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Ethanol, the Agricultural Economy, and Rural Incomes in the United States: A Bivariate Econometric Approach

Samson O. Akinfenwa and Bashir A. Qasmi

We examine the causal relationships between ethanol production and the agricultural economy and rural incomes in the United States for 1981 through 2010. We use bivariate cointegration and Granger causality procedures and account for two structural breaks in ethanol production in the analysis, which shows that ethanol production Granger-caused agricultural net value added, agriculture's share of U.S. employment, net returns to operators, and rural income per capita in the short run. These causal relationships generally persisted in the long run. However, the causality between ethanol and rural incomes diminished in the long run.

Key Words: agricultural economy, bivariate analyses, cointegration, ethanol production, Granger causality, rural income

The U.S. ethanol industry is one of the largest and fastest growing biofuel industries in the world. Beginning in early 2000, the number of U.S. ethanol plants and their production capacities began to increase sharply, driven by government policies such as ethanol blending mandates, budgetary support measures, and import barriers (Josling, Blandford, and Earley 2010). Between 1999 and 2010, the number of plants expanded from 50 to 204 and annual production rose from 1.4 billion gallons to 13.2 billion gallons (Figure 1). The main drivers of such policies are the country's high demand for energy, need to reduce our overdependence on fossil fuels, and concerns about environmental degradation (Natanelov, McKenzie, and Van Huylbroeck 2013).

However, whenever a value-added agricultural industry expands, a rise in demand for the primary agricultural commodity involved and its price follow (Brown 2003, Tokgoz et al. 2006, Leibtag 2008, Zhang et al. 2009). In the United States, corn is the major feedstock for ethanol so greater demand and higher prices for corn are expected as ethanol production expands. But since corn-ethanol has links to several commodities (House, Peter, and Disney 1993), related products such as soybeans (which may be displaced when more corn is planted) and livestock (which depend on corn for feed) can be affected by

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changes in demand for corn. Thus, it is important to examine the impact of ethanol on the agricultural sector as a whole.

Ethanol production also affects agricultural and rural economies by providing members of farm households with off-farm employment in the plants, which typically are located in agricultural areas near sources of feedstocks. As of 2006, most members of farm households in the United States and more than half of all U.S. farm operators earned at least some of their incomes from off-farm employment (Fernandez-Cornejo 2007). Only households associated with the largest commercial farms made most of their incomes from farming operations (Jones, El-Osta, and Green 2006).

For the 18 percent of people in the United States who live in nonmetropolitan areas (a working definition of rural America), poverty and the burdens it imposes are growing problems (Farrigan and Parker 2012). Between 2000 and 2010, the percentage of all rural residents who were impoverished increased from 13.4 percent to 16.5 percent (Economic Research Service (ERS) 2013).

The federal government has attempted to boost rural economies in a number of ways, including financial assistance in the form of loans and loan guarantees to rural entrepreneurs and businesses (U.S. Department of Agriculture (USDA) 2012) and permanent residencies for foreigners who invest at least \$500,000 in select areas (U.S. Department of Homeland Security 2012).¹ However, because rural areas are endowed with a vast wealth of primary resources, promoting value-added activities for agricultural products and operations became a popular strategy for rural economic development (Barkley and Wilson 1995). One such value-added industry is ethanol production. Since about 86 percent of U.S. ethanol plants are located in rural and mixed-rural counties (Low and Isserma 2009),² ethanol production is expected to have a positive impact on rural incomes.

The key question addressed by this study is whether U.S. ethanol production affects the agricultural economy and rural incomes. We are aware of no prior studies that explore this issue in an intertemporal causal framework. Thus, we contribute to the literature on value-added activities and rural economies by examining the causal dynamics between those economies and the ethanol industry using long-run cointegration and causality econometric techniques.

Brief Review of Related Studies

Farm households may earn income from ethanol production directly through increases in the price received for feedstock crops. De La Torre Ugarte et al. (2006) estimated that new demands for agricultural land and crops (mostly from ethanol producers) would likely generate an increase in net farm income of \$11 billion nationwide by 2030. Similarly, De La Torre Ugarte, English, and Jensen (2007) examined three scenarios in which annual ethanol production reached 60 billion gallons by 2030 and estimated that ethanol would provide more than \$210 billion in net farm income between 2007 and 2030. Several

¹ U.S. Citizenship and Immigration Services administers the Immigrant Investor Program, also known as "EB-5," which was created by congress in 1990 to stimulate the U.S. economy through job creation and capital investment by foreign investors (U.S. Department of Homeland Security 2012).

