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SCHOOL OF BUSINESS, ECONOMICS AND LAW

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Real Optionality in Gold Operations

An investigation of Gold Exposure, Asymmetries and Excess Returns

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Abstract

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This thesis examines the gold beta exposure and the usage of real options for 52 listed gold companies in North America between 1997 and 2014. Building on prior research we develop a model that includes a larger set of control variables, this model show that earlier research has suffered from underspecification leading to biases. Standard errors are drastically reduced by more efficient use of the return data. The results show that the gold beta varies largely over time but that an investment in gold companies has on average a gold beta above one. Additionally, we find evidence of asymmetries in the returns due to the usage of real options. The return asymmetries are also shown to vary across companies and over time. Prior work has suggested that it would be better to invest in gold mining companies compared to a direct investment in gold due to the real optionality. To test this statement a performance evaluation is conducted to conclude whether greater asymmetry is associated with higher risk-adjusted returns. The results indicate that stocks with greater asymmetry have provided investors with higher risk-adjusted returns.

Keywords: Real Options, Gold, North American Gold Companies, Gold Beta, Performance Evaluation, Asymmetric Returns

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Contents

List of Figures

List of Tables

1. Introduction

Gold is often viewed as an investment used in order to hedge inflation or currency risk and is historically a safe haven for investors (Mulyadi et al., 2012). Investing in gold can commence by buying physical gold, an ETF investment or through shares in gold mining companies. The creation of indexes of unhedged gold mining companies show that investors are seeking exposure to the gold price (Hu, 1996). There are gold mining companies that put unhedged positions as an advantage of investing in the particular firm. The CEO of Newmont said that investors are probably not willing to pay a premium to hedge potential upside by selling forwards. This is further supported by Coleman (2010) who claims that investors investing in a gold mine are likely to pay for the exposure to the gold price but not the hedging technique of the company. Since investing in a gold company could be used as a substitute for an investment directly into gold, the attributes of gold mining stocks needs to be identified. To fully understand the properties of a gold investment, usage and outcome of real optionality also has to be considered.

As described by Tufano (1996) and discussed by Blose and Shieh (1995), buying shares in a gold mining company offers a leveraged investment in gold, with a relative absence of hedging, as the share in a gold mining company offers a share of both today's production as well as the total future production of the mine. Baur (2014) expands on this by suggesting a share in a gold mining company is potentially a superior investment to one in a share of an ETF. Blose and Shieh (1995) show that the price elasticity of gold producing companies is above one to the gold price, meaning that gold companies hold a leveraged position on the gold price. However, Blose and Shieh (1995) neglect the real optionality that gold producing companies are subject to as the exposure to gold prices, theoretically, should vary with the price of gold. Furthermore Blose and Shieh (1995) suggest that investing in gold companies provides investors with better return than directly investing in gold. The conclusion drawn is, in our view, not complete since higher risk is not always the better investment choice; while correct during bull markets in the gold price, the opposite is true in a gold bear market under the assumption that a gold mine is a leveraged position on the gold price.

The mining industry is associated with high uncertainty, to a large extent due to commodity price fluctuations. It is therefore crucial for managers to understand the value of real options in the mining business. The value of a mine exploiting the real options is shown to be 10 % higher by Zhang et al. (2007). The presence of real optionality introduce managerial flexibility which offer the possibility for managers controlling mines to close or contract operations in periods with low commodity prices and to expand in times with high prices. The real options give the manager the right but not the obligation to continue, to contract or to expand operation, which in theory implies an asymmetric exposure to the price of the underlying commodity. A mining company should therefore, if it uses the real options, have a higher exposure to the underlying commodity as the price of the commodity is higher and lower when the price is lower. By determining if companies have a beta coefficient relative to the commodity that is higher during periods of increased price and vice versa it would be possibly to conclude that real optionality is used within the company (Baur, 2014). Baur (2014) examines the real options during a time period with both bull and bear gold markets and concludes that real options are used by Australian gold companies. However, the results are not statistically significant on average over the whole set of companies and additionally suffers from underspecification, by only including the stock market as control variable, and therefore need a refined model to properly calculate the impact of real options on gold companies. Tufano (1998) includes additional control variables, but examines a short period of only 4 years. The period examined should include both bull and bear market to be able to explain the phenomena of how real options affect gold companies.

The gold sector provides a good setting for understanding how real options are used and the added value of using them efficiently as real options are a fundamental part of the mining industry. Other advantages for studying the gold industry are that the data availability for the gold price is higher compared to other less market traded commodities and that there are many gold companies that almost exclusively focus on gold mining.

The purpose of this thesis is to first analyze the gold sensitivity for gold mining companies and thereby examine if an investment into gold mining companies is a leveraged position on the gold price by using a larger model specification compared to the one used by Baur (2014). Second, determine whether companies use real options (and the managerial flexibility given by these) and third, examine if the usage of real options award investors with higher risk-adjusted returns. The performance evaluation conducted in this thesis is an extension to earlier research and has not been done in the work of Baur (2014) and Blose and Shieh (1995);

even though assumptions and conclusions regarding difference in performance are drawn by the authors. Additionally, the performance measurements are also calculated for a gold investment to be able to compare a direct investment in gold with an investment in a gold company. This study therefore helps academia and investors to better understand the characteristics and the returns provided by the gold industry. A reasonable assumption is that companies in other commodity businesses behave in similar ways as gold mining companies. The results from this paper may therefore be applicable on companies in other industries with embedded real options as well, although this needs to be verified in separate studies.

The contributions made are as follows; first we show that North American gold mining companies provides a leveraged position on the gold price and do have a gold beta above one. There are however vast differences over time and firms. Second we demonstrate that earlier research suffered from underspecification of the models by not taking into account correlation of companies shares' return with precious metals and other mining commodities. The omitted variables lead to an upward bias of the estimate of the gold beta for gold mining firms. Third we expand on earlier research by investigating how the real options affect the risk-adjusted returns for companies and show that companies with greater real optionality have provided higher risk adjusted returns compared to the companies with low usage of the real options.

The remainder of this thesis is organized as follows. Section two gives a summary of past research on the subject. Relevant theories are presented in section 3. Section 4 presents the method used in this thesis. Thereafter the results are presented in section 5 and are analyzed in section 6. Lastly section 7 concludes the thesis.

2. Literature Review and Hypothesis Development

The gold beta exposure for gold mining companies has been studied extensively in earlier research; however the real options embedded in the mining industry have not been studied as comprehensively on market data but often in simulations. Examples of studies of gold beta exposure for North American gold companies are the papers by Tufano (1998) and Blose and Shieh (1995). Tufano studied publically traded gold mines with high stock price volatility and examined the determinants of exposure for the firms. In his work, Tufano controlled for foreign exchange rates, interest rates, inflation and commodity prices; in the same way as earlier studies prior to his work, such as Jorion (1990), Flannery and James (1984), Bilson (1994), Blose and Shieh (1995) and McDonald and Solnick (1977), did. The period examined by Tufano was only 4 years, much shorter than later research by Baur (2014), but used higher data frequency and included a larger number of firms. According to Tufano, high frequency data was chosen since the gold exposure varies over time and firms. This however requires correcting for price changes that are not simultaneous. Tufano's result shows that the stock price of a gold firm has a beta exposure of 2 to 3 on the gold price. The conclusion drawn was that capital markets take firm-specific and market-specific factors into consideration when calculating the exposure of the firms and also incorporate hedging activities if they are officially communicated. The results do not take the real optionality into full consideration, as movements are in both directions. The results suggest that investing in gold companies is solely a leveraged investment on the gold price return. This could however also be desirable by investors seeking exposure to the gold price (Hu, 1996). Baur examined the impact changes in gold price have on equity prices for Australian listed gold companies over the time period of 1980 until the end of 2010. To begin, Baur argues that investors seeking exposure to the gold price can buy gold or invest in a mine, were the latter would give the investor a leveraged position as the investment in a mine also give the investor a share in the total future production of the mine, proposing gold betas to be above 1. Baur however found evidence in contradiction of the suggested leveraged position with an average elasticity of 67 % in mines relative to the gold price. In Twite (2002) Australian gold mines is shown to move on average 76 % of

the movements in the gold price. Both rejecting the suggested leveraged position relative to the gold price. The difference in results compared to Tufano could arise from the fact that Tufano includes more control variables, both financial (such as interest rate, volatility and leverage) and operating (for example cost structure and production quantity). Faff and Chan (1998) also considers a multifactor model of gold industry returns which includes market, gold price, interest rates and foreign exchange rate. The study was conducted on the Australian equity market over the time period 1979-1992. The result from Faff and Chan (1998) shows that only the market and gold price factor have significant explanatory power in the regressions on the returns of the gold companies and that there are large differences in sub-periods of the gold beta. Discussed by Baur (2014) and shown in Tufano (1998) as well as Blose and Shieh (1995) the gold beta is decreased if the gold producing company hedge their exposure to the gold or if the company extract other commodities as well. These commodities should therefore be included as control variables. Due to contradictory results of the gold beta exposure further investigation is needed. The first hypothesis is formed:
Hypothesis 1:

- H_0: An investment into North American gold companies is not a leveraged position on the gold price and therefore has a gold price beta of one or lower.
- H_1: An investment into North American gold companies is a leveraged position on the gold price and therefore has a gold price beta greater than one.

Earlier literature on the subject of real options, i.e. Zhang et al. (2007), Groeneveld and Topal (2011) and Baur (2014), is almost solely focused on examining gold mines and the stochastic process of gold. The standard approach for valuing or analyzing a company is a fixed production schedules for the operations. However, according to Brennan and Schwartz (1985), a fixed production schedule is a strong assumption when valuing mining companies as the uncertainty and real optionality present in the mining industry differ from many other industries. Brennan and Schwartz argue that a flexible production model is a more realistic assumption for a mining company which incorporates the real options characteristics of the mining firm. In such a model the manager holds options on the gold price with the marginal production cost as the exercise prices for the options. According to Twite (2002) there exists an error in valuation of gold mining firms from misusing discounted cash flow models. This arises from the flexible production schedules which are not incorporated into models like discounted cash flow. Zhang et al. (2007) presents a reactive approach which incorporates the different strategies that an operating mines could undertake by altering the plan in every new period in response to new information available on the commodity price and marginal costs. Zhang et al. (2007) simulate the commodity price to show that mines with a reactive strategy, based upon to the commodity price, halt operations several years in the simulated period due to low prices. The conclusions of these results are that the mine can be valued higher with the reactive approach compared to commonly used methods, such as the fixed production assumption, thus captures a higher value than mines stockpiling the commodity during periods of low commodity prices. Groeneveld and Topal (2011) studied the uncertainty in the same sense as Zhang et al. (2007) which show comparable results stating that due to the high uncertainty in the mining industry, companies need to incorporate flexible strategies in their operations. The value of mines using a flexible decision model, which exploits the real optionality, are shown to be around 10 % higher with the models used by Zhang et al. and Groeneveld and Topal on commodity prices. The theory on a flexible mining strategy is simply another way of describing the real option embedded in the operations. The real options on gold held by the mining company, with exercise price at the marginal production costs, can provide an asymmetric return profile for companies. This is possible by temporary closing mines when the price falls below the marginal cost of production and increase the exposure by looking at earlier unprofitable mining opportunities. Despite the theory, Tufano (1998) demonstrate decreased exposure to the gold when price of gold is high. Subsequent research by Baur (2014), Coleman (2010) and Twite (2002) contradicts the findings of Tufano (1998) and suggest a positive relation between the gold exposure and price. The latter results are consistent with mines exercising their real options. Managers also lower the exposure to the gold price when prices are decreasing. However the results given are not statistically significant for the majority of companies examined, this is not discussed as the focus is put on the average effects instead. There is reason to believe that the model used is underspecified as Baur do not take other commodities into consideration, even if the presence of other commodities in the mining of several of the companies in the dataset is mentioned. The method for examining the real optionality used by Baur has yet not been applied to North American firms, to our knowledge.

Hypothesis 2:

- H_0: North American gold companies do not use real options efficiently and therefore have no asymmetric return profile in regards to gold price changes.
- H_1: North American gold companies use real options efficiently and therefore have an asymmetric favorable return profile in regards to gold price changes.

After testing the second hypothesis the benefits from the real options can be explored. That is whether the usage of real options has awarded investors with higher risk-adjusted returns. Coleman (2010) examined gold companies and found betas varying between 0.5 and 1.0, however the gold exposure for companies in the study did not differ regardless of the hedging technique employed. Coleman claims that this is a violation of the efficient market hypothesis as higher risk firms should reward investors with higher expected returns. Though the risk-adjusted returns in the firms are not evaluated since the conclusion is only considering the relation to the gold price. Baur proposes that it might be better to invest in a gold producing company rather than the gold itself as the gold producing company with the real option hold an asymmetric return profile. If the usage of real options make for a superior investment, firms with higher interaction term should have higher risk-adjusted returns than companies with a low interaction term. Thus, the third hypothesis is, if the second hypothesis is rejected, that the usage of real options do not reward investors with higher risk-adjusted returns compared to a direct investment in gold or in a company not using real options.
Hypothesis 3:

- H_0 : There are no differences in risk-adjusted returns between North American gold companies that have greater asymmetric return profiles to the gold price compared to companies with no or lower asymmetric return profiles.
- H_1 : There are differences in risk-adjusted returns between North American gold companies that have greater asymmetric return profiles to the gold price compared to companies with no or lower asymmetric return profiles.

