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2:45 PM – 4:15 PM..Room 2

Forecasting Agricultural and Energy Commodities
Chair: Neil Ericsson

Some Alternative Estimates of Oil Elasticities

Melissa Lynes (U.S. Energy Information Administration)

Studies on elasticities of oil demand vary greatly by regional focus and aggregation level and time horizon. Due to varying scopes of previous research, it can be difficult to know if changes in oil demand are different across countries. This study examines the short- and long-run price and income elasticities of oil demand. A Bayesian Vector Error Correction Model (BVECM) is used to determine the elasticities for three levels of aggregation – world-wide, OECD and non-OECD, and regional. The varying degrees of aggregation will help determine if countries react similarly in the long run to changes in oil price and income.

Projecting Long-Term World Oil Prices using a Structural Price Model

Terry Yen (U.S. Energy Information Administration)

Long-term projections of oil prices enable federal and state governments, industry decision makers, and other planners in government, the private sector, and the general public to make long-term assessments of energy market dynamics. The world oil price (WOP) model is a structural model used by the U.S. Energy Information Administration (EIA) to help prepare its 30-40 year assessments of international energy markets. The WOP takes analyst assumptions for both supply and demand by country/region and projects the real oil prices. The model was developed in EViews and solved as a system of nonlinear equations.

Changing Dynamics of Volatility Spillovers in Agricultural and Energy Commodities

Irene Xiarchos and Wesley Burnett (U.S. Department of Agriculture)

This study uses a spillover index to examine the changing interrelations among corn and energy prices from 1997 to 2014. This index is based on the forecast error variance decomposition of a vector autoregressive model, allowing for endogenous volatility determinants like fundamentals and speculation. Structural break tests are performed and the sample split into two periods for comparing spillovers before and after 2006. Volatility spillovers between corn, crude oil, and ethanol prices increased substantially, yet each commodity's past behavior explained the largest portion of its own variability. As sensitivity analysis the rolling-sample spillover index corresponds to historical market events.

Optimally Reconciling Hierarchical Agricultural Forecasts

Ryan Kuhns (Farmer Mac), Annemarie Kuhns and David Levin (U.S. Department of Agriculture)

Hierarchical time series are prevalent in agriculture and many of the time-series forecast by the USDA Economic Research Service including food price inflation, farm income, farm sector debt, and farmland values. This research considers the impact of different aggregation methods, including optimal hierarchical reconciliation, on several agricultural time-series. To our

Dynamic Volatility Spillovers in Agricultural and Energy Commodities*

Irene M. Xiarchos† and J. Wesley Burnett‡

Abstract§

This study contributes to the literature by using a spillover index method to examine the changing interrelations among corn and energy future prices from 1997 to 2014. The spillover index is based upon a vector autoregressive model, which allows us to account for other determinants of agricultural and energy future prices, including economic fundamentals and market speculation. Utilizing structural break tests, we evaluate the influence of recent policies and market shifts. The overall sample is split into two separate sub-samples (split in 2006) to compare the spillover activities across the two distinct periods of time. While each commodity's past behavior explains the largest portion of its own variability, we find a substantial increase in relative volatility spillovers between corn, crude oil, and ethanol futures prices. As a sensitivity analysis, we extend our study by conducting a rolling-sample analysis of the volatility spillover index through time. As expected, the variations in the estimated volatility spillover index plot correspond to historical market events.

Keywords: Commodity price volatility; Agricultural commodities; Crude oil prices; Volatility spillovers

JEL Codes: Q13, Q14, G12

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* Disclaimer: The views expressed herein are those of the authors and do not necessarily represent those of the U.S. Department of Agriculture, the Office of the Chief Economist, or the Office of Energy Policy and New Uses.

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1 INTRODUCTION

This study is concerned with the volatility of agricultural and energy future prices and recent influences that may have changed the transmission pattern of volatility between commodity markets. More specifically, we seek to better understand volatility spillover behavior among corn, crude oil, and ethanol (future) prices in the United States (U.S.), while accounting for the influence of speculation, inventory levels, and other macroeconomic determinants by using a recent methodology developed by Diebold and Yilmaz (2012).

The study results show that each commodity's past behavior explains the largest portion of its own variability, while the cross-commodity (volatility) spillovers explain a relatively smaller percentage. Nonetheless, unlike other studies, this methodology identifies a sizable (relative) increase in volatility spillovers among corn, ethanol, and crude oil after 2006. More specifically, our estimates suggest that volatility in corn future prices increased on average by approximately eleven percent in the second sub-sample period (2006 to 2014); likewise, the volatility in ethanol future price increased on average by about sixty-eight percent in the second sub-sample; whereas, crude oil future prices decreased slightly over the same period. Finally, our estimates suggest both direct and indirect volatility spillovers, which arguably could explain why past studies have found contradictory or mixed evidence for volatility spillovers between corn and crude oil prices.

Historically, crude oil has been an input to agricultural production; and therefore, the direction of influence tended to go from crude oil prices to agricultural price, but not the other way around. Recent developments have altered this relationship: with an increase of corn utilized for ethanol and distiller's dried grains with solubles (DDGS) production – from five to nearly forty percent – the relationship between agricultural and energy commodity prices has adapted to new market conditions (Abbott et al., 2008). A number of authors have suggested that in this new era, energy prices play a more important role in agricultural commodity prices (Gohin and Chantret, 2010; Tyner, 2010; Zhang et al., 2010). Yet, the literature is still mixed as to how oil and agricultural markets are related or integrated (Du and Hayes, 2009; Thompson et al., 2009; Whistance and Thompson, 2010; Nazlioglu, 2011; Nazlioglu and Soytas, 2011; Reboredo, 2012; Haixia and Shiping, 2013; Algieri, 2014).

Regardless of the debated relationship between energy and agricultural markets, one would expect a connection between the commodities to manifest itself at least through short-run volatility spillovers. At a minimum, the market demand for corn is relatively more inelastic as more of the commodity is going to ethanol production. Further, we expect informational spillovers between corn and crude oil prices due to more tightly integrated markets for corn, crude oil, and ethanol. In other words, a trade of one commodity can provide information about the value of other commodities (particularly if a commodity's value is correlated with another commodity's intrinsic value) (Asriyan et al., 2015). For example, shocks in biofuel renewable identification number (RIN) markets, can create reactions to the regulated oil refineries.[1] Du et al. (2011) find evidence of volatility spillovers among crude oil, corn and wheat markets after the fall season of 2006; however, the degree of transmission between agricultural and energy markets varies with different stochastic representations (Serra, 2011).

This study's objective is to gain additional insights about the increased integration of crude oil and corn markets. Mean and structural break tests evaluate possible structural shifts in the volatility of agricultural and energy prices relative to recent policy and market influences. Moreover, we conduct a spillover analysis with a method that allows for the consideration not only of crude oil and corn prices, but of several simultaneously determined series including factors that would affect storage and expectations of agricultural producers. Several past studies that examine volatility transmissions use sophisticated modeling techniques such as autoregressive conditional heteroskedasticity (ARCH) or generalized autoregressive conditional heteroskedasticity (GARCH) models, which often necessitate limiting the analysis to only two or three separate time series variables (Zhang et al., 2009; Du et al., 2011; Wang et al., 2011; Serra, 2011; Trujillo-Barrera et al., 2012). Although informative to the broader literature, these studies do not (necessarily) account for other important determinants of volatility (Balcombe, 2011). An exception was offered by Serra and Gil (2013), who included the impact of stocks and interest rates; however, their specification did not allow for endogenously determined stock

[1] A RIN is a 38-digit code assigned to biofuels that are registered with the Environmental protection Agency (EPA) for RFS2 compliance. To help obligated parties manage obligations RINs are tradable while for year-to-year uncertainty, banked RINs from past years can help meet current year requirements. Thus RINs are used both for credit trading and compliance demonstration.

levels of corn, crude, or ethanol.

Our volatility transmission analysis represents realized volatilities and is based on a vector autoregressive (VAR) model which allows for all of the variables within the system to be endogenously and simultaneously determined. Furthermore by bypassing the specification of a model of stochastic volatility (Preve et al., 2009) we do not have to worry about the degree of transmission between agricultural and energy markets being influenced from the specification choice. We measure the volatility spillovers based on a framework developed by Diebold and Yilmaz (2009, 2012) which uses the VAR price-volatility specification results. As a robustness check we evaluate the dynamics of spillovers relative to the time profile of policy influences and market conditions.

2 LITERATURE REVIEW

Agricultural price volatility has fluctuated over time. In general, volatility was: low in the 1960s; high in the 1970s; fell in the second half of the 1980s and the 1990s; and, thereafter remained above the level of the 1960s (Gilbert, 2006). There is still no general consensus as to the volatility of the agricultural commodities for the period after 2006. Gilbert and Morgan (2010) argued that volatility between 2006 and 2008 is in line with past historical experience. On the other hand, Sumner (2009) looked at wheat and maize for the period 1866 to 2008 and found that the three-year period between 2006 and 2008 represented one of only a handful of periods when prices have been above the post-war trend – the last event occurring in the 1970s. According to Balcombe (2011) some commodities exhibit a positive time trend while others exhibit a negative time trend.

In order to better understand the volatility behavior among agricultural commodities, Balcombe (2011) highlights the importance of considering the sources of volatility. For many years, the literature focused on the exchange rate and how changes to monetary policies transmitted instability to agricultural prices; however, in more recent years the literature has evolved to examine the impacts associated with speculation and the links between energy and agricultural markets (Saghaian, 2010).

