Inside the Black Box: the Price Linkage and Transmission between Energy and Agricultural Markets

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Abstract

Despite a growing literature on the integration of energy and agriculture, few have rigorously examined structural changes in the evolution of related energy and agricultural prices. Motivated by strong comovement and increasing volatility of energy and agricultural prices, we examine dynamic evolutions of ethanol, gasoline, and corn prices over the period of March 2005 – March 2011. A structural change is found around March 2008 in the pairwise dynamic correlations between the prices in a multivariate GARCH model. A structural VAR (SVAR) model is then estimated on two subsamples, one before and one after the identified change point. Using the novel method of "identification through heteroscedasticity", we exploit the time-varying price volatilities to fully identify the SVAR model. In the more recent period, ethanol, gasoline, and corn prices are found to be more closely linked. Specifically, ethanol (corn) shocks have the largest impact on corn (ethanol) price. The strengthened corn-ethanol relation can be largely explained by the new developments of the biofuel industry and related policy instruments. Variance decomposition shows that for each market a significant and relatively large share of the price variation could be explained by the price changes in the other two markets. For example, corn price changes explain 27% of the variation of ethanol prices, and shocks to ethanol price account for 23% of the variance of corn prices. The results are robust to the inclusion of seasonal dummies, and various representative macroeconomic and financial indicators.

Keywords: identification through heteroscedasticity, structural change, SVAR, variance decomposition

JEL Classifications: C32, Q11, Q42

1. Introduction

As an energy-intensive sector, agriculture has traditionally linked to the energy industry through input channels. While fuel and electricity are used directly for agricultural production, fertilizer and pesticide are two important indirect energy uses by agriculture. In 2003, total direct and indirect energy costs were approximately 14.4% of annual agricultural production expenses (Schnepf 2004). The emergence of large-scale production of biofuels, especially ethanol, in the U.S. fuel market substantially reshapes the relation between energy and agriculture.

Biofuels have grown substantially since 2005 and play an increasingly significant role in meeting U.S. domestic energy demand and policy goals. The expansion was largely driven by, among others, rising crude oil prices and environmental policies with the aim of reducing negative impacts of conventional energy sources. U.S. corn-based ethanol production increased from 3.9 billion gallons in 2005 to 13.2 billion gallons in 2010 (RFA 2011). Blended into over 90% of the nation's motor gasoline, ethanol replaced gasoline produced from about 445 million barrels of imported oil in 2010 (RFA 2011). The share of corn used for ethanol production increased from 5% in the mid-1990s to almost 40% in the 2010/2011 crop year (FAPRI 2011).[1]

The increased use of corn as ethanol feedstock has exposed agricultural markets to both input-related supply shocks stemming from rising energy prices and demand-side shifts based on biofuel's role as a petroleum substitute. Higher energy prices induce higher fertilizer price and other agricultural production costs. Meanwhile, high crude oil prices make ethanol production relatively more profitable and thus increase demand for corn. The strengthened linkage between

[1] It is important to note that in a dry-mill ethanol plant, on average one bushel of corn produces 2.8 gallons of ethanol and 17 pounds of distillers' dried grain, the latter of which returns to the livestock market and replaces about one-third bushel of corn in livestock feeding. Therefore the net percentage of corn used for ethanol production is about 27% in the 2010/2011 crop year.

energy and agricultural markets is indicated by the strong comovements of ethanol, gasoline, and corn prices presented in Figure 1.

Besides the comovement, a clear trend of increasing volatility of ethanol, gasoline, and corn prices occurred over the period of March 2005 – March 2011.[2] Key factors contributing to corn price volatility include the weakening U.S. dollar, crop failure in major producing countries/regions, volatility in the price of oil, and more importantly development of the biofuel industry (OECD/FAO 2011). Gasoline price variations are largely influenced by continuously growing global demand, market concentration, and increasingly stringent product specifications in local markets (EIA 2002). The strong comovement and increasing volatility of agricultural and energy prices have created policy challenges to the long-term success of the biofuel industry and global food security.

Although the integration between energy and agricultural markets has attracted growing interest in the literature, few have examined empirically structural changes in the evolution of closely related energy and agricultural prices. Failure to account for such changes results in undesirable consequences. For instance, estimates based on a model with structural changes being ignored will be biased and unreliable. Employing only partial time series before or after the structural change provides incomplete or misleading information on potential market linkages. This study attempts to fill this gap by identifying structural changes in the dynamic relations of energy and agricultural prices. Specifically, we quantify the time-varying correlations between the prices of corn, ethanol, and gasoline in a multivariate generalized autoregressive conditional heteroscedasticity (GARCH) model. A structural change point around March 2008 is identified from the evolution of dynamic correlations, which is generally

[2] The feature of increasing price volatility, or heterogeneity, is important and used for the model identification in this study.

consistent with the developments in the U.S. biofuel industry and related policy instruments. The finding of structural change allows us to produce one sample before and one sample after the identified change point, to carefully investigate linkage and transmission channels in energy and agricultural markets.

We also contribute to the literature by applying the novel “identification through heteroscedasticity” (IDH) method, which exploits time-varying volatility, to a structural vector autoregressive (SVAR) model of corn, ethanol, and gasoline prices. While the prices are simultaneously determined and thus endogenous, it is hard to find legitimate instruments or natural experiments for identification purpose. Typical ad-hoc restrictions, although widely used, don’t always agree with economic theory or practical experience. Increasing volatilities of energy and agricultural prices shown in Figure 1 lead us to adopt the IDH identification strategy. Employing the SVAR model, we estimate and compare contemporaneous price responses and transmission of price shocks before and after the identified structural change point. We find that in the more recent period, energy and agricultural prices are more closely linked with a strengthened corn-ethanol relation. Variance decomposition shows that ethanol is responsible for explaining about 23% of corn price variation. A relatively large share (27%) of ethanol price changes is driven by corn price fluctuation.

The remainder of the paper proceeds as follows. The next section reviews the recent literature. Section 3 gives a brief introduction to the development of U.S. ethanol industry and related government policies. Empirical models and estimation strategy are described in Section 4. Next, data and estimation results are reported and discussed. Section 6 presents the results of robustness checks to the inclusion of seasonal dummies and various macroeconomic and financial variables. The paper concludes with a summary of key findings.

2. Literature Review

The integration between energy and agriculture has attracted growing interest in the literature. A number of existing studies focus on the direct linkages between oil and agricultural commodity prices (see, for example, Hanson, Robinson, and Schluter 1993; Harri, Nalley, and Hudson 2009; Nazlioglu and Soytas 2011). The development of large scale biofuel production has created an emerging theme in the literature on the interdependencies between energy and agricultural markets. Tokgoz and Elobeid (2006) use a partial equilibrium model of ethanol, sugar, and crops to investigate the dynamic relationship between ethanol-corn markets in the U.S. and ethanol-sugar markets in Brazil. In a partial equilibrium model accounting for the linkages among crude oil, gasoline, ethanol, and corn, Tyner and Taheripour (2008) simulate the impacts of various ethanol supporting policies under different economic conditions. Ciaian and Kancs (2011) identify an indirect input channel and a direct biofuel channel to investigate the interdependencies between the energy, bioenergy, and food prices. Their results confirm the importance of the biofuel channel as a contributing factor to the integration between crude oil and agricultural commodity prices, while the contribution of the indirect input channel is small and statistically insignificant. Nonlinear adjustment to long-run equilibrium relationships of sugar, ethanol, and crude oil prices in Brazil are examined in Balcombe and Rapsomanikis (2008). Their study reveals that oil prices are the fundamental driving force of Brazilian sugar and ethanol prices. In addition, sugar prices are found to Granger-cause ethanol prices. Using a smooth transition vector error correction model, Serra et al. (2011) evaluate price linkages and transmission patterns in U.S. ethanol and related markets.

