Managing Price Risk for an Oil and Gas Company

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Abstract: Oil and gas companies' earnings are heavily affected by fuels price fluctuations. The use of hedging tactics independently by each of their business units (e.g. crude oil production, oil refining and natural gas) is widespread to diminish their exposure to prices volatility. How much should be hedged and which derivatives should be selected according to the company risk profile are the main questions this paper intends to answer. The present research formulates an oil and gas company's integrated earnings structure and evaluates the company's risk tolerance with four approaches: Howard's, Delquie's, CAPM and a risk assessment questionnaire. Stochastic optimization and Monte Carlo simulation with a Copula-GARCH modelling of crude oil, distillates and natural gas prices is used to find the derivatives portfolios according to company risk tolerance hypothesis. The hedging results are then evaluated with a multi-criteria model built in accordance with the expressed company's representatives preferences upon four criteria: payout exposure; downside gains; upside gains; and risk premium. The multi-criteria analysis revealed a decisive role in the final hedging decision.

1 INTRODUCTION

Oil and gas (O&G) companies' earnings are substantially affected by the price fluctuations of crude oil, natural gas and refined products, which induce these companies to find ways to minimize price risk exposure. Almost all O&G companies use derivative instruments, like swaps and options, to share price risks with other counterparties. This research intends to propose a methodology to help answer the main question that an O&G company faces when trying to meet its budget goals: which amount (if any) should be hedged and in which derivatives. This work does not intend to be an intensive research on complex derivatives but instead evaluates the robustness of the hedging decisions based on risk tolerance parameters and confronts the results with a multi-criteria evaluation model. For confidentiality reasons, the name of the company will not be mentioned.

Deregulation of the United States energy markets in the 1970's provided the ingredients for the steady growth of derivatives in the energy markets. Several studies have focused the pros-and-cons of hedging practices in O&G companies, some of them presenting serious doubts on a company's value increase. However, in general, there exists a common agreement on a better financial leverage (Haushalter, 2000) and a lower unpredictability on the earnings side (Jin and Jorion, 2006). The introduction of the decision-maker utility as a decision criterion (von Neumann and Morgenstern, 1944) assured the foundations for risk and return concepts across the economic thinking, including the early use of utility functions in portfolio optimization (Levy and Markowitz, 1979).

The remainder of this paper is organized as follows. Section 2 describes the problem formulation, section 3 presents the price variables stochastic modelling and correlation fitting, section 4 describes the risk modelling, section 5 shows the results obtained by stochastic optimization of four hedging approaches, section 6 presents a multi-criteria model built to evaluate eight hedging options against four criteria (payout exposure, downside gains, upside gains, and risk premium) and section 7 presents the conclusions.

2 PROBLEM FORMULATION

The O&G company is organized in three business units: the Exploration and Production unit (E&P) produces only a partial amount of the crude the

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Refining and Distribution (R&D) unit needs (crude oil buying is regular), and the Natural Gas unit (NG) imports natural gas from foreign suppliers and sells it to final consumers. The company has not an integrated approach to manage price risk, since the price risk management is made separately at each business unit level, missing the risk mitigation benefits across business units and not evaluating the company entire price risk exposure. In fact, does not exist a corporate risk measure to align hedging operations with the company supposed risk preferences. Since this research is focused on commodities price risk, we take as reference the company's revenues affected in first instance by price fluctuations, i.e. the Gross Margin, calculated as the difference between the value of the goods sold (crude oil, refined products and natural gas) and acquired goods (crude oil and natural gas).

2.1 Physical Earnings Formulation

2.1.1 Exploration and Production

Crude oil production in oilfields of the Exploration and Production (E&P) business unit takes place under the two most applied agreements regulating profits between O&G companies and host governments (Kretzschmar et al., 2008): "Production Sharing Contracts" (PSC) and "Concessions". PSC are common in African and non-OECD countries. In these regimes the O&G company receives a defined share of the production remaining after cost recovery, the Entitled Production quantity e_p (in barrels of crude oil, bbl) is given by:

$$e_p = \frac{p_o + c_o}{p} \tag{1}$$

where c_o is the Cost Oil (oil produced and allocated to cover the capital and operating costs of the company project), p_o is the Profit Oil (remaining 'profit' allocated between company and State) and p is the crude oil market price in U.S. dollars per barrel ($/bbl). The Entitled Production quantity is converted in earnings depending on the crude oil market price.

Concession regimes have more straightforward agreements and the earnings e (in $) is given by:

$$e = qp - c - p_o t_x, \tag{2}$$

where q is the total production of crude oil (in bbl), p is the crude price ($/bbl), c denotes the operating costs, p_o is the Profit Oil and t_x is the tax rate due to host governments. The general formula for the E&P earnings for both regimes m_e (in $) is:

$$m_e = e_p p + e \tag{3}$$

The crude oil price has two major world reference indexes: the Brent price in Europe and the Western Texas Intermediate price (WTI) in the U.S.A.

