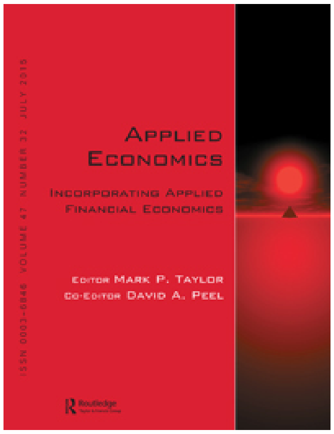

Applied Economics
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/raec20

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Published online: 24 Feb 2015.

Applied Economics, 2015
Vol. 47, No. 32, 3482–3498, http://dx.doi.org/10.1080/00036846.2015.1016210

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This article employs a variety of econometric models (including OLS, VEC/VAR, DCC GARCH and a class of copula-based GARCH models) to estimate optimal hedge ratios for gasoline spot prices using gasoline exchange-traded funds (ETFs) and gasoline futures contracts. We then compare their performance using four different measures from the perspective of both their hedging objectives and trading position using four different measures: variance reduction measure, utility-based measure and two tail-based measures (value at risk and expected shortfall). The impact of the 2008 financial market crisis on hedging performance is also investigated. Our findings indicate that, in terms of variance reduction, the static models (OLS and VEC/VAR) are found to be the best hedging strategies. However, more sophisticated time-varying hedging strategies could outperform the static hedging models when the other measures are used. In addition, ETF hedging is a more effective hedging strategy than futures hedging during the high-volatility (crisis) period, but this is not always the case during the normal time (post-crisis) period.

Keywords: copulas; optimal hedging; futures; exchange-traded funds; gasoline

JEL Classification: C14; C22; C32; G11; Q42

I. Introduction

Gasoline is one of the major fuels consumed worldwide and the main product refined from crude oil. It is primarily used as a motor fuel, but can also be used for other purposes like removing paint and grease. Because of price volatility and its widespread use, it has always been important for large producers and consumers of fuel products – refining and oil companies, airlines and trucking companies – to reduce the price risk where possible. These gasoline producers and consumers can use the futures market to

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reduce exposure to price volatility. The main gasoline futures contracts are traded on the New York Mercantile Exchange (NYMEX) and called Reformulated Blendstock for Oxygenate Blending (RBOB). Their average daily trading volumes are approximately 33 000 contracts in 2008 and about 43 000 contracts in 2011.[1] Ciner (2006) reports that a majority of gasoline futures positions is held by commercial traders (i.e., producers, refiners and retailers) who are commonly referred to as hedgers. This suggests that gasoline producers and consumers indeed resort to futures markets to hedge their exposures to changing gasoline prices.

An alternative hedging tool for gasoline producers (short hedgers) and consumers (long hedgers) is the United States Gasoline Fund (UGA), an Exchange-Traded Fund (ETF) that is designed to track the movements of gasoline prices. It invests exclusively in the front-month RBOB contract, which expires earliest. Since its introduction in February 2008, the fund has maintained a relatively healthy daily trading volume of roughly 40 000 shares on average. The primary benefits of ETFs for hedging are the comparatively low transaction and holding costs compared to those of futures contracts. In addition, the smaller minimum margin requirements and the ability to trade the ETFs in small amounts allow smaller hedgers to participate in hedging activities. While there are some empirical studies regarding the hedging effectiveness of futures contracts in the gasoline market (see, e.g., Alizadeh *et al.*, 2008; Juhl *et al.*, 2012; Alexander *et al.*, 2013), hedging risks arising from gasoline price fluctuations using the gasoline ETFs has not been investigated.

This article investigates and explores the possibility of using gasoline ETFs as an instrument for risk reduction in the gasoline market. We also evaluate the hedging performance of gasoline ETFs against that of gasoline futures contracts.

One of the main issues in hedging involves the determination of the optimal hedge ratio. The most widely used hedging strategy is based on the minimization of the variance of the hedged portfolio.[2] The minimum variance hedge ratio (MVHR) is defined as the number of hedging contracts per unit of the spot asset that will minimize the variance of the hedged portfolio returns. The calculation of MVHRs depends on the way in which the variances and covariances are specified. With the objective of minimizing the unconditional variance of the hedged portfolio, early research simply uses an OLS regression to estimate time-invariant MVHRs (see, e.g. Ederington, 1979; Figlewski, 1984; Benet, 1992). However, given the time-varying nature of the conditional distributions of financial and commodities returns and the development of ARCH and GARCH models, a number of studies have applied various types of bivariate GARCH (BGARCH) models to estimate time-varying conditional variances and covariances and subsequently generate dynamic MVHR. It is often found that dynamic hedge ratios outperform static hedge ratios (see Kroner and Sultan, 1993; Alizadeh *et al.*, 2004; Chan and Young, 2006; among many others). However, most of these studies overlook the possibility that spot and futures prices could be non-stationary and cointegrated (Engle and Granger, 1987). If this is ignored, the estimates of the MVHR may be underestimated (Kroner and Sultan, 1993). Consequently, the bivariate error correction GARCH models have become a very popular method of estimating dynamic MVHRs.

The aforementioned previous studies, however, construct the optimal hedge ratio via the covariance structure under bivariate normal and linear dependence assumptions, contradicting the well-documented nonlinear (and possibly asymmetric) dependence structure in financial and commodity returns. Ignoring these aspects could influence the estimation of the conditional variances and covariances and, hence, the hedging effectiveness obtained. Since the important development in modelling conditional dependence, known as the copula, was proposed by Sklar (1959), several recent studies (Hsu *et al.*, 2008; Lai *et al.*, 2009; Lee, 2009) have introduced copula-GARCH approaches for the estimation of the optimal hedge ratio. They conclude that their proposed models show good performance for hedging stock and currency prices. Nevertheless, the results may be different for the case of gasoline hedging.

The recent literature on hedging strategies mainly focuses on improving the estimation of the optimal hedge ratio by using more sophisticated econometric methods and on comparing the performance of hedge ratios estimated from selected models. However, little research to date has considered the impact of the financial market crisis on the performance of

[1] One gasoline futures contract represents 42 000 gallons of gasoline.
[2] See Chen *et al.* (2003) for a review of different theoretical approaches to the optimal hedge ratios.

different hedging methods. Only Sim and Zurbruegg (2001) attempt to examine the relative effectiveness of various hedging strategies before and after the 1997 Asian financial market crisis. The study considers the case of South Korea stock and futures markets. They find that, after the crisis, the relative performance of using static hedging techniques increases, though not significantly better than sophisticated time-varying hedging strategies. They argue that the general rise in volatility after the crisis has reduced the information content contained in past volatility, and this decline has led to the improvement of the relative performance of constant hedge ratios. Nonetheless, to the best of our knowledge, the potential impact of the recent financial crisis in 2008 on the relative effectiveness of hedging strategies has not been investigated or reported in the literature. Thus, the purpose of this article is to fill this gap. We test for the unknown structural break by adopting the Zivot and Andrews (1992) endogenous beak test. When there is a structural break over the sample period, an analysis for each sub-sample period will provide further insight into the impact of the change in the volatility structures on hedging performance of the two hedging instruments and different hedging models.

Regarding measures of hedging effectiveness, Cotter and Hanly (2006) suggest that the choice of performance measures should be based on hedger's objectives and trading position (short or long) because different performance criteria typically yield different results regarding the best hedging strategies. As gasoline hedgers may have different hedging goals, this study evaluates the performance of different hedging strategies from the perspective of both their hedging objectives and trading position. Specifically, we employ four different performance measures: the variance reduction measure, utility-based measure and two tail-based measures (value at risk (VaR) and expected shortfall (ES)). The first measure is most appropriate for the hedgers whose objective is to minimize the variability of their returns. The second criterion is for those who are concerned with not only the variance of the returns but also the level of expected returns. The last two measures are for hedgers whose objective is to minimize their downside risk. This approach allows us to comprehensively examine hedging effectiveness, during crisis and post-crisis periods, using two hedging instruments (gasoline ETFs and gasoline futures contracts) and a variety of econometric models (including OLS, bivariate vector error correction, bivariate GARCH and a class of copula-based GARCH models) for different types of hedgers.

The remainder of the article is organized as follows. Section II describes the hedging models. Section III details the data and preliminary diagnostic tests on the data. Section IV discusses the empirical results of the different hedging models. Finally, Section V provides the conclusions of the article.

