Demand Shocks and Productivity: Technology Adoption During the U.S. Ethanol Boom

Richard Kneller† and Danny McGowan‡*

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Abstract
We study the causal effect of demand shocks on productivity using an instrumental variable approach. The demand shock we examine leverages reforms to U.S. energy policy that mandated a higher ethanol content of gasoline which subsequently increased demand for corn. Exploiting variation in the demand for corn due to the geographic segmentation of markets we create instruments based on distance and numbers of cattle (as a by-product of ethanol production can be used as an animal feed). To obviate the conflation of productivity and price effects using standard revenue based measures of productivity we use as our outcome physical TFP (yield). We show that the demand shock caused firms to make productivity improvements and provide evidence that this occurred through technology adoption. Other tests reveal that only permanent demand shocks motivate productivity change, suggesting a link between demand uncertainty in the operating environment and investment. We also show that the results are externally valid, invariant to using alternative control groups, and are robust to a battery of robustness, falsification and placebo tests.

Keywords: Demand shocks, productivity, technology adoption
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† University of Nottingham, School of Economics, Nottingham, NG7 2RD. Email: richard.kneller@nottingham.ac.uk; tel: +44 (0)115 95 14734.
‡ (Corresponding author) Bangor University, Business School, College Road, Bangor, LL57 2DG, United Kingdom. Email: d.mcgowan@bangor.ac.uk. Tel: +44 (0)1248 38 3948.
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1. Introduction

In this paper we study whether changes to demand affect producer's decisions to invest in new technologies, raising their productivity. Although not typically assumed to have any direct productivity impacts, it has long been recognized that demand factors can lead producers to innovate new technologies or adopt those produced by others.[1] Schmookler (1954) for example, identified that the larger the target market, the more profitable it is for firms to invest in innovation activities. Profit incentives and market size also feature prominently within endogenous growth models by Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992) and Acemoglu (1999, 2007) and in recent theories within the productivity literature by Chaney and Ossa (2013).[2] The literature has also highlighted theoretically how the expansions in market size can induce firms to adopt more advanced technologies. This can be found within models of growth and development in Parante and Prescott (1999), Bellettini and Ottaviano (2005) and Desmet and Parente (2010), as well as models within the trade literature by Lileeva and Trefler (2010) and Bustos (2011), where the expansion in market size occurs because of trade liberalization.

In order to provide reliable empirical evidence on the demand-productivity nexus two major issues must be confronted. Firstly, there is the endogeneity of demand itself. High productivity firms exist disproportionately in large markets (Syverson, 2004). Secondly, in the absence of producer-specific prices, micro-level estimates of productivity are contaminated by demand shifts and variations in market power across producers (Foster et al., 2008, 2012). Changes in demand, and therefore prices, can make producers appear more productive even when their underlying efficiency is unchanged. De Loecker (2011) demonstrates that these effects can be large. In his study unobserved prices inflate the effects of trade liberalization on firm level productivity by a factor of four.

We by-pass the issue of price effects contaminating our productivity effects by constructing a measure of productivity based on physical quantities. Using data from the U.S. corn industry we measure productivity as the number of bushels of corn per acre (yield) and total factor productivity (TFP).[3] To establish causal effects of demand on productivity we use an instrumental variable approach that exploits exogenous variation in the demand for corn driven by the opening of new ethanol plants in the period following the U.S. Energy Policy Act of 2005 (EPA).

The EPA was designed to improve U.S. energy independence and security by stimulating domestic energy production. Part of this legislative strategy sought to reduce crude oil imports by mandating volumetric increases in the ethanol content of gasoline. In addition, the EPA contained the Renewable Fuel Standard (RFS) which stipulated a target of a minimum 10% ethanol content in future. The EPA led to substantial increases in the number of plants and

[1] Improved access to micro-level production data over the last few decades has led to a rapid expansion in applied economic research that tries to unravel the contribution of supply-side forces, such as the competitive and regulatory landscapes, to productivity levels and growth. In comparison, the productivity effects of fluctuations in demand have been somewhat neglected (Syverson, 2011).

[2] See also Guiso and Parigi (1999) and Collard-Wexler (2013) for evidence that demand affects managers' and entrepreneurs' investment decisions.

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

production capacity within the ethanol industry. This period is commonly labelled the 'ethanol boom'.

As the primary ingredient used to manufacture 90% of U.S. ethanol, a direct consequence of the ethanol industry's expansion was a large increase in the demand for corn. In constructing our demand variable and our instruments we build on the insight of Syverson (2004) and Foster et al. (2012) that products with homogenous characteristics can still be sold in differentiated markets because of geographic variations in demand. As with the market for concrete described in Syverson (2004), market segmentation in the demand for corn from ethanol producers occurs because of transport costs. Ethanol producers are sensitive to transport costs for corn due to their importance within total costs (on average corn accounts for 60% of total costs [Hofstrand, 2013]) and therefore typically procure all of the corn they require from farms within a 50 mile radius of the ethanol plant (USDA, 2007). Negative agglomeration effects exist for ethanol producers as they seek to avoid competition that would drive up the local price of corn (Fatal, 2011). As corn producers cannot re-locate to reduce trade costs and better serve ethanol producers, the demand shocks they received during the ethanol boom was of varying magnitudes.

McAloon et al. (2000) and Sarmiento et al. (2012) have previously shown, and we repeat their analysis using our data, that the location and capacity of new plants was determined by the location of existing ethanol plants and the number of cattle on feed. Using these insights we instrument for the demand for corn from local ethanol producers using the distance of each corn producer to the nearest ethanol plant. The greater is this distance the lower the demand for corn from this and other ethanol plants in the locality is likely to be. The location of cattle affects the location of ethanol producers because a by-product of ethanol production can be used as an animal feed, and simultaneously accounts for 20% of ethanol profits. We use the number of cattle on feed within a 50 mile radius of each county's centroid as a second instrument.[4] Diagnostic tests demonstrate that the instruments are valid and we repeat evidence found in McAloon et al. (2000) and Sarmiento et al. (2012) which shows that expansions of the ethanol industry were independent of corn yields.

We find from this exercise evidence of a positive effect of demand shocks on corn yields. We find an elasticity of corn yields with respect to ethanol capacity of 0.083%. Using the growth in ethanol capacity for the average county between 2004 and 2010 (the end of our data period) our results imply that yields rose around 5% per year. There is also considerable variation in the estimated gains to yields: the productivity of corn producers at the 75th percentile of the demand shock is estimated to have increased by 7.7% per year, whereas for those at the 25th percentile is estimated to have been just 0.4% per year.

Having established a causal effect from demand shocks on physical productivity we move on to explore why productivity increased. We test for a number of possibilities. As the data that are available to answer this question exist at the state rather than the county level this necessitates a change in the methodology to difference-in-differences. We are however, able to establish a

[4] The inability of production to move location in this industry also explains why we focus on the role of market size as the source of the productivity gains rather than say changes to competition or information networks caused by increased industry agglomeration. See Aghion et al, (2005), Blundell et al, (1999), and Cohen and Levin (1989) as examples of the literature on competition and innovation, and Coombes (2012) for a model with agglomeration effects.

clear explanation for the observed rise in corn productivity: the demand shock induced technology adoption.[5] Corn producers rapidly adopted genetically engineered (GE) seeds, and in particular stacked variety GE seeds, that reduce losses due to pests and herbicide over the growing season, and also decrease herbicide and insecticide expenditure. Despite being commercially available since 1996, few corn producers used GE seeds because their high net cost relative to traditional hybrid seeds acted as a barrier to technology adoption. By causing an increase in final goods' prices, the demand shock reduced the effective cost of using the new technology, triggering increases in its adoption. As a consequence TFP rose alongside yields. We show that the permanence of the demand shock is an important element of our results. Using previous examples of permanent and temporary demand shocks for corn (including the switch to high-fructose corn syrup as a sweetener for carbonated soft drinks by Coca-Cola and Pepsi in 1985, and the temporary withdrawal of China from the export market in 1995) we find that a similarly permanent shock also increased productivity in this sector, whereas the temporary one had no effect.

We can relate these findings to several strands of the literature. First, there is a new line of research which expands the sources of heterogeneity between firms to include both technological and demand-based factors. Key references include Das et al. (2007), Eslava et al. (2009), Foster et al. (2008), Kee and Krishna (2008), Park et al. (2010) 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).[6] In this paper we contribute to this literature by demonstrating that changes to demand can have an effect even on physical productivity. In the language of Foster et al. (2012), the demand stock and the physical productivity of the firm may co- rather than independently evolve.

Second, our paper builds on the empirical literature relating market size and technological change. The paper most closely related to our empirical setting is the pioneering work of Griliches (1957), who studies adoption of hybrid corn seed across U.S. states. He identifies market size as a factor that affects the rate of technology diffusion. We find a similar result while dealing with the potential endogeneity of demand. In this regard the mechanism we identify is common within the technology diffusion literature (Hall 2004), including that found previously for a broad range of agricultural technologies.[7] Our findings also complement studies of the diffusion of agricultural technologies in developing countries.[8] A recent example is the work of Suri (2011) who studies the adoption of hybrid-maize and fertilizer in Kenya. Their work suggests heterogeneity in the returns to hybrid-maize and that non-adoption can occur even when the increase in yields are in the order of 150%. Our findings indicate that economic factors can also delay technology adoption in countries that operate close to the technological

[5] Geroski (2000) and Hall (2004) provide interesting overviews of the technology adoption literature. Within this Geroski (2000) includes some discussion of the endogeneity of market size as new technological innovations are targeted at specific consumers.

[6] A separate theoretical literature studies how changes in market size can increase aggregate productivity by inducing reallocation of market share across firms. See, for example, Melitz (2003), Syverson (2004), and Asplund and Nocke (2006).

[7] See for example David (1975a,b) on the factors that affected the diffusion of the mechanical reaper in the U.S. and U.K.

[8] See Feder et al. (1985) for a review of an older literature, while Foster and Rosenzweig (2010) discuss more recent studies.

frontier, albeit where in developed countries constraints appear are more likely to be on the demand side.

Finally, some contemporary studies have estimated the impact of foreign market access on productivity (Lileeva and Trefler, 2010) and technology adoption (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. The inability of corn producers to change location, limits the extent to which changes in competition can occur during the ethanol boom.

Our paper is organized as follows. In the next section we describe the data set. In Section 3 we provide an overview of the ethanol industry and the key legislative changes that motivate our empirical framework. We outline our identification strategy in section 4 and provide the main results in Section 5. Section 6 contains explanations for the productivity increase while in Section 7 we conduct robustness tests. In Section 8 we draw some conclusions from the study.