3. Theory

3.1 Gold Beta

Under the assumption of a fixed production model without any financial risk management taking place the value of a pure gold mining company can, according to Tufano (1998), be expressed as in equation 3.1.

$$V = \sum_{i=1}^{N} \frac{[Q(P-C)-F](1-\tau)}{(1+r)^i} \tag{3.1}$$

Where Q is fixed annual production, P is the price of gold, C is the variable cost from extraction and processing, r is the cost of capital, τ is the corporate tax rate and F is the fixed cost such as general, administrative and fixed financial charges. Under these assumptions the market value of the company is V. By differentiating Equation 3.1 with respect to gold price it follows that the gold beta can be expressed as in Equation 3.2.

$$\beta_g = \frac{\frac{\partial V}{V}}{\frac{\partial P}{P}} = \frac{PQ(1-\tau)\sum_{i=1}^{N}\frac{1}{(1+r)^i}}{V} = \frac{PQ}{Q(P-C)-F} = \frac{P}{P-C-\frac{F}{Q}} \tag{3.2}$$

Equation 3.2 implies that the gold beta for gold producing firms should be above 1 since the numerator is always larger than the denominator with C, F and Q being positive values. (Tufano, 1998)

The beta can however be managed and minimized towards zero by selling future production. Two companies with identical P, Q, C and F can therefore have large differences in beta exposure. A simple extension to equation 3.2 is shown in equation 3.3 which accounts for the possibility to hedge the gold exposure in the fixed production model.

$$\beta_g = \frac{\frac{\partial V}{V}}{\frac{\partial P}{P}} = \frac{(1-\alpha)PQ}{Q[(P-C)-\alpha(P-W)]-F} \tag{3.3}$$

In equation 3.3, α is the proportion of future production sold through forwards with payment W. The other variables are defined as in equation 3.2. From Equation 3.3 it follows that if α is zero it is the same expression as in Equation 3.2 and if $\alpha = 1$ then, obviously, $\beta_g = 0$ (Tufano, 1998).

3.2 Real Options

Like financial options, real options provide the holder the possibility but not the obligation for or against something in the underlying asset. The main difference between a financial option and a real option is the underlying asset. Financial options have stock, currency, bonds, etc. as underlying assets and real options could, for example, have a mining project as underlying asset. The strike price of a real option may vary over time depending on all factors with an effect on the cost associated with the underlying asset; in the case of a mining project the strike price is equal to the marginal cost of extracting the commodity. (Yeo and Qiu, 2003)

Managerial flexibility from real options can help to mitigate problems and difficulties with market timing. The commodity exposure can be decreased or even minimized during periods of low commodity prices as described by Slade (2001) and leveraged in periods of prices associated with positive returns. Armstrong et al. (2004) suggests that managers, who hold real options, can react to changing environment to capitalize on positive development and mitigate negative development, by using the real options to their advantage. According to Armstrong et al. the potential usages of real options are: temporary closing or abandoning project, changing production rate and expand operations. Fernández (2001) divided real options in to three different categories in a similar way as Armstrong et al. (2004) did. The three classes of real options are, according to Fernández (2001), contractual options, growth or learning options and flexibility options. The major difference of this classification in comparison to Armstrong et al. (2004) is the first category of contractual options including oil and mining concessions and franchises. The classes are provided with examples in Table 3.1.

TABLE 3.1: Variety of Real Options

Contractual Options	Growth or Learning Options	Flexibility Options
Oil concessions	Expand	Defer the investment
Mining concessions	R&D	Downsize project
Franchises	Acquisitions	Alternative uses
	New business	Renegotiation of contracts
	New customers	Outsourcing
	Internet venture	Abandon
	Greater efficiency in increasing entry barriers	Modification of products

Source: Fernández (2001)

3.3 Econometric Theory

3.3.1 Ordinary Least Squares

The ordinary least squares (OLS) regression is one of the most fundamental techniques in econometrics and will be used excessively throughout this paper. A simple linear model is presented in Equation 3.4.

$$y_i = \beta_0 + \beta_1 x_{i2} + ... + \beta_k x_{ik} + e_i \tag{3.4}$$

where e_i is the unobserved error term, y_i and x_{ik} are observed variables and β_k is the unknown population parameters (Verbeek, 2004). For the estimator to be the best linear unbiased estimator (BLUE) the first four assumptions of Gauss-Markov must hold, namely:

$$E\{e_i\} = 0, \quad i = 1, \dots, N \tag{3.5}$$

$$e_i, \dots, e_N \; and \; x_i, \dots, x_N \; are \; independent \tag{3.6}$$

$$V\{e_i\} = s^2, \quad i = 1, \dots, N \tag{3.7}$$

$$Cov\{e_i, e_j\} = 0, \quad i, j = 1, \dots, N, \; i \neq j \tag{3.8}$$

One problem with these strong assumptions is that real world data seldom follow these attributes. For example, the assumption of homoscedasticity which follows assumption number three is often violated. This can be mitigated by the use of heteroskedasticity consistent standard error, also called White standard errors, in the regressions (Verbeek, 2004, p. 88). Another common problem is autocorrelation or serial correlation which violates the fourth assumption. Autocorrelation is most common in data sets where there is a time dimension which could imply that there is persistence in the residual of the model (Verbeek, 2004, p. 80). This is further commented upon in section 3.3.3.

3.3.2 Omitted Variable Bias

An occurring problem in research, particularly of interest for this thesis, is violation of the third assumption about no correlation with the error term which often arises from an omitted variable that is correlated with the independent and dependent variable. Suppose that the data generating process of the regression model is shown in Equation 3.9.

$$y = X_1\beta_1 + X_2\beta_2 + \varepsilon, \varepsilon \sim N(0, \sigma^2 I) \tag{3.9}$$

But the estimated model is Equation 3.10:

$$y = X_1\beta_1 + \varepsilon^* \tag{3.10}$$

Where the term X_2B_2 from Equation 3.9 is omitted from the regression and ends up in the error term. The error term therefore looks as in Equation 3.11.

$$\varepsilon^* = X_2\beta_2 + e \tag{3.11}$$

The estimated parameter value for the full population parameter, β_1 , is under usual assumptions expressed as in Equation 3.12 and 3.13.

$$E[\hat{\beta}_1] = \beta_1 + (X_1^{'}X_1)^{-1}X_1^{'}X_2\beta_2 \tag{3.12}$$

$$E[\hat{\beta}_1] = \beta_1 + Bias \tag{3.13}$$

From the two equations it follows that if correlation exists between X_1 and X_2 the estimated parameter value is biased. (Clarke, 2005)

3.3.3 Serial Correlation

With presence of positive serial correlation the standard errors will be downward biased and thus over reject the null hypothesis. R-squared is also overestimated from positive serial correlation. To deal with serial correlation HAC (heteroskedasticity and autocorrelation consistent) or Newey-West standard errors can be used. When strong serial correlation is present the usage of HAC standard errors will not be sufficient to correct for the bias. In the event of strong serial correlation lagged values need to be included in the regressions. (Stock and Watson, 2010, p. 366)

To test if serial correlation is present in a time serie Durbin-Watson or Ljung-Box test can be used. Durbin Watson tests only the first lag, by testing if the errors are serially uncorrelated or follows an AR(1) model (Durbin, 1970). As Durbin Watson statistic cannot be used to test beyond one lag, Ljung-Box needs to be used if higher order of serial correlation is suspected (Ljung and Box, 1978).

4. Data

This paper covers 52 gold exploration, development and mining companies from the U.S and Canada over the period 1997-07-24 until 2014-12-31. 38 of the companies are from Canada and 14 from the US. The companies were the largest pure play companies, measured in market cap, in January 2015 with a minimum market capitalization of $100 million. The period chosen corresponds to the period with data for all control variables (the first day of market prices for LA1 and LX1). Gold companies are chosen as the access to longer data periods as well as there is of a higher number of pure play companies compared to many other mining commodities. The implication of other factors such as diversification are thus minimized. Price data on the companies' shares were, together with the spot price of gold (XAU curcny), the futures price on gold (GC1 comdty) the S&P500 Index (SPX Index), the S&P Toronto Stock Exchange Composite Index (SPTSX Index) and the exchange rate of the US dollar and Canadian dollars, downloaded from Bloomberg and have been adjusted for dividends, splits and other corporate actions. The spot price data for silver (XAG curcny), copper (HG1 comdty), platinum (XPT curcny), aluminum (LA1 comdty) and zinc (LX1 comdty) were also downloaded to be used as control variables. For the performance evaluation data for the one month US treasury bills (GB1M index) were collected as the risk free rate. The prices were collected for daily, weekly and monthly data and converted to return series. The summary descriptive tables, Table 4.1 and Table A.1, show that the standard deviation of the gold price return has been lower compared to the individual companies (0.0112 for gold and 0.0545 for the average of the com-

Table 4.1: Summary Descriptive

Summary Descriptive for the daily returns of the variables. Gold Companies are the pooled returns for all companies. *The Risk Free Rate is presented using monthly data.

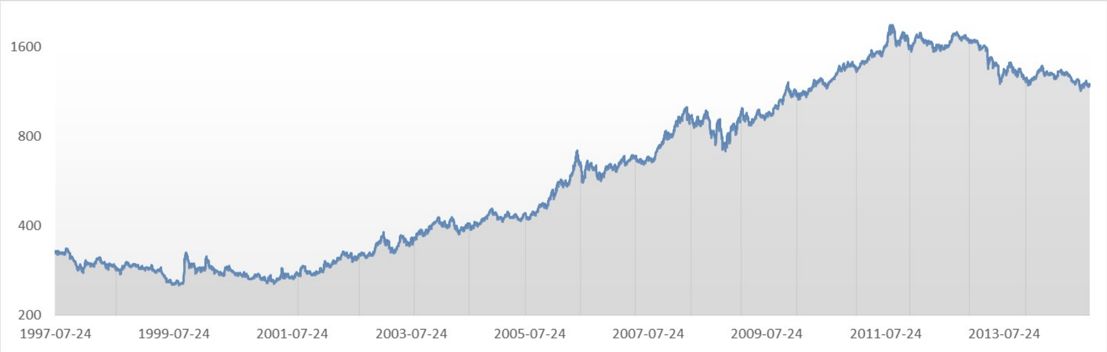
Variable	Obs	Mean	Std. Dev.	Min	Max	Ljung-Box	P-Value
Gold (xau)	4548	0.0003	0.0112	-0.0907	0.1079	17.0859	0.0725
Gold Companies	157629	0.0016	0.0545	-0.6727	2.0000		
Gold Future (gc1)	4220	0.0003	0.0114	-0.0935	0.0929	24.9293	0.0055
Silver (xag)	4532	0.0005	0.0191	-0.1844	0.1409	9.0448	0.5279
Platinum (xpt)	4542	0.0003	0.0142	-0.0975	0.0914	23.0027	0.0107
Copper (hg1)	4220	0.0003	0.0178	-0.1105	0.1235	46.2732	0.0000
Aluminum (la1)	4187	0.0001	0.0141	-0.1077	0.0733	22.8062	0.0115
Zinc (lx1)	4107	0.0005	0.0203	-0.1181	0.2336	37.1497	0.0001
S&P500 (spx)	4233	0.0002	0.0127	-0.0903	0.1158	53.9507	0.0000
Toronto SE (sptsx)	4236	0.0001	0.0113	-0.0932	0.0720	31.1961	0.0005
Exchange rate (cadusd)	4550	0.0001	0.0055	-0.0320	0.0406	50.2572	0.0000
Risk Free Rate* (gb1m)	4403	0.0018	0.0017	0.0000	0.0053	1698.93	0.0000

panies). For the gold companies the highest daily return in the sample period was 200 percent and worst negative 67 percent. The corresponding figures for gold were 11 percent and negative 9 percent. However, the returns for the companies were on average greater than for the investment in gold. Interestingly, during the sample period, the precious metals and other mining commodities have performed very well where all commodities, except of aluminum, have had higher mean returns than the SPX and SPTSX. For a subset of the companies in the sample the high standard deviation might be attributable to the fact that there are periods without return data for every day (this is most occurring in the beginning of the sample period) which leads to large fluctuations of returns. This is likely an effect of low liquidity.

4.1 The Gold Price Performance

In order to obtain reliable econometric results sufficient time series variation in the data is necessary. Managers should, at different price levels, use the managerial flexibility provided by the business model to efficiently use their real options. As seen in Figure 4.1, the gold price started at $323 per ounce in 1997. Thereafter the gold price had a significant price reduction and reached the price of $253.75 the 27th of August 1999. The price drop was followed by a decade long bull market with prices at the top north of $1800 per ounce. At the end of the sample period the gold price fell by almost 35 %. A price drop of this magnitude ought to be large enough for gold mining companies to overlook their production prospects and current production rate. Furthermore the graph shows that during the gold bull market there were times of large price declines, such as the one in 2008. In our view the gold price have had sufficient variation over time to provide reliable estimators.