II. Hedging Models

Let s_t and etf_t be random variables denoting spot returns and ETF returns of gasoline at period t, and $pf_{\mathrm{etf},t}$ denote the portfolio return with ETFs. Accordingly, the portfolio returns for short and long hedgers are respectively given as

$$pf_{\mathrm{etf},t} = s_t - \delta_{\mathrm{etf}}\mathrm{etf}_t \tag{1}$$

$$pf_{\mathrm{etf},t} = -s_t + \delta_{\mathrm{etf}}\mathrm{etf}_t \tag{2}$$

where δ_{etf} is the hedge ratio of ETFs. The variance of each portfolio is thus

$$\begin{aligned}\mathrm{var}(pf_{\mathrm{etf},t}) = \mathrm{var}(s_t) + \delta^2_{\mathrm{etf}}\mathrm{var}(\mathrm{etf}_t)\\ - 2\delta_{\mathrm{etf}}\mathrm{cov}(s_t, \mathrm{etf}_t)\end{aligned} \tag{3}$$

For the case of futures hedging, the futures returns at period t, denoted as f_t, is used in place of etf_t.

The optimal hedge ratio is then obtained by minimizing the variance of the hedged portfolios with respect to δ_{etf}. The calculation of MVHRs depends on the way in which the conditional variances and covariances are specified. The hedging models under study are categorized as OLS, vector error correction (VEC), dynamic conditional correlation (DCC) GARCH and copula-based GARCH (static and dynamic Gaussian, Student-t, Clayton, Gumbel and symmetrized Joe-Clayton) models. This constitutes 13 models under review. Model specification, parameter estimation and specific hedge ratio calculation for each model are presented accordingly.

Ordinary least squares model

A traditional approach to estimating static MVHR is to regress the return on the spot gasoline onto the return on the ETF:

$$s_t = \alpha + \delta_{\mathrm{etf}}^{\mathrm{OLS}} \mathrm{etf}_t + \varepsilon_t \tag{4}$$

where ε_t is a random error assumed to be normally distributed. The slope coefficient $\delta_{\mathrm{etf}}^{\mathrm{OLS}}$ is the OLS minimum variance hedge ratio. This model does not take into account the possibility that the residual series are autocorrelated and that spot and ETF prices could be cointegrated.

Vector error correction model

The vector error correction model considers the possible long-run cointegration between spot and ETF prices. If the spot and ETF price series are cointegrated of the order one, then the VEC model of the series is given as

$$s_t = \alpha_{0,s} + \alpha_{1,s}\mathrm{ECT}_{t-1} + \sum_{l=1}^{n}\beta_{1l,s}s_{t-l} + \sum_{l=1}^{n}\beta_{2l,s}\mathrm{etf}_{t-l} + \varepsilon_{s,t} \tag{5}$$

$$\mathrm{etf}_t = \alpha_{0,\mathrm{etf}} + \alpha_{1,\mathrm{etf}}\mathrm{ECT}_{t-1} + \sum_{l=1}^{n}\beta_{1l,\mathrm{etf}}s_{t-l} + \sum_{l=1}^{n}\beta_{2l,\mathrm{etf}}\mathrm{etf}_{t-l} + \varepsilon_{\mathrm{etf},t} \tag{6}$$

where $\mathrm{ECT}_{t-1} = S_{t-1} - \lambda_0\,\mathrm{ETF}_{t-1} - \text{constant}$ is the error correction term, λ_0 is a cointegrating coefficient, S_t and ETF_t are the log spot and ETF prices, respectively. The error terms, $\varepsilon_{s,t}$ and $\varepsilon_{\mathrm{etf},t}$, are independently identically distributed (*iid*) random vectors. The optimal static hedge ratio for ETF hedging is then calculated as

$$\delta_{\mathrm{etf}}^{\mathrm{VECM}} = \frac{\mathrm{cov}\left(\varepsilon_{s,t}, \varepsilon_{\mathrm{etf},t}\right)}{\mathrm{var}\left(\varepsilon_{\mathrm{etf},t}\right)} \tag{7}$$

The application of these static regression methods, however, ignores that prices and returns of financial assets and commodities exhibit time-varying second moments, and thus, the hedge ratios should be modelled in a dynamic framework.

Multivariate GARCH model

The multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) family of models is a group of models that mimics changing variances and covariances witnessed in the volatility clustering of financial time series. Following Engle and Sheppard (2001) and Engle (2002), we adopt a bivariate error correction model of s_t and etf_t with a DCC GARCH(1,1) structure to estimate the optimal dynamic hedge ratio. The mean equations are given by Equations 5 and 6, whereas the error terms, $\varepsilon_{s,t}$ and $\varepsilon_{\mathrm{etf},t}$, follow the GARCH(1,1) model with a zero mean and a conditional variance matrix H_t with a dynamic correlation ρ_t. Specifically,

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{\mathrm{etf},t} \end{bmatrix} | I_{t-1} \sim N(0, H_t) \tag{8}$$

$$H_t = \begin{bmatrix} h_{s,t}^2 & h_{\mathrm{setf},t} \\ h_{\mathrm{setf},t} & h_{\mathrm{etf},t}^2 \end{bmatrix} = \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{\mathrm{etf},t} \end{bmatrix} \begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix} \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{\mathrm{etf},t} \end{bmatrix} = D_t R_t D_t \tag{9}$$

$$h_{s,t}^2 = \beta_{0,s} + \beta_{1,s}\varepsilon_{s,t-1}^2 + \beta_{2,s}h_{s,t-1}^2 \tag{10}$$

$$h_{\mathrm{etf},t}^2 = \beta_{0,\mathrm{etf}} + \beta_{1,\mathrm{etf}}\varepsilon_{\mathrm{etf},t-1}^2 + \beta_{2,\mathrm{etf}}h_{\mathrm{etf},t-1}^2 \tag{11}$$

where $h_{s,t}^2$ and $h_{\mathrm{etf},t}^2$ are, respectively, the conditional variance for the spot and ETF returns and $h_{\mathrm{setf},t}$ is conditional covariance between spot and ETF returns. $D_t = \mathrm{diag}\left[h_{s,t}, h_{\mathrm{etf},t}\right]$ is a time-varying diagonal matrix of conditional SD. $R_t = J_t Q_t J_t = \mathrm{diag}(Q_t)^{-\frac{1}{2}} Q_t \mathrm{diag}(Q_t)^{-\frac{1}{2}}$ is the time-varying conditional correlation matrix, where $Q_t = (q_{ij,t})_{2\times 2}$ is a positive definite matrix, $J_t = \mathrm{diag}\left[q_{s,t}^{-1/2}, q_{\mathrm{etf},t}^{-1/2}\right]$ and Q_t satisfies

$$Q_t = (1 - \lambda_1 - \lambda_2)\bar{Q} + \lambda_1 \tilde{\varepsilon}_{t-1}\tilde{\varepsilon}_{t-1}' + \lambda_2 Q_{t-1} \tag{12}$$

where $\tilde{\varepsilon}_t = D_t^{-1}\varepsilon_t$ is the standardized disturbance vector, $\bar{Q}$ is the unconditional correlation matrix $\tilde{\varepsilon}_t$ and λ_1 and λ_2 are nonnegative parameters governing the dynamics of a conditional quasi-correlation and satisfying $\lambda_1 + \lambda_2 < 1$.

Following Engle (2002), the parameters for the DCC GARCH model[3] are estimated by a two-step maximum likelihood method. In the first step, the parameters in the univariate GARCH models are estimated for each residual series. In the second step, the parameters of the dynamic correlation are estimated using the results of the first step and the transformed residuals, $\tilde{\varepsilon}_t$. Given the estimates of H_t, the optimal dynamic hedge ratio can then be estimated by

$$\delta_{\text{etf},t}^{\text{DCC}} = \frac{h_{\text{setf},t}}{h_{\text{etf},t}^2} = \rho_t \frac{h_{s,t}}{h_{\text{etf},t}} \tag{13}$$

Copula-based GARCH model

An important limitation of all the models mentioned above is their typical assumption of bivariate normality. By contrast, the use of a copula function allows us to model joint distributions of random variables with greater flexibility both in terms of marginal distributions and the dependence structure. A copula-based GARCH model is, therefore, used to accommodate the deviations from bivariate normality in the financial data. In what follows, the model specification, estimation method, and several copula functions are presented.

Model specification and parameter estimation. Following Glosten *et al.* (1993) and Hansen (1994), we assume that each series i, $i = s, \text{etf}$, follows a GJR-skewed-t GARCH(1,1) model. The conditional mean equations are given by Equations 5 and 6, and the conditional variance for each series $i, i = s, \text{etf}$ is modelled as

$$h_{i,t}^2 = \gamma_{0,i} + \gamma_{1,i}\varepsilon_{i,t-1}^2 + \gamma_{2,i}h_{i,t-1}^2 + \gamma_{3,i}a_{i,t-1}\varepsilon_{i,t-1}^2 \tag{14}$$

$$\varepsilon_{i,t}|I_{t-1} = h_{i,t}z_{i,t}, z_{i,t} \sim \text{skewed} - t(z_i|\eta_i, \lambda_i) \tag{15}$$

where $a_{i,t-1} = 1$ when $\varepsilon_{i,t-1}$ is negative and $a_{i,t-1} = 0$ otherwise. The Hansen's skewed Student-t distribution is

$$\text{skewed} - t(z|\eta, \lambda) = \begin{cases} bc\left(1 + \frac{1}{\eta-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-\frac{\eta+1}{2}} \text{if } z < -a/b \\ bc\left(1 + \frac{1}{\eta-2}\left(\frac{bz+a}{1+\lambda}\right)^2\right)^{-\frac{\eta+1}{2}} \text{if } z \geq -a/b \end{cases}$$

$$a \equiv 4\lambda c \frac{\eta-2}{\eta-1}, b^2 \equiv 1 + 3\lambda^2 - a^2, c \equiv \frac{\Gamma\left(\frac{\eta+1}{2}\right)}{\sqrt{\pi(\eta-2)\Gamma\left(\frac{\eta}{2}\right)}}$$

where $\eta \in (4, 30)$ is the kurtosis parameter and $\lambda \in (-1, 1)$ is the asymmetry parameter.