2. Data

[INSERT TABLE 1]

Much of the data we use in the empirical analysis is drawn from the National Agricultural Statistics Service (NASS). The NASS is the statistics branch of the U.S. Department for Agriculture and conducts hundreds of surveys each year on issues relating to agricultural production, demographics, and the environment. As part of this mission the NASS administers an annual survey of crop yields and output in each U.S. county. From this we have detailed information on the productivity of the corn (NAICS 11115), as well as other crops grown within the county such as soybeans (NAICS 11111), wheat, and barley, for 1,003 Midwest counties between 2000 and 2010. The unit of observation in the sample is the county-industry. Our decision to restrict the sample to only counties located in 12 states that makeup the Corn Belt is predicated on the fact that both industries are ubiquitous throughout the region, and because the ethanol sector is geographically concentrated there as well.[9]

We match the yield data to detailed information on the ethanol industry taken from *The Ethanol Industry Outlook*, an annual industry journal published by the Renewable Fuels Association. This contains plant-level data on the owner, capacity (both operating and under construction), location, and feedstock of every ethanol plant in the U.S. We exclude all plants that do not use corn as a feedstock on the grounds that they are irrelevant to corn producers. Based on this information, for each year we create a binary dummy variable equal to 1 if there is an ethanol plant in county *c*, 0 otherwise; total operating capacity within a 200 mile radius of

[9] 88% of national corn and 81% of national soybean production takes place in the Corn Belt. The 12 states in the sample are Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota and Wisconsin.

each county; and the minimum distance between county c and the nearest operating ethanol plant.[10]

We also incorporate a number of other variables into the data set. We rely on the NASS for data on the number of cattle on feed within the county (to proxy for demand for distillers' dry grains), and retrieve information on the number of corn and soybean firms in each county from the quinquennial Census of Agriculture.[11] The remaining variables used in the econometric analysis are listed in Table 1. This includes the number of banks in each county (SNL Financial), the top state marginal corporate and personal income tax rates (The Tax Foundation), population density (US Census Bureau), agricultural subsidy payments (USDA), industry exports (USDA), GE seed usage (USDA), input usage (ARMS), output (NASS), and precipitation and temperature (measured by growing degree days) over the growing season (Weather Underground).[12]

In the majority of the empirical analysis, productivity is measured as yield (calculated as the number of bushels produced per acre), but we also experiment with physical (TFPQ) and revenue total factor productivity (TFPR) measures in Section 6. Earlier studies have often estimated productivity as a residual in the production function. In the absence of producer-specific prices or detailed production data these residuals capture not only differences in technical efficiency across firms but also differences in market power, factor market distortions, or changes in the product mix (Foster et al. 2008; Hsieh and Klenow, 2009; and Bernard et al., 2010). The yield and TFPQ measures seek to obviate these concerns. The TFP variables are constructed at the state-industry level using data retrieved from the Agricultural Resource Management Survey (ARMS) following the method used by Foster et al. (2008).[13] Each measure is constructed using the typical index form

$$tfp_{ist} = y_{ist} - \alpha_k k_{ist} - \alpha_l l_{ist} - \alpha_m m_{ist} - \alpha_e e_{ist} \qquad (1)$$

where the lower-case letters indicate the natural logarithm of output, capital stock, labour hours, material inputs, and energy inputs, and α_j $(j \in \{l, k, m, e\})$ are the factor elasticities corresponding to the corresponding inputs. 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 reported expenditures on fertilizer, lime, seeds, herbicide and insecticide. We deflate capital, material, and energy inputs into 1992 values using the NASS price index. To measure the input elasticities α_j, we use industries' average cost shares over our sample.

The difference between the TFP variables lies in the output measure y_{ist}. The first index, TFPQ, uses the yield per acre data described above. Variation in TFPQ reflects dispersion in physical efficiency and possibly factor prices; it essentially reflects a producer's average cost per unit (Foster et al., 2008). The TFPR index measures y_{ist} as the deflated nominal revenue from

[10] Distance is calculated as the great circle distance between the midpoint of county c and the midpoint of the nearest county containing an operating ethanol plant.

[11] Because the census is administered in 2002 and 2007 we apply the 2002 figures to the pre-treatment period (2000-2004) and those from 2007 to the post-treatment period (2005-2010). We also have census data for the years 1982, 1987, 1992, and 1997.

[12] Weather stations are not uniformly distributed across counties. We therefore match each county to the nearest weather station.

[13] We are forced to use state-level information because we do not have county-level information on capital, labor, and input expenditure.

product sales, and is similar in many respects to the estimates produced by Olley and Pakes (1996) and Levinsohn and Petrin (2003) estimators.

3. 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, and tests regarding the exogeneity of ethanol plant location with respect to corn productivity.

3.1 The Ethanol Production and Distribution Process

Ethanol is a clean-burning, high-octane motor fuel. Almost all ethanol is derived from starch- and sugar-based feedstocks. The ease with which these sugars can be extracted from corn makes it the preferred feedstock of large-scale, commercial ethanol producers (USDE, 2013).[14] 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 United States 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), which are sold as animal feed, and carbon dioxide. 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 feed ingredient.

Corn accounts for approximately 60% of ethanol production costs, with the remainder due to natural gas (15%), other variable costs (12%), and fixed costs (13%) (Hofstrand, 2013). The distribution process entails shipping harvested corn from farms and co-ops to ethanol plants using trucks. 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.

[Insert Figure 1: Oxygenates in Gasoline]

3.2 U.S. Legislative Changes

The background to the period we study begins with the mandated use of oxygenates in gasoline in response to evidence that poor air quality in certain regions of the U.S. was damaging health. This requirement was contained in the Clean Air Act Amendments of 1990 but was later enforced through the Winter Oxygenate Fuel Program and the Reformulated Gasoline Program in 1995. This legislation sought to improve the efficiency with which gasoline was converted into heat, which was to be achieved by mandating that gasoline must contain a certain percentage of oxygenate.[15]

The main oxygenates blended with gasoline were Methyl Tertiary Butyl Ether (MTBE) and ethanol. Outside of the Midwest, MTBE was the preferred oxygenate based on cost advantages

[14] According to USDE (2013) ethanol produced using wheat, milo and sugarcane is not economically feasible. As a result, 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.

[15] 2.7% under the WOFP and 2.0% under the RFG, where the RFG stipulated that this was year-round.

and its less volatile nature (Tiffany, 2009). In the Midwest, ethanol was more commonly used, a difference that is generally attributed to a desire in corn producing states to help bolster agricultural markets. MTBE's dominance of the oxygenate market began to change when it was detected in water supplies.[16] Bans on the use of MTBE were introduced in some farm states such as Minnesota as early as 2000, but were adopted by heavy users of MTBE, such as California, from 2004 when the health concerns became better known.[17] Figure 1 provides further detail on the use of ethanol and MTBE as oxygenates over time, and Appendix Table A1 provides an overview of the states that adopted these measures, the timing, and type of oxygenate phaseout.

Also of importance for the demand shock that we study were a series of other political issues that culminated in the 2005 EPA. 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). The EPA was formulated in response to these pressures, and aimed to improve energy independence and security by stimulating various forms of domestic energy production. Part of this agenda sought to displace crude oil and gasoline imports by promoting greater use of ethanol in gasoline. Crucially the EPA mandated that the ethanol content of gasoline rise from 4 billion gallons in 2006 to 7.5 billion in 2012, and also contained a Renewable Fuel Standard (RFS) that stipulated a minimum 10% ethanol content in future.[18] The subsequent Energy Independence and Security Act of 2007 (EISA) set yet higher targets, mandating a minimum 36 billion gallon ethanol content by 2022.[19]

It is also recognized within the agricultural and ethanol industries that an important additional demand stimulus was the failure of the EPA to grant the manufacturers of MTBE liability protection from environmental damage and health claims (Tiffany, 2009). Today, ethanol is used as a gasoline oxygenate in all 50 states.

Together the RFS and the volumetric ethanol production targets provided assurance of ethanol demand, and accelerated ethanol production beyond levels that would have been otherwise supported by a free market. Ethanol blenders also benefitted from a 51 cent per gallon tax credit paid through the Volumetric Ethanol Excise Tax Credit (VEETC), and were shielded from competition with foreign ethanol producers by an import tariff of $143/m^3 levied on imported ethanol.[20] This institutional feature is important for our empirical strategy as it means we can study the effects of a demand shock in isolation from changes in the competitive landscape as is the case with trade liberalization.

The rapid rise of blended gasoline (gasoline containing ethanol) was facilitated by the fact that no engine modifications were required in older (post-1992) or newer (post-2001) vehicles. This spurred most gasoline retailers throughout the U.S. to offer E10, a fuel mixture of 10%

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16 State legislators opted to ban MTBE following its discovery in groundwater and medical evidence linking MTBE ingestion to carcinogenic diseases.

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

18 According to the USDA Feed Grains Database 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 10% ethanol content, is readily available throughout all 50 states. Higher ethanol blends are also marketed by gasoline retailers.

19 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).

20 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. Congress allowed the VEETC to expire on December 31 2011.

ethanol and 90% gasoline. Automobile manufacturers also promoted blended gasoline by introducing car engines capable of running on E15 and E85.[21]

3.3 The Ethanol Boom

The surety of demand created by the EPA sparked a wave of investment in building new production plants and expanding existing capacity as shown in Figure 2, and in more detail in Table 2. These display aggregate production and consumption of ethanol across time and the number of ethanol plants, net-entry and capacity respectively. Between 2002 and 2010 this surge in investment increased operating capacity from 2,738 million gallons per year (mgy) to 11,877 mgy (RFA, 2002, 2010), while the volume of ethanol contained in gasoline rose by just under 10 billion gallons in the 6 years from 2004 and 2010.[22] The data in Table 2 shows a 3.3 fold increase in the number of ethanol plants between 2002 and 2010, while the net entry rate jumped to 33% and 53% in the two years after 2005.

[Insert Figure 2: Ethanol Production and Consumption]

[Insert Table 2: Ethanol Industry Evolution]

As illustrated in Figure 3 the expansion of the ethanol industry was both rapid and geographically concentrated in the Midwest. This is the same area in which corn is grown (Figure 4).

[Insert Figure 3: Ethanol Plant Location]

[Insert Figure 4: Average Planted Acres 2000-2010]

The strong geographic concentration of the ethanol industry in the Midwest raises questions about what factors determine where ethanol plants locate. Why are they concentrated near the production of corn, rather than in proximity to gasoline refineries, in particular given the volatile properties of ethanol and the associated transportation dangers? And are locations chosen where corn yields are highest, or have the potential for rapid productivity improvement? As we cannot do this for existing ethanol plants, we can at least establish this for the new ethanol plants that open during the sample period, while we refer to previous literature to infer similar evidence for older plants.

McAloon et al. (2000) and 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, and can be used as a feedstock for farm animals.[23] DDGs have a high cost of shipping but are an important determinant of profitability among ethanol producers, accounting for between 15% and 20% of revenues between 2005 and 2010 (Hofstrand, 2013; USDA, 2013).

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

[22] 3.5 billion gallons of ethanol were contained in gasoline in 2004, compared to 13.3 billion gallons in 2010.

[23] 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).

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 plant locating in a county is 3% lower if that county lies within a 30 mile radius of an existing ethanol plant, a relatively large effect in the context of their model. 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 as this bids up the price of corn. Further evidence in support of this view is provided by Fatal and Thurman (2012). Using spatial econometric techniques they report that "the siting of plants influenced local variation in corn prices … The new plant adds to the local demand for corn and consequently elevates corn prices." They also find that this effect linearly diminishes to zero as the distance between the county and ethanol plant reaches 103 miles. A consequence is that most U.S. counties contain one or no plants. In contrast, Sarmiento et al. (2012) find no significant evidence of corn yields (or indeed corn prices) as a predictor of the location of new plants.

[Insert Table 3: Exogeneity Tests]

We conduct a similar exercise using our data period, and test the exogeneity of ethanol plant location with respect to productivity within the corn sector. We estimate

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

where y_{ct} is a 0/1 indicator if at least one ethanol enters county c at time t; a 0/1 indicator if there is at least one 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; $DDGs_{ct}$ is demand for distillers' dry grains, proxied by the number of cattle on feed[24]; and $Competitors_{ct}$ is the number of other ethanol firms located within a 100 or 200 mile radius of the county. These distances are chosen as conservative estimates of the radius in which other ethanol plants are likely to have an effect on the location of new ethanol plants. A full set of county (γ_c) and year (γ_t) dummies are also included in the model. ε_{ct} is a stochastic error term. We estimate equation (2) using a linear probability model and probit regressions.