² Also see Lambert et al. (2008) and Miao (2013, table 2). Proximity to input suppliers (corn) and users of the byproducts of ethanol production (dried distiller's grains with solubles) are some of the key factors that determine the location of ethanol plants (Lambert et al. 2008).

other studies (Westcott 2007, Coyle 2007, Leibtag 2008, Natanelov, McKenzie, and Van Huylenbroeck 2013) likewise indicated a significant link between ethanol production and income from corn and soybean crops thanks to higher prices.

Farmers and rural households can also earn income through employment in ethanol plants and related business investment opportunities created by ethanol production. The federal government has spent billions of dollars to provide incentives to ethanol producers, and a popular measure used to gauge the success of a development effort is the number of new jobs created (Renkow 2003). Petrusis, Sommer, and Hines (1993) forecasted that an increase in annual ethanol production of 5 billion gallons by 2000 would create more than 60,000 additional jobs and that increased demand for corn would account for about 90 percent of those new jobs. Evans (1997), using a simultaneous equation model, estimated that production of 1.52 billion gallons of ethanol would create about 195,200 jobs in the United States. In 2005 alone, ethanol created about 154,000 jobs, thus accounting for an increase of approximately \$5.7 billion in total U.S. household income that year (Worldwatch Institute 2006). In the context of a less mechanized production economy, Horta (2004) estimated that an 84,500-cubic-meter demand for ethanol (about 22 million gallons) would generate 53,246 jobs in Costa Rica and that 12,499 of those jobs would be in rural areas.

Improved well-being is closely linked to increased wealth (Pender, Marré, and Reeder 2011). Thus, using total rural earnings as a measure of rural economic well-being and a multiple-regression analysis, Aldrich and Kusmin (1997) attempted to identify the key factors that drive the rural economy in the United States. They estimated a model in which total rural earning was a function of demographic, infrastructural, educational, and economic variables.³ Their results suggest that the economic structure of the industry is an important determinant of growth in rural earnings. They also found that a large percentage of employment in extractive and manufacturing sectors is negatively associated with total rural earnings. While ethanol production qualifies as a value-adding agricultural industry, it is also a component of the manufacturing sector. Thus, Aldrich and Kusmin's (1997) results raise the possibility that ethanol production could have a negative impact on rural incomes.

In a nation in which rural residents constitute a large percentage of the population, strategies for promoting rural economic growth are essentially tantamount to strategies for promoting the nation's economy. Gardner (2005) provided insight into what actually causes rural development in such economies using data on rural household incomes from 85 developing countries. He found that growth in the nonagricultural economy is the chief driver of increases in rural incomes. In developed countries such as the United States, a smaller proportion of the population is rural, but expansion of the U.S. ethanol industry may still have a significant impact on rural incomes.

The literature on the impacts of development of ethanol for fuel is relatively limited, perhaps because ethanol currently is not identified separately in national input-output measures. Its impact may be hidden within a much larger sector (Low and Isserma 2009). Also, the amount of data available regarding ethanol in the United States is barely sufficient for a comprehensive time-series study of the industry's impacts. Accordingly, most of the work published on the

³ Total rural earnings are estimated by multiplying total employment by the average wage.

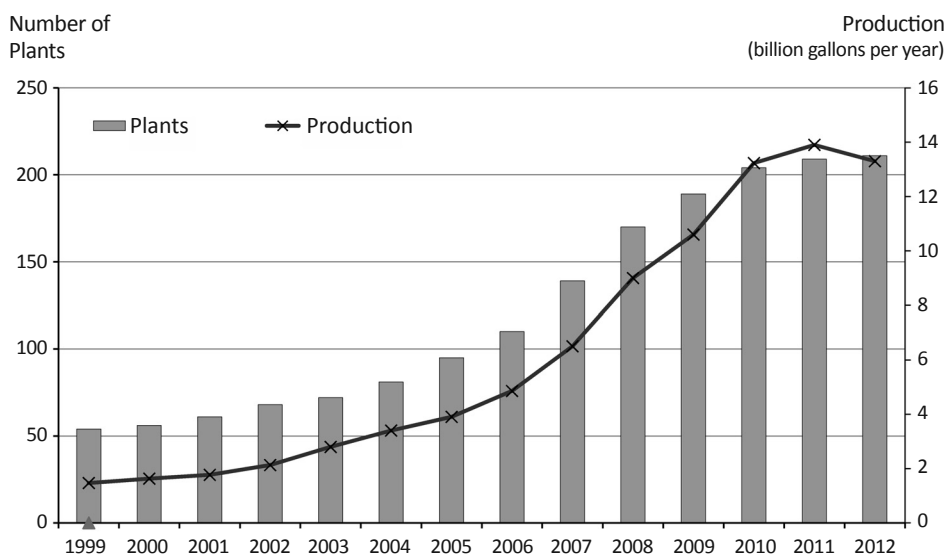


Figure 1. U.S. Ethanol Plants and Production for 1999 through 2012

Source: Renewable Fuels Association (2012).

topic has been based on input-output analyses. While input-output techniques have merits, they require one to make assumptions regarding up-to-date coefficients for inter- and intra-industry purchases and exogenous demand, and the results of such analyses are sensitive to changes in those assumptions.

