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The Risk Profile of Gold Mining Stocks

Gullaksjers risikoprofil

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Preface

This master thesis completes our Master of Science in Business Administration with specialisation in finance, at NTNU Business School.

The subject of the thesis is to model the risk profile of gold mining stocks, using time-series quantile regression and the cross-sectional approach of Fama-MacBeth regression. The process has given us an academic dive into the gold mining industry and its associated risk factors, challenging us on methodology attained through our educational run.

We express our gratitude to our supervisor, Associate Professor Michael Kisser at NHH Norwegian School of Economics, for council and guidance through the writing process.

The contents of this master thesis reflect our own personal views and are not necessarily endorsed by NTNU Business School.

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Abstract

The purpose of this paper is to assess the economic determinants of gold mining stocks. We are especially interested in the relationship between gold stocks and the gold price. To examine the risk profile of the gold stocks, we regress the excess return of a portfolio consisting of 182 gold mining stocks, on seven risk factors: the market return, the gold price, the USD exchange rate, the long-term interest rate, the oil price, the small-minus-big portfolio and the high-minus-low portfolio. The regressions are run both at the mean, using ordinary least squares, and at different quantiles, using the quantile regression approach. To study cross-sectional differences, we apply the Fama-MacBeth regression on the most relevant risk factors. The results from the quantile regression show that only a few factor coefficients significantly differ from the ordinary least squares estimates. However, both the interest rate and the market factor show signs of upper tail dependency with the gold stock portfolio. The gold price is the only factor that is significant over the entire return distribution, even though we find that several factors significantly explain gold stock returns both at the mean and at different quantiles. The gold price factor constitutes most of the explanatory power, consequently being the main driver of the return of gold stocks. Interestingly, we find that big market capitalisation gold stocks exhibit stronger gold risk exposures, and lower average returns, than small capitalisation gold mining companies. This is accompanied by the Fama-MacBeth regression, where we find that both the gold price exposure, market capitalisation and book-to-market equity explain the cross-section of gold stocks. The same analysis shows no significant explanatory power of the market beta on gold stocks. This is of relevance to investors, as it suggests that the market prices gold risk, but not market risk, for gold mining stocks. As such, an individual who invests in a gold mining company should expect higher average returns for a stock with a high gold beta, than for a stock with a low gold beta.

Sammendrag

Formålet med denne artikkelen er å evaluere økonomiske faktorers påvirkning på gullgruveaksjer. Vi er spesielt interessert i forholdet mellom gullaksjer og gullprisen. For å undersøke risikoprofilen til gullgruveaksjer gjennomfører vi en regresjon der meravkastningen til en portefølje bestående av 182 gullaksjer er den avhengige variabelen. Syv potensielle risikofaktorer er de uavhengige variablene: markedsporteføljens meravkastning, gullprisen, USD valutakurs, langsiktig rente, oljeprisen, small-minus-big-porteføljen og high-minus-low-porteføljen. Regresjonene blir gjennomført både på gjennomsnittet, med minste kvadraters metode, og for forskjellige kvantiler, med kvantilregresjon. For å studere tverrsnittlige forskjeller benytter vi oss av en Fama-MacBeth regresjon på de mest relevante risikofaktorene. Resultatene fra kvantilregresjonen viser at få av faktorkoeffisientene er signifikant forskjellige fra koeffisientene estimert med minste kvadraters metode. Likevel finner vi tendenser til haleavhengigheter både for rentefaktoren og markedsavkastningen med vår gullaksjeportefølje. Fra samme metode finner vi at gullprisen er den eneste faktoren som er signifikant over hele avkastningsfordelingen til porteføljen, selv om flere av de andre variablene også er signifikante, både på snittet og for flere kvantiler. Det er likevel gullprisen som bidrar med mesteparten av forklaringskraften i modellen, og er hoveddriveren for avkastningen til gullaksjene. Gullprisens påvirkning på aksjene er ikke konstant. Vi finner at store gullgruveselskaper har høyere sensitivitet ovenfor endringer i gullprisen enn små selskaper, men likevel lavere gjennomsnittsavkastning i undersøkelsesperioden vår. Dette underbygges av Fama-MacBeth regresjonen som finner at både sensitiviteten til gullprisen, selskapenes markedskapitalisering og bok/pris forholdet forklarer tverrsnittlig varians for avkastningen til gullgruveaksjene. Den samme analysen finner ingen tilsvarende effekt for sensitiviteten ovenfor endringer i markedsavkastningen. Dette er relevant for investorer siden analysen indikerer at markedet priser gullrisiko, men ikke markedsrisiko, for gullaksjer. Med andre ord vil en investering i en gullaksje med høy eksponering mot gullprisen i snitt ha høyere avkastning enn en gullaksje med lav eksponering.

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1. Introduction

Gold was considered valuable long before the existence of commodity markets due to its appearance and inability to oxidise, giving it esthetical longevity. In recent years, the introduction of financial derivatives, such as options and futures, on commodities has made the market for gold far more heterogeneous. The demand for gold is no longer driven by jewellery consumption alone, but is also affected by speculation, as gold as an investment has displayed several beneficial properties. Studies have shown that gold not only offers diversification to a portfolio, but it also functions as a hedge against stocks (Jaffe, 1989), inflation (Ghosh et al., 2004) and the U.S. dollar (Capie et al., 2005), as well as being a safe haven in extreme market conditions (Baur and Lucey, 2010; Mulyadi and Anwar, 2012).

Gold mining stocks can be considered a leveraged alternative to gold. Purchasing gold bullions include a certain amount of transaction costs, which increases the incentive of alternatively investing in gold mining stocks. The intuition is that an investor can invest in a gold stock and be indirectly exposed to gold and its several favourable properties. Jaffe (1989) finds that by replacing gold with gold mining stocks, both the average return and standard deviation of a hypothetical portfolio increase. As the Sharpe ratios of the constructed portfolios increase, he suggests that adding gold stocks will be beneficial for his portfolios. The more volatile properties of gold stocks are supported by the findings of Blose and Shieh (1995), Faff and Chan (1998), Moss and Price (2012) and Chau (2012), all estimating gold betas significantly greater than unity, which indicates that gold stocks are riskier than gold itself.