2.1.2 Refining and Distribution

The Refining and Distribution (R&D) business unit is composed by the refining industrial complex and the distribution network (wholesale and retail). The price risk affects essentially the refining business, which is smashed between the very volatile prices of the inputs (crude oil) and outputs (refined products)., The price differential between crude oil and some refined products can be unfavourable for some periods and negative refining margins can occur, especially in older and less complex refineries, explaining why some of them are being shutdown. This turns the yearly earnings of a refinery a difficult guess and explains why hedging is a common practice (Ji and Fan, 2011). On the opposite side, in deregulated markets, Distribution has almost zero risk, since any change in the cost of the refined products is quickly transferred to the final consumer. Therefore, in this paper we will only focus on the refining price risk. The refining gross margin m_r (in $/bbl) is given by:

$$m_r = \left(\sum_{i=1}^{n} y_i x_i - p \right) q_r \tag{4}$$

where y_i is the yield (the percentage of each i refined product taken from a unit of crude), x_i is the unitary price of each refined product i, p is the unitary price of crude and q_r is the yearly crude quantity refined (in tonnes).

2.1.3 Natural Gas

The Natural Gas (NG) business unit buys natural gas from other countries, based on long-term contracts with complex price formulas indexed to the prices of crude oil and refined products baskets. The selling price formulas are diversified according to consumer's types (households, power plants and industrial consumers) and have usually the Brent price as the index reference (*αBrent* formulas) or other indexes. The NG gross margin m_g (in $) is given by:

$$m_g = \left(\sum_{i=1}^{n} z_i s_i - \sum_{j=1}^{n} w_j b_j \right) q_g, \tag{5}$$

where s_i and b_j are respectively the selling and buying price indexes, z_i and w_j are respectively the selling and buying weights, and q_g is the yearly total quantity of natural gas (measured in m^3 or kWh).

2.2 Derivatives Payout Formulation

As the goal underneath this research is at least one year term hedging we will choose the most common and tradable derivatives for each business unit, which includes swaps and european options priced in the OTC (over the counter) market through large banks and Brent crude futures (ICE Brent) priced in the ICE exchange (a NYSE company).

2.2.1 Exploration and Production (E&P)

For the E&P business unit we will consider selling crude oil futures, since the counterparty's risk is almost null and this procedure avoids the options premium's high costs (Energy Information Administration, 2002). The unitary payout d_e (in \$/bbl) is given by:

$$d_e = f - p_t, \tag{6}$$

where f is the future price for the Brent (\$/bbl), and p_t is the Brent price at future exercise time t. If the Brent price p_t before maturity time, is lower than the f sell price, E&P receives the difference between these two prices, otherwise it loses the difference.

2.2.2 Refining

For Refining we will choose the following derivatives: selling swaps which allows protection from lowers margins (even losing the potential benefit of higher margins) and collars (i.e. selling calls and buying puts), since they provide a bandwidth to benefit from price movements without incurring in costs.

These derivatives have as underlying a simplified refining margin (also known as crack spread), based on the refined products with most traded forward prices. We will name this simplified refining margin the "Hedge Margin" m_h (in \$):

$$m_h = \left(\sum_{i=1}^{5} y_i x_i - p \right) q_h, \tag{7}$$

where y_i is the yield of product i entering in the "Hedge Margin" (only 5 of the 18 products from the production of the refinery have enough forward price liquidity to enter in a hedge basket), x_i is the market price of product i, p is the Brent price and q_h is the quantity to be hedged. The difference between the real margin m_r and the hedging margin m_h is called the "basis risk" b (in \$), which is given by:

$$b = m_r - m_h \tag{8}$$

The hedge margin swap is a derivative based on a fixed hedge margin price where the swap seller (the company) receives or pays the price difference between the fixed agreed price and the spot price at each future fixed time legs, usually monthly till the end of contract. The swap payout definition for the swap hedge margin d_s (in \$/bbl) is given by:

$$d_s = f_s - p_h \tag{9}$$

where f_s is the initial agreed fixed price for the hedge margin (\$/bbl), usually the average forward price of the hedging margin m_h for the contract duration, and p_h is the hedge margin spot price at each future month t, until the end of the contract, usually one or more years.

The collar is a derivative instrument resulting from buying a put and selling a call. In practical terms, if the spot price at maturity is between the low ("floor") and the high ("cap") pre-agreed prices, no monthly payout exchange is made between the company and the counterpart. If the spot price at maturity is lower than the floor price, the company receives the difference from the counterparty and in the opposite situation, the company pays. The collar payout d_c (in \$/bbl) is given by:

$$d_c = \min\left(f_c^f - p_h ; 0 \right) + \max\left(f_c^c - p_h ; 0 \right) \tag{10}$$

where f_c^f *and* f_c^c are respectively the floor and the cap agreed fixed price for the hedge margin m_h and p_h is the hedge margin spot price at each future month t until the end of the contract.

2.2.3 Natural Gas (NG)

The NG business unit acts as an importer and distributor and is concerned with natural gas prices increases that may not transfer to clients, affecting the natural gas margin. With the same logic of the refining margin, selling swaps of the natural gas margin allows protection from lower natural gas margins even the potential gains from higher margins are partially transferred to the counterparty, depending on the quantities agreed. The monthly swap payout definition d_g (in \$/kWh) is given by:

$$d_g = f_g - p_g \tag{11}$$

where f_g is the initial fixed agreed price for the natural gas margin, usually the average forward natural gas margin m_g for contract duration and p_g is the natural gas margin spot price at each future maturity month t, until the end of the contract.