The influence of speculation in futures and options trading, particularly on food commodity markets, is still debated in the literature (Trostle et al., 2011). Gilbert (2010) and Gilbert and Morgan (2010) argued that speculation plays a role in agricultural commodity pricing behavior, whereas Irwin and Sanders (2011) concluded that there is little evidence that new speculators (including index funds) drove increased price movements. Harris and Büyükşahin (2009) suggest that speculation's influence is limited to the short run, while in the long run (for example, over an annual time period) price movements likely reflect changes in market fundamentals. Abbott et al. (2008) go on to say that while the increase in trading volume in the futures markets have partially affected agricultural price volatility, it is impossible to determine whether speculative activities have affected price levels.

In terms of the influence of energy markets Gardebroek and Hernandez (2013) showed that the correlation between crude oil and corn volatilities and between ethanol and corn volatilities increased after 2007. The past literature has for the most part focused on links between price (Serra et al., 2011; Serra, 2011).

Examinations of volatility transmissions, between energy and agricultural markets, are scarce and the results for the degree of transmission depend on the methodology used (Serra, 2011). For example, Serra et al. (2011) who examined oil, ethanol and sugar prices between 2000 and 2008 for a parametric MGARCH BEKK representation found that feedstock price volatility increased with directly lagged instability and shocks in the energy markets and indirectly through covariance terms. Conversely, using a semi-parametric, multivariate generalized autoregressive conditional heteroskedasticity approach (restricted to separate pairwise analyses of the ethanol and oil market and the ethanol and sugar market respectively), Serra (2011) showed that energy (represented through ethanol) affected the feedstock market only indirectly through the covariance terms. Similarly, while Gardebroek and Hernandez (2013) show higher correlation between crude oil and corn markets after 2007 with a dynamic conditional correlation MGARCH (1, 1) model, they did not find evidence of volatility transmission from energy markets to grain market through a T-BEKK MGARCH (1, 1) representation. On the other hand Du et al. 's (2011) Bayesian analysis of a stochastic volatility model with Merton jump in return (SVMJ) finds increased volatility spillovers among crude oil, corn and wheats.

In contrast to many past studies, our approach uses a historical measure of volatility (as opposed to an implied measure of volatility), which according to Regnier (2007) does not have as much of an influence on the results (i.e., our method does not specify a particular statistical model to represent stochastic volatility).

3 METHODOLOGICAL APPROACH

3.1 Realized Volatility

To represent the volatility for oil, ethanol and corn prices we examined historical measures of volatility, also referred to as realized volatility, which is an empirical measure of return variability for a given commodity for a specified time frame (Andersen et al., 2003). Andersen et al. (2001) showed that realized volatility can be an unbiased and highly efficient estimator of return volatility. It is easily computed from ex post observations of daily commodity prices. The benefit of treating volatility as observed rather than latent is that our modeling approach can be extended to directly include other endogenous covariates which determine the underlying commodity volatility. This approach is also consistent with Diebold and Yilmaz (2009, 2012) – the methodological framework we followed in the current study – who used historical measures of volatility as calculated from underlying intra-day prices.

The rational for using realized volatility as a measure of volatility comes directly from standard stochastic process theory. A justification for calculating historical volatility, over other latent methods of calculation such as in ARCH or GARCH models, is that commodity prices are commonly found to be highly autocorrelated and mean reverting with stochastic volatility (Schwartz and Smith, 2000; Deaton and Laroque, 1992; Schwartz, 1997). Realized volatility can be advantageous over ARCH and other stochastic volatility models in that it: overcomes the curse-of-dimensionality problem by treating volatility as directly observable; and, it provides a more reliable estimate of integrated volatility leading to forecasting gains (Preve et al., 2009). Regnier (2007) argued in favor of historical measures of commodity price series rather than choosing a specific model of stochastic volatility. Moreover, Andersen et al. (2003) posited that realized volatility is advantageous over traditional conditional heteroskedasticity models and stochastic volatility models, especially given its ease of implementation.

Realized volatility is first computed by transforming the daily prices in levels to returns, r_t, which are calculated as,

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \qquad (1)$$

where p_t is the price in levels at period *t*. Consistent with Andersen et al. (2003) and Ederington and Guan (2004), the series are converted to realized volatility by taking the average weekly sum of squared deviations according to the following formula to

$$RV_t = 100 \times \sqrt{\frac{252}{n} \cdot \sum_{i=1}^{n} r_{t+i}^2} \qquad (2)$$

where *n* denotes the number of trading days (five) in the specified time frame (we compute weekly volatility in the current study), and the number 252 is a constant annualizing factor.[2] After converting the returns to (weekly measures of) realized volatility, the result for each observation is typically a decimal value that is less than 1.00, so we scale the volatility measure by 100 so that the observations can be interpreted as percentages in variability as opposed to decimal form.

Calculating realized volatility allows us to directly examine the structural breaks in the volatility series and how they relate to policy and structural changes in commodity markets. Realized volatility may be more sensitive to structural changes than actual price observations, representing a proxy for information flows (or shocks) through time (Chan et. al., 1991). To evaluate the structural breaks, we used the methodology developed by Bai (1994) and Bai and Perron (1998). In order to carry out the tests, we implemented the "strucchange" package provided within the statistical program R 3.3.1 (Zeileis et al., 2003). The breakpoint tests are essentially time series models estimated via a least squares algorithm that detects one or more structural breaks (dates) within the underlying time series observations (Bai and Perron, 2003). Estimating structural breakpoints is important because a failure to control for a structural break could affect forecast variances and ultimately lead to unreliable time series model estimates (Enders, 2009). As our empirical framework, outlined below, relies heavily on forecast variances, we used the structural breakpoint tests to provide more reliable spillover estimates between the agricultural and energy commodities.

3.2 Vector Autoregressive Framework

This study used a VAR model to analyze the

[2] The constant is simply a normalizing factor to ensure that each of the underlying estimates are consistent according to the approximate number of trading days available within a year's period.

relationship among corn price, crude oil price and ethanol price volatility. The benefit of using a VAR approach is that the model treats each of the series as endogenously determined within the system. In other words, the VAR approach allows us to account for numerous factors that may affect this relationship, including endogenously determined supply and demand fundamentals as well as market speculation. We employ a reduced-form VAR with a Choleski decomposition of the variance-covariance matrix of the residuals. VAR models have been criticized for being sensitive to the ordering of the variables within the system (Enders, 2009); however, we are able to circumvent this by exploiting a generalized VAR framework, which provides parameter estimates and forecasts that are invariant to the ordering of the variables (Koop et al., 1996; Pesaran and Shin, 1998). The VAR reduced-form model can be expressed as follows:

$$\mathbf{y}_t = \mathbf{B}_1\mathbf{y}_{t-1} + \mathbf{B}_2\mathbf{y}_{t-2} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t, \qquad (3)$$

where $\mathbf{y}_t$ dnotes a $k \times 1$ vector of explanatory variables, within the system, observed at time t. The term $\mathbf{B}_i$ denotes a $k \times k$ matrix of parameter estimates on the i^{th} lagged observation of the explanatory variables. Finally, the term $\boldsymbol{\varepsilon}_t$ is $k \times 1$ vector of normally-distributed errors. Each variable is expressed as a linear function of its own past values and the past values of all other variables within the k-variable system. Each equation is estimated by ordinary least squares. The error terms can be interpreted as surprise movements or shocks in the variables after taking past values into account.

3.3 Forecast Error Variance Decomposition

Following the VAR framework presented in the last sub-section, we can now derive the variance decomposition, which separates the variation in an endogenous variable into the component shocks within the system (Enders, 2009). Put simply, the variance decomposition provides information about the relative importance of each random innovation in affecting the variables within the VAR.

Provided that the reduced-form VAR model is covariance stationary, then the model can be written in moving average representation as $\mathbf{y}_t = \mathbf{A}(L) \cdot \mathbf{u}_t$, where L is a lag operator, such that $L \cdot y_t = y_{t-1}$, and $\mathbf{A}(L) = \left(\mathbf{I} - \sum_{i=1}^{p} \mathbf{B}_{t-i} \cdot L^i\right)^{-1}$. The moving average implies that the current realization of a variable is composed of its own shocks and the other shocks within the system. To see this, we can expand the moving average notation as:

$$\mathbf{y}_t = \mathbf{A}_0\mathbf{u}_t + \mathbf{A}_1\mathbf{u}_{t-1} + \mathbf{A}_2\mathbf{u}_{t-2} + \cdots \qquad (4)$$

Given the moving average representation, the error in forecasting $\mathbf{y}_t$ in the future, for each horizon s, is:

$$\mathbf{y}_{t+s} - E_t\mathbf{y}_{t+s} = \mathbf{A}_0\mathbf{u}_{t+s} + \mathbf{A}_1\mathbf{u}_{t+s-1} + \mathbf{A}_2\mathbf{u}_{t+s-2} + \cdots + \mathbf{A}_{s-1}\mathbf{u}_{t+1}. \qquad (5)$$

From equation (5), the variance of the forecasting error is:

$$Var(\mathbf{y}_{t+s} - E_t\mathbf{y}_{t+s}) = \mathbf{A}_0\boldsymbol{\Sigma}_u\mathbf{A}_0' + \mathbf{A}_1\boldsymbol{\Sigma}_u\mathbf{A}_1' + \mathbf{A}_2\boldsymbol{\Sigma}_u\mathbf{A}_2' + \cdots + \mathbf{A}_{s-1}\boldsymbol{\Sigma}_u\mathbf{A}_{s-1}', \qquad (6)$$

where $\boldsymbol{\Sigma}_u$ denotes the variance-covariance matrix of the estimated residuals. On the basis of the error-forecasting variance formula, one can compute the share of the total variance of the forecast error for each variable attributable to the variance of each structural shock (Enders, 2009).