Several studies have addressed the occurrence of structural changes or regime switching associated with the development of ethanol industry. From the perspective of the oil refinery industry, Chaudhuri, Tonsor, and Peterson (2011) test the existence of structural change in the industrial demand for ethanol as an input. Results suggest that after January 2001 ethanol has been increasingly used as a substitute rather than as a complement. Goodwin, Pelletier and Tejeda (2011) empirically examine the impact of increased corn usage for ethanol production on the dynamic relationships between corn, soybean, feeder cattle, and live cattle markets. In their study, the ratios of soybean to corn harvest prices and the corn stock to use ratios are identified to be significant fundamentals for the regime switching process during the post-ethanol mandated period. There are a limited number of studies examining structural changes in the integrated energy and agricultural markets. Tyner (2010) discusses the evolving links between energy and agricultural markets and the corresponding driving forces. Tyner and Viteri (2010) analyze the impact of 10% blending limits on the development of the ethanol industry.

A related strand of literature investigates various issues related to market comovement and interdependency, or so-called contagion, especially in financial markets. Pericoli (2003) provides a recent review on the topic. Forbes and Rigobon (2002) point out that cross-market correlation estimated from the rolling-window method is positively related to the level of market volatility. When markets are more volatile, estimated correlation coefficients tend to increase and can be biased upward by the presence of heteroscedasticity. The reason is that traditional methods focus only on time-varying changes in the mean, without accounting for time-varying variance. The dynamic conditional correlation (DCC) multivariate GARCH (MGARCH) model, introduced by Engle (2002), is one way to solve this issue. The DCC-MGARCH model estimates a weighted average of the variables' correlations over the whole sample period with more weights given to more recent history. It allows for the revision of correlation estimates based on immediate past conditional variances. Compared to other estimators, the DCC-MGARCH model provides a good approximation for different time-varying correlation processes and is often the most accurate. Therefore we employ the DCC-MGARCH model for the first part of our study, which is followed by a SVAR analysis.

SAVR models have been increasingly employed to investigate various issues confronting energy and agricultural markets. Compared with the underlying reduced-form VAR models, SVAR models enable us to associate unique economic shocks to particular variables and to provide meaningful interpretation of the data. For example, Kilian (2009) proposes a SVAR model to (i) identify the underlying demand and supply shocks in the global crude oil market, and (ii) decompose the real price of crude oil into three components: crude oil supply shocks, shocks to aggregate demand for all industrial commodities, and demand shocks specific to oil. In examining the evolution of U.S. retail gasoline prices, Kilian (2010) proposes an integrated SVAR model of the global crude oil market and the U.S. retail gasoline market. McPhail (2011) extends the model in Killian 2010 to include the U.S. ethanol market and finds that a policy-driven ethanol demand expansion causes a decline in crude oil and U.S. gasoline prices.

3. U.S. Ethanol Industry and Policy Background

The development of the U.S. ethanol industry and market has been strongly encouraged and supported by the federal and state government policies. Federal government support started with passage of the 1978 Energy Tax Act, which provided a federal tax exemption or credit for ethanol producers and also imposed a tariff on imported ethanol. The original federal tax incentives have been augmented and revised by later federal legislation and have become stronger in general. As of 2010, one of the most important policy instruments is the Renewable Fuel Standard (RFS). The RFS originated with the Energy Policy Act of 2005, requiring a minimum volume of ethanol and biodiesel to be blended with the U.S. fuel supply starting at 4 billion gallons in 2006 and increasing to 7.5 billion gallons in 2012. The RFS was further expanded in the Energy Independence and Security Act (EISA) of 2007, which set a mandate to increase renewable fuel use to 9 billion gallons in 2008 and 36 billion gallons by 2022, which includes up to 15 billion gallons of corn ethanol. Besides the RFS, other main federal-level supports are a 45-cent-per-gallon tax credit for blending ethanol with gasoline, a 2.5% ad valorem tariff and a per unit tariff of 54 cents per gallon on ethanol imports.

The Clean Air Act Amendments of 1990 is another import piece of federal legislation that created demand for ethanol as a fuel additive. When the commonly used oxygenate methyl tertiary butyl ether (MTBE) was found to contaminate surface and ground water, several states banned or limited its use. Consequently the fuel industry was forced to switch to ethanol, so ethanol demand received a major boost. The blending wall, which refers to the 10% upper limit that ethanol is legally permitted to blend with gasoline, began to restrict the growth of ethanol industry when annul ethanol production reached about 12 billion gallons in 2009-2010. To overcome this obstacle, in October 2010, the U.S. Environmental Protection Agency (EPA) approved E15 gasoline blends (15% ethanol) for model year 2007 and newer cars and light trucks. Additionally, E15 approval for 2001 and newer vehicle was granted in January 2011. Furthermore, the U.S. Department of Agriculture announced that it will assist in the installation of 10,000 blender pumps across the country in the next five years.

Fueled by a combination of strong public support and record-high crude oil prices, the U.S. ethanol industry experienced impressive and sustained growth since 2005. A major wave of investment expanded ethanol production capacity from 3.6 billion gallons in 2005 to 13.5 billion gallons in 2010, of which 13.2 billion gallons were in operation (RFA 2011). However, in 2008 ethanol producers were affected by the collapse of the financial markets and high corn prices

(Tyner 2010). The economic challenges prompted a wave of bankruptcies including one major producer.[3] More than two billion gallons of capacity were idled or shut down permanently during the year. In this situation, the RFS became binding toward the end of 2008 and the key driver of ethanol prices has shifted to the price of corn as ethanol profit margins are mainly driven by ethanol and corn prices (Tyner 2010). The 10% blending wall, which became binding in late 2009, further reinforced the link between ethanol and corn prices as it forces ethanol to be priced on a breakeven basis with corn (Tyner and Viteri 2010). Since the fourth quarter of 2010, U.S. ethanol exports have increased substantially as the domestic market becomes saturated and is largely constrained by the blending wall. The export surge can be attributed to: (i) the high international sugar prices which induced Brazilian millers to maximize the output of sugar at the expense of ethanol production, (ii) strong demand for ethanol and relatively high prices in Brazilian domestic market, and (iii) the increasing value of the Brazil Real making Brazilian ethanol less competitive in world markets.

