Effects of Ethanol Plant Proximity and Crop Prices on Land-Use Change in the United States

Yijia Li, Ruiqing Miao, Madhu Khanna

Abstract: Expansion of ethanol production in the United States has raised concern regarding its land-use change effects. However, little is known about the extent to which observed land use change in the US can be attributed to ethanol plant proximity or is caused by changes in crop prices that may be partly induced by expansion in ethanol production. This study aims to examine the determinants of changes in corn acreage and aggregate crop acreage by simultaneously identifying the effects of establishment of ethanol plants serving as terminal markets for corn and the effects of changes in crop prices in the United States between 2003 and 2014. Our results show that corn acreage and total acreage are fairly inelastic with respect to both changes in ethanol capacity in the vicinity as well as changes in crop prices. Our estimates of acreage elasticity with respect to corn ethanol production are smaller than those obtained by previous studies that disregard the price effect on crop acreage. We find that, *ceteris paribus*, the increase in ethanol capacity alone led to a modest 3% increase in corn acreage and less than 1% increase in total crop acreage by 2012 when compared to 2008. The effect of corn price and aggregate crop price on acreage change over 2008-2012 was more than twice larger than that of effective ethanol production capacity over this period; but this price effect was largely reversed by the downturn in crop prices after 2012. This study shows that land-use change is not a static phenomenon and that it is important to examine how it evolves in response to various factors that may change over time.

Keywords: Aggregate Cropland Acreage, Biofuel, Corn Acreage, Ethanol Plants, Land Use Change
JEL codes: Q11, Q15, Q16

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I. INTRODUCTION

The increase in corn-ethanol production in the United States since 2003 has led to concerns about the expansion of land under corn production and the consequent conversion of non-cropland to crop production in response to higher crop prices induced by corn ethanol (Searchinger et al. 2008; Fargione et al. 2008). Expansion of crop acreage on non-cropland has the potential to reduce soil carbon stocks, to increase greenhouse gas emission and nitrate run-off, as well as to adversely affect biodiversity (Tilman et al. 2002; Parton et al. 2015). The amount of land conversion induced indirectly by higher crop prices that have accompanied the expansion in corn ethanol has been the subject of significant debate in the literature (Khanna and Crago, 2012).

A number of studies have used satellite data to show that there has been substantial expansion of cropland through the conversion of grasslands to crop production in the Midwestern United States since 2007 (e.g., Wright and Wimberly 2013; Lark, Salmon and Gibbs 2015; Mladenoff et al. 2016; Wright et al. 2017). For instance, Lark, Salmon and Gibbs (2015) find that the U.S. aggregate cropland increased by 2.98 million acres over 2008-2012, which contradicts the data from the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA) that show the increase was only 0.94 million acres (Dunn et al. 2017). By comparing land use *before* the expansion of corn ethanol in 2008 to that *after* the expansion in 2012, Wright et al. (2017) show that the rate of grassland-to-cropland conversion increases with proximity to a refinery location and they conclude that the expansion in cropland represents a persistent shift in land use rather than short term variability. They implicitly attribute the entire change to corn ethanol and do not quantify the causal effect of expansion of corn ethanol on land use change while controlling for other factors that affect crop acreage.

A few studies have questioned the effect of corn ethanol on land use and compared trends in cropland acreage and in cropland rents to show that large increases in cropland rents of 56%-64% in the United States were accompanied by small increases of 0.3%-3% in total cropland acreage during biofuel boom, implying that crop acreage has been relatively inelastic to biofuel-induced crop price increases (Barr et al. 2011; Swinton et al. 2011). These studies, like the satellite data based studies, draw circumstantial inferences about the role of biofuels by estimating the amount and type of land use change over time but do not provide direct evidence about the causes of this observed land use change or the extent to which it can be attributed to corn ethanol production.

Studies that have quantified the causal effects of corn ethanol plants on corn acreage in their vicinity include Miao (2013), Brown et al. (2014), Fatal and Thurman (2014), and Motamed, McPhail, and Williams (2016). These studies find a statistically significant increase in corn acreage in the proximity of corn ethanol plants, likely because of increased demand for corn by these plants. This increase in corn acreage can be considered the direct acreage effect of corn ethanol production given the underlying premise that it is producing corn as a feedstock for the ethanol plant. In doing so, however, these studies do not simultaneously examine the indirect effect of the change in crop prices on land use. This is in part because of the sub-state or regional scale of their analyses. Although Miao (2013) controls for corn-soybean price ratios when examining the effect of ethanol plants on corn acreage shares focusing on Iowa, he only covers the 1997-2009 period and does not separately identify the effect of corn price on acreage. Moreover, Miao (2013) does not examine response of total cropland acreage to ethanol plant proximity or to crop prices. Brown et al. (2014) use a cross-sectional dataset on acreage for Kansas that lacks price variation at a sub-state level. Fatal and Thurman (2014) and Motamed, McPhail, and Williams (2016) have included year fixed effects to control for crop prices, which relies on the implicit assumption that there is no spatial variation in crop prices over the studied area. In this study we are examining both the direct effect of corn ethanol production on crop acreage in the vicinity of the corn ethanol plants as well as the indirect effect on acreage due to crop prices.

When we expand the study area to the entire contiguous United States, the law of one price may not hold for commodity markets where there is considerable spatial variability in prices (Miljkovic, 1999); therefore, we cannot rely on year fixed effects to control for the effects of crop prices. In addition, using year fixed effects to control for price effects does not allow for an explicit assessment of the elasticity of acreage with respect to crop prices, or quantification of the temporal and spatial changes in acreage due to the changes in crop prices.[1] Moreover, since crop prices are correlated with aggregate ethanol capacity (Zilberman et al. 2013; Roberts and Schlenker 2013) and aggegate ethanol capacity is correlated with local ethanol capacity, we conjecture that crop prices, particularly at the state-level, may be correlated with local ethanol

[1] Several previous studies have investigated the effect of crop prices on crop acreage and found a postive and statistically significant but relatively inelastic effect (e.g., Roberts and Schlenker 2013; Miao, Khanna, and Huang 2016). These studies, however, analyze changes in acreage prior to the corn ethanol boom and do not consider the effect of ethanol plant proximity.

capacity.[2] Therefore, explictly controlling for state-level crop prices while analyzing the effect of ethanol plant proximity on land use could avoid the potential for omitted variable bias.

In this paper, we aim to identify the effects of ethanol plant proximity and of crop prices on cropland acreage over the 2003-2014 period. The effect of proximity to an ethanol plant on corn acreage is likely to be most evident in the vicinity of the plant because it can pay a higher price to a farmer net of transportation costs than does a distant terminal market. McNew and Griffith (2005) and Lewis and Tonsor (2011) provide evidence of a key driver of the proximity effect by showing that the establishment of ethanol plants had a positive effects on local corn price received by farmers close to the plants. Unlike the effects of ethanol plant proximity, the effect of an increase in crop prices on cropland acreage is expected to be more widespread and not confined to the vicinity of the plants. By enhancing returns from corn production at all locations, an increase in corn price creates incentives to convert land from other uses to corn,

[2] The correlation between local-level ethanol capacity (say, in a county) and crop prices is not direct; instead, both are likely to be correlated with national-level ethanol capacity over 2006-2009 when US ethanol capacity increased from 6.32 to 14.54 billion gallons per year and the number of ethanol plants increased from 95 to 170 (USDOE 2015). Many ethanol plants were constructed simultaneously across the United States in that period, which leads to a positive correlation between local ethanol plant capacity and national-level ethanol capacity. In our dataset (to be described below), the correlation coefficient between the two is 0.17. We also find a positive although small (0.19) correlation between state-level Laspeyres crop price index and county-level ethanol capacity. For state-level corn price and county-level ethanol capacity, the correlation is 0.11.

both in the vicinity of ethanol plants and distant from the plants. Note that we are not examining the relationship between ethanol production and crop prices which has been analyzed by other studies (e.g., Zilberman et al. 2013; Roberts and Schlenker 2013). Instead, we are examining the effects of ethanol plant proximity and crop prices on crop acreage. In our empirical analysis we also investigate the aforementioned omitted variable bias by estimating specifications that include or exclude crop prices and analyzing its implication for the coefficient of the ethanol capacity variable.

We quantify the proximity effect and price effect on both corn acreage and total crop acreage. Existing studies examining the proximity effect of corn ethanol production have tended to focus on corn acreage or its share in total crop acreage.[3] Much of the concern about the land use change caused by corn ethanol production has, however, been not about changes in land use at the intensive margin (from other crops to corn) but about changes at the extensive margin (from non-cropland to cropland). These extensive margin changes could occur both in the vicinity of corn ethanol plants as corn production expands onto marginal land and in further areas from ethanol plants as corn production becomes more profitable. As corn price rises due to increased demand for corn ethanol, prices of other crops are also likely to be positively affected due to increased demand for land. These price changes can lead to changes in cropland at the extensive margin beyond those caused directly by proximity to ethanol plants.

A major difference between this study and existing studies is that we simultaneously identify the acreage effects of ethanol plant proximity and of spatially varying crop prices, while

[3] An exception is M Motamed, McPhail, and Williams (2016) that examines the effects of corn ethanol production capacity on total crop acreage.

controlling for other factors such as input prices, population density, and weather shocks that can also affect crop acreage. The endogeneity of crop prices and of ethanol capacity is addressed by using the instrumental variable approach. Specifically, we instrument for crop prices with lagged crop stocks, and instrument for ethanol capacity with an interaction between a county's railroad density and a year's national ethanol mandate. We also control for unobservable spatial factors that can lead to spatial autocorrelation and affect land use choices by estimating standard errors robust to spatial autocorrelation and heteroskedasticity (Conley 1999; Hsiang 2010).

Furthermore, unlike previous studies, our analysis covers the 2003-2014 period over which there has been substantial fluctuation in crop prices. As shown in Figure 1 (a) and (b), corn ethanol production and the number of corn ethanol plants expanded significantly till 2012 but plateaued after that. Corn price and a total crop price index also increased till 2012 but began declining after that (Figure 1, (c) and (d)). Despite this, corn acreage and total crop acreage increased after 2007 but began to decrease or plateau after 2012 (Figure 1, (e) and (f)); this occurred even as ethanol capacity and the number of ethanol plants remained stable. By expanding our analysis to include the period after 2012 when the changes in crop price and ethanol capacity are likely to have had opposing effects on crop acreage, we distinguish between the effects of proximity to ethanol plants from those due to changes in crop price on crop acreage and identify changes that were transitory versus more permanent with greater precision.

Unlike previous studies that all have a regional focus, our analysis is national in scope and is based on panel data for 2,535 counties in the contiguous United States[4]. This enables us to examine the effects of crop price changes on crop acreage at locations both near and distant from corn ethanol plants. The framework developed here enables us to disaggregate land use change due to various factors and quantify the responsiveness of land use change to these facrors.

Lastly, we use the estimated parameters and the actual change in ethanol capacity and in crop prices in 2012 and 2014 relative to 2008 (or, separately, relative to 2003) to quantify the magnitude of the expansion in crop acreage due to ethanol plant proximity and crop prices over the 2003-2014 period. Our analysis shows that land use is fairly inelastic to changes in corn ethanol production capacity and in crop prices. A 1% increase in the effective ethanol capacity in a county will lead to an increase in corn acreage in that county by about 0.03%-0.1% and an increase in total acreage by about 0.02-0.03%. A 1% increase in corn price will increase corn acreage in a county by 0.18%-0.29%. The elasticity of aggregate cropland acreage with respect to crop price is about 0.07-0.08. Our findings indicate that previous studies may have overestimated the proximity effects of corn-based ethanol plants.

Our results show that the expansion in corn ethanol capacity alone, *ceteris paribus*, led to a 2.9-million-acre increase in corn acreage and a 2.1-million-acre increase in total crop acreage in 2012 relative to 2008. Although substantive in magnitude, these land use changes represented a small percent (3.1%) of total corn acreage and 0.9% of total crop acreage in 2008. Changes in corn price and crop prices over the same period (2008-2012) led to much larger changes in corn

[4] Existing studies examine the effects of corn ethanol production in one state, e.g., Iowa (Miao 2013) and Kansas (Brown et al. 2014), or in one region, e.g., the Midwest (Motamed, McPhail, and Williams 2016).

acreage (8.5%) than in total crop acreage (1.9%); implying that the effect of changes in corn price on land use was largely at the intensive margin rather than at the extensive margin. Moreover, the effect of crop prices on land use was largely reversed by the downturn in prices after 2012 and close to negligible by 2014 relative to 2008.

This analysis shows that land use change is not a static phenomenon and that it is important to examine how it evolves in response to various factors that may also change over time. Our findings also show that all cropland expansion accompanying the corn ethanol boom should not be considered to be irreversible as argued by Wright et al. (2017). By decomposing the various causes of land use change over the 2007-2014 period we show that the direct change in land use caused by proximity to ethanol plants has persisted because of the steady increase in ethanol plant capacity over the study period. On the other hand, the indirect land use change due to higher crop prices has been transitory due to the volatility in crop prices.

