to USDA (2010) the number of planted soybean acres remained constant during the period but small farms exited the industry. On the other hand we observe net entry in the corn sector where the number of firms increased from 127 to 150 firms per county, a possible indication that the increase in corn production was also driven by the entry of new firms.

In Table 1 we also report summary information on other factors that enter as independent variables in the econometric section of the paper. Given the importance of external finance to productivity growth (Butler and Cornaggia, 2011) we include the number of banks and total bank deposits taken from SNL Financial. We also include measures of population density (from the US Census Bureau) as a proxy for urbanization as relatively low productivity land may be brought into production as towns and cities spread. Finally, information on the average real dollar value of inputs used per acre in the two industries is reported in Table 1.

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[7]Foster et al. (2008) show that the distinction between physical TFP (measured in physical output) and revenue TFP (measured using data on firm sales) is important and that each component plays a role in the selection process. They show that failure to account for this can understate the impact of demand-side influences on firm survival.

[8]The results are unchanged if we do not winsorize the data or choose alternative thresholds.

4. U.S. Legislative Changes and the Ethanol Industry

The background to the period we study begins with the mandated use of oxygenates in gasoline in the 1990 Clean Air Act. Enforcement did not occur immediately however, this started in 1995 when the U.S. Environmental Protection Agency sought to address air quality through the Winter Oxygenate Fuel Program and the Reformulated Gasoline Program. These programs were initiated in response to evidence that poor air quality in certain regions of the United States was damaging health, and that the source of this was the pollution from the burning of gasoline. The Winter Oxygenate Fuel Program and the Reformulated Gasoline Program sought to address this problem by improving the efficiency with which the fuel was turned into heat. This was to be achieved by mandating that gasoline must include a certain percentage of oxygenate; 2.7% under the WOFP and 2.0% under the RFG, where the RFG stipulated that this was year-round. The main oxygenates blended with gasoline were Methyl Tertiary Butyl Ether (MTBE) and ethanol, for which corn is the primary input. Outside of the Midwest MTBE was used as the main oxygenate for gasoline. In the Midwest it was ethanol, where this difference is generally attributed to a desire in corn producing states help bolster agricultural markets. Ethanol was commonly less used outside of these states because its characteristics, primarily its greater volatility, made it less attractive to refiners of gasoline and because MTBE could be produced at lower cost (Tiffany, 2009).

The dominance of MTBEs as an oxygenate changed when MTBE was detected in water supplies. Bans on the use of MTBEs were introduced in some farm states such as Minnesota as early as 2000, but were adopted by heavy users of MTBEs, such as California, from 2004 when the health concerns became better known.[9] This preference for the use of ethanol was further reinforced when the Energy Policy Act of 2005 was presented to the House of Representatives in order to tackle the country's growing energy problems. The Act, introduced amid a backdrop of rising oil prices and fear surrounding the future security of overseas energy sources, constituted a multi-faceted approach to address these concerns. Part of this strategy focused on encouraging existing nuclear and fossil fuel energy sources through subsidies, loan guarantees and drilling incentives in the Gulf of Mexico. But the legislation also sought to foster green energy technologies and to stimulate greater use of biofuels in gasoline. The Act mandated that the amount of ethanol (biofuel) contained in gasoline should rise from 4 billion gallons in 2006 to 7.5 billion in 2012. But, as importantly, the Act failed to grant the manufacturers of MTBE liability protection from environmental damage and health claims.[10]

To achieve the target in the use of ethanol in gasoline the EPA approved the payment of the VEETC, worth 51 cents per gallon of gasoline, to US ethanol manufacturers.[11] The subsequent Energy Independence and Security Act of 2007 established the goal of achieving

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[9] California originally introduced a ban on 1st January 2003, but this was delayed by one year out of concern for potential supply disruptions.

[10] The United States Environmental Protection Agency made this applicable to fuel used in both older and newer (post-2001) vehicles, all motorcycles, heavy-duty vehicles and non-road engines (for example, motorboats).

[11] The Volumetric Ethanol Excise Tax Credit was only paid to gasoline manufacturers, not corn producers.

energy independence and security through greater use of alternative energy sources. The EISA extended the previous ethanol targets and mandated that 36 billion gallons of ethanol should be contained within gasoline by 2022.[12]

[INSERT FIGURE 2] [INSERT FIGURE 3]

The combined effect of the Act and EISA and its failure to provide liability protection for MTBE producers was to create a large, exogenous increase in demand for corn, which is used as the primary ingredient in around 90% of US produced ethanol. Moreover, this demand shock occurred as a result of legislation passed outside of the corn producing states, which had largely already banned MTBEs.

The extent of the demand shock on the demand for corn is apparent from Figure 2. In 2004 approximately 11% of corn produced in the United States was used in ethanol production. By 2010 the figure was 40%. The moderate increase in the share of corn used in ethanol production during 2001-2004 is due to state bans on MTBE in some states. Production of corn-based ethanol in the United States rose from 1.63 billion gallons in 2000 to 4.86 billion gallons in 2006 (Renewable Fuels Association, 2007). There is also a discernible rise in the level of corn production coinciding with the passage of the EPA - corn production was 22.4% higher during the period 2005 to 2010 compared with the previous five years. However, according to the NASS the number of planted acres of corn increased by 12% between periods, a first indication of productivity increases within the corn sector. As is made apparent in Figure 3 the ethanol-based demand shock was additive and did not displace other demand sources such as animal feed or exports.

[INSERT FIGURE 4] [INSERT FIGURE 5]

The increase in the production of ethanol necessitated an increase in the number of ethanol production plants. Since 2002 the Renewable Fuels Association (RFA) has published *The Ethanol Industry Outlook* on an annual basis. This contains aggregate-level information on the volume of ethanol produced throughout the United States as well as more detailed information on the location, size (measured in millions of gallons), feedstock and owner of ethanol production plants.

The majority of ethanol plants are single-plant firms. Approximately 87% of U.S. ethanol plants use corn as a feedstock. In most cases these plants only use feedstock to produce ethanol (81%). Although there are a small number of ethanol plants that use cheese whey, beverage waste and potato starch to produce ethanol, the operating capacity of these plants (<4 mgy) is typically much smaller compared to those plants that use corn (73 mgy). In the empirical analysis we include only ethanol plants that use corn to produce ethanol on the

[12] Around this time the United States Environmental Protection Agency set a target of achieving a 10% ethanol content in gasoline. According to USDA (2010) by 2009 the ethanol market share of the U.S. gasoline industry had reached 8% as a result of the energy legislation. E10, gasoline with a 10% ethanol content, is readily available throughout mid-western states. It was mandated for use by all motor vehicles in Florida by 2010 and is available in many other U.S. states. E10 can be used in all vehicles with no engine modifications required.

basis that where ethanol production affects productivity these are the only plants likely to be relevant to corn farmers.

Visual evidence on the aggressive expansion in the number of ethanol plants between 2002 and 2010 is shown in Figure 4 and Figure 5 which displays information on the average number of plants and the total operating capacity within a 200 mile radius of each county. Both show initial evidence of a significant increase in the period after the passing of the EPA, with the average number of ethanol plants increasing from a little over 10 at the start of the period to around 35 by the end of the period. Figure 11 displays the distance to the nearest ethanol plant. Again there is evidence of clear downward trend that accelerates after 2005.