The large scale ethanol industry is reshaping the U.S. corn and related commodity markets, including a significant amount of farmland acreage shifts to corn production. For example, based on the acreage reports released by the U.S. Department of Agriculture, approximately 92.3 million acres were planted with corn in 2011/2012 crop year, the second largest since 1944.[4] Over the 30 years prior to 2006, average U.S. corn prices were approximately $2.4 per bushel. Since late 2006, however, average corn prices have jumped to about $4.00 per bushel in spite of an increase in acres planted.[5] The U.S. biofuel support policies

[3] http://www.ethanolrfa.org/page/-/objects/documents/2187/2008_ethanol_economic_contribution.pdf, retrieved 07/12/2011.
[4] Corn crop in 2007-08 was the largest with 93.5 million acres devoted to corn.
[5] "A new era of corn price?" Farmdoc Daily, March 29, 2011. Retrieved online at http://www.farmdocdaily.illinois.edu/2011/03/a_new_era_in_crop_prices.html (07/19/2011).

and recent rapid growth of biofuel production has not been free of controversy. Their effects on corn price and farm- and retail-level food prices have been at the center of debate. In this regard, examination of the integration between energy and agricultural markets is very much needed to better understand issues regarding food insecurity caused by record high food prices. This is what we attempt to provide in the current study.

4. Modeling and Empirical Strategy

Analysis of dynamic correlation

In this section, a bivariate DCC-MGARCH model is employed to estimate the pairwise time varying correlations between corn, ethanol, and gasoline prices. The purposes of estimating the bivariate DCC models are (i) to establish dynamic pairwise correlation processes, and (ii) to identify the timing of a potential structural change in the correlation between corn, ethanol, and gasoline prices. The model is specified as

(1) $r_t = H_t^{1/2} u_t;\ r_t \mid \Psi_{t-1} \sim N(0, H_t)$ and $r_t = (r_{1t}, r_{2t})'$.

where $r_{it} \equiv \log(p_{i,t} / p_{i,t-1})$ denotes the log-return of market i observed at time t, $u_t = (u_{1t}, u_{2t})' \sim N(0, I_2)$ where I_2 represents the identity matrix of order 2. The information set of time $t-1$ is represented by Ψ_{t-1}. The conditional covariance matrix is decomposed as

(2) $H_t = D_t R_t D_t$ where $D_t = diag\left\{\sqrt{h_{it}}\right\}$.

D_t is a $n \times n$ ($n = 2$ in our case) diagonal matrix of time varying standard variation ε_t from univariate GARCH process, and R_t is the $n \times n$ conditional time-varying correlation matrix.

As mentioned above, the model has GARCH type dynamics for both conditional correlations and conditional variances. The DCC model is estimated by the two-step approach described in Engle (2002). In the first step, the log likelihood is reduced to the sum of the log likelihoods of univariate GARCH equations by replacing R_t with a $n \times n$ identity matrix. By doing so, only the matrix D_t (with elements ε_t) is estimated. Given the estimated D_t, the second step estimates the correlation matrix R_t.

Given the pairwise time-varying correlations in R_t, we test the potential structural change in the dynamic correlation process $corr_i$ ($i = 1, 2, 3$) following the algorithm described in Bai and Perron (2003). Basically a deviation from mean μ, i.e., a "jump", is identified in the classical linear regression model specified as[6]

(3) $corr_i = \mu + \varepsilon_i, \; i = 1, 2, 3.$

The timing of the structural change is expected to be associated with new developments in the biofuel industry. Then we split the sample to two subsamples, one before and one after the estimated change point, and study the price relationship in each period by fitting a SVAR model individually.

A SVAR analysis

A SVAR model is employed to jointly explain the contemporaneous price linkage and shock transmission in energy and agricultural markets.[7] The model is represented as

(4) $$\begin{aligned} &\mathbf{A}\mathbf{y}_t = \mathbf{B} + \Sigma_{j=1}^{J} \mathbf{C}_J \mathbf{y}_{t-j} + \boldsymbol{\varphi}\mathbf{z}_\mathbf{t} + \boldsymbol{\zeta}_\mathbf{t}, \\ &E(\boldsymbol{\zeta}_\mathbf{t}) = 0, \; E(\boldsymbol{\zeta}_\mathbf{t}\boldsymbol{\zeta}'_\mathbf{t-j}) = 0. \end{aligned}$$

where $\mathbf{y}_t = (r_{e,t}, r_{g,t}, r_{c,t})$ with the symbols $r_{e,t}$, $r_{g,t}$, and $r_{c,t}$ denoting the log-return of ethanol, gasoline, and corn prices as defined above, respectively. Off-diagonal elements of Matrix $\mathbf{A}$

[6] We assume one break point in the pairwise correlation process.
[7] We will justify the use of SVAR model in a latter section.

capture the contemporaneous interactions across prices, and $\mathbf{C}_J$ captures the lagged effects of the endogenous variables $\mathbf{y}_t$. $\mathbf{z_t}$ is the vector consisted of observable and unobservable common factors affecting all prices in the system. In our case, crude oil price is included as the observed common factor as it affects the markets through direct and indirect channels simultaneously. The structural residual $\boldsymbol{\zeta}_\mathbf{t}$ relates to reduced form residuals through matrix $\mathbf{A}$. The inclusion of common shocks is to ensure that the structural shocks are uncorrelated.

For the recovery of the structural equation parameters, which can only be estimated indirectly from reduced form, imposing additional ad-hoc restrictions is the typical solution. Parametric restrictions, including short run, long run, exclusion, covariance, and sign restrictions have been widely applied, but the restrictions don't always accord with economic theory or practical experience. In the current study, following the idea of identification through heteroscedasticity (IDH) introduced by Rigobon (2003), we exploit changing volatilities of the prices to fully identify the structural VAR system. Increasing volatility or heteroscedasticity in energy and agricultural prices over the sample period allows us to take full advantage of the IDH method. It solves the identification problem by utilizing the existence of heteroskedastic regimes associated with the endogenous variables in $\mathbf{y_t}$. By assuming that matrix $\mathbf{A}$ is stable across volatility regimes, we obtain more equations than unknown parameters, i.e., the system of equations becomes overidentified.

To illustrate the idea, let's focus on a simplified simultaneous equation system of corn and ethanol prices:

$$(5) \qquad \begin{cases} P_{c,t} = m_c P_{e,t} + \varsigma_t & \text{(i)} \\ P_{e,t} = m_e P_{c,t} + \upsilon_t & \text{(ii)} \end{cases}$$

where $P_{c,t}$ and $P_{e,t}$ are observed corn and ethanol prices, and ς_t and υ_t are the structural shocks. As the two prices are simultaneously determined, it is difficult to identify the parameters m_c and m_e in Eqn. (5). The intuition of IDH is the following: suppose that we can split the whole sample to two or more subsamples and in a given subsample period, corn price has constant variance and ethanol price is significantly volatile. Then in this subsample, the parameter m_c is traced out given wide-spread ethanol price realizations. Similarly the parameter m_e can be traced out during the period when corn price has substantially higher variation.

As Rigobon (2003) points out, for the system in Eqn. (4) to be fully identified, we need to find at least four volatility regimes.[8] The estimation strategy is summarized as follows:[9] First, the ordinary least square (OLS) regression is employed to estimate the reduced form system

$$(6)\qquad \begin{aligned} &\mathbf{y_t} = \mathbf{B_0} + \mathbf{B_1}\mathbf{y}_{t-j} + \mathbf{B}_2\mathbf{z_t^1} + \boldsymbol{\eta}_\mathbf{t}, \\ &\mathbf{B_0} = \mathbf{A}^{-1}\mathbf{B},\ \mathbf{B_1} = \mathbf{A}^{-1}\Sigma_{j=1}^{J}\mathbf{C}_J,\ \mathbf{B}_2 = \mathbf{A}^{-1}\varphi_1, \boldsymbol{\eta}_\mathbf{t} = \mathbf{A}^{-1}\varphi_2\mathbf{z}_t^2 + \mathbf{A}^{-1}\boldsymbol{\zeta}_\mathbf{t}. \end{aligned}$$

where $\mathbf{z^1}$ and $\mathbf{z^2}$ are observable (crude oil price in our case) and unobservable common factors, and φ_i $(i=1,2)$ are the corresponding coefficients. We include two lags ($j=2$) in the VAR system in order to remove any serial correlations.[10] The recovered reduced form residuals contain and reflect contemporaneous relationship between the endogenous variables.