FIGURE 4.1: Gold Price in USD from 1997-07-24 to 2014-12-31



4.2 Correlation and Serial Correlation of Returns

In the correlation matrix, Table 4.2, the two stock market indices, SPX and SPTSX, were correlated to a factor of 0.7540. The level of multicollinearity can create what is called a horse race in econometrics where one of the two indicies catches most of the variation. However, the coefficients for the stock markets are of no interest only that they capture the variation and we therefore see the level of multicollinearity as no concern. The correlation table furthermore shows that there are no correlation between the S&P500 and the gold price. The correlation for the Canadian market is 0.2049, which can be due to the fact that the Canadian stock market is more closely linked to natural resources and also have a higher number of gold companies. Table 4.2 includes the companies' shares' returns to displays the importance of the added control variables. The table demonstrates that the control variables of precious metals and other mining commodities are correlated both with the independent variables (the stock market indices and the gold price return) as well as the dependent variable. Exclusion of these variables would lead to an upward omitted variable bias.

In Table 4.1 and Table A.1 the Ljung-Box Q-statistics are displayed and show presence of serial correlation in the returns. The Q-statistics were calculated using 10 lags as recommended by Hyndman and Athanasopoulos (2014). Table A.2 shows the outcome of regressions of the variables regressed on their own first four lags conducted for the purpose of investigating the serial correlation properties. The first lag is statistically significant for all independent variables except for the gold price and the SPTSX. Furthermore, four of the independent variables are statistically significant at the second lag. While the coefficients are statistically significant they are economically small and a bias from excluding these in a regression will likely be limited. Given the results in Table A.2 we consider including one lag for each variable to be sufficient for mitigating the majority of the serial correlation concerns. There are theoretical economic reasons that the economic magnitude should be insignificantly small in case of statistically significant lags since it otherwise violates weak form efficiency. However, statistical significance alone cannot reject the weak form efficiency theorem since it is dependent on sample size as discussed by Fama (1970).

TABLE 4.2: Correlation Matrix

Pairwise correlation of variables are presented. SPX is the S&P500 and SPTSX the Toronto Stock Exchange index. Companies are the pooled returns. P-values are presented in the parentheses. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively.

	Companies	Gold Futures	Gold	Silver	Platinum	Copper	Aluminium	Zinc	SPX	SPTSX	Cadusd
Companies											
Gold Futures	0.2877***										
	(0.0000)										
Gold	0.3211***	0.8885***									
	(0.0000)	(0.0000)									
Silver	0.2757***	0.6641***	0.7320***								
	(0.0000)	(0.0000)	(0.0000)								
Platinum	0.2107***	0.4597***	0.4864***	0.5045***							
	(0.0000)	(0.0000)	(0.0000)	(0.0000)							
Copper	0.1424***	0.3295***	0.306***	0.4000***	0.3031***						
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)						
Aluminium	0.1111***	0.2595***	0.2346***	0.3192***	0.2896***	0.6211***					
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
Zinc	0.1075***	0.2456***	0.2415***	0.3198***	0.2747***	0.6076***	0.5697***				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
SPX	0.0935***	-0.0171***	0.0046	0.1277***	0.1526***	0.2493***	0.2064***	0.1768***			
	(0.0000)	(0.0000)	(0.0302)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
SPTSX	0.1925***	0.1627***	0.2049***	0.2916***	0.2671***	0.3301***	0.2686***	0.2461***	0.7540***		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
Cadusd	0.1603***	0.2659***	0.2984***	0.3540***	0.2790***	0.3235***	0.2743***	0.2640***	0.4244***	0.3754***	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

5. Methodology

5.1 Measuring the Gold Beta

Five different specifications were used in order to estimate the companies' gold beta exposure and to test the first hypothesis. In the first and most basic model the gold beta were estimated by regressing the specification in Equation 5.1.

$$y_t = \alpha + \beta_1 R_G + e \tag{5.1}$$

Equation 5.1 includes the gold price return as the sole independent variable. The first specification is included out of comparison reasons and to demonstrate the effect of omitting variables in the regressions. Thereafter a larger model specification is specified which includes the stock market return as control variable. The Toronto Stock Exchange (SPTSX) was used as the majority of the sample companies were listed here. This is the corresponding model as used by Baur (2014), before the introduction of the interaction term, shown in Equation 5.2.

$$y_t = \alpha + \gamma_1 R_G + \gamma_2 R_{Mkt} + e \tag{5.2}$$

Equation 5.3 includes all control variables in the data sample and is the main regression in this section of the thesis where the gold beta is estimated.

$$y_t = \alpha + B_1 R_G + \omega_i \chi_i + e \tag{5.3}$$

In this equation R_G is the price change of the gold price and χ_i is a vector of returns for the control variables including indices, the cadusd exchange rate, precious metals and the other mining commodities that are included in the data set. The additional controls are included to account for the fact that the gold companies in our sample also are involved in other mining commodities and therefore, or out of other financial market reasons, the returns possess correlation with the companies' share price returns. Kearney and Lombra (2009) state that precious metals such as gold and platinum have been used in asset allocation as a protection against inflation and political instability. To account for the correlation that these precious metals therefore should exhibit, through the similarities in purpose for the investment, platinum and silver are added as independent variables. Equation 5.3 is regressed first using Newey-West HAC standard errors and thereafter regressed as an AR(1) specification including 1 lag for the dependent and all control variables in order to take the possible effects of serial correlation into consideration. The models are estimated on daily, weekly as well as monthly return data. For daily data the constant is suppressed which otherwise adds noise to the model as the daily mean return is very close to zero. This is done consistently through this paper in specifications for estimating the gold beta exposure and the interaction term. Last, in the examination of the gold beta, changes of the gold beta over time were investigated by performing rolling regressions on one trading year using Equation 5.3. This tests if a rejection of the null of the first hypothesis is time dependent.

The results are robustness tested with winsorization at different levels. Winsorizing is a statistical technique of censoring data which is named after the biostatistician Charles Winsor. The technique is used to reduce the effect of outliers and is a bit more sophisticated than simply excluding outliers. A winsorization at the 99 % level replaces all the values beyond the 0.5th percentile with the value of the 0.5th percentile. The number of observations therefore remains the same but the average value changes. The technique therefore preserves the outliers as the most extreme values in the data set, but they are less extreme than before the winsorization. This thesis investigates the relationship between the gold price and the stock price return and there might be large outliers in the return series that does not capture these effects but instead capture exogenous events such as rumors about the company being acquired, forced selling and buying which can be the case in the event of a list change, illiquidity effects, stock price reaction to corporate events such as a new CEO or other jump effects in the return series; for example in the event of low liquidity.

5.2 Measuring the Real Options

A dummy variable was generated which takes the value 1 if the price change of gold is greater than 0 and otherwise 0. This dummy is added to the basic model as an interaction term with the return of the spot price on gold. The interaction term isolates the days associated with positive gold price return which allows to investigate if the sensitivity (or beta exposure) to the gold price is greater on the upside than on the downside and is therefore used as a test for the second hypothesis. A statistically significantly and positive interaction term shows that companies are exploiting real options in gold mining. According to Baur (2014) hedging and diversification do not imply an asymmetric gold exposure and it is therefore possible to distinguish the companies using the real options. The specification for this econometric model is displayed in Equation 5.4.

$$y_t = \alpha + \theta_1 R_G + \theta_2 R_G D_G^+ + \omega_i X_i + e \tag{5.4}$$

where R_G is the gold return, X_i is the vector of returns for the control variables and $\theta_2 R_G D_G^+$ is the interaction term measuring the possible asymmetry provided from real options. The interaction term was also added to the models specified in Equation 5.1, 5.2 and 5.3. for comparison.

5.3 Performance Evaluation Measurements

To be able to conclude whether companies with greater interaction terms have outperformed companies with lower interaction terms the Sharpe ratio, the Sortino ratio, the Treynor ratio and Jensen's alpha are used. It is not sufficient to solely consider the total return that the portfolios have provided for investors when evaluating performance; it is also crucial to include the risk that was taken to obtain the returns. The ratios are used to create a balanced view of the return performance as they build on different assumptions and have their strengths and weaknesses. The assumptions made are related to the proxy for risk since returns are easily measured. Portfolios are constructed for the performance evaluation and rebalanced on monthly basis. In the performance evaluation the US treasury one month bills are used as risk free rate. Geometric mean returns are used as mean returns in the calculations as it measures the constant return over time that is needed to obtain the total cumulative return and is usually used for the purpose of comparing investment returns. In contrast, the arithmetic return is the best estimate of the next period's return. (Bodie et al., 2009, pp. 823-825)

5.3.1 Measurements Using Standard Deviation as Risk

5.3.1.1 Sharpe Ratio

Sharpe (1964) introduced his measure of mutual fund performance in 1964. In order to obtain the Sharpe ratio, historical data is used and it therefore evaluates historic return and risk performance. The Sharpe ratio measures the excess return per unit of total risk in relation to the capital market line (CML) (Reilly and Brown, 2011). The model is shown in Equation 5.5 and Equation 5.6.

$$D_t = R_{jt} - R_{Bt} \tag{5.5}$$

$$S_h = \frac{r_s - r_b}{\sigma_D} \tag{5.6}$$

where S_h is the Sharpe ratio, r_s is the return of the portfolio or security, r_b equals the return on the benchmark used, σ_D is the volatility of D_t. The risk free rate is commonly used as a benchmark return and the ratio was originally using this as benchmark (Sharpe, 1994). The risk free rate is therefore set as r_b in this study. According to Pav (2014) the statistical significance of the Sharpe ratio can be tested with the following t-statistic:

$$t = \sqrt{n}\hat{SR} \tag{5.7}$$

and a test statistics for testing the null $H_0 : \mu = \mu_0$ versus the alternative hypothesis: $H_1 : \mu > \mu_0$ is obtained by:

$$t_0 = \sqrt{n}\frac{\hat{\mu} - \mu_0}{\hat{\sigma}} \tag{5.8}$$

The null is rejected if t_0 is greater than $t_{(1-\alpha)(n-1)}$.

5.3.1.2 Sortino Ratio

The Sortino ratio is a modification of the Sharpe ratio which like the Sharpe ratio is built on the underlying assumptions of the CML framework. However the Sortino ratio only measures and incorporates total downside risk since the ratio measures the risk of falling below a certain target return, such as the risk free rate. Instead of excess return to a benchmark return, as used in the Sharpe ratio, the Sortino ratio uses excess return over a minimum acceptable return (MAR). Given that gold often is considered a relatively safe investment and a hedge against inflation we think that the risk free rate is the appropriate threshold to use. The Sortino ratio is presented in Equation 5.9. (Le Sourd, 2007)

$$Sortino\ Ratio = \frac{E(R_{jt} - MAR)}{\sqrt{\frac{1}{t}\sum_{t=0,R_{jt}<MAR}^{T}(R_{jt} - MAR)^2}} \tag{5.9}$$

The Sortino ratio only takes volatility of returns below the threshold into account. In contrary to the Sharpe ratio, the Sortino ratio does not penalize portfolios or stocks for returns much higher than their mean. This could be a sound policy since investors should worry about permanent loss of capital and not volatility on the upside.

5.3.2 Measurements Using Beta as Risk

5.3.2.1 Roll's Critique

The Treynor ratio and Jensen's Alpha are built on the assumptions embedded in the capital asset pricing model (CAPM) framework. They therefore need a proxy to be used as the market portfolio, since the market portfolio is unobservable and would include more than only stocks, such as real estate, bonds and human capital. According to Roll (1977) using a proxy for the market portfolio faces two potentially severe problems. First, it could be the case that the market proxy is mean-variance efficient when the market portfolio is not and secondly that the proxy portfolio might be mean-variance inefficient. The arguments made by Roll for the performance measurements based on the Security Market Line (SML) needs to be considered in the evaluation process. We therefore, as a robustness test, investigate if the results are sensitive to the benchmark used by re-calculating the performance measurements using the S&P500 instead of the SPTSX as market portfolio. The choice of the SPTSX as the proxy for the market portfolio is primarily that the majority of the firms in the sample are listed in Canada.

5.3.2.2 Treynor Ratio

In 1966 Treynor was the first to create a performance evaluation for portfolios and funds that included risk and not merely returns. The Treynor ratio is conceptually similar to the Sharpe ratio but uses the security market line with beta as risk measurement in contrast to the Sharpe ratio which uses the capital market line with standard deviation as risk measurement. Therefore the Treynor ratio (as well as Jensen's alpha) measures the return per unit of systematic risk and hence ignores firm specific risk (Reilly and Brown, 2011). It additionally assumes that an investor already has a diversified portfolio. The calculation of the ratio is shown in Equation 5.10.

$$T = \frac{(\bar{R}_{jt} - R_{Ft})}{\beta_j} \tag{5.10}$$

The nominator is simply the excess return above the risk free rate and the denominator is the beta of the portfolio or fund.