The resulting standardized residuals $z_{i,t}$ from the GJR-GARCH model are then transformed into standard uniform random variables: $u_t = G_{s,t}(z_{s,t}|I_{t-1})$ and $v_t = G_{\text{etf},t}(z_{\text{etf},t}|I_{t-1})$, where $G_{i,t}$ is the conditional distribution function (CDF) of $z_{i,t}$ and I_{t-1} denotes all past return information. Using the Sklar's (1959) theorem,[4] the bivariate conditional distribution functions of $z_{s,t}$ and $z_{\text{etf},t}$ can be written as

$$G\left(z_{s,t}, z_{\text{etf},t}|I_{t-1}\right) = C_t(u_t, v_t|I_{t-1}) \tag{16}$$

where $C_t(u_t, v_t|I_{t-1})$ is the conditional copula function, which is defined by the two time-varying CDFs of continuous standard uniform random variables u_t and v_t.

Let $c_t(u_t, v_t|I_{t-1}) = \partial^2 C_t(u_t, v_t|I_{t-1})/\partial u_t \partial v_t$, $g_{z_{s,t}}\left(z_{s,t}|I_{t-1}\right)$ and $g_{z_{\text{etf}},t}\left(z_{\text{etf},t}|I_{t-1}\right)$ denote the conditional copula density function, the conditional density of $z_{s,t}$ and the conditional density of $z_{etf,t}$, respectively. Copula parameters are then estimated by the

[3] The models are fit in *R* using the rugarch (Ghalanos, 2013a) and rmgarch (Ghalanos, 2013b) packages.
[4] Let x_1 and x_2 be continuous random variables with a two-dimensional distribution function G and marginal distributions, G_1 and G_2. Sklar's (1959) theorem ensures the existence of a unique copula representation $C : [0, 1]^2 \to [0, 1]$ such that $G(x_1, x_2) = C(G_1(x_1), G_2(x_2))$. That is, the univariate marginal distributions and dependence structure that is represented by the copula functions can be separated. Such separation enables one to describe the time-varying dependence structure without assuming that the distribution is a multivariate Gaussian or a log normal distribution.

inference for the margins (IFM) method proposed by Joe and Xu (1996). This method is a two-stage estimation procedure; it enables us to estimate the marginal densities and copula density separately. Let the parameters in $c_t(u_t, v_t|I_{t-1})$, $g_{z_s,t}(z_{s,t}|I_{t-1})$ and $g_{z_{\text{etf}},t}(z_{\text{etf},t}|I_{t-1})$ be, respectively, denoted as θ_c, θ_s and θ_{etf}. In the first stage, the parameters of the marginal distribution are estimated from the univariate time series by

$$\hat{\theta}_s \equiv \arg\max \sum_{t=1}^{T} \log g_{z_s,t}(z_{s,t}|I_{t-1}; \theta_s) \tag{17}$$

$$\hat{\theta}_{\text{etf}} \equiv \arg\max \sum_{t=1}^{T} \log g_{z_{etf},t}(z_{etf,t}|I_{t-1}; \theta_s) \tag{18}$$

In the second stage, given the marginal estimates obtained from Equations 17 and 18, the copula parameters are estimated by

$$\hat{\theta}_c \equiv \arg\max \sum_{t=1}^{T} \log c_t(\hat{u}_t, \hat{v}_t|I_{t-1}; \theta_c) \tag{19}$$

Dynamic hedge ratios for copula-based GARCH models are then calculated from Equation 13. The conditional variances $h_{s,t}^2$ and $h_{\text{etf},t}^2$ are obtained from Equation 14, and the dynamic correlation ρ_t are generated from each of the following copula functions.

Copula functions. In this study, ten parametric copulas are used to combine the marginal distributions into the joint distributions. The first five are bivariate static copula functions and the latter five are dynamic versions of the static copulas. The first static copula function is a Normal (Gaussian) copula:

$$C_t^N(u_t, v_t; \rho) = \Phi_\rho(\Phi^{-1}(u_t), \Phi^{-1}(v_t)) \tag{20}$$

where Φ_ρ is a joint distribution of a bivariate standard normal distribution with the linear correlation coefficient, $\rho \in [-1, 1]$, and $\Phi(\cdot)$ represents the CDF of the standard normal distribution. The Normal copula is symmetric and implies zero dependence in the extreme tails. The second copula is the Student-*t* copula:

$$C_t^T(u_t, v_t; \rho, d) = t_{\rho,d}\left(t_d^{-1}(u_t), t_d^{-1}(v_t)\right) \tag{21}$$

where $t_{\rho,d}$ is a joint distribution of a bivariate Student-*t* distribution with the linear correlation coefficient, ρ, and the degrees of freedom parameter, d. $t_d(\cdot)$ is the CDF of the Student-*t* distribution with d degrees of freedom. The Student-*t* copula exhibits tail dependence.

The Normal and Student-*t* copulas belong to the class of Elliptic copulas. The other three static copulas we considered are, however, in the Archimedean class of copulas. The Archimedean copula can be expressed as

$$C(u_t, v_t) = \varphi^{-1}(\varphi(u_t) + \varphi(v_t)) \tag{22}$$

where φ is the generator of the copula, which is a decreasing convex function. Different generators induce different types of Archimedean copulas. In this study, we employ the Clayton, Gumbel and symmetrized Joe-Clayton (SJC) copulas. The Clayton copula implies a higher dependence at left tails of the marginal distribution. It is defined as

$$C_t^C(u_t, v_t; \theta_C) = \left[u_t^{-\theta_C} + v_t^{-\theta_C} - 1\right]^{-1/\theta_C} \tag{23}$$

where the association parameter is $\theta_C = 2\tau/(1-\tau)$, $\tau \in (-1, 1)$, and τ is Kendall's tau measuring the association between two continuous random variables. Its generator is $\varphi_{\theta_C}(x) = \left(x^{-\theta_C} - 1\right)/\theta_C$. Its upper and lower tail dependencies are $\lambda_U^C = 0$ and $\lambda_D^C = 2^{-1/\theta_C}$. The Gumbel copula, which considers the higher dependence at right tails, has the form of

$$C_t^{\text{G}}(u_t, v_t; \theta_{\text{G}}) = \exp\left\{-\left[(-\log u_t)^{\theta_{\text{G}}} + (-\log v_t)^{\theta_{\text{G}}}\right]^{1/\theta_{\text{G}}}\right\} \tag{24}$$

where $\theta_{\text{G}} = (1-\tau)^{-1}$. The generator for the Gumbel copula is $\varphi_{\theta_{\text{G}}}(x) = (-\ln x)^{\theta_{\text{G}}}$. Its upper and lower tail dependencies are $\lambda_{\text{U}}^{\text{G}} = 2 - 2^{-1/\theta_{\text{G}}}$ and $\lambda_{\text{D}}^{\text{G}} = 0$. Although the Clayton and Gumbel copulas only consider asymmetric cases, the SJC copula takes into account both the symmetric and asymmetric cases (see Patton, 2006). Its function is

$$C_t^{\mathrm{SJC}}(u_t, v_t; \tau^{\mathrm{U}}, \tau^{\mathrm{L}}) = \frac{1}{2}(C^{\mathrm{JC}}(u_t, v_t; \tau^{\mathrm{U}}, \tau^{\mathrm{L}}) + C^{\mathrm{JC}}(1-u_t, 1-v_t; \tau^{\mathrm{U}}, \tau^{\mathrm{L}}) + u_t + v_t - 1) \tag{25}$$

where

$$C_t^{\mathrm{JC}}(u_t, v_t; \tau^{\mathrm{U}}, \tau^{\mathrm{L}}) = 1 - \left(1 - \frac{1}{\left(\frac{1}{(1-(1-u_t)^k)^\gamma} + \frac{1}{(1-(1-v_t)^k)^\gamma} - 1\right)^{1/\gamma}}\right)^{1/k}$$

$\tau^{\mathrm{U}}, \tau^{\mathrm{L}} \in (0,1)$ are, respectively, measures of upper tail dependence and lower tail dependence.