Second, residuals of Eqn. (6) are used to choose volatility regimes, across which volatilities of different structural shocks are expected to vary significantly. For doing so, variance for endogenous price variable i, σ_i^2, is calculated based on a 20-days rolling windows.

[8] See Eqn. 13 in Rigobon (2003). Here we have $N=3$ equations and $K=1$ unobservable common shock.
[9] Readers are referred to Rigobon (2003) for details on the estimation procedure.
[10] The lag length is determined using the Akaike Information Criterion (AIC).

Following Ehrmann, Fratzscher, and Rigobon (2010), a threshold rule for regime definition is applied. The threshold is defined as mean of σ_i^2 plus its one standard deviation. When σ_i^2 is above the threshold, the residuals of variable i are considered to be volatile. For identification in our case, which requires four regimes, we employ the three "single market" regimes, in which only one of the three prices exhibits high volatility (i.e., above the threshold) and the other two remain tranquil, and one tranquil regime, in which all three prices are in the tranquil state. We ensure more than 16 observations in each identified regime.

Third, for each identified volatility regime, variance-covariance matrices of the estimation residuals are computed and moment conditions are constructed. Finally, structural parameters of Eqn. (4) are identified using General Method of Moment (GMM) method.

5. Data and Estimation Results

In this study, all prices are daily settlement prices of the nearest to maturity contracts traded in the corresponding futures markets, which are the Chicago Mercantile Exchange (CME) for corn, ethanol, and light sweet crude oil (WTI), and the New York Mercantile Exchange (NYMEX) for RBOB gasoline.[11] The sample period is from March 25, 2005 to March 25, 2011. Figure 2 presents the log-returns of ethanol, gasoline, and corn over the sample period.

Results of the DCC analysis

A bivariate DCC-MGARCH model is estimated for pairwise log-returns of ethanol, gasoline, and corn prices. The model combines univariate GARCH(1,1) models ($i = 1, 2$) and a DCC(1,1) model for each individual price series. For each pair of prices, the model is specified as:

[11] RBOB refers to "reformulated gasoline blendstock for oxygen blending", which is the new benchmark gasoline futures contract on the NYMEX after the phase-out of unleaded gasoline futures in 2006.

$$
(7) \quad \begin{cases} h_{i,t} = \omega_i + a_i \xi_{t-1}^2 + b_i h_{i,t-1},\ i = 1,2. & \text{GARCH(1,1)} \\ R_t = (1-\alpha-\beta)\bar{R} + \alpha \xi_{t-1} \xi_{t-1}^{'} + \beta R_{t-1} & \text{DCC(1,1)} \end{cases}
$$

where $\bar{R}$ denotes a constant conditional correlation. The parameter vector for the GARCH(1,1) model in the first-step estimation is $\Theta = \{\omega_i, a_i, b_i\}\ (i = 1,2)$. Conditional on the estimated ξ_t, elements of D_t, the second step estimates the DCC parameters α and β. The estimation results are presented in Table 1. All parameters for univariate GARCH models are statistically significant at 1% level. It indicates that accounting for time-varying variances is important for the understanding of dynamic correlation processes. Estimates for the DCC(1,1) models, the α 's and β 's, are all highly significant, which justifies the time-varying correlations.

The estimated time-varying correlations of pair-wise ethanol, gasoline, and corn prices are presented in Figure 3, which shows a great deal of variation in the correlations. For corn and ethanol, their correlation slipped below 0 on several occasions in the period of late 2005 to early 2006. The correlation started increasing substantially in March 2008 and peaked in January 2009, indicating a structural change in the process. It is clear that the linkage between corn and ethanol markets is much more strengthened in the later period. Following the discussion in Section 3, the timing is largely consistent with economic conditions in the biofuel and corn market as well as the binding ethanol mandate. Specifically, the supply of ethanol has been badly interrupted in 2008 as a number of established producers went bankrupt, which was in large part caused by the global financial crisis and high corn prices. Under these circumstances, the RFS mandate was binding in the end of 2008. Meanwhile, the ethanol price became more closely linked to the corn price as these two prices determine operating margins of ethanol plants (Tyner 2010).

For ethanol-gasoline (corn-gasoline), the correlation ranges from 0.03 to 0.59 (0.08 to 0.45) over the course of the sample. The correlations of corn-gasoline and ethanol-gasoline show similar pattern over the sample period. Both of them stayed at 0.2 with no apparent trend till April 2006, started a notable increase and peaked at roughly the same time as the peak of corn-ethanol correlation, and then declining in the later period. Arguably the changes in the dynamic relationships of ethanol-gasoline and corn-gasoline are not as dramatic as corn-ethanol, but we did identify structural changes in all three correlation series. Using the structural change test described above, we identify a structural change point on March 24th, 2008, October 22nd, 2007, and August 1st, 2007 for the correlations of ethanol-corn, gasoline-corn, and ethanol-gasoline, respectively. We choose the latest date, March 24th, 2008 as the common structural change point, which is indicated by the vertical line in Figure 3. The whole sample is then split into two subsamples, one before and one after the estimated change point.

Results of the SVAR analysis

Some discussion justifying the use of VAR model instead of a vector error correction (VEC) model is warranted. As compared with VAR, the main characteristic of VEC is that the past disequilibrium or deviation from its long-run relationship is fed into the dynamic behavior of current variables (Maddala and Kim 1998, p. 35). The equilibrium long-run relationship, i.e., cointegration, imposes further restrictions on the parameters of the VAR model. In general, if all variables are stationary, using an unrestricted VAR in levels is appropriate. An unrestricted VAR in first difference is appropriate if all variables are $I(1)$, i.e., integrated of order 1, and no cointegration relation exists. If the $I(1)$ variables are cointegrated, the VEC model should be employed as the VAR model generates erratic estimates (Maddala and Kim 1998, p. 185).

To justify the VAR model in this study, we start with testing stationarity and cointegration relationship of ethanol, gasoline, and corn prices, the endogenous variables being modeled. The Augmented Dickey-Fuller (ADF; Greene 2007, p. 751) and Phillips Perron (PP;

Phillips and Perron 1988) tests are employed to test the stationarity of the log prices and returns (first differences) of each series. The null hypothesis for both tests is the presence of unit root, or the time series is integrated of order 1. The optimal lag length is chosen by the modified Akaike Information Criterion (MAIC). Table 2 summaries the test results for the first and second subsample periods. The ADF and PP test results suggest that the null hypothesis of unit root cannot be rejected in the level forms, but are rejected at 1% significant levels in the first differences of all log-price series in both periods. In other words, all the log-price series are non-stationary but stationary in the first differences of log-prices (log-returns).