3.4 Spillover Table and Index Based on the Variance Decomposition

Diebold and Yilmaz (2009, 2012) developed an elegantly simple framework extracted from the forecast error variance decomposition. Specifically, the framework allows for one to measure the fraction of the h-step-ahead (where again, h denotes the forecasting horizon) error variance in forecasting due to shocks in y_1, shocks in y_2, and so forth. They define *own variance shares* as the fraction of the h-step ahead error variance in forecasting each y_i due to shocks to y_i:

$$\sum_{i=0}^{H-1} a^2{}_{h,\,i,i}, \qquad (7)$$

where the term $a_{h,i,i}^2$ is an individual estimated element corresponding to the i^{th} matrix, $\mathbf{A}_i$, in the forecasting error variance, equation (6), presented above.

Similarly they define *cross variance shares* or *spillovers* as the fraction of the h-step ahead error variances in forecasting each y_i due to shocks to each y_j, $i \neq j$:

$$\sum_{i=0}^{H-1} a^2{}_{h,\,i,j}. \qquad (8)$$

The **spillover table** presents the total *average* own and cross variance shares for each variable within the system **for each period** of investigation. It is an "input-output" decomposition of the spillover index. The spillover index measures the magnitude of spillover activity in the entire system, i.e. the total spillover among all the endogenous variables for period H.

$$S = \frac{\sum_{h=0}^{H-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} a_{h,ij}^2}{\sum_{h=0}^{H-1} trace(A_h A_h^{'})} \bullet 100$$

The spillover index is a percentage on the closed interval [0, 1]; loosely speaking, the larger its value, the greater the spillover activity within the *entire* VAR system, during the defined (sub) sample period. The spillover table and the spillover index can be extended to separate sub-samples, for example in our study we examine changes in spillovers for the subsamples of 1997-2005 and 2006-2014. Moreover, given a sufficiently large number of observations, the investigator can analyze the spillovers over multiple sub-samples. As a result, Diebold and Yilmaz (2009, 2012) also advanced a rolling-sample regression analysis of spillovers through time.

Spillovers through time can be extracted with a rolling-sample regression analysis creating the rolling spillover index plot. The methodology is identical to the process described above, only spillovers are estimated over multiple rolling periods (and VARs). For example in this study we present a 75-week rolling window. The resulting spillover indices are plotted out against time and can allow for comparisons of the VAR system spillover activity to documented market shocks. Hence, as a sensitivity analysis we use the rolling-sample spillover index to compare our estimation results to well-documented (past) market occurrences. More specifically, our rolling-sample spillover index plot will trace out and evaluate the spillover intensity during the different periods identified by Abbott (2013). According to Abbott (2013), as well as Hertel and Beckman (2011) volatility spillovers will vary over time and depend on policies and fundamentals. For example, a binding renewable fuel standard (RFS) and blend wall are generally associated with lower spillovers.[3]

4 MODEL VARIABLES

An explicit model for market volatility was first introduced by Brunetti and Gilbert (1995).[4] In evaluating metal price volatility Brunetti and Gilbert (1995) considered influences from information assimilation, speculative pressure, physical availability, and other economic fundamentals. Price variability from informational influences occurred as market agents reacted to new information (including information from other related markets pertinent to this paper). Price variability from speculative pressure arose as traders adjusted to market positions. The physical availability explanation related more specifically to commodity markets where stocks can become low and impact price volatility; Brunetti and Gilbert (1995) focused on this aspect of volatility behavior and arrived at the explicit, endogenously determined non-linear inverse relationship between volatility and stocks, depicted in Figure 1, with a simple extension of the competitive storage model by Deaton and Laroque (1992).

Volatility has been modeled empirically by Kim and Chavas (2002), Roach (2010) and Balcombe (2011). From this literature, we draw variables to accompany the price volatilities for crude oil, ethanol and corn in a VAR model representation, which allows for all the variables to be endogenously determined. Specifically, we include stocks for oil, corn, and ethanol and a separate speculation indicator for corn and oil markets. Speculation and stocks have been identified as endogenous factors in determining price volatility (Tadesse et al., 2014) which the VAR modeling framework accommodates as endogenously determined. We add two macroeconomic variables identified by Balcombe (2011): interest rate and exchange rate volatility. Thus, as premised by Brunetti and Gilbert (1995) our empirical representation of the volatility transmission between agricultural and energy markets accounts for: (1) informational considerations between agricultural and energy markets; (2) pressure on commodity pricing through market speculation; and, (3) fundamentals through inventories and interest rates.

To account for speculative market activities, we used data for non-commercial long and short positions of corn and crude oil futures prices – the data series are provided by the U.S. Commodity Futures Trading Commission (CFTC) (U.S. Commodity Futures Trading Commission, 2009). To measure market speculation, we estimated "net speculator positions," which is a measure of total daily long positions less total daily short positions (Hedegaard, 2014). To normalize the net speculator positions, the difference was divided by the total number of daily open interest positions on the Chicago Mercantile Exchange, a

[3] The "blend wall" refers to the U.S. regulated level of ethanol gasoline that is required to be blended with traditional crude-oil-based motor gasoline; currently, the U.S. requires a ten-percent minimum limit of ethanol to be blended with refined motor gasoline. The "wall" refers to the required minimum limit.

[4] Brunetti and Gilbert's (1995) work is based on the competitive storage model (Williams and Wright, 1991; Wright and Williams, 1982, 1984; Deaton and Laroque, 1992).

measure referred to as speculative pressure. Agricultural commodity futures have become increasingly appealing as financial vehicles (Aulerich et al., 2009). In both the 2007-to-2008 and 2010-to-2011 period, the relationship between rising crop prices and a rising share of long positions held by non-commercial investors shows some general correlation, but does not necessarily indicate any causal effects (Trostle et al. 2011). Gilbert (2010) and Gilbert and Morgan (2010) argued that speculation plays a role in agricultural commodity pricing behavior, whereas Irwin and Sanders (2011) concluded that there is little evidence that new speculators (including index funds) drove increased price movements. Yet, if non-commercial investors affect prices, their influence is likely temporary and takes place over shorter time periods, and thus could likely be observed in terms of price volatility rather than price in levels (Trostle et al., 2011; Harris and Büyükşahin, 2009).

Stock-over-use (also known as stocks-to-disappearance) are typically used to represent the inverse relationship of stocks to price volatility (Kim and Chavas, 2002; Balcombe, 2011; Serra and Gil, 2011). Similar to Stigler and Prakash (2011), we relied on forecasts for corn stocks over use. Corn stocks and use data are based on monthly projections, which are reported in USDA's "World Agricultural Supply and Demand Estimates" (U.S. Department of Agriculture, 2013). Using a cubic spline method, we interpolated from monthly to weekly values to make the level of observation for stocks-over-use consistent with the rest of the analysis within the study (Hagan and West, 2006). Weekly crude oil and ethanol stocks and use data were obtained from the U.S. Energy Information Administration (2015).

According to Balcombe (2011), interest rates are an important macroeconomic factor that can have a direct effect on the price of commodities, since they represent affect the cost of holding stocks. Exchange rates represent the prices that producers receive once they are deflated into the currency of the domestic producer, which Balcombe (2011) pointed out can affect prices and inventories. The 3-month Treasury bill (constant maturity) and exchange rate data were obtained from the St. Louis Federal Reserve Bank (2015). We chose short-run interest rates as we expect a shorter lag in the reaction time between macroeconomic activity and investment behavior within the futures market. The exchange rate is measured as the trade-weighted U.S. dollar index, which is a weighted average of the foreign exchange value of the U.S. dollar against the currencies of a broad group of major U.S. trading partners (St. Louis Federal Reserve Bank, 2015). Following Balcombe (2011) the data is converted to a realized volatility measure, as per equation (2).

Definitions, data frequency, and sources for the variables are presented in Table 1. Since corn, ethanol and crude oil futures are converted to weekly volatility measures, all other series were also converted to weekly observations. Consistent with Areal and Taylor (2002), a logarithmic transformation was applied to the realized volatility measure of the explanatory variables because it improved the skewness and kurtosis profiles, indicating that the variables are approximately distributed as log-normal. Many other studies have also observed that a natural log transform of realized volatility provides a much closer approximation to a normal distribution, contrary to (non-log transformed) realized volatility, which often departs considerably from normality (Andersen et al. 2003, Koopman et al. 2005, Preve et al. 2009, Brunetti and Gilbert 1995). Table 2 shows how the log-transformed realized volatility measures compared to non-transformed, realized volatility and adjusted mean absolute deviation (AMAD) as historical measures of volatility. AMAD is an alternative measure of historical volatility, argued by Ederington and Guan (2004) to outperform realized volatility and GARCH models. The logarithmic transformed realized volatility indeed provided a much closer approximation to a normal distribution in comparison to both non-transformed realized volatility, and the AMAD volatility indices. This is most clearly indicated by the skewness and kurtosis profiles of the series. (A normally distributed series is characterized by approximately zero skewness and a kurtosis of three).

