Handling Volatility: A simple model for hedging in the biofuels market, by Martin Ziegelbäck, hedging.eu

Abstract

Calculation of hedge ratios is either rather simple or, if dynamic models are used, rather complicated. Hence, in practice, simple models prone to failure are used. However, research shows sophisticated dynamic models on average do not outperform 'simpler solutions'. Therefore, this paper suggests a different method to calculate hedge ratios. The method is easy and reliable. Given the huge discrepancies between, e.g., commodities and commodities-futures that result from economic shocks and given the fact that the adjusted hedge ratio calculated in this paper tries to consider exactly these kind of economic shocks the measure might outperform not only simple ways to calculate hedge ratios.

1. Introduction

Volatility in markets for biofuels proved to be high over the last years: Rising commodity and food prices (Flammini 2008; Kanamura 2008), oscillating demand for biofuels, over-supply of biofuels and increasing links between the energy and the commodity markets (Caesar, Riese & Seitz 2007) resulted in increasing risk for producers of e.g., corn for corn-based ethanol production (Wu & Guan 2009) or rapeseed for rapeseed-based production of biodiesel, but for the producer of biofuels as well. With increasing interconnectedness between energy and commodity markets, risk for biofuels producer and commodity producer alike is linked to two markets (Harri & Hudson 2009), i.e. volatility is amplified. Nevertheless, McKinsey (Caesar, Riese & Seitz 2007) recommends investments in biofuels as a reliable source of income and profit. However, volatilities in energy and commodity markets are the result of increased speculation as well (Robles, Torero & von Braun 2009), hence, the link between futures and spot prices is said to have deteriorated (Power & Vedenov 2008), especially asymptotic price development is supposed to be derailed to a certain degree. Thus, hedging against price-risks has become a major concern and an increasing problem for commodity-producers and biofuels-producers alike. Furthermore, economic shocks like the recent economic crisis tend to derail interconnectedness between commodity markets and markets for derivatives.

This paper investigates for the value chain of biodiesel volatility and price risk for the time frame 2007 to 2009. In doing so two goals are pursued: (1) to establish an understanding for co-variation between the energy and the commodity market, that can be used to form a heuristic model for hedging decisions and (2) to provide a simple model for hedging the price risk, faced by commodity producers. Hence, this paper aims at developing a model that is simple and easy to apply, so that commodity producers can establish their respective hedge ratio in order to minimize their price risk.

The next chapter (chapter 2) will briefly summarize what is know about the movement of biofuels markets and the co-movement between biofuels-markets and commodity markets. Chapter 3 will analyse the interconnectedness between markets for biodiesel and one of its main raw materials, rapeseed, while chapter 4 will produce a simple model for establishing the correct hedge ratio. Chapter 5 will summarize the results.