As the log-prices are integrated of order 1, we proceed to determine whether a stable long-run relationship exists between the log-prices in each sample period. Johansen's test for cointegration (Greene 2007, p. 763) is applied. Table 3 summarizes the test results. In both periods, the trace statistics (of rank=0) are smaller than the critical value at the 5% significance level. It implies that we fail to reject the null hypothesis of no cointegration. The existence of unit roots and lack of cointegration between the prices suggest us to examine the short-run dynamics using an unrestricted VAR model with the log-returns.

The SVAR model specified in Eqn. (4) is then estimated on each of the subsamples. The identification strategy of IDH enables us to fully identify all structural parameters in matrix $\mathbf{A}$, which reveals contemporaneous effects of endogenous variables and transmission channels of structural shocks. One thing worth noting is that the estimation results of the SVAR model are not sensitive to the choice of the structural change point, i.e., the estimated parameters and results are largely the same using each of the three identified change points. Table 4 reports the estimation coefficients and corresponding results of 500 bootstrap replications. The estimated coefficients indicate the contemporaneous effects (occurring in one day) of shocks to endogenous variables, which are listed in the first column, on ethanol, gasoline, and corn prices. Note that all coefficients representing the effects of its own shocks are one.

The results in Table 4 indicate that in period I (March 2005 -- March 2008), for corn, ethanol, and gasoline markets, the contemporaneous effects of one price on the other two are not statistically significant. In period II (March 2008 -- March 2011), the relationships between the three markets are more strengthened, which are verified by the statistically significant contemporaneous price effects on each other. As expected, shocks that increase gasoline and corn prices tend to increase the price of ethanol with corn price shocks having the bigger impact. As corn is the predominant feedstock for ethanol production, it is reasonable to expect ethanol price to reflect increasing input cost. Furthermore, as the U.S. domestic market is largely saturated because of the blending wall, oversupply forces ethanol to be priced at the break-even level (Tyner 2010). Therefore corn and ethanol price linkage is more strengthened in the more recent period.

Our results imply that a rise in ethanol price leads to an increase in the price of gasoline, which reveals strong comovement of ethanol and gasoline markets. Unsurprisingly a shock that raises ethanol price puts upward pressure on corn prices as ethanol producers compete for the feedstock, emphasizing positively related corn and ethanol markets. Corn prices affect gasoline price through the established ethanol channel, therefore we see the significant and positive linkage between corn and gasoline prices. The corn-gasoline linkage can also be attributed to the financialization of agricultural and energy commodities. In the last few years, a negative correlation between commodity return and stock return has attracted a large flow of index investment into the agricultural and energy commodity markets in an attempt to use commodity futures as a new asset class to diversify their portfolios. As a result, agricultural and energy commodities including corn and gasoline are likely to be in the process of financialization and their market variations are more linked with that of the financial market (Tang and Xiong 2010).

We further illustrate the strengthened market relationships and relative and overall importance of each market in the system by variance decomposition. It demonstrates how much of the unanticipated changes of prices are explained by shocks in other markets. The results are reported in Table 5. In period I, all price variations are explained largely by their own structural shocks, indicating by the statistically significant diagonal parameter estimates. However, a very different picture emerges for the more recent period, in which for each market, a significant and relatively large share of the price variation could be explained by the price changes in the other two markets. For example, 27% of the variance of ethanol prices can be explained by corn price changes, and shocks to ethanol prices account for 23% of the variance of corn prices.

At the same time, a significant portion of gasoline price variance can be explained by shocks to ethanol and corn markets, 16% and 17%, respectively. Studies have shown that greater availability and the increasing addition of ethanol into gasoline have significant impact on not only gasoline prices but also the price volatility of the ethanol-gasoline blends (e.g., Du and Hayes 2009; Vedenov, Duffield, and Wetzstein 2006). So it’s not surprising that ethanol price changes partially explain gasoline price variation. The literature also provides evidence of significant volatility spillover between crude oil market and corn market (e.g., Du, Hayes, and Yu 2011; Wu, Guan, and Myers 2011). This, together with the tightened interdependence between corn and ethanol prices discussed above, leads us to posit that the variation of corn prices is a contributing factor to that of gasoline prices. But the dynamic processes of price transmission and market adjustment warrant further study.

6. Robustness Checks

In this section we investigate whether the benchmark SVAR estimates and corresponding variance decomposition presented above are biased due to omitted variables. In the model specified in Eqn. (4), the change in the crude oil price and an unobservable common factor are included to ensure that structural shocks are independent of each other. However, other related factors such as seasonality, macroeconomic, and financial variables, which may have significant impacts on energy and agricultural prices, especially during and after the global financial crisis of 2008. Therefore we include seasonal dummies and commonly used macroeconomic and financial controls to check the robustness of our estimates. This analysis confirms and strengthens the previous findings.

Seasonality

Seasonal factors have been long studied and incorporated into models of gasoline and corn prices (see, for example, Borenstein, Cameron, and Gilbert 1997; Chambers and Just 1981). Gasoline prices are generally high during summer driving season and relatively low in winter months, while corn prices typically tend to peak in June and drop until harvest (September-October). To identify seasonal effects, we employ a seasonal dummy model, which is specified as[12]

(8) $r_{i,t} = \kappa_i + \sum_{i=1}^{s-1} \lambda_i D_{i,t} + e_{i,t}$, $i = \{e, g, c\}$.

where $D_{i,t}$ $(i = 1,...,s-1)$ are seasonal dummies and here we only consider quarter dummies, i.e., $s = 4$. Estimation results indicate that log-returns of corn and ethanol do not show significant seasonality, but log-returns of gasoline exhibit a significant effect for the first quarter.[13] So to control for the potential seasonal effects, we include quarterly dummies (for the first, second, and

[12] Note that in Eqn. (4), log-returns of ethanol (r_e), gasoline (r_g), and corn (r_c) are used as endogenous variables.
[13] Estimation results are available upon request.

third quarters) as common factors into the SVAR system. Column II of Tables 6 and 7 provides the estimation results for the SVAR coefficients and the corresponding variance decomposition, showing that the main results of our benchmark model are robust to the test of incorporating seasonality.

Macroeconomic and financial variables

Because of storability and product homogeneity, gasoline and corn prices have important characteristics of both assets, where price is determined by the stocks' supply and demand, and goods, where price is determined by the flows of supply and demand (Frankel and Rose 2010). Hence, the prices may respond to changes of supply and demand, financial markets, and macroeconomic conditions (Kilian and Vega 2009). Energy and agricultural prices show elastic responses to the exchange rate, which plays an important role in trade balance adjustment. Therefore, robustness tests of the addition of macroeconomic and financial variables as common factors are necessary. However, because the prices included in the SVAR model are sampled at daily frequency, we are limited in the choice of macroeconomic and financial indicators. We choose Baltic Dry Index (BDI), Trade Weighted Exchange Index of Major Currencies (TWEXM), and S&P 500 index to be considered as additional common factors.

The Baltic Dry Index is a daily index published by the Baltic Exchange in London, which indicates maritime transportation costs for major raw materials.[14] The BDI can be viewed as the equilibrium price of shipping raw material across various ocean routes. While the supply curve of shipping is relatively inelastic in the short and intermediate run, changes in BDI are largely determined by the global demand for industrial commodities (Kilian 2009). So the BDI is widely accepted as a leading indicator of the world economic activities. The Trade Weight Index of

[14] The BDI data is available at http://www.eoddata.com/stockquote/INDEX/BDI.htm.