This paper studies economic determinants of gold mining stocks. As the companies mainly produce and sell gold, which is fairly homogenous, there is little doubt that their performance and valuation is dependent on the gold price. Using a multifactor model, we investigate whether the gold price is the only risk factor driving the returns of gold mining stocks. By also applying quantile regression, we aspire to provide a more accurate pricing model. This approach enables us to study differences in dependencies between under- and overperforming gold mining stocks and different risk factors through time. To identify cross-sectional differences, we apply a Fama-MacBeth

(FMB) regression. This allows us to study whether the factors generate significant risk premiums.

The quantile regression method was introduced by Koenker and Basset (1978) as a supplement to least squares estimators. So far, the literature regarding risk modelling in the mining industry has been focused on analysis of the conditional mean. The intuition is that by regressing on different quantiles, it is possible to study tail dependency not captured by ordinary least squares (OLS) estimators. Fin et al. (2009) argue that conditional mean models are inefficient when the data is asymmetric in its distribution, as often is the case with stock returns. Their study of the Australian stock market, including several gold mining companies, find significant differences in the sensitivity towards the market factor at different quantiles. Several applications in quantile regression methods have been conducted on equities (see Tsai, 2012; Badshah, 2013; Mensi et al., 2014). However, our study is the first to apply quantile regression for the risk modelling of gold stocks.

Even though the quantile regression may expand on the time series effect of OLS, the resulting coefficient estimates may still be driven by the return of individual stocks over time. Since we are unable to explain the variation of returns across the gold mining companies, the multivariate model could be prone to spurious regression. According to Babyak (2004), models have been over-fitted for years because of the prevalence of multivariable regression models. If true causality exists between gold stocks and a risk factor, then the factor beta should be able to explain the cross-sectional differences between the gold stocks. We use the two-step cross-sectional approach of Fama-MacBeth (1973) as a robustness check for spurious correlations. In the first step, we estimate the factor betas from time series data. Secondly, we run cross-sectional regressions for each period with the estimated betas as independent variables. The coefficient-estimate from a factor exposure in the second step is interpreted as the factor risk premium. In other words, we can study whether stocks with high factor exposures have higher average returns than stocks with low factor exposures. Intuitively, if a factor beta significantly explains the stock return, an investor will require additional return to take on extra factor risk. Thus, it can be interpreted as the market price of beta risk.

The results of several studies on stocks show that the market factor is not priced. Fama and French (1992) find that the market beta is insufficient to explain the cross-sectional differences of stock returns when controlling for size and book-to-market equity. We follow their approach and include the gold price when examining the cross-section of gold mining stocks, with the intention of examining if gold risk is priced.

Our sample consists of 182 gold mining stocks from around the world, where the majority is based in Canada, Australia, and the U.S. We use monthly observations for the period January 2007 through December 2016. The stocks are allocated to a portfolio which is reweighted every month based on market capitalisation. The excess return of the portfolio is tested against five macroeconomic variables: the excessive market return, the gold price, the USD exchange rate, the 10-year treasury rate and the oil price, and two fundamental Fama and French variables: the small-minus-big (SMB) portfolio and the high-minus-low (HML) portfolio. The factors are chosen based on evidence from specific studies of the gold mining industry and, where we find it relevant, stocks in general.[1]

This paper produces several interesting results. First, the quantile regression reveals some differences in risk factor sensitivities across the quantiles, indicating OLS to be insufficient in the return modelling of gold mining stocks. This can be seen from the interest factor, as it shows lower betas at higher quantiles, exposing a possible upper tail dependency. However, for most of the risk factors, the quantile coefficients are not significantly different from the OLS estimate. Second, the gold beta estimates are higher than the market beta for all quantiles, showing that gold stocks are more sensitive to the gold price than the market return. Third, the paper provides an in-depth analysis of the differences between gold firms with big and small market capitalisation. Interestingly, we find that small gold mining companies exhibit weaker sensitivities towards the gold price, and stronger dependency with the market return, than large companies. Fourth, the differences between gold stocks are studied in the cross-sectional Fama-MacBeth regression. It reveals a significant positive premium to gold price risk, while finding no significant premium associated with market risk. This result is of practical relevance as it shows the market to price gold risk for gold mining

[1] Section 2 reviews previous studies on the chosen factors in our model.

companies. Hence, investors require higher returns for gold mining stocks with higher gold price exposure. Finally, we find that size and book-to-market equity help explain the cross-sectional returns of gold mining stocks.

The remainder of the paper is organised in the following sections: In section 2 we review some theoretical background and empirical results from previous studies on similar topics. Section 3 characterises and presents the data and descriptive statistics. Section 4 describes the empirical methodology used to attain our results. Section 5 contains the results, as well as our interpretation and discussion. Finally, section 6 contains our concluding remarks.

2. Literature review

This section is divided into two parts. In the first part, we review established theories of asset pricing models. In the second part, we review previous studies on each of our chosen risk factors.

2.1 Established theories of asset pricing

Through the work of Sharpe (1964), Lintner (1965), Mossin (1966) and Black (1972), the capital asset pricing model (CAPM) postulates that only the return of the market portfolio significantly influences the return of a stock. Thus, only considering the market beta as a determinant of equity cost. This assumption is frequently used in economic theory, though several studies indicate that the market portfolio is not sufficient to fully explain asset pricing in a risk factor model.[2]

Ross (1976) introduces the arbitrage pricing theory (APT) as an alternative to the CAPM. The theory suggests that the return of an asset or portfolio is related to unanticipated changes in different macroeconomic factors, making it less dependent upon the market portfolio. It also avoids the requirement that the market portfolio is mean variance efficient (Roll and Ross, 1980), though the APT does involve certain more prudent assumptions such as “no arbitrage”. Chen et al. (1986) apply the APT

[2] See for example Fama and French (1992, 1993), Jagannathan and Wang (1996) and Lewellen and Nagel (2006).

version of Roll and Ross (1980) to study how macroeconomic variables, such as the oil price, inflation, treasury rate and market return, influence stock returns. They find that the two proxies used for market return, portfolios of NYSE listed stocks, are the most significant variables included in their time-series regression. However, when applying the FMB regression, their estimated market exposures do not explain the cross-sectional variation in average stock returns.