Summary statistics for the realized volatility measures (based on underlying daily futures prices), stocks-over-use, and net speculator positions are presented in Table 3. Daily corn and crude oil futures prices are available from 1997 to 2014, thus our baseline of analysis for the multivariate model is limited from 1997. Ethanol futures prices are available from only 2005, so spot prices were used for the period 1997 to 2005. For the period of 2005 to 2014, we estimated a 0.95 Pearson's r correlation coefficient between ethanol spot and future prices. Therefore, the ethanol spot and future prices are highly correlated with one another.

5 EMPIRICAL RESULTS

5.1 Preliminary Analysis

Important changes after 2000 in biofuel policies and the financialization of commodities altered the relationships among corn, ethanol and crude markets. Structural changes should be reflected in data-driven structural break tests. We follow the methodology of Bai and Perron (1998, 2003) to test for structural breaks without specifying specific dates a priori. The results, provided in Figure 1, indicate breaks occurred in October of 2005 (the 95% confidence interval suggests the break occurred between May and December of 2005) and January of 2012 (the 95% confidence interval suggests the break occurred between June of 2011 and June of 2012) for the corn futures price volatility series. For the crude oil futures price volatility series, the structural break test estimates suggest breakpoints in October of 2002, March of 2007, and November of 2009. The corresponding 95% confidence intervals for the three estimated (crude oil futures) breakpoints are as follows: May 2002 – March 2004, May 2006 – April 2007, and October 2009 – May 2010. Additionally, we found structural breaks for December of 2000, July of 2005, and February 2011for ethanol price volatility. The 95% confidence interval for ethanol futures are: July 2000 – November 2001, April 2004 – September 2005, and December 2010 – April 2012, respectively.

The financialization of commodity markets, is arguably demonstrated by the structural break point of the net speculator positions in oil and corn in 2002.[5] It also translates to a structural break in price volatility for crude, but not corn. Speculation for crude (as measured by net speculator positions over open interest) also indicated a break in March of 2000, which was within the confidence interval of the corn market speculation. The structural break for speculation in crude can be further explained for the year 2000 by of the meteoric rise in crude oil prices that began around the year 2000 and ultimately reached a high of $147 per barrel in July of 2008. By contrast throughout the 1980s and 1990s, crude oil had a tendency to trade for less than $25 per barrel (adjusted for inflation) on the New York Mercantile Exchange. There is still some debate as to the cause of the increase in crude oil prices during the 2000s; however, most experts agree that is attributable to geopolitical instability and rising global demand during that period (Kailing, 2008). Speculation for corn and crude shared a break point in 2009 with crude oil futures price volatility which arguably corresponds with the global recession (2008-2009).

Corn market speculation has a distinct break in 2005 it shares with corn and ethanol price volatility. This annual break point notably corresponds to the passage of the renewable fuel standard (RFS), with biofuel mandates starting at 4 billion gallons in 2006 and reaching 7.5 billion gallons in 2012 (Figure 2). As the share of corn used in biofuel production increased to 20% by 2006, and was expected by virtue of the RFS to increase even further in the coming years, a structural change was manifested not only in ethanol price volatility, but also in corn price volatility and corn speculation. California's ban on MTBE in 1999 had already allowed for ethanol to become the dominant fuel additive in the Oxygenated Fuels the Reformulated Gasoline Programs which coupled with USDA's CCC Bioenergy Program in 2000 marked the turning point in the ethanol industry. This is manifested as the first structural break in ethanol price volatility after 2000: ethanol capacity began to expand rapidly, and production more than doubled between 1999 and 2004 (Duffield, Xiarchos, Halbrook, 2008). An additional structural break for ethanol volatility is manifested in 2011, with limitations increasing in corn ethanol from changes in RFS2, concerns over the blend wall, and the expiration of the Volumetric Ethanol Excise Tax Credit (VEETC) by the end of 2011.

Given the policy framework and prior emphasis in the literature, along with correspondence of structural breaks (within conference interval ranges) for corn, ethanol, and crude oil, we mark the turn of 2006 as a common threshold for evaluating the realized volatility in corn futures prices. To determine whether the means (of the separate price series) differ across the two sub-samples (1997-2005 and 2006-2014), we employed mean-comparison tests (multivariate Anova tests) for the realized volatility series. A list of the descriptive statistics (across separate sub-samples) and the multivariate Anova test results are provided in Table 4. The test results imply that the average realized volatilities for corn, crude and ethanol price series are statistically different across the sub-samples. Further, the descriptive statistics suggest that the realized volatility of corn futures increased by over ten percent in the latter sub-sample (2006-2014), whereas the realized volatility in crude futures decreased by over five percent in the same period. The realized volatility of ethanol futures also increased. These

[5] After the turn of the century, the market experienced new investment inflows to various commodity futures indices that totaled approximately $200 billion from early 2000 to June 30, 2008 (Cheng and Xiong, 2013). The new investors primarily had financial interest in the markets and were not hedging physical commodities – in other words, the investors were using these commodities as an asset class to diversify their own financial portfolios.

results imply that the increase in corn (future) price volatility is not due to increased volatility in oil prices as suggested by Balcombe (2009).

As demonstrated by Figure 1(a), corn price volatility does appear to be larger in magnitude in the 2006-to-2015 period (over the 1997-to-2005 period), and the structural break test results suggest that this change in volatility is not merely a transitory phenomenon. On the same token, Figure 1(b) seems to suggest a larger magnitude in ethanol price volatility (this is demonstrated by the larger amplitude of the volatility spikes following the year 2005) in the second sub-sample. The Anova test, in Table 4, corroborates this finding (i.e., there is statistical difference between mean in the separate sub-samples), and the summary statistics demonstrate a large difference in the average levels of volatility (for ethanol prices) across the two separate sub-samples. Based on the structural break tests and the mean-comparison tests, we performed two separate spillover analyses (based on the VAR estimation results) for the different sub-sample periods: 1997 to 2005 and 2006 to 2014.

5.2 Spillover Tables

Following the procedure outlined in Diebold and Yilmaz (2009), we next estimated the spillover tables and index based upon the VAR results. The majority of diagnostics suggested that four lags were the optimal specification for the VAR model – that is, the four-lag specification produced the smallest forecast errors within the entire system of equations. However, specifying only four lags led to significant serial autocorrelation within the model's residuals.[6] In order to balance the tradeoff between over-parameterization and autocorrelation, we report the estimated results based on an eight-lag model. As a robustness check we varied the lag length of the VAR and determined the estimates (in this case, the forecast error variance decompositions) were insensitive to alternative lag specifications. Moreover, all cases contained stable characteristic roots (not provided). The coefficients in a VAR model are not presented; they are often imprecisely estimated and not of much interest to the investigator.[7] We focus on the more useful spillover analysis based on forecast error variance decomposition, so we proceed by examining the spillover tables and indexes.

The spillover tables for each sub-sample (1997-2005 and 2006-2014) are provided in Tables 5 and 6. The *ij*th entry in the table is the estimated contribution *to* the forecast error variance of variable *i* coming *from* innovations to variable *j* (Diebold and Yilmaz, 2009). The off-diagonal column sums are labeled as "Contribution to Others," whereas the off-diagonal row sums are labeled as "Contribution from Others." The sum of either the columns or rows across variables yields the numerator in the spillover index. The column or rows sums, including diagonals, are labeled as "Contribution including own."[8] The sum of "Contribution including Own" across variables yields the denominator of the spillover index.

The spillover tables for each sub-sample (1997-2005 and 2006-2014) are provided in Tables 5 and 6. The *ij*th entry in the table is the estimated contribution *to* the forecast error variance of variable *i* coming *from* innovations to variable *j* (Diebold and Yilmaz, 2009). The off-diagonal column sums are labeled as "Contribution to Others," whereas the off-diagonal row sums are labeled as "Contribution from Others." The sum of either the columns or rows across variables yields the numerator in the spillover index. The column or rows sums, including diagonals, are labeled as "Contribution including own."[9] The sum of "Contribution including Own" across variables yields the denominator of the spillover index.

The spillover table provides an "input-output" decomposition of the spillover index (Diebold and Yilmaz, 2009). Using this interpretation, Table 5 reveals that during the 1997-to-2005 period innovations (shocks) to crude oil price volatility accounted for only 0.2% of the error variance in forecasting ten-week ahead corn price volatility; whereas, innovations to corn price volatility were responsible for only 0.5% of the error variance in crude oil price volatility. In general, Table 5 does not reveal a great deal of volatility spillovers among the three commodities (corn, crude oil, and ethanol). That is, own-historical volatility explains a large portion of own-series error variance. Specifically, corn price volatility is responsible for 89.6% of its own error variance in the 1997-to-2005 period as demonstrated in Table 5. Over the sample period,

[6] Recall from the discussion in Section 3, the moving average representation of the VAR, which forms the basis of the forecasts within the spillover analysis, assumes no serial autocorrelation.

[7] As a VAR analysis consists of a system of equations, the number of coefficient estimates can often be overwhelming. For example, considering that we have ten endogenous variables and one exogenous variable (the constant term), and an eight-lag specification, the number of estimated coefficients is 145. VAR models are more often used for forecasting purposes and policy analysis (Robertson and Tallman, 1999).

[8] Note that for ease of exhibition, these totals only appear at the bottom of the Table.