Major Currencies is a daily index published by the Federal Reserve Bank of St. Louis.[15] It is a weighted average of exchange rates of U.S. and a set of major foreign currencies including the euro, Canadian dollars, Japanese yen, British pound, Swiss franc, Australian dollar, and Swedish krona. The weight of the TWEXM for each for each country is equal to its share in trade. The S&P 500 index is a capitalization weighted index, which consists of the prices of 500 large-cap common stocks traded in the U.S. The index is usually considered the benchmark for U.S. equity performance.

Estimation results for the SVAR coefficients and variance decomposition after incorporating above mentioned macroeconomic and financial variables are reported in column III-V of Tables 6 and 7, respectively. The results show that our benchmark estimates are robust to the inclusion of the chosen common factors.

Conclusion

Large scale corn ethanol production and usage has reshaped the relationship between energy and agricultural markets, which is reflected by recent strong comovements of corn, ethanol, and gasoline prices. We have sought to establish the contemporaneous effects of the prices on each market. Accounting for time-varying volatility, a bivariate DCC-GARCH model quantifies the pairwise dynamic conditional correlations between prices over the period of March 2005 – March 2011. One structural break, in March 2008, is identified in the dynamic correlation process. The timing is largely consistent with policy and market developments that greatly affected the U.S. ethanol industry at about this time.

We quantify the contemporaneous price impacts over two time periods, one preceding the estimated structural change point and one following it. On each time interval, we estimate a

[15] The TWEXM data is available at http://research.stlouisfed.org/fred2/series/DTWEXM?cid=105.

structural VAR model using the strategy of identification through heteroscedasticity. Variance decomposition analysis is followed to investigate the channels of variance transmission. Results indicate that, in the earlier period the responses in one market to price changes in another market are not statistically significant, and price variations of individual markets are largely explained by their own shocks. In the later period, corn, ethanol, and gasoline prices are found to have significant and positive impacts on each other. As expected, in each market a significant and relatively large share of the price variation could be explained by the price changes in the other two markets. The ethanol (corn) shocks have the largest impact on corn (ethanol) price. The strengthened corn-ethanol link could be largely explained by market conditions and ethanol policy instruments.

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Table 1. Estimates for the DCC MGARCH Model.

	Ethanol-Corn	Gasoline-Corn	Ethanol-Gasoline
GARCH(1,1)			
ω_1	0.35* (0.18)	0.35* (0.18)	0.51*** (0.04)
a_1	0.09*** (0.004)	0.09*** (0.004)	0.18*** (0.003)
b_1	0.83*** (0.02)	0.83*** (0.02)	0.71*** (0.007)
ω_2	0.51*** (0.04)	0.24*** (0.006)	0.24*** (0.006)
a_2	0.18*** (0.003)	0.12*** (0.001)	0.12*** (0.001)
b_2	0.71*** (0.007)	0.85*** (0.001)	0.85*** (0.001)
DCC(1,1)			
α	0.02*** (0.0001)	0.01*** (0.0001)	0.01*** (0.0001)
β	0.97*** (0.0001)	0.98*** (0.0001)	0.98*** (0.0001)

Note: Standard errors are in the parentheses. Single (*), double (**), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 2. Unit Root Test Results for Log-Prices and Log-Returns of Ethanol, Gasoline, and Corn.

	Period I (March 2005-March 2008)				Period II (March 2008-March 2010)			
Prices	Level		First Difference		Level		First Difference	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
Ethanol	-2.41	-2.17	-4.64***	-26.82***	-1.58	-1.51	-5.87***	-26.89***
Gasoline	-1.54	1.85	-4.85***	-25.29***	-1.22	-1.17	-4.81***	-26.92***
Corn	-0.11	-0.09	-4.77***	-26.27***	-0.97	-0.92	-5.71***	-26.68***

Note: (1) Single (*), double (**), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively. (2) The identified structural change point is on March 24, 2008.

Table 3. Results of Johansen Cointegration Rank Test for Logarithmic Prices of Ethanol, Gasoline, and Corn.

	Period I (March 2005-March 2008)		Period II (March 2008-March 2010)	
	Rank=0	5% critical value	Rank=0	5% critical value
Trace statistics	16.70	29.68	17.83	29.68

Note: The identified structural change point is on March 24, 2008.

Table 4. Estimation Results for the SVAR Model (Contemporaneous Feedback Effects).

Shocks	Point estimate	Bootstrap		
		Mean	Std err	p-value
Period I (March 2005-March 2008)				
Ethanol equation				
ethanol	1.00			
gasoline	0.04	0.04	0.04	0.39
corn	-0.02	-0.02	0.09	0.78
Gasoline equation				
ethanol	0.09	0.09	0.09	0.36
gasoline	1.00			
corn	-0.04	-0.03	0.25	0.80
Corn Equation				
ethanol	-0.007	-0.007	0.03	0.80
gasoline	-0.006	-0.004	0.02	0.84
corn	1.00			
Period II (March 2008-March 2010)				
Ethanol equation				
ethanol	1.00			
gasoline	0.07*	0.08	0.04	0.06
corn	0.45***	0.44	0.09	<0.001
Gasoline equation				
ethanol	0.39***	0.42	0.14	0.004
gasoline	1.00			
corn	0.28**	0.29	0.13	0.03
Corn equation				
ethanol	0.65***	0.68	0.10	<0.001
gasoline	0.07**	0.08	0.04	0.03
corn	1.00			

Note: (1) Single (*), double (**), and triple (***) asterisks denote significance at 0.10, 0.05, and 0.01 levels, respectively. (2) The identified structural change point is on March 24, 2008.

Table 5. Estimation Results for Variance Decomposition (in percentage).

	Point estimate	Bootstrap		
		Mean	Std err	p-value
Period I (March 2005-March 2008)				
Ethanol				
e_ethanol	99.75***	98.95	1.11	<0.001
e_gasoline	0.21	0.42	0.55	0.44
e_corn	0.04	0.63	0.95	0.51
Gasoline				
e_ethanol	0.63	1.17	1.44	0.42
e_gasoline	99.25***	97.76	2.13	<0.001
e_corn	0.12	1.08	1.41	0.45
Corn				
e_ethanol	0.01	0.12	0.19	0.54
e_gasoline	0.01	0.08	0.12	0.49
e_corn	99.98***	99.80	0.22	<0.001
Period II (March 2008-March 2010)				
Ethanol				
e_ethanol	70.08***	69.85	8.72	<0.001
e_gasoline	2.74	3.48	2.71	0.20
e_corn	27.17***	26.67	8.61	0.002
Gasoline				
e_ethanol	15.59***	16.19	5.39	0.003
e_gasoline	67.71***	67.17	9.81	<0.001
e_corn	16.69**	16.64	7.31	0.02
Corn				
e_ethanol	22.97***	24.28	5.85	<0.001
e_gasoline	2.48	3.08	2.20	0.16
e_corn	74.54***	72.64	5.87	<0.001

Note: (1) The table reports the share of the variance of each market (ethanol, gasoline and corn) that is explained by the various structural shocks (e_ethanol, e_gasoline, and e_corn). (2) Standard errors are in the parentheses. (3) Single (*), double (**), and triple (***) asterisks denote significance at 0.10, 0.05, and 0.01 levels, respectively. (4) The identified structural change point is on March 24, 2008.