The results of these tests are provided in Table 3. There are three key findings, all of which are consistent with the evidence for earlier time periods. First, the behavior of ethanol plants is orthogonal to productivity within the corn sector. In the table we find no evidence that entry behavior is related to corn productivity. Second, strategic profitability motives appear to drive location decisions. Entrants are significantly more likely to locate in a county that is far from existing ethanol plants. This behavior has been interpreted within the existing literature as evidence that new ethanol producers seek to minimize procurement costs by locating away from competitors who would otherwise bid up corn prices. From the perspective of corn producers we use this result to infer that the demand for their corn is affected by the location of ethanol plants. Those corn producers located close to many ethanol plants, or large ethanol plants, will have a greater demand for corn. Finally, entrants seek out areas in close proximity to DDG markets.

[24] It was not possible to obtain information on the number of swine and poultry on feed from the NASS.

In Appendix Table A2 we report further evidence that plant operating capacity and capacity under construction are independent of productivity in the corn sector.

4. Empirical Design

As the primary ingredient used to produce U.S. ethanol, the legislative changes culminating in the EPA triggered a large, exogenous increase in demand for corn. Before 2005 corn was mainly used as a feed for livestock with the rest exported or sold to the food industry. That began to change as U.S. states banned the use of MTBE, but as shown in Figure 5, changed even more dramatically following the EPA; the share of corn production used to manufacture ethanol, reached 40% in 2010. Moreover, as illustrated in Figure 6, the higher demand from the ethanol sector did not displace other sources of corn demand such as feed or exports, meaning that the ethanol demand shock was largely additive.

[Insert Figure 5: Share of U.S. Corn Production in Ethanol]

[Insert Figure 6: Sources of Corn Demand]

The hypothesis we test in this paper is whether the surge in demand for ethanol created by the opening of new ethanol plants provided an incentive for corn producers to improve their productivity. We identify the effect of demand by exploiting spatial variation in the magnitude of the demand shock using an instrumental variables estimation strategy. 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, even when the goods produced cannot be differentiated by quality or other characteristics. The estimating equation we use is

$$ln\varphi_{ct} = \alpha + \beta_1 lnD_{ct} + \delta X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct} \ , \qquad (3)$$

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_{ct} is a stochastic error term. We also include county-fixed effects (γ_c) in equation (3) to control for time invariant county-specific factors such as altitude, latitude and soil conditions that might generate differences in the yield across counties. Year fixed effects (γ_t) are also included in the estimating equation.

We proxy demand for corn in equation (3) using the operating capacity of ethanol plants within a 200 mile radius of each county. We choose a radius of 200 miles based on existing evidence. Because ethanol plants pay the shipping costs they purchase corn locally. For example, according to McAloon et al. (2000) ethanol producers located near corn growers have the advantage of lower shipping costs, while USDA (2007) provide evidence that most ethanol plants get their corn supply from within 50 miles of the plant. Fatal (2011) uses a non-linear least squares procedure and estimates that the maximum radius around which ethanol plants affect corn supply exists up to 286 miles. The average county is only 20 miles across. Several hundred counties can be located within a radius of this size.

Our first instrument uses the distance between county c and the nearest county containing an operating ethanol plant in year t. In addition to the geographic limit of the effect of ethanol producers on corn producers, we draw on two features of corn and ethanol production to justify this instrument. First, a feature of agricultural production is of course that the location of corn producers is fixed. It follows that corn producers cannot move location in order to reduce their transport costs to better serve new ethanol producers. Secondly, the evidence in Table 3 and elsewhere suggests that ethanol producers have a strong desire to locate away from other ethanol producers and that location choice is independent of corn yields. Within the ethanol industry there are negative agglomeration effects, and from the perspective of corn productivity, their location is as good as random.

From this we anticipate that the shorter the distance between a corn producer and the closest ethanol producer, the greater is the number of other ethanol plants that are likely to be located within a 200 mile radius of the corn producer. As ethanol plants have a desire to locate away from each other, the distance to the nearest plant will be negatively correlated with the total number of plants that are located within 200 miles of the corn producer and therefore the ethanol capacity within that area. To put this differently, the area of the circle with a radius 200 miles in which other corn producers can be located is greater, the shorter is the initial distance between the corn producer and the ethanol plant. At one extreme, when the corn producer and the ethanol producer are located within the same county then then the area in which other ethanol plants can be located is given by πr^2. At the other extreme of when the nearest ethanol plant is 200 miles away from the corn producer, then other ethanol plants will count towards its demand only if they are located exactly on the perimeter of the circle. It has already been established that corn yields do not determine the location of ethanol plants and we see no reason why this distance between a corn producer and the nearest ethanol producer should be correlated with the productivity of corn within the county other than through its correlation with ethanol capacity within a 200 mile radius.

The second instrument we use is a measure of the number of cattle on feed in county *c* at time *t*. As outlined by Sarimento et al. (2012) and McAloon et al. (2000), sales of DDGs are a key consideration in ethanol plant location as they accounts for approximately 20% of plants' revenues. The high transport costs associated with shipping DDGs (McAloon et al., 2000) means that plants seek to locate close to large DDG markets, a result confirmed earlier in Table 3. We therefore follow Dooley and Martens (2008) and proxy DDGs demand using the number of cattle on feed within 50 miles of each county. Because DDGs demand influences the location and capacity choices of ethanol producers, this in turn generates plausibly exogenous variation in the proximity of corn producers to ethanol plants, and the magnitude of the demand shock they face.[25]

5. Instrumental Variable Estimates

Before reporting formal empirical tests of the above hypothesis, we provide some simple descriptive evidence. Within the raw data presented in Figure 7 Panel A we compare the productivity distribution in the first half of the sample period (up to 2005) and that in the second half of the period (post to 2005). We use 2005 as this was the year in which the EPA was passed. The figure indicates a clear, unambiguous increase in average productivity in the second half of the period, part of the reason for which would appear to be due to the substantial

[25] One could argue that productivity within corn farming might affect the number of cattle on feed leading to a breakdown in the exclusion restriction. We test this directly by regressing the number of cattle on feed on yield and output and show that this is not the case.

rightward shift in the survival productivity threshold.[26] Average corn yield rose by 10% over this period. First evidence that the productivity gains were driven by the opening of ethanol plants can be found in Panel B of Figure 7 where we plot average productivity in counties in which new ethanol plants were opened. This figure indicates a 5% increase in corn productivity during the three years after an ethanol plant enters the county.

[Insert Figure 7: Productivity Response to the Demand Shock]

The instrumental variable estimation results are provided in Table 4. In the first stage of regression 1 we find that demand for corn was lower in counties further away from an ethanol plant, whereas the number of cattle on feed is positively related to ethanol demand. Thus the instruments have the expected relationships with the endogenous variable. The instruments are highly significant individually and collectively in the first-stage regression, as shown by the Kleibergen-Paap F-statistic. They also pass the under-identification and over-identification tests, and are uncorrelated with the error term from the second-stage regression. The instruments therefore pass standard statistical tests for their validity.

In the second stage we find that the demand shock caused a significant increase in productivity with the elasticity estimated to be equal to 0.083%. Between 2004 and 2010 ethanol operating capacity within 200 miles of the mean county increased by 415%. Our results imply that corn yields increased by just under 35% over these 6 years as a result of the increase in ethanol demand, equivalent to an increase in the average annual growth rate in productivity of 5 percentage points. The size of the effect differs with the size of the demand shock. Using the distribution of the change in ethanol production capacity within 200 miles of the county between 2004 and 2010 the value at the 25th percentile was 151mgy. At the 75th percentile it was 4046mgy. These imply an increase in the mean value in 2004 of 27% and 711% respectively, and in turn a 0.4% and 7.7% increase in the rate of productivity growth of corn.

[Insert Table 4: Instrumental Variables Estimates]

In regressions 2 and 3 of Table 4 we add additional control variables to establish that the instruments are not capturing the effect of some other omitted variable. In regression 2 we add supply-side factors, including variables capturing the weather, and in regression 3 we control for other demand-side factors including exports of corn, the price of corn within the state and the subsidy rate. Syverson (2004) suggests that average productivity is higher in larger markets because low-productivity firms are eliminated as markets grow. We attempt to control for such effects using a measure of the number of acres of corn planted, median firm size, and the number of operating firms. We use the number of banks within the county to control for the potential effects of differences in access to finance on corn yields (Butler and Cornaggia, 2011).

In the first stage the instruments continue to behave as expected and remain valid. In the second stage we find the estimated elasticity is similar to that found in regression 1. The demand shock caused a significant increase in productivity with the elasticity estimated to be equal to 0.096% in regression 2 and 0.088% in regression 3. For a 415% increase in the median ethanol operating capacity corn yields would be predicted to increase by between 5.6 points and 5.1 percentage points each year.

[26] The productivity threshold is 138% higher during the post-treatment era relative to pre-treatment.

We show in Appendix Table A3 that our results are robust to proxying corn demand with ethanol capacity within a 100-mile radius. The magnitude of the demand elasticity in these regressions is somewhat larger.

6. Why did Productivity Increase?

The results found thus far suggest that changes in demand can affect productivity. An obvious next question is why did productivity increase? Is it to do with the type of shock that we use? Or do our results for the productivity of land reflect increases in other inputs, such as increased fertilizer use, which may indicate no increase in TFP? Unfortunately, the data that would help to provide answers to the questions on the type of input changes that occur are available at the state, rather than the county level. This prevents us from using the instruments adopted in Section 5. To make progress on this issue we switch to a difference-in-difference approach using the 2005 EPA as the source of the exogenous increase in the demand for corn. Precedent for the use of the EPA as a treatment can be found in Butler and Cornaggia (2011) who study the effect of access to finance on corn yields using county-level data up to 2006. Following Butler and Cornaggia (2011) we use soybeans as a counterfactual.

In order to establish the use of the EPA as a treatment and soybeans as a counterfactual, we proceed in three steps. First, we examine the key identifying assumption of parallel trends between corn and soybean productivity. Second, we test whether the alternative estimation strategy is able to replicate the previous results. Having established the apparent validity of the approach we then consider in more detail why productivity increased, focusing on different types of demand shocks, a measure of physical TFP for corn, technology adoption, and input usage.

6.1 Parallel Trends

Invariably, DID estimates are scrutinized based on the extent to which the control group represents the valid counterfactual. Soybeans are an obvious choice to play such a role for corn as they are also planted during spring and harvested in fall, the majority of output is produced in the Corn Belt, but it is not a crop that can be used to produce ethanol. Historically, the growth rate of soybean yields has closely matched corn yield.[27] Similar machinery (combines, trailers, seeders and tractors) is used to plant and harvest both crops.

[Insert Figure 8: Pre-Treatment Productivity Evolution]

[Insert Table 5: Parallel Trends Tests]

Key to this approach is the identifying assumption of parallel trends. In Figure 8 we plot the annual rate of productivity growth in corn and soybeans during the pre-treatment era.[28] We observe very similar patterns, although corn productivity grew somewhat faster between 2002 and 2003. The important question is of course whether these trends are significantly different. We investigate this issue using t-tests that test for equality between productivity growth in the two sectors in each year. These results are reported in Table 5. We find no significant

[27] The respective average annual growth rates for soybean and corn yields were 3.9% versus 4.5% since 1990 respectively.

