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Reducing Fuel Volatility - An Additional Benefit From Blending Bio-fuels?

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Abstract

Oil price volatility harms economic growth. Diversifying into different fuel types can mitigate this effect by reducing volatility in fuel prices. Producing bio-fuels may thus have additional benefits in terms of avoided damage to macro-economic growth. In this study we investigate trends and patterns in the determinants of a volatility gain in order to provide an estimate of the tendency and the size of the volatility gain in the future. The accumulated avoided loss from blending gasoline with 20 percent ethanol-fuel estimated for the US economy amounts to 795 bn. USD between 2010 and 2019 with growing tendency. An amount that should be considered in cost-benefit analysis of bio-fuels.

Introduction

Establishing a bio-fuel industry is generally seen to come with eclectic benefits. Among them are environmental aspects such as reduced pollutant emissions (Puppán 2002), energy security improvements, foreign exchange savings (Demirbas 2009), and direct employment effects. Another benefit associated with renewable energies results from diversification and is known as the volatility gain. The latter is the reduction in price fluctuations possibly achieved by mixing two energy sources with different price behaviour. Reducing fluctuations in fuel prices is of utmost importance for the economy. Economists have discovered negative effects of oil price volatility on economic output growth (Ferderer 1996). This can be explained by Bernankes (1983) finding that uncertainty delays irreversible business investments. Such uncertainty is for example introduced by high oil price volatility. Moreover, Uri (1996) discovers that oil price volatility has a delayed but negative effect on employment in the United States. The sum of the costs imposed on the United States due to movements in oil prices add up to around 7 trillion US Dollar (present value 2000) over the period of 1970 to 2000 (Greene and Tishchishyna 2000). Awerbuch and Sauter (2006) argue that the costs generated by the adoption of renewable energy strategies can be amortized simply by the reduction of price volatility resulting from diversification. Diversifying into bio-fuels can thus be an important strategy to assist macro-economic stability. Furthremore, this severe impacts highlight that the volatility gain can be regarded as an additional benefit from bio-fuel production that should be encountered when assessing the macro-economic value of investing in a bio-fuel industry.

The possibility of volatility reductions through diversification is a core finding from financial portfolio theory (Markovitz 1952) which has been repeatedly applied to energy economics. For example, Humphreys et al., (1998) make use of portfolio theory to demonstrate how the energy mix in the United States could be chosen to diminish price volatility in order to prevent the damaging effects on the macro-economy resulting from high energy price volatility. Similarly, Huang and Wu (2007) apply portfolio theory to conventional electricity planning using Taiwan as a case study[1]. An application of this theory specifically to the realm of conventional and ethanol-fuel portfolios was presented by Zhang and Wetzstein (2008) who calculate an efficient frontier of different mixing proportions of gasoline and ethanol for the United States under different tariff and subsidy policies. Doing this, the combination of ethanol from the US, ethanol from Brazil and gasoline exhibiting the lowest volatility for a given price can be found. In another study Vedenov et al., (2005) extends the real option pricing approach in order to include the value of volatility reduction into the price for fuels. Thereby they show that switching to

1 Further studies applying portfolio theory to energy economics are: Awerbuch and Berger (2003); Lesbirel (2004).

blended fuels is rational even at a point where bio-fuels are more expensive than conventional fuels.

From the literature on volatility reductions in the context of bio-fuel production it is clear that the the possibility of reductions in price-fluctuations exists. However, non of this papers take into account that diversification does not always lead to this result. Under some conditions diversification can even result in higher price volatility. Additionally, the determinants of diversification can change over time in response to tightened forces between markets or as a result of economic events. The changes and tendencies in the determinants can lead to changes and trends in the size and the sign of a volatility gain, which have not been investigated in the prevailing literature so far. Therefore, this paper attempts to investigate the historical tendencies and patterns of the determinants in order to provide an answer to four main questions. First, did blending fuels (hypothetically) result in overall volatility reductions in the past? Second, are the determinants (the correlation and the volatility of the two fuels) of a volatility gain altered by such changes in market interactions? Third, what can we expect in terms of volatility gains from mixing bio-fuels in the future? And finally, how much additional value can be added to the option of bio-fuels in cost/ benefit evaluations.

The route we take to investigate this starts with the measurement of volatility and correlation using a generalized auto-regressive conditional heteroscedastic model (GARCH) and a multivariate extension (MGARCH) of these models. These models provide an insight into the behaviour of the three determinants over time. In a next step the values estimated for the determinants are examined in a regression analysis in order to detect the patterns and trends. Based on these tendencies an extrapolation into the future will give a picture on the possible gains from bio-fuel production in the future. In order to express the past and future gains in monetary values, we use a formula developed by Awerbuch and Sauter (2006) that estimates the avoided macroeconomic losses from volatility reductions in oil prices.

Assuming a 20% blending ratio, the results show that, historically, a volatility gain would not always have been the result of mixing gasoline with ethanol. In fact, a volatility increase was the outcome for some periods in the past. Examining the time trends and the changes due to evolving market forces between gasoline and ethanol, makes it possible to prophesy a positive and increasing volatility gain in the future. As a result, the added value of diversification into bio-fuels for the US economy from a macro-economic perspective is estimated to add up to 795 bn. USD over the period 2010 to 2019.

Theory and Methods

The concept of volatility reductions

The idea that price fluctuations can be reduced when two prices, which do not move in perfect synchrony, are mixed, is intuitively plausible. This idea is captured by Portfolio Theory as the diversification effect, firstly recognized and documented by Markowitz (1952). The diversification effect manifests itself as a volatility reduction that results from dividing a portfolio into different assets that are not perfectly positively correlated. More precisely, Portfolio Theory shows that the variance of a portfolio of two, not fully positively correlated assets, is less than the weighted average variance of the two assets.[2] Additionally, it is also possible to reduce the variance and hence the volatility of a portfolio below the variance (volatility) of the respective single assets (Bodie et al., 2009). Applying this to the case of fuel blends, it is possible to reduce price fluctuations in fuel prices by mixing two different fuels. The size of the volatility reduction or volatility gain is determined by three variables. These determinants are given by the formula for the portfolio variance provided by Modern Portfolio Theory:

$$\sigma^2_{blend} = \omega^2\,\sigma^2_{cf} + (1\text{-}\omega)^2\,\sigma^2_{bf} + 2\rho\,\omega\,(1\text{-}\omega)\,\sigma_{cf}\,\sigma_{bf} \qquad (1)$$

$$\text{where } \omega < 1 \text{ and } -1 \leq \rho \geq 1$$

The square root of the above expression is the volatility of the portfolio or, here, the volatility of the blended fuel, σ_{blend}. The determining factors of the portfolio volatility are hence the weights ω assigned to the two assets or fuels, the respective volatility, $\sigma_{i,}$ of the fuels (here σ^2_{cf} denotes the variance of the conventional fuel and σ^2_{bf} denotes the variance of the bio-fuel), and most importantly, the correlation, ρ, between the two assets (fuels).