Table 6. Robustness Checks: Estimates of Contemporaneous Feedback Effects.

Shocks	(I) Benchmark model	(II) Seasonality	(III) BDI	(IV) TWEXM	(V) S&P 500
Period I (March 2005-March 2008)					
Ethanol equation					
ethanol	1.00	1.00	1.00	1.00	1.00
gasoline	0.04	0.06	-0.02	0.04	0.05
corn	-0.02	-0.04	0.05	-0.02	-0.01
Gasoline equation					
ethanol	0.09	0.12	0.11	0.10	0.11
gasoline	1.00	1.00	1.00	1.00	1.00
corn	-0.04	-0.12	-0.001	0.02	0.001
Corn Equation					
ethanol	-0.007	-0.01	-0.0035	0.007	0.004
gasoline	-0.006	-0.02	-0.0003	0.003	0.0003
corn	1.00	1.00	1.00	1.00	1.00
Period II (March 2008-March 2010)					
Ethanol equation					
ethanol	1.00	1.00	1.00	1.00	1.00
gasoline	0.07*	0.05*	0.05	0.07**	0.08**
corn	0.45***	0.47***	0.40***	0.45***	0.36***
Gasoline equation					
ethanol	0.39***	0.32**	0.25*	0.39**	0.35**
gasoline	1.00	1.00	1.00	1.00	1.00
corn	0.28**	0.30**	0.31**	0.28**	0.26**
Corn equation					
ethanol	0.65***	0.66***	0.64***	0.68***	0.58***
gasoline	0.07*	0.07**	0.09**	0.07*	0.09**
corn	1.00	1.00	1.00	1.00	1.00

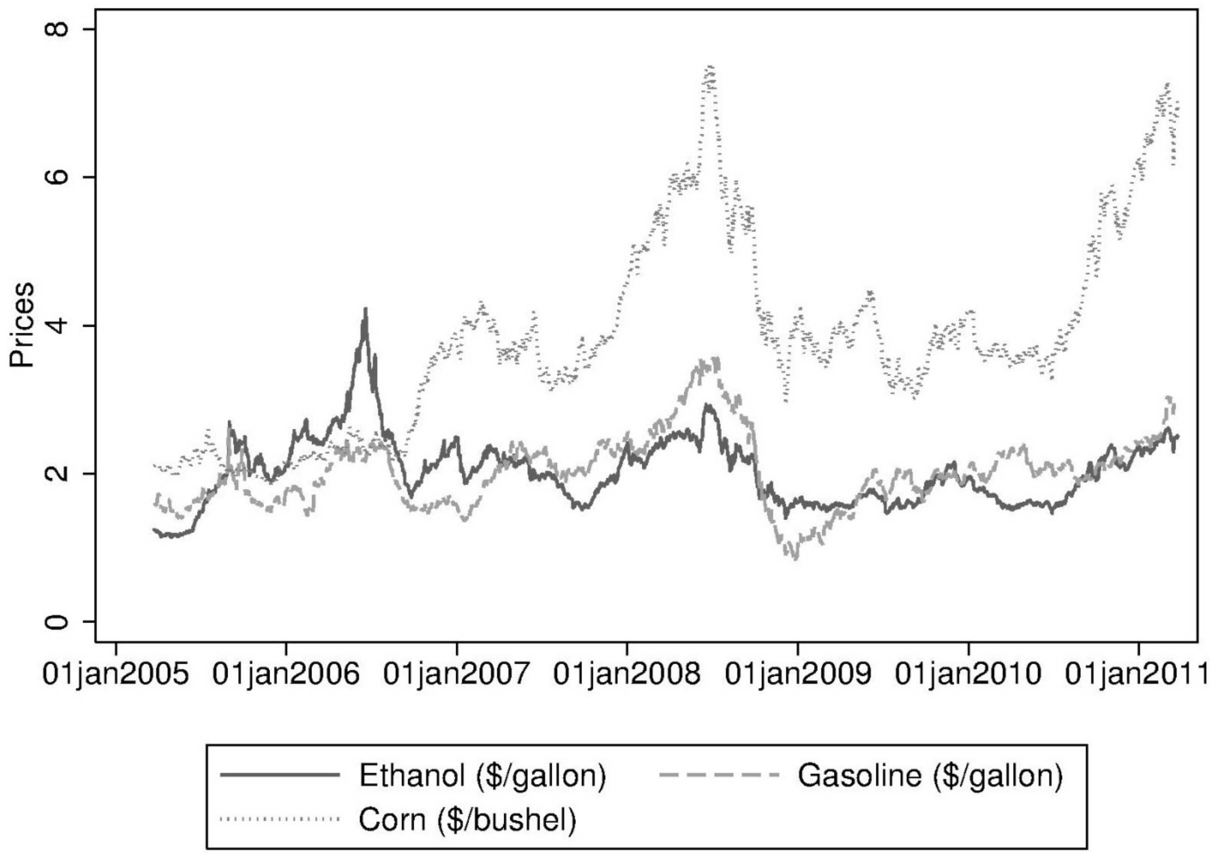
Note: (1) Columns II-V are estimates after incorporating the corresponding variables as common factors. (2) Single (*), double (**), and triple (***) asterisks denote significance at 0.10, 0.05, and 0.01 levels, respectively. (3) The identified structural change point is on March 24, 2008.

Table 7. Robustness Checks: Estimates of Variance Decomposition (in percentage)

	(I) Benchmark model	(II) Seasonality	(III) BDI	(IV) TWEXM	(V) S&P 500
Period I (March 2005-March 2008)					
Ethanol					
e_ethanol	99.75***	99.39***	99.73***	99.70***	99.66***
e_gasoline	0.21	0.45	0.07	0.26	0.33
e_corn	0.04	0.16	0.21	0.04	0.01
Gasoline					
e_ethanol	0.63	1.06	0.18	0.81	0.92
e_gasoline	99.25***	98.00***	98.96***	99.17***	99.08***
e_corn	0.12	0.94	0.87	0.02	0.00
Corn					
e_ethanol	0.01	0.02	0.03	0.01	0.00
e_gasoline	0.01	0.05	0.05	0.00	0.00
e_corn	99.98***	99.92***	99.92***	99.99***	100***
Period II (March 2008-March 2010)					
Ethanol					
e_ethanol	70.08***	68.00***	74.06***	68.93***	76.19***
e_gasoline	2.74	1.86	1.75	2.36	2.89
e_corn	27.17***	30.15***	24.20***	28.71***	20.92**
Gasoline					
e_ethanol	15.59***	11.90**	8.88*	14.49**	10.24**
e_gasoline	67.71***	71.83***	77.79***	69.61***	78.92***
e_corn	16.69**	16.27**	13.34**	15.91**	10.84*
Corn					
e_ethanol	22.97***	20.61***	19.83***	22.37***	17.71***
e_gasoline	2.48	1.74	2.15	2.01	2.59
e_corn	74.54***	77.66***	78.02***	75.62***	79.69***

Note: (1) The table reports the share of the variance of each market (ethanol, gasoline and corn) that is explained by the various structural shocks (e_ethanol, e_gasoline, and e_corn). (2) Standard errors are in the parentheses. (3) Single (*), double (**), and triple (***) asterisks denote significance at 0.10, 0.05, and 0.01 levels, respectively. (4) The identified structural change point is on March 24, 2008.