[28] A within county-industry transformation of the data is applied because in the subsequent econometric tests we include county-industry fixed effects in the estimating equation.

differences for any of the years indicating that the parallel trends assumption is satisfied, and soybeans represent a valid counterfactual. We take form this that the banning of MTBEs by some states had no statistically significant effect on corn yields over this period. Given the EPA was passed due to national policymakers' concerns about the adverse effects of interruptions to foreign energy sources, and their repercussions for the U.S. economy, the legislation represented an exogenous shock.[29]

6.2 Difference-in-Difference Estimates

The difference-in-difference (DID) estimator exploits the asymmetry in treatment status between corn and soybeans using the following equation

$$\varphi_{ict} = \alpha + \beta_1 Corn_{ic} * Treatment_t + \delta X_{ict} + \gamma_{ct} + \gamma_{ic} + \varepsilon_{ict}\ , \qquad (4)$$

where φ_{ict} is productivity in industry i in county c at time t; $Corn_{ic}$ is a dummy equal to 1 if the observation is from the corn industry, 0 otherwise; $Treatment_t$ is a dummy equal to 1 for the years 2005-2010, 0 otherwise; X_{ict} is a vector of control variables measuring competition (number of corn/soybean firms), and acres planted; ε_{ict} is a stochastic error term. We also include a full set of county-year (γ_{ct}) and county-industry (γ_{ic}) dummy variables. The county-year effects capture time-varying productivity influences (common across the treatment and control group) that may coincide with treatment. For example, subsidy payments may affect managerial effort, and therefore productivity, but changes in the generosity of such payments through time are likely to affect both groups equally. An attractive property of including county-year effects in the estimating equation is that the average treatment effect is identified through cross-industry variation within the county-year dimension of the data set. It also seems likely that there exist a number of time-invariant productivity determinants that are county-specific but have differential effects on corn and soybean productivity, hence the inclusion of γ_{ic}.[30] We cluster the standard errors at the county level in line with Bertrand et al. (2004).[31]

[Insert Table 6: Productivity Response to the Demand Shock]

We first examine whether the alternative estimation strategy is able to replicate our previous findings.

In regression 1 of Table 6 we report the estimates of equation (4). The average treatment effect (ATE) of the demand shock is estimated to be 6.3 bushels per acre. In column 2 we collapse each variable on its pre- and post-treatment mean for each county-industry. We now have just two observations for each county-industry; one before, and one after treatment. This procedure has two advantages: 1) we are able to establish the average annual ATE effect of the demand shock, and 2) it provides further evidence against the claim that our inferences are driven by artificially low standard errors (Bertrand et al., 2004). The ATE is now estimated to be equal to 6.8 bushels per acre per year (t-statistic = 7.00). This implies a net productivity

[29] If farmers were aware of the potential effect ethanol would have on their businesses, we would expect to see a jump in lobbying contributions as they attempt to pressure policymakers to include such legislation. However, there is no evidence of an increase in contributions to the National Corn Growers' Association (the industry lobby) before 2005. For further details see http://www.opensecrets.org .

[30] For example, Grau et al. (2002) find soybean yields are affected to a greater extent by high soil pH values because this results in cyst nematode and brown stem rot. Equally, corn yields tend to be proportionately lower in more northern areas while altitude influences crop yields.

[31] The coefficient estimate of the first order autoregressive productivity parameter is 0.9309 (t-statistic = 313.39) indicating serial correlation in the dependent variable.

improvement over the post-treatment period of 32% [(6.8*6)/128 = 0.32] which is very close to the estimates using IV.

Given that soybeans represent a good counterfactual, and the similarity between the DID and IV estimation results, we conclude that the DID identification strategy is valid.

6.3 Type of Demand Shock

Our first test for why productivity increased focuses on the type of the demand shock. Through the RFS, the EPA provided surety of corn demand in all future years. It was therefore a permanent demand shock. Previous research has typically emphasized that permanent demand shocks motivate firms to make investments as they increase expected revenues and reduce the uncertainty of investment (Schmookler, 1954; Campbell and Hubbard, 2009), whereas transitory demand shocks do not.

We consider this question using two historical changes to the demand for corn. 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. As with the ethanol-boom period this was likely to have been viewed by corn producers as a permanent demand shock.

Again we draw upon data from the NASS for information on corn and soybean productivity in the Corn Belt. The HFCS 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 (4) using the new data set and report the results in regression 3 of Table 6.[32] We continue to find large productivity effects of demand: following the HFCS demand shock corn firm productivity increased by 10 bushels per acre, equivalent to an 11.8% productivity gain relative to pre-treatment levels.

We then compare this outcome to the withdrawal of China from the export market announced in December 1994, which it undertook in an attempt to fight inflation related to its domestic grain shortages. According to Stevens (2000) over the previous four years China had aggressively expanded its corn exports to 465 million bushels per annum and that, "This was hard on U.S. corn exports … China had taken over about one fourth of the U.S. share of the market. Getting this market back was good news indeed", but, "[T]he Chinese withdrawal from the world corn export market had the tone of a one-time shock." We test for the effect on corn and soybean yields using data from the NASS covering the years 1992 to 1997 and set the treatment indicator equal to 1 for the period 1995 to 1997, and 0 otherwise.[33]

The results in regression 4 of Table 6 show no significant effect of the temporary demand shock on productivity. That producers did not respond in the same manner as to the permanent demand shocks suggests that demand structure has important implications for productivity

[32] 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 the years 1985 onwards.
[33] Data on the number of firms is drawn from the 1992 and 1997 Census. The values for 1992 are applied across the years 1992 to 1994 and those for 1997 are applied to the years 1995 onwards.

investments. In particular, it would seem that the renewable fuel standard raised the surety of future demand, and reduced the uncertainty surrounding investment. The observed productivity movements are therefore likely to stem from reduced uncertainty (Guiso and Pagini, 1999; Bloom et al., 2007; Bloom, 2009).

6.4 Did TFP or Input Use Increase?

The increase in corn yields following the ethanol boom could have occurred because of adjustment in the intensity with which other inputs are used, rather than actual improvements to technical efficiency. In this section we explore in more detail whether TFP was also affected, and the investments made by producers that raised corn yields.

6.4.1 Total Factor Productivity

One constraint we face is the construction of total factor productivity in the corn and soybean industries is that the NASS does not release data on capital stocks, labor, material, and energy inputs at the county level. However, such information is available from the ERS Agricultural Resource Management Survey (ARMS) at the state-industry level from 2003 onwards for eight states.[34] This allows us to construct physical and revenue TFP as described earlier in Section 2.

Foster et al. (2008) note that there are important differences between revenue and physical productivity. First, in the absence of producer-level price data, revenue productivity is unable to distinguish whether output is high because of price shocks or technical efficiency. In the context that we consider where there were large changes to the price of corn and soybeans, in part associated with movements in global commodity prices, such price effects are likely to be important.

We first examine whether the yield per acre variable we have used until now is a good proxy for both TFP variables. The data suggest this to be the case, in particular for TFPQ: the correlation (p-value) between yield and TFPQ is 0.9842 (0.00), while it is 0.4941 (0.00) for TFPR. When TFPQ is used as the dependent variable the average treatment effect is estimated to be 7% (regression 5 in Table 6). In regression 6 we repeat the exercise but use TFPR to measure productivity instead. Again, we find that the treatment effect is statistically significant, but now implies a productivity increase of 18%. The difference between the two coefficients serves to illustrate the importance of controlling for producer prices when estimating productivity and reinforces the argument made in De Loecker (2011) who finds a similar upward bias in the estimated effects of trade liberalisation. This issue is particularly acute in our context and these results show a strong upward bias to the estimated productivity effects from demand shocks that occur because prices also rose.

6.4.2 Changes to Input Use

We next try to obtain a fuller understanding of why productivity increased by honing in on the investments and organizational innovations firms instigated. Using data from the ARMS and the NASS, we estimate the equation

$$y_{ist} = \alpha + \beta Corn_{is} * Treatment_t + \gamma_{is} + \gamma_{st} + \varepsilon_{ist} \ , \qquad (5)$$

[34] The reporting states are Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, and Wisconsin.

where y_{ist} denotes the share of corn acres planted with GE seeds, seed and plant expenditure, irrigation technology, machinery and equipment, land and buildings, rented machinery, labor, and fertilizer expenditure. The subscript s denotes the unit of observation (either the county or state); and ε_{ist} is the error term.

[Insert Table 7: Productivity Drivers]

The evidence from Table 7 suggests that the primary explanation behind the productivity increase was that the demand shock triggered new technology adoption.[35] Historically, and in marked contrast to soybeans, the share of corn acres planted with GE seed had been low. However, as shown in regression 1 in Table 7, the EPA caused a 19 percentage point increase in the share of acres planted with GE seeds. As shown in Figure 9 Panel A, corn farmers throughout the Corn Belt started to plant stacked gene variety seeds from 2005 onwards. In Figure 9 Panel B we also observe that there was no equivalent change in the use of GE seeds in the soybean industry, which were already high prior to the ethanol boom period.

[Insert Figure 9: Stacked Varieties GE Seed Usage]

The stacked variety seeds adopted by corn producers were developed by Monsanto in the mid-1990s and became commercially available from 1997. Irrespective of which state we consider, the incidence of stacked varieties was low pre-2005 (used in only 3% of planted acres) but accelerated afterwards, and accounted for much of the increase in GE acreage. Stacked gene varieties raise productivity by reducing crop losses over the growing season. For example, they are resistant to pests such as the European corn borer, and prevent herbicide intolerance. As reported by Shi et al. (2013) and Marra et al. (2010), stacked varieties are expected to increase corn yields by 7 bushels per acre (6%), which is very close to the average treatment effect we estimated previously in Table 6.

[Insert Table 8: Seed Profitability]

An obvious question would be, why did firms not adopt stacked gene varieties earlier if they knew this would raise productivity, and profits? The answer would appear to be that because stacked gene varieties are sold at a premium to regular seeds, they were not a profitable option before 2005. As shown in Table 8, despite being expected to raise yields by 7 bushels per acre, the net cost of planting an acre of stacked variety seeds (defined as the seed cost minus 7 times the price of a bushel of corn) was in fact higher compared to the cost of planting regular hybrid seeds plus additional herbicide and insecticide expenses. However, because the demand shock brought about an increase in corn prices, by 2007 it was less expensive to plant an acre of corn using stacked variety rather than hybrid seeds. In summary, the GE seed price premium acted as a fixed cost that stifled productivity improvements through technology adoption, and the demand shock allowed producers to overcome this barrier by raising the price of their output. This implied mechanism would therefore appear to be similar to that described in David (1975a,b) regarding differences in the timing of the introduction of the mechanical reaper between the U.K. and U.S. in the 19th century. As part of this he finds that diffusion of this

[35] This result echoes the findings by Griliches (1957) on new technology adoption and market size within the corn industry.

technology into the U.S. was delayed until the price of labour rose to a level that made the investment in the reaper (a labour-saving device) profitable.[36]

In Table 7 we also consider whether corn firms adjusted their use of other inputs and technologies. In regression 2 we find that expenditure on seed and plants increased (reflecting the switch to more expensive GE seeds), although the coefficient is only significant at the 10% level. Consistent with the view that technology adoption was the main driver of productivity, we do not find any increase in the capital stock measured by machinery and equipment (either owned or rented), land and buildings, or labor usage, and no effect on the incidence of irrigation technology (regressions 3 to 8).

7. Threats to Identification

To establish the robustness of these findings we undertake a large number of tests, the results for which are contained in the supplementary Appendix to the paper.

