Corn Ethanol and US Biofuel Policy Ten Years Later: A Systematic Review and Meta-analysis

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Abstract

We use data and estimates on biofuel impacts reported in the literature to assess some of the controversy surrounding the introduction of biofuels by conducting meta-analyses on the impacts of corn ethanol on food and fuel prices, greenhouse gases, employment, rural income, balance of trade, the United States government budget, and learning-by-doing. The meta-analyses suggest that corn ethanol has had a relatively significant impact on the income of agricultural and related agribusiness industries, employment in farm states, fuel security in terms of reducing the import of oil from abroad, and the overall balance of trade. These effects are likely the main drivers behind biofuel policies.

JEL code: Q4

Keywords: Biofuels, Energy policy, Impacts, Meta-analysis

I. Introduction

Corn ethanol entered large-scale production in the United States (US) in 2004 to address energy security, climate change, and concerns about peak oil. Desiring a path that would lead to national energy security, the US developed policies in the early 2000s to promote the production and consumption of biofuels.

Since the US is the biggest producer of corn in the world, government policy makers saw corn as a promising path for developing a sustainable fuel source. In 2000, the United States produced 1.65 billion gallons of corn-based ethanol before any significant policies to promote its use were actually put in place. A big jump in the biofuel supply began in 2005 with introduction of the Energy Policy Act and then further increased with passage of the Energy Independence and Security Act of 2007. By 2008, production had risen to 9 billion gallons; in 2015, the output surpassed 13 billion gallons. Indeed, by 2015, corn ethanol had become the largest biofuel feedstock utilized globally.

However, over the past 10 years, the use of biofuels has also become a source of controversy, with a large body of literature debating the effect of biofuels on food prices and food security, including arguments that question the overall merit of using biofuels to mitigate climate change.

Now that we have sufficient data and estimates of the biofuel impact to reassess some of these claims, this paper analyzes previous findings and predictions, confronts them with existing evidence, and offers a fresh perspective on the impacts of biofuels to date and their potential for future decades. The paper evaluates and assesses findings from the literature on the impacts of biofuels by conducting several meta-analyses on the impacts of corn ethanol on food and fuel prices, greenhouse gases (GHGs), employment, rural income, balance of trade, and learning-by-doing. Although the overall analysis surveys a vast body of literature, the statistical analyses focus on corn ethanol because of its importance, the large volume of research available, and the intense political debate on its continued use.

These meta-analyses combine the results from multiple studies to better understand and reduce the uncertainty surrounding simulated estimates of the effects of the introduction of biofuels on key economic and environmental variables. The statistical analysis investigates the main reasons for the differences found in the literature that reflect their heterogeneity in terms of the period covered, methods, and regional coverage, among other factors. Our statistical analyses use different sequences of stepwise and multivariate regressions to evaluate the robustness of the results through the revealed preference approach à la McFadden (1975, 1976). This part of the analysis is followed by a Bayesian analysis to estimate the distribution of the parameters of concern. Finally, actual data are used to validate the conclusions of the meta-analyses, and simple calculations are used to understand the economic and environmental implications of those conclusions.

The meta-analyses suggest that the total effect of biofuels on food and fuel prices is limited. Specifically, the studies surveyed propose that corn ethanol has contributed to (i) an average increase in agricultural commodity prices of 61 US cents per bushel, which is about 20% at current prices, and (ii) a decrease in the average price of gasoline of 12 US cents per gallon, which is about 5% at current prices. The studies suggest that the gain to drivers was slightly larger than the loss to food consumers, but food price increases have affected the poor the most. However, there have been periods when corn ethanol has had significant impacts on prices. Biofuels also contributed to the spike in food commodity prices in the short run (e.g., the 2007/2008 food price spike). The meta-analyses indicate that, on average, the price changes associated with corn ethanol have resulted in a small aggregate economic gain to the US. However, they also put forward that corn ethanol had a relatively significant impact on the income of agricultural and related agribusiness industries, employment in farm states, fuel security in terms of reducing the import of oil from abroad, and the overall balance of trade; the annual net gain of the balance of trade due to biofuels has been tens of billions of dollars.

To understand the differences between the studies, we investigate the sources of heterogeneity among them and find that differences in the assumptions used in assessing the impacts of biofuels on food and fuel prices matter. In particular: (i) Assuming feedback effects among food commodities and petroleum refining products results in biofuel having a smaller impact on prices than otherwise, (ii) on the other hand, greater inelastic demand and supply curves result in biofuels having a greater impact on prices, and (iii) when using a later year to calibrate the numerical model, that choice suggests a higher ratio of biofuels to petroleum fuels and results in biofuels having a greater impact on prices.

Overall, these analyses indicate that biofuels were mostly used as a mechanism to improve US energy security and balance of trade as well as to improve rural employment in agricultural states. The emergence of fracking has introduced an alternative to the use of biofuels to reduce fuel imports and enhance the balance of trade, and thus fracking may reduce the importance of biofuels. The meta-analyses performed in this study may indeed explain why the environmental support for corn ethanol is lukewarm, at best, but the support for corn ethanol in the corn-producing states remains strong.

The next section (section II) builds on McFadden's (1975, 1976) revealed preference approach and develops the empirical model used to estimate the importance of the various factors affecting the different studies. Section III describes the meta data used, and the results of the meta-analyses are presented in section IV, with policy and concluding remarks offered in section V.

II. The empirical approach

Because we cannot evaluate the quality of politicians' decisions using profitability and welfare maximization measures, we directly examine policy outcomes and evaluate and assess their performance (McFadden, 1975, 1976).

While examining the performance of the US energy policy and evaluating the consequences or outcomes of energy policy decisions, we search for an implicit choice criterion that guides US energy policy choices. Since policy choices are driven by a myriad of facades, it is unrealistic to search for a single choice criterion that rationalizes all outcomes. The meta-analysis comprises statistical methods for contrasting and combining results from different studies in the hope of identifying patterns among study results, thus shedding light on the "location" of the decision rules and the (relative) weights placed by leaders on energy security, rural development, and the environment; a larger impact suggests the factor receives more weight during the decision process.

Assume an observation includes the factual and counterfactual, and that if the paper also reports sensitivity analysis, those parameters are also coded. Let N denote the total number of observations. Let subscript ($_1$) denote the policy outcome and subscript ($_0$) denote the counterfactual with no policy. In addition, let *i* denote observation ($i \in N$), and *j* a study (paper). Then, each observation includes a vector of observed time-varying covariates, $\boldsymbol{X_{ij}}$, and a vector of (unobserved) study-fixed variables (confounders), $\mathbf{S_j}$. Let Y_{ij} denote the outcome, that is, the dependent variable, where Y_{ij} of observation *i* of study *j* is either $Y_{ij,0}$ or $Y_{ij,1}$. Suppose further that

$$\varepsilon_{ij} \equiv Y_{ij,0} - E\left[Y_{ij,0} | S_j, X_{ij}\right].$$

And assume that the causal effect of policy, denoted μ, is additive and that it depends on the study variables (confounders). Let ΔY_{ijt} denote the difference between the two states of nature; hence

$$\Delta Y_{ij} = Y_{ij,1} - Y_{ij,0}.$$

Then, we can show that

$$\Delta Y_{ij} = \mu + S_j{}'\beta_S + X_{ij}{}'\beta_X + \Delta\varepsilon_{ij} \tag{1}$$

Equation (1) is the empirical equation used to evaluate the significance of the policy with respect to the various effects.

Next, we provide a non-parametric interpretation, thus making probability statements about the observed outcomes. To this end, a Bayesian approach is utilized. Bayesian analysis is a statistical procedure that endeavors to estimate parameters of an underlying distribution based on the observed distribution. Beginning with a "prior distribution" (in our case, either an uninformed distribution over the range of values reported in the various studies or an informed one that is based on the parameters estimated under Eq. [1]), we generate the posterior distribution. We generate data to calculate the likelihood of the observed distribution, multiply the likelihood function by the prior distribution, and normalize the product to obtain a unit probability over all possible values. This is called the posterior distribution.

The mode of the distribution is then the parameter estimate, and "probability intervals" (the Bayesian analog of confidence intervals) can be calculated using the standard procedure. Bayesian analysis is somewhat controversial because the validity of the result depends on how valid the prior distribution is, and this cannot be assessed statistically. However, the estimated posterior mean is similar to that estimated in the meta-regression analysis. The "location" of the estimated distribution provides information pertaining to the average weighting of factors on decisions whereas the "dispersion" supplies a measure of the internal consistency of the policy decisions made. We use these measures and Bayesian inference to assess the magnitude of the various outcomes affected by policy.

III. Data

The search for empirical studies uses the search engine *Google Scholar* and employs the following keywords: biofuels, ethanol, biodiesel, food prices, fuel prices, welfare, employment, and poverty. We focus on the population of studies that offered a numerical analysis which evaluated the economic and environmental effects of the renewable fuel standards. The list of studies reviewed in this paper is in Appendix B.