The price volatility reduction in fuel prices that can be achieved through the blending of bio-fuels is then defined as:

$$\text{Variance Reduction} = \sigma^2_{cf} - \sigma^2_{blend} \quad (2a)$$

$$\text{or Volatility Reduction (VR)} = \sigma_{cf} - \sigma_{blend} \qquad (2b)$$

For the purpose of this study, the volatility of the fuel portfolio has to be compared to the status quo, that is, the volatility of the conventional fuel.

(1) in (2b): $$\mathrm{VR} = \sigma_{cf} - \sqrt{\omega^2\,\sigma^2_{cf} + (1-\omega)^2\,\sigma^2_{bf} + 2\rho\,\omega\,(1-\omega)\,\sigma_{cf}\,\sigma_{bf}} \quad (2c)$$

2 For a formal derivation see Bodie et al., (2009).

If the volatility of the blended fuel, σ_{blend}, is lower than the volatility of the conventional fuel, σ_{cf}, the term on the right hand side is positive and a volatility reduction can be achieved.

The table below summarizes the possible combinations of the values for the correlation and the volatility of each fuel. A volatility gain is not a guaranteed outcome from blending fuels.

Volatility Reduction	$\rho = 1$	$1 < \rho \geq 0$	$0 < \rho \geq -1$
$\sigma_{cf} > \sigma_{bf}$	+	+	+
$\sigma_{cf} = \sigma_{bf}$	0	+	+
$\sigma_{cf} < \sigma_{bf}$	–	–/+	–/+

Table 1

In case the volatility of the conventional fuel is larger than the volatility of the biofuel ($\sigma_{cf} > \sigma_{bf}$), a volatility reduction is always achieved. In contrast, if the volatility of the bio-fuel is larger, an increase in the price volatility of fuels is as well as a volatility reduction is possible.[3]

Trends in the values for volatilities and correlation result in different effects for a volatilities reduction. Increasing volatilities in gasoline prices always increases the volatilities reduction. Also, the volatilities reduction is a declining function of correlations. Finally, changes in volatilities of ethanol pricers can have adverse effects on the volatilities gain.[4]

GARCH Models – Measuring Time-Varying Volatility and Correlation

Different methods for the estimation of the volatility and correlation of the fuels can be used. In general, price volatility is commonly measured as the unconditional standard deviation of price-changes (Regnier 2007). However, as demonstrated above, fuel prices are found to exhibit volatility clustering[5], just like many financial time-series. In order to model this time-series behaviour of financial data, Engle (1982) proposed what is called the Auto-regressive Conditional Heteroscedastic (ARCH) model.

The GARCH methods are especially appealing, since they not only allow to investigate whether a volatility gain could have been realized historically, but also allow to explore how the volatility of the variables changes over time.

3 For a formal treatment of the different options summarized in table two see APPENDIX I.
4 For a more elaborate discussion of these effects see APPENDIX I.
5 Volatility clustering describes the phenomenon of serially correlated price-changes. That means high volatility is followed by high volatility and low volatility is ensued by low price fluctuations.

The variance at time t measured with a GARCH(p,q) model is:

$$\sigma_t^2 = \alpha_0 + \alpha_1\, \varepsilon^2_{t-1} + ... + \alpha_p\, \varepsilon^2_{t-q} + \beta_1\, \sigma^2_{t-1} + ... + \beta_q\, \sigma^2_{t-q} \quad (5)$$

Where ε^2_{t-p} is an innovation term, i.e. the returns of the past p periods and σ^2t-q is the variance of the past q periods. The long run volatility is incorporated into the model by the constant α0 which is really the product of a weight and the long run volatility, $\alpha_0 = \gamma$ VL. Because the weights sum up to unity ($\gamma + \alpha + \beta = 1$), the long run volatility is equal to VL= $E(\sigma_t^2) = \alpha_0/(1- \alpha - \beta)$. Most financial data is found to be fitted best as a GARCH(1,1) model where one past innovation term, ε^2_{t-1}, and one past variance term, σ^2_{t-1}, is included.

A multivariate GARCH (MGARCH) model is used in order to estimate the covariance between the fuel prices. Using the covariance estimates from the MGARCH model, together with the variance estimates from the uni-variate models, the time-varying correlation will be calculated. The uni-variate GARCH model, as explained above, has been extended to multivariate GARCH models in several manners in order to investigate interactions between two or more financial markets (e.g. Bollerslev et al. 1988). In general a MGARCH model has the mean equation of

$$\mathbf{y_t} = \mathbf{c} + \boldsymbol{\varepsilon_t}, \quad (6)$$

$$\text{where} \quad \boldsymbol{\varepsilon_t \mid \Omega \sim N(0,H_t)}$$

restricted to the bi-variate case the vectors are:

$$\mathbf{y_t} = [y_{1t}\ y_{2t}],\ \boldsymbol{\varepsilon_t} = [\varepsilon_{1t}\ \varepsilon_{2t}],$$

and

$$\mathbf{H_t} = \begin{vmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{vmatrix}$$

Ht is the covariance matrix, where h11t is the variance of the variable **y1t** and **h12t** is the covariance between **y1t** and **y2t**. Depending on the specification of the MGARCH, this covariance matrix is designed in different ways. It cannot be estimated in a general specification as this would involve an extremely complex estimation. One of the most parsimonious specifications is the so-called, diagonal VECH MGARCH model. In this specification, the covariance matrix is converted to a vector of variance and covariance, which is possible because $\mathbf{h2_{1t} = h12t}$ and hence the model estimated becomes:

$$\mathrm{vech}(\mathbf{H_t}) = \mathrm{vech}(\mathbf{A_0}) + \Sigma\, \mathbf{A_i}\, \mathrm{vech}(\boldsymbol{\varepsilon}_{\mathbf{t-i}}\, \boldsymbol{\varepsilon}_{\mathbf{t-i}}\mathbf{'}) + \Sigma\, \mathbf{B_j}\, \mathrm{vech}\, (\mathbf{H_{t-j}}) \quad (7)$$

where A_0 is a vector of the long run variance and long run covariance, A_i is the matrix of coefficients on the innovations $\varepsilon_{t-i}\, \varepsilon_{t-i}'$ and $\mathbf{B_j}$ is the matrix of coefficients on the past variances and covariance terms H_{t-j}. The covariance estimations with this model depend only on the past covariance and the past innovation term but not directly on the past variances of the variables (Wang 2009).