7.1 Falsification Tests

Our main finding that demand shocks motivate productivity change could be contested on the grounds that we are capturing wider industry trends unrelated to demand. Ideally we would test this by observing the treatment group in the untreated state. While this is clearly impossible, we are able to inspect what happened to productivity among Canadian corn producers who did not receive a demand shock. Owing to climatic conditions, Canadian corn and soybean producers are concentrated at more temperate latitudes near the U.S. border, and use the same technologies and production methods practiced in the Corn Belt. They therefore operate under very similar conditions. However, Canadian producers were unaffected by the ethanol boom for two reasons. First, the prohibitively high ethanol import tariff levied by the U.S. denied Canadian ethanol manufacturers (and by extension Canadian corn growers) the possibility of exporting ethanol to the U.S. Second, Canadian producers sell virtually all their output to the domestic feed market. Moreover, as shown in Appendix Table A4 there was no increase in Canadian exports or the share of production exported to the U.S. post-2005. Exporting to the U.S. is rare: only 2.3% of Canadian corn is exported and over the sample period this has actually fallen (Appendix Table A4 Panel A). Moreover, using data retrieved from the USDA Feed Grains Database, a t-test cannot reject the null that the volume of exports, and the share of production exported to the U.S. were significantly different after the introduction of the EPA. Canadian corn producers therefore did not experience a demand shock due to the EPA.

Using data on yield per acre for corn and soybean production in 9 Canadian provinces obtained from Statistics Canada, we re-estimate equation (4).[37] The results in Appendix Table A4 show no increase in yield post 2005 for corn producers when we consider all provinces, or just Manitoba and Ontario on the basis that because these provinces border the northern Corn

[36] Hall (2004) describes similar empirical findings for other technologies.

[37] The provinces are Alberta, Manitoba, Newfoundland and Labrador, New Brunswick, Nova Scotia, Ontario, Prince Edward Island, Quebec, and Saskatchewan.

Belt, the operating environment is likely to be most similar.[38] This result confirms that the demand shock in the U.S. caused the productivity increase in the U.S..

7.2 Anticipation Effects

A major reform to energy policy was first mooted in 2002, and previous versions of the EPA were defeated in Congress in 2002 and 2003.[39] If farmers expected that the EPA would be introduced, and that it would increase demand for corn, the optimizing decision may have been to make productivity investments in preparation for the heightened demand. If so, the productivity effects we ascribe to the demand shock will be biased and calls into question the claim that the EPA was an exogenous event.

We address this by running a placebo test that uses annual corn yield data from the NASS for the years 1998 to 2004. We then generate a placebo treatment dummy equal to 1 for the period 2002 to 2004 (0 otherwise) and randomly assign 50% of counties to placebo treatment status. Next, we regress yield on the placebo treatment, year and county dummies 1,000 times. If anticipation effects are present in the data we would expect to observe rejection rates of the placebo treatment at a much higher frequency than if we were making type-1 errors. The rejection rates reported in Appendix Table A5 Panel A are remarkably close to those we would expect if the null hypothesis is only rejected by chance. Based on this evidence, corn farmers did not make productivity investments ahead of the EPA.

7.3 Spillover Effects

Next we try to establish whether there were spillover effects on the soybean industry. Our first approach to tackling whether soybean yields are a suitable counterfactual is to randomly assign placebo treatments to post-2005 observations of soybean productivity. We would expect that if spillover effects are important for soybean yields, then the null hypothesis that soybean productivity is unaffected by the placebo treatment would be rejected more often than would be expected. Again, we randomly assign placebo treatments (equal to 1 for 2005 to 2010, 0 otherwise) to 50% of soybean observations, and regress yield on the placebo treatment, year, and county dummies, 1,000 times. The rejection rates reported in Appendix Table A5 Panel B are consistent with the rejection rate associated with type-1 errors. Soybean productivity was therefore unaffected by the EPA.

The second procedure considers an alternative control group. In Panel C of Appendix Table A5 we test report the robustness of our findings to using barley instead of soybeans as the control group. Like corn, barley is a major cereal grain that can be used for animal fodder, but like soybeans is not used to produce ethanol. It has the additional advantage that barley is not usually used in rotation with corn and should therefore be unaffected by concerns of possible spillover effects.[40] Despite the drop in the number of observations when barley is used as the control group, we reach the same conclusion as before. Indeed, the average treatment effect of

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

[39] http://www.ucsusa.org/clean_energy/smart-energy-solutions/increase-renewables/energy-bill-2005.html

[40] Rotations are typically either corn-soybean or soybean-barley.

the demand shock on productivity is somewhat larger, equal to an 8.5% increase. The results are unchanged when we use wheat as the control group.[41]

Finally, we repeat the placebo treatment procedure but use GE acreage in the soybean industry as the dependent variable to check that technology adoption was specific to corn. The rejection rates reported in Appendix Table 5 Panel D are very close to type-1 errors indicating that technology adoption was unique to the corn sector.

8. Conclusions

The key result in this paper is that changes in the demand environment trigger productivity improvements. Our research builds on a quickly evolving body of literature that hones in on the potentially wide-ranging effects of demand on producers (Syverson, 2004; De Loecker, 2011; Foster et al., 2008, 2012; Pozzi and Schivardi, 2012).

Exploiting natural variation in the size of the demand for corn that occurs due to the opening of new ethanol plants following modifications to U.S. energy policy, we use an instrumental variable estimation strategy to pin down the causal effect. We find evidence that positive demand shocks increase quantity based measures of productivity. The economic magnitude of the treatment effect we uncover is economically important, equivalent to a 6% annual productivity increase. The reason for this productivity increase was that the demand shock caused a substantial rise in the price of corn, and that this made it possible for producers to overcome the fixed costs of adopting a new technology (GE seeds). A battery of robustness, falsification, and placebo tests confirm our main results. Finally, we find that the *structure* of demand also matters: we only find significant productivity effects following permanent, but not temporary demand shocks.

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, the local ATE we estimate is somewhat smaller. But major supply-side shocks and changes in competition are often landmark events whereas firms are confronted by quickly changing demand environments as incumbent rivals and entrants seek to appropriate their market share. The effect of demand shocks may also be larger in industries where productivity is more dispersed and knowledge of the optimal production methods is not as well understood.

Based on this, and the fact that our setting is highly stylized, and considers an industry that in most developed countries accounts for a relatively small share of total output and employment, an interesting question for future research would be to examine the productivity effects of demand shocks in other industries using firm-level data to gauge the pattern of adjustment.

[41] We do not have data on the number of barley or wheat firms in each county.

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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	3,528	52.67	13.18	8.9	94	County	NASS
Wheat yield	14,776	48.20	16.85	0	104	County	NASS
TFPQ	127	3.90	0.63	2.67	4.72	State	Authors' calculations
TFPR	127	20.85	0.73	18.92	22.31	State	Authors' calculations
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
Ethanol production plant	19,749	0.11	0.31	0	1	County	RFA Outlook
Operating capacity	7,907	1133	1083	5	5865	County	Authors' calculations
Capacity under construction	7,907	368	483	0	2596	County	Authors' calculations
Minimum distance	7,907	56.42	38.45	10.66	225.80	County	Authors' calculations
DDG demand (ln)	7,845	7.08	3.54	-4.61	13.41	County	NASS
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
Irrigation	19,749	0.07	0.21	0	1	County	Authors' calculations
GE share	132	81.02	14.54	22	98	State	ARMS
Seed and plant expenditure	126	19.10	14.89	1.24	60.33	State	ARMS
Machinery and equipment	127	123.25	112.96	0	379.15	State	ARMS
Land and buildings	122	669.05	519.24	0.01	1812.31	State	ARMS
Rented machinery	120	3.23	2.23	0.12	10.58	State	ARMS
Labor	118	5.47	3.83	0.02	13.85	State	ARMS
Fertilizer	125	36.34	29.36	2.00	114.84	State	ARMS

Notes: This table provides summary statistics on the dependent and independent variables used in the empirical analysis. Ethanol production plants include only plants that use corn as their feedstock or one of their main feedstocks. Operating capacity and capacity under construction are measured in millions of gallons per year. Minimum distance is measured in miles and is the great circle distance between the mid-point in a given county and the mid-point of the nearest county containing an ethanol plant. Where a county contains an ethanol plant minimum distance is set equal to 10.66 miles – the average radius between a county's mid-point and border. DDG demand is proxied using the number of cattle on feed in the county.

Table 2
Ethanol Industry Evolution

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

Notes: This table provides information on the number of ethanol plants, the net entry rate, operating capacity in the industry (in mgy) for each year of the sample. Multi-plant is the percentage of plants within the industry that belong to a multi-plant firm. The variable Corn Belt is the percentage of ethanol plants sited in the Corn Belt region.

Table 3
Exogeneity Tests

Regression No.	1	2	3	4	5	6	7	8
Dependent variable	Entry				Plant			
Estimator	LPM	LPM	Probit	Probit	LPM	LPM	Probit	Probit
Yield	-0.0003	-0.0002	0.0036	0.0043	-0.0002	-0.0002	-0.0051	-0.0030
	(-1.44)	(-1.22)	(1.21)	(1.43)	(-1.28)	(-1.44)	(-0.58)	(-0.32)
Output	0.0243	0.0191	-0.0654	-0.1286	-0.0055	-0.0039	-0.3882	-0.6969
	(1.61)	(1.25)	(-0.43)	(-0.81)	(-0.46)	(-0.32)	(-0.58)	(-0.94)
DDG demand	1.4428*	1.5728*	8.9506+	10.2288+	0.7290	0.7154	-20.9939	-20.7939
	(1.97)	(2.20)	(1.65)	(1.74)	(0.91)	(0.91)	(-1.43)	(-1.36)
Plants within 100 miles	-0.0052**		-0.0670**		0.0104**		0.0587	
	(-4.46)		(-4.24)		(4.63)		(0.99)	
Plants within 200 miles		-0.0028**		-0.0358**		0.0039**		-0.0143
		(-5.19)		(-4.93)		(4.38)		(-0.49)
Observations	8,209	8,209	8,171	8,171	8,209	8,209	1,177	1,177
R^2	0.74	0.74	-	-	0.75	0.74	-	-
County effects	√	√	√	√	√	√	√	√
Year effects	√	√	√	√	√	√	√	√

Notes: Entry is a dummy variable equal to 1 if at least one plant enters county *c* at time *t*, 0 otherwise. Plant is a dummy variable equal to 1 if there is at least one plant in county *c* at time *t*, 0 otherwise. Yield is corn yield within county *c* at time *t*. Output is the annual number of bushels of corn produced within the county. DDG demand is proxied by the number of cattle (in millions) on feed in 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*. The number of observations in the probit regressions is lower compared to the LPM model because of perfect collinearity between the dependent variable and the county fixed effects. 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.