2. Volatility in and co-movements between energy, biofuels and commodity markets and price risk hedging

In a recent study Zulauf and Roberts (2008) found for corn, soybeans and wheat in the period 1989 to 2007 a rising volatility. E.g. the volatility of corn markets when compared for the periods 1989 to 2003 and 2003 to 2007 jumped from 25% to 35%. Volatility in soybean and wheat markets rose by 15% and 20% respectively. With volatility being a measure of price risk, this clearly indicates a huge increase in price risk faced by commodity producers. However, increasing interconnectedness of energy and commodity markets results in a particular form of risk-sharing: Because first-generation biofuels like bio-ethanol and biodiesel rely on commodities such as sugar cane, corn or rapeseed, energy producers compete directly with animal-feeding operations and food processors for the respective commodities: An individual farmer, consequently will produce feedstock for biofuels if the net revenue he earns “is greater than for alternative crops or uses” (FAO 2008, p.33). From this point of view one could argue that increase in choice for farmers has led to decreasing risk. However, this argument ignores the interconnectedness of energy and commodity markets. E.g., Tiffany and Eidman showed for ethanol plants great volatility in net returns that was clearly linked with prices for maize ethanol and natural gas (Tiffany & Eidman 2003). Biofuels, however, are highly subsidised, i.e. not only have most industrialized countries implemented blending requirements for biofuels, but most countries have a sophisticated set of tax-incentives, tariffs for protection of the own producers of biofuels and subsidies to promote investments in biofuels and use of biofuels (FAO 2008, p.27-29). Several studies have calculated that were these subsidies to cease, it would hardly be feasible to produce biofuels. E.g. Tyner and Taheripour (2007) calculated that the breakeven point for most biofuels would be too expensive to compete with crude oil. However, even with subsidies in place, demand for biofuels is highly dependent on market developments, i.e. the development of crude oil prices. With high oil prices biofuels can compete and accordingly demand for biofuels is high. Low prices for crude oil, however, lead to a decline in demand for biofuels, i.e. demand for biofuels is highly sensitive to overall market conditions: “The recent economic crisis led to a decline of oil prices and reduced the demand for first-generation biofuels, affecting various production facilities. For example, many of the biodiesel plants in Argentina were not working at the beginning of 2009” (Bringezu et al. 2009, p.35). The interconnectedness between demand for biofuels and, hence, price for biofuels and crude oil prices has been established in a series of publications: Wu and Feng (2009) found spillover effects between the energy market and the commodity market for crude oil spot and futures markets and corn spot and futures markets. Harri and Hudson (2009) were able to establish a Granger-causation between crude oil price and variance of crud-oil prices and corn prices as well as corn price variance. Accordingly, the authors concluded that “information flows from the energy markets into the corn markets” (Harri & Hudson 2009, p.np) exist. Kanamura (2008) shows increasing correlations between petroleum and soybeans as well as between petroleum and three sources of bio-ethanol, e.g., sugar, wheat and corn. Hence, that there is a link between energy markets and commodity markets with the former directly influencing the latter is a well established fact.

With demand for biofuels increasing with increasing crude oil prices and higher demand for biofuels resulting in a higher demand for feedstock that can be processed into biofuels, it is apparent that prices in energy markets directly influence prices for commodities: “Therefore crude oil prices will drive biofuels prices and, in turn, influence agricultural commodity prices” (FAO 2008, p.23). As a result, farmers face higher volatilities in commodity markets and more urgency for hedging price risks. Hedging of price risks, however, depends on the availability of an appropriate hedging tool, e.g., a financial derivative like a futures contract. Hedging as such is a “transactions or positions in any futures contract that (a) represent a temporary substitute for a transaction or position to be made or taken at a later time in a physical marketing channel; (b) are economically appropriate to the reduction of risk in the conduct and management of a commercial enterprise, and (c) arise from potential changes in the price of assets, liabilities, and services (existing or anticipated) associated with the operation of a business enterprise” (Powers 2001, p.148). The core of hedging strategies is the exploitation of reverse movements in two highly correlated markets. Thus, the precondition for any hedging activity is the existence of a commodity market and a commodity-derivatives market that are both highly correlated with each other. High correlated markets make the minimization of price risks possible. Accordingly, a hedge is defined as “a position in market j of size x_j* units such that the ‘price risk’ of holding x_j and x_j* from time t_1 to time t_2 is minimized” (Johnson1960, p.142). Starting from here this paper will exploit the expected close relationship between spot-markets and respective futures-markets. As has been elaborated in this chapter, demand for biofuels that exceeds the government mandate and prices for biofuels and commodities as such depend on the level of crude oil prices. The higher the prices for crude oil the higher demand for biofuels, this should result in a highly volatile relationship between spot prices for biofuels and prices for crude oil futures that reflect price developments in the energy market. Accordingly, hedging biofuels with crude oil futures should show distinctive traits of the underlying economic development. If this assumption holds true, this will be a major blow to dynamic methods to calculate the hedge ratio, because it shows that to find a futures-contract corresponding to the position in a commodity market that is suitable for a hedge is by far more important than to calculate the “correct” hedge ratio.