Stationarity conditions for GARCH specifications state that the sum of the weights for the past innovations ε^2_{t-1} and the past volatility σ^2_{t-1} should be below one: $\alpha_1+\beta_1<1$. If this is not given, then the process is not covariance stationary. However, Nelson (1990) and Bougerol and Picard (1992) show that if a GARCH model is not covariance stationary, the standard asymptotically-based inference procedures are generally valid because the model is still strictly stationary or ergodic[6] (Wang 2009). Moreover, the coefficients should be greater than zero as otherwise the model is unstable.

Regression Analysis

For a statistical assessment of the various cases of interest (explained in more depth later in the paper), the estimated values for time-varying volatility and especially time-varying correlation will be regressed on a time trend and dummy variables that indicate the times of economic crisis as well as dummy variables that were created for the period of extraordinary high oil prices. Furthermore, the amount of corn used for fuel production in the US will be included. The model is then estimated by OLS, using the following specification:

$$\sigma_t = \beta_0 + \beta_1 t + \beta_2\, \mathrm{EthanolProd} + \boldsymbol{\beta}'\mathbf{DU} + u_t \quad (8a)$$

$$\rho_t = \beta_0 + \beta_1 t + \beta_2\, \mathrm{EthanolProd} + \boldsymbol{\beta}'\mathbf{DU} + u_t \quad (8b)$$

where σ_t is the estimated volatility and ρ_t is the estimated correlation. Furthermore, u_t is a white noise process with zero mean, β_1 is the coefficient on the time trend t, β_2 is the coefficient on the variable “Fuel” which denotes the fraction of corn used for ethanol production from total corn supply in the US. The vector $\boldsymbol{\beta}$ consists of coefficients on the respective dummy variables **DU**. Two dummy variables are used in the regression analysis. The first dummy variable is created for the oil price peak between October 2007 and September 2008. Another dummy variable for the economic crisis is set to begin in July 2008 as the GDP growth in the United States became substantially negative in the third quarter of 2008 as reported by the US Department of Commerce (BEA 2010). December 2009 was set as the

6 A process is ergodic for the second moment, if its temporal covariance converges with probability 1 to the ensemble covariance.

ending date for the for the economic crisis due to the fact that the GDP started rising slowly again at this time.

A time trend clarifies whether one of the main determinants of the volatility gain is significantly increasing or decreasing over time. This will serve as an indication of what can be expected concerning the future tendency of the determinants. Assuming that the causes underlying the trend will continue in the future, an extrapolation of the trend into the future gives an estimate how the reduction from mixing bio-fuel will develop.

The percentage of the amount of corn used for fuel production in total US corn supply[7] is included in order to investigate whether there is a significant relationship between the upsurge of a bio-fuel industry and the behaviour of one of the determinants of the volatility gain.[8] The rationale stems from findings and claims in the prevailing literature about bio-fuel production. It is often claimed that energy and agricultural markets are more integrated since bio-fuel production was established (Tyner 2009) meaning that new market forces are created between oil, gasoline and agricultural markets (Thompson et al., 2009).[9] The argument is based on the fact that energy and agricultural markets will interact more strongly when agricultural products are used for energy production. On the one hand, this can result in increased correlation between them as price links increase which will result in increasing correlations between ethanol and gasoline prices. On the other hand, volatility spillovers between the markets may occur. Provided that volatility and correlation change when bio-fuels are produced, important implications for the volatility gain are the result. For instance, if the volatility of ethanol increases with higher production levels, the volatility gain decreases at the same time. Hence, the expected benefits from establishing a bio-fuel industry will diminish. Similarly, if the price links between gasoline and ethanol strengthen with growing ethanol use for transportation, the volatility gain will decline.

Extraordinary high oil price periods are associated with higher production costs in energy intensive industries. Ethanol production costs are mainly determined by the cost of corn production. The agricultural sector is such an energy intensive industry. If the oil prices increase strongly their share in the production costs of ethanol increases. This can in turn lead to increasing correlations between gasoline and ethanol prices. Also, volatility in oil prices will be transmitted more strongly to ethanol

7 Data for the two variables (corn used for ethanol production and total corn supply) was only available in quarterly terms. Therefore, it is assumed that the values smoothly grow/decline from one month to the next.
8 Corn is the most relevant feedstock used for ethanol production in the U.S. (Serra et al., 2008).
9 Further studies supporting these claims and similar findings about the increasing links and volatility spillovers between energy and crop prices as well as between conventional and alternative fuels are Hertel and Beckman (2010); Kanamura (2008); Serra and Zilberman (2009); Zhang et al., (2009).

prices if its share in production costs increases. The dummy variable will therefore serve as a control variable for the extreme peak in oil prices in 2007 and 2008 in order to separate this influence from the effect of other variables such as the time trend.

Finally, the inclusion of a dummy variable for the economic crisis will provide information about the importance of a volatility gain for an economy. As fuel price volatility has negative effects on economic growth (Ferderer 1996; Guo and Kliesen 2005; Awerbuch and Sauter 2006), the possibility of reducing the price volatility in such times is very beneficial. Regressing the determinants on the dummy will therefore reveal whether there is indeed an additional value from bio-fuel blending.

Data and Descriptive Statistics

Monthly ethanol and gasoline wholesale prices stem from the US market. The U.S. produced over 50% of world ethanol output in 2008, (RFA 2010) and the proportion of ethanol consumed in the US of overall gasoline consumption lies at roughly seven percent (CARD 2010). The main sources of the data collected are the International Sugar Organization, the Energy Information Administration and the International Monetary Fund.[10]

Price volatility is usually measured as the standard deviation of the price-changes. Fuel price-changes, like most financial time-series, usually change over time and often are serially correlated. That is, high returns are followed by high returns and low returns are followed by low returns - a phenomenon Engle (2001) called 'volatility clustering'. An indication of non-normality and serial correlation of the price-changes are excess kurtosis and skewness. Kurtosis measures the magnitude of the extremes. If the data has a normal distribution, the kurtosis should be three (Engle 2004). Table 2 summarizes the statistical properties of the data.[11] The time-series of ethanol and gasoline prices clearly exhibit large excess kurtosis as the value is above three. Furthermore, the variables exhibit negative skewness, indicating the presence of a left skew. This suggests that there are few extremely low values, whereas the mean is above the median as most of the values are agglomerated there. The graphs one and two of the fuel price-changes indicates serial correlation as high returns are followed by high returns.