Data

We evaluate four annual indicators of the nationwide agricultural economy and incomes of rural residents: agricultural net value added, agriculture's share of total U.S. employment, average household income of farm operators in the United States, and average net return to farm operators. We obtained data on agricultural employment as a percentage of total employment (*agemploy%*) from the World Bank's World Development Index database.⁴ The series for agricultural net value added (*agvalue*), average farm operator household income (*farmincome*), and net return to operator (*netreturn*) were obtained from the USDA ERS.⁵ Data on rural household income per capita (*ruincome*) and rural income's share of total national income (*ruincome%*) were obtained from the U.S. Bureau of Economic Analysis.⁶ Data that were measured in dollars (i.e., *agvalue*, *farmincome*, *netreturn*, and *ruincome*) were deflated using the consumer price index (CPI) (2005 = 100) from the World Development Index database. Lastly, data on U.S ethanol production (*production*) were obtained from the U.S. Energy Information Administration (EIA).⁷ The collected data cover 1981 through 2010.

⁴ World Bank World Development Index, <http://data.worldbank.org/data-catalog/world-development-indicators>.

⁵ Economic Research Service, <http://ers.usda.gov/data-products>.

⁶ Bureau of Economic Analysis, www.bea.gov/regional/index.htm.

⁷ Energy Information Administration, www.eia.gov/state/?sid=US.

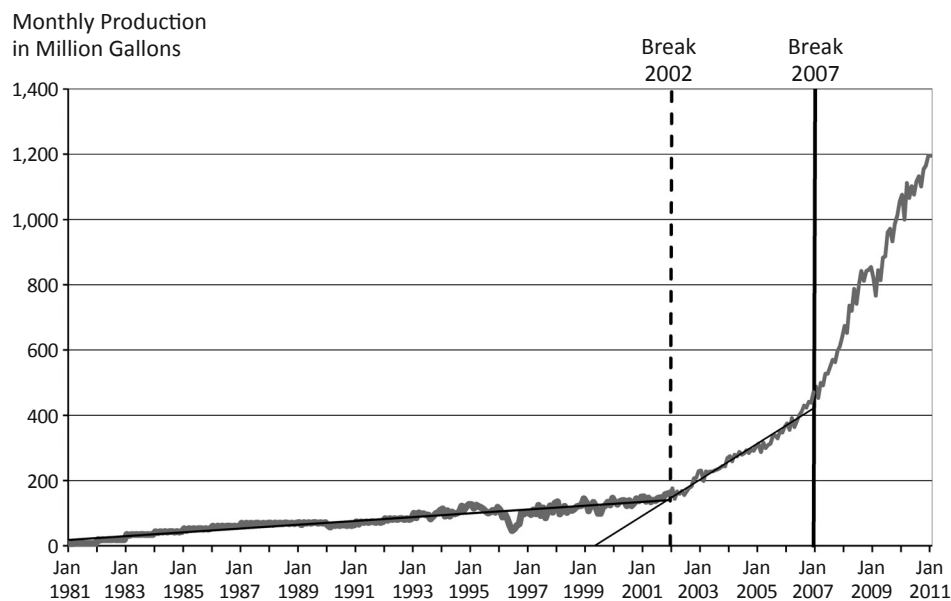


Figure 2. U.S. Fuel Ethanol Production for January 1981 through January 2011

Source: Authors' calculation using ethanol production data from the U.S. Energy Information Administration online database.

Data on ethanol plants and production in the United States between 1999 and 2012 are reported in Figures 1 and 2. There is a distinct upward trend in both the number of ethanol plants and production starting early in 2000. At that time, the U.S. Environmental Protection Agency (EPA) drafted a plan to phase out methyl tertiary-butyl ether (MTBE), a gasoline additive, and replace it with ethanol. By 2005, at least 25 states had passed laws banning or limiting the use of MTBE with effective dates ranging from 2000 to 2009 (EIA 2006). Also, the Energy Policy Act of 2005 established the first renewable-fuel-standard mandate in the United States, requiring that 7.5 billion gallons of renewable fuel be blended into gasoline by 2012. The mandate was later expanded under the Energy Independence and Security Act of 2007. This expansion set the target for the amount of ethanol blended into transportation fuel at 9 billion gallons in 2008 and 36 billion gallons by 2022 (Schnepf and Yacobucci 2013).