3. Finding the optimal hedge

Hedging it seems, is all about finding the optimal hedge. Usually, the view for, e.g., a suitable futures-contract is not to “extraordinary” and stops with a corresponding futures, i.e. rapeseed producer will look for rapeseed futures, biodiesel producers will look for biodiesel futures. However, up to now, there are no biodiesel futures available and while there is prospect of a biofuels-futures-contract in the not so far future for industrialized nations in the western hemisphere,[1] prospect for Asia and Europe is rather gloomy.[2] Accordingly, a bio diesel producer in need for a hedge will look elsewhere. The first alternative that comes to mind (especially after what has been said in the previous chapter), when thinking about a futures-contract alternative to a biofuels-future is a crude-oil futures-contract. With increasing demand for crude oil decreasing demand and price for biofuels, crude oil futures should provide a rather good hedging-opportunity. A producer of biofuels could hedge against rising prices for crude oil and respectively decreasing prices for biofuels by going short in oil futures, when he expects prices in biofuels to rise (and hence, prices in oil futures to fall) and long in crude oil futures when he expects prices in biofuels to fall and, accordingly, prices in crude oil futures to rise. The question is, whether a crude oil futures contract fit the needs of a biofuels producers and whether the relationship between the development of biofuels’ prices and price development of crude oil futures is close enough and reliable enough to make a good hedge. Usually, it is some kind of a rule of thumb, that correlation between commodity and futures must be high (Powers 2001, p.150), with futures’ prices ranging above the respective commodity prices to allow for the “convenience yield of the commodity” (Cortazar& Schwartz 2002, p.2). The art of hedging can be transformed into the quest for the suitable futures contract that shows a price movement largely similar to the movement of the commodity.

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1 http://blogs.reuters.com/summits/2007/01/16/audio-biodiesel futures-3-5-years-away/

2 http://www.reuters.com/article/idUSSIN23648020070117

To provide a first insight into hedging problems faced by biofuels producer this paper will look into the biodiesel-commodity-chain. It will start with the producer of rapeseed who is lucky enough to be provided with a rapeseed futures contract and it will compare the relationship between rapeseed futures and its underlying with the performance and the relationship between spot prices for biodiesel and price developments for crude oil futures.[3] The time frame covered by this analysis ranges from the start of 2007 to the end of 2009.[4] This time frame encloses the heyday of the subprime-mortgage crisis and subsequent economic recession (Arestis & Karakitsos 2009, Bordo 2008). Hence, additional to the normal price-movements of crude oil, biodiesel and rapeseed we have price movements induced by economic shocks that reduced demand and decrease prices. Therefore, one would expect this economic shock to be visible in the data. Figures 1 and 2 provide a first glimpse at the price development of rapeseed (spot prices) and rapeseed futures contracts, and biofuels (spot prices) and crude oil futures' prices respectively. As becomes apparent by the first look at figures 1 and 2, relationship between rapeseed and rapeseed futures is as expected. For the entire time frame, both are highly correlated (r=.9897) and prices for rapeseed futures exceed spot prices for rapeseed. For biodiesel and crude oil futures this is different. With only one exception, crude oil futures are lower priced than biodiesel, however, the correlation between biodiesel and crude oil futures is reasonably high (r = .619). But, correlation with rapeseed futures is even higher (r = .786) suggesting rapeseed futures to provide a better hedge than crude oil futures and hinting at the possibility that biodiesel spot prices are more closely related to commodity than to energy markets. However, these results provide only a short and rather broad view of the data. More information can be gained if the

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3 Data has been assembled from different sources ranging from data provided by PLATTS, to data provided by EURONEXT and data assembled at http://www.tradingeconomics.com. Calculations are performed on the basis of weekly data. Data has been standardized due to differences in currencies.

4 Demand plummeted at the end of 2008 due to the evolving economic crisis. Hence, one would expect to see major disruptions when the years 2007, 2008 and 2009 are compared. (IMF 2009, p.190)

three years covered with the dataset and expected to show signs of a major economic shock, are more closely surveyed.