Table 4
Instrumental Variables Estimates

Regression No.	**1**	**2**	**3**
	Yield	**Yield**	**Yield**
A: Second-stage: dependent variable = ln(dependent variable)			
ln(Ethanol Demand)	0.0834**	0.0964**	0.0883*
	(2.67)	(2.98)	(2.45)
Number of firms	0.0004**	0.0004**	0.0007**
	(2.74)	(3.01)	(6.59)
Acres planted	-1.2572**	-1.1020**	-1.0230**
	(-4.13)	(-3.54)	(-3.45)
Precipitation		0.0231**	0.0224**
		(7.82)	(7.71)
Growing degree days (ln)		0.0182*	0.0108
		(2.19)	(1.25)
Population density		0.0002	0.0003
		(0.68)	(0.91)
Number of banks			0.0004
			(0.25)
Prices			1.6990*
			(2.55)
Subsidy payments			0.0015
			(1.30)
Median firm size			0.0002+
			(1.76)
Ethanol imports			-0.0001**
			(-2.62)
Corn exports			13.5551**
			(2.64)
Corn imports			0.0000**
			(2.63)
B: First-stage: dependent variable = ln(Demand)			
Min. distance	-0.0032**	-0.0031**	-0.0027**
	(-8.53)	(-8.37)	(-7.22)
DDG demand	1.5110**	1.5612**	2.0629**
	(7.07)	(7.18)	(8.48)
Under-identification test	83.93	86.05	169.78
Kleibergen-Paap F-statistic	55.78	55.04	179.93
Exogeneity test (p-value)	0.34	0.11	0.18
Observations	7,692	7,692	6,953
County effects	√	√	√
Year effects	√	√	√

Notes: The table reports the instrumental variable estimated of equation (3). The dependent variable in all regressions is corn yield per acre. Demand is measured as the natural logarithm of ethanol industry operating capacity within a 200 mile radius of county *c* at time *t*. The sample contains observations between 2002 and 2010 because the RFA publish The Ethanol Industry Outlook from 2002 onwards. For reasons of parsimony we do not report the coefficient estimates on the included instruments in the first-stage results. Min. distance is the great circle distance between the midpoint of county *c* and the midpoint of the closest county with an ethanol plant in each year. DDG demand is proxied by the number of cattle (in millions) on feed in the county. Standard errors are clustered at the county level and the accompanying *t*-statistics are reported in parentheses. +, *, ** denote significance at the 10%, 5% and 1% levels respectively.

Table 5
Parallel Trends Tests

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

Notes: Δ $Yield_t$ denotes the annual rate of productivity change measured as $(yield_t - yield_{t-1})/yield_{t-1}$. Standard errors are reported in parentheses. Treatment is the average annual rate of productivity growth (in bushels per acre) within the treatment group. Control is the average annual rate of productivity growth (in bushels per acre) within the control group.

Table 6
Productivity Response to the Demand Shock

Regression No.	**1**	**2**	**3**	**4**	**5**	**6**
Control group	**Soybeans**	**Soybeans**	**Soybeans**	**Soybeans**	**Soybeans**	**Soybeans**
Dependent variable	**Yield**	**Yield**	**Yield**	**Yield**	**TFPQ**	**TFPR**
Event	**EPA**	**EPA**	**HFCS**	**Chinese exports**	**EPA**	**EPA**
Corn * Treatment	6.3120**	6.7972**			0.0728*	0.1796**
	(8.98)	(7.00)			(2.48)	(6.38)
Corn * HFCS Treatment			10.7411**			
			(18.97)			
Corn * China Treatment				0.9387		
				(1.19)		
Number of firms	0.0102	0.0140	0.0092*	-0.001	0.0030	-0.0194+
	(1.63)	(1.56)	(2.52)	(-0.07)	(0.27)	(-1.88)
Acres planted	0.0001**	-0.0000	0.7264*	0.0004**	-0.0826	0.6918**
	(3.56)	(-1.05)	(1.31)	(7.15)	(-0.63)	(4.77)
Observations	19,115	3,614	21,114	11,245	127	127
R^2	0.98	0.99	0.96	0.97	0.99	0.99
County effects						
Year effects						
County-industry effects	√	√	√	√		
County-year effects	√		√	√		
County-period effects		√				
State-industry effects					√	√
State-year effects					√	√

Notes: The table reports estimates of equation (4). County-level data is used in regression 1, 2, 3, and 4 and state-level data from the ARMS database is used in regressions 5 and 6. The treatment used in regression 1, 2,5, and 6 is the Energy Policy Act of 2005. The treatment in regression 3 is the HFCS shock following the switch in sweetener by Coca-Cola and Pepsi. The treatment in regression 4 is the temporary withdrawal of China from the export market. In regression 3 the equation is estimated using data from 1980 to 1990. The HFCS Treatment variable is equal to one for the years 1985 to 1990, zero otherwise. In regression 4 the equation is estimated using data from 1992 to 1997. The China Treatment variable is equal to one for the years 1995 to 1997, zero otherwise. Yield is measured as bushels per acre. The standard errors are clustered at the county level in regression 1, 2, 3, and 4 and at the state level in regressions 5 and 6; the associated t-statistics are reported in parentheses.. +, *, ** denote significance at the 10%, 5% and 1% levels respectively.

Table 7
Productivity Drivers

Regression No.	1	2	3	4	5	6	7	8
Dependent variable	GE Share	Seed & Plants	Irrigation	Mach & Equip	Land & Buildings	Rented Mach	Labor	Fertilizer
Corn * Treatment	18.8833**	5.7611+	0.0022	18.3283	141.2071	0.4607	1.3436	-1.1413
	(4.03)	(2.33)	(0.72)	(0.43)	(1.22)	(0.99)	(0.64)	(-0.33)
Observations	264	126	19,749	127	122	120	118	125
R^2	0.95	0.92	0.97	0.87	0.91	0.87	0.82	0.95
State-industry effects	√	√		√	√	√	√	√
State-year effects	√	√		√	√	√	√	√
County-industry effects			√					
County-year effects			√					

Notes: The table reports estimates of equation (5). State-level data is used in all regressions except regression 3 where county-level data is used. In regressions 2, 4, 5, 6, 7, and 8 the dependent variable is expenditure (in 1992 U.S. dollars). All values are deflated using the NASS Agricultural Price Index. GE share is the percentage of acres within the state-industry planted using GE seeds. Irrigation is the percentage of acres within the county-industry that are irrigated. Treatment is equal to one for the post-EPA period (2005-2010), zero otherwise. Standard errors are clustered at the state level in all regressions except in regression 3 where they are clustered at the county level; the accompanying *t*-statistics are reported in parentheses. +, *, ** denote significance at the 10%, 5% and 1% levels respectively.

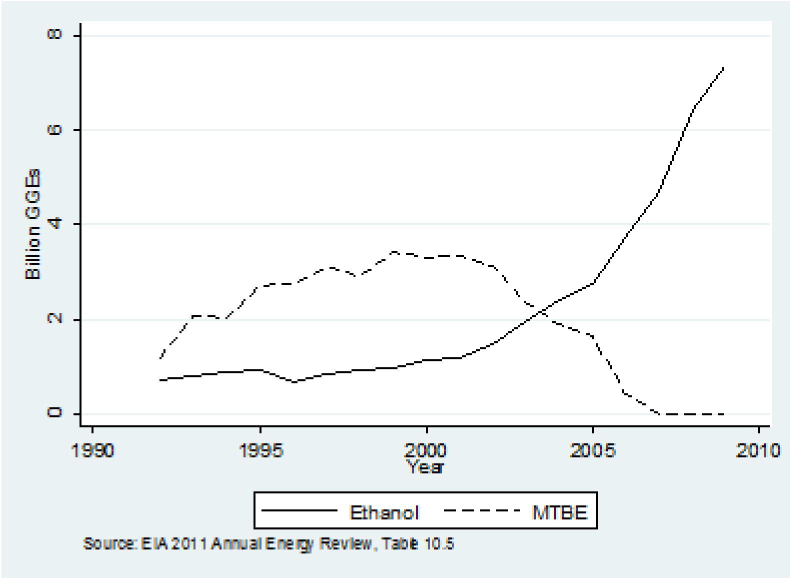
Table 8
Seed Profitability

	Hybrid Seed				GE Seed		
Year	Seed	Herbicide	Insecticide	Net Cost	Seed	Corn Price ($ bu)	Net Cost
2000	30.61	30.61	14.29	75.51	126.53	1.87	113.43
2001	32.26	32.26	15.05	79.57	133.33	2.10	118.64
2002	30.93	31.96	14.43	77.32	127.84	2.40	111.04
2003	30.00	28.30	13.21	71.51	116.98	2.28	101.05
2004	23.73	27.12	11.86	62.71	105.08	1.71	93.10
2005	32.46	28.07	15.79	76.32	108.77	1.72	96.75
2006	34.78	27.83	15.65	78.26	107.83	2.63	89.39
2007	40.07	17.65	12.50	70.22	91.18	3.09	69.57
2008	42.28	16.91	11.98	71.17	83.22	2.69	64.37
2009	71.68	28.85	13.63	114.16	94.66	2.69	75.81
2010	60.99	17.73	7.09	85.82	87.94	3.71	62.00

Notes: Thus table reports the real per acre net cost of hybrid seeds, herbicide, insecticide, and GE seed, as well as the real price of a bushel of corn. All values are deflated into 1992 U.S. dollars using the NASS Agricultural Price Index. Hybrid seed, herbicide, and insecticide costs were obtained from the annual Estimated Costs of Crop Production in Iowa database provided by Iowa State University. The price of GE seeds is taken from GM Watch and corresponds to the price of SeedStax, a GE seed variety produced by Monsanto. The final price of corn is taken from the NASS for each Corn Belt state, and the mean calculated for each year.

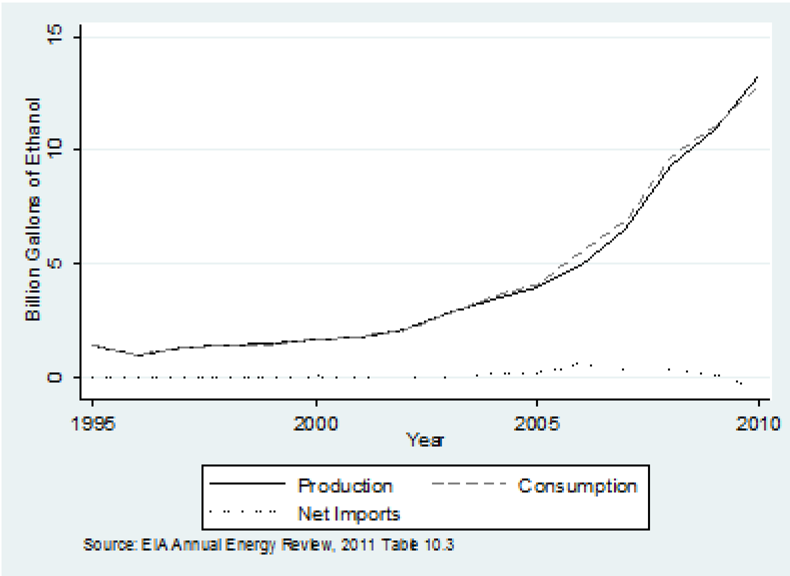
Figures

Figure 1
Oxygenates in Gasoline



Notes: The chart shows trends in ethanol and methyl tertiary-butyl ether (MTBE) consumption as oxygenates from 1992 to 2009. Fuel volumes are expressed in gasoline gallon-equivalents (GGEs), representing a volumne of fuel with the same energy content as a gallon of gasoline. The data are taken from the EIA 2011 Annual Energy Review, Table 10.5.