2.3 Company Earnings Formulation

The company's total derivatives payout d (in \$) is given by:

$$d = d_e q_e + d_s q_s + d_c q_c + d_g q_g \tag{12}$$

where q_e, q_s, q_c *and* q_g are the quantities (a.k.a notional amounts in swaps and options and number of contracts in futures market) hedged and to be found in the hedging optimization, ahead in the present research.

The sum of the total derivatives payout d with the physical margin of each business unit, m_e, m_r *and* m_g gives the gross margin for the company m (in \$):

$$m = d + m_e + m_r + m_g \tag{13}$$

The option to include all physical earnings and derivatives payouts to evaluate the company's risk reduction instead of doing it separately by business unit is based on previous analyses where the risk reduction is more effective by optimizing at once all business units and inherent derivatives basket (Quintino et al., 2013), having also the advantage of minimizing the "basis risk", b, since physical margin m_r and hedged margin m_h will be optimized in the same process.

3 PRICES MODELING

3.1 Stochastic Prices Modelling

For this research we will follow the main historic pricing reference for energy markets, the Platts (2012) quoted for the Northwest Europe (a.k.a. Rotterdam prices) from 2006 to 2012. For the OTC forward prices we follow the Reuters (2012) quoted monthly prices for the Northwest Europe to 2013 and the ICE Brent for future prices.

3.2 Time Series Modelling

Historic prices will be modelled by their monthly price returns and used to define the stochastic behaviour of the forward prices, permitting to evaluate how the margin m in expression (13) varies in the months ahead.

The price return r_t (in %) for a product is given by:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{14}$$

where p_t is the average price of month t and p_{t-1} is the average price in month $t-1$. The Generalized Autoregressive Conditional Heteroscedasticity model (GARCH) proposed by Bollerslev (1986) achieved the best fit for each of the prices returns (SIC-Schwarz information criterion and the AIC-Akaike information criterion were used as goodness of fit measures), which was also confirmed by Nomikos and Andriosopoulos (2012). The monthly spot prices returns r_t (in \$) for a GARCH(1,1) process is given by:

$$r_t = \mu + \sigma_t z_t$$

with

$$\sigma_t^2 = \omega + \alpha\left(r_{t-1} - \mu\right)^2 + \beta\sigma_{t-1}^2 \tag{15}$$

where μ is the series trend, z_t are independent variables from a Normal distribution $\mathcal{N}(0,1)$ and the conditional variance σ_t^2 assumes an autoregressive moving average process (ARMA), with α weighing the moving average part and β affecting the auto-regressive part, being $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$. The term $(\alpha + \beta)$ should be less than one to assure long-term stability and β is defined as the "persistence term", reflecting the speed at which the shocks to the variance revert to the long run variance. The higher the persistence the slower the times series revert to the long run variance. The absence of autocorrelation was confirmed by the Ljung-Box statistic. Figure 1 shows the high variability of Brent prices returns, with other refined products exhibiting a similar pattern.

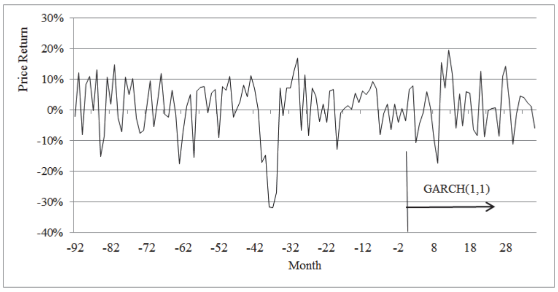

Figure 1: Brent monthly price returns modelled with a GARCH(1,1) model.

3.3 Correlation Modelling

Modelling correlation between the different products prices, assuring nonlinear and complex interdependencies, leads us to copula's functions. The Sklar (1959) theorem provides the theoretical foundation for the application of copulas' functions. It assumes a stochastic multi-variable vector (X_1, X_2,...X_n), where X_i is in our case the price of product i with continuous marginals and cumulative density function $F_i(x_i)$=P($X_i \leq x_i$). Applying the probability integral transform to each component: $[U_1,U_2,\ldots U_n]=[F_1(X_1),F_2(X_2),\ldots,F_n(X_n)]$, having $U_i \in]0;1[$ continuous margins.

The copula function C is defined as the joint cumulative distribution function of $[U_1,U_2,\ldots U_n]$, where $C[u_1,u_2,\ldots,u_n]=P[U_1 \leq u_1, U_2 \leq u_2,\ldots, U_n \leq u_n]$. The copula C contains all information on the dependence structure between the components of $(X_1, X_2,\ldots X_n)$, whereas the marginal cumulative distribution functions F_i contain all information on the marginal distributions. The great advantage of copula's functions is to allow the correlation pattern modelled by the copula function to be independent from the random variable X_i marginal's. Copula's functions are considered the most powerful and flexible tool for portfolio management and risk analysis (Jobst et al., 2006); (Rosenberg and Schuermann, 2006); (Chollete, 2008).