Figure 1. Ethanol, Gasoline, and Corn Futures Prices, 03/25/2005-03/25/2011.



Note: All prices are in nominal terms.

Figure 2. Log Returns of Ethanol (upper panel), Gasoline (middle panel), and Corn (lower panel), 03/25/2005-03/25/2011.

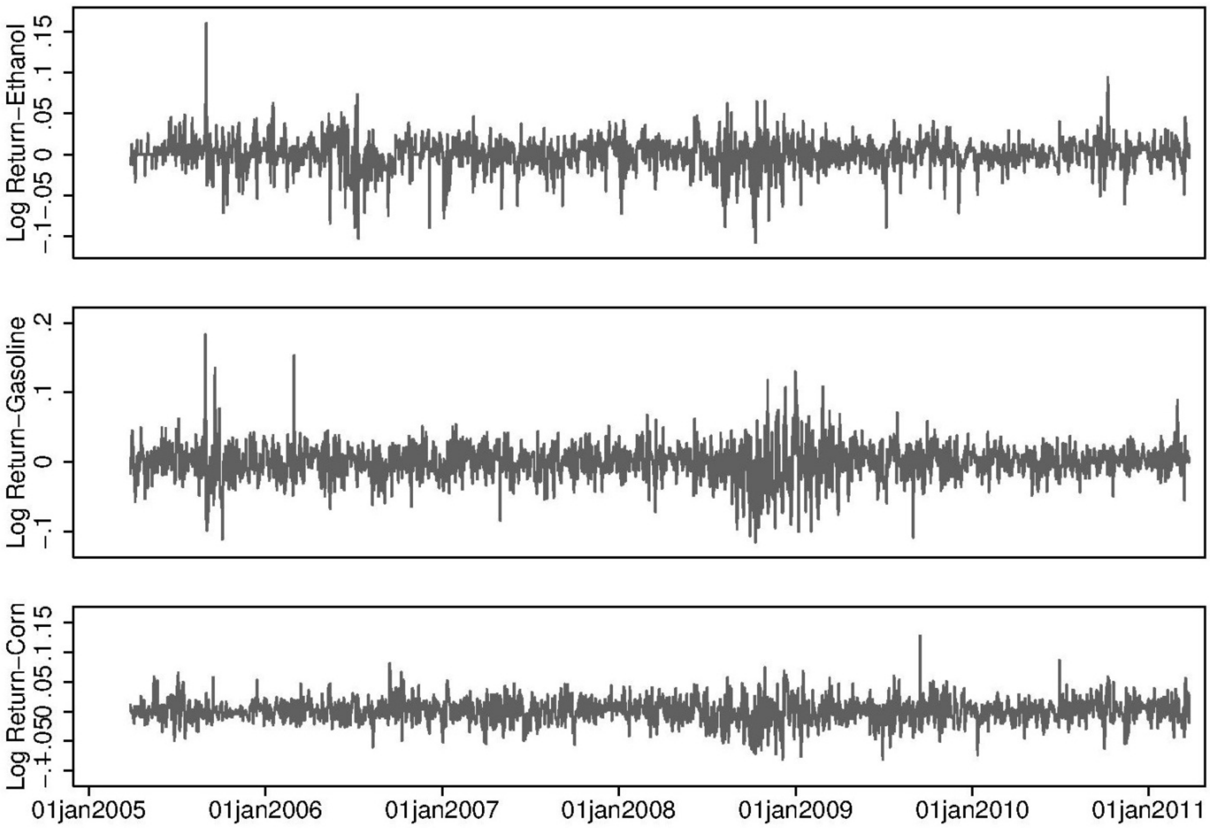
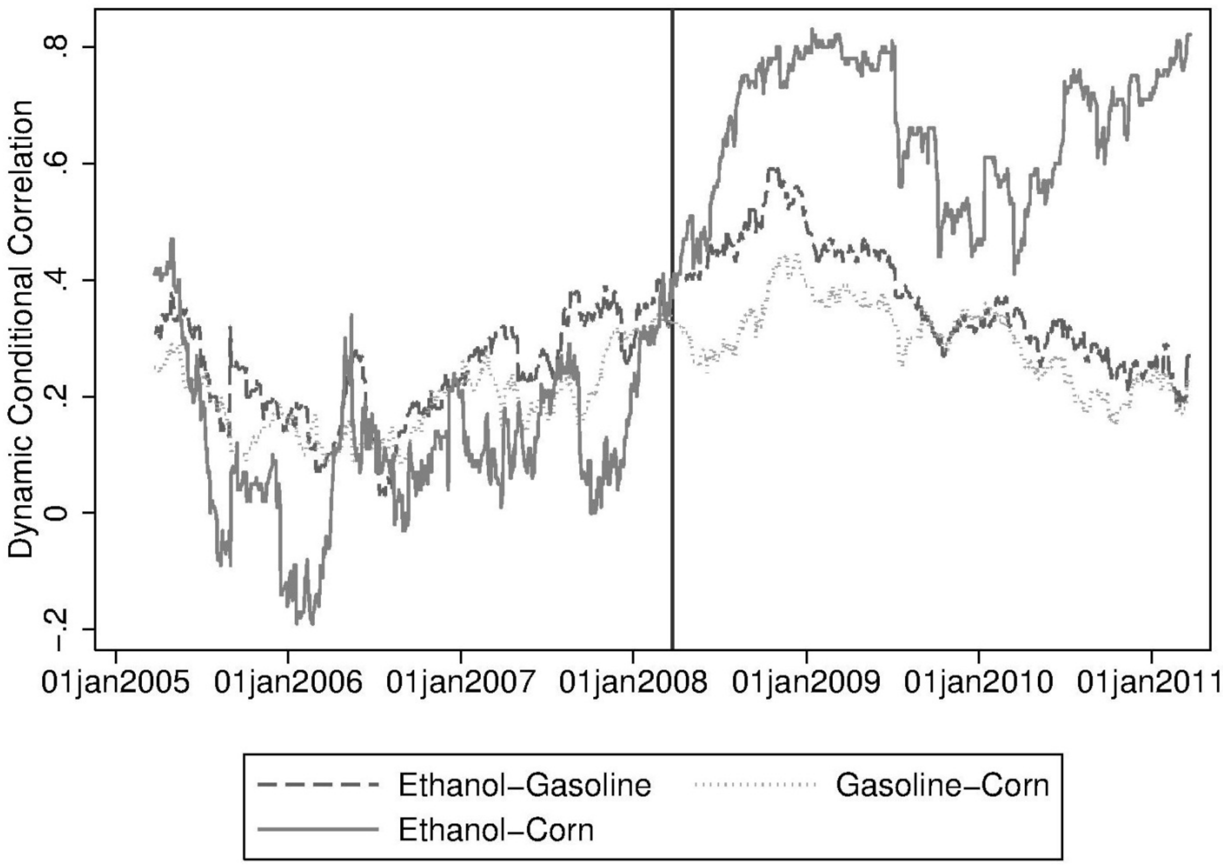


Figure 3. Estimated Dynamic Conditional Correlations, 03/25/2005 – 03/25/2011.



Note: The vertical dash line indicates the identified structural change point, March 24, 2008.