A basic trend-line analysis (see Figure 2) and Chow breakpoint test (see Table 1) confirm two structural breaks, in 2002 and 2007, in the ethanol production data. To account for these breaks, we introduce two dummy variables, *dbreak02* and *dbreak07*; *dbreak02* is set to zero for all periods prior to 2002 and to one otherwise, and *dbreak07* is set to zero for all periods prior to 2007 and to one otherwise.

Empirical Approach

In this bivariate study, we use a test for long-run cointegration and two Granger causality procedures. First, we test for the presence of long-run cointegrating vectors between ethanol production and the agricultural economic and rural

Table 1. Chow Breakpoint Test for U.S. Ethanol Production

Year	F-statistic	p-Value	Decision
1999	1.980	0.158	Fail to reject H_0
2000	2.603	0.093	Fail to reject H_0
2001	3.270	0.054	Fail to reject H_0
2002	4.417	0.022*	Reject H_0
2003	5.358	0.011*	Reject H_0
2004	0.4129	0.677	Fail to reject H_0
2005	0.817	0.480	Fail to reject H_0
2006	2.138	0.189	Fail to reject H_0
2007	4.887	0.047*	Reject H_0
2008	11.757	0.006**	Reject H_0
2009	1.272	0.440	Fail to reject H_0
2010	2.496	0.286	Fail to reject H_0

Notes: * and ** denote significance at a 5 percent and 1 percent level respectively. H_0 : No breaks at the specified breakpoint. The estimated equation is $production = f(production(-1))$.

income variables. Then, for a closer look at the dynamics of the interactions between ethanol and the explained variables, we perform a short-run causality test. Lastly, we test for long-run causalities between ethanol production and the dependent variables. These bivariate empirical methods are comparable to the ones employed by Lau et al. (2008) and Natanelov, McKenzie, and Van Huylbroeck (2013).

Cointegration Procedure

The test for cointegrating vectors is performed using the procedure proposed by Johansen (1988) and Johansen and Juselius (JJ test) (1990). Let \mathbf{W}_t be the vector of the two variables in a single equation. Thus, a vector autoregressive with k lags, $VAR(k)$, can be specified as

$$(1) \quad \mathbf{W}_t = \beta_1 \mathbf{W}_{t-1} + \beta_2 \mathbf{W}_{t-2} + \dots + \beta_k \mathbf{W}_{t-k} + \mu_t.$$

To use the JJ test, we must transform the $VAR(k)$ model to a vector error correction (VEC) model (Harris and Sollis 2003). Therefore,

$$(2) \quad \Delta \mathbf{W}_t = \Pi \mathbf{W}_{t-k} + \Gamma_1 \Delta \mathbf{W}_{t-1} + \Gamma_2 \Delta \mathbf{W}_{t-2} + \dots + \Gamma_{k-1} \Delta \mathbf{W}_{t-k+1} + \mu_t$$

where Γ_i , $i = 1, 2, \dots, k-1$, represents the 2×2 parameter matrices. Since we are examining bivariate relationships, Π is also a 2×2 matrix that contains long-run information. Π can be further decomposed into $\alpha\beta'$ where α is the speed of adjustment and β' is the long-run coefficient matrix. Hence, $\beta' \mathbf{W}_{t-1}$ contains $n - 1$ vectors and is equivalent to the error-correction term in a single-equation case. To check cointegration, we examine the rank of the Π matrix using both the trace statistics and the maximum eigenvalues:

$$(3) \quad [\lambda_{\text{trace}} = -T \sum_{i=r+1}^n \ln(1 - \gamma_i^2)] \text{ and}$$

$$(4) \quad [\lambda_{\text{max}}(r, r + 1) = -T \ln(1 - \gamma_{r+1})]$$

where r is the number of cointegrating vectors, γ_i is the estimated eigenvalues obtained from the estimated matrix, and T is the number of observations after lag adjustments.

Johansen and Juselius (1992) suggested that the variables must be stationary in first difference for the JJ test result to be valid. Therefore, we perform a unit root test for each variable. The JJ approach for studying cointegration is preferred to an Engle-Granger test because the JJ test does not depend on the choice of normalization (Lau et al. 2008).