According to Fama and French (1992), the CAPM fails to explain the cross-section of average stock returns. They point out that the CAPM assumes that expected stock returns are a linear function of the market betas. As such, the cross-section of stock returns is assumed to be described with these betas. In their paper, they study the explanatory power of the market return on the cross-section of stock returns. They use stock returns of nonfinancial firms from the NYSE, AMEX and NASDAQ as their dependent variable. As independent variables, they use different combinations of market beta, size, book-to-market equity, leverage and earnings-price ratios. To estimate the factor exposures, they use the cross-sectional regression introduced by Fama and MacBeth (1973), finding that size and book-to-market equity capture the effects associated with these five variables. In other words, when including size and book-to-market equity, they find that the market beta fails to explain the cross-sectional differences in stock returns. In their sequel paper, Fama and French (1993), the effects of firm size and book-to-market equity on bonds and stocks are studied using time-series regression. To estimate meaningful exposures for firm specific factors on bonds, they create mimicking portfolios for size and book-to-market equity. Together with the market return, these portfolio factors build the famous three-factor model. Their results show higher average return for small firms than large firms, as well as higher average returns for firms with high book-to-market equity (low stock price relative to book value) than low book-to-market equity. The positive effect of high book-to-market equity is studied and confirmed for markets around the world by Fama and French (1998).

2.2 The relationship between gold stocks and our selected risk factors

Market return

Several studies provide evidence of a relationship between gold mining stocks and the market return. Faff and Chan (1998) use a multifactor model for Australian gold stocks in five different periods from 1979 to 1992, estimating positive and significant market betas for all five. Moss and Price (2012) study North-American gold stocks in a five-factor model between 1998 and 2010. They also find that the market factor significantly explains the return of gold mining stocks. Similar results are reported from Chau (2012) when examining the effects of different risk factors on the NYSE Arca Gold BUGS index (HUI)[3] – and the Philadelphia Gold and Silver index (XAU)[4], estimating positive market betas for both indices. Barnes and Hughes (2002) study the conditional CAPM[5] at different points of the distribution in a cross-sectional analysis using quantile regression. They estimate a strongly significant beta on higher and lower quantiles, though finding weak dependencies around the mean of the distribution. Consequently, they argue that quantile regression sheds a light on previous inconclusive studies on the importance of the market beta in asset pricing.

Gold price

Previous studies examining the relationship between gold stocks and the gold price find a strong dependency between the two. Blose & Shieh (1995) study the gold price risk and valuation of 23 publicly traded North-American gold stocks in the period 1981 to 1990. They estimate a gold exposure greater than unity for 22 of the 23 examined companies. Similarly, Tufano (1998) studies the determinants of gold price exposure of 48 North-American gold mining firms and reports that the average gold beta is close to 2. Moss and Price (2012) estimate a gold beta at 1.39 for their North-American gold stock portfolio. For the Australian market, Faff and Chan (1998) estimate gold betas for their gold stock portfolio in the range of 0.52 to 1.54 for different time periods between 1979 and 1992. For indices, Chau (2012) estimates gold betas at 1.6 for the

[3] The HUI index is an equal- dollar weighted index of gold mining companies, consisting of 15 NYSE stocks.
[4] The XAU index is an equal- dollar weighted index of gold and silver mining companies, consisting of 30 NYSE stocks.
[5] The conditional CAPM differs from the traditional CAPM in that is allows for time varying betas and returns. For more detailed information, see Jagannathan and Wang (1996)

HUI index and 1.4 for the XAU index. The strong dependency between the return of gold stocks and the gold price motivates Gilmore et al. (2009) to study a possible cointegrating relationship, finding one such relationship between the Chicago Board Options Exchange Gold Index (GOX)[6] and the gold price. In addition, Moss and Price (2012) and Chau (2012) both find higher gold betas than market betas for gold stocks. This indicates that gold mining stocks are more sensitive to changes in the gold price than changes in the market returns.

Foreign exchange rate

Loudon (1993) and Khoo (1994) find a significant negative relationship between the return of Australian gold stocks and changes in the Australian dollar. They use multifactor models to study the impact of exchange rates when controlling for the market return in different time periods. Faff and Chan (1998) find no significant relationship between Australian dollars and the return on Australian gold mining stocks. They include the gold price as a factor, and argue that this could explain the different results from Loudon (1993) and Khoo (1994). Moss and Price (2012) report a significant negative relationship between North-American gold mining stocks and changes in the U.S Dollar. Chau (2012) finds that the U.S Trade Weighted Dollar Index significantly explains the HUI and XAU indices when lagged three months. Tsai (2012) studies the relationship between stock indices and foreign exchange rate for six Asian countries using quantile regression. She finds a negative dependency for very high or low exchange rates in all examined countries. In addition, Capie et al. (2005) test the sterling-dollar and yen-dollar exchange rates link to gold between 1971-2004. They find that gold is a hedge against the dollar, though somewhat varying and dependent on political events. Hence, a similar relationship could exist between gold mining stocks and the USD.

Interest rate

Stone (1974) studies interest rate risk and suggests that gold, bank and public utility stocks are equities susceptible to strong interest rate sensitivity. Martin and Keown (1977) test for interest rate sensitives in the equity sectors suggested by Stone (1974).

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[6] The GOX index is an equal- dollar weighted index of gold mining companies, consisting of 12 NYSE stocks.