When collecting studies, the population is not limited to peer-reviewed studies but expands to reports and unpublished papers – to the “gray literature” (Lommis and White, 1996). Some unpublished studies are not only newer and use newer data, but all studies, independent of their quality, contribute to the statistical identification of the factors responsible for the heterogeneity among studies (Stanley, 2001; Stanley et al., 2013). The meta-analysis also includes books, book chapters, and dissertations.

The collected data from the population of studies include two alternative datasets: (i) an average set whereby the average of all reported change in each study is used and (ii) an all-inclusive set whereby all relevant estimates reported in each study are used.

IV. Results

Our analysis evaluates multiple criteria used to assess the effect of the introduction of biofuels, including GHGs and land use changes, food and fuel prices, terms of trade, welfare, employment, balance of trade, and learning-by-doing. While the various details pertaining to the empirical analysis are presented in the Appendix A, key results are discussed below.

4.1. GHG and ILUC effect of corn ethanol

The statistical analysis leading to the results discussed below is presented in section 1A of Appendix A.

Our meta-analysis suggests that change in GHG emissions due to the introduction of biofuels depends on the specific geographic location, biofuel feedstock, and type of land used to grow the crop (Fargione, 2008) and that there is much variability among studies. While the average indirect land use change (ILUC) reported in the literature is 0.81 kg CO_2 per liter of corn ethanol in gasoline-equivalent units, when dropping the Searchinger et al. (2008) paper from the sample, the average drops to 0.67 kg CO_2 per liter of corn ethanol.[1] The literature proposes that corn ethanol yielded a decline of 0.19 kg CO_2 per liter. That is, if gasoline emits 3 kg CO_2 per liter, then corn ethanol, in gasoline-equivalent units, emits 2.81 kg CO_2 per liter. However, the standard deviation is 0.87, resulting in some papers arguing for net carbon savings and others calculating a carbon debt.

Our meta-regression, which focuses on corn ethanol, offers further support to these claims. The meta-regression investigates reasons for differences across studies. The baseline specification (i.e., the stepwise regression with cluster standard deviations) is depicted in Table 1 with robustness of the regression outcomes investigated in section 1A of the Appendix A.

The analysis indicates that the studies modeling crude oil markets, in addition to land, are also the studies that used earlier years to calibrate their model. Early studies not only assessed the impact of the introduction of corn ethanol on GHG emissions but also the effect of biofuels on food and fuel prices. Later studies focused more on the GHG effects of ethanol and did not model the petroleum markets. The studies that calibrated later years reported lower CO_2 per liter of corn ethanol; that is, the crude oil dummy parameter is 0.4412 and is significant at the 1% significance level.

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[1] To this end, Searchinger et al.'s (2008) analysis suggests that production and consumption of corn ethanol is 2.21 kg CO_2 per liter.

Comparing results across studies also suggests that initially GHG emissions were lower than those calculated in 2008, where the literature recognized the unintended effect of corn ethanol on land use and its ILUC. However, since 2008, ILUC calculations have declined several fold; while Searchinger et al.'s (2008) results suggest that ILUC is more than 2.2 g CO2 per liter, Hertel et al.'s (2010) calculations indicate ILUC at 0.57 to 0.85 g CO2 per liter.

The meta-regression analysis also indicates that the introduction of economic linkages (via partial and general equilibrium models), as opposed to life-cycle analysis (LCA) and/or agent models, results in corn ethanol having a larger GHG footprint; the model dummy parameter, which equals zero if an economic model is assumed and one if it is an LCA or agent model, is -0.1879 and is significant at the 1% significance level.

	stepwise (0.2) + cluster
Crude oil dummy	0.4412*** (0.0780)
Model dummy	-0.1879*** (0.0501)
Constant	-0.2314** (0.0848)
R^2	0.1485
N	58

Table 1. Heterogeneity among studies and the impact of corn ethanol on GHG emissions.

To further assess the robustness of the results, we turn to Bayesian analysis and estimate the posterior distribution (Table 2). The models are simulated with the all-inclusive dataset. We subsample the Markov Chain to reduce the storage burden of the output and improve statistical efficiency by taking every fifth observation instead of all observations (Owen, 2015), while burn-in the first 50,000 to minimize the effect of the prior on the statistical analysis. That is, the sample analyzed is 200,000 in size. We assume that the prior is the normal distribution with a mean of one and a standard deviation of zero but that the joint prior distribution of the coefficients and the variance is an inverse Gamma distribution. The trace, autocorrelation, histogram, and density are visually checked for the convergence of Markov Chain Monte Carlo (MCMC), and all are well behaved (section 1A of the Appendix A).

The sign and size of the crude oil dummy in the Bayesian regression is similar across both methods and specifications, while the other parameters' value varies across models and specifications (section 1A of the Appendix A). However, other than the crude dummy parameter, the coefficients are not significantly different than zero.

	OLS specification
Crude oil dummy	0.4061***
	(0.0650)
Year calibrated	-0.0002
	(0.1053)
Model dummy	-0.0427
	(0.1053)
Constant	-0.0311
	(0.9992)
Burn-in	50,000
MCMC iterations	1,049,996
Acceptance rate	0.358

Table 2. GHG emissions and the Bayesian analysis: Posterior means.

The meta-analysis suggests that corn ethanol resulted in a small reduction in total GHG emissions: The introduction of corn ethanol via the US mandate resulted in a 0.19 kg CO_2 per liter reduction, on average, but with a standard deviation of 0.87. The magnitude of the decline/increase in GHG emissions depends on the ILUC estimated. To this end, the funnel plot indicates no systematic biases (see section 1A in the Appendix A, Fig. 1A). GHG emissions did not yield much, if any, net benefit and are not likely the driver behind corn ethanol policies.

4.2 Food prices

In recent years, concerns that corn ethanol is responsible for rising food prices by diverting the grains that would have been consumed in developing countries as food and feed to ethanol have raised serious questions regarding the use of corn ethanol. The understanding that corn ethanol is not making a substantial dent in the transportation sector's GHG emissions resulted in a demand to stop support for corn ethanol because of its negative effect on food consumption. Even so, does the existing literature support these claims? We investigate the food vs. fuel debate and the claims that corn ethanol significantly strains food prices.

This section investigates the empirical literature on the food vs. fuel debate and uses meta-analysis to make statistical claims on the effect of the introduction of corn ethanol on food commodity prices. To better understand the heterogeneity among various studies numerically assessing the effect of introducing biofuels on food commodity prices, our meta-analysis includes data on the assumed demand and supply elasticity of various crops, whether the study included fuel and other petroleum/crude oil markets, whether the analysis focused on the US or also included the rest of the world, the year data were calibrated, a dummy that equals 1 for food commodity price inflation (2007/2008), and assumptions on a mandate and tax credit as well as type of analysis, such as partial versus general equilibrium (see also Appendix A, section 2A, where summary statistics and more detailed presentation of the statistical analysis are supplied).

On average, ethanol resulted in the price of corn increasing by 24.5%, although we observe a larger impact in the short run. Figure 1 depicts estimates of the effect of the introduction of biofuels on food commodity prices, while focusing on corn. The various studies are depicted on the x-axis with the y-axis measures the change in price per bushel. On average, the introduction of biofuels resulted in the price per bushel of corn increasing by 61 US cents, where the standard deviation is 0.65 and the maximum increase estimated is $3.29 US.

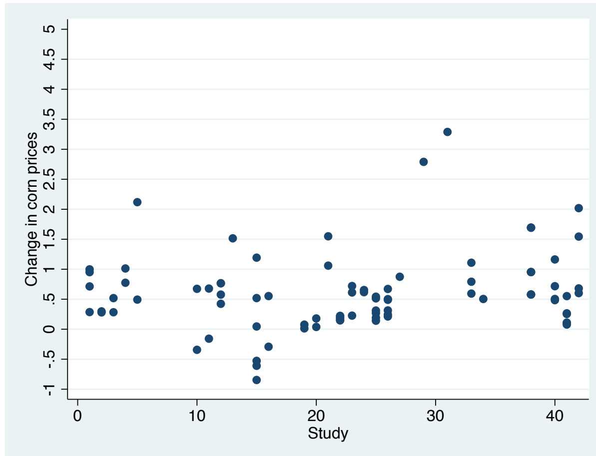

Figure 1. The introduction of biofuels and corn prices.

The stepwise regression results, assuming backward-selection estimation (i.e., it starts with the full specifications), are depicted in Table 3. Because this part of the analysis uses the all-inclusive dataset whereby all relevant estimates reported in each study are documented, the empirical analysis needs to address heteroskedasticity. For these studies, we estimate a weighted regression, where the weights per observation are inversely related to the number of observations per study (the outcome of these regressions is also compared to those assuming clustered analysis; however, most of the results are the same – see Appendix A section 2A).

Introducing more flexibility in adjunct markets (i.e., the petroleum market) results in a smaller effect of biofuels on food commodity prices. Modeling the petroleum market allows petroleum producers to respond to prices and changes in demand and thus mitigates the effect of biofuels on demand for corn (the oil/petroleum markets coefficient is negative and significant at the 1% level). Another outcome of the meta-analysis, which is common among all estimated models, is that more inelastic demand or supply for corn has a larger effect on food commodity prices (recall that demand elasticity is negative while supply elasticity is positive, and more inelastic curves are those with elasticity closer to zero). Finally, while the effect of the introduction of biofuels on corn prices increases as the year used to calibrate the numerical model increases (i.e., the coefficient of year calibrated is positive) and using 2007/2008 increases the effect of corn ethanol on food commodity prices even further, the effect of increasing the number of countries beyond the US is mixed (i.e., rest of the world).