[INSERT TABLE 2]

We use Table 2 to report on regression evidence that the increase in the number of ethanol plants is associated with the passing of the Energy Policy Act in 2005. In this table we report regressions for 0/1 indicator of there being an ethanol plant in country *c* at time *t* (regression 1); total operating capacity in mgy (in natural logarithms) of all ethanol plants located within a 200 mile radius of county *c* at time *t* (regression 2); total ethanol plant capacity in mgy (in natural logarithms) currently under construction within a 200 mile radius of county *c* at time *t* (regression 3); and the distance to the nearest ethanol plant of county *c* at time *t* (regression 4). Treatment refers to the post-EPA period (2005-2010). In all regressions we include county and year effects. We find from this table strong evidence of an increase in the number, capacity and construction of ethanol plants that is associated with the EPA.

Also apparent in Figure 4 is the strong geographical concentration of the ethanol industry in the mid-west. This raises a question about what factors determine the location of ethanol plants. Why are they concentrated near the production of corn, rather than say gasoline refineries, in particular given the volatile nature of ethanol? And, are locations chosen where corn yields are highest, or have the potential for rapid productivity growth? Sarmiento et al (2012) argue that for the first question a key factor are the distillers' dry grains (DDGs) which are the principal by product of ethanol production. These have a low-value but a high cost of shipping and can be used as a feedstock for farm animals.[13] This would appear to suggest that location is determined by the characteristics of a by-product of ethanol production and is independent of corn yields.

Sarmiento et al (2012) also provide more formal evidence on the location of new ethanol plants. Here the major determinant would appear to be competition from other ethanol plants. Using data for ethanol plant entry for 2,979 counties over the period 1995 to 2005 and a discrete spatial autocorrelation model they find that the probability of a new ethanol plants locating what within a 30 mile radius of an existing ethanol plant is significantly

[13] The maximum amount that can be used in rations varies by animal type and herd composition. The rate of adoption of DDGs for corn is less than the rate of substitution in corn rations. The substitution rate of DDGs for corn in livestock is 40 lbs. of corn displaced by 400 lbs. of DDGs; and for swine and poultry, 177 lbs. of corn is displaced by 200 lbs. of DDGs (Urbanchuk, 2003).

reduced, but by 60 miles this distance effect is close to zero. They infer from this a strong desire to avoid competition in procurement of corn from other ethanol plants. They also find a spatial lag associated with corn acreage, with the corn acreage of neighbouring counties having a strong positive effect on new entry. They interpret this as a need to procure corn from neighbouring counties. In contrast they find no significant evidence of corn yields (or indeed corn prices) as a predictor of the location of new plants.

[INSERT TABLE 3]

We find similar evidence in Table 3. Here we report probit regressions for a 0/1 indicator of an ethanol plant within the county. We find from the table strong evidence that new production plants were opened in locations where there were currently few other plants rather than locations with high corn yields. The probability of a county having an ethanol plant is a decreasing function of the number of ethanol plants within a 100 or 200 mile radius. In contrast the level of corn production or productivity within the county has no significant effect on this decision.

In summary: ethanol is very relevant to the corn industry because it is an important component of ethanol production. Ethanol production and the demand for corn are therefore very likely to move together. Ethanol demand is also unlikely to be affected by productivity in the production of corn. The demand for ethanol as an oxygenate for gasoline is instead determined by the legislative changes discussed and the demand for gasoline more generally. Given this is likely to be strongly associated with the state of the economy and the price of gasoline it seems reasonable to assume that movements in the productivity in the production of corn are uncorrelated with the demand for ethanol, satisfying the exogeneity criterion.

5. Research Design

We take two approaches to deal with the more difficult issue of unobservable factors both of which exploit the considerable cross-time variation in the demand for corn that exists within the data period. The first approach builds on this but uses introduction of the 2005 US Energy Policy Act as a discrete shift in the demand for corn and considers the productivity changes in corn production relative to a crop that is not used in ethanol production, namely soybeans.

Our identification strategy in this part of the paper exploits: a) the productivity response to the cross-time change in demand and b) differences in the response of productivity between the treatment (corn) and control (soybeans) groups. We therefore estimate a model of the form:

$$\varphi_{ict} = \alpha + \beta_1 Corn_{ic} * Treatment_t + \delta X_{ict} + \gamma_{ct} + \gamma_{ic} + \varepsilon_{ict}, \qquad (1)$$

where φ_{ict} is productivity in industry i in county c at time t, $Corn_{ic}$ is a dummy equal to 1 if the industry produces corn and zero otherwise, $Treatment_t$ is a dummy equal to 1 for the years 2005-2010 (the 'ethanol period') and zero otherwise, X_{ict} is a vector of other control variables and ε_{ict} is a stochastic error term.

As we argue in detail, demand for ethanol is unlikely to be itself affected by productivity changes of corn producers. Simultaneity bias therefore would seem an unlikely explanation of the results that we find.[14] A greater providence in the current context are the effects of observable as well as more difficult to observe shocks that affect both the incentive to invest in productivity but also the demand for ethanol. To deal with observable factors we add to the regression a set of controls which capture changes to the demand and supply of corn. To control for observable supply side factors we include within X the (log) number of growing days within the country and the participation levels.

As well as the control variable described in Section 3 we include a full set of county-year dummies (γ_{ct}) and county-industry effects (γ_{ic}).[15] These will capture factors at the county level (such as infrastructure improvements and ethanol plants) and more aggregate variables (infrastructure, policy, price effects etc.) that change through time that may affect the incentive to make productivity enhancing investments in both sectors. Another attractive property of including county-year effects in the model is that the treatment effect of the demand shock is identified through between industry variation within the county-year dimension, thereby providing a very clean test of the hypothesis. The county-industry effects will capture any differences in the natural productivity of the land for producing corn or soybeans.[16]

Following Bertrand et al. (2004) we cluster the standard errors at the county level. This is motivated by the possibility that by focusing on serially correlated outcomes, difference-in-difference estimators produce spurious results by underestimating the true magnitude of the standard errors. In the context of this paper this is likely to be a valid concern. For example, where productivity enhancing investments are irreversible, investments that raise productivity in year t may mean that productivity is high in period t+1 and all future periods.[17] Bertrand et al. (2004) demonstrate that clustering is a suitable means of obtaining the correct standard errors although we also experiment with block bootstrapping and collapsing the sample into single pre- and post-treatment periods as they also suggest in the following section.

As mentioned previously in Section 3, the treatment period coincides with a change in the behavior of soybean producers: there is substantial net exit in soybeans and net entry in the corn sector. Given the similarities between production methods in both industries it may be

[14] Simultaneity bias would also imply that the EPA was enacted in order to raise productivity in the corn industry. Careful inspection of the EPA documents indicate this was not the case. Moreover, data on contributions to the National Corn Growers Association, the corn industry lobby group, remain static in the years preceding 2005 implying that farmers were unaware of the treatment (see http://www.opensecrets.org).

[15] The corn dummy is collinear with the county-industry dummy meaning that it is dropped from equation (6). Likewise the treatment dummy is omitted due to the presence of the county-year effects.

[16] The experimental evidence reported in Grau et al. (2002) suggests that soil pH values have a large effect on soybean yield loss through soybean cyst nematode and brown stem rot.

[17] The coefficient estimate of the first order autoregressive parameter is 0.9309 (t-statistic = 313.39) showing that productivity is serially correlated across time.

possible that soybean producers switched to corn production post 2005. The incentive to do so was greatest for low productivity producers that could earn higher profits by producing corn (because of the increase in prices) rather than soybeans. According to the data plotted in Figure 6, the large amount of exit from soybean production did not beget productivity declines. Together with the evidence that it was mainly small firms that exited (USDA, 2010), this tends to suggest that low-productivity firms exited soybean production.[18] A possible limitation to using a difference-in-difference estimation strategy is that we underestimate the implied counterfactual. Because low productivity soybean firms switch into corn production, the treatment effect will be biased downwards.