II. CONCEPTUAL FRAMEWORK

We now present an intuitive conceptual framework that underpins our empirical model to quantify the effects of ethanol plant proximity and crop prices on land use. We hypothesize that a farmer's crop acreage decisions are influenced by numerous factors such as input and output prices, soil quality, and local climate (Lee and Sumner, 2015). Specifically, a key determinant of corn acreage is the expected corn price received at the farm-gate, which is defined as the corn price at terminal markets net of transportation cost per bushel from the farm to the closest terminal (McNew and Griffith 2005; Motamed, McPhail, and Williams, 2016). With the establishment of an ethanol plant in the vicinity of the farmer's cropland, the cost of transportation of corn to the plant will be lower than that of transporting it to a distant existing terminal. As a result, the received price at the farm-gate will increase with the establishment of an ethanol plant in vicinity because the ethanol plant serves as a closer terminal market for corn. The extent to which the ethanol plant will directly affect the choice of acreage planted under corn, namely the proximity effect of a corn ethanol plant, will depend on (a) the extent to which transportation costs are lowered and (b) the capacity of the ethanol plant. These factors together will influence the magnitude of demand for corn for ethanol at the relatively higher price than in the absence of the plant.

Moreover, the received farm-gate price by a farmer is also affected by the price of corn at existing terminals, regardless of the farm's location relative to the ethanol plants. Changes in corn price at the terminals could occur for various reasons, such as large-scale weather shocks, international trade, and increased aggregate demand for corn for ethanol. By diverting corn from food and feed markets, increased corn ethanol production has been shown to at least partly explain the higher crop prices that were observed after 2007 (Roberts and Schlenker 2013; Zilberman et al. 2013). Higher price of corn at terminals will create indirect incentives for corn acreage to expand even in locations that are distant from ethanol plants. For farmers close to ethanol plants, an overall increase in corn price across terminals will strengthen the incentive to grow corn in addition to the incentive provided by ethanol plants in proximity. We, therefore, hypothesize that corn acreage planted by a profit maximizing, price taking farmer will depend on the ethanol capacity in the vicinity of the farmer's land, the price of corn at the terminals, as well as other factors, such as input prices, soil quality, and climate variables.

The presence of a corn ethanol plant can also be expected to affect total acreage as it increases demand for corn and expands corn acreage either on existing cropland or land not currently used for crop production. Expansion in corn acreage through displacement of other crops could also expand total acreage as the displaced crops may shift to marginal land.

Similarly, increase in returns to cropland as proxied by a higher aggregate crop price index is also hypothesized to indirectly increase total land under crop production by making it profitable to incur the costs of converting non-cropland to cropland. In the next section we discuss the econometric approach to be used to identify these price and proximity effects on corn acreage and aggregate crop acreage.

III. EMPIRICAL MODEL

Our empirical analysis is based on county-level data because that is the smallest scale for which data on crop acreage are available to us over 2003-2014. We believe that county-level data provide a reasonable approximation for farm-level acreage decisions because (a) a county is still a relatively small unit for crop production in the grain market; and (b) there is significant heterogenity across counties in their access to ethanol plants as well as in their input and output prices, soil quality, and climate.[5] Based on the conceptual framework discussed above, we seek to estimate the effect of ethanol plant proximity and the effect of crop prices on crop acreage by directly including ethanol plant capacity and state-level crop price as explanatory variables in the reduced form econometric model. We approximate the reduction in transportation costs of corn grain due to ethanol plant establishment by constructing an effective ethanol production capacity variable, κ, for each county (discussed below). We estimate a reduced-form econometric model for corn acreage and total cropland acreage each as specified below:

$$(1) \qquad A_{ijt}^{c} = \beta_0 + \beta_1 p_{it}^{c} + \beta_2 \kappa_{ijt} + \boldsymbol{\beta_3 \Gamma_{ijt}} + u_{ij} + \varepsilon_{ijt},$$

[5] Numerous studies have used county-level data to examine the response of crop acreage to prices and other factors and we refer readers to Miao, Khanna, and Huang (2016) for a brief review of these studies.

(2) $$A_{ijt}^{a} = \gamma_0 + \gamma_1 p_{it}^{a} + \gamma_2 \kappa_{ijt} + \boldsymbol{\gamma_3 \Lambda_{ijt}} + v_{ij} + \xi_{ijt},$$

where A^c and A^a are corn acreage and aggregate crop acreage, respectively; subscripts *i*, *j*, and *t* denote state *i*, county *j* and year *t*, respectively; β_0 to $\boldsymbol{\beta_3}$ and γ_0 to $\boldsymbol{\gamma_3}$ are parameters or parameter vectors to be estimated, u_{ij} and v_{ij} are county-level fixed effects; and lastly, ϵ_{ijt} and ξ_{ijt} are error terms. We include time-varying and spatially varying corn prices (i.e., p_{it}^{c}) and the aggregated crop price index (i.e., p_{it}^{a}) as an explanatory variable in the corn acreage model and aggregated acreage model, respectively. Note that prices are measured at the state-level and therefore p_{it}^{c} and p_{it}^{a} do not contain subscript *j*. Vectors of variables ($\boldsymbol{\Gamma_{ijt}}$ and $\boldsymbol{\Lambda_{ijt}}$) include factors other than crop prices and effective ethanol plant capacity that may influence corn acreage and total acreage, respectively. Specifically, $\boldsymbol{\Gamma_{ijt}}$ includes a fertilizer price index, population density, and March to May monthly precipitation. It also includes the linear and quadratic time trend terms to capture other factors that change over time and may affect crop acreage, such as overall technology advances and yield increases. The definitions of these variables are presented below in the Data and Variables Section. Precipitation in March, April, and May are included for corn acreage regression because precipitation during planting season can delay planting and affect corn acreage decision (Miao, Khanna, and Huang 2016). Vector $\boldsymbol{\Lambda_{ijt}}$ includes the same variables as those in $\boldsymbol{\Gamma_{ijt}}$ but excludes monthly precipitation because planting seasons of major crops differ widely and hence the effects of precipitation are expected to vary across the crops in ways that make the effects on total acreage negligible; for example, heavy precipitation in April may delay and reduce planting of corn and lead farmers to plant more soybeans in May instead (NASS 2010), resulting in negligible changes in total planted crop acreage.

Crop acreage in one county can be correlated with that in the neighboring counties due to the similar geographical, climatic, and socioeconomic factors shared by neighboring counties. Therefore, in the econometric models described in equations (1) and (2), we allow for spatial autocorrelation of the error terms ϵ_{ijt} and ξ_{ijt}. We correct for this spatial autocorrelation in the error terms by estimating Conley standard errors.[6] Failure to take spatial autocorrelation into account may lead to underestimation of the standard errors (Schlenker, Hanemann, and Fisher 2006).

A key econometric issue is the endogeneity of ethanol capacity and of the price variables in models (1) and (2). Since input costs account for a large share of the total production costs of ethanol, ethanol plants tend to locate within the corn producing regions (Lambert, et al. 2008; Haddad, Taylor, and Owusu 2010; Sarmiento, Wilson, and Dahl 2012; Duffield, Johansson, and Meyer 2015). For example, ethanol plants in Iowa, the top corn producing state in the United States, account for about 25% of total ethanol plant capacity in the country (Renewable Fuels Association 2017). Therefore, the effective ethanol capacity in a region can be determined by corn acreage and hence is endogenous. Moreover, farmers make acreage decisions based on their output price expectation and input prices at the time of planting. These prices may, however, not be strictly exogenous because they are likely to be affected by planted acreage.

[6] We are indebted to an anonymous referee for suggesting this approach. We refer readers to Conley (1999) for details about the Conley standard error and to Hsiang (2010) for an application.

To address the endogeneity of the ethanol capacity and price variables, we apply a panel data instrumental variable estimator with county fixed effects. Specifically, we use an interaction term between railroad density associated with a county and volume of ethanol mandated under the Renewable Fuel Standard (RFS) as an instrument for the effective ethanol capacity variable. Output prices are instrumented by using lagged stocks of corresponding crops and the input price variable (fertilizer index in this study) is instrumented by using natural gas price. We explain the rationale for the choice of instruments in the next section. Furthermore, we employ fixed effects models to control for unobserved time-invariant factors that might affect ethanol plant locations such as a county's geographical location. As robustness checks, we also use different instrumental variables and find that the main results are unchanged in signs and statistical significance. We describe the construction of explanatory variables and instrumental variables in the next section.

IV. DATA AND VARIABLES

The econometric analysis is based on county-level data for 2,535 counties of the contiguous United States in period 2003-2014. These counties are selected because they produce at least one of the ten major crops considered in this study in at least one year during 2003-2014.[7] The selection is based on the rationale that the existence of a non-zero production year of crop demonstrates that the county has the potential to grow crops if it is profitable to do so. Excluding

[7] The ten crops are: barley, corn, cotton, oats, peanuts, rice, rye, soybeans, sorghum, and wheat. Since these crops account for more than 85% of the cropland acreage in the United States (Nickerson et al. 2011), we expect that changes in total acreage of these ten crops will reflect most of the changes in aggregate cropland acreage.

counties that did not continuously produce corn or all crops could result in sample selection bias. Of these 2,535 counties covered in our dataset, 2,077 counties produced corn in at least one of the years over 2003-2014 and form our sample for corn acreage. Table 1 provides the summary statistics for all the dependent, independent, and instrumental variables used in the regressions. The data sources and definitions of these variables are explained below.

Crop Acreage

Annual crop acreage data over 2003-2014 are obtained from NASS of the USDA. We measure corn acreage by planted acres in a county and construct a balanced panel of 2,077 counties by assuming that counties with non-reported corn acreage in a year have zero corn acreage in that year; this enables us to examine the effects of changes in corn ethanol production and in crop prices on acreage in counties that have the potential to grow corn even if they do not grow it continuously.[8] Similarly, we construct a balanced panel for the 2,535 counties that produced at least one of the ten major crops in any of the years over 2003-2014, in which aggregate cropland acreage is constructed by aggregating planted acreage of the ten major field crops considered in this study. To test the robustness of our results to county-year selection, we also conduct the same econometric analysis based on an unbalanced dataset that includes a county-year observation only if it has strictly positive value of acreage reported by NASS. We find that our

[8] NASS of the USDA does not report a county's acreage if the total number of growers in that county is extremely small (NASS 2018). Therefore, the non-reported value of acreage indicates either there is no production or the production is small. We hence approximate a non-reported value with zero.

results for both corn acreage and aggregate acreage models are robust across the balanced and unbalanced datasets.

Crop Prices

We hypothesize that farmers' make planting decisions based on their price expectation during the planting season. A number of studies assume that the law of one price equalizes prices across regional markets and that the effet of price on acreage can be captured using year fixed effects (Motamed, McPhail, and Williams, 2016; Roberts and Schlenker, 2013; Xie et al., forthcoming). Studies analyzing the support for the law of one price suggest that crop prices can vary across states for a number of reasons, including differences in transportation costs, processing costs, sales taxes, transactions costs and delivery dates that vary across locations (Thompson et al. 1990; (Goodwin, Grennes and Wohlgenant, 1990). We consider the state level prices received by farmers in the previous year as one proxy for expected prices (Miao, Khanna, and Huang 2016). We consider futures price in the current year as another proxy for expected prices. Previous studies have shown that futures prices are highly correlated with lagged received prices and that futures prices and lagged received price can be used interchangeably without strong evidence to suggest that one outperforms the other in describing farmers' price expectations (e.g., Miao, Khanna, and Huang 2016). State-level data for received prices are obtained from NASS and futures prices for corn are from the Chicago Board of Trade. All the crop prices are converted to year 2000 prices by using the GDP Implicit Price Deflator reported by U.S. Bureau of Economic Analysis.

While received prices vary by state and year, corn futures prices are available at the national level. However, as the active planting date for each state differs, there is variation in the planting-season prices of futures contracts that mature in the harvest season. We rely on this variability to construct a futures price variable that varies by state due to the variation in corn planting date across the states included in this study. Specifically, by following Miao, Khanna, and Huang (2016), for each state we first identify its most active window for planting based upon "Field Crops Usual Planting and Harvesting Dates" reported by NASS (2010). We then calculate the average of October corn futures prices during these planting windows. The calculated average prices, now varying across states, are used as planting season futures prices at the state-level.

For the aggregate crop acreage models, we construct the Laspeyres price index based upon deflated state-level received prices and production levels for each crop using 2002 as the base year. In year $t \in \{2002, ..., 2014\}$ the price index is defined as: $p_{it}^{a} = (\sum_{l=1}^{10} p_{lit} q_{li2002}) / (\sum_{l=1}^{10} p_{li2002} q_{li2002})$, where p_{lit} is the received price of crop *l* in state *i* in year *t*; and q_{li2002} is the production of crop *l* in state *i* in the base year, 2002. Data for production of the ten crops are obtained from NASS. We use the one-year lagged Laspeyres price index as a proxy for the expected aggregate crop price. For the aggregate crop acreage models, we do not use the futures price as a proxy because futures markets do not exist for all of the ten field crops considered in the present study.

Effective Ethanol Capacity

We measure the effect of the establishment of an ethanol plant on the farm gate price and therefore on crop acreage by constructing an effective ethanol capacity variable for each county. Studies differ in the methods they used to measure the effective ethanol capacity. Fatal and Thurman (2014) develop a measure of effective ethanol capacity for a county by weighting ethanol capacity by its distance to the centroid of the county while Brown et al. (2014) use a county centroid's distance to the nearest ethanol plant as the effective ethanol plant capacity for the county. These two studies implicitly assumes that all corn production is concentrated at the centroid of a county. Motamed et al. (2016) define neighborhood capacity for a grid cell as the sum of the capacity within a 100-km radius around the grid cell, implying that all ethanol capacity within the radius has the same effect on a grid cell's acreage irrespective of the distance to the grid cell.