Variable	Model I Weighted	Model II Weighted
Oil/petroleum markets	-1.1992 (0.3850)	-0.9795 (0.3321)
Rest of the world	removed	removed
Demand elasticity of crops	1.4119 (0.2145)	1.5098 (0.2257)
Supply elasticity of crops	-0.7796 (0.3976)	removed
Year calibrated	0.1004 (0.0327)	0.1525 (0.0215)
2007/08 food commodity Inflation	0.2662 (0.1498)	removed
Mandate		-0.5005 (0.0900)
Constant	-200.15 (65.4768)	-304.66 (43.0954)
N	25	25
R^2	0.5436	0.6060

Table 3. Stepwise regression and the effect of corn ethanol on food commodity prices.

When assessing the distribution of the various parameters using Bayesian techniques, the estimations derived are similar to those obtained above. The models are simulated with the *all-inclusive* dataset. Each simulation uses 200,000 iterations. The prior is the normal distribution with a mean of 1 and a standard deviation of 0, but the joint prior distribution of the coefficients and the variance is an inverse Gamma distribution. The estimation outcomes of the Bayesian analysis are depicted in Table 4. The trace, autocorrelation, histogram, and density are visually checked for the convergence of the MCMC, and all are well behaved (section 2A in the Appendix A).

	Model I
Acceptance rate	0. 3044
Efficiency:	
Minimum	0.1058
Average	0.2394
Maximum	0.8053

Fuel market	0.3892 (0.0574)
Oil/petroleum markets	-0.9179 (0.0602)
Demand elasticity of crops	0.0933 (0.0475)
Year calibrated	0.1203 (0.0077)
2007/08 food commodity Inflation	*-0.0731* *(0.0492)*
Mandate	*-0.2984* *(0.0408)*
Constant	*-0.2675* *(0.0665)*
Variance	*0.1322* *(0.0068)*

Table 4. Bayesian analysis with all dataset: The posterior means.

Next, we simulate the Bayesian models using the *average dataset* and use that dataset to calculate the funnel graph (see Figure 2). Although the plot suggests that studies are slightly biased because of the introduction of corn ethanol (some of the dots appear above the dashed line), we think these biases are negligible.

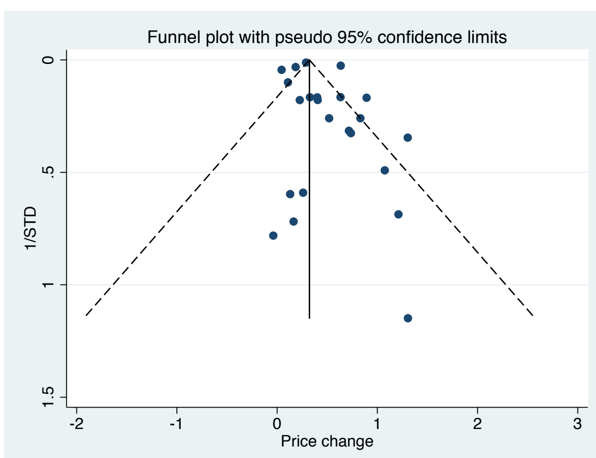

Figure 2. Funnel plot.

While looking at all biofuels surveyed in the literature and focusing on food prices, the literature indicates a small effect on US consumers. The estimated effect of biofuels on the US consumer price index averaged less than one percentage point (Anderson et al., 2008; Collins, 2008; Gecan et al., 2009; Glauber, 2008, among others).

Measures such as the Renewable Fuel Standards (RFS) divert resources of land away from food and feed, but the literature argues that their impact on the price of food commodities is moderate at best, with most of the effect washing away as we move throughout the supply chain; corn ethanol's effect on US food prices is small. This, however, may change in the short run as documented in the literature for the food commodity spike of 2007/2008.

Based on existing literature, we argue that the environmental benefits of corn ethanol are limited, and its impact on food commodity prices is moderate. The next two subsections investigate the economic benefits of the introduction of corn ethanol and biofuel policy in the US.

4.3 Fuel prices

We begin with fuel prices; the collection of data pertaining to the effect of the introduction of biofuels on fuel prices includes changes in fuel prices, demand elasticity, whether the study is peer-reviewed, the year used to calibrate the model, the year published, the numerical method employed (whether agriculture production is modeled – that is if the analysis assumes partial, multi-market, or general equilibrium), whether the petroleum markets were modeled (other than fuel), and whether the analysis focuses on the US or also includes the rest of the world. Summary statistics are presented in the Appendix A, section 3A.

The estimate of Eq. (1) is depicted in Table 5. Because the analysis uses the all-inclusive dataset whereby all relevant estimates reported in each study are documented, the empirical analysis needs to address heteroskedasticity. For these studies, cluster standard errors are employed. We also compare the clustered errors with weighted ordinary least squares (OLS) in the supplementary material, section 2.3A, where the weights per observation are inversely related to number of observations per study. The results of the cluster analysis are also compared with a stepwise OLS regression that performs backward-selection estimation (i.e., it starts with the full model) and also assumes clustered errors.

Variable	OLS (Cluster)
Demand elasticity	0.0313
	0.0188
Peer reviewed	-0.1043
	0.0792
Year calibrated	-0.0083
	0.0054
Year published	-0.0259
	0.0193
Petroleum products	0.2324
	0.1059
Rest of the world	0.0601
	0.1388
Model	0.0299
	0.0340
Constant	68.4477
	39.0621
Statistics	
N	43
R^2	0.5659

Table 5. Estimations of Eq. (1).

The results depicted in Table 5 suggest similar and significant effects across different specifications for both the size of the demand elasticity and the modeling of petroleum markets. Assuming a more elastic demand for fuel results in a larger reduction in the price of fuel. However, modeling petroleum markets results in the introduction of biofuels having a smaller negative effect on the price of fuel.

Figure 3 plots the predicted values of the stepwise OLS regression with clustered errors using the average dataset, while separating those that focus on petroleum markets from others. It also includes out-of-sample empirical studies investigating the effect of corn ethanol on fuel prices. The demand elasticity is depicted on the x-axis and the effect of the RFS on fuel prices is measured on the y-axis. We also include a fitted value line. Figure 3 offers further support to the regression outcomes summarized in Table 5, where explicitly modeling petroleum markets results in more price stickiness and the RFS results in smaller changes to fuel prices.

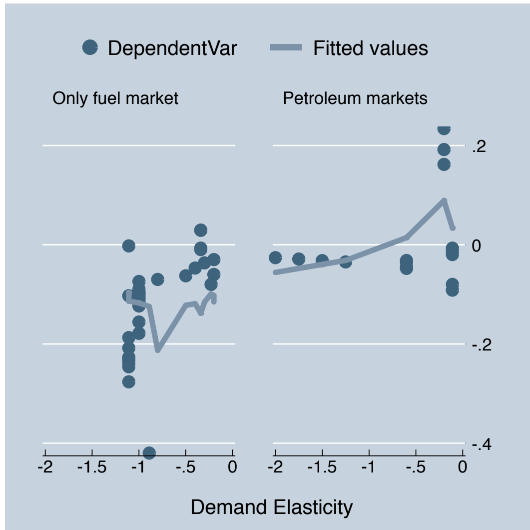

Figure 3. Price stickiness and the petroleum markets.

The averages in most of the studies fall to the left of the zero line (where the average for each study is the simple average of all estimates reported in a study), thus indicating that the introduction of biofuels resulted in a decline in the price of fuel. The standard deviation is calculated using all estimates of a study and is used to construct the 95% confidence interval. For most studies, the 95% confidence interval is located to the left of the zero line – again, indicating that the introduction of biofuels has a negative effect on the price of fuel.

When including all data points (e.g., results of statistical studies), the negative effect of the introduction of biofuels on gasoline prices increased over time. However, when we exclude Due and Hayes' (2008) study, there is no change over time, with biofuels, on average, resulting in fuel prices declining by 4.5%.

The meta-analysis suggests that petroleum refineries respond to the introduction of biofuels and alleviate the effect of biofuels on fuel prices; see also Knittel and Smith (2015). The meta-analysis indicate that although biofuel production increases, its effect on gasoline prices is relatively constant. However, the numbers imply that the refineries' response is limited and that biofuels do make a dent in the refineries' profit margins and negatively affect fuel prices (as well as crude oil prices).

When comparing results across studies, models that include food commodity, as well as fuel markets, result in estimates that on average predict that the introduction of biofuels will result in a few percentage points of decline in fuel prices. On the other hand, models that focus more on fuel/ethanol markets predict that the introduction of biofuels results in a larger impact on fuel prices.