The second estimation approach deals accounts for this possibility by using cross-county differences in the demand for corn by ethanol plants in an instrumental variable approach. Specifically, we estimate the following equation

$$ln\varphi_{ct} = \alpha + \beta_1 lnD_{ct} + \delta X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ict} \ , \qquad (2)$$

where φ_{ct} is productivity of corn production in county c at time t, D_{ct} is the demand for corn, X_{ct} is a vector of other control variables and ε_{ict} is a stochastic error term. We proxy for the demand for corn in equation (2) using the operating capacity of ethanol plants within a 200 mile radius of each county.

Our instrument set is as follows:

1. Distance between county c and the nearest county containing an operating ethanol plant in year t. We anticipate that because ethanol plants incur the shipping costs, counties that are located close to ethanol plants will have the greatest demand shock.

2. Number of cattle on feed in county c at time t. As outlined by Sarimento et al. (2012) DDGs are a key consideration in ethanol plant location. Owing to the high costs associated with transporting DDGs, an ethanol plant is more likely to be located nearby counties with large numbers of livestock on feed. In turn this influences the proximity of ethanol-based demand for corn.[19]

The construction of our instrument set draws closely on the ideas in Syverson (2004) that an industry or economy-wide market is actually comprised of a collection of heterogeneous local markets which can then be exploited in the construction of appropriate instrumental variables.

We also include county-fixed effects (γ_c) in equation (2) to control for time invariant county specific factors such as altitude, latitude and soil conditions that might generate differences in the yield across counties. On the demand side we control for the number of acres planted, exports of corn, the price of corn within the state, the subsidy rate and the

[18] Firm size has long been shown to be highly correlated with productivity (Helpman et al., 2004).
[19] We were only able to extract information for the number of cattle on feed within each county from the NASS. Similar data for swine and poultry was not available.

number of banks within the county. Year fixed effects (γ_t) are also included in the estimating equation.

6. Empirical Results

We begin the empirical analysis by providing some simple descriptive analysis of the data. We then examine the hypothesis more formally by testing whether the positive demand shock arising from passage of the Energy Policy Act of 2005 affected productivity within the corn industry compared to the soybean industry in a difference-in-difference approach. Finally we present the results from the instrumental variable regressions in Section 6.3.

[INSERT FIGURE 6] [INSERT FIGURE 7] [INSERT FIGURE 8]

Even within the raw data we find evidence that the demand shock may have caused productivity to increase in the corn sector. In Figure 6A yield per acre is clearly higher post-2005 in the corn sector compared to the soybean sector where the productivity gain is comparatively small. If anything corn farm productivity evolves negatively in the years preceding the introduction of the Act although 2004 is an exception.[20] There are also clear differences in the average productivity level across the crops. Whereas an acre of land tends to yield almost three times as many bushels compared to soybeans the flipside is that a bushel of soybeans retails for approximately three times as much. First evidence of a treatment effect emerges from Figure 6B. Here we plot the change in mean productivity between the pre- and post-treatment period for each county-industry. Although productivity falls for some corn producers, the general tendency is towards productivity gains. In the majority of counties the size of these gains are larger among corn producers than soybean producers. Figure 7 confirms that following the demand shock, there was a clear rightward shift of the productivity distribution. Additionally, we find an increase in the minimum productivity to occur in both sectors, but the size of the increase is markedly larger for corn (138% compared to 22% for soybeans).

The data also provide some initial evidence that the productivity improvement is associated with the opening of new ethanol plants. This is shown in Figure 8 where we display corn productivity in the three years before and after the opening of a new ethanol plant. As can be seen productivity rises significantly.

6.1 Difference-in-Difference Results

[INSERT TABLE 4]

In Table 2 we provide the results of difference-in-difference estimates of equation (1) before subjecting the results to increasingly stringent testing procedures.

[20] The increase in corn productivity in 2004 may be due to producers responding to the sharp increase in corn prices that resulted from supply shocks in both the U.S. and Brazil.

The results reported in the first column of Table 1 show strong support for our main hypothesis: the demand shock caused corn producers to increase their productivity by 8.19 bushels per acre relative to the control group. Our results therefore identify a new channel that influences productivity: changes in the demand environment directly cause firms to make productivity investments. Why might this be the case? A permanent positive demand shock reduces the uncertainty surrounding the future level of demand, makes available new revenues, and raises the expected returns to investment, all of which might be expected to encourage firms to invest to raise their productivity.

What are the mechanisms underlying this effect? Theory predicts that expansions in market size lead incumbents to produce higher levels of output. Under these conditions the marginal costs of production become more important relative to fixed costs which spur firms to make investments to become more efficient. In effect, firms must decide whether to respond to the increase in output through the extensive or intensive margin. The larger is the increase in output, the greater is the incentive to invest in productivity because of diminishing returns to employing factor inputs.

Our core finding is in line with the theoretical predictions made by Desmet and Parente (2010) and Chaney and Ossa (2012). However, in terms of the mechanism involved, the framework proposed by Chaney and Ossa represents a better fit with observed behavior in the corn industry. In their model productivity improvements arise because firms hire more production teams (and thereby incur fixed investment costs) leading to a deeper division of labor. The higher degree of specialization reduces marginal costs (increases productivity) as each team can focus on its core competences. Although we do not view the division of labor to be the vehicle through which the productivity gains accrued, the evidence we present in subsequent sections of the paper augurs with the idea that demand shocks cause firms to invest in altering the production process.

The average treatment effect reported in column 1 of Table 1 is estimated conditional on the number of firms in the country-industry. This variable is included as a proxy for the intensity of competition producers face but could equally measure the productivity effects of agglomeration (Coombes et al., 2012) or product substitutability (Syverson, 2004). We find that increasing the number of firms operating in a county is predicted to increase crop yields. We also control for economies of scale by including a variable measuring the number of planted acres. Here we find an insignificant relationship although in subsequent regressions a positive effect is found.

Agricultural yields are closely tied to meteorological conditions. Insufficient rainfall and low temperatures over the course of the growing season tend to result in lower yields. The results indicate that precipitation and temperature, as measured by the sum of growing degree days, are both positively correlated with yield. The final control variable we include is designed to capture the quality of land used in agricultural production. In more urban environments increasingly marginal land may be used thereby reducing productivity. We find that urbanization is positively related to productivity but that the effect is weak.

As outlined previously, there is a distinct possibility that in the context we consider the difference-in-difference estimator may yield artificially low standard errors because productivity investments are long lasting. Although we cluster the standard errors at the group level (the county) to obviate such concerns we also test the robustness of our findings to application of the collapse procedure recommended by Bertrand et al. (2004).[21] To conduct this robustness check we define the pre-treatment period as the years 2000-04 with the remaining years constituting the post-treatment group. Yield and the other control variables are collapsed upon their mean values for each county-industry-period. In order that we replicate the results in column 1 as closely as possible we include period effects, the natural extension of the year dummies, which take a value of 0 for the pre-treatment period and 1 otherwise. The results of this exercise are reported in column 2 of Table 1. We continue to find emphatic support for our core hypothesis although the corn-treatment interaction coefficient is now slightly higher at 4.83 compared to the results in column 1.