5.3.2.3 Jensen's Alpha

In 1968 Michael Jensen introduced his performance evaluation model. The model originates from the CAPM and calculates the excess return above the expected return given from CAPM. In Equation 5.11 the CAPM is shown with the risk free return moved to the left hand side and Equation 5.12 shows the Jensen's alpha.

$$R_{jt} - R_{Ft} = \alpha_j + \beta_j(\bar{R}_{Mt} - R_{Ft}) + \bar{u}_t \tag{5.11}$$

$$\alpha_j = R_{jt} - [R_{Ft} + \beta_j(\bar{R}_{Mt} - R_{Ft}) + \bar{u}_t] \tag{5.12}$$

In the equations above R_{jt} is the return of the portfolio or security, R_{Ft} is the risk free rate and α_j is a measure of excess return over the level given by expected return in CAPM. The risk is considered in this model as β_j is included. If markets are efficient then the α_j is expected to be zero in Equation 5.12 (Jensen, 1968).

6. Empirical Results

6.1 Gold Beta Exposure for Gold Companies

6.1.1 Average Gold Beta Exposure

In Table 6.1 five specifications are regressed using Pooled OLS to estimate the gold beta. The specifications yields an interval of gold beta from 1.200 to 1.496. In the first specification ,where the gold price is the only independent variable, the coefficient estimate is 1.496, indicating that for every one percent change in the gold price the gold companies' return is 1.496 percent. This is statistically significant at the 1 % level and economically significant. Furthermore, the coefficient is statistically significantly greater than 1 at the 1 % level. The second specification, the one used by Baur (2014), yields an estimated gold beta of 1.358. The stock market index coefficient is estimated to 0.598. The gold beta coefficient is once again statistically significantly larger than 1 at the 1 % level. Specification three follows

Table 6.1: Gold Beta Exposure of Gold Mining Returns

Specification 1 is a regression of the gold companies on the gold price return solely. Specification 2 includes index as dependent variables in excess to the gold price. Specification 3 and 4 is regression on the whole set of control variables, including commodities, indices and the cadusd exchange rate. Specification 4 uses Newey-West HAC standard errors. Specification 5 is a regression including all control variables with 1 lag for all variables. Standard errors are presented in the parentheses. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively. ###, ## and # refers to the statistical significance at the 1%, 5% and 10% level respectively based on the null hypothesis of gold beta equal to one.

	1	2	3	4	5
Gold	1.496*** ###	1.358*** ###	1.200*** ###	1.200*** ###	1.259*** ###
	(0.0142)	(0.0144)	(0.0271)	(0.0271)	(0.0294)
L.Gold					-0.130***
					(0.0075)
Spx			-0.168***	-0.168***	-0.177***
			(0.0248)	(0.0249)	(0.0266)
Sptsx		0.598***	0.693***	0.693***	0.707***
		(0.0166)	(0.0277)	(0.0282)	(0.0304)
Controls	No	No	Yes	Yes	Yes
Lags	No	No	No	No	Yes
St. Err.	White	White	White	Newey-West	White
Obs	157,629	155,749	142,752	142,752	106,065
R^2	0.103	0.118	0.124		0.162

Equation 5.3 and adds a set of control variables including precious metals, the exchange rate and other mining commodities. The estimated coefficient on the gold price return is in this specification lowered to 1.200. This shows that the previous specifications had problems with under-specification and therefore suffered from a

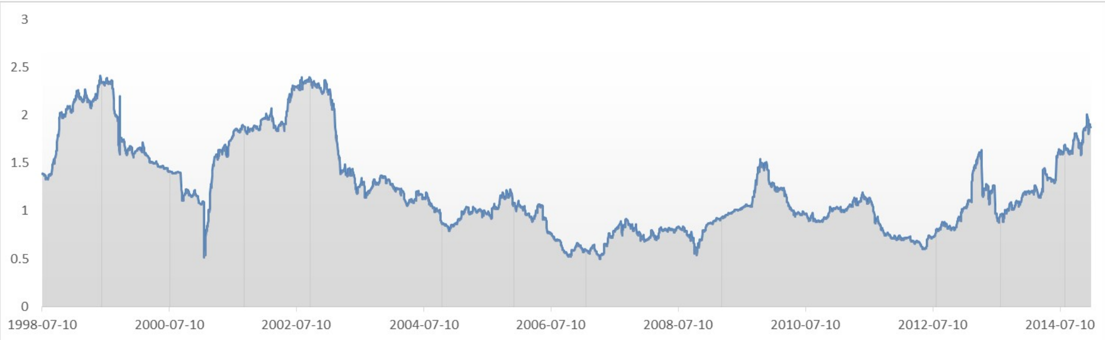
missing variable bias which amounted to an upward bias of 0.158 for specification two compared to specification three. The next regression, specification four, has the same specification as three but uses Newey-West HAC standard errors. There are only minor changes of the standard errors in this specification compared to the previous one. The last specification, the fifth, has the same control variables as the third specification but includes one lag of all the independent variables and the dependent variable. The coefficient estimate on the gold price return is in this regression 1.259 and the coefficient for the first lag of the gold price return is -0.130 which sum up to a gold beta exposure of 1.129. All specifications in Table 6.1 rejects the null of the first hypothesis, that the gold beta is equal to or lower than one.

6.1.2 Rolling Gold Beta

After rejecting the null of the first hypothesis, the time variation of the gold beta is investigated in Figure 6.1. The gold beta shows large time series variation and the beta varied from highs of around 2.5 to lows of about 0.5. Figure 6.1 reveals that the rejection of the null of the first hypothesis is time dependent.

FIGURE 6.1: Rolling Gold Beta Exposure

Rolling gold beta using Pooled OLS and a rolling estimation window of 252 days.



6.2 Real Options in Gold Mining

Table 6.2 extends the regressions used to obtain Table 6.1 by including an interaction term which measures the usage of real options. The coefficients on the gold price return are with the interaction term included lower than in Table 6.1, in the interval of 1.005 to 1.367. This is simply a result of taking the positive return days out of the estimation process of this coefficient. Therefore, as expected, the beta coefficient on gold in 6.1 is in-between the gold coefficient in Table 6.2 (representing days with negative return and zero return) and the sum of the gold coefficient and the interaction term. The coefficient estimate of the interaction term ranges from 0.259 in the first specification up to 0.407 in the fifth specification.

Taking the estimates from specification 3 and 4 the coefficients suggests that a one percent decline of the gold price leads to a negative stock price reaction of 1.005 percent while a one percent increase of the gold price leads to a 1.354 percent increase in the market value. From the results in Table 6.2 the null of the second hypothesis, which states that gold companies do not use real options efficiently and therefore have no asymmetric return profile in regards to gold price changes, can at the 1 % level be rejected.

Table 6.2: Gold Beta Exposure with Interaction Term

Specification 1 is a regression of the gold companies on the gold price return and an interaction term. The interaction term is set to zero when the gold return is below zero and otherwise equals the gold return. Specification 2 includes index as dependent variables in excess to the gold price. Specification 3 and 4 is regression on the whole set of control variables, including commodities, indices and the cadusd exchange rate. Specification 4 uses Newey-West HAC standard errors. Specification 5 is a regression including all control variables with 1 lag for all variables. Standard errors are presented in the parentheses. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively.

	1	2	3	4	5
Gold	1.367***	1.201***	1.005***	1.005***	1.046***
	(0.0161)	(0.0164)	(0.0275)	(0.0275)	(0.0291)
L.Gold					0.096***
					(0.0328)
Interaction	0.259***	0.313***	0.349***	0.349***	0.376***
	(0.0286)	(0.0280)	(0.0289)	(0.0276)	(0.0373)
L.Interaction					0.031
					(0.0355)
Spx			-0.174***	-0.174***	-0.186***
			(0.0247)	(0.0248)	(0.0265)
Sptsx		0.606***	0.702***	0.702***	0.714***
		(0.0166)	(0.0276)	(0.0282)	(0.0303)
Controls	No	No	Yes	Yes	Yes
Lags	No	No	No	No	Yes
St. Err.	White	White	White	Newey-West	White
Obs	157,629	155,749	142,752	142,752	106,065
R^2	0.104	0.119	0.125		0.165

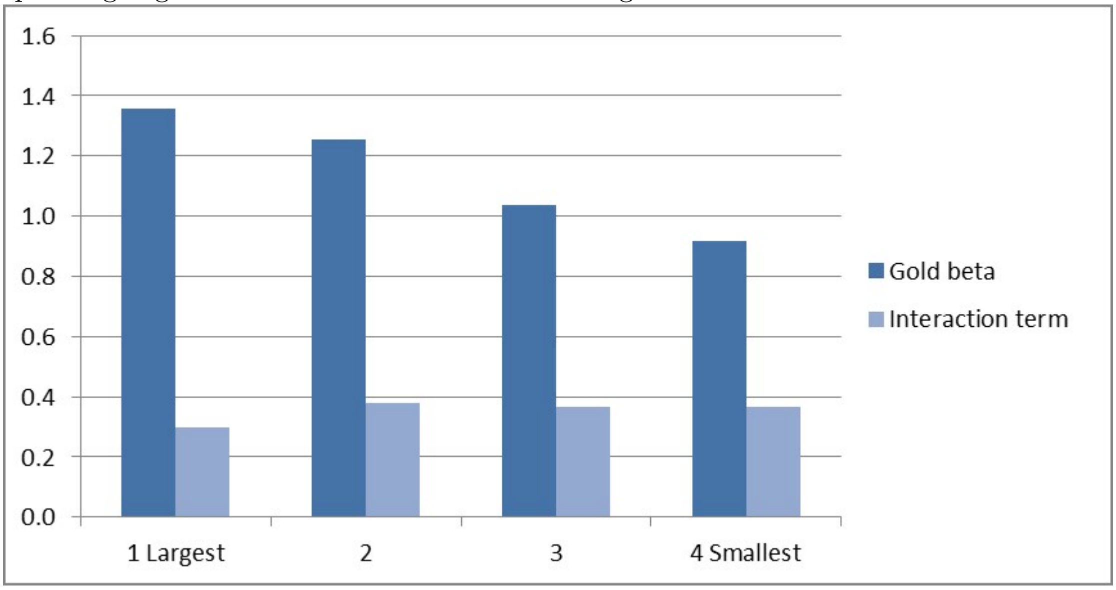
For individual firms the interaction term, presented in Table A.3, is statistically significant at the 10 % level for 30 out of the 52 firms in the sample using specification 3. At the 5 % level 25 firms have a statistically significant interaction term. Table A.3 shows that a greater proportion of larger companies have a statistically significant interaction term. This is probably due to lower liquidity and higher standard deviation of returns for small capitalization companies which generates larger standard deviation of the estimated coefficients. Almost all gold companies in the data set show statistically significant coefficients on the gold price return.

Although the coefficients for the control variables are not shown in Table A.3, companies show statistically significant coefficients for the market indices, the return on silver as well as on the cadusd exchange rate. The larger model enhanced the statistical power of the regression for individual companies as in the Baur specification only 25 firms have a significant interaction term at the 10 % level. Durbin's alternative test in Table A.3 displays serial correlation in the residuals for the majority of firms using specification three. After the inclusion of lags in specification 5 only few residuals exhibit autocorrelation.

From Table A.3 it follows that there is a size effect to the gold sensitivity for firms. In Figure 6.2 the quartile containing the companies with the highest market capitalization (as of January 2015) have a gold beta of 1.358 compared to 0.917 for the smallest companies. The figure displays a monotonic increase of the gold beta as company size increases. A similar monotonic relationship cannot be found between company size and the size of the interaction term although the table suggests that the interaction term for the largest companies is slightly lower than for the other quartiles.

FIGURE 6.2: Gold Beta Exposure and Interaction Term for Different Firm Sizes

The chart displays the gold beta and the estimated interaction term for different firm sizes measured in market capitalization. The companies are divided in to four quartiles with the 25 % largest companies in the first quartile and the 25 % smallest in the fourth quartile. The gold beta comes from the regression made in Table 6.1 with specification 3 and the interaction term from the corresponding regression in Table A.3. Both the regressions include all control variables.