A recurring outcome of the meta-analysis is that a more detailed and explicit modeling of related markets positioned throughout the supply chain results in the analysis predicting smaller effects on prices; linkages among markets matter and mitigate the price effect of the introduction of corn ethanol. Here, the introduction of other petroleum markets and food markets yields a smaller negative effect on fuel prices. When looking at food commodity prices, introducing the oil and petroleum markets results in corn ethanol having a smaller net effect on food commodity prices.

Next, we want to further understand the distribution of the parameters affecting the results presented in the population of studies analyzed. Thus, we employ Bayesian estimation techniques, where a petroleum market dummy and demand elasticity are introduced to the empirical specification, as is the year the model is calibrated. Other specifications are introduced in the Appendix A section 3A. These specifications are simulated twice: (i) the *all-inclusive* dataset whereby all the results are included in the data and (ii) the *average* dataset whereby only the average of each study is included in the data.

We present here the results of the *all-inclusive* dataset. Each simulation assumes 200,000 MCMC iterations and we burn-in the first 5,000 iterations. An uninformed prior is assumed for the models' coefficients. We also assume that the joint prior distribution of the coefficients and the variance are proportional to the inverse of the variance – namely, the Jeffrey prior. The estimation outcome of the Bayesian analysis, while employing the *all-inclusive* dataset, is depicted in the Appendix A section 3A. Overall, the analysis supports the assumption that the magnitude of the effect of the RFS depends on several key parameters, which can explain some of the differences among the various studies; key parameters that we identify in the regression analysis are presented in Table 5.

The meta-analysis and the robustness of the analysis suggest that the introduction of corn ethanol yielded a decline in the price of fuel, albeit a small one, and that the heterogeneity observed in the literature can partly be explained by differences in assumptions: A higher demand elasticity and the modeling of petroleum markets yield a smaller change in fuel prices with introduction of the RFS. Linkages among markets result in reducing the effects of corn ethanol on prices, and this is true for both fuel prices and food commodity prices (see section 4.2).

4.4 The macro-economic effect of biofuels and learning

To better understand the heterogeneity among various studies numerically assessing the effect of the introduction of corn ethanol on economic surplus, our meta-analysis includes data on the measured effect of corn ethanol on US welfare, terms of trade, year calibrated, period investigated, and method employed (see Appendix A section 4A, where summary statistics and a more detailed presentation of the statistical analysis is supplied).

When comparing changes in economic surpluses that are attributed to the introduction of biofuels, the median is around 0% with US (and Brazil) slightly positive but the rest of the world slightly negative. To this end, the mean change in US welfare because of the introduction of corn ethanol is $1.4 billion US.

The OLS stepwise regression analysis (Table 6) shows that models that introduce the ripple effect of economic activity, namely, the direct (i.e., *directly* related to the corn ethanol industry), indirect (i.e., *indirectly* related to the corn ethanol industry, e.g., input suppliers), and induced (i.e., coming from the expenditure of incomes earned from direct and indirect employment) effects of corn ethanol, result in larger estimates of the economic benefits of corn ethanol to the US. To this end, the case studies presented in the literature looking at employment and the economic activity generated by the introduction of biofuels in rural communities suggest that biofuels stimulated rural communities and created economic value. Although the case studies we surveyed concluded that biofuels resulted in a net economic benefit to rural communities, the introduction of biofuels did negatively affect livestock farmers and reduce employment in conventional biomass industries (Remedio and Domac, 2003; Domac et al., 2005).

We depict two regression models (Table 6): OLS stepwise regression and an OLS stepwise regression model with clustered standard deviations. The results of the regression indicate that introducing other countries, in addition to the US, and explicitly modeling trade between regions leads to estimates of higher benefits to the US from the introduction of corn ethanol. The analysis introduces a dummy variable that equals 1 if the study explicitly assumes other regions or the rest of the world, thus explicitly capturing the economic effect of trade with the US. Both specifications suggest higher net economic value to the US if trade is explicitly modeled; the empirical analysis suggests a $5.6 billion US difference, and the coefficient is significant at the 1% level (Table 6).

The analysis introduces a dummy variable that equals one if the method employed is a computational general equilibrium (CGE) model and zero otherwise. The dummy variable distinguishes among models that capture the ripple effect of corn ethanol versus those that do not. The outcome presented in Table 6 shows a significant and positive effect of almost $3 billion US in models that explicitly model the ripple effect of the introduction of biofuels on the US economy.

Although policies promoting corn ethanol achieve only modest environmental improvements (section 4.1), these policies do result in substantial improvements to the US balance of trade and its energy balance, resulting in a significant positive effect on rural employment and the economy at large. Even though in 2005 the US consumed 3.34 billion barrels of finished motor gasoline annually, in 2011 US consumption of finished motor gasoline declined to 3.19 billion barrels annually. The amount of ethanol consumed in the US in 2011 equaled 67.25% of the decline of finished motor gasoline consumption from 2005 to 2011. On the other hand, production of US gasoline in 2005 was 3.04 billions of barrels annually but it increased to 3.31 in 2011, an increase of 9%. While focusing on US energy policy, similar conclusions can be demonstrated using the petroleum-refining and coal industries as examples (Hochman and Zilberman, forthcoming; San et al., 2008).

Variable	OLS Stepwise Regression	OLS Stepwise Regression (Cluster)
Year Calibrated	0.2756	0.1125
	0.0544	0.1160
Year Published	-0.1208	-0.1126
	0.0585	0.1159
ROW	5.6125	5.6119
	0.5002	0.3312
Model	2.9829	2.9850
	0.7740	0.8236
Constant	-310.1964	-310.7661
	109.0287	99.5104
Statistics		
N	16	16
R^2	0.9722	0.9354

Table 6. The effect of the introduction of corn ethanol on the economic welfare of the US economy: estimations of Eq. (1) and measuring the effect of various factors on the US economic welfare reported in the literature.

Based on a separate strand of this literature that estimates the learning-by-doing in the corn and sugarcane ethanol industries, the economic benefits from the introduction of ethanol are expected to increase over time. The concept used in this literature measures and quantifies the aggregated effect of technological development using the experience curve approach. This approach assumes that costs decline with a fixed percentage over each doubling in cumulative production, namely, learning-by-doing is measured by the progress ratio (PR) that represents the cost of production after cumulative production doubles. The results of this part of the meta-analysis indicate that the average PR for production is 0.32, but that the PR for processing equals 0.86.

These outcomes are important and imply that the economic benefits from the introduction of biofuels will only increase with time. The outcomes also suggest that to fully understand the economic value of the introduction of biofuels to the US economy, dynamics need to be incorporated into the analysis, including the dynamics of production and the dynamics of agricultural commodities, as well as the importance of inventories (Hochman et al., 2015).

V. Policy discussions and concluding remarks

The results of our meta-analysis indicate that the introduction of biofuels resulted in a moderate increase in food commodity prices, but a small impact on food prices and a small reduction in fuel prices. The analysis also implies that even though first-generation biofuels did not yield much benefit to the environment, they substantially affected the macro economy and rural development. To this end, evidence presented in the papers suggests a small positive net effect on aggregate US welfare.

A recuiring outcome of the meta-analysis is that a more detailed and explicit modeling of related markets positioned throughout the supply chain results in the analysis predicting smaller effects on prices; economic linkages matter and alleviate the price effects attributed to the introduction of corn ethanol. The introduction of other petroleum markets and food markets resulted in a smaller negative effect of corn ethanol on fuel prices, while introducing the oil and petroleum markets resulted in corn ethanol having a smaller positive net effect on food commodity prices. GHG emission savings were also smaller if economic models were used.

Biofuel policy, similar to oil, natural gas, and coal policies, results in political and economic gains and affects macroeconomic parameters that are key to politicians. Macro-level aggregate considerations, in addition to special interests, guide policy makers, and biofuel policy has resulted in macro-level aggregate outcomes that are emphasized by the executive branch. However, this may come at the expense of the environment.

The meta-analysis indicates that dynamics matter, as do commodity inventories, implying that dynamic welfare analysis that includes learning and the dynamics of agricultural commodities is needed to better understand the effect of biomass on the economy. In the 20th century, technology moved the US from traditional agriculture to modern agriculture, thereby yielding higher return on investments in agriculture (Schultz, 1964). Technology will likely have similar effects on the bioeconomy in the 21st century, resulting in high returns on investment and technologies that transform the bioeconomy beyond first-generation biofuels and expand the portfolio of bioproducts produced and consumed.

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Appendices

Appendix A:

1A. GHG emissions and indirect land use

To better understand the heterogeneity among the various studies that numerically assess the effect of the introduction of biofuels on GHG emissions, the following variables where included: CO_2 emissions (percent and kg CO_2e per liter of ethanol), g CO_2 emissions due to ILUC per liter, biofuel production, US land use change, and global land use change. Summary statistics of the variable is presented in Table 1A.