[9] Note that for ease of exhibition, these totals only appear at the bottom of the Table.

crude oil price volatility accounted for 93.3% of its own error variance and ethanol price volatility accounted for 92.9% of its own error variance. The total contributions from the other variables to corn price volatility, listed in column under the title "From Others," is only 10%; likewise, the total contributions from others to crude and ethanol were both 7%. As Table 5 demonstrates, stocks-over-use in ethanol and corn received the most influence from the other variables within the system at (20% and 16%, respectively) followed by exchange rate and corn speculation (at 13% and 12%).

By comparison of Table 5 and 6 we can remark about the difference in the results between the first and second sub-samples. The volatility spillover index (representing total volatility within the system) increased in the second sub-sample 2006-2014, going from 10.3% to 12.5%. This implies increased integration between energy and agricultural markets in terms of volatility transmissions. As can be gleaned in Table 6, the volatility spillovers between the corn and crude, commodities increased markedly in the second period. In particular, the volatility spillovers from crude to corn increased by approximately 1400% ((0.03-0.002)/0.002), whereas the spillovers from corn to crude increased by approximately 880% ((0.049-0.005)/0.005). Further, the volatility spillovers from corn to ethanol increased by 2775% ((0.115 – 0.004)/0.004) from the first to second sub-sample period.

To the casual reader this may seem like trivial changes. However, the average future contract price in corn, from 1997-2014, was approximately US$3.50 and one contract was comprised of 5,000 bushels. Thus, the average notional value of one corn future contract (over the same period) was approximately worth US$17,500 (3.50 x 5000), and the standard deviation, which is an approximation of the historic volatility, of that notional value is roughly equal to US$8,315. These calculations are based on one contract, and the average, daily number of open interest positions (outstanding contracts held by market participants) was nearly 1.5 million over the period 1997-2014 (not provided). Assuming that all the open interest positions are settled, a one standard deviation difference (an approximate one unit difference in volatility) is approximately equal to US$12.5 billion, on average, in total notional value of the future contracts in corn. Based on these calculations, a one percent difference in volatility is approximately equal to a change of US$125 million in the total (notional) market value of corn future contracts.

Despite these large implied increases, the cross-commodity spillovers only account for a relatively small percentage in explaining the error variance of the other individual volatility series. In the 2006-to-2014 subsample, corn volatility only explains 4.9% of the total error variance of crude volatility, and crude volatility only explains 3.0% of the total error variance in corn volatility. On the other hand, corn volatility explains 11.5% of the total error variance of ethanol in the second subsample (Table 6).

Contrary to what was found in the earlier sub-sample, stocks-over-use played a less substantial role in explaining the speculative activities in corn in the second period. Put differently, the effect of corn inventory levels in predicting net speculator positions in corn decreased by approximately 55% ((0.005-0.011)/0.011). This finding implies that economic fundamentals (such as, inventory levels) now play a less substantive role in speculative activities. This could be a reflection of the increasing financialization of these commodity markets (Cheng and Xiong, 2013).

Despite the lack of evidence of transmissions from inventory levels to speculation, the opposite is not true. That is, speculative activities seem to have affected inventory levels over time. For the period 2006-to-2014, the results indicated substantial increases in spillovers from speculative corn activities to corn stocks-over-use; i.e., the influence of innovations to net speculative positions in corn futures on the error variance in forecasting the corn stocks-over-use increased by 3700% ((0.076 – 0.002)/0.002) over the preceding sub-sample. Conversely, the transmission from net speculative positions in crude oil to crude inventory levels arguably decreased by nearly 30% ((0.016 – 0.023)/0.023) in the second sub-sample. Further, the transmission from net speculative position in crude oil to ethanol inventory levels arguably decreased by roughly 83% ((0.002 – 0.012)/0.012) in the second sub-sample period.

Our results suggest that the transmission from speculative positions to own price volatility changed substantially in the 2006-to-2014 sub-sample period. That is, crude speculation to crude oil (future) price volatility increased by 400% ((0.025 – 0.005)/0.005). Whereas, the transmission of corn speculation to corn (future) price volatility decreased by approximately 27% ((0.015 – 0.011)/0.015).

Differing from the first sub-sample, stocks-over-use in corn and volatility in ethanol prices received the most contributions from others (21 and 22%, respectively), followed by crude oil price volatility (17%) and exchange rate volatility (17%). All of the increased transmissions (spillovers) among these commodities suggest perhaps a non-transitory integration of the markets.

Our findings, seem consistent with the narrative offered by Saghaian (2010). That is, he explained that the early literature tended to focus on the exchange rate and how changes to monetary policies transmitted instability to agricultural prices; whereas, in more recent years the literature has evolved to examine the impacts associated with speculation and the links between energy and agricultural markets. In the context of our findings, shocks to the exchange rate arguably played a much smaller role in predicting corn price volatility as the former explained approximately 3.5% of corn price variability in the 1997-to-2005 period; whereas, it only explained 1.4% in the subsequent 2006-to-2014 period. Thus, the transmission (direct and indirect), between the agricultural and energy commodity prices, seems to offer more explanatory power over the second sub-sample period (that is, in the more recent past). This may, in part, explain the evolution of the empirical literature.

5.3 Rolling-sample Spillover Index

The spillover tables provide a useful summary of average behavior over the sub-samples, but are likely to miss the potentially important secular and cyclical movements in spillovers (Diebold and Yilmaz, 2009). As Abbott (2013) indicates "the turbulence in recent economic events has caused the mechanisms through which biofuels demands influence corn and other agricultural commodity prices to vary over time." Hertel and Beckman (2011) further argue price volatility and volatility spillovers will depend on policy regimes.

Figures 3 and 4 demonstrate the rolling-sample spillover volatility index plots through time for each sub-sample. The spillover index plot provides an interpretation of the total amount volatility spillovers within the system (of endogenous variables) through time for each sub-sample. Both are calculated using 75-week rolling window with ten-week-ahead and two-week-ahead forecasting horizons, respectively. Both of the rolling-sample indexes are based on an underlying VAR model with eight lags specified. Despite the difference in lag specification, the index plots in both figures provide a relatively similar set of results.

The rolling-sample indexes for the first sub-sample, Figures 3(a) and 3(b), demonstrate the largest spillover volatility index spike in or around 1997. This spike is consistent with the U.S. grain price shocks in 1995 and 1996, which were caused by a significant Midwestern drought during that same period. The second rolling-sample indexes (for the 2006-to-2014 sub-sample) in Table 6 suggest the largest spike in volatility spillovers in 2009 corresponding to the tail of the US Great Recession (National Bureau of Economic Research, 2015). This spike in spillovers is arguably due to the meteoric decline in crude oil prices, trading for over $145 per barrel in July 2008 and falling close to $40 per barrel by January 2009 – prices are adjusted for inflation and quoted based on the historical price series from the New York Mercantile Exchange.

Our estimated volatility spillover index plot as premised by Hertel and Beckman (2011) and Abbott (2013) shows lower volatility transmissions between crude and corn markets when the RFS mandate and blend wall are binding (Figure 4). Our index plot estimates seem consistent with high oil price spikes in the first half of 2008, which led to a non-binding RFS and higher spillovers. More specifically the spillover volatility index behaved exactly as described in Abbott (2013); it decreased when the RFS became binding as prices started falling after the middle of the year, and increased again as the RFS became temporarily binding at the start of 2009. By 2010, concerns over the blend wall reduced spillovers, but exports relieved pressure on ethanol production towards the end of the summer allowing for higher volatility spillovers (Abbott, 2013). As the subsidies to ethanol neared expiration and exports slowed, spillovers again are reduced consistent with Abbott (2013) while the drought increased prices and volatility in 2012. By 2013 the Environmental Protection Agency (EPA) responsible for administering the RFS2 acknowledged that the blend wall was officially binding production, and spillovers again were reduced as prefaced by Abbott (2013). Capacity constraints, inventory conditions, and information assimilation in the markets accounted for finer changes and discrepancies in spillover estimates.

6 CONCLUSIONS AND POLICY IMPLICATIONS

Our study, by means of an estimated spillover table and spillover index, demonstrated increasing volatility spillover transmissions in a system of corn (future) prices, crude (futures) prices, ethanol (futures) prices, interest rates, exchange rates, inventories, and speculation. Additionally, our findings suggest increasing cross-commodity volatility spillovers from crude oil to corn (future prices) and vice versa from the period 2006 to 20145 (while at the same time accounting for other endogenous factors that affected the observed historical volatility spillovers). Our estimated spillover tables and rolling-sample spillover indexes prove robust to the predictions for spillover intensity changes based on policies and fundamentals according to Abbott (2013) and Hertel and Beckman (2011).

However, even though the volatility spillovers between corn and crude oil prices have increased more than eightfold, it is important to note that these cross-commodity (price) volatility spillovers still only constitute a relatively small portion of a commodity's total price volatility. Put differently, our results suggest that the influence of a commodity's own past volatility increased slightly for corn price volatility (from 89.6 to 91.7); whereas, own past volatility decreased somewhat substantially for crude oil price volatility (93.3 to 82.8) and ethanol price volatility (92.9 to 77.9). Furthermore, while the spillover results arguably imply that biofuel policies have led to increasing spillovers from corn markets to crude oil and ethanol price volatility, it also indicates that other influences have led to an increasing volatility of crude oil prices.