Test for Granger Causality

According to Granger (1988), if two nonstationary series are cointegrated, there must be evidence of Granger causality in at least one direction. Therefore, we examine the direction of causality in the cointegrated bivariate relationships.

In any bivariate relationship, when both variables are stationary in first difference and are cointegrated, any standard Granger causality inference will be invalid. In this case, we can infer causality based on a VEC model (Engle and Granger 1987). However, a major drawback of using a VEC-based Granger causality model is the requirement that a differencing filter be included in the variables. At the same time, differencing essentially removes long-run information that can be crucial to policymakers (Masih and Masih 1997). We thus use the VEC-based Granger only for short-run causal inferences.

To test long-run causality, we employ the procedure proposed by Toda and Yamamoto (1995) (hereafter referred to as TY noncausality), which is a modified Granger causality test. Results generated using this method are valid regardless of whether the series are stationary (around a linear trend), first-order integrated, second-order integrated, or cointegrated (Toda and Yamamoto 1995). The TY noncausality test is performed in the following VAR framework:

$$(5) \quad \text{agric}_t = \alpha_1 + \sum_{i=1}^{(k+d)} \phi_i \text{agric}_{t-i} + \sum_{j=1}^{(k+d)} \tau_j \text{production}_{t-j} + \mu_{1t}$$

$$(6) \quad \text{production}_t = \alpha_2 + \sum_{i=1}^{(k+d)} \Phi_i \text{production}_{t-i} + \sum_{j=1}^{(k+d)} \Psi_j \text{agric}_{t-j} + \mu_{2t}$$

$$(7) \quad \text{rural}_t = \alpha_3 + \sum_{i=1}^{(k+d)} \beta_i \text{rural}_{t-i} + \sum_{j=1}^{(k+d)} \gamma_j \text{production}_{t-j} + \mu_{3t}$$

$$(8) \quad \text{production}_t = \alpha_4 + \sum_{i=1}^{(k+d)} \delta_i \text{production}_{t-i} + \sum_{j=1}^{(k+d)} \theta_j \text{rural}_{t-j} + \mu_{4t}$$

where *agric* represents the agricultural economy variables in natural log, *rural* represents the rural income variables in natural log, and *production* symbolizes ethanol production in natural log; d is the maximum order of integration of the

variables in the system, k is the optimal lag, and $\mu_{1t}, \mu_{2t} \dots \mu_{4t}$ are the white-noised error terms.⁸ To test whether *production* Granger-causes *agvalue* in the long run, for example, we test the following hypotheses:

$$H_0: \sum_{j=1}^k \tau_j = 0; H_1: \sum_{j=1}^k \tau_j \neq 0$$

where τ_j is the coefficient of *production* in equation 5. Thus, the Granger causality from *production* to *agvalue* can be established by rejecting H_0 , which requires a significant modified Wald statistic for *production* _{$t-1$} . . . *production* _{$t-k$} . Note that *production* _{$t-k+d$} is unrestricted to accommodate the long-run correction mechanism and to adjust the asymptotics. The null and alternative hypotheses for *production* paired with each of the other agricultural sector and rural income variables are defined in the same way.

The TY noncausality procedure is preferred over the likelihood ratio test in the context of a VEC model (Zapata and Rambaldi 1997) because the VAR model involves using data in their level form (that is, the series are not differenced). Thus, the TY noncausality procedure retains the long-run information and, unlike most time-series procedures, does not require that the variables be of the same order of integration.

Lag Selection Process

The dynamic specification of the equation orders (k) can affect the number of cointegrating vectors in the system and the causality results. Therefore, it is important to select the optimal lag length for each bivariate analysis to limit the chance of obtaining spurious causal relationships. Since lag-selection criteria such as the Akaike information criterion and Bayesian information criterion do not guarantee that the residual will be white-noised, especially when the sample size is small, we employ an iterative approach for lag selection similar to the one used in Ibrahim (2011).

First, we estimate the bivariate system of equations with one lag. The residual of that regression is then tested for serial correlation. If evidence of serial correlation is found, we re-estimate the equation using two lags. This process is continued iteratively until we identify the smallest lag length at which the error terms of the system are devoid of serial correlation—the optimal lag.

Results and Discussion

Table 2 presents summary statistics for each variable. As shown, ethanol production (*production*) was least in 1981 and greatest in 2010. The skewness of the statistics, a measure of symmetry, suggests a substantial probability that future values of *agvalue*, *agemploy%*, and *netreturn* will be less than their respective average values. Also, the measure of kurtosis shows that *production*, *farmincome*, and *netreturn* have leptokurtic distributions. Thus, those series have a greater probability of having extreme values. Since our sample consists of 30 observations, caveats associated with small sample sizes apply.