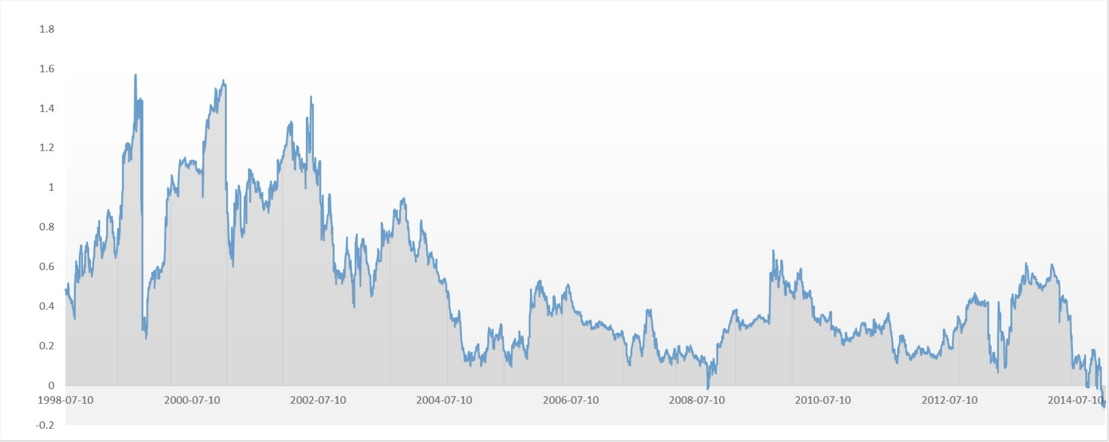


6.2.1 Rolling Coefficient of the Interaction Term

In line with Section 6.1.2 the interaction term was estimated using rolling regression windows of 252 trading days on specification 3. From Figure 6.3 it follows that the interaction term has large time series variation. The figure is consistent with managerial flexibility during the full period, with the exception of the last couple of months in the sample. A rejection of the second null hypothesis is therefore, not to any great extent, time dependent within the sample period.

FIGURE 6.3: Rolling Interaction Term

Rolling interaction term using Pooled OLS and a rolling estimation window of 252 days.



Rolling interaction terms for eight individual companies are in Figure A.1 displayed. The companies chosen were the largest eight companies that traded during the whole period. The figure shows larger time series variation for individual firms than for the average of the set of companies and it might therefore be hard to create portfolios based on historical data under the assumption of persistence of the interaction term.

6.2.2 Gold Futures Beta with Interaction Term

One could argue that mining firms looking to expand or contract operations are considering the price of gold in the future and not the spot price. For example Blose and Shieh (1995) used future prices on gold when examining the gold beta since they claim that the gold futures are the markets unbiased expectations of future spot prices. With this reasoning in mind the gold beta and the interaction term were re-estimated using the gold futures price. The estimated coefficient on the gold future price return is lower than compared to the same regressions on the spot price. The gold futures beta is presented in Table A.4 is 0.868 using specification

3 compared to 1.200 with the spot price. The null of the first hypothesis cannot be rejected in specification 3 to 5.

Table 6.3 presents the results of the regressions with the interaction term included. The interaction term is in the interval of 0.264-0.381 while using the gold futures instead of the spot price.

Table 6.3: Gold Futures Beta Exposure with Interaction Term

Specification 1 is a regression of the gold companies on the gold futures price return and an interaction term. The interaction term is set to zero when the gold futures return is below zero and otherwise equals the gold futures return. Specification 2 includes index as dependent variables in excess to the gold price. Specification 3 and 4 is regression on the whole set of control variables, including commodities, indices and the cadusd exchange rate. Specification 4 uses Newey-West HAC standard errors. Specification 5 is a regression including all control variables with 1 lag for all variables. Standard errors are presented in the parentheses. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively.

	1	2	3	4	5
Gold Future	1.206***	1.044***	0.668***	0.668***	0.694***
	(0.0163)	(0.0164)	(0.0242)	(0.0243)	(0.0275)
L.Gold Future					0.149***
					(0.0292)
Interaction	0.264***	0.332***	0.378***	0.378***	0.467***
	(0.0287)	(0.0280)	(0.0284)	(0.0270)	(0.0358)
L.Interaction					-0.086**
					(0.0335)
Spx			-0.252***	-0.252***	-0.267***
			(0.0244)	(0.0245)	(0.0262)
Sptsx		0.706***	0.798***	0.798***	0.814***
		(0.0167)	(0.0275)	(0.0282)	(0.0302)
Controls	No	No	Yes	Yes	Yes
Lags	No	No	No	No	Yes
St. Err.	White	White	White	Newey-West	White
Obs	157,610	155,735	142,752	142,752	106,065
R^2	0.084	0.104	0.116		0.155

6.3 Performance Evaluation

6.3.1 In-Sample Performance Evaluation

Gold companies were in Section 6.2 shown to have an asymmetric return profile against the gold price. This section examines if the asymmetry attribute has rewarded investors with superior risk-adjusted returns. Generally when conducting a performance evaluation the portfolios or funds have been active during the full sample period. This is not the case in this setting. Since the Sharpe ratio and the Sortino are time dependent performance measurements we created portfolios instead of comparing mean performance measurements of groups of companies. This mitigates the time dependence problem as the portfolios are fully invested at all times. The performance evaluation was conducted using monthly return data.

First, two portfolios were created; the first portfolio consist of companies with a statistically significant interaction term and the second portfolio including companies with an interaction term that could not be distinguished from zero. One concern for the portfolios is that a positive bias in performance could exist for the companies with a significant interaction term. This bias could arise from the fact that a stock with considerably more positive return days will more likely find a statistical significance, in the model used in the previous section, due to the larger sample size of the estimator of the interaction term. Consequently two additional portfolios are formed which are based on the value of the interaction term and the companies is divided by the mean value of the interaction term to mitigate the concerns of sample size bias. The Top Portfolio includes the companies with values of the interaction term above the mean and Bottom contain the companies with those below the mean value. This portfolio structure might be more reasonable due to the higher standard errors of the interaction term for small capitalization stocks with low daily trading volume. However, there are significant overlaps in the two portfolio setups. Since there are companies that do not trade during the whole period, there are times when the portfolio includes different number of stocks. Last, the Top and Bottom portfolio are split in half which generates four quartile portfolios. T-values are not included for the Treynor ratio and the Sortino ratio as there are no higher order moments, sampling distributions or significance tests available (Jobson and Korkie, 1981). Jobson and Korkie claim that the same applies to the Sharpe ratio but asymptotic tests have been developed after the writing of their paper. The test used in this paper is shown in 5.3.1.1. The results from the performance evaluation are presented in Table 6.4.

Panel A of Table 6.4 indicates that the portfolio consisting of companies with a statistically significant interaction term had superior risk-adjusted returns compared to the non-significant portfolio for all of the performance measurement. However, the economic significance of the difference appears limited. In addition, the Sharpe ratio and Jensen's alpha could not be shown to differ statistically. The portfolio including the statistically significant companies had lower risk, measured both in beta and standard deviation and probably a consequence of the size effect. This group also had greater average interaction term than the non-significant

Table 6.4: Performance Evaluation

Panel A and B include four portfolios, one with the companies with a statistically significant interaction term and the second with the companies with a statistically insignificant interaction term. The Top and Bottom portfolios sort the companies into two equally sized portfolios based on the absolute value of the interaction term. The performance measurements in Panel B are calculated using winsorized data at the 95 % level. Panel C divides the companies into four quartile portfolios based on the size of the interaction term with portfolio 1 has the largest interaction term. The table is presented in monthly return figures. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively for Jensen's alpha and the Sharpe ratio.

Panel A: Performance for the Portfolios

	Interaction	Average	Std. Dev.	Beta	Sharpe	Sortino	Treynor	Jensen
Portfolio Sign	0.4426	0.0175	0.1238	1.0620	0.1268*	0.2625	0.0148	0.0178**
Portf. Non sign	0.2314	0.0167	0.1345	1.1980	0.1107	0.2433	0.0124	0.0174**
Portfolio Top	0.5055	0.0228	0.1350	1.1880	0.1556**	0.3350	0.0177	0.0259***
Portf. Bottom	0.2010	0.0124	0.1156	1.0300	0.0916	0.1876	0.0103	0.0138*
Gold	0.0000	0.0056	0.0462	0.2460	0.0746	0.1438	0.0143	0.0026

Panel B: Winsorized Performance for the Portfolios

	Interaction	Average	Std. Dev.	Beta	Sharpe	Sortino	Treynor	Jensen
Portfolio Sign	0.4426	0.0182	0.1086	0.9780	0.0980	0.1950	0.0109	0.0133*
Portf. Non sign	0.2314	0.0133	0.1105	1.0390	0.0496	0.0953	0.0053	0.0082
Portfolio Top	0.5055	0.0143	0.1160	1.0660	0.1078	0.2168	0.0118	0.0157**
Portf. Bottom	0.2010	0.0065	0.1015	0.9340	0.0460	0.0878	0.0050	0.0068

Panel C: Performance for Quartiles Based on Interaction Term

Quartile	Interaction	Average	Std. Dev.	Beta	Sharpe	Sortino	Treynor	Jensen
1 Largest	0.6452	0.0243	0.1539	1.2090	0.1464**	0.3278	0.0186	0.0293***
2	0.3659	0.0169	0.1342	1.1950	0.1122	0.2398	0.0126	0.0195**
3	0.2744	0.0151	0.1368	0.9440	0.0971	0.2193	0.0141	0.0190**
4 Smallest	0.1276	0.0077	0.1106	1.1150	0.0530	0.0530	0.0053	0.0081

(0.4426 compared to 0.2314).

The difference in performance was larger between the Top and Bottom Portfolios, based on the value instead of statistical significance of the interaction term. The Top Portfolio was the riskier portfolio but compensated with higher mean returns and better performance measurements. The Top Portfolio has considerably larger Sharpe ratio of 0.1556 than the bottom portfolio of 0.0916. Additionally the Sortino ratio was 0.3350 compared to 0.1876. Similar results are given for the systematic risk performance measurements. The Treynor ratio and Jensens's alpha is 0.0177 and 0.0259 for the Top Portfolio and 0.0103 and 0.0138 for the Bottom portfolio. Given the results in Panel A, it is likely that the slight out-performance of the statistically significant portfolio was driven from having the larger interaction term. Last, Panel A shows that the gold companies performed better than an investment into gold. The exception is the Treynor ratio, which is affected by the low beta for the gold investment. However these results should be taken with caution since the outcomes are not controlling for selection and survivorship bias. The outcomes from Panel A are shown to be robust to winsorization at the 95 % level in Panel B of 6.4.

The quartile portfolio setting in Panel C in Table 6.4 displays an almost perfect monotonic ranking of the risk-adjusted returns for the four portfolios. The highest risk-adjusted returns are accordingly found in Quartile 1, consisting of the companies with the largest interaction term. The only exception to this relationship is in the Treynor ratio between Quartile 2 and 3. Jensen's Alpha is for Quartile 1 statistically different from Quartile 4 at the 5 % level. Furthermore, the difference between Quartile 1 and 4 are economically large compared to the results in Panel A. A closer analysis of the companies in respective quartile revealed that Quartile 1 included, to a considerably higher proportion, companies focusing on exploration and development with restricted gold production. These characteristics were least common in the fourth quartile.

From Panel A together with Panel C in 6.4 it is shown that the companies with the largest interaction term, Quartile 1, performed better for every performance measurement compared to an investment into gold. Quartile 4 shows only marginally better performance measurements for the Sharpe ratio, the Sortino ratio and Jensen's alpha and displays worse performance measured by the Treynor ratio than the gold investment. From Table 6.4 the null of the third hypothesis can be rejected. In Figure A.2 the portfolio returns are shown for the quartile portfolios. Each portfolio started with $1 invested in July of 1997.

To account for the possibility that the first quartile performed best due to high gold beta and not real optionality we constructed a modified version of Jensen's alpha. The modified version takes the average gold beta exposure out of the alpha and therefore leaves the asymmetries of gold as the only gold factor in the evaluation of the alpha value. The model adds excess return of gold as dependent variable and looks as following:

$$\alpha_j = \bar{R}_{jt} - [R_{Ft} + \beta_K(\bar{R}_{Mt} - R_{Ft}) + \beta_L(\bar{R}_{Gt} - R_{Ft}) + \bar{u}_t] \tag{6.1}$$

The adjusted Jensen's alpha measurement presented has similarities to the Fama-French three factor model by excluding factors which we do not want to credit portfolio managers for. In this model it is the gold price return and in Fama-French three factor model it is typically that it does not reward managers for superior stock picking skills who overweight their portfolios to small companies and value stocks. Table 6.5 shows that the alpha return of the first quartile did not, to a great extent, depend on the gold beta. Only the first and second quartiles are shown to have a statistically significant alpha at the 1% and 10 % level respectively.

Table 6.5: Adjusted Jensen's Alpha

The table divides the companies into four quartile portfolios based on the size of the interaction term where quartile portfolio 1 has the greatest interaction term. Standard errors are presented in the parentheses. The table is presented in monthly return figures. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively.

Quartile Portfolio	Sptsx	Gold	Alpha	St. Err	Obs	R^2
1 Largest	0.778***	1.658***	0.022***	White	210	0.393
	(0.1907)	(0.2016)	(0.0082)			
2	0.805***	1.519***	0.013*	White	210	0.457
	(0.1741)	(0.1449)	(0.0067)			
3	0.512***	1.687***	0.011	White	210	0.449
	(0.1566)	(0.1419)	(0.0068)			
4 Smallest	0.769***	1.356***	0.002	White	210	0.554
	(0.1138)	(0.1234)	(0.0050)			

6.3.2 Out-of-Sample Performance Evaluation

In this section the performance of portfolios based on the size of the interaction term estimated on the time window from 1997 to 2007 is investigated. The time period for the performance evaluation is 2008-2014 and is associated with lower gold price appreciation than during the full sample period. Companies that did not trade at the beginning of the period or with less than 1000 observations in the estimation window were dropped. If there is persistence of the interaction terms then the first quartile could reward investors with risk-adjusted excess returns. The findings are presented in Table A.5.