In parallel with the static case, five types of dynamic copulas are considered.[5] Following Patton (2006), the evolution model for the dynamics of the correlation for a bivariate Normal copula has the following form:

$$\rho_t = \Lambda_1\left(\omega_{\rho,1} + \omega_{\rho,2}\rho_{t-1} + \omega_{\rho,3} \cdot \frac{1}{10}\sum_{j=1}^{10} \Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j})\right) \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \tag{26}$$

where $\rho_t \in (-1,1)$ is the time-varying correlation coefficient and $\Lambda_1(x) = (1-e^{-x})(1-e^{-x})^{-1}$ is the modified logistic transformation, designed to keep ρ_t constrained within the interval $(-1,1)$ at all times. The Student-t copula correlation parameter is modelled with dynamics similar to Equation 26, where $t_d^{-1}(\cdot)$ replaces $\Phi^{-1}(\cdot)$.[6]

For time-varying Clayton and Gumbel copula models, their evolution equation is

$$\tau_t = \Lambda_2\left(\omega_{\tau,1} + \omega_{\tau,2}\tau_{t-1} + \omega_{\tau,3} \cdot \frac{1}{10}\sum_{j=1}^{10} |u_{t-j} - v_{t-j}|\right) \tag{27}$$

where τ_t is the time-varying Kendall tau coefficient and $\Lambda_2(x)$ is the modified logistic transformation designed to keep the parameters within the interval $(0,1)$: $\Lambda_2(x) = (1+e^{-x})^{-1}$ for the Clayton copula and $\Lambda_2(x) = 1 + e^x$ for the Gumbel copula. Finally, the evolution equations of the upper and lower tail dependences for a time-varying SJC copula model are given as

$$\tau_t^{\mathrm{U}} = \Lambda_3\left(\omega_{\mathrm{U},1} + \omega_{\mathrm{U},2}\tau_{t-1}^{\mathrm{U}} + \omega_{\mathrm{U},3} \cdot \frac{1}{10}\sum_{j=1}^{10} |u_{t-j} - v_{t-j}|\right) \tag{28}$$

$$\tau_t^{\mathrm{L}} = \Lambda_3\left(\omega_{\mathrm{L},1} + \omega_{\mathrm{L},2}\tau_{t-1}^{\mathrm{L}} + \omega_{\mathrm{L},3} \cdot \frac{1}{10}\sum_{j=1}^{10} |u_{t-j} - v_{t-j}|\right) \tag{29}$$

where τ_t^{U} and τ_t^{L} and the time-varying upper and lower tail dependence, and $\Lambda_3(x) = (1+e^{-x})^{-1}$ is again the modified logistic transformation. The unconditional correlation from the static Gaussian copula and the upper and lower tail dependences from the static SJC copula are used as initial values for Equations 28 and 29.

III. The Data and Preliminary Diagnostic Tests

The data set includes daily closing spot prices for RBOB regular gasoline, daily settlement prices of front-month futures contracts on unleaded gasoline and daily closing ETF prices for the United States Gasoline Fund (NYSE Arca: UGA). The choice of a daily hedging horizon is in line with previous

[5] Although the static specification of the copula model assumes that the dependency structure of the two data series does not vary in time, the dynamic specification models explicitly account for the dynamics of the parameters of the copula functions.

[6] For simplicity, the number of the degrees of freedom d is assumed to be constant over time.

empirical studies such as Choudhry (2003), Park and Jei (2010) and Chang *et al.* (2010). To deal with expiration effects, we assume that a hedger will shift from the nearest contract month to the next trading contract month when the contract reaches its expiry date. The data cover the period beginning 1 March 2008 to 31 December 2011. Earlier periods were not used as trading did not begin for the gasoline ETF until 26 February 2008. The spot and futures prices are obtained from the US Energy Information Administration, and the ETF price data are obtained from Datastream. Since the objective of this article is to examine the performances of alternative hedging strategies before and after the 2008 financial crisis, we first adopt Zivot and Andrews (1992) model[7] to determine the break point endogenously from the data. From the results of the unknown structural break test, one structural break point is found on 29 April 2009. Accordingly, the entire sample is split into two periods: crisis period (from March 2008 to April 2009) and post-crisis period (from May 2009 to December 2011). The asset returns are defined as changes in the logarithm of the daily prices. In Fig. 1, daily returns for spot, ETF and futures markets are presented. Clearly, the first sub-period was highly volatile, as it covered the majority of the duration of the 2008 financial crisis. The post-crisis period was much less volatile, as markets began to recover from the crisis.

Table 1 reports the results of the diagnostic analysis for daily log returns. The average daily returns for all three time series are negative during the crisis period and positive after the crisis period. The unconditional sample SDs indicate that the crisis period is more volatile than post-crisis period for all markets. The stylized facts of asset returns, such as skewness, leptokurtosis and significant Jarque-Bera statistics, are present in all data, implying that the unconditional distributions of spot, ETF and futures returns are asymmetric, fat-tailed and non-normal. The Ljung-Box tests show that there is no serial correlation in most of the returns; however, serial correlation is displayed in the ETF returns (for the whole-sample period) and futures returns (for both the whole-sample and the crisis periods). Both the Q^2 and Lagrange multiplier (LM) statistics for the ARCH effects present strong autocorrelations in the squared returns for most assets, implying that there is nonlinear dependence in the return series. This indicates volatility clustering, and a GARCH type modelling should be considered in the estimation of optimal hedge ratios. In addition, the augmented Dickey–Fuller (ADF) tests show that all asset prices have a unit root, but first differencing leads to stationarity.

Table 1 also shows that spot returns are positively correlated with both the ETF and futures returns. For the crisis period, the spot-ETF returns correlation (both linear and Kendall's Tau correlations) is higher than the spot-futures returns correlation, but the opposite is observed for the post-crisis period. For the whole-sample and post-crisis periods, the Johansen trace statistics suggest that the spot and ETF prices, as well as the spot and futures prices, are cointegrated. Therefore, the error correction terms are included in the model specification. For the crisis period, the trace statistics suggest otherwise, and thus, the error correction terms are omitted in Equations 5 and 6.

IV. Empirical Results

In this section, we present the main empirical results of the study. We first examine the parameter estimation results for all the models considered. We then comprehensively examine the hedging performance of alternative hedging strategies using a broad range of hedging effectiveness measures.

Model estimation

Parameter estimates from alternative models for the case of ETF hedging are presented in Tables 2 and 3. To save space, estimation results for the futures hedging models are not presented here, but are available upon request. Several observations merit attention. First, for all relevant models, the estimated coefficient of the speed of adjustment of the spot price ($\alpha_{1,s}$) is negative, whereas that of the ETF price ($\alpha_{1,\mathrm{etf}}$) is positive. For the post-crisis period, the estimated $\alpha_{1,s}$ is not significant but $\alpha_{1,\mathrm{etf}}$ is significant. This implies that, in response to a positive error correction term, the ETF price in the next period will increase, while the spot price will remain unresponsive. Second, for the DCC GARCH model, the estimates of $\lambda_1 + \lambda_2$ are close to (but less than) 1. This

[7] The Zivot and Andrews (1992) model is a sequential test incorporating one structural break in the time series and using a different dummy variable for each possible break date.