They find a significant interest rate risk for the bank and utility sector, but are unable to implement the analysis on gold stocks due to lack of available data. Neither Faff and Chan (1998) nor Chau (2012) find a significant relationship between changes in the interest rate and the return on gold stocks. However, several studies support a significant relationship between changes in interest rate and stock returns (see Flannery and James, 1984; Elyasiani and Mansur, 1998; Nathan 2002). Jareño et al. (2016) use quantile regression to study the relationship between the US stock market and interest rates for the period 2003 to 2013. They find different sensitivities for the real and nominal interest rate over time, quantiles and sectors, with the highest dependencies in extreme market conditions.

Oil price

Arouri and Nguyen (2010) study oil price effects on different European industries. They find that several oil input industries have positive sensitivities to the oil price. To study the causality of oil price changes on stock returns, they test for Granger-causality, finding bidirectional causality for oil-input industries.[7] Elyasiani et al. (2011) use a GARCH (1,1) model to identify risk factors for thirteen U.S. industries, providing evidence of the metal industry having a positive relationship with the oil price. Moss and Price (2012) examine the oil price sensitivity of gold stocks. They estimate significant positive coefficients, proposing that a positive relationship exists due to commodity co-movements. Previous studies on the relationship between oil and gold prices show that the two commodity prices are co-integrated (see Zhang and Wei, 2010; Simakova, 2011). In addition, both Zhang and Wei (2010) and Bampinas and Panagiotidis (2015) find a one-way Granger causality, suggesting that oil is a driver for gold prices, but not vice versa. Mensi et al. (2014) examine different global macroeconomic factors of the BRICS[8]. They find that factors, such as the oil price (among others), exhibit different dependencies across the quantiles, though the results vary for each country.

SMB and HML

Faff (2004) applies the three-factor model of Fama and French (1993) to study the

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[7] El Hedi and Nguyen (2010) oil-input industries consists of; *food and beverages, automobile and parts,* and *industry*.
[8] BRICS countries consists of; Brazil, Russia, India, China and South Africa.

Australian equity market between 1996 and 1999. He divides the stocks into industry specific portfolios, testing each portfolio for the HML and SMB factors using generalised method of moments (GMM). He estimates significant positive coefficients for gold stocks, indicating both size and value premium to be evident for the gold mining industry. Allen et al. (2011) study 30 induvial stocks from the Dow Jones Industrial average index using the SMB and HML portfolio factors. They use quantile regression on their sample for the period 2002 to 2009 and find significant differences between stock returns and the factors, both through time and quantiles.

3. Data

Our data sample consists of 182 gold mining companies from around the world, of which the majority is based in Canada, Australia and the U.S.[9] We use monthly observations (start of month) in a ten-year time frame for the period 2007 through 2016, giving 20,531 return observations for the portfolio.[10] The time frame was chosen to facilitate the FMB regression, where we use the first five years to estimate coefficients for the latter five. The sample originally consisted of the 185 largest gold mining companies by market capitalisation[11], however we had to remove three[12] due to errors in the available data.[13] There could be a sample selection bias driving our results. First, even though all the selected companies have gold mining as their main focus, many are also involved in the mining of other precious metals. Second, the selection is based on current market capitalisation, thus excluding gold companies going bankrupt between 2007 and 2016, possibly giving our sample a survivorship bias. Survivorship bias may cause skewness in the results, as there could be a systematic relationship between the companies that did not go bankrupt. The consequence could be that our sample is not accurately representing the gold mining industry. As part of our sample period is in the wake of the financial crisis of 2007-08, companies that are highly exposed to the market

[9] Companies based in Canada, Australia and the U.S. constitute 55.45%, 16.07% and 12.8% of our sample respectively.

[10] As our portfolio is weighted, companies not listed at the start of the research period will not be counted in the portfolio until the first return observation after their initial public offering date.

[11] The market capitalisation is based on the information by miningfeeds.com. We collected the tickers from their website and generated a list of gold mining stocks, using Thomson Reuters Datasteam.

[12] Pretium Resources Inc.(PVG)(TSE), Osisko Mining Inc. (OSK)(TSE) and Talga Resources Ltd. (TLG)(ASX).

[13] A complete list of selected companies is available in Appendix A.

could have gone bankrupt. Thus, the surviving companies might have a lower market exposure. This would in turn make our estimated market beta biased.

For the FMB regression, we use ten years of monthly stock returns, a total amount of 120 observations for each company. Out of the 182 companies used in the time series sample, 61 were listed after the start of our sample period. Hence, we exclude them from the cross-sectional sample. Out of the remaining companies, eight have periods of negative book value. As we use the logarithm of book-market-equity as an independent variable in the FMB regression, negative book-to-market equities cannot be used. We exclude these eight firms, leaving us with a sample of 113 gold mining companies.

The stock data are collected from Thomson Reuters Datastream and are closing prices adjusted for dividends and splits, denominated in USD. The portfolio is constructed by weighting each company in accordance with their market capitalisation, also collected from Thomson Reuters Datastream. The weight of each share is calculated as:

$$W_{it} = \frac{MC_{it}}{MC_{st}} \tag{1}$$

where W_{it} is the weight of stock i at time t, MC_{it} is the market capitalisation for company i at time t, and MC_{st} is the total market capitalisation across for all companies at time t.

The logarithmic excessive monthly returns are calculated by subtracting the 1-month U.S. Treasury rate as a proxy for the risk-free rate for each stock price.[14] We then multiply the stock return with its corresponding weight:

$$ERP_t = \sum_{i=1}^{182} \left(ln\left(\frac{P_{it}}{P_{i(t-1)}}\right) - r_{ft}\right) W_{it} \tag{2}$$

where ERP_t is the excessive return of the portfolio at time t, P_{it} is the stock price for company i at time t, $P_{i(t-1)}$ is the stock price for company i at time $t-1$, r_{ft} is the 1-month U.S. Treasury rate at time t and W_{it} is the weight of stock i at time t.

[14] The rate is the yield for holding a 1-month daily traded treasury bill.