In Panel A of Table A.5 it is shown that the Top Portfolio had positive mean returns compared to the Bottom Portfolio which had negative mean returns. Although negative ratios make inference more complicated it seems clear that the Top Portfolio had best risk-adjusted returns. Jensen's alpha, which does not have the same problems in case of negative mean returns, also supports this. The performance measurements cannot be statistically separated from each other or from zero; most likely due to small sample size. Panel B displays that the second quartile had the best risk-adjusted returns. Since the first quartile did not perform best, the results show weaker support for outperformance based on the interaction term than in the in-sample analysis. This could be the results of limited persistence in the interaction term for individual companies which was partly suggested by A.1. The average interaction term for Quartile 1 is considerably larger than in the previous performance evaluation and compared to the other quartiles during this period. This could be due to the fact that the average number of observations in the estimation process of the interaction term is the lowest for this quartile, making the estimated coefficients more sensitive.

6.4 Robustness Tests

A variety of robustness tests have been used in this study to validate the results and to further understand the characteristics of the data set. In this section a selection of robustness tests are briefly discussed and presented.

6.4.1 Results on Weekly and Monthly Data

The models have so far been estimated on daily return data compared to Baur (2014) who focused on weekly data, but also included daily and monthly data in his paper. With the aim of comparability to the results by Baur (2014) and to control that the outcomes are not dependent on data frequency the third specification was also regressed on weekly and monthly data with results presented in Table 6.6. For the companies alone, the statistical significance is decreasing with less frequent data points due to smaller samples. As the results are robust and similar in regressions using different data frequencies worries about underspecified models in regards to lag length are mitigated.

TABLE 6.6: Gold Beta and Interaction Term for Different Sample Frequencies

The regressions presented include all control variables for different data frequency using specification 3. The column named "Total" present the coefficient by summing gold and the interaction term. The coefficients in the gold column can be seen as the coefficients for days with negative gold return, when we have included the interaction term. ***, ** and * refer to statistical significance at 1%, 5% and 10% level respectively.

Frequency	Gold	R^2	Gold	Interaction	Total	R^2	Obs
Daily	1.200***	0.1236	1.005***	0.349***	1.354***	0.1251	142,752
Weekly	1.082***	0.1218	0.888***	0.317***	1.205***	0.1229	36927
Monthly	1.382***	0.1527	1.120***	0.369***	1.489***	0.1539	8709

6.4.2 Winsorized Estimation of Real Options

To test if the results are robust after reducing the effect of outliers the data was winsorized at the 99 %, 98 % and 95 % level. The data in Table A.6 was winsorized at the 99 % level and includes the interaction term. The coefficient estimates are, both for the gold price and the interaction term, slightly lower but still consistent Table 6.2. We therefore conclude that the results in the previous section were not driven by outliers.

6.4.3 SPX as Proxy for Market Portfolio

The performance measurement were re-estimated with the SPX as proxy for the market portfolio instead of the SPTSX. The outcome is presented in Table A.7 and is similar to the performance evaluation using SPTSX as market portfolio. The main difference is that the beta coefficients are much lower which enhances the Treynor ratio since it uses the beta value as denominator. However, we find that the results are robust for both SPX and SPTSX as proxy for the market portfolio.

7. Analysis

An investigation of the beta for the gold spot price and its characteristics showed that all specifications used in this study rejected the null of the first hypothesis. This means that an investment into a gold mining company is, on average, a leveraged position on the gold price return. The results on the gold beta are thus consistent with the findings by Blose and Shieh (1995) and Tufano (1996) as well as the theoretical framework developed by Tufano (1998) and differs largely from the lower gold beta found by Baur (2014). The larger models of the gold price return sensitivity, including a greater set of control variables, demonstrated that a basic gold market model and the model used by Baur possess an upward bias in the estimation of the gold beta and a downward bias for the coefficient of the interaction term. The statistical significance in the regressions were greatly improved, compared to Baur, due to the usage of Pooled OLS which radically reduced the standard errors compared to regressing every company's returns by themselves. The beta for gold futures was found to be slightly lower than 1 in specification 3 to 5. The two first specifications yielded inconsistent results compared to these due to the upward bias. One explanation for lower gold futures beta could come from storage costs included in the pricing of the future.

Differences of the estimated gold beta in studies could emerge from the time periods used as the rolling beta regressions displays. Figure 6.1 demonstrates that the gold beta have had significant variation over time and suggest that the null of the first hypothesis could potentially not be rejected during sub-periods. Variation of the gold beta is consistent with managerial flexibility, but could also be created by different hedging and diversification policies. Interestingly, the rolling beta does not follow the gold price trend in Figure 4.1, which had a stable upward trend during the time period, with the exception of the last years. However, other factors such as marginal costs, annual production and fixed costs, shown in equation 3.2, also affect the gold beta. Tufano's findings of a gold beta between 2 and 3 probably come from a short time period associated with higher gold betas for the average gold company. During the period when our dataset and Tufano's overlap the gold betas in this study are in line with his results. The differences compared to results by Baur with a gold beta of 0.67 could indicate that hedging and diversification activities are more common for Australian listed gold companies. The different time period is another plausible explanation for the differences.

A size effect is displayed for the gold beta where larger companies have on average higher gold betas. This is consistent with the findings of Tufano (1998) who argues that the greater part of this most likely comes from the fact that the stock market more quickly incorporates gold price shocks into the valuation of larger companies. Another explanation in our data set, given that the market cap is measured after the end of the sample period, could be that companies with a high gold beta have grown large due to the bull market in gold.

Especially the silver price and the cadusd exchange rate were shown to be important in terms of statistical significance as control variables. However, we still consider the inclusion of the precious metals and mining controls to be of importance to reduce omitted variable bias due to correlation of returns.

Section 6.2 provided statistical significance at the 1 % level that returns for gold companies are characterized by a favorable asymmetric return profile with greater upside than downside sensitivity to changes in the gold price. The interaction term is marginally larger when considering futures on the gold price. It thereby rejects the second null hypothesis. These characteristics should be attractive for an investor wanting gold exposure in the portfolio and supports the idea of Baur (2014) that an investment into a gold mining company might be superior to an investment in gold itself. A larger interaction term for gold futures is logical since managers have more time to adjust their production as a response to the price change which might be hard to do for the change in the spot price. From the data it can be shown that above half of the companies have statistically significant interaction terms and asymmetric return profiles to the gold price. The interaction term was shown to vary considerably over time and between companies. A greater proportion of larger companies had a statistically significant interaction term; the size effect may originate from higher standard deviations of returns for smaller companies, for example due to low liquidity. It is shown that the coefficient of the interaction term is not to any great extent dependent on the size of the company. It is therefore interesting to investigate why there are large variation of the interaction terms which cannot be explained by size effects.

The Black-Scholes option pricing formula provides one possible explanation for the variation of the interaction term between companies and over time. Since the volatility of the underlying security is gold for all companies, the spot price is the gold spot price, the risk free is either the US or the Canadian risk free rate which are approximately the same and there is no fixed time to maturity, the only variable in this option pricing model to affect the value differently for the companies is the strike price. We know from Black-Scholes that the gamma is the greatest around the strike price and that non-linear price changes have the greatest impact at this point. We would therefore expect gold producing companies that have marginal costs around the spot price to have the greatest interaction term in the model. At this point the managerial flexibility is maximized since the companies are both close to using the option of contracting production if the gold price decreases or increase production in the event of higher gold price. In the sample we found that 10 out of the 13 companies in the first quartile, with the highest interaction term, had no or limited production and focused instead on exploration and development of mines. In our view this is not surprising as these companies likely can both faster and easier respond to gold price changes by either increase their exploration projects or put the development of mines on hold. Additionally, the real options for these companies (or for the acquirer of the mines) include all future production and should therefore be less constrained than gold producing companies. For miners that have low marginal costs in relation to the spot price the delta is close to one and the gamma zero. Managers are constrained to producing and will with very low probability decrease future production rate. These attributes corresponds to a common equity position and do therefore not provide an asymmetric return profile for small changes in the spot price. It is important to note that if the gold beta is zero for a company, which would be the case if the company has sold all their future production through futures, that there is no managerial flexibility. Another, more concerning, explanation for the difference of the size of the interaction term could be that some managers simply do not use the real options efficiently and uses a fixed production schedule or that they have constrained the production processes.

Compared to the work by Baur (2014) the interaction term is in this study larger on average for individual companies and a higher share is statistically significant at the 5 % level (25 out of 52 compared to 7 out of 41). The interaction term in the third specification is 0.349 compared to 0.21 found by Baur. After including lagged values the interaction term is 0.407. The interaction term is also statistically significant in all of the specifications in this study which they are not for the full sample in the article by Baur. The lower value of the optionality in Baur's paper is further an indication that Australian firms more actively hedged and diversified than the North American companies in this study. As already stated, hedging and diversification does not imply a asymmetric return profile but it do affect the proportion of the business activities that potentially could have asymmetric returns.

Compared to Baur (2014), there is no monotonically increasing gold beta as sampling frequency decreases. The gold betas are also more similar in our estimation in different sampling frequencies which probably is a result of the larger model used in this thesis. We see no reason to why there should be any economic reason for a difference of the beta coefficient estimate, given a large enough sample. However, both results are still consistent with managerial flexibility.

In the third part of the results the returns as well as the risk-adjusted returns are compared between the groups of firms with high and low interaction terms. We find that there is only a marginal difference in risk-adjusted returns for an investment into companies with a statistically significant interaction term compared to one in companies with no statistical significance of the interaction term. As already mentioned, it seems as the size and liquidity affect the statistical significance of the interaction term. We therefore think that an analysis based on the size of the coefficient and not the statistical significance is more sensible.

In the quartile portfolios based on the size of the interaction term we show that the portfolio with the greatest interaction term has outperformed the other portfolios on a risk-adjusted return basis for an in-sample evaluation, thus rejecting the null of the third hypothesis. In an out-of-sample performance evaluation, in a quartile setting, the results are less clear, but the Top portfolio performs better than the Bottom portfolio. However, since the interaction term and the value of the real option are not constant, it might be hard for an investor to profit from the historical interaction term unless there is at least some persistence in the real option. Additionally, many data points are needed to estimate the interaction term for a company. Investors therefore need to form other strategies for estimating the current asymmetries provided by the real options. The results suggest that investors should first invest in exploration and development companies as the presence of real optionality should be easier to exploit in the early stages of mining operations and affects a larger quantity of future production. Second, investors could collect information about marginal costs and invest in companies that have marginal costs close to the spot price. Last, and least desirable, is to invest in companies with high profit margins (spot price much greater than the marginal cost of extracting the gold) as the asymmetries should be lower for companies with high profit margins.

8. Conclusion

In this thesis we have studied the gold beta for 52 gold companies in North America over the time period 1997 to 2014 and the presence and performance of real options in their business models. Consistent with earlier research by Blose and Shieh (1995) and Tufano (1998) the results find a gold beta above one, meaning that an investment into a gold mining company is a leveraged position on the gold price. However, investigation of the rolling gold price beta revealed great variation over time. The gold beta on the future price was found to be less than one. Problems with underspecification for a basic gold market model and the model used on Australian gold mining companies by Baur (2014) were displayed. The underspecified models lead to an upward bias of the gold beta and a downward bias of the term measuring real optionality due to omitted variables which were mitigated by including controls for precious metals and other mining commodities.

This study finds that real options are being used by the North American gold companies. The managerial flexibility creates an asymmetric return profile with greater upside sensitivity but with approximately the same downside sensitivity to the gold price return than an ETF investment in gold. The return asymmetry should be attractive for gold investors but is shown to fluctuate largely over time and across companies.

The results show that companies with greater asymmetric return profile to the gold price have provided investors with excess risk-adjusted returns. This therefore suggests that analysts and investors do not, or only partially take, real optionality into consideration and thereby creates a market inefficiency. Additionally, the Black-Scholes option pricing model supports the results that it may be better to invest in less profitable gold miners than in highly profitable ones.

Implications of the findings for gold investors are that there are difficulties associated with buying shares of gold companies as a substitute of a gold investment, due to the variability of the gold exposure. Furthermore, the level of risk and exposure to market risk is much greater compared to the gold investment. If the gold position was built as a hedge against systematic risk in the equity portfolio the investment into gold companies is not suitable, since the investment holds considerable systematic risk.

Future research could investigate the risk-adjusted returns for portfolios based on the marginal cost of extracting gold for mining companies. Another possible division of companies could be to compare profitable mining firms against exploration and development companies to conclude whether return differences exist arising from the different operations. A third area of future research could investigate real options and beta exposure for other mining commodities.

A. Appendix

A.1 Appendix of Figures

Figure A.1: Rolling Interaction Term for Individual Companies

Estimated rolling gold beta using a rolling estimation window of 1000 days. The companies chosen were the largest 8 companies that traded during the whole period.