A series is said to be stationary if it reverts back to its long-run trend, and a mean-reverting (stationary) series is one in which a rise is likely to follow

⁸ We describe the optimal lag selection process in the next subsection.

a fall and a fall is likely to follow a rise. Most economic data are trended but can be stationary when differenced (Phillips 2005). When a nonstationary series is differenced d times before it becomes stationary, the series is said to be integrated of order d ; that is, the series is $I(d)$. We use both an augmented Dickey-Fuller test and a Phillips-Perron test to determine the stationarity of each series.

Table 2. Descriptive Statistics for Ethanol Production and Indicators of Agricultural Economy and Rural Incomes for 1981 through 2010

	<i>Production in Million Gallons</i>	<i>Agvalue in U.S. Dollars</i>	<i>Agemploy% % of U.S. Total</i>	
Mean	2,572.606	112,269.00	2.627	
Median	1,288.623	113,120.40	2.850	
Maximum	13,297.910	131,127.70	3.600	
Minimum	83.074	85,829.89	1.400	
Standard deviation	3,286.733	10,635.89	0.679	
Skewness	2.067	-0.336	-0.584	
Kurtosis	6.320	2.770	2.243	
Observations	30	30	30	

	<i>Farmincome Average in U.S. Dollars</i>	<i>Netreturn in U.S. Dollars</i>	<i>Ruincome in U.S. Dollars</i>	<i>Ruincome% % of U.S. Total</i>
Mean	9,784.280	55,201,561	23,727.21	12.458
Median	8,440.323	55,411,560	23,075.62	12.465
Maximum	26,895.97	81,763,243	28,759.15	14.180
Minimum	3,257.129	16,374,059	18,873.47	11.430
Standard deviation	5,326.567	12,766,704	3,149.648	0.755
Skewness	1.742	-0.748	0.138	0.793
Kurtosis	5.791	4.444	1.743	2.760
Observations	30	30	30	30

Table 3. Unit Root Test: t-Statistics in Level and First Difference with Trend and Intercept

	Augmented Dickey-Fuller		Phillips-Perron	
	Level	First Difference	Level	First Difference
<i>Production</i>	-3.349	-5.066**	-3.456	-6.712**
<i>Agvalue</i>	-5.263**	-5.384**	-5.281**	-21.657**
<i>Agemploy%</i>	-1.699	-5.782**	-1.690	-5.782**
<i>Farmincome</i>	-3.267	-6.556**	-3.351	-12.606**
<i>Netreturn</i>	-3.873*	-4.353**	-3.873*	-18.949**
<i>Ruincome</i>	-2.875	-6.566**	-2.924	-6.693**
<i>Ruincome%</i>	-1.897	-4.115*	-1.390	-4.101*

Note: * and ** denote significance at a 5 percent and 1 percent level respectively.

Table 4. Johansen-Juselius Cointegration Test Trace Statistics

Hypothesized	<i>Agvalue</i>	<i>Agemploy%</i>	<i>Farmincome</i>	<i>Netreturn</i>	<i>Ruincome</i>	<i>Ruincome%</i>
$r = 0$	6.698*	103.660*	38.710	58.630*	45.140	37.810
$r \leq 1$	20.015	30.496*	20.903	20.032	25.064	22.231
$r \leq 2$	9.110	12.764	8.912	8.047	9.905	11.336
$r \leq 3$	0.006	0.021	0.022	0.010	2.149	2.578

Notes: The dependent variable is production. * indicates significance at a 5 percent level. r is the number of cointegrating vectors. The p-values are MacKinnon, Haug, and Michelis (1999) p-values. Since the maximum eigenvalue results are similar to the trace-statistic results, we present only the trace statistics. However, the maximum eigenvalue figures are available upon request.

The unit root results shown in Table 3 suggest that our series are all stationary in first difference (they are $I(1)$ series). The *agvalue* variable seems to be stationary both in level and first difference. However, since the t-statistics are greater in first difference in absolute terms, we assume that *agvalue* is $I(1)$.

The results of the JJ tests presented in Table 4 show that ethanol production has significant long-run cointegrating relationships with *agvalue*, *agemploy%*, and *netreturn*. Thus, there is evidence of long-run Granger causalities between ethanol and those three indicators. Conversely, *production* has no long-run cointegrating relationship with *farmincome*, *ruincome*, and *ruincome%*, suggesting that changes in *farmincome*, *ruincome*, and *ruincome%* are independent of ethanol production in the long run.