Five out of the seven independent variables are macroeconomic risk factors, all collected from Thompson Reuters Datastream. As a proxy for the market portfolio, we use Morgan Stanley Capital International All Country World Index (MSCI ACWI).[15] We choose this index because it contains emerging countries as well as developed ones, thus better representing the market our portfolio is exposed to, in comparison to for example the MSCI World Index. We compute the monthly logarithmic excessive return in the same manner as our portfolio with gold stocks:

$$ERM_t = ln\left(\frac{M_t}{M_{t-1}}\right) - r_{ft} \qquad (3)$$

where ERM_t is the excessive return of the market portfolio at time t, M_t is the market portfolio price at time t, and M_{t-1} is the market portfolio price at time $t\text{-}1$, and r_{ft} is the 1-month U.S. Treasury rate at time t.

The gold price variable is London Bullion Market gold bars measured in USD per troy ounce. We use the monthly log changes in the gold price and denote the variable as *GOLD*. As a proxy for foreign exchange risk, we use the Trade-Weighted U.S. Dollar Index, which is a weighted average of exchange values between the USD and several other major currencies.[16] The monthly log changes of the index are denoted as *FXR*. For the interest risk variable, we use the 10-year constant maturity treasury rate, where the monthly log changes are denoted as *I*.[17] For our last macroeconomic variable, the oil price, we use the West Texas Intermediate crude oil spot price, denominated in USD per barrel of oil. We use the monthly log changes in the oil price and denote the variable as *WTI*.

Our models also include two of the factors from the three-factor model introduced by Fama and French (1993): SMB and HML. SMB is the spread between the returns of firms with large and small market capitalisation. The variable measures the firm size

[15] The MSCI ACWI index consists of stocks from 23 developed markets and 23 emerging markets. See the MSCI ACWI website for information: https://www.msci.com/acwi
[16] This includes the EURO-area, Canada, U.K, and Australia, which all have gold mining companies included in our portfolio.
[17] The rate is the yield for holding a 10-year constant maturity treasury bill for one month.

effect on our portfolio, referred to as the "size premium". The idea is that, on average, small companies historically have produced higher returns than big companies. HML is the spread between firms with high- and low book-to-market (B/M) ratios. Companies with high B/M ratios are often referred to as "value stocks" while companies with low B/M ratios are referred to as "growth stocks". This factor measures the effect of the "value premium" on our portfolio. The intuition is that value stocks historically have outperformed growth stocks. Both fundamental factors are collected from Kenneth French's web page, and are monthly data.[18]

For the FMB regression, we calculate risk premiums in a cross-sectional analysis. Hence, we cannot use the SMB and HML factors as they are already denominated as premiums (Fama and French, 1993). Instead, we use the approach of Fama and French (1992), where the logarithm of both B/M equity and market capitalisation are used as independent variables. Individual market capitalisation data and B/M for the companies are collected using Thomson Reuters Eikon. The B/M ratios are calculated as the company´s book value per share, divided by closing price. Book value per share is calculated by dividing total equity from the latest fiscal period by current total shares outstanding.

3.1 Descriptive statistics

Table 1 displays the definitions of the variables used in our models. Table 2 lists the descriptive statistics for the variables. The average excessive return of our portfolio is -0.055% with a standard deviation at 11.327%. The high standard deviation combined with a large spread between the minimum and maximum observed values, indicate a high portfolio risk on a monthly basis. Jaffe (1989), Faff and Chan (1998) and Chau (2012) all find similar results on the risk measures for their gold stock portfolios, with gold stocks displaying higher volatility than gold. Jaffe (1989) studies gold stocks in the period 1971 to 1987, while Faff and Chan (1998) study the period between 1979 and 1992, with both of their portfolios displaying higher average returns than gold.

[18] For more information on the construction of the SMB and HML portfolios see Kenneth French's website:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

Table 1: Variable definitions

Variable	Definition
ERP	Log changes in excessive returns of the gold stock portfolio
ERM	Log changes in the excessive return of the market portfolio
GOLD	Log changes in the gold price (Gold bars)
FXR	Log changes in the USD-index (Trade-Weighted USD-Index)
I	Log changes in the risk-free rate (10-year Treasury Rate)
WTI	Log changes in the oil price (WTI crude oil)
SMB	Log changes in the Small-Minus-Big portfolio
HML	Log changes in the High-Minus-Low portfolio
Size	Logarithm of the market cap of the gold mining stocks (FMB)
BM	Logarithm of the book-to-market equity for gold mining stocks (FMB)

Note: The variables are collected from Thomson Reuters DataStream and modified in Excel.

The Size and BM variables are only used for the FMB regression.

Table 2: Descriptive statistics

	ERP	ERM	GOLD	FXR	I	WTI	SMB	HML
Mean (%)	-0.055	0.059	0.493	0.139	-0.543	-0.181	0.148	-0.071
St.Dev. (%)	11.327	5.502	5.663	2.270	9.964	10.324	2.405	2.756
Max. (%)	32.366	14.240	12.120	7.590	25.680	25.390	7.030	8.440
Min. (%)	-41.304	-21.720	-18.780	-7.100	-35.210	-43.290	-4.820	-11.250
Skewness	-0.126	-0.818	-0.360	0.164	-0.467	-0.848	0.239	0.034
Kurtosis	1.119	2.274	0.308	1.055	1.509	2.107	0.046	2.629
JB	5.861*	35.748*	2.823	5.156*	14.020*	33.439*	1.117	30.564*
ADF	-5.071*	-4.054*	-4.927*	-4.265*	-4.861*	-5.336*	-4.284*	-5.019*
N	120	120	120	120	120	120	120	120

Note: Descriptive statistics of the variables used in the model are from the period January 2006 to January 2016. JB is the Jarque-Bera test statistic and ADF is the test statistic from the Augmentet Dickey Fuller test.

* Indicates rejection of the null hypothesis at 1% level

** Indicates rejection of the null hypothesis at 5% level

*** Indicates rejection of the null hypothesis at 10% level

Oppositely, our sample shows that gold outperforms gold stocks, with both higher mean and lower standard deviation. This is similar to Chau (2012), who studies the HUI and XAU indices between 1996 and 2011. Gold mainly produced higher returns than our portfolio during the financial crisis (2007-2008), while performing similar in the post financial crisis (2009-2016) period.[19] The descriptive statistics for our sample period suggest that gold performs well under extreme market conditions, while gold stocks do not display the same properties.