Variable	Total # of observations	Mean	Std. Dev.	Min	Max
Percent change in CO2	62	-0.06	0.28	-0.67	0.93
kg CO2e per liter of ethanol	70	-0.19	0.87	-2.01	2.71
ILUC g CO2 per liter	23	0.81	0.52	0.19	2.36
biofuel production (Mtoe)	12	122.07	102.92	11.35	295
US land use change (000 ha)	6	1005.67	617.13	390	1844
Global land used change (000 ha)	20	9863.71	11390.77	699.6	44000

Table 1A. Summary statistics

The variables summarized in Table 1 are used to estimate Eq. (5A), whose results are depicted in Table 2A. Because this part of the analysis uses the all-inclusive dataset whereby all relevant estimates reported in each study are documented, the empirical analysis needs to address heteroskedasticity. For these studies, cluster standard errors are employed (Model IA). We also compare the clustered errors with weighted OLS (Model IVA), where the weights per observation are inversely related to number of observations per study (the two options are denoted with Cluster or Weights, respectively). The results of the cluster analysis are also compared with a stepwise OLS regression (Model IIA) that performs backward-selection estimation (i.e., it starts with the full model).

Model IA **Model IIA** **Model III** **Model IV**

	stepwise (0.2) Cluster	OLS	Stepwise (0.2)	Weighted
Crude oil dummy	0.4412*** (0.0780)	0.5041* (0.2772)	0.5373*** (0.1818)	0.4089* (0.2216)
Year calibrated		0.0147 (0.0421)		
Model dummy	-0.1879*** (0.0501)	-0.1388 (0.2464)		
Constant	-0.2314** (0.0848)	-29.6703 (84.4438)	-0.4095*** (0.1491)	-0.3879* (0.2148)
R^2	0.1485	0.1504	0.1349	0.1011
N	58	58	58	58

Table 2A. Estimating the DIFF model

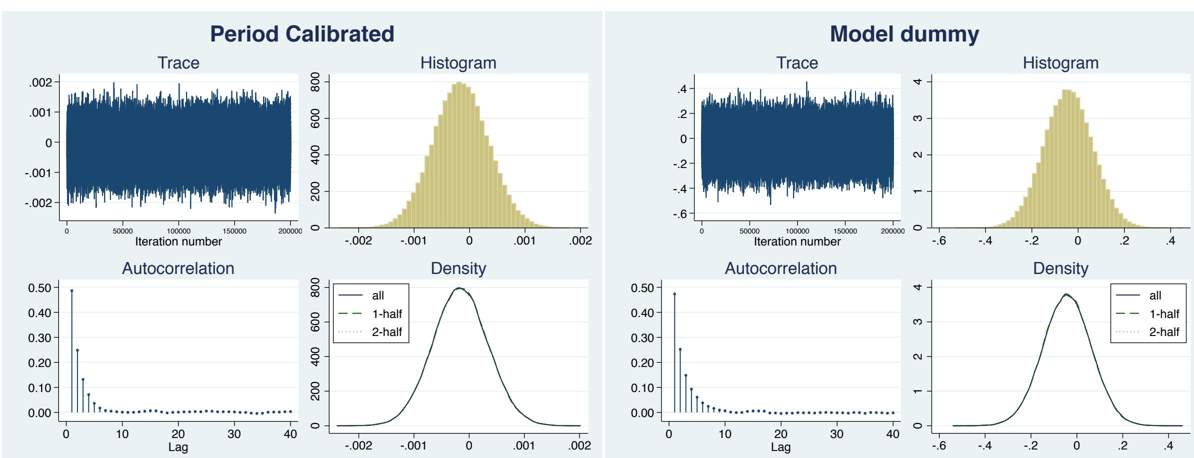
Next, we simulated Markov Chain Monte Carlo (henceforth, MCMC), and subsampled the Markov Chain to reduce storage burden of the output and improved statistical efficiency (Owen, 2015). We thin the Markov Chain sample, taking every 5th observation instead of all of them. We also burn-in the first 50,000 to minimize the effect of the prior on the statistical analysis. That is, we had 1,049,996 iterations that led to a sample size of 200,000. The prior is the normal distribution with mean 1 and standard deviation 0 but the joint prior distribution of the coefficients and the variance is an inverse Gamma distribution. We ran the Bayesian estimation twice: with and without weights.

	OLS specification Weighted	***OLS specification***
Crude oil dummy	0.4061	0.4216

	(0.0650)	(0.2349)
Year calibrated	-0.0002	-.0001
	(0.1053)	(0.0005)
Model dummy	-0.0427	-0.1904
	(0.1053)	(0.2260)
Constant	-0.0311	-0.0053
	(0.9992)	(0.9991)
Burn-in	50,000	50,000
MCMC iterations	1,049,996	1,049,996
Acceptance rate	0.3580	0.3355

Table 3A. The posterior means: comparing the Bayesian outcome

The trace, autocorrelation, histogram and density were visually checked for the convergence of MCMC, and all are well behaved and depicted in Figure 1A, assuming the specification of Model IA yet assumed a weighted regression, where the weights per observation are inversely related to number of observations per study. Similar outcomes were also obtained under the alternative models.



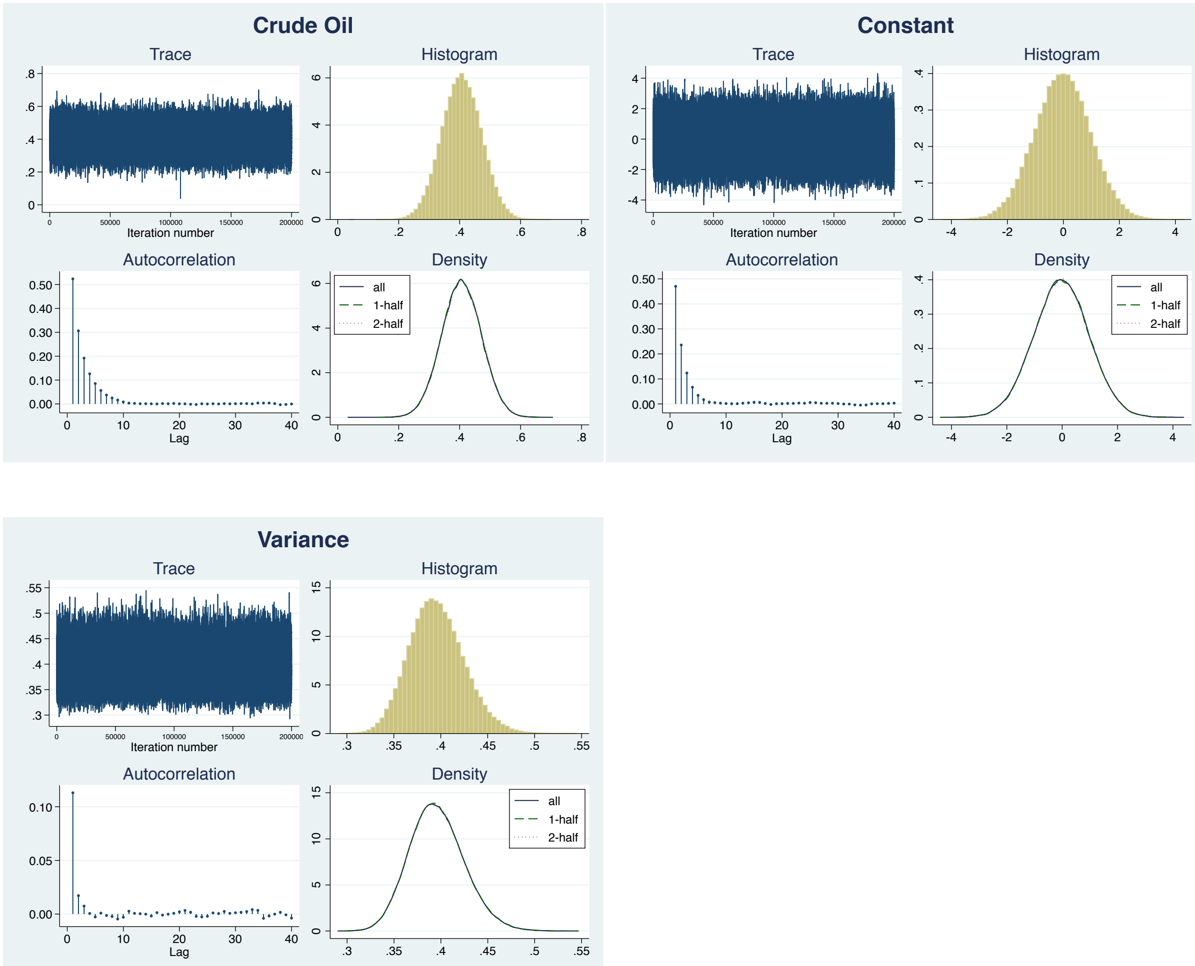


Figure 1A. The trace, autocorrelation, histogram and density assuming weighted regression and specification of Model IA.

2A. Food prices

To better understand the heterogeneity among various studies numerically assessing the effect of the introduction of biofuels on food commodity prices, our meta-analysis included data on the assumed demand and supply elasticity of various crops, inclusion of a fuel and other petroleum/crude oil markets, did the analysis focus on the US or also include the rest of the world, year data calibrated, dummy that equals one for the food commodity price inflation (2007/08), and assumptions on a mandate and tax credit as well as type of analysis (partial versus general equilibrium).