Consistent with the literature, we found little direct evidence that speculation in corn futures played a significant role in directly explaining corn (future) price volatility. However, we found that speculation in crude oil futures explain approximately three percent of the price volatility in crude (future) prices, and the spillovers from crude speculation to crude oil price volatility increased by considerably between the two separate sub-sample periods. While speculation in corn positions does not seem to directly play a large role in predicting corn price volatility, we found indirect channels from speculation in corn positions explaining approximately seven percent of the variation in ethanol volatility and corn stocks-over-use. Notably increased transmissions after 2006 are not necessarily direct.

In summation, results of our empirical model imply relatively small volatility spillovers between corn, crude oil, and ethanol (in the range of three-to-twelve percent) even after tremendous increases (eightfold) in spillovers after 2006. Further, by utilizing a relatively large set of endogenous determinants of commodity price volatility, we also discovered that spillovers are not always direct but may in fact be indirect. These findings might explain the contradictory estimates of volatility spillovers in prior studies.

The modeling framework, presented in this study, can be applied to a whole range of agricultural commodities to facilitate the study of both crisis and non-crisis episodes, including trends and sudden bursts in spillover activity. With the blend wall applying pressure on the ethanol market, the ethanol industry slowing since 2014,crude oil prices predicted to remain relatively low (compared to the average price over the past couple of decades) for the near term, and policy choices still to come future research can evaluate if volatility levels and interconnections might change yet again.

All the same crude oil and grain commodity markets are expected to continue to be more tightly integrated than in the pre-ethanol era (independent of future energy policies or renewable fuel standards). Characteristically, ethanol is blended in gasoline not only to comply with policies like the renewable fuel standard, but also to improve octane and to add to gasoline volume under favorable prices. Ethanol has become ingrained in the U.S. retail gasoline market over the past decades. For example, refineries now produce more unfinished gasoline specifically formulated for blending with ethanol to increase octane, and the majority of finished gasoline production has shifted from petroleum refiners to gasoline blenders. Moving finished product decisions for gasoline to blenders rather than refiners will arguably further increase the integration between crude oil and grain markets. Of course choices about the future direction of the RFS and fuel support will still play a critical role in shaping the biofuels industry and the integration of energy and agricultural markets. For example, enlarging ethanol use beyond the blend wall with higher blends (than the existing E10 standard) will likely result in increased spillovers between agricultural and energy markets. Conversely, an increase in future cellulosic ethanol production will like reduce integration between the markets. The impact of increases in drop-in fuels will depend on the biomass source, but will in any case remove infrastructure barriers in blending, and move the market biofuel market from mainly an oxygenate to a competitive gasoline volume market.

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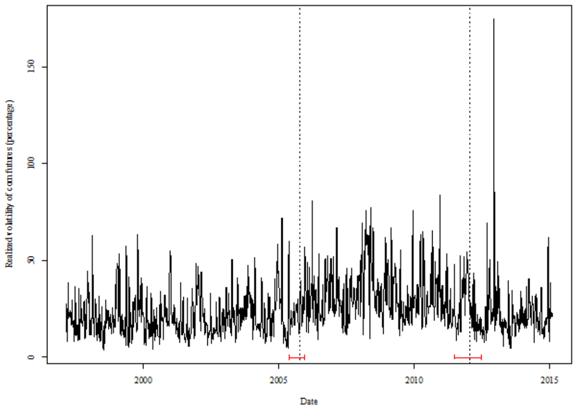
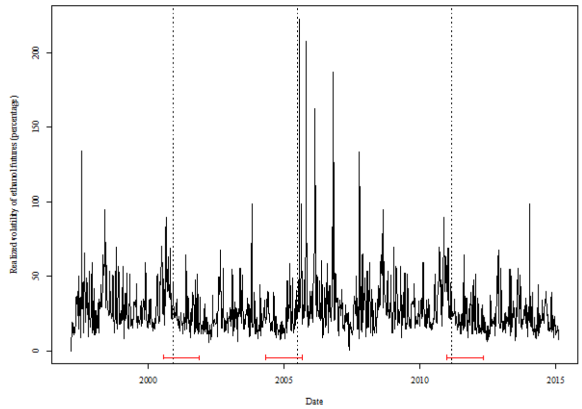
FIGURE

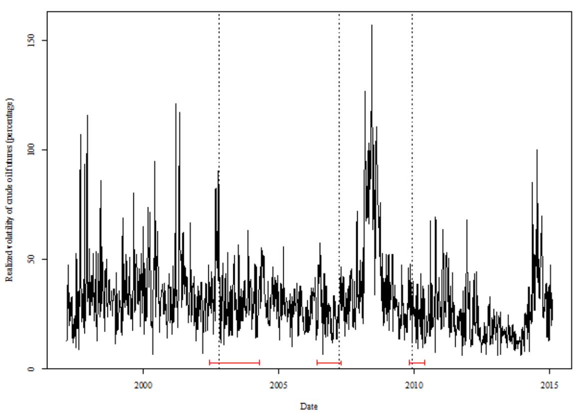
Figure 1. Break points within the realized volatility series of corn, ethanol, crude oil, and net speculator positions for corn and crude oil, 1997-2014



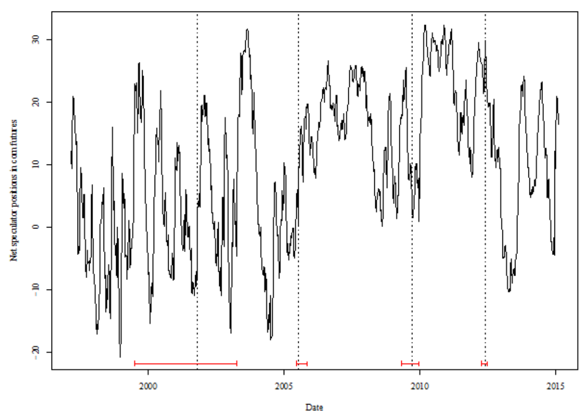
a. Corn



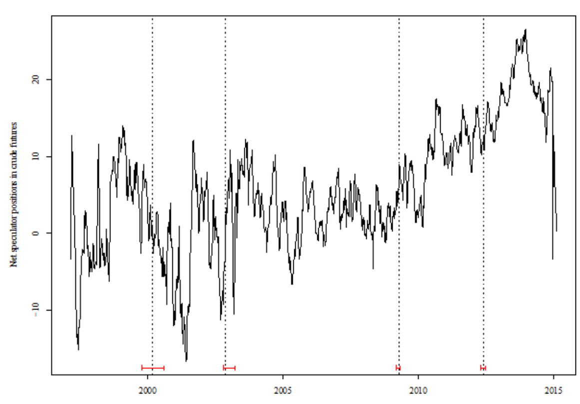
b. Ethanol



c. Crude Oil



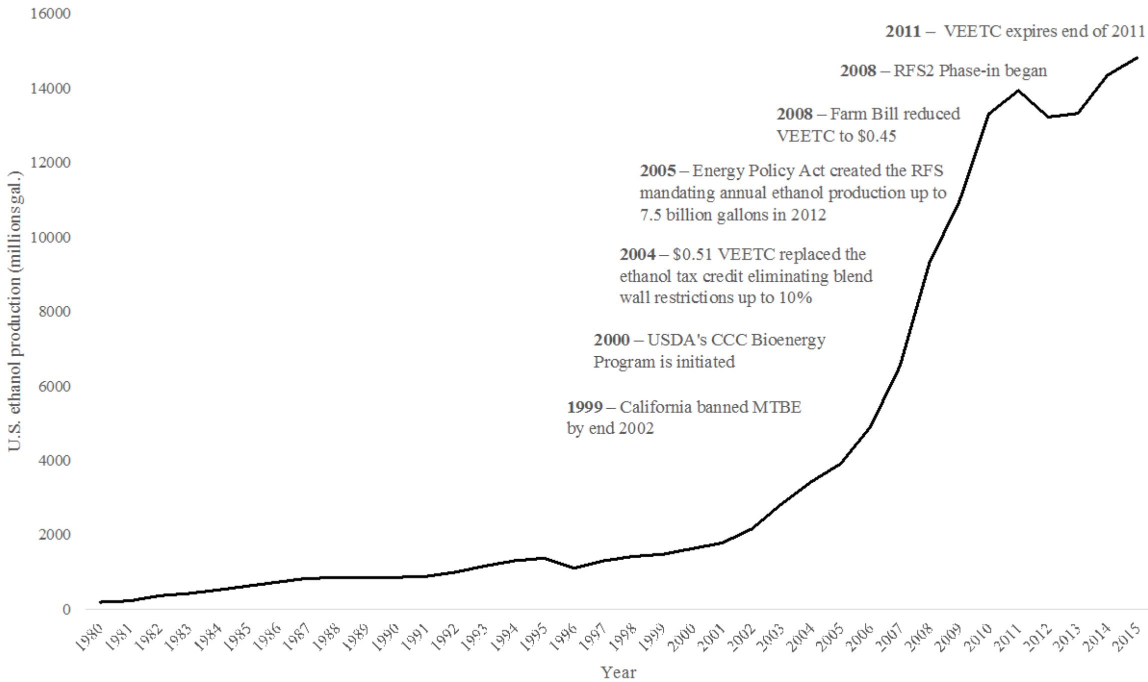
d. Corn, net speculator positions (percentage)



e. Crude, net speculator positions (percentage)