Figure 1: Price development of rapeseed and rapeseed futures, 2007 to 2009

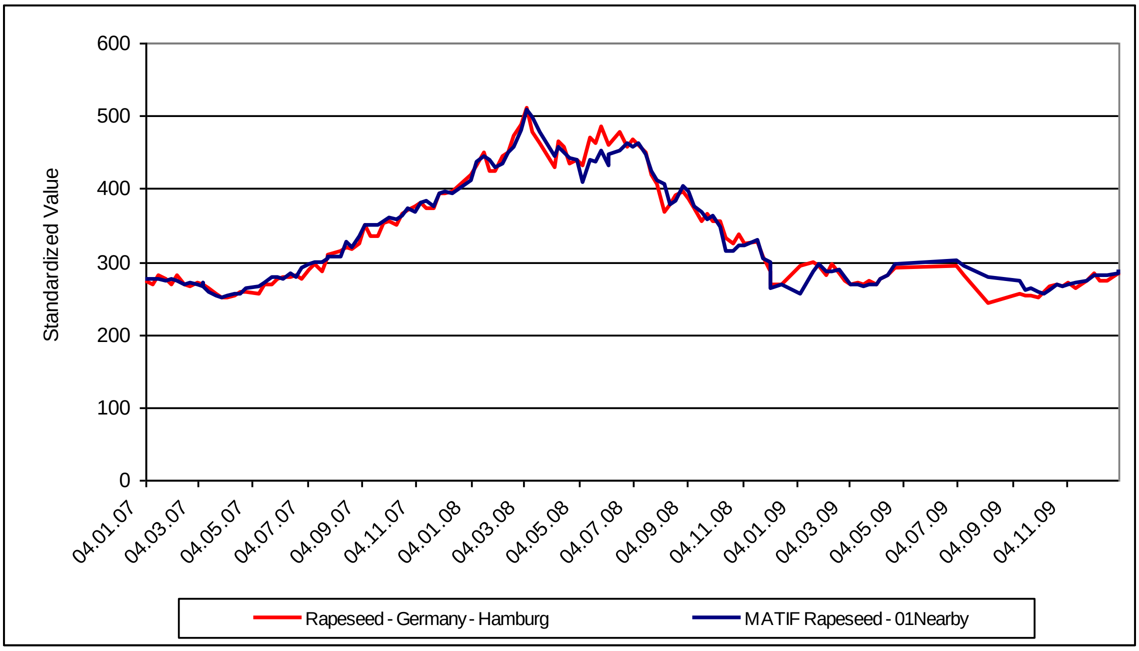
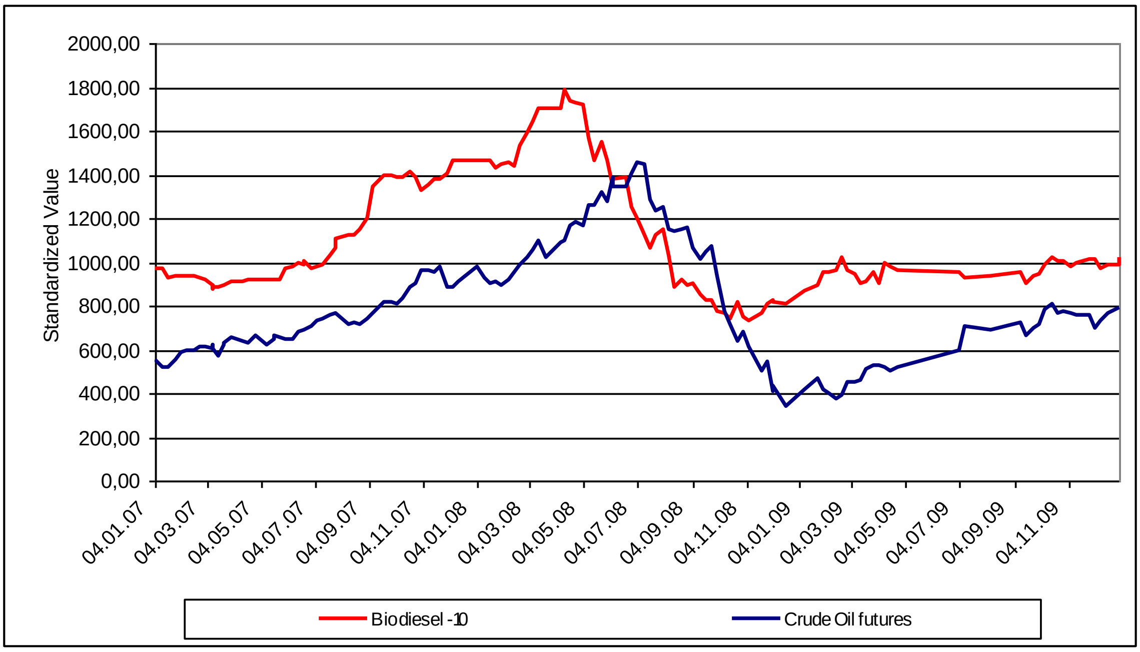