Table 4A summarizes corn data used in this part of the analysis where the dependent variable is the price difference in constant 2005 US$ with and without biofuels.

Variable	# of observation (corn)	Mean	Std. Dev.	Min	Max
Difference (constant 2005 US$)	88	0.6090	0.6513	-0.85	3.29
Fuel Market	91	0.6813	0.4685	0	1
Oil/Petroleum Markets	91	0.3407	0.4766	0	1
Rest of the World	91	0.4176	0.4959	0	1
Demand elasticity of crops	31	-0.4716	0.5039	-1.67	-0.16
Supply elasticity of crops	28	0.3339	0.1035	0.15	0.50
Year Calibrated	93	2005.85	3.8106	2000	2012
2007/08 Food commodity Inflation	93	0.2688	0.4457	0	1
Mandate	91	0.5824	0.4959	0	1
Tax credit	91	0.3187	0.4685	0	1

Table 4A. Summary statistics of food commodity price data

The variables summarized in Table 4A are used to estimate Eq. (5A), whose results are depicted in Table 5A. Because this part of the analysis uses the all-inclusive dataset whereby all relevant estimates reported in each study are documented, the empirical analysis needs to address heteroskedasticity. For these studies, we estimate a weighted OLS, where the weights per observation are inversely related to number of observations per study. Furthermore, we focused on the stepwise OLS that performs backward-selection estimation (i.e., it starts with the full specifications). The parsimonious model was then estimated using multiple regression model and the estimated parameters were very similar to those of the stepwise regression.

Variable	Model I OLS Weighted	Model II OLS Weighted	Model III Stepwise (0.2) Weighted	Model IV Stepwise (0.2) Weighted	Model V Stepwise (0.2) Weighted	Model VI Stepwise (0.2) Weighted
Gasoline market	0.7400 (0.4815)	0.6667 (0.3605)	removed	removed	removed	removed
Oil/Petroleum Markets	-1.2967 (0.4397)	-1.1420 (0.3787)	-1.1992 (0.3850)	-0.9795 (0.3321)	-1.4465 (0.4328)	-0.9795 (0.3321)
Rest of the World	-0.2372 (0.3423)	-0.3024 (0.2656)	removed	removed	0.1521 (0.0507)	removed

Demand elasticity of crops	1.1801 (0.3890)	1.4196 (0.3025)	1.4119 (0.2145)	1.5098 (0.2257)	2.1126 (0.3458)	1.5098 (0.2257)
Supply elasticity of crops	-1.6305 (1.0111)	-1.2362 (0.9737)	-0.7796 (0.3976)	removed	removed	removed
Year Calibrated	0.0932 (0.02990)	0.1407 (0.0345)	0.1004 (0.0327)	0.1525 (0.0215)	0.1481 (0.0358)	0.1525 (0.0215)
2007/08 Food commodity Inflation	0.7869 (0.2479)	0.6133 (0.2410)	0.2662 (0.1498)	removed	0.4763 (0.0826)	removed
Mandate		-0.4659 (0.1635)		-0.5005 (0.0900)		-0.5005 (0.0900)
Tax credit					0.4801 (0.1616)	removed
Constant	-186.16 (60.16)	-281.27 (69.30)	-200.15 (65.4768)	-304.66 (43.0954)	- 296.0887 (71.83)	-304.66 (43.0954)
N	58	58	25	25	25	25
R^2	0.3222	0.3385	0.5436	0.6060	0.6019	0.6060

Table 5A. Stepwise regression and the effect of biofuels on food commodity prices.

The 2007/08 Food Commodity Inflation pairwise correlation coefficient with the dependent variable is small (-0.03) and the t-test cannot reject the hypothesis that it is different than zero at a 10% significance level. However, the pairwise correlation of the Food Commodity Inflation with other covariates is significant different than 0 at a 10% significant level including the Demand Elasticity (-0.5646), Oil/Petroleum Markets (-0.2346), and Year Calibrated (0.2033). Thus, because the 2007/08 Food Commodity Inflation is correlated with other covariates but not with the dependent variable, stepwise regression does not add it to Model IV. To this end, correlation among covariates will cause the regression estimates to change depending on which independent variables are entered into the regression model (Cody & Smith, 1987, p. 184).

Next, instead of a weighted regression, assume clustered standard deviations and the following specifications.

Variable	Multiple regression I Cluster
Oil/Petroleum Markets	-0.2842 (0.1683)
Year Calibrated	0.0447 (0.0217)

Mandate	-0.4019 (0.1368)
Constant	-88.8060 (43.4560)
N	88
R^2	0.1614

Table 6A. Assuming clustered standard deviations

When assessing the distribution of the various parameters using Bayesian technics, the estimated derived were similar to those obtained above. The models were simulated twice: first with the *all-inclusive* dataset, and then with the *average* dataset.

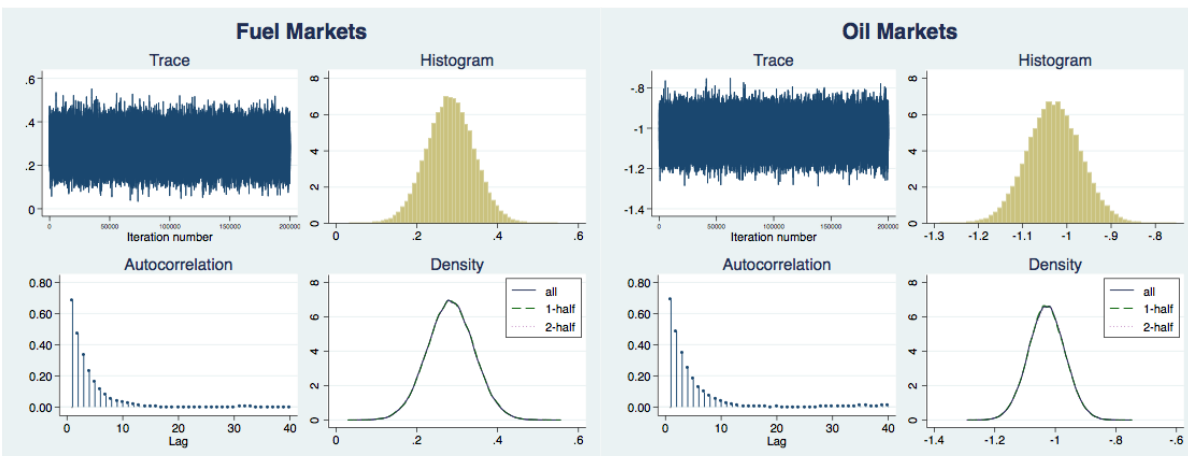
The sample size is 200,000 and the burn-in is 5,000. The prior is the normal distribution with mean 1 and standard deviation 0 but the joint prior distribution of the coefficients and the variance is an inverse Gamma distribution. The estimation outcome of the Bayesian analysis, while employing the *all-inclusive* dataset, are depicted in Table 7A.

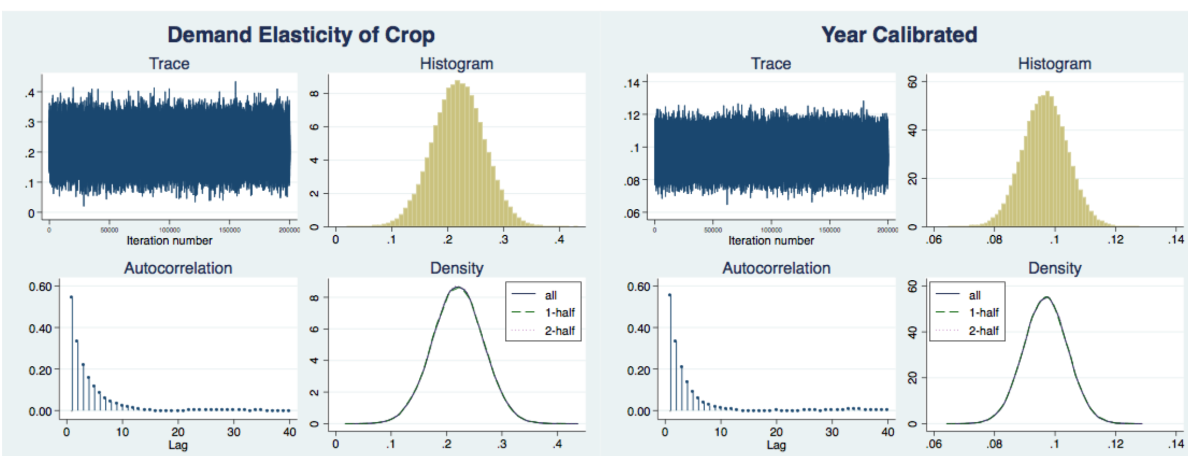
	Model I	**Model II**	**Model III**
Acceptance Rate	0. 3627	0. 3044	0. 3290
Efficiency:			
Minimum	0.0659	0.1058	0.1526
Average	0.1950	0.2394	0.2859
Maximum	0.8030	0.8053	0.7971
Fuel Market	0.2981 (0.0614)	0.3892 (0.0574)	0.2839 (0.0578)
Oil/Petroleum Markets	-1.0516 (0.0687)	-0.9179 (0.0602)	-1.0286 (0.0601)
Demand elasticity of crops	0.2393 (0.0532)	0.0933 (0.0475)	0.2204 (0.0457)
Year Calibrated	0.0997 (0.0083)	0.1203 (0.0077)	0.0969 (0.0072)
2007/08 Food commodity Inflation	*0.0313* *(0.0544)*	*-0.0731* *(0.0492)*	*0.0154* *(0.0491)*
Mandate		*-0.2984* *(0.0408)*	
Tax credit	*0.0315* *(0.0458)*		
Constant	*-0.1643* *(0.0931)*	*-0.2675* *(0.0665)*	*-0.1193* *(0.0657)*

Variance	*0.1416* *(0.0073)*	*0.1322* *(0.0068)*	*0.1415* *(0.0073)*

Table 7A. Bayesian analysis with all dataset

The trace, autocorrelation, histogram and density were also visually checked for the convergence of MCMC, and all are well behaved and depicted in Figure 2A, assuming the specification of Model II Table 7A. Similar outcomes were also obtained under the alternative models.