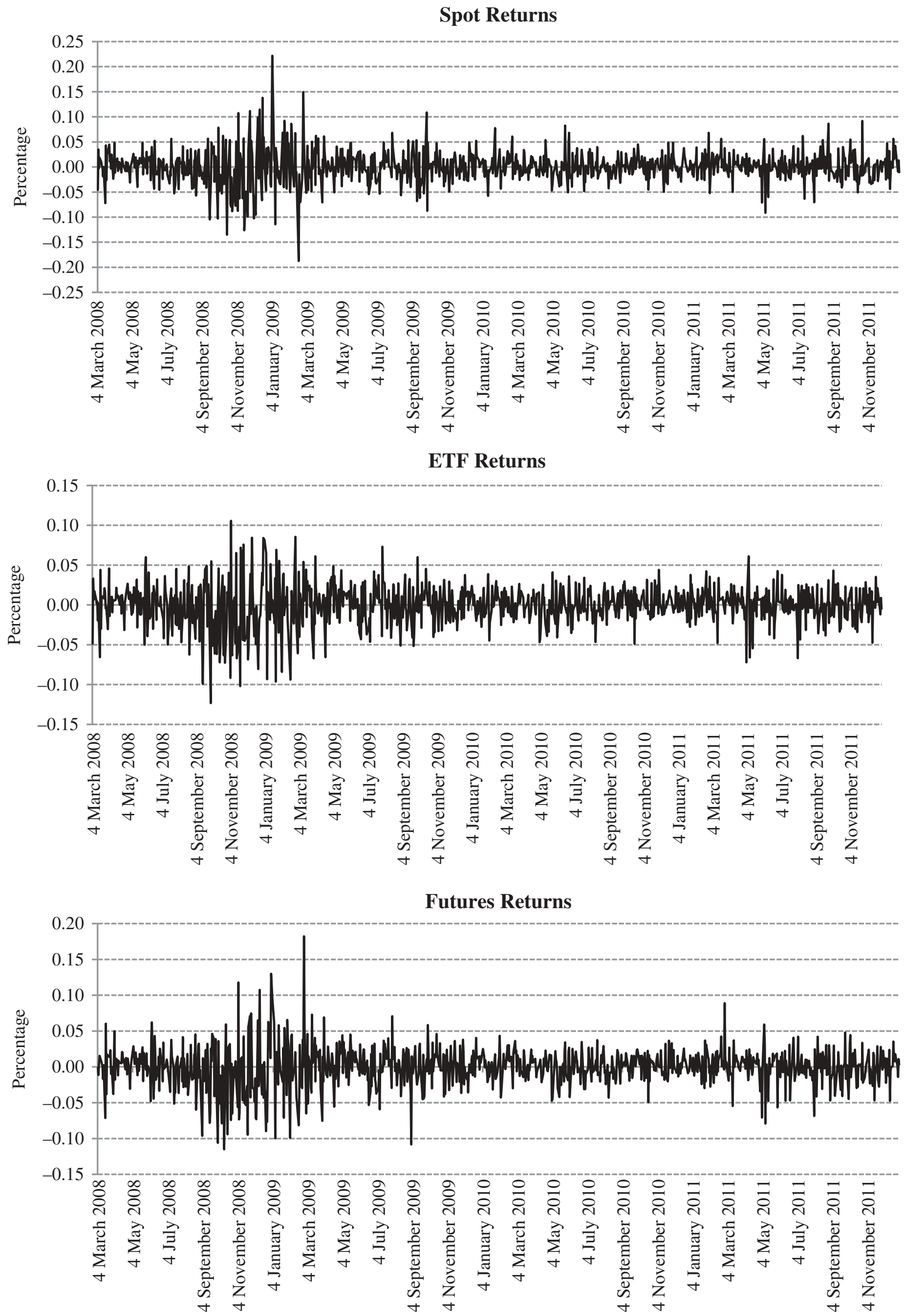

Fig. 1. Daily log returns of gasoline spot, futures and ETF

means that the correlation between the spot and ETF markets is highly persistent. The striking aspect of the results is that $\lambda_1 + \lambda_2$ estimates are higher, though not much different, for the post-crisis period than for the crisis-period, which implies that shocks can push the correlations further away from their long-run averages for a longer amount of time during the crisis period than the post-crisis period. Third, for the copula-based GARCH models, almost all $\gamma_{3,i}$ estimates are significant and their signs are positive. This indicates that previous negative shocks generate higher volatility than positive shocks. The asymmetric effect for the ETF returns for the post-crisis period is stronger than that for the crisis period. However, this effect is not significant for spot returns for the post-crisis period.

Table 1. Summary statistics for daily log returns

	Whole sample			Crisis period			Post-crisis period		
Statistics	Spot returns	ETF returns	Futures returns	Spot returns	ETF returns	Futures returns	Spot returns	ETF returns	Futures returns
Mean	0.0043%	−0.0032%	0.0006%	−0.1892%	−0.2435%	−0.2044%	0.0886%	0.1016%	0.0898%
Maximum	22.1673%	10.5719%	18.2291%	22.1673%	10.5719%	18.2291%	10.8506%	7.3079%	8.8908%
Minimum	−18.7445%	−12.3313%	−11.5037%	−18.7445%	−12.3313%	−11.5037%	−9.1580%	−7.2141%	−10.8224%
SD	3.2334%	2.5745%	2.7949%	4.5517%	3.6301%	3.9619%	2.4463%	1.9375%	2.0900%
Skewness	0.1851	−0.4287	−0.048	0.2292	−0.2734	0.1944	0.2239	−0.2544	−0.4108
Kurtosis	8.1968	5.2080	7.0701	6.0293	3.5440	4.9364	4.5433	3.7908	4.8849
J-B test	1091.76**	226.188**	667.131**	116.920**	7.5821*	48.9329**	73.0756**	25.1517**	119.304**
$Q(24)$	25.1761	39.6857*	45.2591**	21.4603	35.2085	43.1578**	21.2143	16.5350	20.7123
$Q^2(24)$	593.875**	1043.76**	556.257**	113.360**	159.108**	80.2115**	33.3435	42.5262*	25.4231
ARCH(5)	77.3992**	111.527**	72.4323**	16.3930**	16.9938**	10.7784	15.0289*	19.3002**	5.4992
ADF (price)	−1.7604	−1.3751	−1.4353	−0.8704	−0.5064	−0.7419	−2.1239	−1.9897	−2.0329
ADF (return)	−22.4743**	−22.4822**	−22.7387**	−12.2129**	−12.7170**	−12.6614**	−19.2045**	−18.4396**	−18.8769**
With spot returns									
Linear Correlation		0.7591	0.6988		0.7642	0.6978		0.6992	0.7504
Kendall's Tau		0.6152	0.5811		0.6238	0.5957		0.5679	0.6074
Trace		30.4481**	34.7091**		8.8199	10.9816		23.1886**	32.5539**
$\hat{\lambda}_0$		0.9106	0.8923		0.8887	0.9126		0.9418	0.9181
Constant		−2.4853	0.1421		−2.4247	0.1392		−2.5909	0.1070

Notes: J-B test is the Jarque-Bera test for normality; $Q(24)$ and $Q^2(24)$ are the Ljung-Box statistics for up to 24th order serial correlation in the asset returns and in the squared asset returns, respectively; ARCH(5) is the Lagrange Multiplier (LM) test for up to the 5th order ARCH effects in the asset returns. The ADF tests are applied to test the null hypothesis of a unit root for the asset prices and returns. The number of lags in the ADF tests is selected as a result of the majority rule among the four criteria: the final prediction error, Akaike, Schwarz and Hannan–Quinn information criteria. Trace is the Johansen trace test; the null hypothesis of the Johansen test is there is no cointegration. $\hat{\lambda}_0$ is the estimated cointegrating coefficient and constant is the estimated constant term in the cointegrating relationship. * and ** denote the rejection of the null hypothesis at the 5% and 1% levels, respectively.

Table 2. Parameter estimates of alternative models

	Whole sample		Crisis period		Post-crisis period	
	$i = s$	$i =$ etf	$i = s$	$i =$ etf	$i = s$	$i =$ etf
OLS Model: $s_t = \alpha + \delta_{\text{etf}}^{\text{OLS}}\text{etf}_t + \varepsilon_t$						
α		0.000080		0.000442		−0.000076
		(0.000681)		(0.001728)		(0.000627)
$\delta_{\text{etf}}^{\text{OLS}}$		0.95339**		0.958256**		0.947465**
		(0.026503)		(0.047569)		(0.032339)
VEC/ VAR Model: $s_t = \alpha_{0,s} + \alpha_{1,s}\text{ECT}_{t-1} + \varepsilon_{s,t}$; $\text{etf}_t = \alpha_{0,\text{etf}} + \alpha_{1,\text{etf}}\text{ECT}_{t-1} + \varepsilon_{\text{etf},t}$						
$\alpha_{0,i}$	0.000074	0.000046	−0.001892	−0.002436	0.000913	0.000882
	(0.001044)	(0.000829)	(0.002668)	(0.002128)	(0.000948)	(0.000750)
$\alpha_{1,i}$	−0.017197	0.027917**			−0.022760	0.023563*
	(0.014425)	(0.011449)			(0.017412)	(0.013767)
DCC GARCH Model: (equations below)						
$\alpha_{0,i}$	0.001286	0.000657	0.000205	−0.000394	0.001283	0.001157
	(0.000890)	(0.000699)	(0.001891)	(0.001824)	(0.000964)	(0.000753)
$\alpha_{1,i}$	−0.026505*	0.017832			−0.022141	0.022061*
	(0.015871)	(0.012517)			(0.016288)	(0.013261)
$\beta_{0,i}$	0.000016	0.000007*	0.000012	0.000014	0.000062	0.000073**
	(0.000011)	(0.000004)	(0.000014)	(0.000015)	(0.000048)	(0.00004)
$\beta_{1,i}$	0.065305**	0.050733**	0.102186**	0.080385**	0.049837**	0.079485**
	(0.013947)	(0.015997)	(0.021520)	(0.018990)	(0.025244)	(0.039596)
$\beta_{2,i}$	0.916235**	0.936397**	0.896814**	0.910841**	0.846231**	0.722831**
	(0.020692)	(0.020646)	(0.022485)	(0.018473)	(0.091229)	(0.115853)
λ_1	0.057330**		0.087320**		0.060129**	
	(0.01350)		(0.042592)		(0.016732)	
λ_2	0.878368**		0.827204**		0.860218**	
	(0.031413)		(0.110346)		(0.044614)	