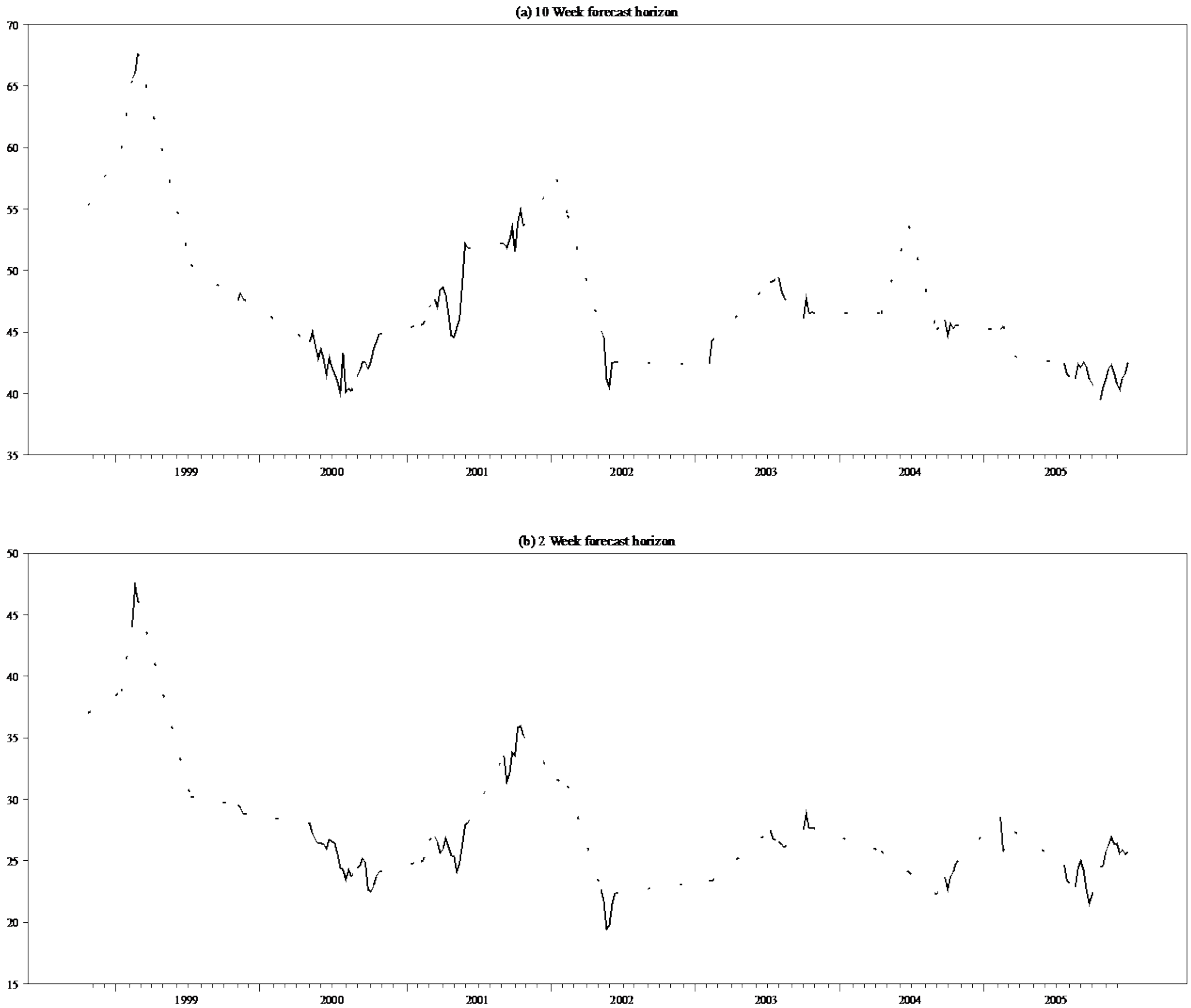
Notes: The estimated break points are represented by the broken vertical lines in the figure. The horizontal whisker plots at the bottom of the figure indicate the confidence intervals for the estimates.

Figure 2. Policy influences versus total U.S. ethanol production through time



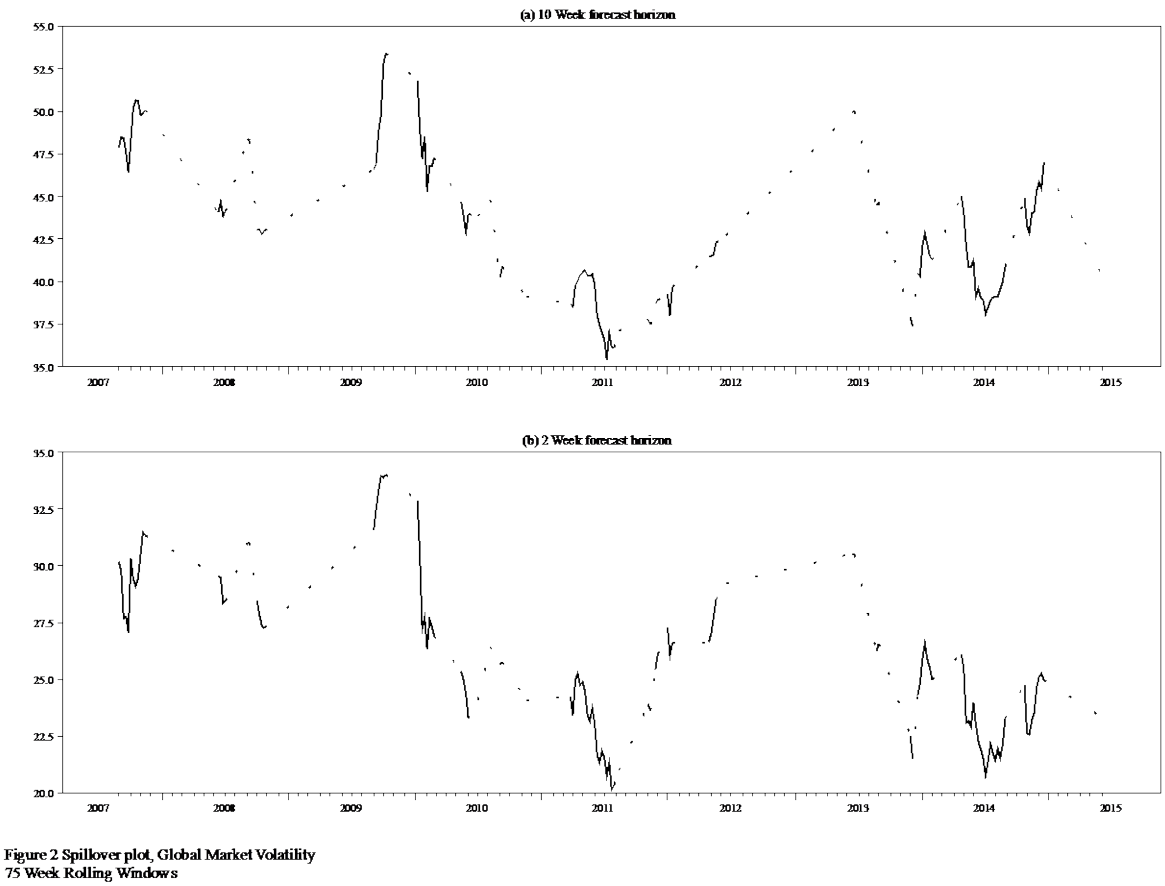
Notes: After 2014 production is estimated based on the RFS2 volume requirements. The source for Ethanol production data is the Renewable Fuels Association (2016). Policies are sourced from Duffield, Xiarchos, Halbrook (2008), and the National Agricultural Law Center.

Figure 3. 75 Week Rolling Windows: Ten-Week-Ahead and Two-Week-Ahead Forecast Horizons. Results based on a VAR(8) model for the sub-sample period: 1997-2005



Notes: These plots demonstrate a moving volatility Spillover Index (based on a VAR model with one lag specified), defined as the sum of all variance decomposition "contribution to others" from Tables 5 and 6, estimated using a 75-week rolling window

Figure 4. 75 Week Rolling Windows: Ten-Week-Ahead and Two-Week-Ahead Forecast Horizons. Results based on a VAR(8) model for the sub-sample period: 2006-2015.



Notes: These plots demonstrate a moving volatility Spillover Index (based on a VAR model with eight lags specified), defined as the sum of all variance decomposition "contribution to others" from Tables 5 and 6, estimated using a 75-week rolling window.

TABLES

Table 1. Explanatory Variables within Vector Autoregressive Model

Definitions (data units)	Computation	Data Frequency[b]	Source
Corn			
Price volatility (future, USD/bu)	Natural log transform of realized volatility	Daily	Chicago Board of Trade, U.S. Department of Agriculture
Net speculator position[a]	(Non-commercial long – non-commercial short) / Open interest	Weekly	U.S. Commodity Futures Trading Commission
Stocks-over-use (million bu)	Expected stocks/(Domestic use + Exports)	Monthly	U.S. Department of Agriculture
Crude			
Price volatility (WTI futures, USD/bbl)	Natural log transform of realized volatility	Daily	U.S. Energy Information Administration
Net speculator position[a]	(Non-commercial long – non-commercial short) / Open interest	Weekly	U.S. Commodity Futures Trading Commission
Crude Stocks (million bbls)	Week-ending stocks levels	Weekly	U.S. Energy Information Administration
Ethanol			
Price volatility [c] (spot, futures USD/gal)	Natural log transform of realized volatility	Daily	Chicago Board of Trade, U.S. Department of Agriculture
Ethanol stocks (million bbls)	Week-ending stocks levels	Weekly, Monthly	U.S. Energy Information Administration
Macroeconomic Factors			
Interest rate volatility (U.S. 3-month Treasury yield (constant maturity))	Natural log transform	Daily	St. Louis Federal Reserve Bank
Exchange rate volatility (Trade-weighted USD Index)	Natural log transform	Daily	St. Louis Federal Reserve Bank

a. Based on contracts of 5000 bushels for corn and 1000 bbls for crude oil. Corn contracts measured in 1000 bushels till January 1997 where converted to 5,000 equivalent contracts for consistency. b. The study is performed on weekly values. If not available on a weekly frequency, variables were converted to weekly measures. Volatility variables are the natural logs of each respective intraweek realized volatility, estimated from observed daily values. Monthly stocks and use data were interpolated to weekly values using a cubic spline method. Ethanol stocks and use data were available on a weekly basis since June 2010. c. Ethanol futures prices are available only from 2005 to 2015, so spot prices were used for the 1997-to-2005 period.