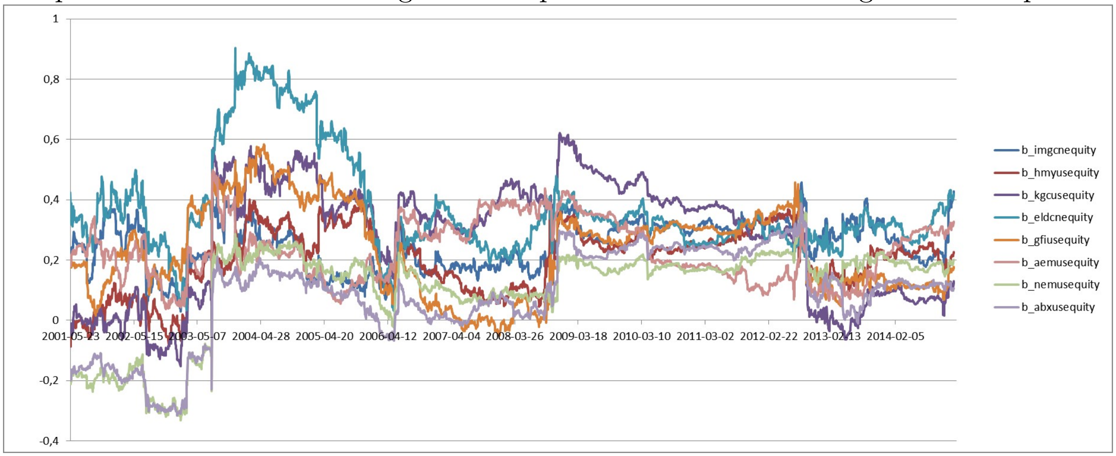
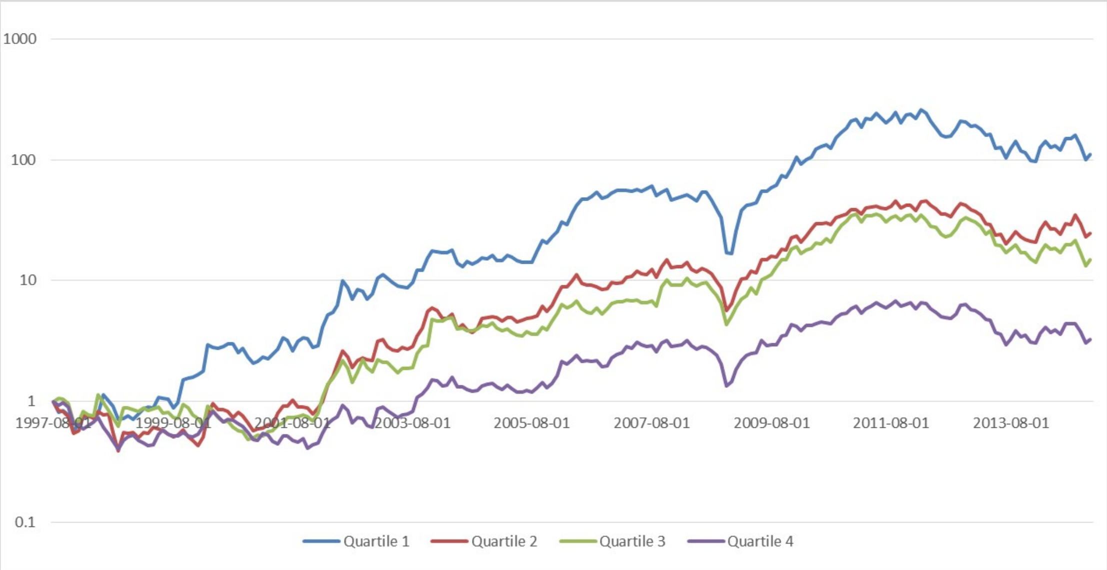


Figure A.2: Returns for Quartiles Based on Size of the Interaction Term

Equally weighted quartiles portfolios based on the size of the interaction term where quartile 1 has the greatest interaction term. All portfolios start with a portfolio worth of $1 in August 1997. The portfolios were rebalanced every month within the quartiles.



A.2 Appendix of Tables

Table A.1: Summary Descriptive of Companies' Shares' Return

The companies are sorted on size using market capitalization. A Company name that ends with "us" indicates a US firm while "cn" indicates a Canadian company. The Ljung-Box Q statistics are estimated using a lag length of 10 lags.

Company	Obs	Mean	Std. Dev.	Min	Max	Ljung-Box	P-Value
ggus	4133	0.0009	0.0314	-0.1748	0.2727	24.5914	0.0062
abxus	4233	0.0002	0.0271	-0.1464	0.3131	25.9753	0.0038
nemus	4233	0.0002	0.0284	-0.1669	0.2517	40.3656	0.0000
fnvcn	1712	0.0009	0.0264	-0.1672	0.1994	20.8092	0.0225
goldus	3029	0.0015	0.0332	-0.1808	0.7400	17.9371	0.0560
aemus	4233	0.0008	0.0341	-0.2518	0.2500	18.7482	0.0436
rgldus	4185	0.0010	0.0348	-0.3265	0.3029	28.0508	0.0018
gfius	4233	0.0006	0.0357	-0.2468	0.5048	53.4280	0.0000
eldcn	4230	0.0009	0.0452	-0.2618	0.6109	45.5888	0.0000
kgcus	4227	0.0006	0.0408	-0.2140	0.2905	82.3571	0.0000
yricn	4155	0.0004	0.0570	-0.3571	1.0800	109.7951	0.0000
ngdcn	3451	0.0019	0.0474	-0.2778	0.5753	35.7495	0.0001
btocn	1698	0.0005	0.0422	-0.1538	0.2903	19.4483	0.0349
dgccn	1908	0.0011	0.0433	-0.2478	0.2864	44.6006	0.0000
cgcn	2538	0.0008	0.0451	-0.3304	0.6544	38.8976	0.0000
hmyus	4224	0.0005	0.0373	-0.1875	0.3477	21.4830	0.0180
ngcn	3992	0.0021	0.0656	-0.6727	0.7498	38.3634	0.0000
imgcn	4185	0.0005	0.0361	-0.1949	0.2776	22.6904	0.0119
auqcn	3930	0.0008	0.0440	-0.2826	0.2999	9.3522	0.4990
smfcn	3998	0.0017	0.0551	-0.3572	0.3636	64.1910	0.0000
txgcn	2328	0.0058	0.0871	-0.3750	0.6364	47.6657	0.0000
pvgus	950	0.0008	0.0502	-0.3058	0.8157	10.1273	0.4294
nsucn	3985	0.0022	0.0587	-0.3060	0.5383	33.3660	0.0002
cggcn	3164	0.0018	0.0565	-0.2931	0.5600	31.3716	0.0005
agicn	2877	0.0010	0.0372	-0.2287	0.3520	37.8913	0.0000
ogccn	1769	0.0002	0.0473	-0.2203	0.4815	7.6969	0.6584
pcn	1272	0.0012	0.0571	-0.2857	0.7500	14.7174	0.1427
seacn	3351	0.0024	0.0558	-0.2857	0.6000	33.6945	0.0002
vgqcn	2108	0.0008	0.0293	-0.1497	0.3565	14.4117	0.1550
rmxcn	3390	0.0014	0.0517	-0.2729	0.8147	9.6373	0.4729
prbcn	2049	0.0057	0.0786	-0.2857	1.0000	58.7596	0.0000
lsgcn	2891	0.0011	0.0523	-0.3725	0.5625	20.4865	0.0250
muxus	3972	0.0027	0.0683	-0.4667	1.0765	83.8814	0.0000
guycn	3763	0.0030	0.0700	-0.3333	0.7857	50.5093	0.0000
arcn	1191	0.0006	0.0695	-0.4333	2.0000	25.2548	0.0049
rcn	3568	0.0022	0.0710	-0.4074	0.5909	152.7444	0.0000
kgicn	3442	0.0020	0.0556	-0.3889	0.6129	57.4178	0.0000
gbucn	3929	0.0018	0.0561	-0.5374	0.6000	80.4581	0.0000
pgcn	2024	0.0009	0.0422	-0.1704	0.2717	22.3510	0.0134
edvcn	3124	-0.0004	0.0389	-0.2203	0.2500	20.8592	0.0221
cnlcn	2089	0.0043	0.0867	-0.5556	1.2353	42.1420	0.0000
gorous	2000	0.0015	0.0408	-0.3061	0.3288	17.6001	0.0621
ricus	3862	0.0011	0.0418	-0.2513	0.2846	34.9532	0.0001
tgzcn	992	-0.0008	0.0385	-0.1600	0.3182	20.8722	0.0220
tmmcn	1964	0.0013	0.0518	-0.2700	0.4286	35.6335	0.0001
ngqcn	3919	0.0018	0.0713	-0.4545	1.2500	77.4784	0.0000
rogcn	2018	0.0099	0.1297	-0.5556	1.7000	39.6773	0.0000
aotcn	3177	0.0046	0.0840	-0.4000	1.2353	57.1724	0.0000
wdocn	3672	0.0006	0.0481	-0.2361	0.3273	94.1828	0.0000
gqmcn	3359	0.0036	0.0866	-0.3778	1.6000	131.0046	0.0000
anvus	1857	0.0003	0.0516	-0.3304	0.5850	32.9339	0.0003
dnacn	1046	0.0012	0.0476	-0.2149	0.3158	15.3329	0.1204

Table A.2: Examining AR(4) Processes

The L1, L2, L3 and L4 are the lagged values of the 1st, 2nd, 3rd and 4th lag respectively on the corresponding dependent variable. Standard errors of the coefficients are presented in the parentheses. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively.

Variables	Firms	Gold	Silver	Platinum	Copper	Aluminum	Zinc	Spx	Sptsx	Cadusd
L1	-0.096***	-0.017	-0.030**	0.042***	-0.089***	-0.074***	-0.048***	-0.071***	0.0024	-0.045***
	(0.0062)	(0.0135)	(0.0136)	(0.0135)	(0.0151)	(0.0167)	(0.0169)	(0.0151)	(0.0150)	(0.0136)
L2	-0.040***	-0.008	0.010	-0.036***	-0.022	-0.025	-0.017	-0.046***	-0.047***	0.010
	(0.0062)	(0.0135)	(0.0136)	(0.0136)	(0.0152)	(0.0167)	(0.0170)	(0.0151)	(0.0150)	(0.0136)
L3	-0.0066	0.014	0.0048	-0.021	-0.014	-0.015	-0.026	-0.011	0.011	0.007
	(0.0062)	(0.0135)	(0.0136)	(0.0136)	(0.0152)	(0.0168)	(0.0169)	(0.0152)	(0.0150)	(0.0136)
L4	0.017***	0.015	-0.0069	0.0032	0.016	0.020	0.042***	-0.023	-0.014	0.028**
	(0.0059)	(0.0135)	(0.0136)	(0.0135)	(0.0152)	(0.0169)	(0.0161)	(0.0151)	(0.0149)	(0.0136)
Constant	0.005***	0.000*	0.000	0.000	0.000	0.000	0.000	0.000**	0.000	0.000
	(0.0003)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)
Obs	25,574	5,461	5,404	5,451	4,356	3,587	3,458	4,376	4,437	5,402
R^2	0.011	0.001	0.001	0.004	0.009	0.007	0.005	0.007	0.002	0.003

TABLE A.3: Gold Betas and Interaction Terms for the Companies

The table shows regression results using specification 3. On the left the regression includes all control variables, only gold price is presented due to space limitations. The companies are sorted on market capitalization from largest to smallest. To the right the regression includes all control variables and the interaction term. Durbin is Durbin's alternative test statistic. Standard errors are presented in the parentheses. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively.