DCC GARCH Model equations:

$s_t = \alpha_{0,s} + \alpha_{1,s}\text{ECT}_{t-1} + \varepsilon_{s,t}$

$\text{etf}_t = \alpha_{0,\text{etf}} + \alpha_{1,\text{etf}}\text{ECT}_{t-1} + \varepsilon_{\text{etf},t}$

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{\text{etf},t} \end{bmatrix} | I_{t-1}\tilde{N}(0, H_t)$$

$$H_t = \begin{bmatrix} h_{s,t}^2 & h_{\text{setf},t} \\ h_{\text{setf},t} & h_{\text{etf},t}^2 \end{bmatrix} = \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{\text{etf},t} \end{bmatrix} \begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix} \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{\text{etf},t} \end{bmatrix} = D_t R_t D_t$$

$h_{s,t}^2 = \beta_{0,s} + \beta_{1,s}\varepsilon_{s,t-1}^2 + \beta_{2,s}h_{s,t-1}^2$

$h_{\text{etf},t}^2 = \beta_{0,\text{etf}} + \beta_{1,\text{etf}}\varepsilon_{\text{etf},t-1}^2 + \beta_{2,\text{etf}}h_{\text{etf},t-1}^2$

$R_t = J_t Q_t J_t = \text{diag}(Q_t)^{-\frac{1}{2}} Q_t \text{diag}(Q_t)^{-\frac{1}{2}}$

$Q_t = (1 - \lambda_1 - \lambda_2)\bar{Q} + \lambda_1\tilde{\varepsilon}_{t-1}\tilde{\varepsilon}_{t-1}' + \lambda_2 Q_{t-1}$

where $\tilde{\varepsilon}_t = D_t^{-1}\varepsilon_t$ is the standardized disturbance vector, $\bar{Q}$ is the unconditional correlation matrix $\tilde{\varepsilon}_t$.

GJR-skewed-t GARCH Model (Copula-based GARCH Model)

$s_t = \alpha_{0,s} + \alpha_{1,s}\text{ECT}_{t-1} + \varepsilon_{s,t}$

$\text{etf}_t = \alpha_{0,\text{etf}} + \alpha_{1,\text{etf}}\text{ECT}_{t-1} + \varepsilon_{\text{etf},t}$

$h_{i,t}^2 = \gamma_{0,i} + \gamma_{1,i}\varepsilon_{i,t-1}^2 + \gamma_{2,i}h_{i,t-1}^2 + \gamma_{3,i}a_{i,t-1}\varepsilon_{i,t-1}^2$

$\varepsilon_{i,t}|I_{t-1} = h_{i,t}z_{i,t}, z_{i,t} \sim \text{skewed} - t(z_i|\eta_i, \lambda_i)$

$$\text{skewed} - t(z|\eta, \lambda) = \begin{cases} bc\left(1 + \frac{1}{\eta-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-\frac{\eta+1}{2}} \text{if } z < -a/b \\ bc\left(1 + \frac{1}{\eta-2}\left(\frac{bz+a}{1+\lambda}\right)^2\right)^{-\frac{\eta+1}{2}} \text{if } z \geq -a/b \end{cases}$$

(*continued*)

Table 2. Continued

	Whole sample		Crisis period		Post-crisis period	
	$i = s$	$i =$ etf	$i = s$	$i =$ etf	$i = s$	$i =$ etf
$a \equiv 4\lambda c\frac{\eta-2}{\eta-1}, b^2 \equiv 1 + 3\lambda^2 - a^2, c \equiv \frac{\Gamma\left(\frac{\eta+1}{2}\right)}{\sqrt{\pi(\eta-2)}\Gamma\left(\frac{\eta}{2}\right)}$						
$\alpha_{0,i}$	0.000926	0.000413	0.000413	−0.001044	0.001086	0.000960
	(0.000858)	(0.000675)	(0.001957)	(0.001829)	(0.001016)	(0.00072)
$\alpha_{1,i}$	−0.023549**	0.013151			−0.013130	0.021121*
	(0.01316)	(0.010096)			(0.017191)	(0.012678)
$\gamma_{0,i}$	0.000015*	0.000009**	0.000023	0.000019*	0.000074	0.000080**
	(0.000008)	(0.000004)	(0.000017)	(0.000011)	(0.000177)	(0.000041)
$\gamma_{1,i}$	0.007588	0.000000	0.046596	0.011372	0.029474	0.000000
	(0.022772)	(0.000769)	(0.044852)	(0.048792)	(0.054625)	(0.000700)
$\gamma_{2,i}$	0.931819**	0.938668**	0.884703**	0.913579**	0.822347**	0.701993**
	(0.026467)	(0.016301)	(0.03208)	(0.03404)	(0.356608)	(0.128868)
$\gamma_{3,i}$	0.090813**	0.083531**	0.125524*	0.112955*	0.061105	0.154001**
	(0.026738)	(0.022927)	(0.074646)	(0.063126)	(0.075567)	(0.064728)
λ	1.054148**	0.856346**	0.981523**	0.789143**	1.108479**	0.899267**
	(0.048368)	(0.041177)	(0.091911)	(0.068536)	(0.06718)	(0.050739)
η	5.792840**	11.848875**	5.828454**	12.194012	5.893560**	14.830259*
	(1.126229)	(4.209357)	(2.076506)	(9.678546)	(1.410402)	(7.890739)

Notes: Figures in parentheses are SE. * and ** denote the rejection of the null hypothesis at the 5% and 1% levels, respectively. The optimal lag for the vector autoregressive model is one, and thus the optimal lag for the vector error autoregressive model is zero.

Finally, all the parameters of different static copulas (Table 3) are significant at the 1% level. For the dynamic copulas, the parameters that control the dynamics of the tail dependence are generally statistically significant, except for the parameters in dynamic Clayton copula for the crisis period. This provides some evidence of time variation in the degree of volatility clustering in the return series.

Measuring hedging effectiveness

To analyse hedging effectiveness of alternative hedging strategies, we use four different performance measures. Each measure corresponds to a different hedging objective. The first measure is the percentage reduction in the variance of the hedged portfolio returns as compared with the variance of the unhedged portfolio returns. The second measure considers the economic benefits of different hedging strategies using the hedger's utility function. As in other empirical studies in Kroner and Sultan (1993), Alizadeh *et al.* (2008) and Lee (2010), we assume that the hedger has an expected utility function given by

$$E_t[U(x_{t+1})] = E_t(x_{t+1}) - k \operatorname{var}_t(x_{t+1}) \quad (30)$$

where x_{t+1} represents the returns from the hedged portfolio, and k is the hedger's degree of risk aversion (normally assumed to be 4).

The third measure is the VaR of the portfolio (Cotter and Hanly, 2006; Alizadeh *et al.*, 2008; Salvador and Aragó, 2014). In this study, the VaR at the confidence level $1 - m$ is the smallest amount of loss l such that the probability that the loss over the next day L exceeds l is no larger than m. Following Salvador and Aragó (2014), the VaR is calculated using the empirical quantiles of the portfolio returns:

$$\mathrm{VaR}_m = \inf\{l \in \mathbb{R} \mid \Pr(L > l) < m\} \quad (31)$$

The last performance measure is the ES of the portfolio. The ES at the confidence level $1 - m$ is the expected loss, given that the VaR_m has been exceeded. It can be calculated as