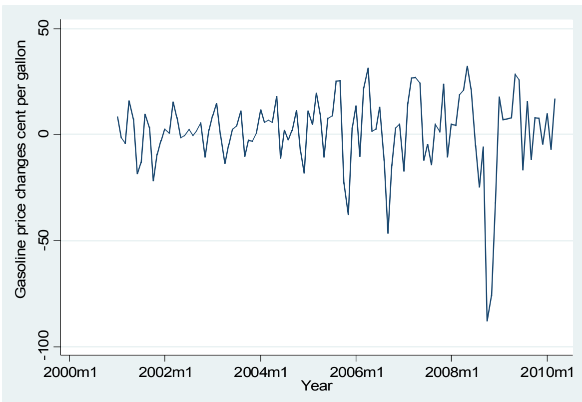
10 An exhaustive list of all sources can be found in the APPENDIX table 4.
11 Test results for the statistical tests in table 2 are attached in APPENDIX II

Descriptive Statistics

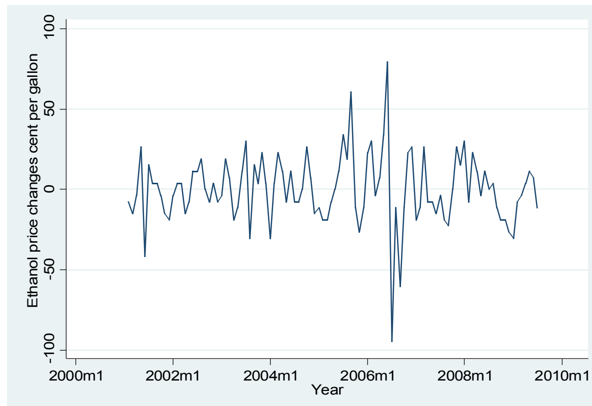
	Statistics of level of prices					Statistics of price-changes				
	Obs.	Mean	Standard Deviation	Min.	Max.	Standard Deviation	Skewness	Kurtosis	Changing Variance (Levine Test)	ARCH Effects (LM-Test) Chisq
Gasoline USD ct/gallon	195	117	67	39	337	22	-2.17	14.71	19.51*** Df(3,190)	47.404*** Df(1)
Ethanol USD ct/gallon	103	185	54	95	379	14	-0.26	6.89	4.92*** Df(4,97)	13.379*** Df(1)

***, **, and *, indicate significance on 1%,5%, and 10% level. Df(*) denote the degrees of freedom for the Levene test statistic and the Lagrage-multiplier test respectively.

Table 2



Graph 1: Gasoline price-changes in cent per gallon

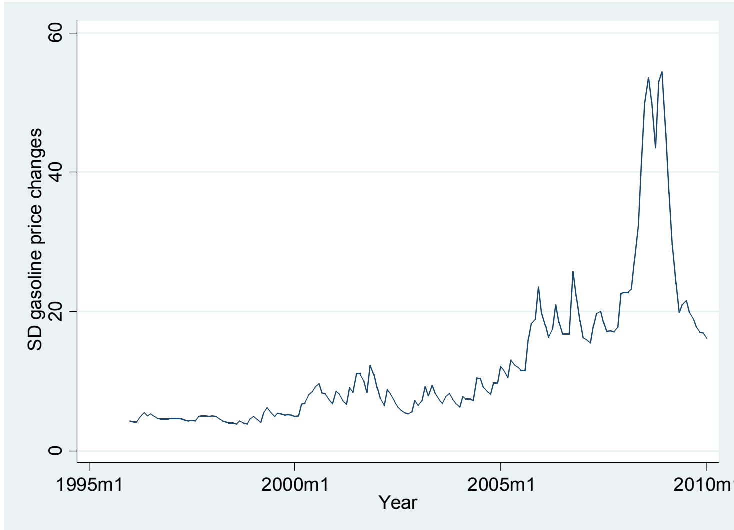


Graph 2: Ethanol price-changes in cent per gallon

In order to test for changing variance over time, a Levene test was performed. For that purpose the data was grouped into different time intervals. The null-hypothesis of equal variance is tested against the alternative hypothesis of changing variance. In both price series of the suspicion of changing variance was confirmed. Furthermore, the Lagrange-Multiplier test as proposed by Engle (2004) was employed in order to test for auto-regressive conditional heteroskedasticity. The null-hypothesis of no ARCH-effect was tested against the alternative hypothesis of ARCH disturbances in the first lag of the price-changes. The null-hypothesis of no ARCH-effects was rejected for gasoline and ethanol price-changes.

Empirical results

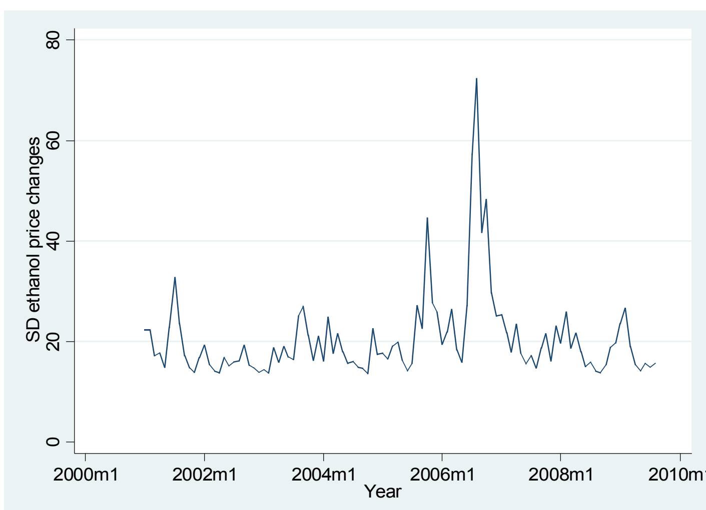
The best model to measure volatility in gasoline prices includes one arch and one garch term, as well as the lagged value of crude oil prices. Robust standard errors are used as the data is not normally distributed. All terms included in the maximum likelihood estimation are significant on a 1% level which indicates that the model fits the data very well. Stability conditions are met as the weights assigned to the terms included are positive and below one. Furthermore, tests on the residuals (see APPENDIX III) provide evidence, that there is no (very small amounts of) auto-correlation left in the lags. Hence, the model exploits the available information in the data reasonably well.



Graph 3: Volatility of gasoline prices in cent per gallon

The graph illustrates the conditional volatility in gasoline prices over time where gasoline price volatility clearly increased over the past decade. The minimum value of volatility in gasoline prices is measured to be 3.8 cent per gallon while the maximum volatility is 54.4 cent per gallon. On average gasoline prices fluctuate with a volatility of 11.6 cent per gallon.