In contrast, similar to Miao (2013), we assume that an ethanol plant has a radial catchment area for their feedstock to minimize transportation costs. USDA (2015) reports that about half of the ethanol plants draw its feedstock within a 25-mile radius. Therefore, we first construct a buffer zone with a 25-mile radius for each ethanol plant and calculate the portion of the buffer zone that falls within a county. Thus, the effective ethanol capacity from this plant in the county is defined by the plant's capacity times the buffer area that falls in the county divided by the total area of the plant's buffer zone.[9] By aggregating the effective ethanol capacity from all plants with buffer zones falling in the county we obtain the total effective ethanol capacity of that county. Unlike the approach in Motamed, McPhail, and Williams (2016), this approach uniquely assignes a portion of the plant's capacity to a county. Figure 2 depicts the locations of ethanol plants and the effective ethanol capacity by county in 2003 and 2014. Data for capacity of ethanol plants and their geographical locations are readily available in the Renewable Fuels

[9] For example, suppose an ethanol plant's capacity is 100 million-gallon per year (MGPY). We draw a circle around this plant with a radius of 25 miles. If, for instance, 200 square miles of the circle area falls in county j then the effective ethanol capacity of this plant for county j is $100 \times 200 / 1963.5 = 10.2$ MGPY, where 1,963.5 square miles is the area of a circle with radius of 25 miles.

Association annual industry outlook and the U.S. Department of Energy Alternative Fuel Data Center, respectively. We restrict the analysis to plants that use corn grain as feedstock.

Other Control Variables

We also control for fertilizer price because fertilizer is an important input for agricultural production. Fertilizer costs make up about an average of 29% of the total operating costs for all major field crops and about 42% for corn (USDA 2016). We therefore expect that fertilizer prices will affect crop acreage decisions by affecting the net returns from crop production and the relative returns of various crops. Data on annual national fertilizer price index between 2003 and 2014 are obtained from USDA Economic Research Service. The expected sign of the coefficient of fertilizer price index is ambiguous because it can be negative if fertilizer leads farmers to switch to crops that require less fertilizer to save input costs or it could be positive as farmers substitute land for fertilizer and expand crop acreage. Here we use one-year lagged fertilizer price index because farmers typically purchase fertilizer in the fall prior to the spring planting season (Borchers et al. 2011).

Moreover, county-specific monthly precipitation in millimeters for the months of March, April, and May between 2003 and 2014 are reported by Parameter-elevation Regression on Independent Slopes Model (PRISM).[10] We also control for the county-level population density because increasing population might compete for agricultural land, so we would expect the coefficient of population density to have a negative sign. County-specific population density data from 2003 to 2014 are obtained from the U.S. Census Bureau's County Intercensal Datasets:

[10] The weather data are aggregated to the county-level by Ag-Analytics.org (available online at: www.ag-analytics.org; accessed July 24, 2017).

2000-2010 and County Population Totals Datasets: 2010-2016.[11] Linear and quadratic time trend variables are also included to control for technological advances (e.g., yield increases) over time.

Instrumental Variables

To address the potential endogeneity of crop prices, we use one-year lagged corn stock as an instrumental variable for corn price and one-year lagged aggregated crop stock as an instrument for the Laspeyres price index. Lagged stock is a valid instrumental variable for crop prices because, as illustrated in Wright (2011) and Roberts and Schlenker (2013), crop stocks in the previous year will affect the current year crop supply (i.e., lagged stock plus new production), and hence is correlated with expected crop prices. Farmers then respond to expected crop prices to make acreage decisions. There does not appear to be any evidence to suggest that lagged stocks will cause changes in current year acreage through channels other than crop prices. One concern with using lagged crop stock as an instrumental variable is the potential autocorrelation of the stock time series. As pointed out by an anonymous referee, if the crop stock time series is autocorrelated then the lagged crop stock will be more likely to be correlated with the current error term, and therefore the exclusion restriction for lagged stock as a valid instrument will be violated. The national-level stocks are less prone to autocorrelation than the state-level crop stocks are, because local shocks on stocks may cancel each other across regions.[12] Therefore, we

[11] The two datasets are available at https://www.census.gov/programs-surveys/popest/data/data-sets.All.html (accessed on July 4, 2017).

[12] We are indebted to an anonymous referee for suggesting national-level stock as an instrumental variable because it is less likely to be autocorrelated.

consider both state-level and national-level stocks as candidates for instruments and perform autocorrelation tests for these two variables. Details about the procedures and results of the tests are presented in the online Appendix A.

From the test results we find that we cannot reject the null hypothesis that there is no autocorrelation for state-level or national-level corn stocks. Therefore, we can use either of these two variables as an instrumental variable for corn price in our analysis. Since state-level corn stocks have larger spatial variation than do the national-level corn stocks, we use the state-level stock variable as an instrument in our preferred specification of the corn acreage models and present the results that use the national-level corn stock as an instrument as part of the robustness check. The test results also show that while for the national-level aggregate crop stock we cannot reject the null hypothesis that the time series is not autocorrelated, we can reject the same null hypothesis for the state-level aggregate crop stock. As a result, we use the national-level aggregate crop stock as the instrumental variable for the crop price index in the preferred specification of the aggregate acreage models.

Data for crop stocks are obtained from NASS of the USDA. The national-level aggregate crop stocks of the ten crops are calculated by using an approach similar to that of the Laspeyres price index described above. Specifically, we first convert all stocks into tons and then calculate the weighted national level stock by using relative weights of commodity values reported by NASS (2011, p.2T-32) for the 1990-1992 period. These weights are not available at the state level and therefore we determine the state-level aggregate stock as a simple sum of crop specific stocks after converting all crop stocks into tons.

To address the potential endogeneity of the effective ethanol capacity we use the interaction term between the total length of railroads within a 25-mile boundary of a county and the annual volume of corn ethanol mandated by the RFS as an instrumental variable.[13] We believe that this instrument is valid for the following reasons. First, ethanol plant locations are correlated with railroad density (Motamed, McPhail, and Williams 2016). This is because about 60%-70% of ethanol produced in the United States was transported by rail between 2003 and 2014 (Association of American Railroads 2015). Railroad density affects crop acreage by affecting effective ethanol capacity and does not directly affect planting decisions of farmers at the county level. As is discussed in Motamed, McPhail, and Williams (2016), railroads were "built in already-established farm regions." In recent decades, trucks displaced railroads as a more efficient way for short-distance transportation of grains. Sparger and Marathon (2015) report that about 66%-82% of the corn are transported by truck domestically from 2002-2011. Therefore, railroad density is unlikely to have a direct influence on farmer's planting decisions other than through its effect on inducing ethanol refinery establishment.

Second, the amount of ethanol production capacity is expected to be correlated with the nationally mandated volume of ethanol production under the RFS because the establishment of volumetric mandates by the RFS incentivized the expansion of existing ethanol plant capacity and investments in new plants (Lambert et al. 2008). We also expect that the RFS mandate will

[13] The area within a 25-mile-boundary of a county covers the county and a 25-mile belt along the county boundary but outside the county. The choice of 25 miles is consistent with the assumed 25-mile radius for each ethanol plant when constructing the effective ethanol plant capacity. Railroad length between 2003 and 2014 is obtained from United States National Transportation Atlas Database.

affect farmers' crop acreage decisions only through the ethanol plant capacity and crop prices which will be controlled for in the econometric models.

Third, we do not include railroad density and national mandate individually as instrumental variables because the year-by-year variation of railroad density is small, while the RFS mandate is at the federal level and by definition does not have any spatial variation. The spatial variation in railroads will be absorbed by county fixed effects and the temporal variation of national mandates will be absorbed by the time trend variables; this would weaken the explanatory power of these variables individually if included with county and year variations. Instead we include the interaction of these two variables as an instrumental variable for effective ethanol capacity because it acquires temporal variation from national mandates and spatial variation from railroad density. The interaction term also captures the importance of railroads as a determinant of ethanol capacity location increasing only as the volume of ethanol mandated by the RFS expanded the demand for corn ethanol. Even though railroads have existed for a long time, ethanol capacity increased significantly only after the RFS was established. Therefore, we believe that the interaction of railroad density and volume of ethanol mandated by the RFS is likely to be strongly correlated with the effective ethanol capacity in a county which is a proxy for both location and capacity of ethanol production.

We use natural gas prices as an instrumental variable for the fertilizer price index for two reasons. First, the natural gas price is correlated with fertilizer price because natural gas is one of the most important raw material for various nitrogen fertilizers (Huang 2007). Second, the natural gas price does not directly affect crop acreage in a county because it is not directly used in farming operations. The primary direct energy sources for different farming operating practices are gasoline, diesel, and electricity (Marshall et al. 2015), and the prices of these energy sources are affected by crude oil prices which are mainly determined by worldwide geopolitical and economic events (USEIA 2016). So we expect that the natural gas price only affects cropland acreage through fertilizer prices.[14] Annual data on natural gas price are obtained from U.S. Energy Information Administration (USEIA 2017).

In the regression analyses, we use the Kleibergen-Paap *rk* LM test to detect under-identification and use the Cragg-Donald Wald F statistic and the Kleibergen-Paap Wald *rk* F statistic to examine if the instruments are weak.[15] Over-identification does not apply here because we have exactly the same number of instruments as the endogenous variables.

V. REGRESSION RESULTS

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[14] While natural gas price could affect the price of electricity, its effect on crop acreage through affecting electricity price is likely to be small, since electricity costs for a farm are a fixed cost and also a relatively small share of overall costs (ERS 2018). Therefore, the link through which natural gas price affect electricity price and then affect crop acreage would be weak and negligible.

[15] Kleibergen-Paap *rk* LM statistic is built on a Langrange-Multiplier (LM) test to determine if the excluded instruments are correlated with the endogenous variables. The Cragg-Donald Wald *F* statistic and the Kleibergen-Paap Wald *rk F* statistic are based on the first-stage *F* statistic to determine if the excluded instruments are only weakly correlated with the endogenous variables. We refer readers to Baum, Schaffer, and Stillman (2007) and Bazzi and Clemens (2013) for further details about these tests. The Kleibergen-Paap *rk* LM statistic, Cragg-Donald Wald statistic and Kleibergen-Paap *rk* Wald statistic have a chi-squared distribution with one degree of freedom.

For each of the corn acreage and total acreage regression models, we estimate four specifications as follows. Model (1) is a fixed effects (FE) model, which assumes that all variables are exogenous. Model (2) is a fixed-effects model with instrumental variables (IVs) (FE-IV) and is the preferred model because it controls for endogeneity of various explanatory variables as described above. Models (3) and (4) are the same as Model (2) except that Model (3) excludes effective ethanol capacity as an explanatory variable whereas Model (4) excludes crop price. Estimating Models (3) and (4) allows us to examine the presence of omitted variable bias when either crop price or ethanol capacity are excluded as determinants of crop acreage over the 2003-2014 period. These four models account for spatial autocorrelation by estimating standard errors robust to spatial aotucorrelation and heteroskedasticity (Conley, 1999). For the corn acreage models, corn price is used whenever we control for output price (see Table 2). For total acreage models we use the total crop price index to control for output price (see Table 3).

Results from Hausman's endogeneity tests for crop price, effective ethanol capacity, and fertilizer price index show that both crop price and effective ethanol plant capacity are endogenous across all the corn acreage and aggregate crop acreage models (p-value < 0.05). For the fertilizer price index, results show that we can reject the null hypothesis that the variable is exogenous in corn acreage models (p-value < 0.05) but we fail to reject this null hypothesis in the total acreage models (p-value = 0.1661). One possible explanation for this is that fertilizer accounts for a large share of total production costs for corn. Therefore, changes in corn acreage may cause fluctuation in fertilizer prices. However, many of the other crops included in total acreage models are not fertilizer intensive (e.g., soybeans) and the error terms in the aggregate acreage models may include opposing factors that weaken the correlation between the fertilizer price index and the error term. Therefore, the fertilizer price index is endogenously determined with corn acreage but not with aggregate cropland acreage. To be consistent across models, however, we also present the total cropland acreage model treating fertilizer price index as endogenous in the robustness checks.

Corn Acreage

Table 2 presents the regression results for the four corn acreage models. By comparing results under Model (1) and those under Model (2) we can see that ignoring the endogeneity of price variables and of effective ethanol capacity will attenuate the estimated coefficients toward zero, underestimating the true underlying effects. When we do not control for effective ethanol plant capacity, we find that a one-dollar increase in corn received price increases corn acreage by 3,494 acres (or about 8.6% of average corn acreage) in a county (see Model (3)). If we do not control for corn price, a one-million-gallon increase in the effective ethanol plant capacity in a county increases corn acreage by 3,200 acres in this county (see Model (4)). Both of these effects are significantly larger than those obtained in Model (2), indicating a positive omitted variable bias due to the positive correlation between corn price and ethanol capacity. All the models that involve instrumental variables in Table 2 pass the under-identification test and weak instruments tests. The *p*-values of the Kleibergen-Paap *rk* LM statistic are much smaller than the critical value of 0.01 showing that we can reject the null of no correlation between the endogenous variables and the instrumental variables at 1% significance level. Moreover, the Cragg-Donald F Wald statistic and Kleibergen-Paap Wald *rk* F statistic are much larger than 10 in most cases, indicating that we can safely reject the null hypothesis that the instrumental variables are just weakly correlated with the endogenous variables (Stock and Yogo 2005).[16] Associated first stage results of the regressions are presented in Appendix B.