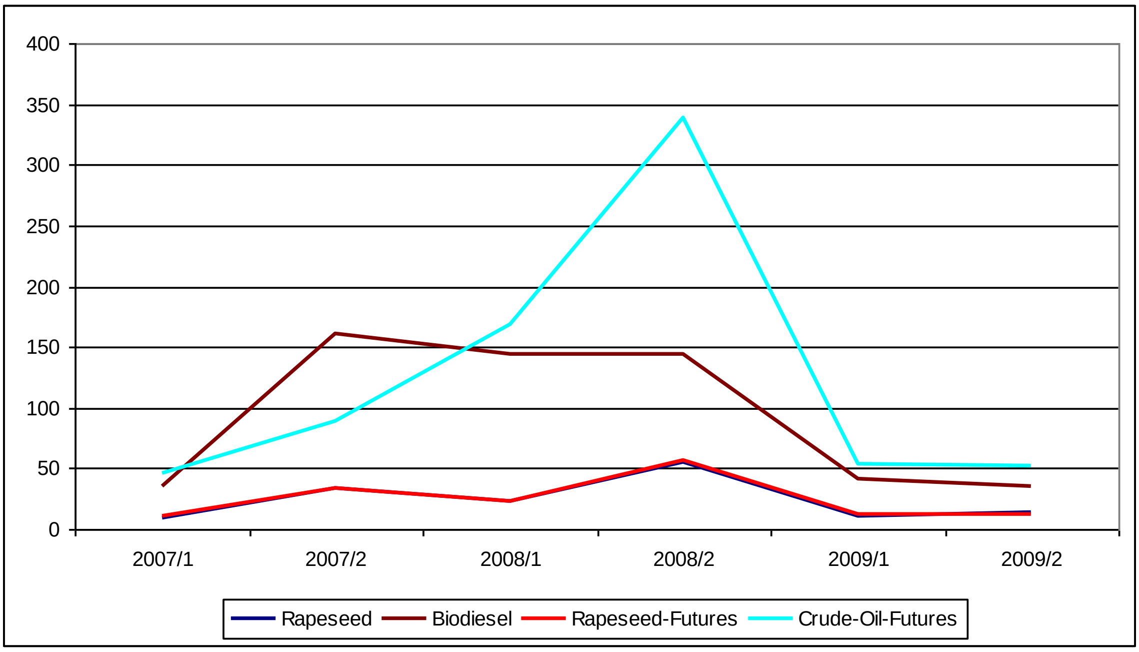
Figure 2: Price development of biofuels and crude oil futures, 2007 to 2009



Closer scrutiny of price developments in this paper means a breakdown of time points, i.e. I will present results for each separate year in the sample and further subdivide the data, so that the basis for statements will be coefficients calculated on the basis of 6-months-data. This incremental approach can be seen as a “discrete-dynamic” model. In any case it will allow conclusions about the magnitude and intensity of co-movements between commodities and derivatives, and hence, the effect of economic shocks on hedge ratios.