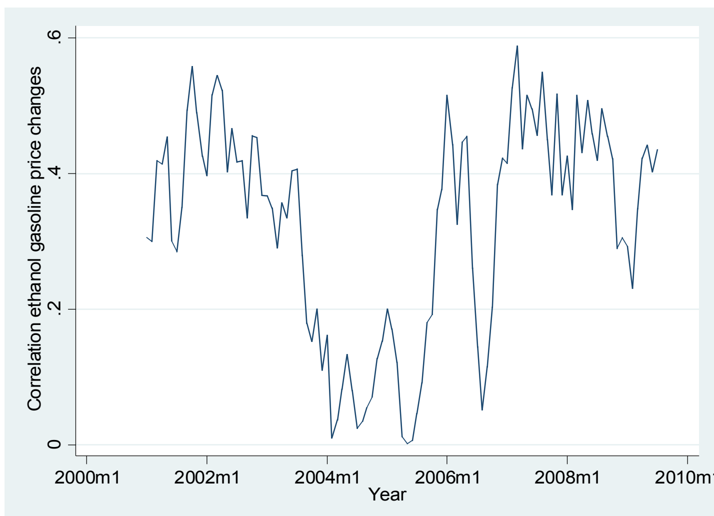
Ethanol price volatility is modelled as a GARCH(1,1) process. Again robust standard errors are used and the coefficients on the arch and garch terms are significant on a 5% level. The weights are below one and therefore the model is stationary. The portmanteau-test on the residuals is furthermore sufficiently low.



Graph 4: Volatility of ethanol prices in cent per gallon

Graph 4 above shows the behaviour of ethanol price volatility over the past decade. On average volatility in ethanol prices is 21.6 cent per gallon while the lowest volatility is 13.7 and the largest value for price volatility of ethanol is 72.3 cent per gallon. Unlike gasoline price volatility, ethanol price volatility does not seem to follow a trend over time.

The best model for the estimation of correlation between gasoline and ethanol prices turns out to be a multivariate GARCH(1,1) process. Here, the covariance and variance equations includes one lag of the innovation term and the second lag of the past covariance and variance term respectively. In order to account for the fact that the lag of oil prices has explanatory power for the volatility of gasoline prices, the latter where filtered by the former before correlation is estimated. This is done by using the residuals of the regression of gasoline price-changes on the lagged value of oil prices.[12] The correlation is then calculated by dividing the monthly values measured for the covariance by the product of the square-root of the simultaneously measured variances.



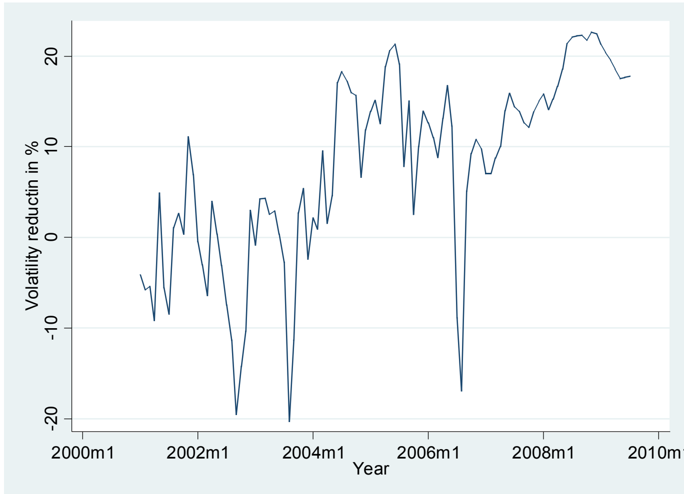
Graph 5: Correlation between gasoline and ethanol prices

The time-series of estimated correlation coefficients as illustrated in graph 5 above. According to these estimations the correlation between gasoline and ethanol prices is on average 0.32. The lowest value measured is close to zero with a value of 0.00149 and the maximum correlation in this time period was 0.588.

The volatility of the alternative fuel is higher on average as well as in its extremes. Hence, as illustrated in table 1 above, whether a volatility gain could have been achieved is uncertain but possible as the correlation is never perfectly positive. The graph below illustrates the volatility gain

12 This method can result in a generated variable bias. This affects the standard errors and therefore the statistical inference. In order to account for this, the estimated coefficient is only regarded as significant at least on the 5% level.

possibly achieved in the past using a 20% blending ratio. As can be seen, historically, a volatility gain would not always have been the result of diversification.



Graph 6: Historical volatility reduction using a 20% blending ratio

Therefore, an investigation of the trends in order to predict the possibility of a volatility gain for the future is quite important in order to evaluate whether this benefit can de facto be achieved when establishing a bio-fuel industry.

Regression Analysis

The results of the regression analysis[13] and the implications are summarized in table 3 below. The correlation does not change with the level of ethanol production. There is a U-shaped time trend found in the regression results which implies that the correlation first decreased and is now on an increasing path. However, dividing the observation into sub-samples shows that increasing correlation is followed by decreasing correlation which in turn is followed by increasing correlation. This finding mirrors the fact that there is a unit root in the time-series of correlations. Therefore, it cannot be inferred, that the correlation will follow an increasing trend in the future, but is rather floating within the bounds of the minimum and maximum values. Furthermore, the correlation significantly deceases in times of an economic crisis. Ethanol price volatility does not show significant trends over time. Higher ethanol production results in significant decreasing volatility in ethanol prices. There is no significant difference in ethanol price volatility during an economic crises. In contrast to ethanol price volatility there is a positive upward trend in the volatility of gasoline prices but no change as a result of growing production of ethanol for fuel use. Besides that, the volatility in gasoline prices is significantly higher during an economic crisis. Not surprisingly, the volatility in gasoline prices also increased during the

13 The regression-analysis output table is included in APPENDINX IV

high oil price period.

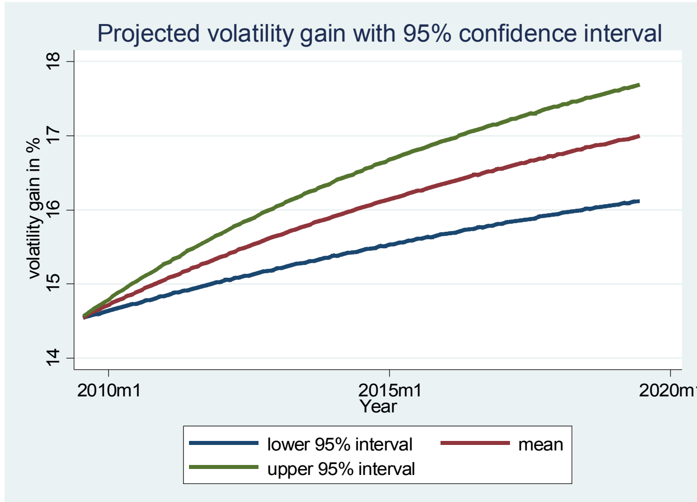
	Time trend	Bio-fuel production	Economic crisis	High oil prices	Overall tendency
Corr($p_{ethanol}$;$p_{gasoline}$)	⇵	→	↘	→	⇵
$\sigma_{ethanol}$	→	↘	→	→	↘
$\sigma_{gasoline}$	↗	→	↗	↗	↗
Implication for the volatility gain	↗	↗	↗	↗	↗