Results under Model (2) in Table 2, the preferred model for corn acreage, show that corn price and effective ethanol plant capacity have positive and statistically significant effect on corn acreage. We find that, all else equal, if effective ethanol plant capacity in a county increases by one million gallons then corn acreage in this county will increase by about 884 acres (or by about 2.2% if evaluated at sample mean of county corn acreage of 40,400 acres). A one-dollar increase in corn received price, which represents about a 30% increase in average corn price, will increase corn acreage in a county by 2,532 acres, about 6.3% of average corn acreage in a county. Both the fertilizer price index and population density have a negative and statistically significant effect on corn acreage. April precipitation has a statistically significant and negative impact on corn acreage across all specifications, which is intuitive because heavy precipitation in April can delay planting of corn. May precipitation has a positive and statistically significant effect on corn acreage. The magnitude of May precipitation's effect is much smaller than that of April

[16] Table 5.1 in Stock and Yogo (2005) presents the critical values for the weak instrument test based on Cragg-Donald Statistic when the number of endogenous variables ranges from 1 to 3 and the number of instrumental variables ranges from 3 to 30, among which the largest critical value is 11.32 if the maximum tolerable bias of the IV estimator over OLS is 10%. All the Cragg-Donald Wald F statistic and the Kleibergen-Paap Wald *rk* F statistic values in Tables 2-5 are much larger than 11.32, indicating that the bias was less than 10% compared to OLS and thus we can reject the null hypothesis of a weak correlation between the instrumental variables and the endogenous variables.

precipitation (0.00766 vs. -0.0278). However, the effects of March precipitation on corn acreage are statistically insignificant.

Total Acreage

Results for the total cropland acreage models are presented in Table 3. Here the Laspeyres price index and the effective ethanol capacity are treated as endogenous whenever the instrumental variable approach is utilized. However, the fertilizer price index is treated as exogenous because, as we have discussed above, the Hausman's endogeneity test does not reject the null hypothesis that the fertilizer price index is exogenous in the total acreage models. Associated first stage results of the regressions are presented in Appendix B. Since the coefficient of the quadratic term of time trend is not statistically significant in most cases, we do not include it in aggregate acreage models.

By comparing results under Models (1) and (2) in Table 3 we find that if the endogeneity of the crop price index and of the effective ethanol production capacity is not considered then the estimates will be significantly biased. Moreover, unlike the finding in the case of the corn acreage models, the omitted variable biases shown by Models (3) and (4) for the total acreage regressions in Table 3 are positive but quite moderate in magnitude.

The following discussion on the determinants of aggregate acreage is based on Model (2) in Table 3, the preferred model. We find that price and effective ethanol capacity have a positive and statistically significant effect on aggregate cropland acreage. The coefficient estimates in Model (2) indicate that a one million-gallon increase in effective ethanol capacity in a county increases aggregate crop acreage of that county by 599 acres (about 0.65% of aggregate cropland if evaluated at the mean of aggregate crop acreage). A one-unit increase in the crop price index contributes to about 4,484 acres of increase in aggregate cropland acreage, which is about 4.8% of average aggregate cropland acreage in a county.

The coefficient of fertilizer price is negative and statistically significant in Model (2) of Table 3. The estimated coefficient, -0.0354, in Model (2) indicates that if evaluated at the sample means then a 1% increase in the fertilizer price index leads to about 0.086% (about 80 acres) decrease in aggregate cropland acreage of a county. We can see that the elasticity of aggregate cropland acreage with respect to the fertilizer price index is about 0.086. Given that, on average, the fertilizer price index increases about 9% annually over 2003-2014, then *ceteris paribus*, the aggregate acreage in a county will decrease about 720 acres due to fertilizer price increases. Population density has a statistically insignificant effect on aggregate cropland acreage. The linear time trend variable, however, has a negative and statistically significant coefficient, which reflects increasing competition for land from non-agricultural sectors and changes in farm technology (Nickerson and Borchers 2012).

Robustness

Tables 4 and 5 investigate the robustness of the effects of crop prices and effective ethanol capacity on corn acreage and aggregate crop acreage, respectively.[17] We find that the results are robust to various specifications of explanatory variables, instrumental variables, and datasets.

We first examine the robustness of the results of the preferred corn acreage model (i.e., Model (2) in Table 2) to an unbalanced panel dataset in which a county-year observation is

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[17] In addition to the robustness tests presented in this section, we also conduct model validation for both preferred corn acreage model and preferred aggregate acreage model. Due to space limitation these results are presented in Appendix C.

excluded from the dataset if there is no corn acreage reported by NASS for that county-year.[18] The results are presented in column (1) of Table 4, from which we can see that the coefficients under the unbalanced panel dataset are similar in magnitude and statistical significance to those under the balanced panel dataset.

We then examine the robustness of the results of the corn acreage model to using corn futures price as a proxy for the expected price. The results are presented in column (2) in Table 4. We find that both the coefficients of corn futures price and effective ethanol capacity are positive and statistically significant at 1% level, although the magnitude of the coefficients is smaller than that in Model (2) in Table 2.

Columns (3) to (5) in Table 4 present the regression results of corn acreage models when we use alternative instrumental variables for the received corn price. These alternative instruments are state-level lagged corn yield shocks, national-level lagged corn yield shocks, and national-level lagged corn stocks.[19] Lagged yield shocks are used as an instrument for crop

[18] Recall that Model (2) in Table 2 is based on a balanced panel dataset in which missing acreage values are assumed to be zero. Removing these counties with missing acreage values reduces the sample size from 24,924 to 20,825, a 16% decrease.

[19] State-level corn yield shocks are residuals obtained by regressing state level yield over 1950-2017 on linear time trend. The regression is performed state by state to allow a unique time trend for each state. National-level corn yield shocks are residuals obtained by regressing the national-level corn yields over 1950-2017 on linear time trend. Data for state-level corn yields, national-level corn yields, and national-level corn stocks are obtained from NASS.

prices by following Roberts and Schlenker (2013).[20] Lagged national-level corn stock is used as an instrument for corn price to be consistent with the instrumental variable approach used in the aggregate acreage models.

Column (3) in Table 4 presents the results based on specifications using state-level lagged yield shocks as an instrument for corn received price. It shows that the coefficients of corn price and effective ethanol capacity are statistically significant and qualitatively the same as those in Model (2) in Table 2. The coefficient of corn price is larger in Column (3) of Table 4 than that in Model (2) in Table 2 whereas the coefficient of effective ethanol capacity is smaller. Columns (4) and (5) present the results from specifications using national-level corn stocks and yield shocks as instruments for corn price, respectively. The estimates are qualitatively the same as in our preferred model except that when the national-level corn stock is used as the instrument for corn price, then the coefficient of the effective ethanol capacity becomes statistically insignificant.

For the total acreage models, we examine the effect of corn price on aggregate crop acreage to investigate the extent to which changes in corn price alone led to changes in land use at the extensive margin. The results are presented in column (1) in Table 5. We find that the coefficient of received corn price is not statistically significant, possibly because the effect of corn price is largely at the intensive margin and leads to substitution of crop acreage among

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[20] We check whether corn yield shocks are autocorrelated by conducting autocorrelation tests for both state-level and national-level corn yield shocks. Results show that we cannot reject the null hypothesis that no autocorrelation exists in the two types of corn yield shocks (see Appendix A for details about the tests procedures and results).

crops. However, column (1) shows that total cropland acreage does still respond positively and statistically significantly to effective ethanol capacity when we control for corn price in the aggregate acreage model; its magnitude is slightly larger than that in Model (2) in Table 3 (i.e., the preferred model for aggregate acreage).

To check the robustness of the aggregate acreage results with respect to county selection in the sample, we further remove county-years with zero aggregate crop acreage from the dataset and then conduct the analysis with everything else being the same as that in Model (2) of Table 3. The results presented in column (2) of Table 5 are robust to this change in the data. Estimates in column (3) show that using state-level aggregated crop stocks as an instrument for the price index only creates a negligible change in the estimated coefficient of effective ethanol capacity (0.604 vs. 0.599), although it increases the estimates of the price index coefficient from 4.484 to 5.656, when compared with Model (2) in Table 3. Lastly, to be consistent with corn acreage models in which the fertilizer price index is treated as endogenous, we also estimate the aggregate acreage regression by treating the fertilizer price index as endogenous and by using natural gas price as its instrument. Results are presented in column (4) of Table 5. We find that our results are robust to this change in specification.

Elasticities of Acreage with Respect to Crop Price and Effective Ethanol Capacity

To put the magnitude of the land-use change effects of crop prices and effective ethanol capacity into perspective, we compute the own-price acreage elasticities and the acreage elasticity with respect to the effective ethanol capacity at the sample means using parameter estimates from the models presented in Tables 2 to 5. The results are shown in Table 6. Based on the preferred corn acreage model (i.e., Model (2) in Table 2) and its associated models for robustness checks (Table 4), the elasticity of corn acreage with respect to corn received price ranges from 0.18 to 0.29 (see the upper panel in Table 6), which is comparable to Lin and Dismukes (2007) and in the lower end of estimations by previous studies ranging from 0.05 to 0.95. We refer readers to Miao, Khanna, and Huang (2016) for a summary of previous estimates of corn acreage's elasticity with respect to corn price. In addition, based on the preferred model for the aggregate crop acreage (i.e., Model (2) in Table 3) and its associated models for robustness checks (Table 5), the price elasticity of aggregate cropland acreage with respect to the Laspeyres price index is 0.07-0.08, which is close to the estimate of 0.077 obtained by Roberts and Schlenker (2013).

We find that in most cases the corn acreage elasticity with respect to effective ethanol plant capacity lies in the range of 0.03 to 0.1, which implies that 1% increase in a county's effective ethanol plant capacity would cause 0.03% to 0.1% increase in corn acreage in that county. If corn prices were omitted from the regression, then the elasticity of corn acreage with respect to the effective ethanol capacity would be as high as 0.36 (calculated based on Model (4) in Table 2), about four to twelve times larger than the estimates under the preferred model and its associated robustness check models. This is because the coefficient of effective ethanol capacity under Model (4) of Table 2 is significantly larger due to the positive omitted variable bias. Therefore, omitting corn price when estimating the effect of ethanol plant proximity on corn acreage leads to an over-estimate of that effect. This finding may partially explain why the corn acreage elasticity with respect to ethanol production capacity in our study is much lower than that in Motamed, McPhail, and Williams (2016) which does not include crop price as an explanatory variable in the econometric analysis. Motamed, McPhail, and Williams (2016) report that the corn acreage elasticity with respect to effective ethanol capacity ranges from 1 to 1.5, which is about 10 to 15 times larger than what we find in our study. Although not directly comparable because data sources and definitions of the effective ethanol capacity differ in the two studies, the large difference indicates the importance of explicitly controlling for crop prices when estimating ethanol production's impact on crop acreage.

The estimated elasticity of total crop acreage with respect to effective ethanol capacity in the preferred model and associated specifications for robustness checks ranges between 0.02 and 0.03 (see the lower panel of Table 6). We also find that the estimated elasticity of aggregate crop acreage with respect to crop price is much lower than that for corn acreage. This is consistent with intuition because the establishment of a corn-based ethanol plant can be expected to first increase corn acreage by converting land use from other crops to corn and then by conversion of non-cropland to corn. Expansion in corn acreage through displacement of other crops could expand total acreage as the displaced crops may shift to marginal land; however, these changes in total crop acreage caused by an increase in ethanol capacity are secondary effects. For the aggregate acreage models, the exclusion of crop price from the specification only leads to a slightly higher estimate of the acreage elasticity with respect to ethanol capacity than that under the preferred model (0.026 vs. 0.024). This is because the coefficient of ethanol capacity under the model excluding price index (i.e., Model (4) in Table 3) is only slightly higher than that under the preferred model (i.e., Model (2) in Table 3).

Effects of Crop Price and Ethanol Plant Proximity on Land-Use Change

We use the estimates from Model (2) in Tables 2 and 3 (the preferred models) to compute changes in corn acreage and total cropland acreage due to the changes in state-specific crop prices and county-specific effective ethanol production capacity between different periods. For instance, to calculate the change in corn acreage in a county during period 2008-2012 due to the effective ethanol capacity, we use the coefficient of effective ethanol capacity from Model (2) in Table 2, i.e., 0.884, and multiply it with the change in the effective ethanol capacity in each county between 2008 and 2012 to obtain county-specific changes in acreage over this period. The same procedure is applied when calculating changes in aggregate acreage due to effective ethanol capacity. The sum of changes in each county provides an estimate of the change due to the expansion in ethanol capacity at national level, holding all else constant (Table 7). The spatial distribution of these changes at a county level is illustrated in Figures 3 and 4.

From Table 7 we see that the increase in corn acreage due to the change in corn price over the period 2003-2014 is about 5.9 million acres whereas the increase in corn acreage due to increase in ethanol capacity is about 8.8 million acres. This finding indicates that the impact of corn price is surpassed by that of ethanol production capacity in that period. In the period 2003-2012, however, the opposite is true because corn prices were significantly higher in 2012 than in 2014 (see Panel (c) in Figure 1). The same pattern carries over when comparing the change in corn acreage over 2008-2014 with that over 2008-2012, or when comparing total acreage changes over these periods.