3.4 Copula-GARCH Model

Natural Gas and Refining business units have very narrow gross margins, which depend on complex formulas involving several products prices, demanding a powerful correlation method to assure the margins' values adhere to reality. Time series functions and correlation functions, after long testing, led us to the Copula-GARCH models (Lu et al., 2011). Our method can be synthesized in three steps: first, modelling the independent prices returns with a GARCH model as described in (15) and, second, find the best copula function to correlate each GARCH price returns residuals z_t.

$$z_t = \frac{r_t - \mu}{\sigma_t} \tag{16}$$

Applying the SIC and the AIC criteria (Fermanian, 2005) we obtained the Student's t copula (t-copula) as the best copula function to model the prices return residuals correlation. The Student's t copula is defined by:

$$C(u_1;u_n;\rho,d) = T_{d,\rho}\left[t_d^{-1}(u_1), t_d^{-1}(u_n)\right] \tag{17}$$

where T is the t-copula with d degrees of freedom and correlation matrix ρ, t^{-1} is the inverse Student's t distribution with d degrees-of-freedom, and u_n are the marginal distributions of the n variables (the price returns residuals, z_t in our case).
The degree of tail dependency in the t-copula is defined by d (degrees of freedom).

Finally, the third step evaluates each stochastic price return p_t using:

$$p_t = pe^{r_t} \tag{18}$$

where p is each forward price and r_t is each price return, given by the combination of a GARCH and a t-copula function T being z_t^* the residual correlated with each other price returns residuals:

$$r_t = \left[\omega + \alpha\left(r_{t-1} - \mu\right)^2 + \beta\sigma_{t-1}^2\right]\underbrace{T_{d,\rho}\left[t_d^{-1}(\mathrm{u_t})\right]}_{z_t^*} \tag{19}$$

Unlike the Gaussian copula, the t-copulas have the advantage of preserving the tail dependence in extreme events (Asche et al., 2003), having steady use in advanced portfolio risk estimation (Huang et al., 2009), (Shams and Haghighi, 2013) and oil hedging strategies (Chang et al., 2011).

4 RISK MODELLING

4.1 Risk Measures

Exposure, also called impact (Kaplan and Mikes, 2012), is the foreseen potential loss in money or in other measurable variable if the risk occurs. The importance of confronting an O&G gross margin "exposure" with a measure of the respective "uncertainty" is to guarantee that a company meets its obligations with a previously imposed degree of confidence (Haushalter, 2000). Artzner et al., (1999) defined the axioms necessary and sufficient for a risk measure to be coherent: positive homogeneity, translation-invariance, monotonicity and sub-additivity. Rockafellar and Uryasev (2000) proved that standard deviation and Value-at-Risk (VaR) created by J. P. Morgan (1992) are not coherent risk measures, because the first violates translation invariance and monotonicity, while VaR fails sub-additivity. They proposed Conditional Value-at-Risk (CVaR) as a coherent risk measure, which assures the essential sub-additivity property and, as presented in Figure 2 measures how large is the average loss into the left tail ($\$720 \times 10^6$), while VaR only defines the loss frontier for a given probability ($\$600 \times 10^6$).

Conditional Value-at-Risk (CVaR) is given by:

$$\mathrm{CVaR}_{1-\alpha} = E\left(X_\alpha \leq \mathrm{VaR}_{1-\alpha}\right) \tag{20}$$

where X_α is the value defined for having VaR for a confidence level of $1 - \alpha$.

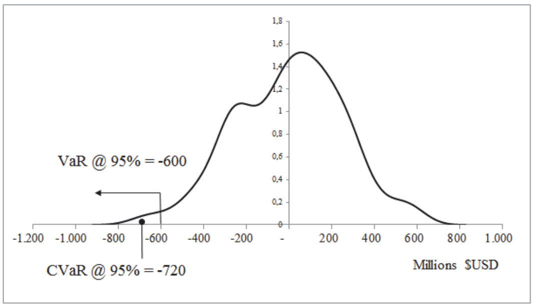

Figure 2: Company downside earnings measured by VaR and CVaR with a 95% confidence level.

4.2 Risk Tolerance

Utility theory, firstly proposed by Bernoulli (1738) and developed by von Neumann and Morgenstern (1944), allows determining a rational decision-maker behaviour under risk and uncertainty. A utility function $u(x)$ describes a decision-maker preferences and risk attitude allowing to translate, e.g., dollars into utility units. A risk-averse decision-maker would have a concave utility function, meaning that she would exchange a higher expected value of an uncertain game by a lower sure amount. A risk-prone decision-maker (one that prefers a higher expected value of an uncertain game to a lower certain amount) would have a convex utility function. A risk neutral decision-maker would have a linear utility function.

The Certainty Equivalent (CE) is a key concept in risk analysis. In the simple example lottery depicted in Figure 3, the decision-maker may consider the option "gamble", with an outcome of \$100 ($u(x) = 1$) with a probability of 60%, and an outcome of \$0 ($u(x) = 0$) with a probability of 40% indifferent to the option "not gamble", if the certain outcome of "not gamble" is \$45. Thus, we would say that CE = \$45 and $u(\$45) = u(\$100) \times 0.6 + u(\$0) \times 0.4 = 0.6$. The risk premium r (in \$) is given by:

$$r = E(x) - \text{CE}. \tag{21}$$

Consequently, for the above presented example, $r = (\$100 \times 0.6 + \$0 \times 0.4) - \$45 = \$15$.