Table 2. A comparison of historical measures of volatility

	Variable	Obs	Mean	Median	Std. Err.	Skewness	Kurtosis
Logarithmic transformation of realized volatility	corn	926	3.08	3.07	0.02	-0.10	0.18
	crude	926	3.35	3.36	0.02	-0.01	0.43
	ethanol	926	2.60	2.81	0.03	-0.86	0.76
	ex. rate	926	1.74	1.76	0.02	-0.45	1.00
	int. rate	926	3.82	3.44	0.05	0.32	-0.99
Realized volatility	corn	926	24.95	21.51	14.09	2.31	14.62
	crude	926	32.58	28.71	18.46	2.07	6.70
	ethanol	926	28.95	23.35	21.53	4.33	29.50
	ex. rate	926	6.40	5.83	3.17	1.65	6.34
	int. rate	926	139.11	25.50	258.63	3.85	26.85
Adjusted, mean absolute deviation	corn	926	25.28	22.51	13.68	1.52	6.96
	crude	926	30.71	26.60	21.22	2.73	18.92
	ethanol	926	28.33	23.61	19.43	3.42	22.10
	ex. rate	926	6.45	5.84	3.17	1.14	5.32
	int. rate	926	131.73	25.41	251.57	3.96	27.55

Table 3. Descriptive statistics and unit root tests for the model time series variables

Variable	Variable Description	Mean	Median	Std. Err.	Skewness	Kurtosis	Obs.	P-P[a]	Prob[b]
Corn futures	Log (realized volatility) of intra-week	3.08	3.07	0.02	-0.10	0.18	926	-683.46	0.00
Crude futures	Log (realized volatility) of intra-week	3.35	3.36	0.02	-0.01	0.43	926	-611.04	0.00
Ethanol spot/futures	Log (realized volatility) of intra-week	2.60	2.81	0.03	-0.86	0.76	926	-404.04	0.00
Exchange rate	Log (realized volatility) of intra-week	1.74	1.76	0.02	-0.45	1.00	926	-707.74	0.00
Interest rate	Log (realized volatility) of intra-week 3-mos. Treasury	3.82	3.44	0.05	0.31	-0.99	926	-150.77	0.00
Corn stocks	Log of weekly stocks-over-use	2.47	2.56	0.01	-0.47	-0.74	926	-43.59	0.00
Crude stocks	Log of weekly stocks	6.89	6.92	0.00	-0.27	-1.34	926	-784.71	0.00
Ethanol stocks	Log of weekly stocks	2.18	2.16	0.02	-0.13	-1.40	926	-464.22	0.00
Corn speculation	Log of net speculator positions on corn futures	3.33	3.46	0.02	-1.41	3.23	926	-75.32	0.00
Crude speculation	Log of net speculator positions on crude oil futures	3.07	3.11	0.01	-1.95	8.14	926	-70.47	0.00

Notes: *a*. Phillips and Perron (1988) unit root test. Rejection of null indicates that the time series was generated by a stationary process. *b*. MacKinnon (1996) one-sided reported *p*-values. The reported Phillips and Perron test static (and *p*-value) for the stocks (corn, crude, and ethanol) are based on first-differenced series.

Table 4. Mean-Comparison Tests for Sub-Samples

Period of Observation	Obs	Mean	Std. Err.
Full Sample (1997-2015)			
Corn volatility	926	3.08	0.02
Ethanol volatility	926	2.60	0.02
Crude oil volatility	926	3.35	0.02
First Sub-Sample (1997-2005)			
Corn volatility	433	2.91	0.03
Ethanol volatility	433	1.91	0.05
Crude oil volatility	433	3.46	0.02
Second Sub-Sample (2006-2015)			
Corn volatility	493	3.23	0.02
Ethanol volatility	493	3.20	0.02
Crude oil volatility	493	3.26	0.03

Multivariate Anova Tests	df	F-stat	*p*-value
Wilks' lambda	(3, 922)	251.78	0.0000
Pillai's trace	(3, 922)	251.78	0.0000
Lawley-Hotelling trace	(3, 922)	251.78	0.0000
Roy's largest root	(3, 922)	251.78	0.0000

Notes: The realized volatility for ethanol futures is only available starting in 2005; therefore, we used the realized volatility of ethanol spot prices for 1997-2005. The mean realized volatility of ethanol spot prices for the 2006-2014 were also higher than the mean realized volatility of ethanol spot prices for the 1997-2005. The multivariate Anova tests are based on the Stata 14.1 routine entitled "manova." The null hypothesis is that there is no statistical difference between the mean values in the separate sub-samples.

Table 5. Spillover Table for Sub-Sample, 1997-2005

Endogenous variables	Corn volatility	Crude volatility	Ethanol volatility	Corn stocks	Crude stocks	Ethanol stocks	Corn speculation	Crude speculation	Exchange rate	3-mos. T Bill	From Others
Corn volatility	89.6	0.2	0.1	0.2	2.7	0.3	0.9	1.5	3.5	0.7	10
Crude volatility	0.5	93.3	0.9	0.5	0.2	0.7	0.1	0.5	2.3	1.1	7
Ethanol volatility	0.4	1.2	92.9	0.2	0.0	1.1	0.7	2.9	0.3	0.2	7
Corn Stocks	1.6	1.2	0.1	84.1	7.8	0.2	0.2	3.2	0.9	0.7	16
Crude Stocks	1.9	0.8	0.0	0.2	93.2	1.1	0.0	2.3	0.4	0.0	7
Ethanol Stocks	1.3	0.2	3.5	0.0	13.0	80.3	0.0	1.2	0.0	0.4	20
Corn Speculation	9.1	0.1	0.6	1.1	0.1	0.0	87.8	0.0	0.6	0.5	12
Crude Speculation	0.1	0.4	3.6	0.0	0.4	0.4	0.0	94.6	0.1	0.4	5
Exchange Rate	6.0	1.5	0.4	0.6	0.1	0.7	0.6	0.8	86.8	2.6	13
3-mos. Treasury Bill	1.6	0.2	0.6	0.1	0.2	0.3	1.1	0.8	1.2	93.9	6
Contribution to Others	23	6	10	3	24	5	4	13	9	7	103
Contribution including Own	112	99	103	87	118	85	92	108	96	101	10.3%

Notes: The underlying variance decomposition is based upon a weekly VAR of order eight, identified using the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998). The (i, j) th value is the estimated contribution to the variance of the ten-week-ahead real return forecast error of variable i coming from innovations to the real return of variable j.

Table 6. Spillover Table for Sub-Sample, 2006-2014

Endogenous variables	Corn volatility	Crude volatility	Ethanol volatility	Corn stocks	Crude stocks	Ethanol stocks	Corn speculation	Crude speculation	Exchange rate	3-mos. T Bill	From Others
Corn volatility	91.7	3.0	0.5	0.2	0.7	0.1	0.1	1.1	1.4	1.3	8
Crude volatility	4.9	82.8	1.4	0.1	0.3	0.0	0.5	2.5	3.6	4.0	17
Ethanol volatility	11.5	1.1	77.9	0.0	0.8	2.6	0.1	0.8	1.3	3.9	22
Corn Stocks	0.0	0.4	0.1	78.7	5.1	5.9	7.6	1.4	0.3	0.4	21
Crude Stocks	0.6	0.2	0.3	1.8	90.7	1.4	0.3	1.6	0.7	2.4	9
Ethanol Stocks	0.0	0.7	0.6	0.1	0.8	97.3	0.0	0.2	0.1	0.2	3
Corn Speculation	0.3	0.1	0.1	0.5	0.2	0.1	98.0	0.5	0.2	0.1	2
Crude Speculation	3.8	7.2	1.0	0.1	1.3	0.1	1.2	84.4	0.1	0.8	16
Exchange Rate	1.9	5.9	0.4	0.2	0.4	0.0	0.7	2.4	83.3	4.7	17
3-mos. Treasury Bill	1.6	0.6	1.6	0.0	0.7	0.7	0.1	2.5	1.7	90.3	10
Contribution to Others	25	19	6	3	10	11	11	13	9	18	125
Contribution including Own	116	102	84	82	101	108	109	97	93	108	12.5%

Notes: The underlying variance decomposition is based upon a weekly VAR of order eight, identified using the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998). The (i, j) th value is the estimated contribution to the variance of the ten-week-ahead real return forecast error of variable i coming from innovations to the real return of variable j.