Our research design is founded upon the belief that there may be a number of difficult to observe variables that may explain agricultural yields. In columns 1 and 2 we assumed that these were either time invariant, applicable to all counties or were captured by climatic conditions, population density and industry structure. To deal with the more difficult issue of unobservable factors, in column 3 we include county-industry dummy variables in the estimating equation to capture time-invariant county-level characteristics which may have a differential effect on the productivity of each crop. Corn may grow better relative to soybeans in certain soil profiles while some counties may be better suited to growing crops, because of their latitude or altitude for example. The inclusion of county-industry dummies in the regression changes the source of identification in the model. The demand shock is now identified by variation within the county-industry across time. Despite these changes the results remain highly statistically significant but the economic magnitude of the treatment effect is considerably greater than in column 1. The demand shock is now estimated to cause productivity in the treatment group to increase by 6.92 bushels per acre.

The structure of our data set provides sufficient variation that we are also able to eliminate myriad unobservable time-varying factors that may be coincident with the demand shock. In column 4 of Table 4 we append the estimating equation with county-year dummy variables. While inclusion of county-year effects wash out numerous potentially important omitted variables, the source of identification in the model now comes through between industry variation within the county-year dimension of the data. This provides a very clean test of our hypothesis as we now compare the productivity response of corn producers relative to soybean producers within the same county. Following this modification to the estimation procedure the treatment effect is estimate to be a 6.31 bushel per acre increase.[22] This corresponds to a 4.9% productivity gain among corn producers as a result of the change in the demand environment.

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[21] We choose to report these results rather than those obtained from the block bootstrap procedure on the basis that the Bertrand et al. collapse is appropriate where laws (the Act in this case) are passed at the same time for all treated units. The results are unchanged when we instead use block bootstrapping.

[22] We also experimented with including industry-year effects in the regression equation. However, it proved impossible to estimate the model with county-year, county-industry and industry-year dummies included simultaneously. However, the results were quantitatively similar, and remained highly significant when the model was estimated with county-year and industry-year dummies, or alternatively, county-industry and industry-year dummies included in the specification.

6.2 Parallel Trends and Alternative Control Groups

[INSERT FIGURE 9]

The crucial assumption underlying the difference-in-difference estimator is that of parallel trends. That is, in the absence of treatment, productivity in the corn sector would have evolved in parallel with soybean productivity. Following convention in the literature we check for this by examining the pre-treatment evolution of productivity in the two industries. In addition to our aforementioned concerns regarding the productivity effects of retrenchment in the soybean industry, Figure 9 provides evidence that based on trends in pre-treatment productivity, wheat and barley may represent superior control groups. We test the sensitivity of our results by estimating equation (1) using barley and wheat as the control group.[23] This does not alter our previous findings. The demand shock continues to cause significant productivity increases in the treatment group. The treatment effect is somewhat larger. When barley is used as the control group, the demand shock is found to increase corn firm productivity by 8.4%. When wheat is used in column 6 the estimated magnitude is 6.3%.

6.3 Instrumental Variables Estimates

Low switching costs between corn and soybean production raise the prospect that our DID results are biased downwards as the least productive soybean firms switch to corn production post treatment. To account for this we use an instrumental variables technique which exploits exogenous variation in the location of ethanol plants as instruments for demand. Our instruments are 1) the minimum distance between a county and the nearest county containing an ethanol plant and 2) number of cows on feed in the county. The intuition behind these instruments is that ethanol plants create demand for corn but because ethanol plants pay the shipping costs they prefer to buy corn located close by. Following treatment, distance is expected to be of less importance because ethanol producers need to buy more corn than before in order to meet higher demand for ethanol. At the same time ethanol plants are more likely to locate nearby a county with high demand for DDGs. A large fraction of DDG demand is due to cattle feeding.

[INSERT TABLE 5]

The instrumental variable estimation results are provided in Table 5. In the first stage we find that demand for corn in lower in counties that are further away from an ethanol plant but that this effect was lower following passage of the Act. We also find that the number of cattle on feed is positively related to ethanol demand but the effect is statistically insignificant. It seems that ethanol plants are more concerned about the cost of inputs rather than the propensity to sell DDGs.

[23] Both barley and wheat are not used to produce ethanol by any of the plants in our data set.

In the second stage we continue to find that the demand shock caused a significant increase in productivity. This effect is much larger than found previously. In column 1 of Table 5 we estimate that productivity increased by 9.9% because of the demand shock. When we include a number of time-varying control variables in the estimating equation the magnitude of the treatment effect is yet larger. In the results reported in column 3 we find a 26.2% productivity increase. The diagnostic tests confirm that our instruments are relevant (Cragg-Donald and Kleibergen-Paap F-statistics comfortably exceed the critical threshold of 10) and valid (the p-value on the exogeneity test is larger than 0.05 all columns of the table).

How does the impact of demand compare to other factors that have also been shown to influence productivity? By comparison adoption of modern management practices is estimated to raise firm productivity by 17% (Bloom et al., 2013). De Loecker (2011) reports a 4% productivity gain among Belgian textile firms following trade liberalization. The case studies of the U.S. iron ore and cement industries by Schmitz (2005) and Dunne et al. (2010) find TFP gains between 35% and 48% due to an increase in competition. Although comparison of such effects between studies is difficult due to contextual and industry environments, it is difficult to ignore the fact that demand is an important source of productivity improvement.

7. Why did Productivity Increase?

We next try to obtain a fuller understanding of *why* the demand shock spurred the large productivity improvements. In order to gain a fuller understanding of the mechanisms involved, we look to dissect what changes were made to the production process. As net entry/exit is less of a concern in this case, we choose to rely on a DID estimation strategy though the results are unchanged when instrumental variables are used instead.

[INSERT TABLE 6] [INSERT TABLE 7]

We first study how capacity utilization, as measured by the ratio of harvested to planted acres, evolves through time. In comparison to soybean producers, corn producers display substantially lower capacity utilization rates. For example, during the pre-treatment period only 87% of planted acres of corn were ever harvested compared to 97% for soybeans. The results in column 1 of Table 6 show that following treatment corn producers increased capacity utilization rates by 1.25 percentage points. Several factors may be responsible for this change. For example, more intense harvesting methods may be employed. Alternatively, the demand shock may simply have provided farmers with greater incentives to become more efficient in collecting corn perhaps by ensuring a greater portion of planted seed survive until maturity.

We also obtained data on county-industry expenditures on different inputs used in the production process. This information, available in the Iowa State University Cost of Crop Production database contains information on the dollar value of machinery, fertilizer, seed, herbicide and labor used per acre for all counties in Iowa between 2000 and 2010. We deflate these values using the NASS agricultural price index. Although the data are restricted to just one state we believe that Iowa provides a good barometer of national corn and soybean production. Of the states in our data, Iowa records the highest average yield for both crops suggesting that the producers located there are close to the technical frontier. Their response to the demand shock is therefore likely to reflect the optimal strategy.

In column 2 and 7 of Table 6 we find that machinery and labor expenditure actually decreased among corn producers following treatment. It would therefore seem that deepening the division of labor (Chaney and Ossa, 2012) or improvements to the capital stock (van Biesebroeck, 2003) did not bring about the productivity gains observed previously. However, we find strong evidence that seed and fertilizer were used more intensively because of the demand shock.

As shown in Table 7, the increase in fertilizer usage occurred across the board albeit to a lesser extent among ex ante low productivity firms. However, in line with evidence that there are diminishing returns to fertilizer application (Cerrato and Blackmer, 1990), the effect of higher fertilizer expenditure did not translate into one-for-one productivity increases. Whereas firms in the first quartile of the pre-treatment productivity distribution increased yields by 17.67 bushels per acre the increase was only 10.36 bushels for those in the upper quartile. These findings help to explain 1) the increase in average industry productivity, and 2) the rightward shift of the productivity survival threshold observed previously in Figure 7.