Once cointegration between two time series is established, it is of interest to analyze the causality direction of each cointegrating pair (Natanelov, McKenzie, and Van Huylenbroeck 2013). We present the results of tests of short-run Granger causality in Table 5 and long-run Granger causality in Table 6.

For the VEC-framed short-run Granger causality, we test the null hypothesis that the joint contribution of the lags of the endogenous variables (including the dummy variables) equals zero. Our bivariate results reveal that ethanol production has Granger causal relationships with *agvalue*, *agemploy%*, *netreturn*, and *ruincome* in the short run at a 1 percent level of significance.

For the long-run causality results reported in Table 6, column A presents p-values of the Wald statistics for the bivariate ethanol/agriculture and ethanol/rural-income relationships prior to the structural breaks in 2002 and 2007. Column B reports p-values for the joint contribution of the righthand-side variable and the 2002-break dummy variable. Column C shows p-values for the joint contribution of the explanatory variable and the 2007-break dummy variable.

According to the long-run causality results, ethanol production had an effect only on agricultural net value added and net returns to operators prior to the structural breaks. The ethanol production Granger causality extends to agriculture's share of total U.S. employment after the first break and to rural income as a percentage of total U.S. income after the second break. Also, we find significant evidence of reverse Granger causality running from rural income per capita to ethanol production.

The causality relationship between ethanol production and agricultural net value added is significant at a 99 percent confidence level throughout the

Table 5. Short-run VEC-based Granger Causality Results

	χ^2 Statistics of Lagged First Differenced Term
$H_0: \Delta production \rightarrow \Delta agvalue$	16.521**
$H_0: \Delta agvalue \rightarrow \Delta production$	3.236
$H_0: \Delta production \rightarrow \Delta agemploy\%$	80.306**
$H_0: \Delta agemploy\% \rightarrow \Delta production$	0.485
$H_0: \Delta production \rightarrow \Delta farmincome$	2.695
$H_0: \Delta farmincome \rightarrow \Delta production$	2.192
$H_0: \Delta production \rightarrow \Delta netreturn$	17.008**
$H_0: \Delta netreturn \rightarrow \Delta production$	3.4720
$H_0: \Delta production \rightarrow \Delta ruincome$	11.545**
$H_0: \Delta ruincome \rightarrow \Delta production$	4.232
$H_0: \Delta production \rightarrow \Delta ruincome\%$	0.448
$H_0: \Delta ruincome\% \rightarrow \Delta production$	0.926

Notes: * and ** denote significance at a 5 percent and 1 percent level, respectively. Δ signifies that the series are in first difference. Other than the *production-ruincome* equation, which has an optimal lag length of 2, each bivariate equation's optimal lag is 1. We apply the Wald test with the null hypothesis that the joint contribution (χ^2) of the righthand-side variables equals zero.

Table 6. Toda-Yamamoto Granger Noncausality Results

	A p-Value before Breaks	B p-Value with <i>dbreak02</i>	C p-Value with <i>dbreak07</i>	D Optimal Lag
$H_0: production \rightarrow agvalue$	0.000**	0.002**	0.002**	1
$H_0: agvalue \rightarrow production$	0.679	0.156	0.189	1
$H_0: production \rightarrow agemploy\%$	0.073	0.000**	0.000**	2
$H_0: agemploy\% \rightarrow production$	0.553	0.091	0.109	2
$H_0: production \rightarrow farmincome$	0.097	0.087	0.243	1
$H_0: farmincome \rightarrow production$	0.920	0.163	0.324	1
$H_0: production \rightarrow netreturn$	0.003**	0.012*	0.012*	1
$H_0: netreturn \rightarrow production$	0.703	0.171	0.388	1
$H_0: production \rightarrow ruincome$	0.072	0.198	0.192	1
$H_0: ruincome \rightarrow production$	0.366	0.146	0.009**	1
$H_0: production \rightarrow ruincome\%$	0.415	0.541	0.018*	1
$H_0: ruincome\% \rightarrow production$	0.931	0.147	0.185	1

Notes: The \rightarrow represents "does not Granger cause." * and ** denote significance at a 5 percent and 1 percent level respectively. Optimal lags are those that whiten the residuals.

sample period. This result is expected since ethanol is directly linked to other agricultural value-added industries such as the animal feed sector. Although ethanol production reduces the amount of corn available for feed, one-third of every bushel of grain processed into ethanol is enhanced and returned to the animal feed market as distiller's grain, corn gluten feed, or corn gluten meal (Renewable Fuels Association 2013). Also, since the agricultural net value added is net income plus direct government payments and payments to stakeholders, this result could further imply that an increase in net value added is influenced by ethanol-induced increases in direct government payments, corn production, and prices. As ethanol production increases demand for corn, it also raises demand for arable land, which may increase the price of competing crops and land rent.