We notice that gold produced nearly ten times higher monthly returns than the market portfolio during our sample period. When comparing the returns during and after the financial crisis, we find the market portfolio to outperform gold during the 2009-2016 period, while exhibiting much lower returns during the financial crisis (2007-2008).[20]

A positive mean for the FXR factor suggests that the USD appreciates during our research period, relative to other major currencies. A negative mean for changes in the interest rate shows that the research period is characterised by declining long-term interest rates. Our study covers a period of declining oil prices, indicated by a negative mean. In addition, the oil price factor exhibits a low minimum value (-43.29%) and relatively high standard deviation, due to the oil price shocks of 2008 and 2014. The SMB portfolio displays a positive average return, implying that small capitalisation companies outperform big capitalisation companies in our research period. Interestingly, the average return of the HML portfolio is slightly negative (-0.071%), showing growth stocks to outperform value stocks between 2007 and 2016. This contrasts with previous findings, where value stocks historically performed better than growth stocks.[21]

The Jarque-Bera test shows that all the variables, except GOLD and SMB, are non-normally distributed. All the variables, except FXR, SMB and HML, show negative skewness, implying thicker lower tails in their return distribution. This supports our motivation for quantile regression, as it is better suited in the case of non-normality

[19] When comparing our portfolio with gold during the financial crisis (2007-2008), we find average returns at-1.53% (excess return) for our portfolio and 0.75% for gold, while the post financial crisis (2009-2016) show our portfolio's average return to be 0.31% (excess return), while 0.43% for gold.
[20] The average excess return of the market portfolio is -2.58% during the financial crisis (2007-2008), and 0.72% in the post financial crisis period (2009-2016).
[21] See for example Fama and French (1998), who find value stocks to outperform growth stocks in twelve out of thirteen countries between 1975 and 1995.

than OLS. The Augmented Dickey-Fuller (ADF) test rejects the null-hypothesis of a unit root, thus concluding that all the variables are stationary on a 1% significance level. The test uses the same critical values as Dickey and Fuller (1979), and the lag length is chosen by Akaike information criterion.

3.2 Correlations

Table 3 shows the correlations between the variables in the model. The excessive return of the gold stock portfolio is stronger correlated with the return of gold (0.857) than it is with the return of the market portfolio (0.239). This is in accordance with most findings regarding the relationship between gold stocks and gold.[22] It is, however, interesting to see such strong correlations between the two when they exhibit different signs on their average returns. Intuitively, it seems that the negative return of our portfolio is driven by outliers, as indicated by the low minimum observation. This further motivates for the use of quantile regression, as it is more robust to outliers in the distribution than OLS.

Table 3: Correlation matrix between variables

	ERP	ERM	GOLD	FXR	I	WTI	SMB	HML	VIF
ERP	1.000								
ERM	0.239	1.000							2.309
GOLD	0.857	0.124	1.000						1.564
FXR	-0.465	-0.678	-0.469	1.000					2.973
I	-0.282	0.207	-0.251	-0.025	1.000				1.313
WTI	0.310	0.579	0.254	-0.598	0.327	1.000			2.048
SMB	0.109	0.073	-0.024	0.093	0.022	0.073	1.000		1.184
HML	-0.099	0.095	-0.162	0.050	0.147	0.158	0.341	1.000	1.213

Note: The table shows the Pearson correlation between the variables used in the models for the period January 2006 to December 2016.

[22] See for example Faff and Chan (1998), Moss and Price (2012) and Chau (2012).

The correlation between the changes in the foreign exchange rate index and the gold stock portfolio is moderately negative (-0.465). We find a weak negative correlation between the gold stock portfolio and changes in the interest rate (-0.282), while the correlation between the gold stock portfolio and changes in the oil price is positive (0.310). The correlation between our gold stock portfolio and the fundamental factors are generally very weak.

For the independent variables, various correlations exist. The changes in the oil price have moderate positive correlation with the changes in excess return of the market portfolio, and a moderate negative correlation with the changes in the USD-index. The rest of the variables exhibit weak correlations with each other, except for the changes in the USD index, which have a moderate negative correlation with the changes in the gold price, and a strong negative correlation with the changes in excessive return of the market portfolio. However, as all the variance inflation factor (VIF) values are below 3, we have little, if any, problems with multicollinearity in our data.[23]

3.3 In-depth gold beta analysis

We do an in-depth gold beta analysis similar to that of Tufano (1998). He finds high gold beta variation through both time and the cross-section of gold mining companies. Figure 1 shows different betas for different years, and specifically the average individual firm betas for 2011 and 2014. The top plot illustrates how the beta varies over the years, both for our portfolio and the average of individual stocks. From the bottom plots, it is clear that the cross-sectional variance is not constant over time. The yearly beta for the gold stock portfolio is lowest in 2011 and displays a lower cross-sectional variance than the individual firm betas for 2014, which has the highest estimated portfolio beta.

[23] The VIF values measures how much the variance of an estimated coefficient are inflated due to multicollinearity. As a rule of thumb, a VIF value above 5 implies high multicollinearity.