Results published by Kanamura suggest increasing correlation between energy and commodity markets starting with the year 2004 (Kanamura 2008, p. 11-12). However, results on the basis of weekly data for spot prices for rapeseed and biodiesel and prices for rapeseed futures and crude oil futures show a different pattern: They do not only react to economic shocks. This, one would have expected. However, they do react differently. Figures 3 and 4 show standard deviations and price volatilities (in percent) for rapeseed, biodiesel, rapeseed futures and crude oil futures for six six-month periods. Differences in price development can be clearly seen. However, while rapeseed and rapeseed futures react fairly similar across the period of observation, standard deviations of crude oil futures and biodiesel spot prices react violently to changing economic conditions. Given that all economic indicators show a slump for the second half of 2008 (IMF 2009, p.190) it is clearly to be seen that after a raid in previous years, prices in crude oil futures and – to a lesser degree – in biofuels get out of hand. Markowitz (1959) defined the risk of an investment as function of its standard deviation. The more standard deviation, the more risk. Clearly, crude oil futures and biofuels are associated with a huge amount of risk.

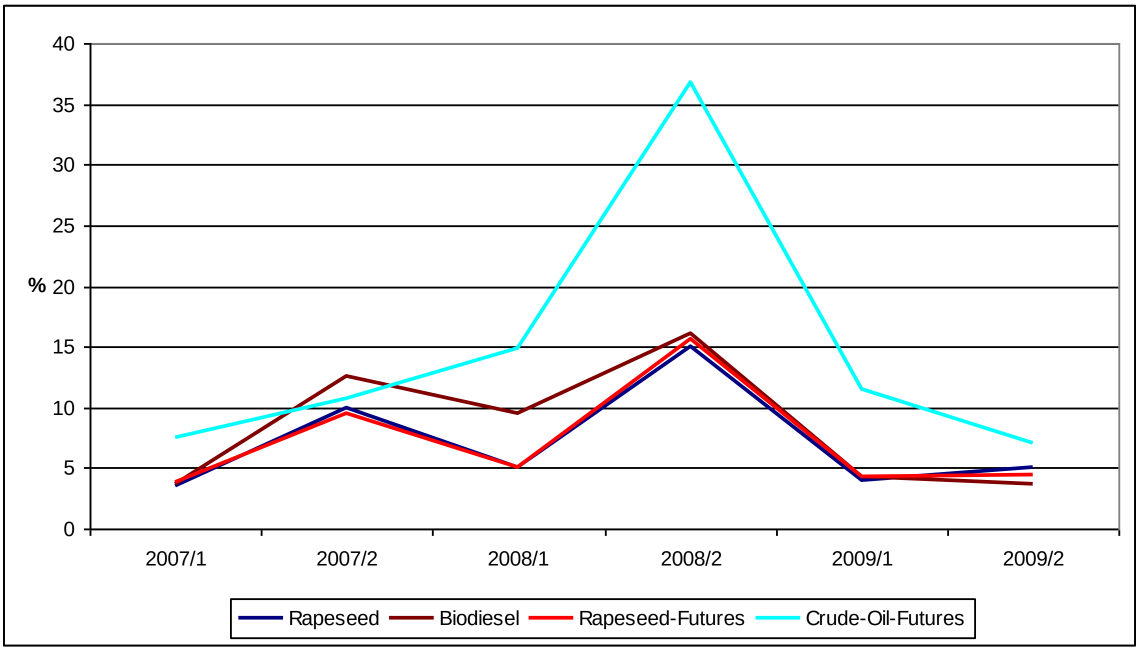
Figure 3: Standard deviation for rapeseed, biodiesel, rapeseed futures and crude oil futures' prices, 2007-2009



However, while figure 3 offers a view of the risk associated with investments in the respective equities or assets, it does not say too much about the magnitude of price changes. One can deduce that price changes are highest between the second half of 2007 and the first half of 2009. But not more. Accordingly, figure 4 gives account of the magnitude of price-movements.