→no change; ↗ increase; ↘decline; ⇵ effect unclear (values float within a range)

Table 3

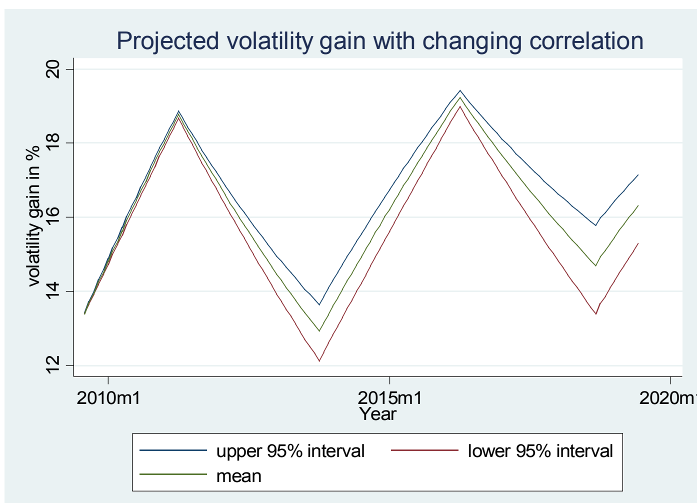
The overall effect on the volatility gain is clearly positive. The correlation strongly fluctuates around 0.32 but is always positive. Ethanol price volatility is decreasing with the level of ethanol production, which increased on average by 0.06 percentage points per month. Since the correlation is always positive, the effect of a decrease in ethanol price volatility is unambiguously positive. Finally, the volatility in gasoline prices is increasing over time which also results in increasing gains from blending gasoline with ethanol.

Assuming a 20 percent blending ratio and an on average constant correlation between the two prices, the volatility gain increases from 14.56 percent in 2009 to 16.99 percent in 2019. Using the 95% confidence interval of the trending coefficients measured in the regression analysis, the lower bound of the volatility gain will increase from 14.55 percent in 2009 to 16.12 percent in 2019, while the upper bound will be an increase in the volatility gain from 14.58 percent in 2009 to 17.68 percent in 2019.



Graph 7: Volatility gain projection assuming constant correlation.

Taking into account that the correlation fluctuates around its mean within the measured extremes of 0.14 percent and 58.82 percent in an interval of approximately 30 month, the volatility gain will fluctuate roughly between 12 and 19 percent with a general upward trend.



Graph 8: Volatility gain projection with up and downward trends in correlation.

In addition to the trending behaviour, a positive increase in the volatility gain is also found in times of an economic crisis. Gasoline price volatility appears to be higher compared to the rest of the observation period during a crisis. At the same time, the correlation between gasoline and ethanol prices is lower than usually. The net effect of these two changes on the size of the volatility reduction will be positive. Therefore, blending is especially valuable as it diminishes the increasingly negative effects of gasoline price volatility under such circumstances and may thus contribute to faster recovery.

How valuable would such a volatility gain be? In order to give an estimation about this, we make use of a formula developed by Awerbuch and Sauter (2006)[14]. The formula is constructed from several GDP-oil-price elasticities which puts the percentage change in oil prices in relation to the resulting percentage change in GDP. Taking the average of sixteen studies conducted on this relationship gives an average oil-GDP elasticity of 7.3% (Awerbuch and Sauter 2006: 2814). The avoided loss is then calculated as

% oil price change x GDP-elasticity x GDP

Since the data used in this paper, stems from the US market, the projection will be calculated for the US economy. In 2010 the US GDP amounted to $13,220.502 bn. (constant USD) (IMF 2011). Gasoline consumption accounts for around 45 percent of total oil use in the US (EIA 2011). Thus, 45% of the oil-GDP effect can be mitigated by using ethanol fuel blends. The prevented loss from using a 20% blending ratio in gasoline is then calculated as 0.45 x VR % x GDP-elasticity x GDP: For 2010 this would have been on average 0.45 x 0.1491 x 0.073 x 13,220.502 = 64.73 bn. USD. Assuming an annual growth rate of 2.8% per year[15] the accumulated prevented loss from mixing between 2010 and 2019 amounts to 795 bn. USD in the mean scenario assuming constant correlations.

Conclusion

This paper investigated the possibility, historical patterns and future tendencies of a volatility gain from blending ethanol with conventional gasoline on the basis of US market data. Although the average and extreme values of the bio-fuel volatility are larger than the volatility in the conventional fuel, a volatility gain can be achieved. This is a result of the underlying trends in the volatility of ethanol and gasoline prices which were detected in this study. Gasoline price volatility increased over time, while ethanol price volatility decreased with increasing production of ethanol. As a result volatility in gasoline prices became larger than the volatility in ethanol prices which in turn always results in a diversification gain. According to the underlying trends detected via the regression analysis, diversifying into ethanol fuels, will become increasingly beneficial in the future. Furthermore, additional value from blending fuels results from the fact that increasing volatility reductions and thus high benefits from ethanol blending,

14 It is recognized that the formula given by Awerbuch and Sauter (2006) is supposed to measure the effect of oil price changes on GDP. In this paper the effect of reduced *volatility* in gasoline prices is measured. However, the formula still gives a reasonable approximation of the value as higher price changes also increase volatility. Furthermore, Ferderer (1996) finds that volatility in oil prices may be more important in explaining fluctuations in industrial production than the level of oil prices. Thus, the calculated losses are rather underestimated.

15 As assumed by the US bureau of Labor Statistics for the period of 2006-2016. http://www.bls.gov/opub/ooq/2007/fall/art05.pdf

will also appear in times of an economic crisis. From the projections drawn in this study it can be estimated, that the cumulated benefits from ethanol blending in the future amount on average to 795 bn. USD for the US market. Hence, the volatility gain from blending fuels is another benefit that should be accounted for in cost benefit analysis that are conducted in order to assess the an investment in the establishment of a bio-fuel industry form a macro-economic point of view.

Further research should focus on shedding more light into the driving forces behind the trends in the volatility of gasoline prices as well as the driving forces behind the changes in the correlation between gasoline and ethanol prices. This is important to determine with higher certainty whether a volatility gain will be the outcome of blending fuels in the future. Also, the cause of the immense increase in the volatility of ethanol prices around 2007 should be investigated. Such an extreme increase of ethanol price volatility, above the level of gasoline price volatility, makes a volatility increase from blending fuels very likely. Thus, it is important to find out, by what this increase is caused an how likely it is that it will occur again. Finally, the findings in this studies are based on the US market. The ethanol fuel market in the US is regulated by different policies. These policies may result in distortions of the market links between ethanol and gasoline prices that may establish in their absence. Therefore, it should also be explored, whether the implications for blending fuels may also result in less regulated markets.