If such productivity gains were possible, a question that arises is why firms did alter the production process earlier? The evidence we uncover is consistent with the view that demand shock affect the expected return to investment. By reducing the uncertainty surrounding the future level of demand, a permanent positive demand shock makes available new revenues, and raises the expected returns to investment. Under these conditions firms can more easily overcome the fixed costs of investment leading them to raise productivity.

8. Alternative Explanations

Numerous explanations have been suggested for the widespread heterogeneity in firm productivity (see Bartelsman and Doms (2000) and Syverson (2011) for reviews). In order to rule out changes in the level of competition, aspects of fiscal policy or access to finance coincide with the treatment period in our data, we use a triple-difference specification that includes these factors directly in the estimating equation. The results of these robustness tests are relegated to Appendix 1. Although we find some evidence that high marginal corporate and income tax rates stymie the productivity response, our main findings remain robust.

9. External Validity - The High Fructose Corn Syrup Demand Shock

An important question is whether the results we have so far uncovered hold more generally or whether they are a consequence of the context and ethanol-based demand shock we study. In short, do the results have external validity and would we obtain similar results if we were to look at other demand shocks?

[INSERT TABLE 8]

In 1985 Coca-Cola and Pepsi switched from using a sugar cane-based glucose sweetener to high fructose corn syrup (HFCS). The change in sweetener was driven by cost concerns as HFCS was considerably cheaper than sugar cane. As approximately 90% of HFCS consumed in the U.S. is contained within soft drinks, the actions of the major cola manufacturers had a large impact on demand for corn: in the five years prior to 1985, HFCS production consumed 227 million bushels of corn per annum compared to 338 million between 1985 and 1990.

Again we draw upon data from the NASS for information on corn and soybean productivity in the Corn Belt. The treatment dummy takes a value of 1 for the years 1985 to 1990 and 0 for 1980 to 1984. Applying a DID estimation approach we estimate equation (1) using the new data set and report the results in column 1 of Table 8.[24] Demand continues to exert a large causal effect on productivity. Following the HFCS shock corn farms raised productivity by 10.74 bushels per acre, equivalent to a 11.8% productivity gain relative to pre-treatment levels.

10. Conclusions

The key result in this paper is that changes in the demand environment trigger productivity improvements.

Exploiting a natural experiment originating from modifications to U.S. energy policy, we use DID and instrumental variable estimation strategies to pin down the causal effect of positive demand shocks on productivity using data on physical output of mid-western corn and soybean producers. The economic magnitude of the treatment effect we uncover is large: the increase in demand caused productivity within the treatment group to rise by 26%. Our more detailed analyses illustrate that the increase in productivity is brought about by higher capacity utilization rates and through alterations in the production process by using more fertilizer inputs.

Our research builds on a quickly evolving body of literature that hones in on the potentially wide-ranging effects of demand on producers (De Loecker, 2011; Foster et al., 2008, 2012; Pozzi and Schivardi, 2012). In contrast to Syverson (2004) we document a direct causal link between the demand environment and firm productivity. Demand shocks lead to productivity improvements because at high levels of output the marginal costs of production become more important relative to fixed costs.

[24] Data on the number of firms is drawn from the 1982 and 1987 Census. The values for 1982 are applied across the years 1980 to 1984 and those for 1987 are applied to 1985 onwards.

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Tables

Table 1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max	Level of Aggregation	Data Source
Corn yield	10,170	136.11	32.11	22.10	203	County	NASS
Soybean yield	9,579	40.37	9.50	10.40	62	County	NASS
Barley yield	4,914	63.71	23.10	0	177	County	NASS
Wheat yield	1,511	54.39	12.71	11	93.3	County	NASS
Capacity utilization	19,749	93.77	0.11	0.01	1	County	NASS
Machinery per acre ($)	2,152	30.83	3.71	13.63	42.65	County	Iowa State University
Fertilizer per acre ($)	2,152	24.40	25.31	0.55	108.92	County	Iowa State University
Herbicide per acre ($)	2,152	21.41	7.13	6.05	39.20	County	Iowa State University
Seed per acre ($)	2,152	35.04	14.65	14.05	92.98	County	Iowa State University
Labor per acre ($)	2,152	20.10	2.53	9.09	26.13	County	Iowa State University
Corn firms	9,867	143.12	141.81	1	1034	County	NASS
Soybean firms	9,248	82.20	75.59	1	645	County	NASS
Number of banks	19,749	7.92	7.60	1	171	County	SNL Financial
Population density	19,749	116.48	325.99	0.5	5685.60	County	US Census Bureau
Ethanol production site	19,749	0.12	0.36	0	4	County	RFA Outlook
Corporate tax rate	19,749	7.00	3.15	0	12	State	The Tax Foundation
Income tax rate	19,749	5.75	2.43	0	14	State	The Tax Foundation
Precipitation (mm)	19,749	2.63	1.24	0	8.8	County	Weather Underground
Growing degree days (ln)	19,749	7.96	0.31	3.97	8.47	County	Weather Underground
Population density	19,749	106.51	256.87	0.48	3286.41	County	U.S. Census Bureau

Table 2: Ethanol Industry Evolution

Regression No.	**1**	**2**	**3**	**4**
Dependent variable:	**Ethanol Plant$_{ct}$**	**Operating Cap.$_{ct}$**	**Construction Cap.$_{ct}$**	**Min. Distance$_{ct}$**
Treatment	0.1042**	2.5137**	1.1439**	-34.6335**
	(12.43)	(18.01)	(3.90)	(-26.97)
Observations	8,431	8,417	8,431	8,431
R^2	0.74	0.67	0.50	0.72
County effects	√	√	√	√
Year effects	√	√	√	√

Notes: ** denote significance at the 1% level. Heteroskedastic robust standard errors are used and the associated t-statistics are reported in parentheses. Treatment refers to the post-EPA period (2005-2010). The ethanol plant variable takes a value of 1 if there is an ethanol production plant within county *c* at time *t*. Operating Cap. is the total operating capacity in mgy (in natural logarithms) of all ethanol plants located within a 200 mile radius of county *c* at time *t*. Likewise Construction Cap. is the total ethanol plant capacity in mgy (in natural logarithms) currently under construction within a 200 mile radius of county *c* at time *t*. Min. Distance is the number of miles between a county and the nearest county housing an operating ethanol plant.

Table 3: Ethanol Plant Locations

Regression No. **Dependent variable: ethanol plant$_{ct}$**	**1**	**2**
Corn production (ln)	-0.1225	-0.0600
	(-0.87)	(-0.43)
Yield	0.0040	0.0033
	(1.45)	(1.21)
Plants within 100 miles	-0.0348**	
	(-5.35)	
Plants within 200 miles		-0.0665**
		(-4.57)
Observations	8,239	8,239
County effects	√	√
Year effects	√	√

Notes: ** denote significance at the 1% level. Robust standard errors are used and the associated t-statistics are reported in parentheses. Production is the natural logarithm of the number of bushels of corn produced within the county and yield is corn yield within the county. Plants within 100 (200) miles represents the total number of plants within a 100 (200) mile radius of county *c* at time *t*.