From Table 7 we also find that, in most cases, the impact of effective ethanol capacity or of crop price on corn acreage is much larger than that on aggregate acreage, indicating that corn acreage is more sensitive to ethanol production capacity and crop prices than is aggregate acreage. For instance, our estimated parameters imply that the expansion in corn ethanol capacity alone, *ceteris paribus*, led to an 8.8 million acre (11.4%) increase in corn acreage and a 6.9 million acre (2.8%) increase in total crop acreage over 2003-2012. In the same period, changes in corn price and the aggregate crop prices led to much larger changes in corn acreage and total crop acreage, 13.9 million acres and 10.5 million acres, respectively. Similarly, over the 2008-2012 period, the effect of the change in crop price index was smaller than the effect of change in corn price, indicating that most of the effect of a change in corn price was at the intensive margin and not at the extensive margin. The increase in the crop price index over the 2008-2012 period led to only a 1.9% increase in total acreage and this effect was significantly lower over the 2008-2014 period (0.5%). Therefore, unlike the effect of the expansion in corn ethanol capacity, the effect of crop price on land use was largely reversed by the downturn in crop prices after 2012.

Maps in Figure 3 show the predicted change in county-level corn acreage due to changes in corn price or in effective ethanol capacity while holding all other variables constant. During the period 2008-2012, the increase in corn acreage due to corn price increase was evenly distributed across counties (see Map (a) in Figure 3). However, over the period 2008-2014, the change in corn acreage due to changes in corn price differs considerably across states because of heterogeneity in changes in received price across states. This heterogeneity was particularly evident in states outside the Midwest that are relatively smaller producers of corn. The impact of effective ethanol plant capacity is observed mainly in the Midwest because this is where the majority of ethanol plants are located (see Maps (b) and (d) in Figure 3). From map (d) in Figure 3 we also can see that the eastern part of the Dakotas and Nebraska had large increase in corn acreage due to the expansion in effective ethanol capacity over the period 2008-2014. We observe a similar pattern of effects on aggregate crop acreage across counties and periods caused by changes in crop prices and ethanol plant capacity (see Figure 4).

VI. CONCLUSIONS

We estimate the land use change effects of corn ethanol plant proximity and crop prices with a nationwide county-level panel dataset for 2,535 counties over 2003-2014. Our empirical methods allow us to identify the causal effects of ethanol plant proximity and separate these effects from those of crop prices. By covering the 2003-2014 period over which there was substantial fluctuation in crop prices we also examine the extent to which changes in land use due to crop prices. This study differs from the existing literature that has focused on analyzing the direct effects of corn ethanol production on land use in its vicinity without explicitly controlling for the effect of crop prices. Given the small but positive correlation between crop prices and county-level effective ethanol production capacity, our study avoids the omitted variable bias that results in an overestimate of the effect of corn ethanol production on crop acreage when there is no control for crop price effects.

We find that corn ethanol production has a positive and statistically significant direct effect on corn acreage and aggregate cropland acreage at the county level. However, land use is fairly inelastic to both changes in ethanol production capacity and in crop prices, resulting in a small indirect effect on corn acreage and total crop acreage. A 1% increase in the effective ethanol capacity in a county increases corn acreage in that county by about 0.03%-0.1% and total acreage by about 0.02-0.03%. This estimate of elasticity is smaller than that obtained by previous studies which can be as large as 1.5. A 1% increase in corn price increases corn acreage in a county by 0.18%-0.29%, which is at the lower end of the range of the estimates of elasticity 0.1-0.95 obtained by previous studies (see Table 1 in Miao, Khanna, and Huang 2016). The elasticity of aggregate crop acreage with respect to the aggregate crop price index is about 0.07-0.08, close to the estimate of 0.077 obtained by Roberts and Schlenker (2013).

Overall we find a 3.1% increase in corn acreage and a 0.9% increase in total acreage due to expansion in corn ethanol capacity over the 2008-2014. Over the same period, the change in corn acreage was -0.004% and in total acreage was 0.5% due to crop price changes. Our findings, therefore, show that the overall effects of corn ethanol capacity and price changes on crop acreage over 2008-2014 were relatively small. Our analysis estimates the marginal effect of a unit increase in ethanol production and in crop price on the conditional mean of crop acreage across counties; these marginal impacts may, however, differ across counties. We leave it to future research to quantify the heterogeneity in this marginal impact.[21] Nevertheless, our findings show that while the land use change caused by the expansion in corn ethanol capacity persisted even after 2012 because ethanol capacity had been growing, the effect of crop price on crop acreage was largely reversed by the downturn in crop prices after 2012. Analyzing the reasons underlying the reduction in crop prices since 2012 despite the relatively constancy in corn ethanol production is beyond the scope of this paper. We leave the analysis of the dynamic effects of corn ethanol production on crop prices and therefore on land use change to future research.

[21] We are thankful to an anonymous referee for this point.

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Table 1. Summary Statistics of Variables

Variables	Mean	SD	Min	Max
Dependent variables				
Corn acreage (1,000 acres)	40.4	55.6	0.0	397.0
Aggregate cropland acreage (1,000 acres)	92.8	111.9	0.0	926.2
Explanatory variables				
Corn received price ($/bushel)	3.3	1.1	1.6	6.2
Corn futures price ($/bushel)	4.3	1.5	2.2	7.3
Laspeyers price index	1.4	0.4	0.8	2.8
Effective ethanol capacity (mil. gallons)	3.7	11.8	0.0	164.8
Fertilizer price index (base year 1990-92)	225.2	78.2	108.0	336.0
Population density (people/sq miles)	132.0	324.3	0.3	5598.9
March precipitation (mm/month)	73.5	50.6	0.0	506.4
April precipitation (mm/month)	91.93	55.0	0.0	545.6
May precipitation (mm/month)	102.7	57.0	0.0	434.2
Instrumental variables				
State level corn stocks (mil. Bu)	389.5	554.021	0	2,177.5
National level corn stocks (mil. Bu)	10,007.4	893.8	8,032.7	11,235.2
State level corn yield shocks (bu)	-1.5	18.7	-73.5	36.8
National corn yield shocks (bu)	-0.2	12.3	-33.4	18.2
National weighted stocks (1,000 tons)	228,827.6	91,635.7	192.1	348,346
State level sum of stocks (1,000 tons)	4412.7	4755.0	0.0	18543.2
Railroad length (miles in 25-mile boundary)	550.3	316.7	0.0	3,401.3
RFS final rule (billion gallons/year)	7.9	5.5	0.0	14.4
Natural gas price ($/1,000 cubic feet)	6.6	1.9	3.7	9.9

Notes: The sample for total cropland acreage covers 2,535 counties and the sample for corn acreage covers 2,077 counties. The temporal framework is 2003-2014. Prices are in 2000 dollars.

Table 2. Determinants of Corn Acreage (State-level corn received price as the output price)

Corn acreage	(1) FE	(2) FE-IV	(3) FE-IV	(4) FE-IV
Lagged corn received price	1.738***	2.532***	3.494***	
	(0.123)	(0.263)	(0.262)	
	(0.138)	(0.3736)	(0.4345)	
Effective ethanol capacity	0.135***	0.884***		3.200***
	(0.0332)	(0.134)		(0.396)
	(0.0255)	(0.1449)		(0.807)
Lagged fertilizer price index	-0.0304***	-0.238***	-0.447***	-0.677***
	(0.00280)	(0.0245)	(0.0394)	(0.104)
	(0.0037)	(0.0286)	(0.0657)	(0.1697)
Population density	-0.0378***	-0.0224***	-0.0484***	0.0283*
	(0.00539)	(0.00603)	(0.00586)	(0.0161)
	(0.0036)	(0.0059)	(0.0056)	(0.0203)
March Precipitation	-0.00710***	0.00329	-0.00274	0.0407***
	(0.00120)	(0.00224)	(0.00217)	(0.00604)
	(0.0015)	(0.003)	(0.0028)	(0.0121)
April Precipitation	-0.00480***	-0.0278***	-0.0442***	-0.0799***
	(0.00131)	(0.00322)	(0.00423)	(0.0117)
	(0.0016)	(0.0039)	(0.0069)	(0.0197)
May Precipitation	-0.00860***	0.00764***	0.0265***	0.0502***
	(0.00102)	(0.00257)	(0.00394)	(0.00970)
	(0.0014)	(0.0031)	(0.0062)	(0.0157)
Linear time trend	1.800***	8.120***	16.45***	21.48***
	(0.125)	(0.833)	(1.413)	(3.404)
	(0.1693)	(0.9321)	(2.3382)	(5.16)
Quadratic time trend	-0.0843***	-0.252***	-0.485***	-0.562***
	(0.00696)	(0.0232)	(0.0390)	(0.0874)
	(0.0085)	(0.0263)	(0.0638)	(0.1323)
N	24,924	24,924	24,924	24,924
Kleibergen-Paap *rk* LM statistic (p-value)	-	< 0.001	< 0.001	< 0.001
Cragg-Donald Wald F statistic	-	97.298	104.235	12.887
Kleibergen-Paap *rk* Wald F statistic	-	34.946	247.915	51.779

Notes: * 10% level, ** 5% level, *** 1% level. The sample mean of corn acreage is 40.4 thousand acres. Un-adjusted standard errors are included in the first set of parentheses under each coefficient; Conley Standard errors are included in the second set of parentheses under each coefficient. Specifications of the models: (1): FE, (2): FE-IV (Instrumental variables: state-level corn stocks, railroad density × RFS mandated volume of corn ethanol, natural gas price), (3): FE-IV excluding effective ethanol capacity in a county (Instrumental variables: state-level corn grain stocks, natural gas price), and (4): FE-IV excluding corn price (Instrumental variables: railroad density × RFS mandated volume of corn ethanol, natural gas price). Kleibergen-Paap *rk* LM statistic, Cragg-Donald Wald statistic and Kleibergen-Paap *rk* Wald statistic are distributed as chi-squared with degrees of freedom of 1.

Table 3. Determinants of Total Cropland Acreage (Laspeyres price index as output price)

Total cropland acreage	(1) FE	(2) FE-IV	(3) FE-IV	(4) FE-IV
Lagged Laspeyres price index	0.303	4.484***	4.647***	
	(1.515)	(1.001)	(0.990)	
	(0.7297)	(1.2768)	(1.2533)	
Effective ethanol capacity	0.00864	0.599***		0.657***
	(0.0817)	(0.205)		(0.205)
	(0.0345)	(0.1484)		(0.1565)
Lagged fertilizer price index	-0.00921	-0.0354***	-0.0265***	-0.0183***
	(0.00978)	(0.00605)	(0.00577)	(0.00465)
	(0.0049)	(0.0074)	(0.0071)	(0.0062)
Population density	-0.00903	0.00322	-0.00854	0.00367
	(0.0101)	(0.00786)	(0.00635)	(0.00784)
	(0.0043)	(0.0061)	(0.0046)	(0.0066)
Linear time trend	-0.468*	-0.629***	-0.511***	-0.594***
	(0.247)	(0.111)	(0.098)	(0.113)
	(0.117)	(0.133)	(0.127)	(0.1412)
N	30,420	30,420	30,420	30,420
Kleibergen-Paap *rk* LM statistic (p-value)	-	< 0.001	< 0.001	< 0.001
Cragg-Donald Wald F statistic	-	363.052	1.30e4	729.868
Kleibergen-Paap *rk* Wald F statistic	-	31.261	2.90e4	62.681

Note: * 10% level, ** 5% level, *** 1% level. The sample mean of aggregate cropland acreage is 92.8 thousand acres. Un-adjusted standard errors are included in the first set of parentheses under each coefficient; Conley Standard errors are included in the second set of parentheses under each coefficient. Specifications of the models: (1): FE, (2): FE-IV (Instrumental variables: weighted national crop stocks, railroad density × RFS mandated volume of corn ethanol), (3): FE-IV excluding effective ethanol capacity in a county (Instrumental variables: weighted national crop stock), and (4): FE-IV excluding crop price index (Instrumental variable: railroad density × RFS mandated volume of corn ethanol). Fertilizer price index is treated as exogenous. Kleibergen-Paap *rk* LM statistic, Cragg-Donald Wald statistic and Kleibergen-Paap *rk* Wald statistic are distributed as chi-squared with degrees of freedom of 1.