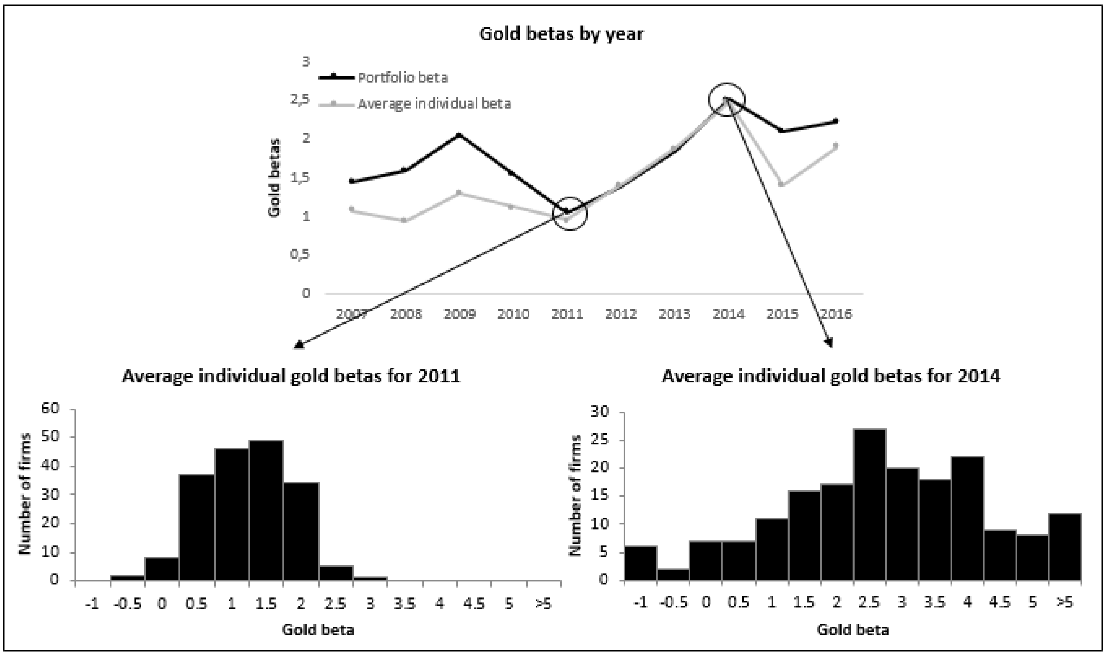

Figure 1: Graphical illustration of gold betas through time and across firms.

Note: The top figure illustrates the yearly beta for the portfolio, and the yearly average of the individual betas. The bottom figures illustrate the different firm betas for year 2011 and 2014.

This suggests that a time-series analysis does not adequately describe the cross-section of the betas. This paper analyses both the time series and cross-sectional variance by applying quantile and FMB regressions to supplement OLS.

4. Empirical methodology

In order to examine the risk profile of gold mining stocks, we apply OLS and quantile regression on a set of macroeconomic and fundamental factors. Then we use FMB regression on the market return and gold price to study whether those estimated factor exposures are priced, when controlling for size and book-to-market equity. As such, the methodology of this paper is divided into two parts.

4.1 OLS and quantile regression

First, we estimate a multifactor model using the OLS regression, giving the following multivariate linear model:

$$ERP_t = \alpha_1 + \beta_{11}ERM_t + \beta_{12}GOLD_t + \beta_{13}FXR_t + \beta_{14}I_t + \beta_{15}WTI_t + \beta_{16}SMB_t + \beta_{17}HML_t + \varepsilon_{1t} \quad (4)$$

where ERP_t is the excess return of the gold mining stock portfolio at time t, α_1 is the coefficient of the regressions constant for the model, and the seven risk factors sensitivities is given by β_{11}, β_{12}, ..., β_{17}. ERM_t is the excess return of the MSCI All Country World Index (ACWI) at time t, $GOLD_t$ is the log change in gold price at time t, FXR_t is the log change of the Trade-Weighted U.S. Dollar Index, I_t is the log change in the 10-year Constant Maturity Treasury Rate at time t, SMB_t is the spread between the returns of small- and big capitalisation firms at time t, and HML_t is the spread between firms with high- and low book to market ratios (B/M) at time t.

Then, we estimate a model using quantile regression. While OLS only considers the conditional mean of the dependent variable´s distribution, quantile regression allows us to study various quantiles of the same dependent variable. The quantiles are given as the q in superscript of each coefficient and the relevant quantiles will be 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95 in the following model:

$$ERP_t^{(q)} = \alpha_2^{(q)} + \beta_{21}^{(q)}ERM_t + \beta_{22}^{(q)}GOLD_t + \beta_{23}^{(q)}I_t + \beta_{24}^{(q)}FXR_t + \beta_{25}^{(q)}WTI_t + \beta_{26}^{(q)}SMB_t + \beta_{27}^{(q)}HML_t + +\varepsilon_{2t}^{(q)} \quad (5)$$

where $ERP_t^{(q)}$ is the excess return of the gold mining stock portfolio at time t for quantile q, $\alpha_2^{(q)}$ is the coefficient of the regressions constant at quantile q, and the seven risk factors sensitivities is given by $\beta_{21}^{(q)}$, $\beta_{22}^{(q)}$, ..., $\beta_{27}^{(q)}$ for quantile q. This method differs from OLS as least squares estimation minimises the squared sum of absolute errors, while the quantile regression approach minimises the weighted sum of absolute errors. The weighting is done by applying a weight in accordance with the quantile studied. To obtain robust standard errors, we employ the pairs-bootstrapping technique suggested by Buchinsky (1995). For more details on the quantile regression and the bootstrapping procedure, see Appendix E.

4.2 The FMB regressions

The second part of the methodology seeks to uncover whether the relevant factor exposures are priced. Both the OLS and the quantile regression, estimate coefficients representing correlations between the dependent- and independent variables. This can lead to models suffering from potential over-fitting, causing spurious correlation in the results, which in turn can make our interpretation misleading. Fama and MacBeth (1973) introduce a two-step procedure, which is commonly referred to as the Fama-MacBeth regression, to deal with the question of priced factors. In the first step, we use time series regression to estimate the factor exposures of the gold price and the excessive market return. In the second step, we run a cross-sectional regression on the estimated factor exposures from step one. Consequently, the independent variables in the second step are estimated with an error. This issue is addressed to as the errors in variables (EIV) problem. To control for this problem, we use 11 portfolios based on firm size and then assign the portfolio betas to each firm in their associated portfolios as suggested by Blume (1970).[24] The model for the first step estimation is given by:

$$ERP_{ti} = \alpha_i + \beta_{it} ERM_t + \beta_{it} GOLD_t + \varepsilon_{it} \qquad (6)$$

where ERP_{ti} is the excessive return of portfolio *i* at time *t*.