Granger causality from *production* to *agemploy%* is significant at a 99 percent confidence level after the first break. Before the breaks, this causality was barely significant (90 percent confidence level). This suggests that periods of sudden accelerated growth in U.S. ethanol production strengthened the association between ethanol production and agriculture's share of total U.S. employment. Evidently, the increase in ethanol production during the first and second boom periods was instrumental in creating employment in the agricultural sector. These results reinforce the estimate by Urbanchuk (2014) that the U.S. ethanol industry created about 242,348 agricultural jobs in 2013 alone.

Furthermore, there is only minimal causality from *production* to *farmincome* (significant only at 90 percent confidence level). However, as with agricultural value added, net return to operators exhibits a persistent unidirectional association with ethanol production both before and after the breaks. So, while ethanol production has relatively little impact on farm household income, it has a significant impact on net returns to operators, which makes ethanol an important factor in the economic well-being of farm households. Unlike measures of net returns, measures of total income do not account for expenses incurred during farm operations (e.g., the cost of feed). These results also imply that ethanol production contributes to farm households' economic well-being more through gains obtained from farm activities than through income from off-farm ethanol-related undertakings. Hence, a study of the effectiveness of bioenergy policies on improving producers' economic well-being would not be complete without an examination of impacts on net returns.

Interestingly, although we have evidence of causality between *production* and *ruincome* in the short run, we find very little evidence of causality between *production* and *ruincome* and *ruincome%* in the long run. This result suggests that ethanol production significantly impacts rural economies only when a plant is being built or expanded (by providing short-term jobs such as construction work to rural dwellers). Thus, government efforts to improve rural incomes by providing incentives to ethanol producers may yield only short-term impacts.

Since the majority of U.S. ethanol plants are located in the Midwest (89 percent as of 2013 (EIA 2013)), studies of the impact of ethanol production on agricultural and rural sectors in the Midwest region (one of our works in progress) may yield results that are more significant.

At this time, it is difficult to determine whether the incentives currently being paid to producers of non-corn-ethanol through the Advanced Biofuel Payment Program would yield similar results⁹ because the program has been around for

⁹ The program provides incentives to produce biofuel from sources other than corn kernel starch.

only six years. Also, production of ethanol from cellulose is in early stages, and it is not yet clear how a significant breakthrough in that ethanol technology would change the causal interactions between the ethanol industry and the agricultural economy and rural incomes. Our proposition is that the impact will depend on the cellulosic materials predominantly used. Using primarily corn stovers, for example, rather than switchgrass will further increase the profitability of growing corn and consequently increase the area under corn. Whatever the predominant feedstock, production of bioethanol in any form will continue to impact the agricultural sector by increasing agricultural value added.

Overall, U.S. ethanol production appears to have a strong impact on the agricultural sector through agricultural value added, agriculture's share of total U.S. employment, and net returns to farm operators. However, it has very little or no significant impact on incomes of farm households or on rural income per capita, especially in the long run.

Summary

As part of efforts to reduce the country's dependence on fossil fuels, decrease greenhouse gas emissions, and expand the agricultural value-added industry, the U.S. government has supported policies that promote the production and use of renewable energy sources. Evidently, these policies have triggered the boom in ethanol production in the United States that began in 2002. Since the ethanol industry's immediate stakeholders are agricultural producers and rural dwellers, we examine the causal interactions between ethanol production and select agricultural and rural economic indicators. Our analysis, which accounts for structural breaks in ethanol production in 2002 and 2007, shows a significant causal connection between ethanol production and the agricultural economy between 1981 and 2010. The structural shifts brought about by federal ethanol policies also strengthened the causal link between ethanol production and the agricultural economy. Therefore, policies that promote production of corn-ethanol will significantly impact agricultural value added, producers' net gains, and agriculture's share of total U.S. employment in both the short run and the long run. Furthermore, we find that ethanol production Granger-causes rural incomes in the short run but fails to significantly do so in the long run.

The results should be interpreted with some caution because of the possibility of loss in power associated with the small sample size and omitted-variable bias, which are common in bivariate studies. Accordingly, future research could quantify the marginal effects of ethanol production on the agricultural sector in a well-specified model and identify additional rural-economic variables that may be impacted by ethanol production to extend this study and thus provide valuable information to policymakers.

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