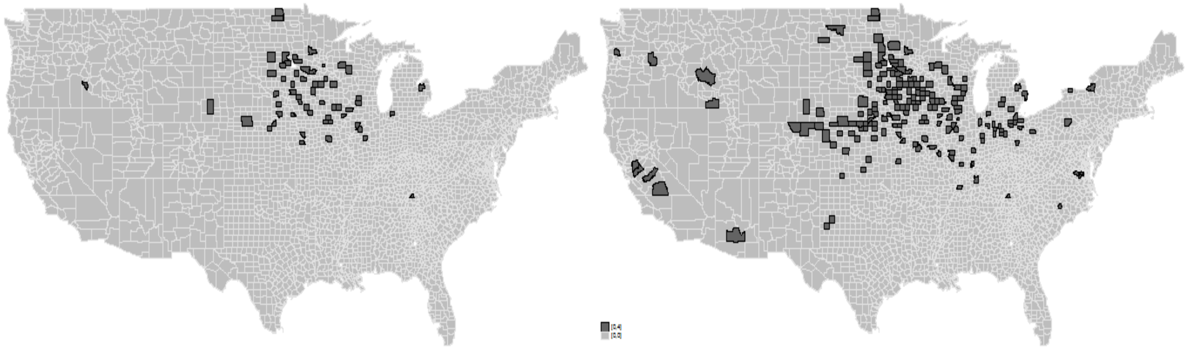
Figure 2
Ethanol Production and Consumption



Notes: This chart shows ethanol fuel production and consumption from 1995 to 2010. The data are taken from the EIA 2011 Annual Energy Review, Table 10.3.

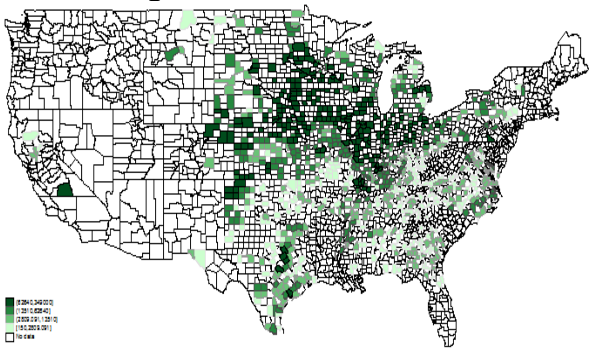
Figure 3
Ethanol Plant Location

A: 2002 B: 2010



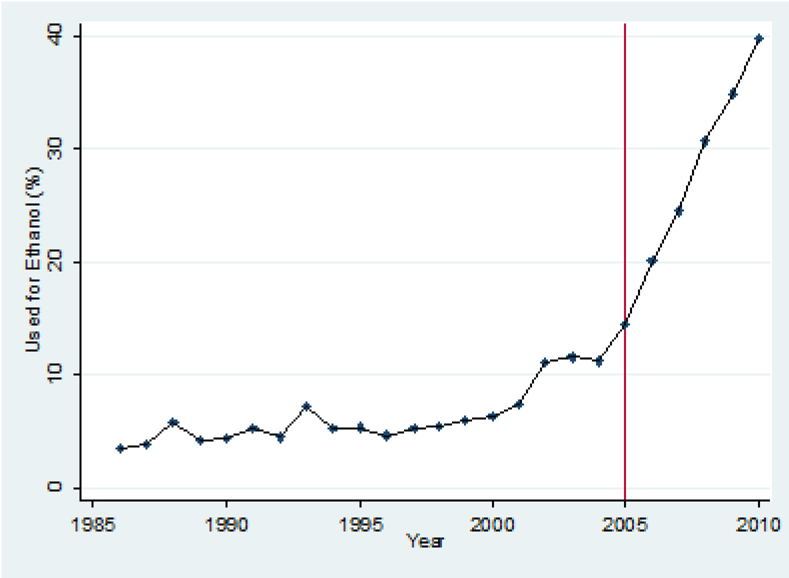
Notes: This figure plots the location of ethanol plants in the continental U.S. for the years 2002 (Panel A) and 2010 (Panel B). Counties with at least one ethanol plant are shaded dark, all other counties have zero ethanol plants. The figure is constructed using data on only ethanol plants that use corn as their main, or as one of their main, feedstocks.

Figure 4
Average Planted Acres 2000-2010



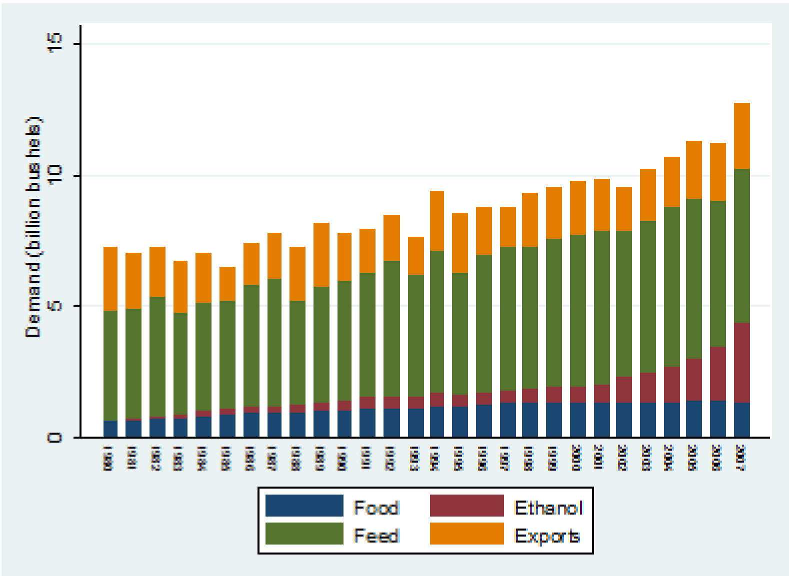
Notes: This figure plots the average annual number of planted corn acres in each county. Darker shading indicates a larger number of planted acres. Counties with no shading have zero planted acres.

Figure 5
Share of U.S. Corn Production in Ethanol



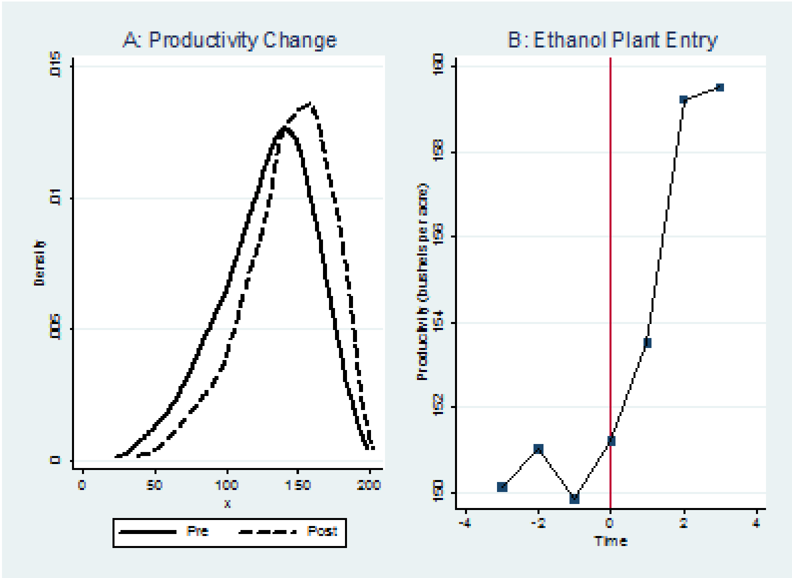
Notes: This figure plots the annual percentage of national corn production used to manufacture ethanol between 1986 and 2010. Information on the share of corn output used for ethanol production is taken from the USDA Economic Research Service – Feed Grains Database.

Figure 6
Sources of Corn Demand



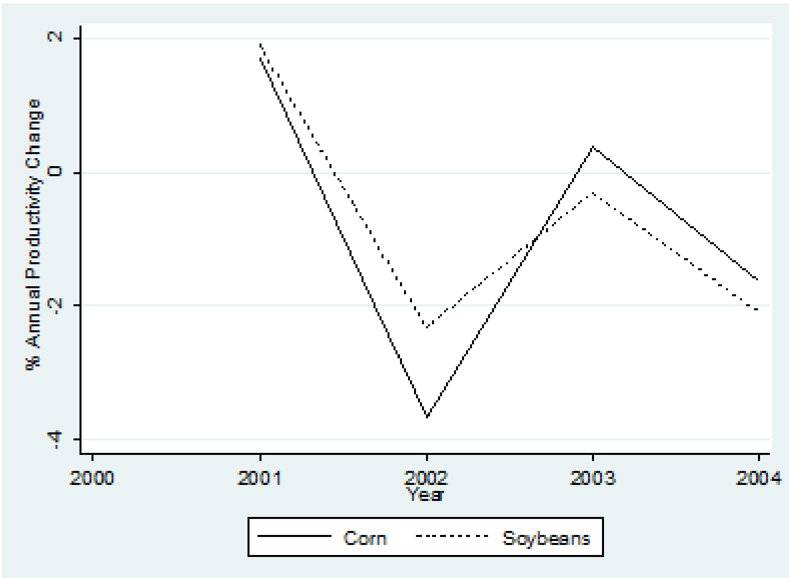
Notes: This figure plots the annual number of bushels of corn purchased for use in the food, seed, and industrial sector, the ethanol sector, the feed and residual uses sector, and exports between 1980 and 2007. The data are taken from the USDA Economic Research Service – Feed Grains Database.

Figure 7
Productivity Response to the Demand Shock



Notes: Panel A plots the distribution of productivity (bushels per acre) in the corn industry pre- and post-EPA. Panel B illustrates the productivity response of corn firms to the entry of an ethanol plant within the county. Time equal to 0 is the year in which the plant becomes operational, time less (greater) than 0 correspond to years before (after) entry.

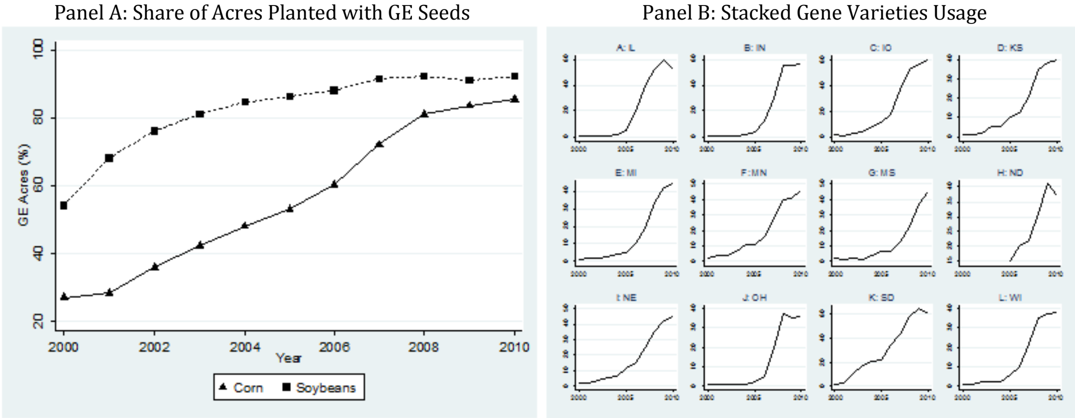
Figure 8
Pre-Treatment Productivity Evolution



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

Figure 9
GE Seed Incidence

Panel A: Share of Acres Planted with GE Seeds   Panel B: Stacked Gene Varieties Usage



Notes: This figure plots the percentage of corn acres that are planted using stacked gene variety genetically engineered seeds in each state within our sample. Years are plotted on the x-axis in all panels, and percentage of planted acres is on the y-axis.