Table 4: Productivity Response to the Demand Shock

Regression No.	**1**	**2**	**3**	**4**	**5**	**6**
Control group	**Soybeans**	**Soybeans**	**Soybeans**	**Soybeans**	**Barley**	**Wheat**
Dependent variable: Yield_{ict}						
Corn	91.6088**	90.3113**				
	(152.13)	(81.90)				
Treatment	8.4355**	6.2451**	6.0154**			
	(16.00)	(11.08)	(11.91)			
Corn * Treatment	3.7065**	4.8263**	6.9216**	6.3120**	10.8243**	8.0515**
	(8.51)	(4.13)	(14.63)	(8.98)	(2.97)	(10.48)
Number of firms	0.0706**	0.0663**	0.0111*	0.0102		
	(14.26)	(9.30)	(2.51)	(1.63)		
Acres planted	-0.0000	-0.0000	-0.0000**	0.0001**		
	(-1.61)	(-0.65)	(-2.60)	(3.56)		
Precipitation	2.2494**	3.1466**	2.1402**			
	(14.44)	(7.03)	(13.36)			
Growing degree days (ln)	1.1771*	-1.0755	1.2143*			
	(2.15)	(-0.42)	(2.17)			
Population density	0.0213+	0.0472+	0.0191			
	(1.78)	(1.65)	(1.55)			
Observations	19,115	3,561	19,115	19,115	15,084	15,338
R^2	0.93	0.93	0.94	0.98	0.99	0.97
County effects	√	√				
Year effects	√		√			
Ethanol period effects		√				
County-industry effects			√	√	√	√
County-year effects				√	√	√

Notes: +, *, ** denote significance at the 10%, 5% and 1% levels respectively. Standard errors are clustered at the county level and the accompanying t-statistics are reported in parentheses. The treatment dummy refers to the post-EPA period (2005-2010). In column 5 (6) the control group is barley (wheat). The Bertrand et al. (2004) collapse procedure is used in column 2.

Table 5: Instrumental Variables Regressions

Regression No.	1	2	3
Second stage IV: dependent variable ln($Yield_{ct}$)			
Treatment = ln(Demand)	0.0994*	0.0950*	0.2617**
	(2.39)	(2.37)	(3.54)
Number of firms		0.0004**	0.0009**
		(2.94)	(3.24)
Acres planted (ln)		-0.0759**	-0.1036**
		(-3.84)	(-4.68)
Precipitation		0.0219**	0.0249**
		(6.99)	(6.98)
Growing degree days (ln)		0.0192*	0.0216**
		(2.29)	(2.61)
Population density		0.0003	0.0009*
		(0.92)	(2.30)
Number of banks			-0.0002
			(-0.13)
Farm Subsidy			-0.0000
			(-0.02)
Price			-0.0541**
			(-3.49)
Exports			0.0575
			(0.34)
GE seed usage			-0.0062**
			(-6.95)
First stage IV: dependent variable ln($Demand_{ct}$)			
Min. distance	-0.1626**	-0.1767**	-0.1311**
	(-6.07)	(-6.51)	(-5.19)
Cattle on feed (ln)	0.0043	0.0055	0.0047
	(0.78)	(0.91)	(0.77)
Cragg-Donald F-statistic	85.24	97.75	51.74
Kleibergen-Paap F-statistic	18.58	21.42	13.66
Exogeneity test (p-value)	0.72	0.50	0.55
Observations	7,826	7,641	7,641
County effects	√	√	√
Year effects	√	√	√

Notes: * and ** denote significance at the 5% and 1% levels respectively. Standard errors are clustered at the county level and the accompanying t-statistics are reported in parentheses. For reasons of parsimony we choose not to report the first-stage coefficient and t-statistics for the included instruments.

Table 6: Productivity Mechanism

Regression No.	1	2	3	4	5	6
Input type	**Fixed**		**Variable**			
Dependent variable	**Cap. Utiliz.$_{ict}$**	**Machinery$_{ict}$**	**Fertilizer$_{ict}$**	**Seed$_{ict}$**	**Herbicide$_{ict}$**	**Labor$_{ict}$**
Corn * Treatment	0.0125**	-0.9798**	18.0046**	19.4785**	0.3266+	-2.0059**
	(5.54)	(-4.76)	(34.55)	(40.98)	(1.69)	(-15.22)
Observations	19,749	2,152	2,152	2,152	2,152	2,152
R^2	0.95	0.90	0.93	0.89	0.94	0.90
County-year effects	√	√	√	√	√	√
County-industry effects	√	√	√	√	√	√

Notes: ** denote significance at the 1% level. The standard errors are clustered at the county level with the corresponding t-statistics reported in parentheses. All dependent variables are measured in real 2007 dollars per acre.

Table 7: Fertilizer Usage

	Pre-treatment		Post-treatment			
Productivity quartile	**Fertilizer**	**Yield**	**Fertilizer**	**Yield**	**Δ Fertilizer**	**Δ Yield**
1	28.86	98.75	44.51	116.42	15.66	17.67
2	34.73	119.48	52.22	134.48	17.49	14.99
3	40.84	142.71	58.72	153.86	17.87	11.15
4	44.42	153.67	62.24	164.03	17.82	10.36

Notes: Fertilizer measures the real dollar value of fertilizer applied per acre. Yield is the number of bushels produced per acre.

Table 8: External Validity

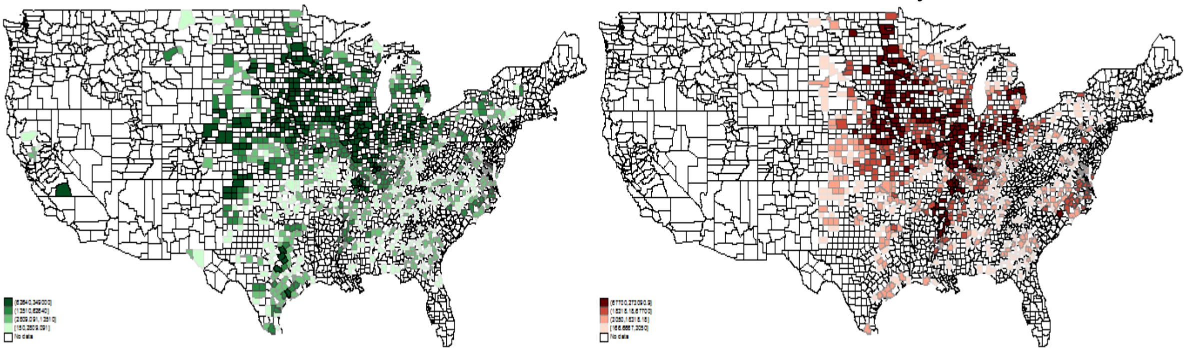
Regression No.	**1**
Shock	**HFCS**
Dependent variable:	**$Yield_{ict}$**
Corn * Treatment (HFCS)	10.7411**
	(18.97)
Number of firms	0.0092*
	(2.52)
Acres planted	0.7264*
	(1.31)
Observations	21,114
R^2	0.96
County-industry effects	√
County-year effects	√

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

Figures

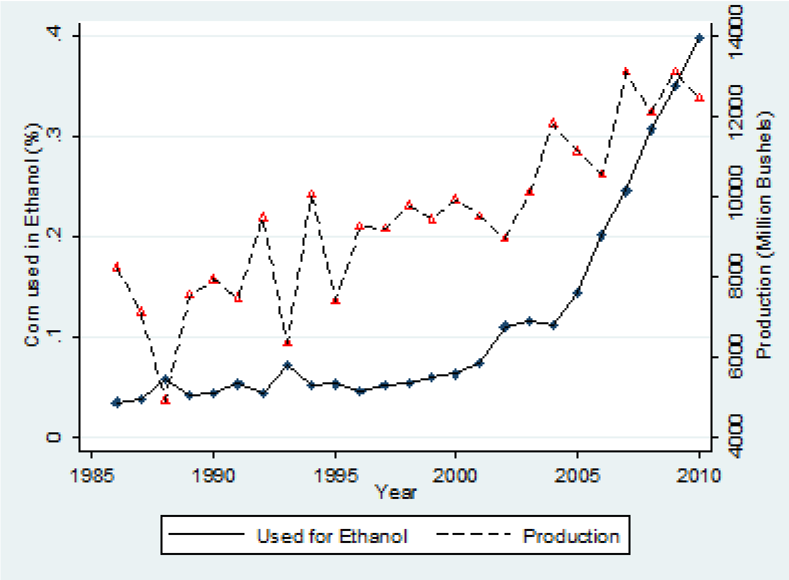
Figure 1: Average Planted Acres 2000-2010

A. Corn **B: Soybeans**



Notes: Darker shading corresponds with a larger number of planted acres. Counties with no shading have zero planted acres.