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Data Sources

Variable	Source
Crude Oil Prices WTI	International Monetary Fund (2010) *www.imf.org/external/np/res/commod/externaldata.csv*
Gasoline Prices U.S.	U.S. Energy Information Administration (2010) *http://tonto.eia.doe.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RRUNYH&f=M*
Ethanol Prices U.S.	International Sugar Organization. (2009). "Ethanol Supplement to the Sugar Year Book: 2009." *www.isosugar.org*.
Corn used for ethanol production in US	United States Department of Agriculture (2011) http://*www.ers.usda.gov*/Data/FeedGrains/CustomQuery/Default.aspx
Total US Corn supply	United States Department of Agriculture (2011) *http://www.ers.usda.gov/Data/FeedGrains/CustomQuery/Default.aspx*

Table 4

APPENDIX I The possibility of a volatility reduction from mixing bio-fuels

Volatility Reduction	ρ= 1	1< ρ ≥0	0< ρ≥ -1
$\sigma_{cf}>\sigma_{bf}$	+	+	+
$\sigma_{cf}=\sigma_{bf}$	0	+	+
$\sigma_{cf}<\sigma_{bf}$	–	–/+	–/+

Table 2

In the first case, (referring to the first row) when the volatility of the conventional fuel is higher than the volatility of the bio-fuel ($\sigma_{cf}>\sigma_{bf}$), there will always be a volatility reduction. The size will vary with the degree of correlation and the mixing proportions. This can be derived as follows. The highest possible value for the volatility of the fuel portfolio is reached when the prices are perfectly positively correlated, i.e. if the correlation equals one, ρ=1. Then the expression in (1) reduces to

$$\sigma^2_{blend} = [\omega\ \sigma_{cf} + (1-\omega)\ \sigma_{bf}]^2 \qquad (3a)$$

$$\text{or } \sigma_{blend} = [\omega\ \sigma_{cf} + (1-\omega)\ \sigma_{bf}] \qquad (3b)$$

which is the weighted average variance or weighted average volatility of the two assets. Inserting (3b) in (2a) yields for the volatility reduction

$$VR = \sigma_{cf} - [\omega\ \sigma_{cf} + (1-\omega)\ \sigma_{bf}] \quad (4)$$

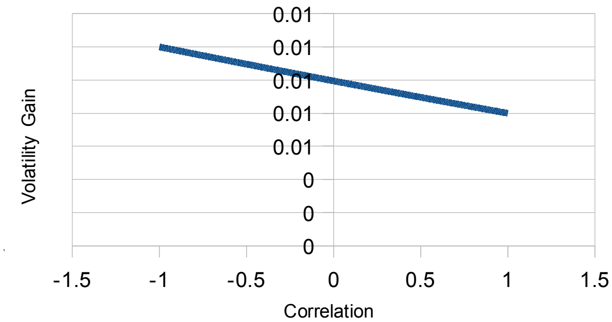
which is always positive under the condition of $\sigma_{cf}>\sigma_{bf}$ as adding an asset with a lower volatility will reduce the average volatility below the volatility of the first asset, σ_{cf}. Expressed formally: because the correlation is equal to one, the volatility of the fuel blend is the weighted average of the fuels [$\omega\ \sigma_{cf}$ + (1-ω) σ_{bf}] then if $\sigma_{cf}>\sigma_{bf}$, the average volatility of the fuel mix will be lower σ_{cf} > [$\omega\ \sigma_{cf}$ + (1-ω) σ_{bf}] than the volatility of the conventional fuel and hence, the volatility reduction will be positive VR>0. Under this circumstances of $\sigma_{cf}>\sigma_{bf}$ in conjunction with a price correlation in the interval of]1,-1], the volatility of the blend is always even lower than the weighted average volatility of the two assets and therefore always lower than the volatility of the conventional fuel. Hence, in case the conventional fuels volatility is higher than the volatility in the bio-fuel, the outcome is always a volatility reduction.

Under the condition of equal volatility $\sigma_{cf}=\sigma_{bf}$, (second row in table 2) there is no volatility reduction if the prices are perfectly correlated, ρ=1. This is because the volatility of the blend is then just equal to the volatility of the conventional fuel, $\sigma_{cf} = \sigma_{blend} \leftrightarrow \sigma_{cf}$ = [$\omega\ \sigma_{cf}$ + (1-ω) σ_{bf}], and then the expression in (4) becomes exactly zero. In contrast, there is always a volatility reduction achieved under this condition for fuel prices with a correlation below one, ρ<1. A correlation below one indicates that the price fluctuations of the two prices cancel each other out to the degree to which they are not correlated. The smaller the price correlation, the higher the amount of the changes that cancel out in the mix. If some of the price changes cancel out, the volatility of the blend will be lower than the weighed average volatility of the two assets. Under the condition of $\sigma_{cf}=\sigma_{bf}$ the blended fuel will always be less volatile than one single fuel. Therefore, equation (4) is positive for all correlations below one.

The last row summarizes the case where the volatility of the bio-fuel is higher than the volatility of the conventional fuel, $\sigma_{cf}<\sigma_{bf}$, with respect to different correlation intervals. Here, no volatility reduction can be achieved if the two prices are perfectly positively correlated, ρ= 1. In fact, it will always be negative i.e. a volatility increase will be the effect of blending. This can be seen if we consider that the volatility of the blend will be the weighted average of the volatility of the two prices. Mixing the conventional fuel with a fuel that has higher volatility will increase the average volatility above the volatility of the conventional fuel. Hence, the expression in (4) will always be negative.

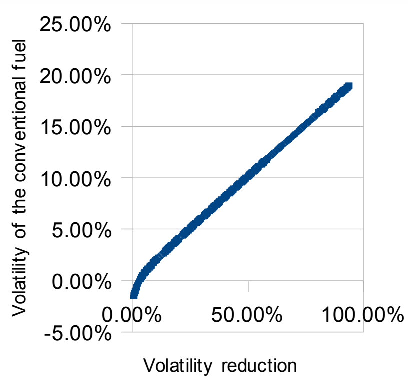
If the correlation is less than one, both a volatility reduction and a negative volatility effect can be the result under the condition of higher bio-fuel volatility, $\sigma_{cf}<\sigma_{bf}$,. The outcome in this case depends on the difference between the volatility of the two fuels (σ_{cf} - σ_{bf}), on the degree of correlation, and the mixing proportions can also tip the balance between a positive and a negative value for the volatility reduction. If the difference between the conventional and bio-fuel volatility is too high, i.e. if σ_{bf} -σ_{cf} is very large, there will never be a volatility reduction even if there is a perfect anti-correlation between the prices.