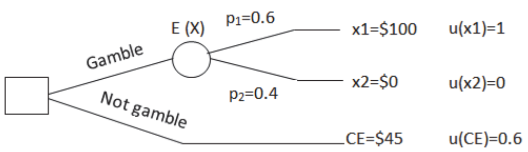

Figure 3: Certainty equivalent meaning in a lottery.

Measuring corporate risk tolerance requires assessing tradeoffs between potential upside gains and downside losses under conditions of uncertainty.

As a result, the selection of the optimal derivatives portfolio is influenced by the decision-maker's attitudes towards financial risk. This is the point where utility theory commands the evaluation of the optimal portfolio, assessing the decision maker's risk tolerance. The exponential utility function (22) is one of the most widely used, and is well tested on portfolio risk management in the oil industry (Walls, 2005).

$$u(x) = 1 - e^{-\frac{x}{\rho}} \tag{22}$$

Its single parameter (the risk tolerance ρ), no initial wealth dependence and constant absolute risk aversion ($-u''(x)/u'(x)=c^{te}$) (Pratt, 1964) explain the exponential utility function wide use. In a lottery game, the risk tolerance value ρ is the value that the decision maker is willing to accept in order to play a game where there are only two outcomes: winning the amount ρ with a 50% probability or lose $\rho/2$ with 50% probability.

The exponential utility function performs better than other utility functions, including the quadratic utility function inherent to the Markowitz's portfolio optimization (Kirkwood, 2004) but using a utility function advises a post sensitivity analysis to assure the results robustness. The exponential utility function certainty equivalent is:

$$CE_x = -\rho \ln\left(\sum_{i=1}^{n} p_i e^{\frac{-x_i}{\rho}}\right) \tag{23}$$

but can be simplified (Pratt, 1964, Clemen, 1996) for outcomes with normal distributions (which is our case, after K-S test) to:

$$CE \approx \mu(x) - \frac{\sigma_x^2}{2\rho} \tag{24}$$

where $\mu(x)$ is the yearly average gross margin for the company according to expression (13), σ_x^2 is the gross margin variance and ρ is the company's risk tolerance.

4.3 Risk Tolerance Estimation

Numerous studies proposed evaluation methods for corporate values of risk tolerance for exponential utility functions. The most referred research suggests setting the risk tolerance ρ at 6% of sales, 1 to 1.5 times net income, or 1/6 of equity in the "O&G" companies (Howard, 1988). A more analytic approach presented by Delquie (2008) proposes the risk tolerance to be set to a fraction of the maximum acceptable loss the company can afford for a given p significance level, which can be considered a proxy for the Value-at-Risk (VaR_{1-p}):

$$\rho = \frac{\text{VaR}(p)}{-\ln p} \tag{25}$$

With a significance level p = 5% this implies that the risk tolerance ρ is equal to one third of the $\text{VaR}_{95\%}$.

Another common way to estimate corporate risk tolerance is through a questionnaire answered by a decision group panel who represents the company risk profile (Board, CEO, CRO, CFO) for the most important decisions.

Confronting each decision maker with a list of questions in which he must choose between one of two outcomes, x_1 or x_2, with probabilities p_1 and p_2, respectively, it is possible to calculate iteratively the certainty equivalent CE and the inherent risk tolerance ρ that matches equation (23) (Walls (2005)).

Another risk tolerance method estimation, derived from the Capital Asset Pricing Method-CAPM (Sharpe, 1964) is to assume the CE as the effective cash-flow when each year t nominal cash-flow CF_t is discounted through the ratio of the risk free rate r_f to the rate that the company demands for investments, the Weighted Average Cost of Capital (WACC).

$$CE_t = CF_t\left[\frac{(1+r_f)^t}{(1+WACC)^t}\right] \tag{26}$$

where CF_t is the Project Cash-Flow in year t and r_f is the free rate of return.

4.4 Risk Tolerance Results

Let us now explaining the results of the four approaches employed:

a) With Howard's we obtain the most conservative estimation, e.g. one year of the company's net results is assumed to be the company's risk tolerance ($\$317\text{x}10^6$);

b) For Delquie's, we estimate the $\text{VaR}_{95\%}$ for the company's one year gross margin ($\$505\times10^6$) with p=5% in expression (25), which gives a risk tolerance of $\$166\times10^6$;

c) For CAPM, we evaluated all the forecasted project cash-flows 10 years ahead (essentially E&P based) and we estimate the average certainty equivalent applying (26), which gives a risk tolerance of $\$220\times10^6$;

d) For the risk assessment questionnaire, we confronted the CFO and his advisers with a set of questions to evaluate the amount of money about which they were indifferent, as a company, in order to have a 50-50 chance of winning that sum or losing half of it. A complementary set of questions was made on the risk premium they were willing to pay in order to receive with certainty the average gross margin estimated for next year's budget. Applying expression (23) to the first set of answers and expression (21) to the second set of answers, it was possible to have a series of risk tolerances values, with a mean of $\$180\times10^6$ and a standard deviation of $\$42\times10^6$.

The risk tolerance results for the four methods are presented in Table 1.

Table 1: Risk Tolerance results (in $\$10^6$).