Figure 2: Share of U.S. Corn Production in Ethanol



Notes: Corn production data is from the NASS (quick stats). Corn used for ethanol is from the USDA Economic Research Service – Feed Grains Database.

Figure 3: Sources of Corn Demand

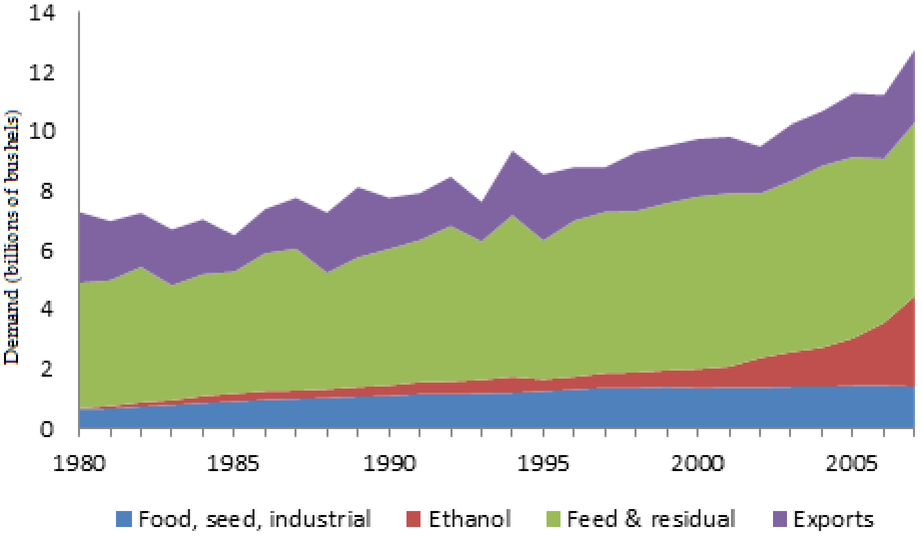
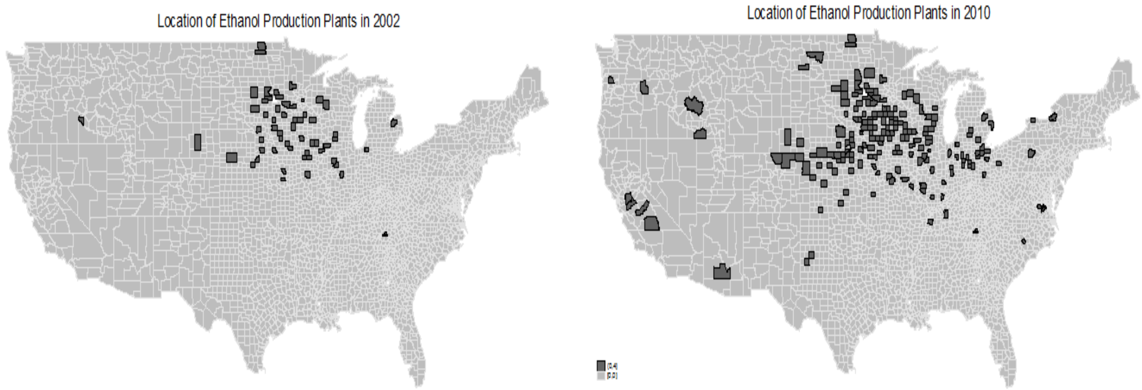
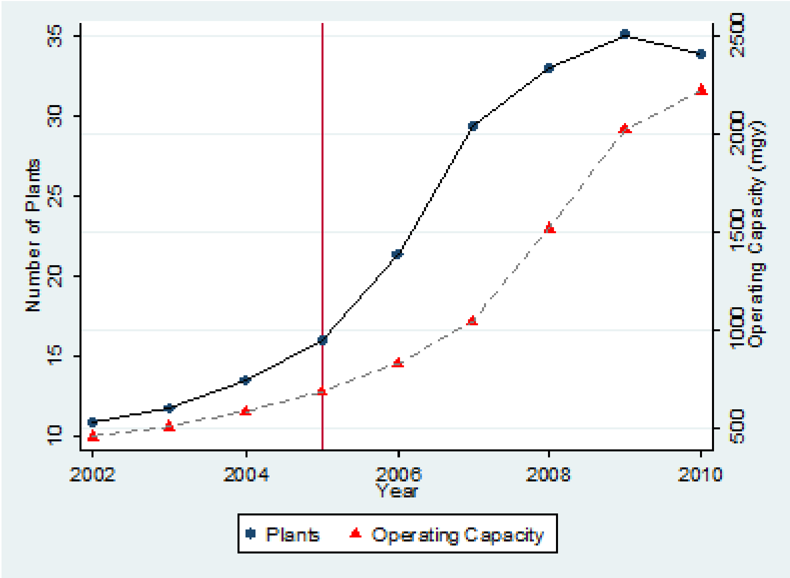


Figure 4: Ethanol Plant Location



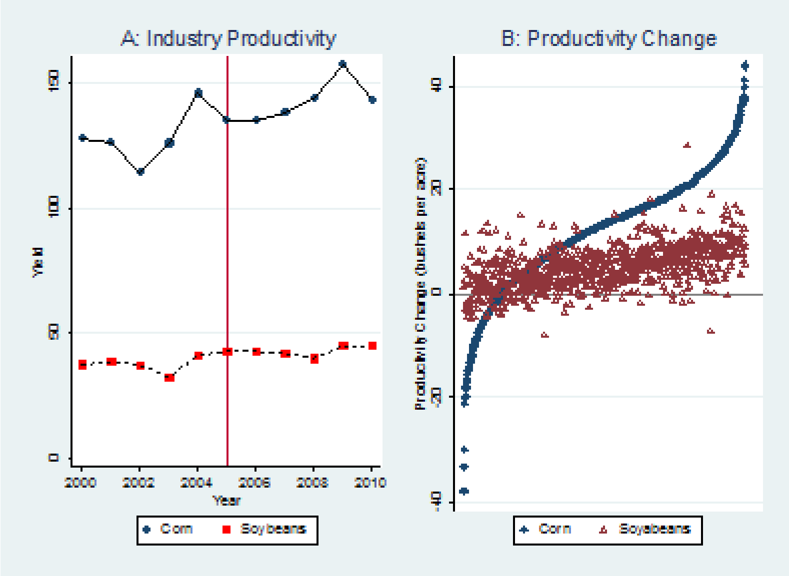
Notes: The figure plots the location of US counties in which ethanol production plants are located. All ethanol plants contained in the figure use corn as their main, or as one of their main, feedstocks.