Table 3. Parameter estimates for families of copulas

	Whole sample		Crisis period		Post-crisis period	
Copula	Coefficient	SE	Coefficient	SE	Coefficient	SE
Static Normal: $C_t^N(u_t, v_t; \rho) = \Phi_\rho(\Phi^{-1}(u_t), \Phi^{-1}(v_t))$						
ρ	0.786236**	0.012343	0.799606**	0.021177	0.778227**	0.015281
Static Student-*t*: $C_t^T(u_t, v_t; \rho, d) = t_{\rho,d}\left(t_d^{-1}(u_t), t_d^{-1}(v_t)\right)$						
ρ	0.808152**	0.011185	0.816529**	0.018251	0.807957**	0.012714
d	4.263967**	0.647001	5.008644**	1.692756	3.671049**	0.570449
Static Clayton: $C_t^C(u_t, v_t; \theta_C) = \left[u_t^{-\theta_C} + v_t^{-\theta_C} - 1\right]^{-1/\theta_C}$						
θ_C	2.020768**	0.092182	2.122574**	0.174274	1.988638**	0.109648
Static Gumbel: $C_t^G(u_t, v_t; \theta_G) = \exp\left\{-\left[(-\log u_t)^{\theta_G} + (-\log v_t)^{\theta_G}\right]^{1/\theta_G}\right\}$						
θ_G	2.301394**	1.000000	2.335814**	0.584697	2.302663**	1.000000
Static SJC: $C_t^{SJC}(u_t, v_t; \tau^U, \tau^L) = \frac{1}{2}\left(C^{JC}(u_t, v_t; \tau^U, \tau^L) + C^{JC}(1-u_t, 1-v_t; \tau^U, \tau^L) + u_t + v_t - 1\right)$						
τ^U	0.538952**	0.027582	0.521911**	0.056570	0.549239**	0.033234
τ^L	0.655731**	0.017209	0.676772**	0.026299	0.646717**	0.021575
Dynamic Normal: $\rho_t = \Lambda_1\left(\omega_{\rho,1} + \omega_{\rho,2}\rho_{t-1} + \omega_{\rho,3} \cdot \frac{1}{10}\sum_{j=1}^{10}\Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j})\right)$						
$\omega_{\rho,1}$	4.251484**	0.077181	5.000000**	0.119297	3.677283**	0.088512
$\omega_{\rho,2}$	−3.375591**	0.095994	−4.689974**	0.102055	−2.755764**	0.111991
$\omega_{\rho,3}$	0.697342**	0.082719	1.154721**	0.159452	0.739819**	0.094433
Dynamic Student-*t*: $\rho_t = \Lambda_1\left(\omega_{\rho,1} + \omega_{\rho,2}\rho_{t-1} + \omega_{\rho,3} \cdot \frac{1}{10}\sum_{j=1}^{10}\Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j})\right)$						
$\omega_{\rho,1}$	2.070224**	0.071170	0.641470**	0.047983	−0.172015**	0.000015
$\omega_{\rho,2}$	−0.073117	0.130582	0.834673**	0.032442	2.522860**	0.000014
$\omega_{\rho,3}$	−2.094290**	0.038118	−0.019451	0.103456	0.006390**	0.000033
Dynamic Clayton: $\tau_t = \Lambda_2\left(\omega_{\tau,1} + \omega_{\tau,2}\tau_{t-1} + \omega_{\tau,3} \cdot \frac{1}{10}\sum_{j=1}^{10}\left\|u_{t-j} - v_{t-j}\right\|\right)$						
$\omega_{\tau,1}$	2.286563**	0.020687	1.000000	1.000000	4.433169**	0.003043
$\omega_{\tau,2}$	0.094169**	0.009850	0.000000	1.000000	−0.891224**	0.002226
$\omega_{\tau,3}$	−5.968372**	0.157205	0.000000	1.000000	−2.186118**	0.135736
Dynamic Gumbel: $\tau_t = \Lambda_2\left(\omega_{\tau,1} + \omega_{\tau,2}\tau_{t-1} + \omega_{\tau,3} \cdot \frac{1}{10}\sum_{j=1}^{10}\left\|u_{t-j} - v_{t-j}\right\|\right)$						
$\omega_{\tau,1}$	1.931674**	0.035176	1.173077**	0.029869	2.217351**	0.052187
$\omega_{\tau,2}$	−0.152622**	0.015078	0.150886**	0.011337	−0.273164**	0.021631
$\omega_{\tau,3}$	−3.183343**	0.236762	−2.709573**	0.216174	−3.208932**	0.334407
Dynamic SJC: $\tau_t^i = \Lambda_3\left(\omega_{i,1} + \omega_{i,2}\tau_{t-1}^i + \omega_{i,3} \cdot \frac{1}{10}\sum_{j=1}^{10}\left\|u_{t-j} - v_{t-j}\right\|\right), i = U, L$						
$\omega_{U,1}$	3.591802**	0.085530	−1.354517**	0.036428	3.864991**	0.198991
$\omega_{U,2}$	−10.319827**	0.394275	−2.687594**	0.246388	−12.317511**	1.558546
$\omega_{U,3}$	−3.974771**	0.065985	3.489764**	0.057384	−3.965794**	0.110977
$\omega_{L,1}$	2.720275**	0.051186	5.719485**	0.194075	2.487069**	0.083076
$\omega_{L,2}$	−8.487851**	0.283567	−20.260080**	1.774438	−6.367121**	0.641505
$\omega_{L,3}$	−1.400760**	0.040424	−4.291079**	0.164470	−1.510700**	0.125393

Note: ** denotes the rejection of the null hypothesis at the 1% level.

$$\mathrm{ES}_m = E(y|y < \mathrm{VaR}_m) \tag{32}$$

where y is the portfolio returns. The VaR and ES are tail-specific measures, and thus are appropriate measures for the hedgers whose objective is to minimize downside risks. Similar to Cotter and Hanly (2006), we use $m = 1\%$ in calculating the VaR and ES measures.

Comparing hedging effectiveness

Table 4 presents the results of out-of-sample[8] hedging performance of alternative hedging strategies during the crisis period (Panel A) and post-crisis period (Panel B). The tables display both ETF and futures hedging results. The results for futures hedging are reported in parentheses. The best performing hedging strategy according to each performance measure (or hedging objective) and trading position is highlighted in bold type.

In terms of variance reduction, the out-of-sample results (Column 2) display significant percentage reductions in variance for each hedging strategies as compared with the unhedged position. For the crisis period, the static models (the OLS and VAR models) display the greatest variance reduction. For the post-crisis period, the VEC model outperforms the rest of the models for the case of ETF hedging, whereas the DCC GARCH model provides the greatest variance reduction, followed by the OLS model, for the case of futures hedging. Compared with the other models under consideration, the dynamic copula models, especially the dynamic Clayton model, perform quite poorly in term of variance reduction in all cases. This result contradicts the findings in Hsu *et al.* (2008), Lai *et al.* (2009) and Lee (2009) that the copula-based GARCH models perform more effectively than other static and dynamic hedging models in reducing portfolio variance. In addition, we find that ETF hedging is more effective than futures hedging in reducing return variability. Therefore, we can conclude that the best strategy for gasoline hedgers whose objective is to minimize portfolio variance is to use a static model with the ETF as a hedging instrument.

The utility analysis, which considers both the variance and level of portfolio returns, yields a similar conclusion. We first consider the results for short hedgers (Column 3). The best strategies for short hedgers are ETF hedging with the DCC GARCH model during the crisis period and futures hedging with the static Student-*t* copula model. For long hedgers (Column 6), the most effective strategy is ETF hedging with a dynamic model (the static Student-*t* copula model during the crisis period and the DCC GARCH model during the post-crisis period). It should be noted that dynamic hedging strategies are more costly to implement than the static OLS and VEC/VAR hedging models because of the frequent rebalancing requirement. Therefore, it is essential for us to account for transaction costs when comparing the economic benefits from dynamic hedging with those from static hedging. We find that the hedger's benefit (before transaction costs) from using the best dynamic hedging model over the best static hedging model $(E_t[U(x_{t+1})]_{\mathrm{Dynamic}} - E_t[U(x_{t+1})]_{\mathrm{Static}})$ varies between 0.002% and 0.036%. As the typical round trip transaction costs of futures hedging is around 0.02–0.04% (possibly lower for ETF hedging as some brokerage firms allow their clients to trade the gasoline commission-free), these mean-variance expected utility-maximizing hedgers would not benefit from the dynamic hedging strategy unless they are able to participate in either the ETF or futures market at the lower cost.

We next consider the performance results for hedgers whose objective is to minimize their downside risk. We first discuss the results for those hedgers who are concerned with the maximum probably loss (measured by VaR). For short hedgers (Column 4), the best hedging strategies are ETF hedging with static models during the crisis period and futures hedging with a DCC GARCH model during the post-crisis period. For long hedgers (Column 7), the most effective strategies are ETF hedging with the static Normal copula model during the crisis period and ETF hedging with the VEC model during the post-crisis period. For those hedgers whose objective is to minimize the expected extreme loss (measured by ES), the

[8] For the out-of-sample analysis, we split the crisis period into two periods: from March 2008 to December 2008 (209 observations) and from January 2009 to April 2009 (83 observations), and the post-crisis period into two periods: from May 2009 to August 2009 (584 observations) and from September 2009 to December 2009 (85 observations). Each dynamic model is estimated using a recursive estimation scheme. Although not reported here, the in-sample results are available upon request.