Method	Measure	Value	Risk Tolerance
Howard	Net Income	317	317
Delquie	$\text{VaR}_{95\%}$	505	166
CAPM	CE	370	220
Questionnaire	Gross Margin	760	180

Delquie (2008) method has the most conservative risk tolerance, while Howard's method estimated the highest value. The other ratios proposed by Howard (equity and sales) give us even larger risk tolerance values.

5 OPTIMIZATION RESULTS

In order to evaluate the consequences of the risk tolerance estimates in Table 1, we ran optimizations for a range of eight risk tolerance values, including the four presented in Table 1, maximizing the company certainty equivalent by inserting expression (13) into expression (24):

$$\max CE \approx \max\left\{m(d, m_e, m_r, m_g) - \frac{\sigma_m^2}{2\rho}\right\} \tag{27}$$

We used a stochastic optimization algorithm (Optquest, 2012) having the hedge quantities q_e, q_s, q_c *and* q_g in expression (12) as the variables to be determined. The stochastic price p_t of each product is embedded in the gross margin of each business unit, m_e, m_r, m_g and in the derivatives payout d, at the same time.

After having achieved the optimal solution for each of the eight risk tolerance values, we ran a Monte Carlo simulation (5000 runs) using ModelRisk (2012).

The solutions from the integrated model (27) have the advantage of obtaining the eight optimal derivatives solutions while minimizing the "basis risk" *b*. Figure 4 presents the density probability curve for the un-hedged and hedged scenario for a risk tolerance of $\$25\times10^6$.

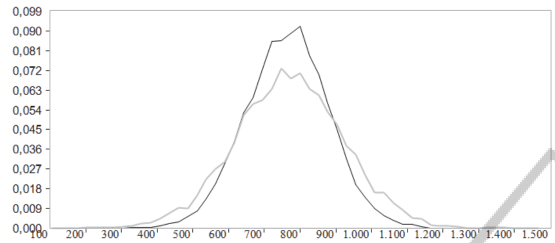

Figure 4: Hedged and un-hedged margin for a $25×106 risk tolerance.

Figure 5 shows the risk tolerance impact in the company certainty equivalent and into the $CVaR_{95\%}$ (the risk measure).

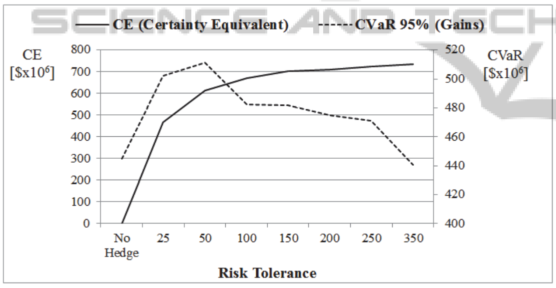

Figure 5: CE and $CVaR_{95\%}$ as a function of risk tolerance.

As risk tolerance increases, the certainty equivalent increases, since the risk premium decreases (see (24)). However, after a risk tolerance of $ 50×10^6, we see a drop in the company CVaR.

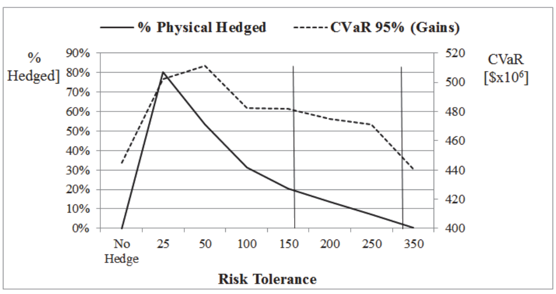

Figure 6: $CVaR_{95\%}$ and % Physical Hedged as a function of Risk Tolerance ($\$10^6$).

Looking at Figure 6, the decrease in CVaR is explained by the decreasing amount of derivatives *d* in the optimized solutions, which allows greater potential upside gains but greater potential downside losses. The "% Physical Hedged" is the ratio between the notional amounts of derivatives contracts and the total physical company production, both amounts in tons.

Less hedging means that the minimum gains (or losses) get lower. Looking at the risk tolerance vertical lines, the Delquie method implies about 20% hedging, the risk questionnaire about 15%, CAPM about 7% hedging and Howard method would imply only 3% hedging. The main question that arises is about the "real" company risk tolerance, because different risk tolerances imply noticeable differences in terms of potential derivatives losses, as is shown in Figure 7. Yearly potential derivatives losses may vary from $\$20\times10^6$ to $\$140\times10^6$, which can have a heavy impact in the Mark-to-Market (MTM) company quarterly financial statements.

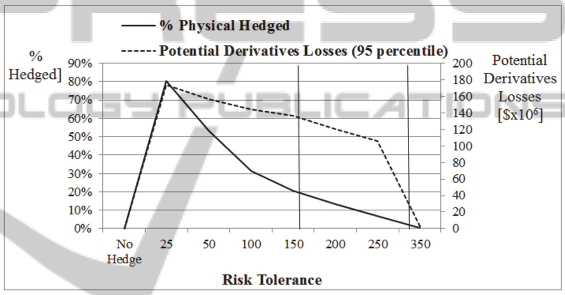

Figure 7: % Physical hedged and potential derivatives losses as a function of risk tolerance.