Company	Gold	Std. Err	R^2	Gold	Std. Err	Interaction	Std. Err	Durbin	P-value	R^2	Obs
ggus	1.361***	(0.076)	0.474	1.145***	(0.080)	0.381***	(0.094)	6.234	0.013	0.479	3,698
abxus	1.344***	(0.081)	0.530	1.269***	(0.070)	0.132	(0.098)	17.148	0.000	0.531	3,785
nemus	1.420***	(0.087)	0.423	1.315***	(0.079)	0.185*	(0.105)	25.656	0.000	0.424	3,785
fnvcn	0.990***	(0.109)	0.415	0.890***	(0.126)	0.182*	(0.110)	7.505	0.006	0.417	1,613
goldus	1.194***	(0.097)	0.387	1.016***	(0.103)	0.328***	(0.097)	4.651	0.031	0.391	2,740
aemus	1.594***	(0.097)	0.463	1.423***	(0.094)	0.301***	(0.113)	6.229	0.013	0.465	3,785
rgldus	1.326***	(0.097)	0.270	1.151***	(0.089)	0.310***	(0.103)	58.056	0.000	0.273	3,740
gfius	1.659***	(0.096)	0.365	1.484***	(0.099)	0.309**	(0.122)	69.538	0.000	0.368	3,785
eldcn	1.896***	(0.112)	0.274	1.655***	(0.128)	0.424***	(0.132)	17.466	0.000	0.277	3,781
kgcus	1.759***	(0.107)	0.366	1.584***	(0.108)	0.308**	(0.124)	196.317	0.000	0.368	3,779
yricn	1.312***	(0.142)	0.125	1.248***	(0.158)	0.112	(0.136)	94.147	0.000	0.125	3,720
ngdcn	0.987***	(0.210)	0.172	0.669***	(0.175)	0.557***	(0.213)	4.843	0.028	0.176	3,125
btocn	0.807***	(0.195)	0.199	0.602***	(0.205)	0.374*	(0.212)	33.196	0.000	0.202	1,601
dgccn	1.534***	(0.174)	0.394	1.286***	(0.185)	0.449**	(0.184)	12.274	0.001	0.398	1,796
cgcn	1.442***	(0.236)	0.234	1.335***	(0.189)	0.191	(0.281)	0.322	0.570	0.235	2,334
hmyus	1.777***	(0.092)	0.367	1.616***	(0.098)	0.284**	(0.112)	28.532	0.000	0.369	3,780
ngcn	1.514***	(0.205)	0.100	1.259***	(0.207)	0.457*	(0.236)	25.505	0.000	0.101	3,563
imgcn	1.352***	(0.099)	0.311	1.191***	(0.101)	0.282**	(0.120)	22.508	0.000	0.313	3,737
auqcn	0.866***	(0.120)	0.169	0.742***	(0.115)	0.214	(0.131)	3.239	0.072	0.170	3,521
smfcn	1.229***	(0.144)	0.127	1.026***	(0.148)	0.357**	(0.155)	71.235	0.000	0.129	3,587
txgcn	0.704**	(0.321)	0.049	0.266	(0.347)	0.787**	(0.371)	49.053	0.000	0.052	2,144
pvgus	0.986***	(0.290)	0.204	0.809***	(0.294)	0.36	(0.272)	0.148	0.700	0.206	899
nsucn	1.608***	(0.219)	0.146	1.209***	(0.181)	0.699***	(0.219)	45.673	0.000	0.151	3,571
cggcn	1.148***	(0.162)	0.127	0.944***	(0.182)	0.373**	(0.183)	10.531	0.001	0.128	2,839
agicn	1.092***	(0.130)	0.308	0.882***	(0.137)	0.388***	(0.131)	13.881	0.000	0.312	2,623
ogccn	1.053***	(0.244)	0.178	1.001***	(0.250)	0.0942	(0.285)	12.881	0.000	0.178	1,668
pcn	0.890***	(0.246)	0.056	0.749***	(0.264)	0.292	(0.267)	17.789	0.000	0.057	1,197
seacn	1.339***	(0.182)	0.153	0.938***	(0.200)	0.736***	(0.180)	24.504	0.000	0.159	3,006
vgqcn	0.425***	(0.121)	0.125	0.462***	(0.144)	-0.067	(0.120)	17.944	0.000	0.125	1,975
rmxcn	1.231***	(0.147)	0.123	1.147***	(0.143)	0.154	(0.154)	5.367	0.021	0.123	3,036
prbcn	0.216	(0.308)	0.040	0.0846	(0.346)	0.237	(0.366)	14.329	0.000	0.040	1,912
lsgcn	1.155***	(0.152)	0.144	0.968***	(0.165)	0.339**	(0.165)	22.338	0.000	0.145	2,634
muxus	1.344***	(0.211)	0.118	1.004***	(0.179)	0.598***	(0.217)	123.016	0.000	0.121	3,562
guycn	0.973***	(0.186)	0.076	0.714***	(0.189)	0.451**	(0.202)	39.524	0.000	0.077	3,384
arcn	1.014***	(0.208)	0.104	0.646	(0.402)	0.747	(0.613)	0.119	0.730	0.107	1,122
rcn	1.140***	(0.218)	0.068	0.979***	(0.203)	0.284	(0.250)	159.574	0.000	0.068	3,236
kgicn	1.431***	(0.176)	0.150	1.211***	(0.190)	0.405**	(0.165)	121.035	0.000	0.152	3,078
gbucn	1.114***	(0.163)	0.096	0.861***	(0.191)	0.440**	(0.186)	60.530	0.000	0.098	3,517
pgcn	1.211***	(0.162)	0.283	1.124***	(0.169)	0.160	(0.167)	4.682	0.031	0.284	1,902
edvcn	0.950***	(0.132)	0.172	0.952***	(0.138)	-0.004	(0.148)	22.721	0.000	0.172	2,832
cnlcn	1.244***	(0.320)	0.043	1.119***	(0.365)	0.242	(0.314)	51.234	0.000	0.043	1,898
gorous	0.557***	(0.157)	0.243	0.405**	(0.177)	0.276*	(0.163)	4.075	0.044	0.245	1,877
ricus	1.179***	(0.109)	0.240	1.030***	(0.114)	0.257**	(0.123)	52.280	0.000	0.241	3,464
tgzcn	1.503***	(0.195)	0.194	1.340***	(0.223)	0.335	(0.237)	7.977	0.005	0.196	931
tmmcn	0.927***	(0.214)	0.159	0.801***	(0.219)	0.226	(0.224)	24.680	0.000	0.159	1,844
ngqcn	0.195	(0.173)	0.033	0.122	(0.177)	0.13	(0.199)	52.889	0.000	0.033	3,524
rogcn	-0.169	(0.765)	0.006	-0.852	(0.882)	1.305**	(0.618)	31.183	0.000	0.009	1,848
aotcn	0.584**	(0.228)	0.029	0.366	(0.242)	0.408	(0.286)	48.128	0.000	0.030	2,874
wdocn	1.218***	(0.180)	0.095	1.117***	(0.155)	0.175	(0.197)	106.709	0.000	0.096	3,310
gqmcn	1.107***	(0.365)	0.046	0.675**	(0.321)	0.737**	(0.367)	127.078	0.000	0.049	3,066
anvus	1.548***	(0.275)	0.309	1.328***	(0.274)	0.399	(0.272)	1.473	0.225	0.312	1,741
dnacn	1.083***	(0.243)	0.153	0.952***	(0.264)	0.269	(0.254)	5.739	0.017	0.154	983

Table A.4: Gold Futures Beta Exposure

Specification 1 is a regression of the gold companies on the gold futures price return solely. Specification 2 includes index as dependent variables in excess to the gold futures price. Specification 3 and 4 is regression on the whole set of control variables, including commodities, indices and the cadusd exchange rate. Specification 4 uses Newey-West HAC standard errors. Specification 5 is a regression including all control variables with 1 lag for all variables. Standard errors are presented in the parentheses. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively. ###, ## and # refers to the statistical significance at the 1%, 5% and 10% level respectively based on the null hypothesis of gold beta equal to one.

	1	2	3	4	5
Gold Futures	1.336*** ###	1.210*** ###	0.868***	0.868***	0.943***
	(0.0143)	(0.0145)	(0.0237)	(0.0240)	(0.0269)
L.Gold Futures					-0.134***
					(0.0075)
Spx			-0.251***	-0.251***	-0.263***
			(0.0244)	(0.0246)	(0.0263)
Sptsx		0.697***	0.790***	0.790***	0.808***
		(0.0166)	(0.0276)	(0.0283)	(0.0303)
Controls	No	No	Yes	Yes	Yes
Lags	No	No	No	No	Yes
St. Err.	White	White	White	Newey-West	White
Obs	157,610	155,735	142,752	142,752	106,065
R^2	0.083	0.103	0.115		0.153

Table A.5: Out-of-Sample Performance Evaluation

In this setting the division of portfolios is based on the interaction term estimated in the time window from 1997 to 2007. The time period for the performance evaluation is 2008-2014. Panel A include the Top and Bottom portfolios. Top and Bottom portfolios sort the companies into two equally sized portfolios based on the absolute value of the interaction term. Panel B divides the companies into four quartile portfolios based on the size of the interaction term with portfolio 1 has the largest interaction term. The table is presented in monthly return figures.

Panel A: Performance for the Top and Bottom Portfolios

	Interaction	Average	Std. Dev.	Beta	Sharpe	Sortino	Treynor	Jensen
Top	0.7796	0.0064	0.1394	1.5970	0.0448	0.0850	0.0039	0.0135
Bottom	0.2284	-0.0027	0.1088	1.2290	-0.0268	-0.0469	-0.0024	0.0012
Gold	0.0000	0.0042	0.0591	0.3844	0.0681	0.1213	0.0105	0.0052

Panel B: Performance for Quartiles Based on Interaction Term

Quartile	Interaction	Average	Std. Dev.	Beta	Sharpe	Sortino	Treynor	Jensen
1 Largest	1.0726	0.0031	0.1448	1.6920	0.0199	0.0352	0.0017	0.0113
2	0.4866	0.0087	0.1410	1.5020	0.0607	0.1281	0.0057	0.0158
3	0.3208	-0.0003	0.1166	1.0910	-0.0038	-0.0073	-0.0004	0.0046
4 Smallest	0.1361	-0.0060	0.1089	1.3680	-0.0569	-0.0946	-0.0045	-0.0022

Table A.6: Winsor Adjusted Gold Beta Exposure with Interaction Term

The data is winsorized at the 99% level. Specification 1 is a regression of the gold companies on the gold price return and an interaction term. The interaction term is set to zero when the gold return is below zero and otherwise equals the gold return. Specification 2 includes index as dependent variables in excess to the gold price and interaction term. Specification 3 and 4 is regression on the whole set of control variables, including commodities, indices and the cadusd exchange rate. Specification 4 uses Newey-West HAC standard errors. Specification 5 is a regression including all control variables with 1 lag for all variables. Standard errors are presented in the parentheses. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively.

	1	2	3	4	5
Gold	1.344***	1.186***	0.977***	0.977***	1.002***
	(0.0134)	(0.0138)	(0.0212)	(0.0210)	(0.0275)
L.Gold					-0.049*
					(0.0283)
Interaction	0.177***	0.228***	0.263***	0.263***	0.359***
	(0.0219)	(0.0214)	(0.0219)	(0.0211)	(0.0325)
L.Interaction					-0.0257
					(0.0327)
Spx			-0.177***	-0.177***	-0.178***
			(0.0198)	(0.0200)	(0.0242)
Sptsx		0.573***	0.667***	0.667***	0.683***
		(0.0132)	(0.0223)	(0.0229)	(0.0271)
Controls	No	No	Yes	Yes	Yes
Lags	No	No	No	No	Yes
St. Err.	White	White	White	HAC	White
Obs	157,629	155,749	142,752	142,752	108,423
R^2	0.132	0.150	0.158		0.157

Table A.7: Performance Evaluation Using SPX as Market Portfolio

Panel A and B include four portfolios. First two portfolios, Sign & Non Sign, based on the statistical significance of the interaction term. The Top and Bottom portfolios sort the companies into two equally sized portfolios based on the absolute value of the interaction term. The performance measurements in Panel B are calculated using winsorized data at the 95 % level. Panel C divides the companies into four quartile portfolios based on the size of the interaction term with portfolio 1 has the largest interaction term. The table is presented in monthly return figures. ***, ** and * refers to statistical significance at 1%, 5% and 10% level respectively for Jensen's alpha and Sharpe ratio.

Panel A: Performance for the Portfolios

	Interaction	Average	Std. Dev.	Beta	Sharpe	Sortino	Treynor	Jensen
Portfolio Sign	0.4426	0.0175	0.1238	0.2350	0.1268*	0.2625	0.0668	0.0223***
Portf. Non sign	0.2314	0.0167	0.1345	0.3930	0.1107	0.2433	0.0379	0.0221**
Portfolio Top	0.5055	0.0228	0.1350	0.2760	0.1556**	0.3350	0.0761	0.0161***
Portf. Bottom	0.2010	0.0124	0.1156	0.3000	0.0916	0.1876	0.0353	0.0287*
Gold	0.0000	0.0056	0.0462	0.0528	0.0746	0.1438	0.1035	0.0053

Panel B: Winsorized Performance for the Portfolios

	Interaction	Average	Std. Dev.	Beta	Sharpe	Sortino	Treynor	Jensen
Portfolio Sign	0.4426	0.0182	0.1086	0.1960	0.0980	0.1950	0.0543	0.0158**
Portf. Non sign	0.2314	0.0133	0.1105	0.3540	0.0496	0.0953	0.0155	0.0103
Portfolio Top	0.5055	0.0208	0.1160	0.2820	0.1078	0.2168	0.0444	0.0181**
Portf. Bottom	0.2010	0.0115	0.1015	0.2400	0.0460	0.0878	0.0195	0.0090

Panel C: Performance for Quartiles Based on Interaction Term

Quartile	Interaction	Average	Std. Dev.	Beta	Sharpe	Sortino	Treynor	Jensen
1 Largest	0.6452	0.0243	0.1539	0.1960	0.1464**	0.3278	0.1149	0.0343***
2	0.3659	0.0169	0.1342	0.4980	0.1122	0.2398	0.0302	0.0229**
3	0.2744	0.0151	0.1368	0.1880	0.0971	0.2193	0.0707	0.0228**
4 Smallest	0.1276	0.0077	0.1106	0.3640	0.0530	0.0530	0.0161	0.0118

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