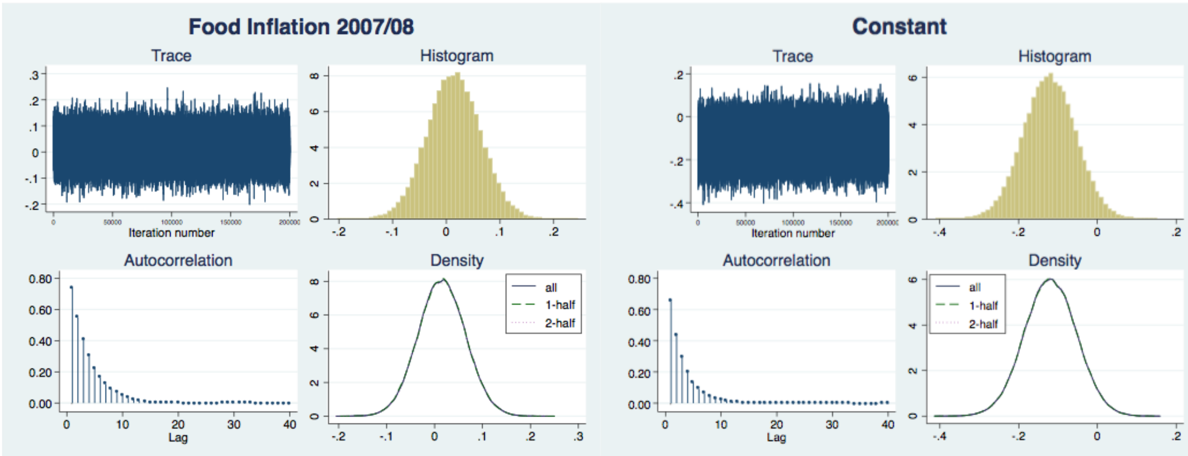


Figure 2A. The factors affecting the food commodity price outcome

Next, we simulated the Bayesian models using the *average dataset*. The average dataset was also used to calculate the funnel graph (see Figure 2 of the paper). The results from the Bayesian analysis is presented in Table 8A.

	Model IB	**Model IIB**
Acceptance Rate	0. 3044	0. 3627
Efficiency:		
Minimum	0.1058	0.0659
Average	0.2394	0.1950
Maximum	0.8053	0.8030
Fuel Market	0.3829	0.2981
	(0.0574)	(0.0614)
Oil/Petroleum Markets	-0.9179	-1.0516
	(0.0602)	(0.0687)
Year Calibrated	0.1203	0.0997
	(0.0077)	(0.0083)
2007/08 Food commodity Inflation	*-0.0731*	*0.0313*
	(0.0492)	*(0.0543)*
Mandate	*-0.2984*	
	(0.0408)	
Tax credit		*0.0314*
		(0.0458)
Constant	*-0.2675*	*-0.1643*
	(0.0665)	*(0.0931)*
Variance	*0.1322*	*0.1455*
	(0.0068)	*(0.0073)*

Table 8A. Bayesian analysis with the average dataset

3A Fuel prices

The collection of data, pertaining to the effect of the introduction of biofuels on fuel prices, included changes in fuel prices, demand elasticity, whether the study was peer-reviewed, the year used to calibrate the model, the year published, the numerical method employed (whether agriculture production was modeled, and if it was did the analysis assume partial, multi-market, or general equilibrium), was the petroleum markets modeled (other than fuel), and did the analysis focus on the US or also included the rest of the world.

Table 9A depicts the summary statistics of the population of studies. The dependent variable, i.e., change in fuel prices caused by the introduction of biofuels, suggests that for some studies corn-ethanol resulted in fuel prices increasing with the introduction of biofuels (e.g., de Gorter et al. 2015 BOOK) while others suggest it led to a decline in fuel prices (e.g., Chen 2010). The simple average of the population of studies suggests the introduction of corn-ethanol yielded a decline of 12 US cents in the price of gasohol (i.e., the mixture of gasoline and ethanol – ethyl alcohol – used as fuel in internal combustion engines). The summary below also suggests about 60% of the data is peer reviewed; 35% of the data is calculated assuming explicit markets for petroleum products (i.e., "Petroleum markets"); and that most of the models are either multimarket or general equilibrium models. The population of studies suggests heterogeneity among studies – a hypothesis we will return to below.

Variable	# Observations	Mean	Std. Dev.	Min	Max
Change in fuel price	68	-0.1200	0.1269	-0.42	0.23
Demand elasticity	43	-0.9407	1.4974	-10	-0.11
Supply elasticity	42	1.3624	1.4897	0.1	5.5
Peer Reviewed	68	0.5735	0.4982	0	1
Year calibrated	68	2009	5.3645	2000	2010
Year Published	68	2011	3.1379	2003	2015
Petroleum markets	68	0.3529	0.4814	0	1
Rest of the world	68	0.4265	0.4982	0	1
Model	68	3.1618	1.0164	1	4

Table 9A. Summary statistics

The variables summarized in Table 9A are used to estimate Eq. (5A), whose results are depicted in Table 10A. Because this part of the analysis uses the all-inclusive dataset whereby all relevant estimates reported in each study are documented, the empirical analysis needs to address heteroskedasticity. For these studies, cluster standard errors are employed. We also compare the clustered errors with weighted OLS, where the weights per observation are inversely related to number of observations per study (the two options are denoted with Cluster or Weights, respectively). The results of the cluster analysis are also compared with a stepwise OLS regression that performs backward-selection estimation (i.e., it starts with the full model) and also assumes clustered errors.

Variable	**OLS (weights)**	**OLS (Cluster)**	**OLS Stepwise regression (Cluster)**
Demand elasticity	0.0327	0.0313	0.0345
	0.0116	0.0188	0.0092
Peer Reviewed	-0.1126	-0.1043	Removed
	0.0418	0.0792	
Year Calibrated	-0.0058	-0.0083	-0.0042
	0.0050	0.0054	0.0026
Year Published	-0.0311	-0.0259	Removed
	0.0147	0.0193	
Petroleum products	0.2020	0.2324	0.1239
	0.0608	0.1059	0.0583
ROW	0.0731	0.0601	Removed
	0.0731	0.1388	
Model	0.0086	0.0299	Removed
	0.0235	0.0340	
Constant	74.0164	68.4477	8.4234
	31.7488	39.0621	5.2378
Statistics			
N	43	43	43
R^2	0.5849	0.5659	0.4861

Table 10A. Estimating the DIFF model

The forest plot, which provides context to the meta-analysis, is depicted in Figure 3A. The population of studies is depicted to the left, the 95% confidence interval is depicted to the right (presented in the plot as a line, with the center of the line being the mean) and is adjunct to the weights the meta-analysis places on each study. The averages of most of the studies fall to the left of the zero line (where the average for each study is the simple average of all estimates reported in a study), thus suggesting the introduction of biofuels resulted in a decline of the price of fuel. The standard deviation was calculated using all estimates of a study and was used to construct the 95% confidence interval. For most studies the 95% confidence interval is locate to the left of the zero line – again, suggesting introduction of biofuels has a negative effect on the price of fuel.