6 MULTI-CRITERIA EVALUATION

As we can observe in the results presented in section 5, the risk tolerance estimation widely affects the hedging optimal solutions, and it is not clear if the in-house risk assessment questionnaire defined accurately the company risk profile. Therefore, we will test in what extent the questionnaire reflects with confidence the decision maker's risk preferences.

The company is interested in selecting the most attractive hedging option from the set of eight options previously built. However, the CFO and his advisers, which constitute the company's decision-making group (DM), are not sure about which one to select. In fact, they suspect that there is no option that is the best according to all points of view that came to their mind. To help the DM we developed a multi-criteria evaluation model (Belton and Stewart (2002)) using the MACBETH approach (Bana e

Costa and Vansnick, 1999; (Bana e Costa et al., 2012), which required the group to: discuss their points of view and select the criteria that should be used to evaluate the hedging options; associate a descriptor of performance to each criterion; build a value function for each criterion; and weight the criteria.

The additive value function model was selected to provide an overall measure of the attractiveness of each hedging option:

$$v(x_1,\dots x_n)=\sum_{i=1}^{n} w_i v_i(x_i) \text{ with } \sum_{i=1}^{n} w_i = 1,\ w_i > 0 \qquad (28)$$

where v is the overall score of an hedging option $\boldsymbol{x}$ with the performance profile $(x_1,\dots, x_n)$ on the n criteria, v_i (i =1, …, n) are value functions, w_i (i =1, …, n) are the criteria weights. (Note that by applying the additive value function model we are admitting that a poor performance of an option in one criterion may be compensated by good performances of that option in other criteria. However, this working hypothesis must be validated by the decision-making group.)

The DM members discussed the points of view they considered relevant for evaluating hedging options having in mind the next year gross margin budget as overall objective. After discussion, four evaluation criteria were selected: 1) downside gains, 2) upside gains, 3) payout exposure and 4) risk premium.

The performances of the hedging alternatives in all criteria are their earnings expressed in $\$10^6$. The 5th and 95th earnings' percentiles from the Monte Carlo simulation results were used to define the upper and lower reference levels, respectively, on each descriptor of performance; three other intermediate levels, between the upper and the lower reference levels, were created on each descriptor of performance. For example, Figure 8 presents the performance levels of criterion "payout exposure", where 0 and 200 were defined as the upper and lower reference levels, respectively, and 50, 100 and 150 are the intermediate levels; Figure 11 shows the performance levels of all criteria).

Performance levels :

	Quantitative level
1	0
2	50
3	100
4	150
5	200

Figure 8: Performance levels for the "payout exposure" criterion (in $\$10^6$).

A value function was built for each criterion using the MACBETH method and software (www.m-macbeth.com), fixing 100 and 0 as the value scores of the upper reference level and lower reference level, respectively, on all criteria. According to the MACBETH questioning protocol, the decision-makers had to judge the difference in attractiveness between each two levels of the descriptor of performance using the semantic scale: *very weak*, *weak*, *moderate*, *strong*, *very strong* or *extreme*. For example, in the matrix of judgments for criterion "payout exposure" (see Figure 9) the decision-makers considered the difference in attractiveness between \$0 and $\$150\times10^6$ to be *very strong* ("v. strong" in Figure 9). After, M-MACBETH proposed a value function scale compatible with all the judgments inputted in the matrix of judgements, using the linear programming procedure presented by Bana e Costa et al. (2012). The decision-makers were then asked to validate the proposed scale in terms of the proportions between the resulting scale intervals, and adjust them, if needed. Figure 10 shows the value function scale for the "payout exposure" criterion.

	0	50	100	150	200
0	no	weak	strong	v. strong	extreme
50		no	moderate	strong	v. strong
100			no	strong	v. strong
150				no	moderate
200					no

Figure 9: MACBETH matrix of judgments for the "payout exposure" criterion.

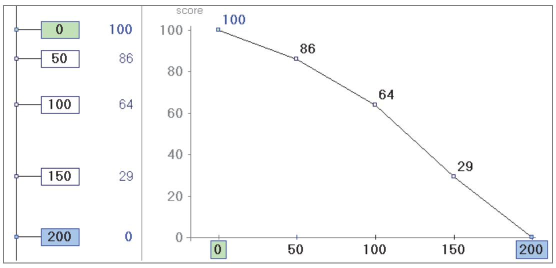

Figure 10: Value function for the "payout exposure" criterion (performances in $\$10^6$).

The following step consisted in eliciting weights for the criteria. For that purpose five hedging fictitious options were built: one option with a performance at the upper reference level in one criterion and performances at the lower reference levels in the other three criteria with no repetitions (what gives four fictitious options), and one fictitious option with performances at the lower reference levels in all the four criteria. Figure 11 shows that the fictitious option "[Dwn Gains]" (see the cell at top in column "Overall references" in Figure 11) has a performance at the upper reference level in criterion "Dwn Gains" (600) and performances at the lower reference levels in the other three criteria ("PayoutExp" – 200; "Up Gains" – 950, "Risk premium" – 400). Then, the decision-makers ranked the fictitious options by decreasing order of their overall attractiveness, which resulted in the rank shown in the "Overall references" column in Figure 11.