Table 4. Robustness Checks for Determinants of Corn Acreage

	Unbalanced panel (1)	Futures price (2)	State yield shocks (3)	National stocks (4)	National yield shocks (5)
Corn price	3.039***	1.651***	3.018***	3.476***	3.232***
	(0.3726)	(0.2355)	(0.2989)	(0.3183)	(0.2863)
Effective ethanol capacity	0.766***	0.693***	0.439***	0.0199	0.241**
	(0.1508)	(0.1473)	(0.13)	(0.1083)	(0.0973)
Lagged fertilizer price index	-0.251***	-0.197***	-0.154***	-0.0742***	-0.116***
	(0.0298)	(0.0278)	(0.0185)	(0.0144)	(0.0138)
Population density	-0.0423***	-0.0277***	-0.0322***	-0.0414***	-0.0365***
	(0.0080)	(0.0059)	(0.0055)	(0.005)	(0.0049)
March Precipitation	-0.00285	0.000643	-0.00391*	-0.0107***	-0.00710***
	(0.0033)	(0.0031)	(0.0024)	(0.0022)	(0.002)
April Precipitation	-0.0320***	-0.0289***	-0.0178***	-0.00841***	-0.0134***
	(0.0040)	(0.0038)	(0.0027)	(0.0022)	(0.0021)
May Precipitation	0.00586*	0.00635**	-0.000533	-0.00822***	-0.00415***
	(0.0030)	(0.0031)	(0.0022)	(0.002)	(0.0017)
Linear time trend	8.523***	6.469***	5.553***	3.138***	4.416***
	(0.9103)	(0.9209)	(0.5743)	(0.4789)	(0.4513)
Quadratic time trend	-0.240***	-0.183***	-0.192***	-0.136***	-0.166***
	(0.0253)	(0.0255)	(0.0186)	(0.0157)	(0.016)
N	20,825	24,924	24,924	24,924	24,924
Kleibergen-Paap *rk* LM statistic					
(p-value)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Cragg-Donald Wald F statistic	60.150	99.650	62.568	88.007	104.134
Kleibergen-Paap *rk* Wald F statistic	31.149	29.496	14.589	17.728	18.916

Notes: * 10% level, ** 5% level, *** 1% level. Conley standard errors are presented in parentheses. Column (1) is based on the unbalanced panel. Column (2) uses corn futures price as the proxy for expected corn price. The instrument for corn price in both Columns (1) and (2) is lagged state-level corn stocks. Columns (3), (4) and (5) use lagged state-level corn yield shocks, lagged national-level corn stocks, and lagged national-level corn yield shocks, respectively as an instrument for received corn price. Columns (2) to (5) are all based on the balanced panel. Ethanol capacity and fertilizer price index in all columns are instrumented by railroad density × RFS mandated volume of corn ethanol and natural gas price, respectively. Kleibergen-Paap *rk* LM statistic, Cragg-Donald Wald statistic and Kleibergen-Paap *rk* Wald statistic are distributed as chi-squared with degrees of freedom of 1.

Table 5. Robustness Check for Determinants of Aggregate Cropland Acreage

	Corn received price (1)	Unbalanced panel (2)	State-level stocks (3)	Fertilizer price index (4)
Crop prices	0.0416	6.265***	5.656*	4.416***
	(0.9759)	(1.3376)	(3.5912)	(1.2625)
Effective ethanol capacity	0.657***	0.469**	0.604***	0.688***
	(0.1579)	(0.157)	(0.1530)	(0.156)
Lagged fertilizer price index	-0.0188	-0.0425***	-0.0404***	-0.0493***
	(0.0141)	(0.0081)	(0.0144)	(0.0148)
Population density	0.00367	-0.0120	0.00350	0.00508
	(0.0066)	(0.0083)	(0.0062)	(0.0062)
Linear time trend	-0.594***	-0.474***	-0.645***	-0.372*
	(0.1415)	(0.1488)	(0.1403)	(0.2582)
N	30,420	26,607	30,162	30,420
Kleibergen-Paap *rk* LM statistic (p-value)	< 0.001	< 0.001	< 0.001	< 0.001
Cragg-Donald Wald F statistic	325.823	295.236	323.799	183.184
Kleibergen-Paap *rk* Wald F statistic	32.528	28.521	32.442	23.517

Notes: * 10% level, ** 5% level, *** 1% level. Conley standard errors are presented in parentheses. Column (1) uses state-level received corn price as a proxy for crop prices and uses state-level corn stocks as an instrument for the corn price. Columns (2) to (4) use Lagged Laspeyres price index as a proxy for crop prices. Column (2) uses the unbalanced panel dataset. Column (3) uses state-level crop stocks as an instrument for the crop price. Column (4) treats the lagged fertilizer price index as endogenous and instruments it by natural gas price. Kleibergen-Paap *rk* LM statistic, Cragg-Donald Wald statistic and Kleibergen-Paap *rk* Wald statistic are distributed as chi-squared with degrees of freedom of 1.

Table 6. Estimates of Acreage Elasticities with Respect to Crop Price and Effective Ethanol Production Capacity

Corn Acreage

	Preferred specification	Unbalanced panel	Futures price	State yield shocks	National stocks	National yield shocks
Corn acreage with respect to:						
Corn received/futures price	0.21	0.2	0.18	0.25	0.29	0.27
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
Effective ethanol capacity	0.1	0.08	0.08	0.05	0.00	0.03
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)

Total Acreage

	Preferred specification	Unbalanced panel	State-level stocks	Fertilizer price index
Total acreage with respect to:				
Laspeyres price index	0.07	0.08	0.08	0.07
	(0.02)	(0.02)	(0.01)	(0.02)
Effective ethanol capacity	0.024	0.02	0.02	0.03
	(0.00)	(0.01)	(0.01)	(0.01)

Notes: Standard errors are presented in the parentheses. For corn acreage, the elasticities under the preferred specification are calculated based on regression results under Model (2) in Table 2; and the elasticities in other columns are based on robustness check results reported in Table 4. For example, the elasticities in column "Unbalanced panel" are calculated based on regression results reported in the "Unbalanced panel" column in Table 4. For total acreage, the elasticities under the preferred specification are calculated based on regression results under Model (2) in Table 3; and the elasticities in other columns are based on robustness check results reported in Table 5. For example, the elasticities in column "State-level stocks" are calculated based on regression results reported in the "State-level stocks" column in Table 5.

Table 7. Changes in Corn Acreage and Total Cropland Acreage due to Changes in County-specific Ethanol Capacity and Crop Prices in Different Periods

Corn acreage change due to:	**2003-2014**	**2003-2012**	**2008-2014**	**2008-2012**
Corn price	5,934	13,932	-3	7,995
	(35.265)	(54.298)	(15.7)	(40.985)
	7.6%	17.9%	-0.004%	8.5%
	(0.0005)	(0.0007)	(0.0002)	(0.0004)
Effective ethanol capacity	8,844	8,845	2,892	2,892
	(15.376)	(15.257)	(6.11)	(6.054)
	11.4%	11.4%	3.1%	3.1%
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Total acreage change due to:	**2003-2014**	**2003-2012**	**2008-2014**	**2008-2012**
Crop price index	6,915	10,541	1,127	4,585
	(97.584)	(120.773)	(43.163)	(80.233)
	2.8%	4.3%	0.5%	1.9%
	(0.0004)	(0.0005)	(0.0002)	(0.0003)
Effective ethanol capacity	7,041	6,915	2,271	2,145
	(14.413)	(14.39)	(6.051)	(5.89)
	2.9%	2.8%	0.9%	0.9%
	(0.0001)	(0.0001)	(0.00003)	(0.00002)

Notes: Standard errors are presented in parentheses. The absolute numbers are in 1,000 acres. The percentages are calculated by using the absolute numbers divided by the acreage in the starting year for a specific period.

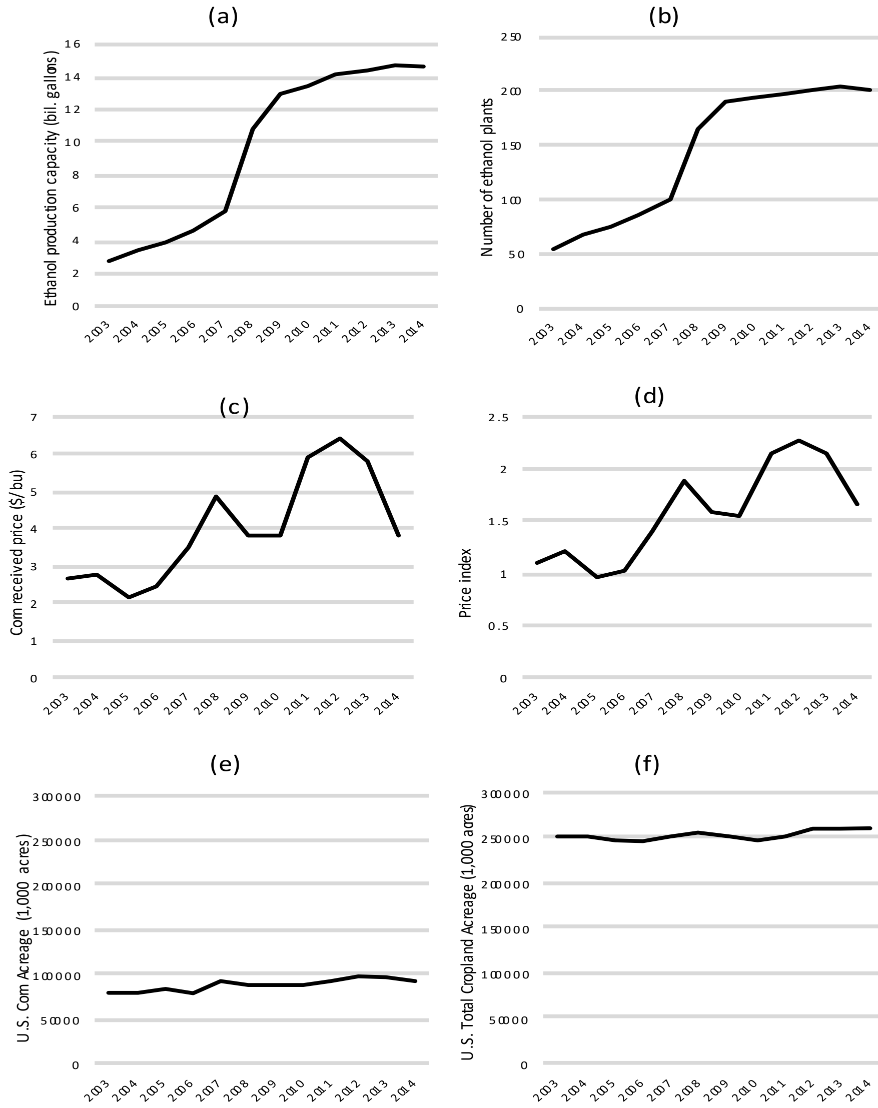

Figure 1. Key Variables over 2003-2014

Notes: (a): aggregate ethanol production capacity in the United States; (b): number of ethanol plants in the United States; (c): U.S. corn received price; (d): U.S. aggregate crop price index; (e): U.S. corn acreage; (f): U.S. aggregate cropland acreage.

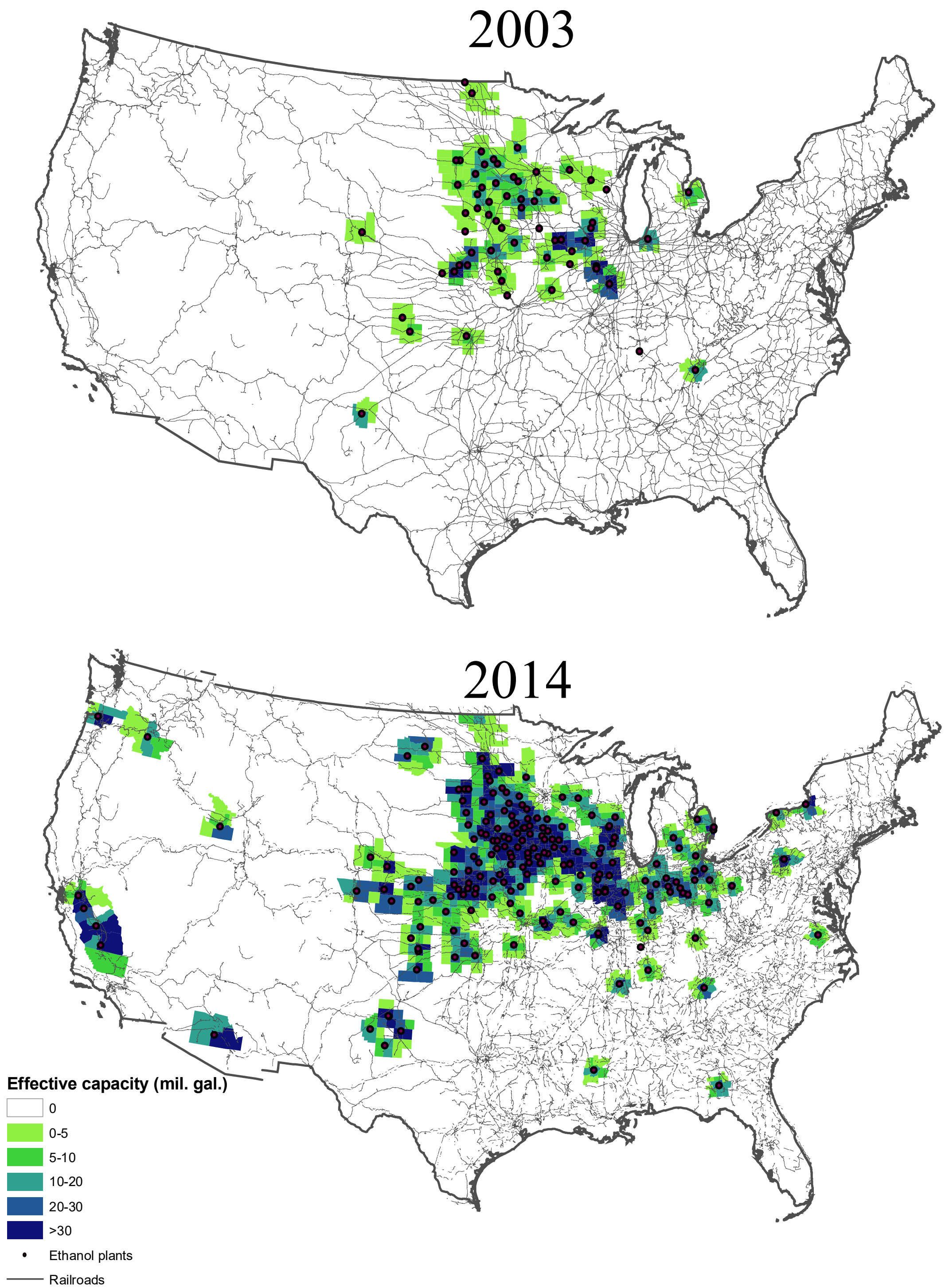

Figure 2. Effective Ethanol Plant Capacity at County-level, Ethanol Plant Locations, and Railroads in 2003 and 2014

Notes: Unites of effective capacity is million gallons. Shaded areas are counties that have positive effective ethanol plant capacity. The darker the shade, the larger the effective ethanol plant capacity. Non-shaded areas are counties without any effective ethanol plant capacity.