Figure 5: Evolution of the Ethanol Industry



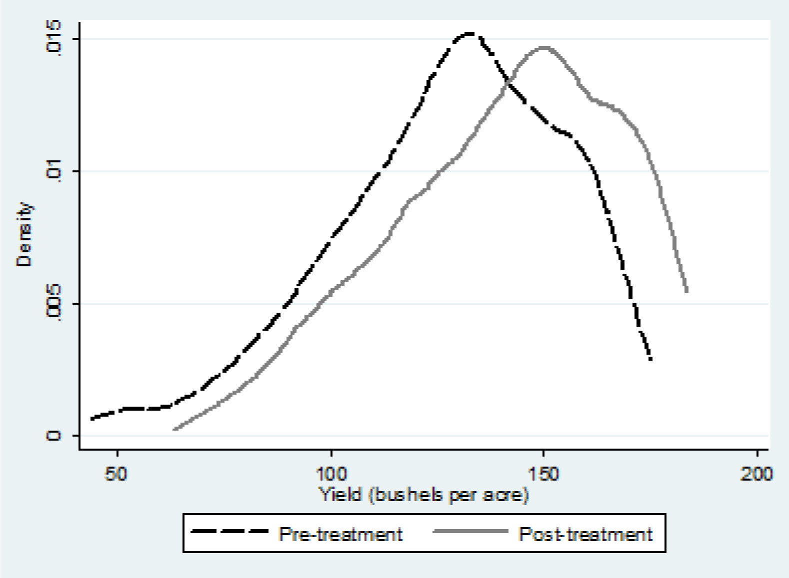
Notes: This figure plots the average number of ethanol plants within a 200 mile radius of each county and the total operating capacity of ethanol plants within a 200 mile radius.

Figure 6: Productivity Evolution in Treatment and Control



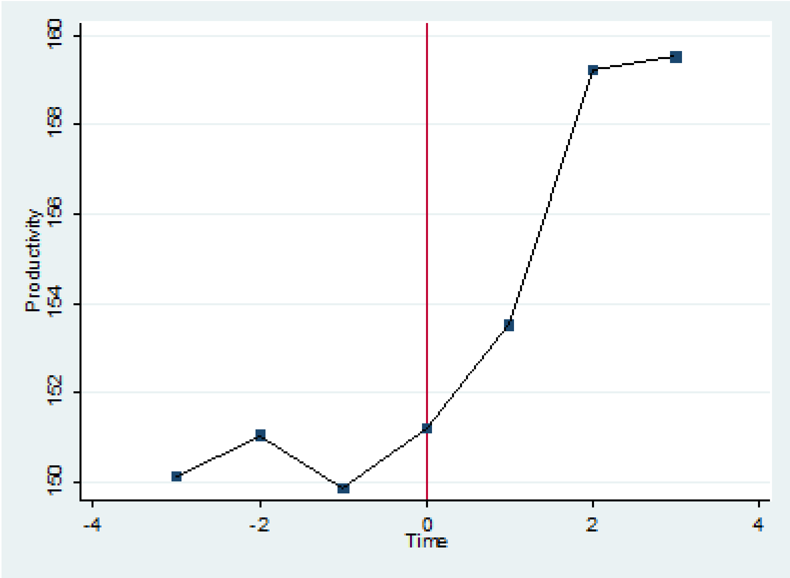
Notes: Panel A plots average annual productivity, measured by mean bushels produced by acre, of corn and soybeans producers between 2000 and 2010 in the Corn Belt. The vertical line corresponds to the year 2005 when the Energy Policy Act was passed. Panel B plots the average productivity change between the pre-treatment (2000-2004) and the post-treatment (2005-2010) periods for each county-industry. The blue kites denote the change in corn productivity between the two periods for county c. This is plotted against the change in soybean productivity (red triangles) in the same county.

Figure 7: Productivity Distribution in the Corn Industry



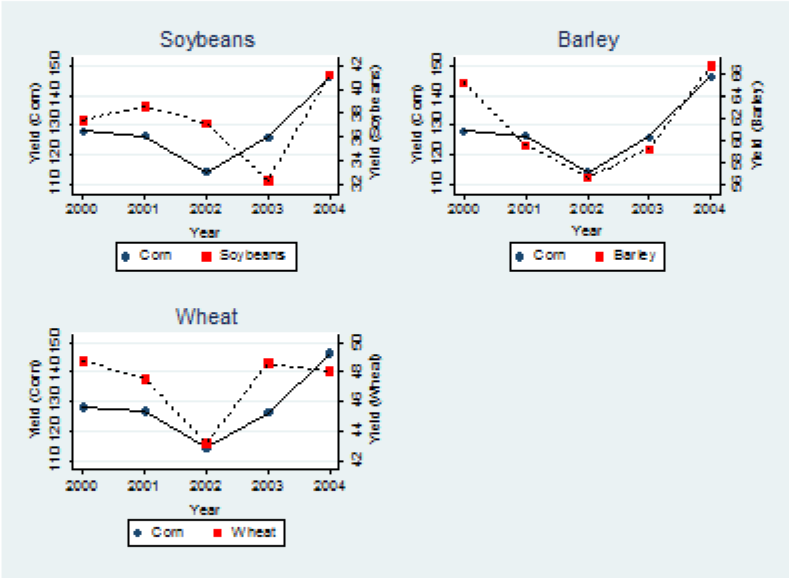
Notes: This graph shows kernel density plots of the productivity distribution within the corn sector for the pre-treatment (2000-2004) and post-treatment (2005-2010) periods.

Figure 8: Productivity Response to the Establishment of an Ethanol Plant



Notes: This figure plots average corn productivity in the years surrounding the establishment of an ethanol plant (which uses corn feedstock) within the county. Time 0 corresponds to the opening of the ethanol plant.

Figure 9: Parallel Trends



Notes: In each panel the left hand y-axis measures corn yield. The right hand y-axis measures yield in the control group. Time measures the number of years until treatment (2005). Time equals to "-1" therefore refers to 2004.

Appendix 1. Robustness testing: alternative explanations

Appendix Table 1: Robustness Tests

Regression No.	1	2	3	4	5	6
Notes	**Competition**	**Corp. Tax**	**Inc. Tax**	**Subsidy**	**Ext. Finance**	**Int. Finance**
Dependent variable: $yield_{ict}$						
Corn * Treatment	7.0246**	11.4675**	9.0740**	11.0461**	7.1614**	6.6036**
	(7.75)	(9.46)	(8.57)	(11.71)	(10.69)	(9.38)
Corn * Number of firms	0.0134					
	(0.92)					
Treatment * Number of firms	-0.0045					
	(-0.55)					
Corn * Treatment * Number of firms	0.0041					
	(0.45)					
Corn * Corporate tax rate		0.1047				
		(0.54)				
Corn * Treatment *Corporate tax rate		-0.5659**				
		(-3.74)				
Corn * Income tax rate			-0.0439			
			(-0.14)			
Corn * Treatment * Income tax rate			-0.2970+			
			(-1.67)			
Corn * Subsidies per farm				-0.1387*		
				(-2.29)		
Corn * Treatment * Subsidies per farm				-0.4239**		
				(-5.76)		
Corn * Number of banks					-0.0133	
					(-0.05)	
Corn * Treatment * Number of banks					0.0281	
					(0.53)	
Corn * Farm income						0.0000+
						(1.69)
Corn * Treatment * Farm income						-0.0000
						(-1.19)
Observations	19,115	19,749	19,749	19,749	19,749	19,749
R^2	0.98	0.98	0.98	0.98	0.98	0.98
County-year effects	√	√	√	√	√	√
County-industry effects	√	√	√	√	√	√

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