Overall references
[Dwn Gains]
[PayoutExp]
[Risk Premium]
[Up Gains]
[all lower]

PayoutExp	Dwn Gains	Up Gains	Risk Premium
0	600	1150	0
50	550	1100	100
100	500	1050	200
150	450	1000	300
200	400	950	400

Figure 11: Performance levels on the four criteria (in \$10[6]).

After, the decision-making group judged the differences in attractiveness between each two fictitious options, which allowed filling in the MACBETH weighting judgments matrix show in Figure 12. We underline that by accepting to make these trade-offs, the group is validating our working hypothesis of compensation between criteria.

	[Dwn Gains]	[PayoutExp]	[Risk Premium]	[Up Gains]	[all lower]
[Dwn Gains]	no	strong	v. strong	v. strong	positive
[PayoutExp]		no	v. strong	v. strong	positive
[Risk Premium]			no	strong	positive
[Up Gains]				no	positive
[all lower]					no

Figure 12: MACBETH weighting judgments.

M-MACBETH then generated the criteria weights by linear programming (see Bana e Costa et al., 2012), which were show to the group for validation and possible adjustment. The final criteria weights (in %) were: Downside Gains (47%); Payout exposure (33%); Risk premium (16%); and Upside gains (4%).

In the last step, the performances of the eight hedging options – from A (no hedge) until H (tolerance risk of $\$350\times10^6$) – were inputted in M-MACBETH (see Figure 13).

Options	PayoutExp	Dwn Gains	Up Gains	Risk Premium
Alt A (No hedge)	0	445	1080	0
Alt B (RT=25)	174	502	1012	293
Alt C (RT=50)	157	511	1032	155
Alt D (RT=100)	144	482	1036	90
Alt E (RT=150)	137	485	1025	59
Alt F (RT=200)	120	475	1030	51
Alt G (RT=250)	106	471	1043	38
Alt H (RT=350)	30	441	1089	33

Figure 13: Performances of the eight alternatives on the four criteria (in \$10[6]).

Note that the performances of the options are the results generated for each of the eight risk tolerance scenarios in section 5. With these data inputted the partial (on each criterion) and overall value scores of the hedging options were calculated by M-MACBETH (see Figure 14).

Options	Overall	PayoutExp	Dwn Gains	Up Gains	Risk Premium
[all upper]	100.00	100.00	100.00	100.00	100.00
A (No hedge)	66.17	100.00	30.00	65.00	100.00
H (RT=350)	60.92	91.43	27.33	69.50	92.24
G (RT=250)	56.64	60.00	42.67	46.50	91.06
F (RT=200)	53.41	50.00	44.45	40.00	88.00
E (RT=150)	51.04	37.86	48.89	37.50	86.12
C (RT=50)	48.35	24.57	60.45	41.00	63.53
D (RT=100)	47.72	32.86	47.56	43.00	78.82
B (RT=25)	37.50	14.86	56.45	31.00	31.06
[all lower]	0.00	0.00	0.00	0.00	0.00
Scaling constants :		0.33	0.47	0.04	0.16

Figure 14: Overall and partial value scores of the alternatives and criteria weights.

In Figure 14 (column "Overall") we see that the most overall attractive option considering the expressed preferences of the decision-makers is option A (No hedge). Option H which corresponds to the highest risk tolerance (ρ = $\$350\times10^6$), is ranked second, whereas the least preferred hedging option is B, which corresponds to lowest risk tolerance (ρ = $\$25\times10^6$).

7 CONCLUSIONS

The multi-criteria evaluation of the hedging options using the judgments of the same decision-makers who answered the questionnaire gave us different results in terms of preferred hedging options. The most preferred hedging option "A", and inherent null hedging is closer to the Howard risk estimation ($\rho \approx \$350\times10^6$) and confirms Smith (2004)'s findings that "large companies with reasonably diversified shareholders should have risk tolerances that are much larger than those typically suggested in the decision analysis literature" (p. 114). In fact, our research suggests the most preferred alternatives have higher risk tolerance values than initially estimated by the questionnaire.

With this research we show that it is possible to perform a structured approach to model the entire O&G company business model and evaluate price risk management in an integrated way. Gross margins from the three business units and a basket of derivatives enter at once in a certainty equivalent maximization problem and it becomes clear how the hedging solutions vary with risk tolerance.

Defining a preliminary risk tolerance measure for the company through a tailored risk assessment questionnaire and comparing with other reference methods of risk tolerance estimation allows achieving preliminary solutions based on stochastic portfolio optimization for each risk tolerance. However, a multi-criteria final assessment should be done, using the Monte Carlo simulation results, in order to ascertain how decision-makers valuate the underneath multiple consequences from each hedging option. This multi-criteria final risk tolerance evaluation can in fact help the company in the always difficult decision "to hedge or not to hedge" and, if yes, which amount to hedge.

It is important to note that these results were obtained with data and preference judgements concerning a specific moment in time. Few months before or later, with different crude and refined products prices, would lead to different decisions under this approach. On the other side, each year, the company has different goals, the market value can grow or shrink along with the earnings and gross margins. Further research should be done to evaluate the results of the model in different price conditions and involving other decision makers, preferably also including board directors.

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