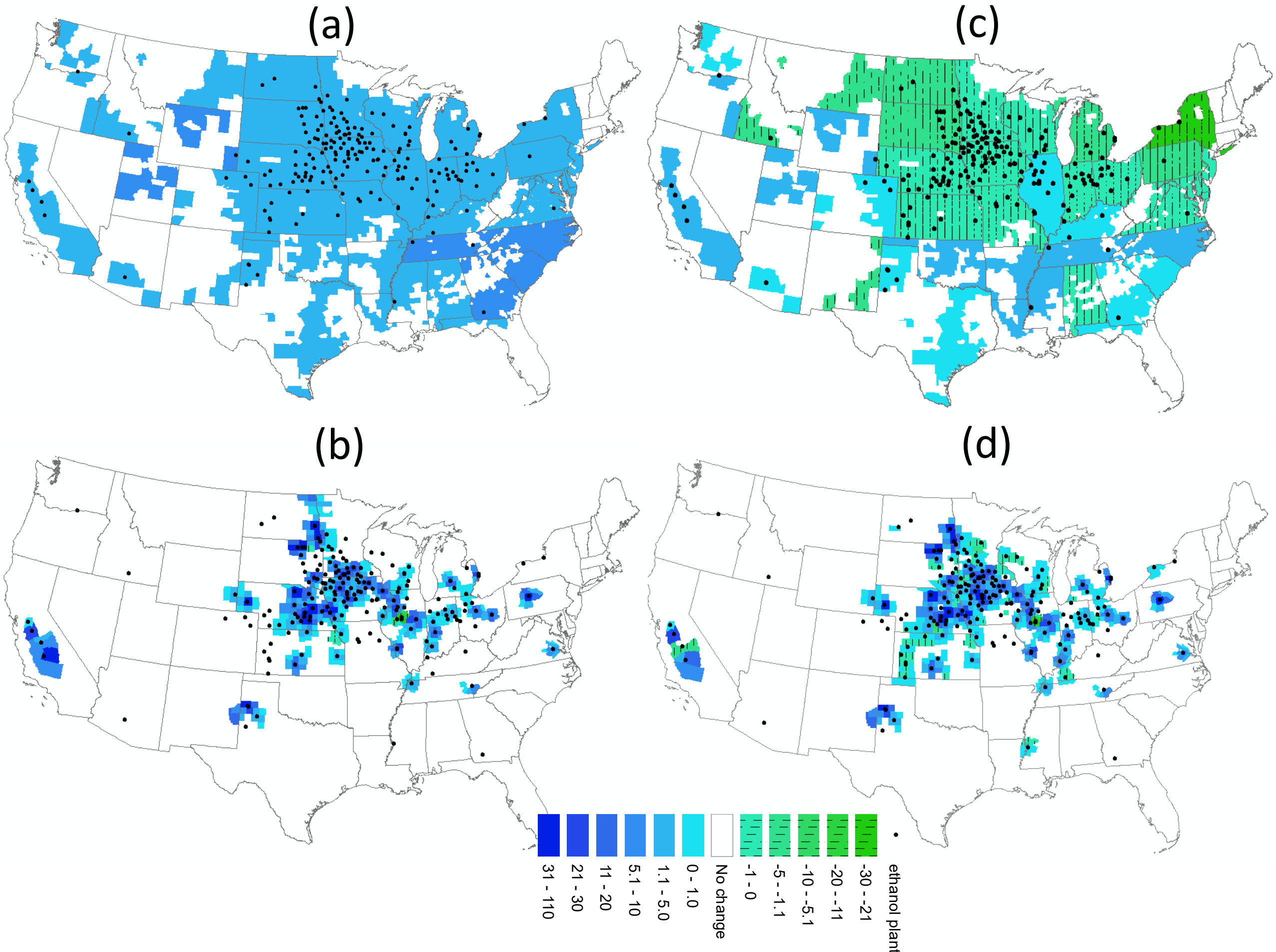

Figure 3. Changes in Corn Acreage due to Corn Price or Effective Ethanol Capacity (in 1,000 acres)

Notes: Maps (a) and (b) represent changes over the 2008-2012 period. Map (a) is for changes due to corn price, and map (b) is for changes due to effective ethanol capacity. Maps (c) and (d) represent changes over the 2008-2014 period. Map (c) is for changes due to corn price, and map (d) is for changes due to effective ethanol capacity.

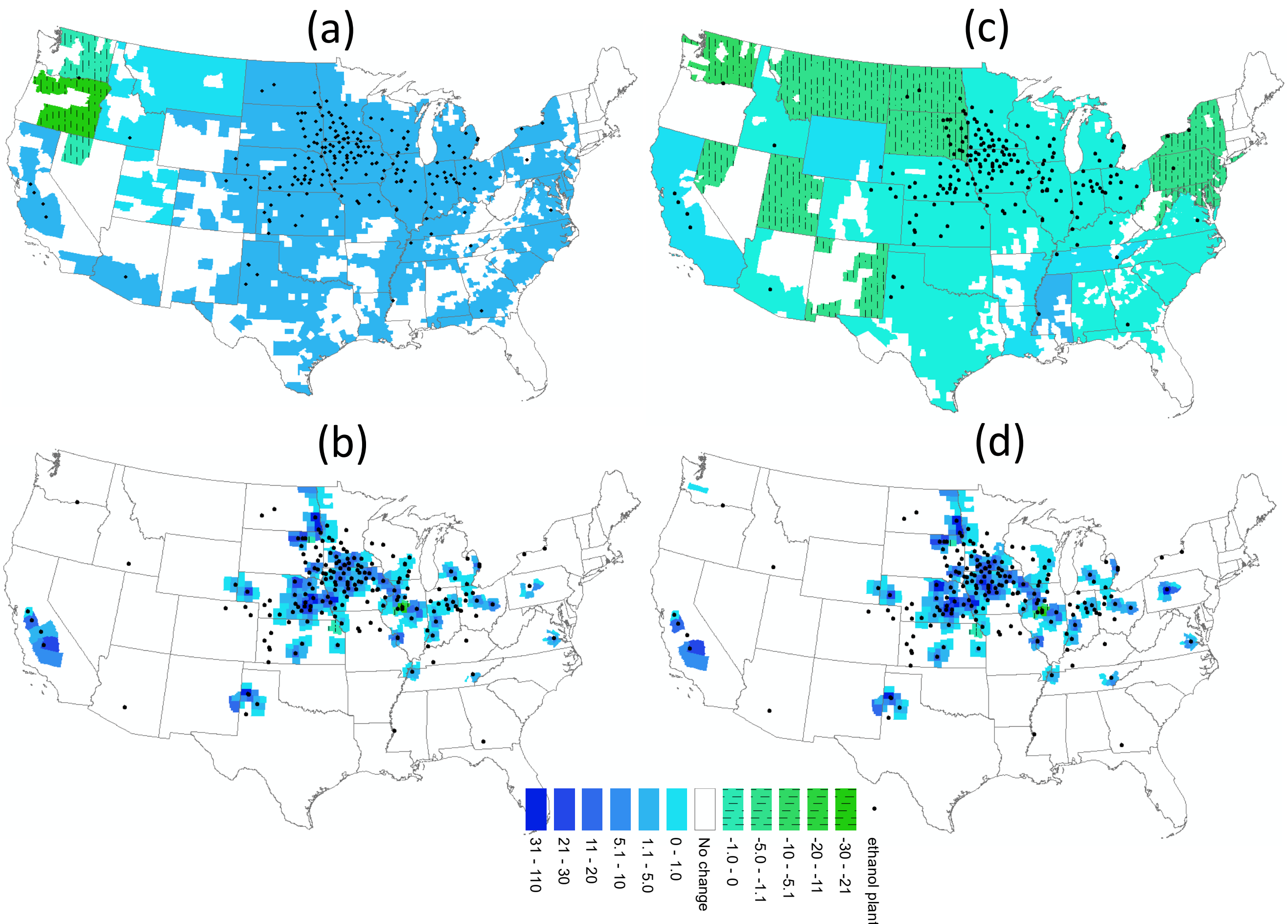

Figure 4. Changes in Aggregate Crop Acreage due to Crop Price or Effective Ethanol Capacity (in 1,000 acres)

Notes: Maps (a) and (b) represent changes over the 2008-2012 period. Map (a) is for changes due to crop price, and map (b) is for changes due to effective ethanol capacity. Maps (c) and (d) represent changes over the 2008-2014 period. Map (c) is for changes due to crop price, and map (d) is for changes due to effective ethanol capacity.

Appendix A: Autocorrelation tests for crop stocks and corn yield shocks

In this appendix we describe the autocorrelation tests for crop stocks and corn yield shocks that are used as instrumental variables in the regressions. We consider three types of autocorrelation tests here: the Durbin-Watson test, white noise test, and a Wooldridge type test. The Durbin-Watson test is performed by following Roberts and Schlenker (2013, footnote 17 on page 2275). Specifically, we first regress a variable on a linear time trend and then perform the Durbin-Watson test by using Stata command “estat durbinalt”. The white noise test is performed by Stata command “wntestq”. The Wooldridge type test is based on Wooldridge (2002, p.282) who use the following property of a time series to test if it is not autocorrelated. That is, if a time series $u_t,\ t \in \{1,...,T\}$ is not autocorrelated, then its first-order difference, $e_t \equiv u_t - u_{t-1}$, satisfies $\mathrm{cov}(e_t, e_{t-1}) = -0.5.$ See Drukker (2003) for more details about this test. The Durbin-Watson test and the white noise test used here are not applicable to panel data; so we do not have the *p*-values of these two tests for the state-level data which are in panel format. The test results are presented in Table A1 below.

Table A1. *p*-values of autocorrelation tests for crop stocks and yield shocks
(null hypothesis: no autocorrelation)

Variable	Durbin-Watson test	White noise test	Wooldridge type test
national-level aggregate crop stock	0.3032	0.4208	0.1815
state-level aggregate crop stock	-	-	0.0003
national-level corn stock	0.5513	0.9013	0.9136
state-level corn stock	-	-	0.1320
national-level corn yield shock	0.8260	0.7574	0.9945
state-level corn yield shock	-	-	0.1175

Appendix B: First Stage Results

In this appendix we present the first stage results of the preferred model specifications for corn acreage and aggregate acreage models. Specifically, Table A2 includes the first stage results of Model (2) in Table 2, the preferred corn acreage model. Table A3 includes the first stage results of Model (2) in Table 3, the preferred aggregate acreage model that treats fertilizer price index as exogenous. Table A4 includes the first stage results of Model (4) in Table 5, a robustness check for the preferred model in which fertilizer price index is treated as endogenous.

Table A2. First stage results for corn acreage model (Model (2) in Table 2**)**

	Received corn price	Effective ethanol capacity	Fertilizer price index
Lagged corn stocks	-0.00220***	0.00472***	-0.0353***
	(0.0000625)	(0.000847)	(0.00162)
Railroad length×RFS	0.0000288***	0.000469***	0.00249***
	(0.00000178)	(0.0000768)	(0.000144)
Lagged natural gas price	-0.208***	-0.177***	0.563***
	(0.00159)	(0.0237)	(0.0442)
Population density	-0.00109***	-0.0364***	-0.0859***
	(0.000170)	(0.00664)	(0.0117)
March Precipitation	0.00176***	-0.00959***	0.0223***
	(0.0000761)	(0.000979)	(0.00361)
April Precipitation	0.000397***	0.00367***	-0.101***
	(0.0000755)	(0.000780)	(0.00364)
May Precipitation	0.00114***	0.000211	0.0801***
	(0.0000705)	(0.000685)	(0.00364)
Linear time trend	0.588***	0.699***	32.96***
	(0.00544)	(0.119)	(0.222)
Quadratic time trend	-0.0261***	-0.0342***	-0.865***
	(0.000339)	(0.00496)	(0.00954)
N	24,924	24,924	24,924

Notes: Standard errors are in parentheses. * 10% level, ** 5% level, *** 1% level.