While crude oil futures prices are distinctly more volatile than prices of rapeseed, rapeseed futures or biodiesel, price changes of the latter three are fairly similar, i.e. the magnitude of change does not differ too much. While figures 3 and 4 give a good picture of the magnitude of changes, they provide information on an aggregate level. Figure 4 shows the magnitude of price movements. Figure 3 shows the intensity of price movements.

Figure 4: Price volatility of rapeseed, biofuels, rapeseed futures and crude oil futures, 2007 to 2009



Given the high intensity of price movements shown in figure 3 and the magnitude of volatility displayed in figure 4, it is fairly obvious, that aggregate measures hide more of the truth than they reveal. The main omission is the standardisation of data, shown in figure 3 and 4, i.e., there is no differentiation between downside and upside movements. Hence, behind the scenes shown in figures 3 and 4, there may be more. The main interest of this paper is the structure behind optimal hedging. E.g., how do economic shocks affect relationships between hedge and underlying? Figures 3 and 4 show different intensities and magnitudes in reactions to economic shocks and accordingly, it can be assumed that correlations between derivatives and underlying will be affected. Because close correlation between, e.g., commodity and commodity futures is a precondition for an optimal hedge, this assumption is no good news. However, table 1 clearly shows that external economic conditions quite seriously shake the relationship between commodity and futures.

Table 1: Cross-correlations between rapeseed, rapeseed futures, biodiesel and crude oil futures, 2007 to 2009

	Biodiesel	Rapeseed Futures	Crude Oil Futures
First-half 2007			
Rapeseed	0.66	**0.86**	0.12
Biodiesel		0.72	**0.22**
Rapeseed-Futures			0.12
Second-half 2007			
Rapeseed	0.91	**0.98**	0.86
Biodiesel		0.94	**0.73**
Rapeseed-Futures			0.84
First-half 2008			
Rapeseed	0.08	**0.31**	-0.05
Biodiesel		0.32	**-0.19**
Rapeseed-Futures			-0.05
Second-half 2008			
Rapeseed	0.80	**0.98**	0.95
Biodiesel		0.82	**0.79**
Rapeseed-Futures			0.96
First-half 2009			
Rapeseed	-0.02	**0.55**	-0.5
Biodiesel		0.56	**-0.08**
Rapeseed-Futures			-0.28
Second-half 2009			
Rapeseed	0.37	**0.76**	-0.02
Biodiesel		-0.01	**0.71**
Rapeseed-Futures			-0.32

Coefficients displayed in table 1 are Pearson's correlation coefficients. In their squared version they show the amount of variance between two variables that can be explained or is "overlapping". Three main results are salient:

- Correlations between rapeseed and rapeseed futures vary considerably in their magnitude, ranging from r=.31 to r=.98, i.e. explained variance spreads between 9,6% and 96%, i.e., if one considers a close relationship between commodities and commodities-futures essential for the success of hedging, this precondition is not always a given;
- Correlations do not only vary in magnitude but also in direction. Correlations between biodiesel and crude oil futures, vary between r=-.19

and r=.79. Hence, the direction of the relationship, required to be rather parallel than working in opposite direction, is unsuitable for hedging;

- Finally, correlations begin to deteriorate as early as the first-half of 2008; Hence, the economic shock in the aftermath of the sub-prime mortgage crisis is either earlier affecting the relationship between commodities and futures markets than the entire economy or the relationship between commodities and futures is not as stable as it is expected to be, i.e., prone to short-term changes.

Results so far suggest that assumptions that must be met for hedging to be successful are time-dependent, i.e. some time they are met, some time they are not. This requires the hedge ratio to be calculated either on a daily or weekly basis, i.e. in the context of a dynamic model like GARCH(1.1) or one has to find a simpler method to adjust hedge ratios to alterations in the economic environment.