A quick look at the behaviour of function (2c), which expresses the volatility reduction, may be very useful for the understanding of the effects of the changes in the determinants of the volatility gain due to their time-varying behavior.

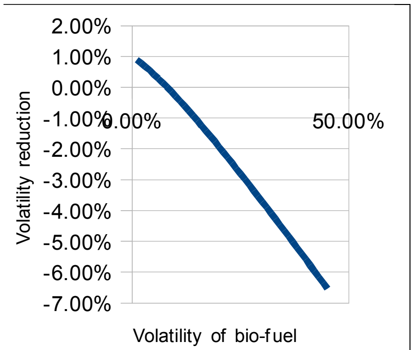


Graph 9: Volatility reduction as a function of correlation

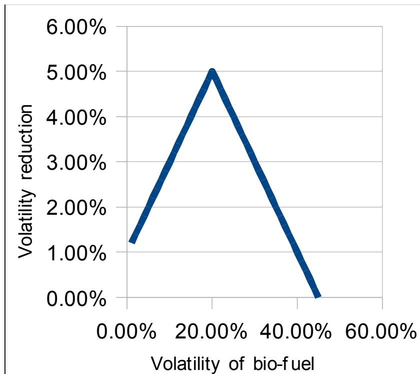
The graph on the left illustrates the volatility reduction as a function of correlation. The former is, ceteris pariubus, always larger the lower the correlation between the fuels. Furthermore, as shown in graph 10, the volatility reduction always increases with increasing values of the volatility of the conventional fuel, holding all other factors fixed.



Graph 10: Volatility reduction as a function of the volatility of the conventional fuel



Graph 11: Volatility reduction as a function of the volatility of the bio-fuel in conjunction with a positive correlation



Graph 12: Volatility gain as a function of the bio-fuel volatility in conjunction with a negative correlation

Finally, increasing values of the volatility of the bio-fuel have diverse effects within different correlation intervals. If the correlation is within the interval of [1,0], the volatility gain declines (increases) with increasing (decreasing) values of the volatility of the bio-fuel, σ_{bf}. This can be seen in graph 11. A negative correlation, in contrast yields ambiguous outcomes for the volatility gain when the volatility of the bio-fuel changes. First, the volatility gain increases with increasing values of the bio-fuel volatility and at a certain point, the volatility gain decreases with further growing volatility of bio-fuel prices. The inflection point varies with the weights assigned to the two assets and the difference in volatility between both fuels. In graph 6 the inflection point is reached at a volatility in bio-fuel prices of 20%.

APPENDIX II Test results for descriptive statistics

Augmented Dickey-Fuller test for unit root and test for presence of ARCH effects

Variable	Dicky-Fuller-test	Variable	Test for ARCH effects
Gasoline	-4.220***	Δ Gasoline	47.404***
Ethanol	-2.073	Δ Ethanol	13.379***
Volatility Ethanol	-7.315***		
Volatility Gasoline	-3.394*		
Correlation between corn and ethanol	-2.575		
% of corn used for fuel production	-6.363 ***		

*,** and *** denote significance on 10%,5% and 1% level respectively. A variable is considered to be integrated of order zero if the null-hypothesis was rejected at least on a 5% percent level.

Table 6

Test for seasonal effects

Before measuring price volatility of the series, it is also of relevance to test whether the price series show significant seasonal effects. The rationale behind this is that volatility is supposed to measure risk and as seasonal patterns are observed on a very regular basis, they are sufficiently predictable such that they should not be considered as imposing risk. Therefore, the prices will be seasonally adjusted in case they exhibit significant seasonal patterns. The test results indicate that there is no evidence of seasonal patterns in all the price series examined in this part, and therefore there is no need to filter out seasonal effects.

APPENDIX III

GARCH estimations and test results

	Volatility estimation ethanol GARCH(1,1)	Volatility estimation gasoline GARCH(1,1)
Exogenous variables - l.oil_wti	-	0.0476 (0.0059)***
ARCH	0.462 (0.217)***	0.1985 (0.0673)***
GARCH	0.2995 (0.127)***	0.62 (0.092)***
Constant	122 (41.8)***	0.822 (0.659)
Portmanteau-test statistic	Lag(20) 30.09*	Lag(27) 32.6
Observations	102	194

*,** and *** denote significance on 10%, 5% and 1% level respectively. Newy-West robust standard errors are used.

Table 7

Diagonal vech multivariate GARCH model

MGARCH D-VECH of gasoline and ethanol price-changes

Sigma	Gasoline	3.98 (8.31)
	Covariance	1.75 (3.39)
	Ethanol	164.9 (50.6)***
ARCH	Gasoline	0.196 (0.06)***
	Covariance	0.068 (0.034)**
	Ethanol	0.533 (0.231)**
GARCH	Gasoline	0.835 (0.074)***
	Covariance	0.9197 (0.0444)***
	Ethanol	0.202 (0.147)

*,** and *** denote significance on 10%,5% and 1% level respectively. Newy-West robust standard errors are used.
It is recognized that the coefficients in equation for gasoline prices, are slightly above 1 which would indicate, that the stationarity conditions are not met. However, a standard t-test on the sum of the coefficients was not able to reject the null-hypothesis that the sum of the coefficients is equal to one.

Table 8

APPENDIX IV

Regression analysis

Output regression-analysis

	Volatility ethanol	Volatility gasoline	Correlation gasoline – ethanol prices-changes
Time trend	0.022759 (0.0162429)	.0794637 (0.0118453)***	-0.072586 (0.0122445)***
Squared time trend	-	-	0.0001609 (0.0000276)***
% of corn used for fuel production	-0.305131 (0.1269276)**	0.0019573 (0.2200341)	0.00011257 (0.0035225)
Crisis	-2.701671 (1.591828)	14.77269 (3.413754)***	-0.2559655 (0.0721607)***
Oil peak	-1.96827 (1.424858)	12.95749 (2.459619)***	0.0160884 (0.0468173)
Prob > F	0.0000	0.0000	0.0000

** and *** denote significance on 5% and 1% level respectively. Newy-West robust standard errors are used.

A generated variable is subject to measurement error. As described in Wooldridge (2006), if there is a measurement error in the dependent variable and the measurement error has not zero mean then the intercept will be biased, which is not a problem for the inferences drawn in this paper. However, as standard errors are likely to be biased downwards, the 10% level will not be accepted as a level of significance.

Table 9