Table 4. Out-of-sample gasoline ETF (futures) hedging effectiveness (in percentage) during the crisis and post-crisis periods

	Variance	Short hedgers			Long hedgers		
Hedging strategy	Reduction	Utility	VaR (1%)	ES (1%)	Utility	VaR (1%)	ES (1%)
Panel A: Crisis period							
Unhedged	0.280	−0.790	−12.818	−18.745	−1.450	−16.311	−22.167
OLS	**55.422** (**44.440**)	−0.427 (−0.660)	**−8.937** (−10.279)	**−10.165** (−12.261)	−0.572 (−0.**584**)	−10.428 (−1**4.572**)	**−14.681** (−1**4.938**)
VAR	**55.422** (**44.440**)	−0.427 (−0.660)	**−8.937** (−10.279)	**−10.165** (−12.261)	−0.572 (−0.**584**)	−10.428 (−1**4.572**)	**−14.681** (−1**4.938**)
DCC GARCH	52.035 (40.142)	**−0.419** (−0.711)	−9.243 (−11.522)	−10.308 (−1**1.924**)	−0.655 (−0.630)	−10.491 (−15.137)	−17.133 (−15.986)
Static Normal	52.892 (37.728)	−0.485 (−0.785)	−9.226 (−12.480)	−10.771 (−13.538)	−0.570 (−0.610)	**−10.221** (−15.033)	−15.508 (−15.441)
Static Student-*t*	53.254 (37.565)	−0.488 (−0.798)	−9.220 (−12.437)	−10.584 (−13.965)	**−0.559** (−0.600)	−10.224 (−14.987)	−15.265 (−15.195)
Static Clayton	43.425 (34.305)	−0.486 (−0.654)	−9.235 (−10.013)	−13.612 (−14.871)	−0.781 (−0.818)	−12.165 (−15.553)	−17.817 (−18.174)
Static Gumbel	46.213 (36.956)	−0.480 (−0.673)	−9.243 (−10.175)	−13.080 (−14.132)	−0.725 (−0.738)	−11.661 (−15.384)	−17.321 (−17.287)
Static SJC	47.307 (37.400)	−0.478 (−0.679)	−9.244 (−10.203)	−12.829 (−13.955)	−0.702 (−0.723)	−11.435 (−15.355)	−17.107 (−17.136)
Dynamic Normal	47.849 (35.888)	−0.470 (−0.804)	−9.427 (−12.615)	−10.992 (−13.737)	−0.698 (−0.632)	−10.741 (−15.159)	−17.603 (−16.102)
Dynamic Student-*t*	14.550 (34.514)	−0.699 (−0.640)	−9.339 (**−9.844**)	−18.086 (−15.147)	−1.214 (−0.827)	−14.796 (−15.560)	−18.475 (−18.212)
Dynamic Clayton	27.038 (24.265)	−0.583 (−0.664)	−10.339 (−10.458)	−16.042 (−16.474)	−1.051 (−1.032)	−14.113 (−15.865)	−19.924 (−19.817)
Dynamic Gumbel	33.390 (32.921)	−0.511 (−0.688)	−10.646 (−10.245)	−13.577 (−14.037)	−0.981 (−0.814)	−13.356 (−15.784)	−19.924 (−19.394)
Dynamic SJC	31.589 (34.042)	−0.526 (**−0.578**)	−10.737 (−10.198)	−14.484 (−13.966)	−1.007 (−0.900)	−13.880 (−15.821)	−22.040 (−19.584)
Panel B: Post-crisis period							
Unhedged	0.065	−0.360	−4.501	−5.077	−0.160	−6.221	−9.172
OLS	55.811 (43.687)	−0.145 (−0.128)	−4.004 (−3.793)	−4.230 (−4.253)	−0.085 (−0.165)	−4.662 (−6.422)	−7.005 (−6.**423**)
VEC	**55.893** (43.674)	**−0.144** (−0.127)	−4.011 (−3.797)	−4.251 (−4.269)	−0.085 (−0.165)	**−4.660** (−6.411)	**−6.986** (−6.448)
DCC GARCH	55.332 (**48.074**)	−0.183 (−0.182)	−3.463 (−3.**369**)	−3.947 (−3.702)	**−0.049** (**−0.088**)	−4.669 (−4.**757**)	−7.132 (−6.639)
Static Normal	54.950 (43.531)	−0.151 (−0.131)	−3.983 (−3.810)	−4.195 (−4.309)	−0.083 (−0.163)	−4.669 (−6.378)	−7.116 (−6.501)
Static Student-*t*	55.508 (43.430)	−0.147 (**−0.125**)	−4.018 (−3.840)	−4.294 (−4.422)	−0.084 (−0.168)	−4.661 (−6.301)	−7.031 (−6.660)
Static Clayton	44.509 (37.470)	−0.201 (−0.188)	**−3.462** (−3.609)	−3.756 (−3.651)	−0.087 (−0.136)	−4.744 (−5.465)	−7.846 (−7.405)
Static Gumbel	47.825 (39.913)	−0.188 (−0.173)	−3.590 (−3.588)	−3.798 (−3.**624**)	−0.083 (−0.138)	−4.726 (−5.659)	−7.675 (−7.173)
Static SJC	49.315 (40.914)	−0.181 (−0.166)	−3.681 (−3.645)	−3.821 (−3.687)	−0.082 (−0.141)	−4.717 (−5.773)	−7.585 (−7.051)
Dynamic Normal	54.228 (43.508)	−0.150 (−0.131)	−3.965 (−3.776)	−4.144 (−4.146)	−0.088 (−0.162)	−4.676 (−6.363)	−7.173 (−6.433)
Dynamic Student-*t*	42.952 (34.289)	−0.207 (−0.205)	−3.594 (−3.624)	**−3.720** (−3.895)	−0.089 (−0.136)	−4.764 (−5.252)	−7.997 (−7.724)
Dynamic Clayton	31.789 (28.621)	−0.252 (−0.253)	−3.695 (−3.712)	−3.993 (−4.079)	−0.102 (−0.118)	−5.055 (−5.246)	−8.330 (−7.923)
Dynamic Gumbel	47.618 (42.003)	−0.176 (−0.165)	−3.599 (−3.441)	−3.774 (−3.626)	−0.096 (−0.136)	−4.753 (−5.470)	−7.810 (−7.249)
Dynamic SJC	47.707 (43.115)	−0.162 (−0.165)	−3.692 (−3.411)	−3.803 (−3.635)	−0.109 (−0.130)	−4.740 (−5.355)	−7.704 (−7.177)

Notes: Figures in parentheses are gasoline futures hedging effectiveness. The best performing hedging strategy for each criterion is highlighted in bold type.

results are slightly different. For short hedgers (Column 5), the best performing strategy is still ETF hedging with static models during the crisis period, whereas the most effective strategy is futures hedging with a DCC static Gumbel copula model during the post-crisis period. For long hedgers (Column 8), the ES measure favours the static models during both periods. However, ETF hedging is only best during the crisis period when using the ES measure.

These results confirm the previous findings that hedging effectiveness is affected by hedger's objectives and trading position (short or long). In addition, we find that, for all types of hedgers, ETF hedging is more effective than futures hedging during the high-volatility (crisis) period. However, the results are mixed during the normal time (post-crisis) period. There is no immediate explanation for this result. Nevertheless, the findings (at least for the case of short hedgers) are in agreement with the results in Moosa (2003) that what matters most is the correlation between the prices of the unhedged position and the hedging instrument.

V. Conclusions

In this study, we consider the impact that the recent 2008 financial crisis had upon the performance of different hedging strategies by dividing the data into the crisis and post-crisis periods. Over these two periods, we compare the hedging performance of a variety of econometric models (including OLS, bivariate vector error correction, bivariate GARCH and a class of copula-based GARCH models) from the perspective of both their hedging objectives and trading position. We also investigate the effectiveness of two hedging instruments: gasoline ETFs and gasoline futures contracts. Specifically, we employ four different hedging performance criteria: the variance reduction measure, utility-based measure and two tail-based measures (VaR and ES). Each measure corresponds to a different hedging objective.

The effectiveness of dynamic models relative to static models depends on hedger's objectives and trading position (short or long) because different performance criteria suggest different hedging models. In contrast with most recent findings, e.g. Hsu *et al.*, 2008; Lai *et al.*, 2009; Lee, 2009), our results reveal that compared with the static models, the complicated dynamic hedging models such as DCC GARCH and copula models, in most cases, are less effective in reducing variance. One possible explanation is that most previous research evaluates the hedging performance of those models using either stock or currency market data, whereas our study focuses on the gasoline market. This suggests that the effectiveness of the DCC GARCH and copula-based models depends on the markets under consideration. Nevertheless, if hedgers could enter either the ETF or futures markets at the sufficiently low costs, sophisticated time-varying hedging strategies may outperform traditional static hedging strategies when utility-based and tail-based criteria are used.

In addition, the results reveal that ETF hedging is a more effective hedging strategy than futures hedging during the high-volatility (crisis) period, but not always during the normal time (post-crisis) period. Overall, hedgers with different hedging objectives and trading positions would prefer different econometric model and hedging instrument. The results, therefore, suggest that the hedging objectives, market volatility and the position of the hedgers (short or long) should be considered when choosing the best econometric model and hedging instrument. These findings have crucial implications for portfolio and risk management in unleaded gasoline markets.

Acknowledgement

We are grateful to an anonymous referee for many valuable comments and suggestions.

Disclosure Statement

No potential conflict of interest was reported by the authors.

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