Supplementary Appendix

Demand Shocks and Productivity: Evidence from the Ethanol Boom

- *For Online Publication* –

Appendix 1: Gasoline Oxygenate Usage

Table A1
State MTBE Bans

State	Phaseout Date	Complete/Partial ban	Oxygenate	Date of Adoption
Iowa	7/1/2000	Partial	MTBE	5/11/2000
Minnesota	7/2/2000 (partial) 7/2/2005 (complete)	Partial/then complete: no more than 1/3 of 1% oxygenate as of 7/2/2000; complete ban as of 7/2/2005	MTBE, ETBE, TAME	Early 2000
Nebraska	7/13/2000	Partial	MTBE	4/11/2000
South Dakota	7/1/2001	Partial	MTBE	2/28/2001
Colorado	4/30/2002	Complete	MTBE	5/23/2000
California	12/31/2002	Complete	MTBE	3/15/2002
Michigan	6/1/2003	Complete	MTBE	6/26/2000
Connecticut	1/1/2004	Complete	MTBE	1/1/2004
New York	1/1/2004	Complete	MTBE	5/24/2000
Washington	1/1/2004	Partial	MTBE	5/10/2001
Kansas	7/1/2004	Partial	MTBE	4/19/2001
Illinois	7/24/2004	Partial	MTBE	6/24/2002
Indiana	7/24/2004	Partial	MTBE	3/14/2002
Wisconsin	8/1/2004	Partial	MTBE	8/11/2003
Ohio	7/1/2005	Partial	MTBE	5/29/2002
Missouri	7/31/2005	Partial	MTBE	7/11/2002
Kentucky	1/1/2006	Partial	MTBE	4/23/2002
Maine	1/1/2007	Partial	MTBE	4/14/2004
New Hampshire	1/1/2007	Partial	MTBE	5/27/2004

Notes: This table reports information on states that banned MTBE as a gasoline oxygenate. Partial bans typically permitted no more than 0.5% (vol.) MTBE in gasoline sold or stored. Exceptions to this were Washington (0.6%), Minnesota (1%) and Nebraska (1%). ETBE denotes ethyl tertiary butyl ether. TAME denotes tertiary amyl methyl ether. Arizona adopted legislation on 4/28/2000 calling for a complete phaseout of MTBE as soon as feasible but in no event later than 6 months after California's phaseout. The legislation expired on June 30 2001 and while no longer official state policy, the state informally still encourages phaseout of MTBE. All data are taxen from the Environmental Protection Agency (http://www.epa.gov/mtbe/420b04009.pdf).

Appendix 2: Additional Exogeneity Tests

Table A2
Exogeneity Tests

Regression No.	1	2	3	4
Dependent variable	Operating Capacity		Under Construction	
Estimator	LPM	LPM	LPM	LPM
Yield	0.0491	0.0290	-0.0419	-0.0398
	(0.82)	(0.50)	(-0.83)	(-0.84)
Output	-3.9866	-1.6604	3.3840	3.1349
	(-1.36)	(-0.62)	(0.66)	(0.69)
DDG demand	177.6434*	101.3960	226.8531+	239.6622+
	(2.03)	(1.05)	(1.72)	(1.80)
Plants within 100 miles	0.0949		-0.4888	
	(0.22)		(-1.28)	
Plants within 200 miles		0.3182+		-0.2117
		(1.66)		(-1.00)
Observations	834	834	834	834
R^2	0.78	0.78	0.36	0.35
County effects	√	√	√	√
Year effects	√	√	√	√

Notes: Operating capacity is the operating capacity of plant *p* in year *t*. Under Construction is the total capacity currently being installed at plant *p* in year *t*. Yield is corn yield within county *c* at time *t*. Output is the annual number of bushels of corn produced within the county. DDG demand is proxied by the number of cattle (in millions) on feed in 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*. We winsorize the data at the 5th and 95th percentiles of the distribution of the capacity distribution to eliminate outliers. The standard errors are clustered at the plant level and the associated t-statistics are reported in parentheses. +, *, and ** denote significance at the 10%, 5% and 1% levels.

Appendix 3: IV Regressions Using 100 Miles Radius

Table A3
Additional Instrumental Variables Estimates

Regression No.	1	2	3
Demand radius		100 Miles	
	Yield	Yield	Yield
A: Second-stage: dependent variable = ln(dependent variable)			
ln(Ethanol Demand)	0.1236**	0.1239**	0.0932**
	(2.89)	(2.92)	(3.24)
Number of firms	0.0003*	0.0003*	0.0006**
	(2.04)	(2.12)	(5.89)
Acres planted	-1.0905**	-0.9724 **	-0.8029**
	(-3.29)	(-2.91)	(-2.87)
Precipitation		0.0158**	0.0195**
		(5.14)	(6.65)
Growing degree days (ln)		0.0292**	0.0191*
		(3.49)	(2.24)
Population density		0.0000	0.0004
		(0.06)	(0.81)
Number of banks			-0.0001
			(-0.06)
Prices			-0.0046
			(-0.39)
Subsidy payments			0.0014
			(1.19)
Median firm size			0.0002
			(1.44)
Ethanol imports			-0.0000+
			(-1.95)
Corn exports			0.0827**
			(3.33)
Corn imports			0.0000**
			(4.47)
B: First-stage: dependent variable = ln(Demand)			
Min. distance	-0.0039**	-0.0039**	-0.0044**
	(-5.04)	(-5.04)	(-6.13)
DDG demand	1.7680**	1.7680**	2.9778**
	(4.92)	(4.92)	(7.12)
Under-identification test	43.34	43.81	133.58
Kleibergen-Paap F-statistic	23.15	23.40	121.57
Exogeneity test (p-value)	0.22	0.16	0.19
Observations	6,308	6,308	5,808
County effects	√	√	√
Year effects	√	√	√

Notes: The table reports the instrumental variable estimated of equation (3). The dependent variable in all regressions is corn yield per acre. Demand is measured as the natural logarithm of ethanol industry operating capacity within a 100 (50) mile radius of county *c* at time *t*. The sample contains observations between 2002 and 2010 because the RFA publish The Ethanol Industry Outlook from 2002 onwards. For reasons of parsimony we do not report the coefficient estimates on the included instruments in the first-stage results. Min. distance is the great circle distance between the midpoint of county *c* and the midpoint of the closest county with an ethanol plant in each year. DDG demand is proxied by the number of cattle (in millions) on feed in the county. Standard errors are clustered at the county level and the accompanying *t*-statistics are reported in parentheses. +, *, ** denote significance at the 10%, 5% and 1% levels respectively.

Appendix 4: Canadian Production and Exports

Table A3
Canadian Corn Production and Exports to the U.S.

Panel A: Descriptive Statistics

Year	Production	Yield (all)	Yield (MB & OT)	Exports to U.S.	Export Share (%)
2000	6954	119	120	297	4.27
2001	8389	111	101	111	1.32
2002	8999	117	110	194	2.16
2003	9587	120	112	297	3.10
2004	8837	114	104	294	3.33
2005	9332	124	116	203	2.18
2006	8990	138	132	108	1.20
2007	11649	142	122	117	1.00
2008	10643	141	137	360	3.38
2009	9796	139	130	226	2.31
2010	12043	133	140	124	1.03

Panel B: T-tests

Variable	Pre-2005	EPA	Difference	t-stat
Exports	238.60	189.67	49.93	0.89
	(37.52)	(39.49)	(55.25)	
Export share	2.83	1.85	0.98	1.58
	(0.51)	(0.39)	(0.63)	

Notes: Panel A reports descriptive statistics for corn production in Canada. Production and Exports to U.S. are measured in 1,000 metric tons. Yield is measured in bushels per acre. Yield (all) denotes average yield across all Canadian provinces whereas Yield (MB & OT) is average yield in Manitoba and Ontario. Export Share is the percentage of production that is exported to the U.S. Production data are taken from Statistics Canada and export data are taken from the U.S. Feed Grains Database Table 24. Panel B reports *t*-tests on the null of equality between exports and export shares during the pre- (2000 to 2004) and post-EPA (2005 to 2010) periods.

Panel A in Table A3 reports summary statistics on the Canadian corn sector. Exports to U.S. is the total tons of corn (in 1,000 metric tons) exported to the U.S., taken from the USDA Food Grains Database. Export share is the ratio of exports to U.S. divided by production. In Panel B we report the results of t-tests that examine whether the volume of exports, or the share of corn production exported to the U.S. changed following implementation of the EPA. In both cases we find that these values actually decreased, but there are no statistically significant differences between periods. Combined with the persistently low incidence of exporting by Canadian corn producers, we conclude that there was no increase in demand for corn in Canada because of the demand shock in the U.S.

Table A4
Canadian Producers and Alternative Control group

Regression No.	1	2
Canadian Provinces	**All**	**MB & OT**
Dependent variable	**Yield**	**Yield**
Corn * Treatment	28.1408	36.9967
	(1.39)	(1.08)
Observations	137	43
R^2	0.99	0.99
Province-industry effects	√	√
Province-year effects	√	√

Notes: This table reports the Canadian falsification tests, estimated using equation (4). Regression 1 uses data from all Canadian provinces. Regression 2 uses data from Manitoba and Ontario only. Yield is measured as bushels per acre. The treatment dummy is equal to one for the post-EPA period (2005 to 2010), and zero for the pre-EPA period (2000 to 2004). Standard errors are clustered at the province level and the accompanying *t*-statistics are reported in parentheses. +, *, ** denote significance at the 10%, 5% and 1% levels respectively.

Appendix 5: Placebo Tests and Alternative Control Groups

Table A5
Placebo Tests and Alternative Control Groups

Panel A: Placebo test 1 Corn Yield (Anticipation Effect)	**Panel B: Placebo test 2 Soybean Yield (Spillover Test)**	**Panel C: Alternative Control Groups**			**Panel D: Placebo test 3 Soybeans GE Acreage Share**
Number of replications: 1,000	Number of replications: 1,000	Variable / Control group	Barley	Wheat	Number of replications: 1,000
		Corn * Treatment	12.3506*	8.4244**	
Rejection rate at the 1% level (2-tailed test): 0.7%	Rejection rate at the 1% level (2-tailed test): 1.3%		(2.28)	(7.96)	Rejection rate at the 1% level (2-tailed test): 2.7%
		Acres planted	-0.0001	-0.0001*	
			(-0.68)	(-2.29)	
Rejection rate at the 5% level (2-tailed test): 4.1%	Rejection rate at the 5% level (2-tailed test): 5.1 %	Observations	13,646	24,946	Rejection rate at the 5% level (2-tailed test): 6.8%
		R^2	0.99	0.98	
		County-industry effects	√	√	
		County-year effects	√	√	
Rejection rate at the 10% level (2-tailed test): 9.5 %	Rejection rate at the 10% level (2-tailed test): 10.8%				Rejection rate at the 10% level (2-tailed test): 9.9%

Notes: The table reports results of placebo tests (Panels A, B, and D), and estimates of equation (4) using alternative control groups (Panel C). In Panels A, B, and D equation estimated is $yield_{ict} = \alpha + \beta placebo_{it} + \gamma_c + \gamma_t + \varepsilon_{it}$. The placebo treatment is randomly assigned to approximately 50% of observations in the corn sector (Panel A), and the soybean sector (Panels B and D). In Panel A the sample spans the years 1998 to 2004. In Panels B, C, and D the sample spans the years 2000 to 2010. County-level data is used in Panels A, B, and C; state-level data is used in Panel D. Data on wheat is only available until 2008. The standard errors are clustered at the county level in Panels A, B, and C; at the state-level in Panel D. The rejection rate is the percentage of t-statistics that exceed the critical value at the 10%, 5%, and 1% levels, and denote the percentage of times the null hypothesis that β is equal to zero in the above equation. In Panel C t-statistics are reported in parentheses. +, *, ** denote significance at the 10%, 5% and 1% levels respectively.