4. Determining the hedge ratio

On the basis of the results presented in the previous chapter, how does one calculate an accurate hedge ratio? One thing that has become obvious is that the hedge ratio depends on the period its calculation is based upon. A prospective hedge ratio calculated for the entire period 2007 to 2009 will differ considerably from the hedging rate calculated on the basis of data for the first half of 2009. Accordingly, the art of hedging is concerned with how to deal with deviations, i.e. with volatility. The number of models proposed to adequately deal with deviation and volatility is big. The best know models belong to the family of GARCH or ARCH models (Bollerslev 1986, Engle 1982). However, the benefit that can be squeezed from these models is rather obscure: Wu and Feng (2009) could show that hedging strategies did not differ in performance. The complicated GARCH model did not yield any better results as the constant or the cross hedge (Wu & Feng 2009, p.14). Their results compare to results published by Myers and Thompson (1989) who equally were not able to show that one of the abovementioned hedging models was able to outperform the others. Given the "apparent failure of dynamic hedging models" (Power & Vedenov 2008, p.3), and given that most models that claim to improve dynamic hedging techniques, need to alter the main assumption that makes GARCH models quite easy to apply, the assumption of joint multivariate normality" (Bollerslev 1986) is void. However, models that try to circumvent the respective assumption, like Copula-procedures (Ibragimov 2009; Granger, Terasvirta & Patton 2006) are far too complicated to be used as a hedging tool on a daily basis. So, how could a commodity position be hedged without much mathematical ado? The answer proposed in this paper is, by calculating moving averages multiplying them with the β-coefficient, the slope that is, of a regression model that covers the entire period of observation, i.e. by reducing a GARCH model to its main component, omitting the long-range variation and adding a linear component. To see how this works, table 2 presents the results of hedge ratio calculations performed on the basis of data, shown in the last chapter.

Table 2: Hedge ratios for rapeseed and rapeseed futures and for biodiesel and crude oil futures[5]

	Rapeseed/Rapeseed Futures (Hedge ratios)	Biodiesel/Crude Oil Futures (Hedge ratios)
First-half 2007	0.88	0.28
Second-half 2007	0.91	0.38
First-half 2008	0.75	0.22
Second-half2008	0.97	1.77
First-half 2009	0.55	0.10
Second-half 2009	0.66	1.01
Inclination of slope (b)	1.02	0.63

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5 Calculation is based on: $X = [\frac{Cov(r_p r_f|\phi)}{Var(r_f|\phi)}]Q = hQ$,

with r_p = return on spot-markets, r_f = return on futures markets, and ϕ information available to the hedger;

Moving average	0.79	0.52
Adjusted Hedge-Ratio	0.801	0.3276
Standard hedge ratio	0.95	0.59

Calculation of the adjusted hedge ratio is simple. First calculate the moving average for the different hedge ratios, than multiply the moving average with the slope of the regression line (OLS-line for r_p regressed against r_f) that can be calculated on basis of weekly data for the entire period of time (2007 to 2009).

As can be seen from table 2, hedge ratios calculated in this paper differ considerably from standard hedge ratios. However, a first test of performance shows that the newly calculated hedge ratios outperform standard hedge ratios by about 15%. Further tests and a comparison of the simple method proposed in this paper with GARCH models and more sophisticated dynamic models will follow.

5. Conclusion

Further performance tests pending, this paper proposed a method to calculate hedge ratios that is easy to calculate and claims to represent changes in the data quite well. As has been shown in preceding chapters, correlations between, e.g. commodities and commodities-futures are volatile, i.e. they react to changes in their economic environment. However, changes in spot prices and changes in futures' prices do not necessarily correspond with each other. Hence, a method is needed to smoothly adapt hedging ratios. Dynamic models claim to do just that, but dynamic models are hard to calculate and do not always stand-up to their task (Myers & Thompson 1989). Accordingly, this paper proposes an alternative measure, that is easy to calculate and quite reliable. Although, a first test of the measure proved to be satisfactory, to determine reliability and validity of the adjusted hedge-ratio remains a task for further research.

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