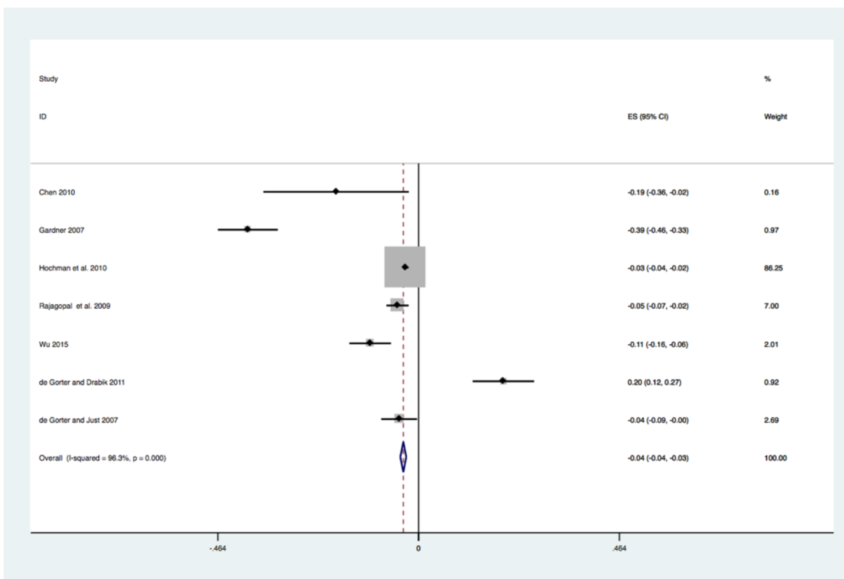


Figure 3A. The forest plot assuming the average dataset

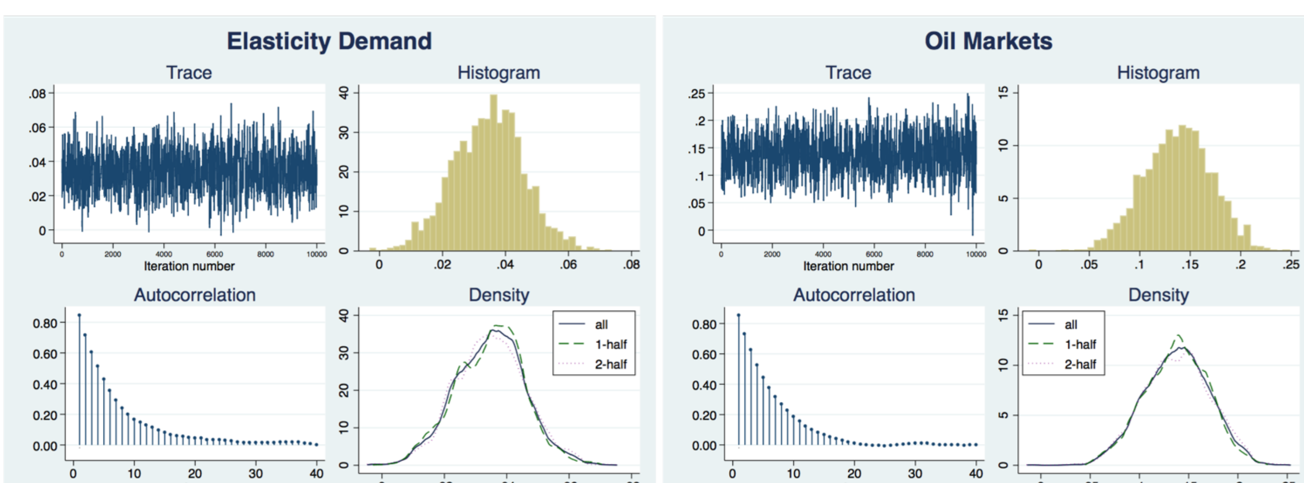
Next, we wanted to further understand the distribution of the parameters affecting the results presented in the population of studies analyzed. Thus, we employed Bayesian estimation techniques which are simulated twice: (i) the *all-inclusive* dataset whereby all the results are included in the data, and (ii) the *average* dataset whereby only the average of each study is included in the data.

We first present the results of the *all-inclusive* dataset. Each simulation assumed 12,500 MCMC iterations and we burned the first 2,500 iterations. An uninformed prior is assumed for the models' coefficients. We also assume the joint prior distribution of the coefficients and the variance is proportional to the inverse of the variance – namely, the Jeffrey prior.

The estimation outcome of the Bayesian analysis, while employing the *all-inclusive* dataset, are depicted in Table 11A. We also checked the trace, autocorrelation, histogram and density to visually check the convergence of MCMC (Model I depicted in Fig. 4A). Overall, all figures (for the all the specification presented in Table 11A) support the assumption that the effect of the Renewable Fuel Standard depends on the several key parameters that can explain some the differences among the various studies.

Variable	Model I	Model II
Demand elasticity	0.0347	0.0344
	0.0111	0.0103
Year Calibrated		-0.0044
		0.0023
Petroleum products	0.1379	0.1250
	0.0332	0.0322
Constant	-0.1107	8.6540
	0.0235	4.6308
Acceptance Rate	0. 3321	0. 2025
Efficiency:		
Minimum	0.0746	0.0245
Average	0.1011	0.0412
Maximum	0.1597	0.0716

Table 11A. Bayesian analysis with all dataset



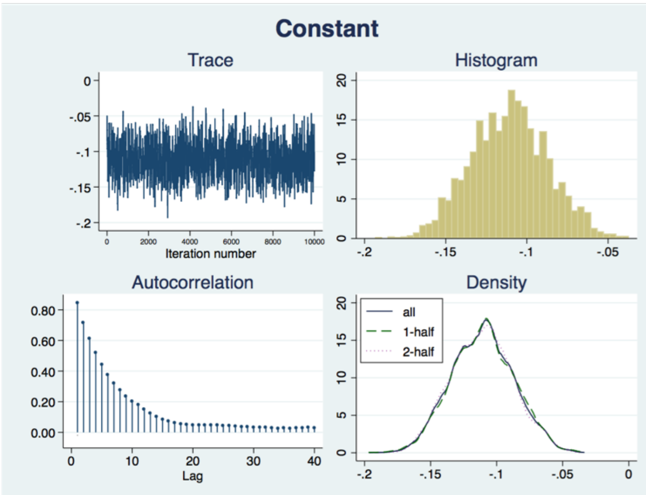


Figure 4A. Trace, autocorrelation, histogram and density of Model 1 (Table 10A)

Table 12A depicts the effective sample size, correlation times, and efficiencies of the two models and compares them to a model that only has a constant. The results suggest the parsimonious model (Model I) is marginally better than the Full model (Model II) but the analysis also suggests autocorrelation is a concern in the Full model. The coefficients of the demand elasticity and the existence of an explicit petroleum market, however, have similar effects on fuel prices under both models (see Table 12A).

	DIC	log(ML)	log(BF)
Constant	368.99	-169.56	.
Model II	-69.77	24.37	193.93
Model I	-67.90	28.16	197.72

Table 12A. Efficiency of the Bayesian models

Figure 5A presents the bivariate scatterplots of the parsimonious model’s coefficients. The plot suggests a general shape of the multivariate posterior distribution. A larger demand elasticity (in absolute value) and an explicit petroleum market results in a smaller constant.

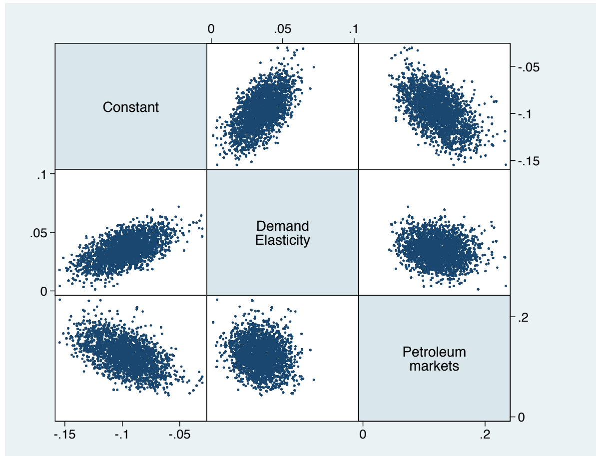


Figure 5A. The multivariate posterior distribution

Because of concerns from the use of the *all-inclusive dataset* – over emphasizing certain studies but not others (i.e., those with many observations) and heteroskedasticity – we also simulated the empirical models using the *average dataset*. The results of the Bayesian analysis assuming the *average dataset* are presented in Table 13A.

Variable	Model I (AVE)	Model II (AVE)
Demand elasticity	0.0672	0.0661
	0.0171	0.0161
Year Calibrated		-0.0046
		0.0001
Petroleum products	0.1138	0.1143
	0.0467	0.0383
Constant	-0.0488	9.1523
	0.0358	0.1235
Acceptance Rate	0. 3483	0. 3253
Efficiency:		
Minimum	0.0644	0.0118
Average	0.0816	0.0189
Maximum	0.1089	0.0634

Table 13A. The Bayesian simulation and the average dataset

The Bayesian information criterion are depicted in Table 14A. Although the Full model is marginally better, its convergence is still of a concern.

	DIC	log(ML)	log(BF)
Full model	-26.75	0.60	.
Parsimonious model	-24.95	9.02	8.42

Table 14A. The Bayesian information criterion assuming average dataset

The meta-analysis, and the robustness of the analysis, suggests that the introduction of biofuels yielded a decline in the price of fuel, albeit a small one, and that the heterogeneity observed in the literature can partly be explained by differences in the assumptions: a higher demand elasticity and the modeling of petroleum markets yields a lower fuel price with the Renewable Fuel Standards. Furthermore, the output of the OLS stepwise regression with clustered errors is very similar to the outcome of the Parsimonious model under the *all-inclusive dataset*.

4A. The macro-economic effect of biofuels

Appendix B: List of publication used in the meta-analyses

References to papers used in the meta-analyses

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