Table A3. First stage results for total cropland acreage model (Model (2) in Table 3, fertilizer price index treated as exogenous)

	Received crop price index	Effective ethanol capacity
Lagged national weighted stocks	-0.00000118***	8.01e-08
	(1.03e-08)	(0.000000357)
Railroad length×RFS	0.00000348***	0.000504***
	(0.000000476)	(0.0000188)
Lagged fertilizer price	0.00401***	0.00830***
	(0.0000369)	(0.00129)
Population density	0.00000297	-0.00518***
	(0.00000671)	(0.000607)
Linear time trend	0.00961***	-0.0498*
	(0.000849)	(0.0298)
N	30,420	30,420

Notes: Standard errors are in parentheses. * 10% level, ** 5% level, *** 1% level.

Table A4. First stage results for total cropland acreage model (Model (4) in Table 5, fertilizer price index treated as endogenous)

	Laspeyres price index	Effective ethanol capacity	Fertilizer price index
Lagged national weighted stocks	-0.00000171***	-0.000000374	-0.000112***
	(1.79e-08)	(0.000000539)	(0.00000225)
Railroad length×RFS	0.0000101***	0.000527***	0.000945***
	(0.000000522)	(0.0000185)	(0.0000479)
Lagged natural gas price	0.0399***	0.0360	8.321***
	(0.000952)	(0.0286)	(0.119)
Population density	-0.0000207***	-0.00529***	-0.00333***
	(0.00000677)	(0.000607)	(0.000455)
Linear time trend	0.102***	0.120***	23.04***
	(0.000608)	(0.0200)	(0.0664)
N	30,420	30,420	30,420

Notes: Standard errors are in parentheses. * 10% level, ** 5% level, *** 1% level.

Appendix C: Comparing Predicted Acreage with Observed Acreage

To examine the validity of our models, we compare predicted corn acreage and aggregated cropland acreage in each year with observed corresponding acreage levels. Basically, given that we have 12-year data, we re-run our models based on an arbitrary 11-year data and then used the regression results to predict the crop acreage in the year that are left out of the estimation. For instance, we first leave year 2014 data out and re-run the regressions based on data over 2003-2013. We then use the regression results to predict corn acreage for each county in year 2014. We do so for each year in our sample and obtain the predicted acreage for each county and for each year. Figure A1 presents the ratio of the sum of predicted corn acreage across counties to the sum of observed corn acreage across counties in each year in the period 2003-2014. The same ratio for aggregate crop acreage is included as well. As shown in the figure, these ratios are around one for both corn and total acreage, indicating our models predict the observed acreage well. Maps in Figures A2 and A3 in this appendix depict the county-level predicted acreage and observed acreage in the year 2012 and 2014, respectively. From these maps we can see that the predicted and observed acreage values have the same geographical pattern.

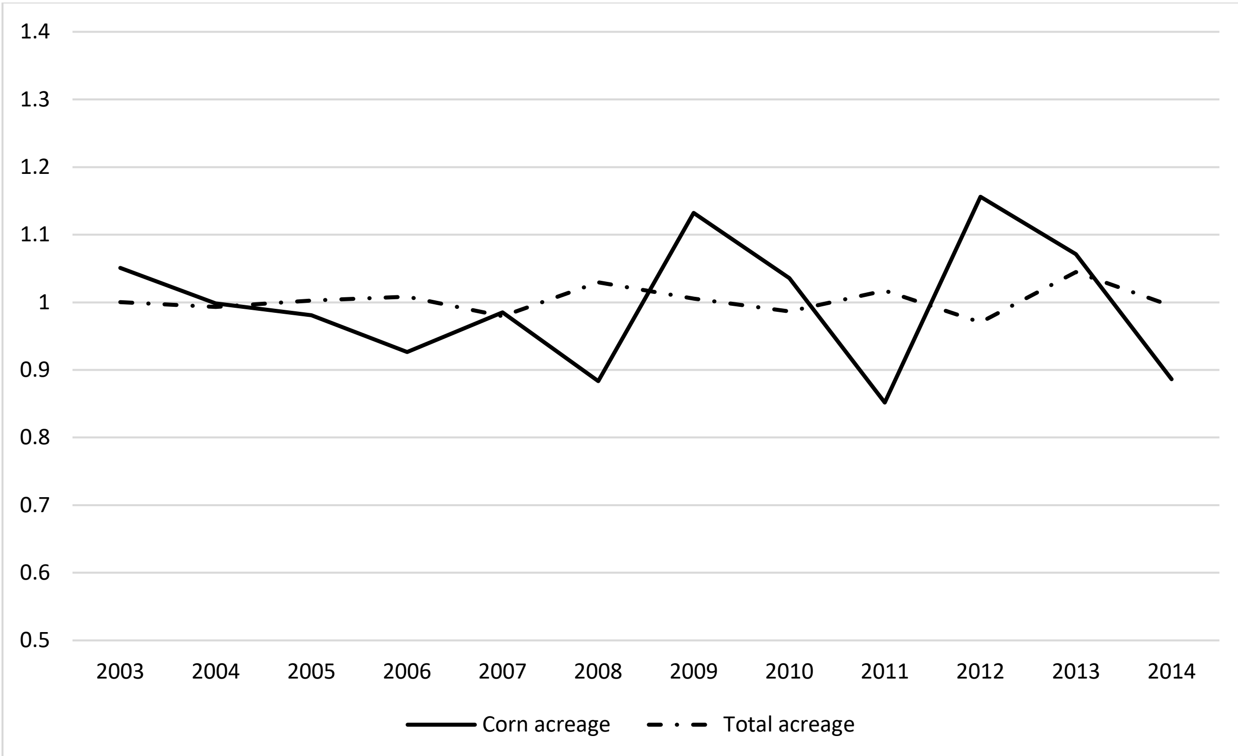

Figure A1. Ratio of Predicted Acreage over Observed Acreage (2003-2014)

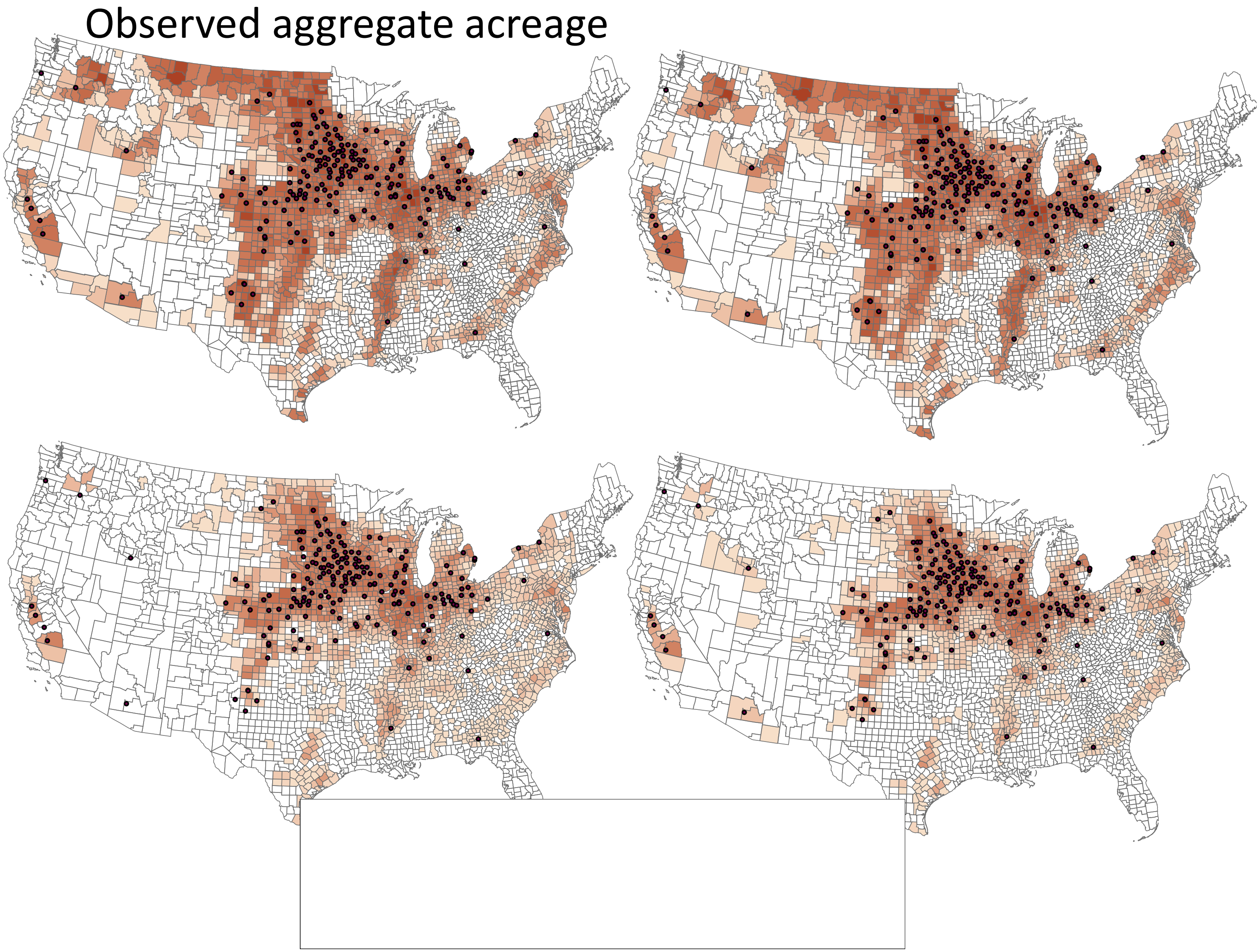

Figure A2. County-level Predicted and Observed Acreage in 2012 (in 1,000 acres)

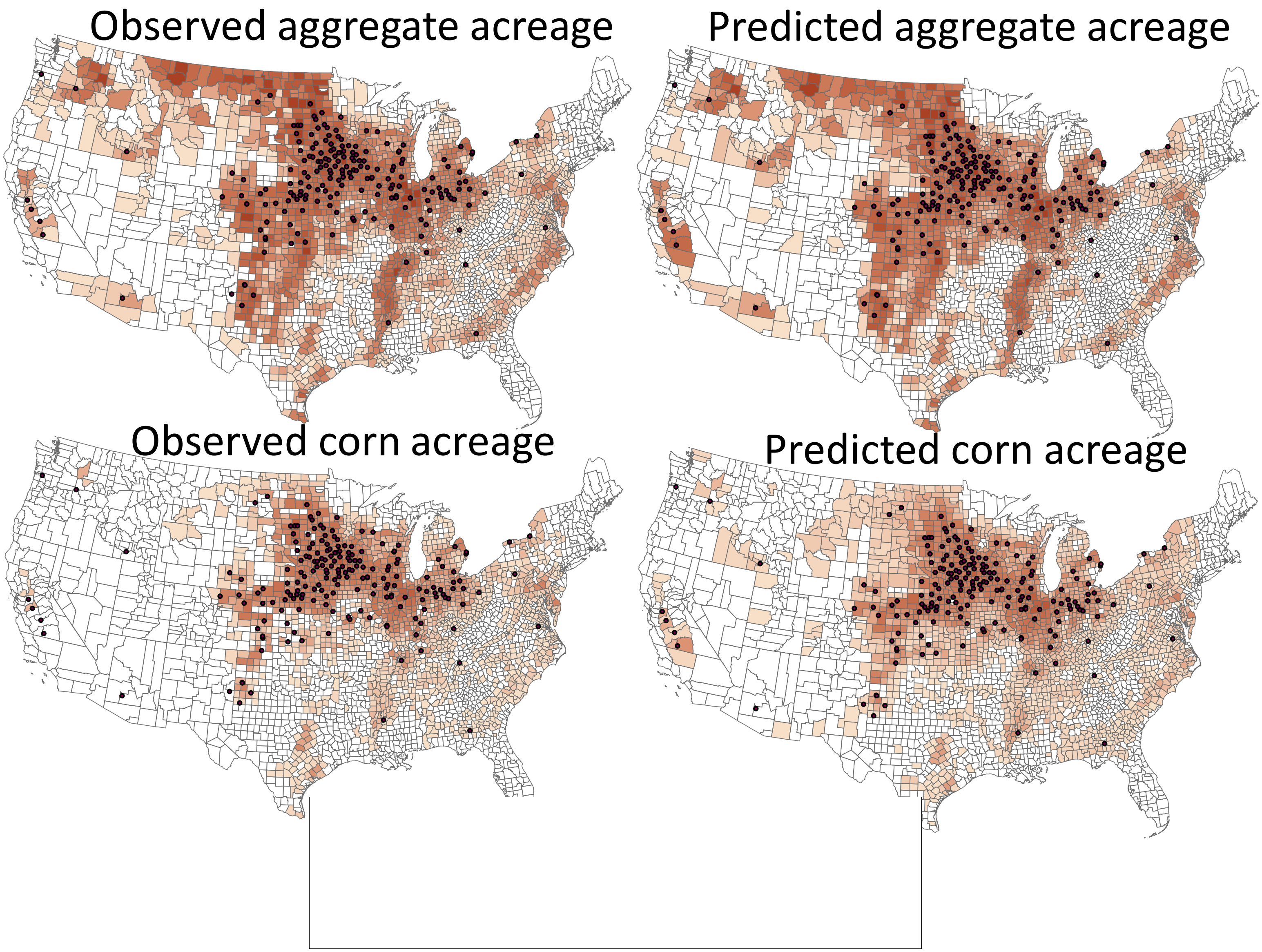

Figure A3. County-level Predicted and Observed Acreage in 2014 (in 1,000 acres)

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