Our sample consists of 120 monthly returns for 113 firms. We use the first five years of monthly observations to estimate the betas for the 60th month, and then roll the estimation window one month ahead until we get a time series of 60 betas associated to each factor for each portfolio. In the second step, we run a cross-sectional regression for the excess return of each portfolio at time *t* against the estimated betas at the same points in time. Hence, we estimate the gamma-coefficients associated to each of the factor exposures from (6):

$$ER_i = \gamma_0 + \gamma_{ERM} \hat{\beta} ERM_i + \gamma_{GOLD} \hat{\beta} GOLD_i + \varepsilon_i \qquad (7)$$

[24] The same procedure for beta estimation has also been used by Chen et al (1986) and Fama and French (1992)

$$ER_i = \gamma_0 + \gamma_{ERM}\hat{\beta}ERM_i + \gamma_{GOLD}\hat{\beta}GOLD_i + \gamma_{ME}Size_i + \varepsilon_i \quad (8)$$

$$ER_i = \gamma_0 + \gamma_{ERM}\hat{\beta}ERM_i + \gamma_{GOLD}\hat{\beta}GOLD_i + \gamma_{Size}Size_i + \gamma_{BM}BM_i + \varepsilon_i \quad (9)$$

where *Size* is calculated as $\ln(ME)_t$,the logarithm of Market Equity (ME) of firm *i* at time *t* and *BM* is calculated as $\ln(\frac{BE}{ME})_{it}$,the logarithm of book-to-market equity of firm *i* at time *t*. ER_i is the excessive return of firm *i*. Equation (7) contains only the gold price and the excessive market return, as we are most interested in the relationship between the returns of gold stocks and these two factors. Equation (8) adds size, while (9) includes a value factor, BM to equation (8). The gamma-coefficients (γ) from these regressions show the risk premium for the risk factors included in the model, at each point in time. To test the hypothesis of whether the risk factor premium is significantly different from zero, we calculate the mean of the estimated gamma-coefficients and run a two-sided t-test on the results.

5. Empirical results and discussion

In this section, we first present the OLS and quantile regression results. Then we discuss the relationship between the returns of the gold stock portfolio and each of our factors, and look at differences between big and small gold mining companies. Finally, we present the results from the Fama-Macbeth regression.

Table 4 shows the regression results for our multifactor model, both at the mean and at different quantiles. The assumptions for using OLS hold, as the Breusch-Godfrey and Breusch-Pagan tests conclude that the models do not contain autocorrelation or heteroscedasticity.[25] Figure 2 illustrates the estimated coefficients for the factors from the quantile regression. The thick red lines show the OLS-estimates, and the stippled red lines are the corresponding 90%-confidence bands. The quantile regression estimates are illustrated by the stippled black line, and the shaded areas represent estimators within 90% confidence bands.

[25] For more information, see appendix C.

Table 4: Estimated coefficients from OLS and quantile regressions

Q	α	βERM	βGOLD	βFXR	βI	βWTI	βSMB	βHML	Pseudo R^2 / R^2
.05	-0.103* (-10.89)	0.250 (0.79)	1.850* (7.70)	0.875 (0.93)	-0.016 (-0.14)	0.150 (1.01)	0.101 (0.22)	0.216 (0.46)	0.606
.10	-0.073* (-9.0)	0.105 (0.39)	1.678* (8.55)	0.428 (0.53)	-0.067 (-0.66)	0.262** (2.08)	0.571 (1.23)	0.047 (0.10)	0.579
.25	-0.050* (-6.13)	0.167 (0.75)	1.363* (7.30)	0.128 (0.18)	-0.092 (-0.99)	0.210*** (1.81)	0.420 (1.13)	-0.489 (-1.19)	0.527
.50	-0.007 (-0.95)	0.333*** (1.71)	1.573* (11.86)	0.127 (0.23)	-0.147 (-1.53)	0.051 (0.45)	0.641*** (1.86)	-0.038 (-0.14)	0.511
.75	0.029* (4.23)	0.398** (2.30)	1.608* (9.25)	0.094 (0.19)	-0.265* (-2.77)	-0.014 (-0.16)	0.638*** (1.89)	0.173 (0.54)	0.541
.90	0.056* (6.20)	0.396*** (1.78)	1.520* (6.92)	0.071 (0.13)	-0.296** (-2.27)	0.098 (0.85)	0.366 (0.95)	0.191 (0.51)	0.587
.95	0.080* (7.74)	0.450 (1.61)	1.739* (6.96)	0.838 (1.23)	-0.166 (-1.22)	0.136 (0.97)	0.599 (1.32)	-0.17 (-0.39)	0.602
OLS	**-0.011** (-2.07)**	**0.294** (2.13)**	**1.609* (14.58)**	**0.253 (0.67)**	**-0.157* (-2.74)**	**0.102 (1.47)**	**0.545*** (2.41)**	**-0.076 (-0.38)**	**0.782**

Note: The table presents the coefficient-estimates from the OLS and quantile regression from equation (4) and (5). The first column explains which quantile the corresponding regression is run for. Test statistics in parenthesis. For the quantile regression, the t-statistics are obtained using the pairs-bootstrapping technique, with 1000 replications. We use pseudo- R^2, as suggested by Koenker and Machado (1999), to find the explanatory powers for model at different quantiles.

* Denotes statistical significance at 1% level.

** Denotes statistical significance at 5% level.

*** Denotes statistical significance at 10% level.

The OLS regression yields a R^2 at 0.782, showing that our model explains a significant amount of the variance of the excess return of the gold stock portfolio.[26] The high explanatory power of the model is mainly attributed to the strong dependency between the gold stocks and gold. In unreported results, we find that the explanatory power of the model falls to 0.368 when running the same regression without gold as an independent variable.

[26] Faff and Chan (1998) explain 70.1% of the variance of their gold stock portfolio between 1979-1992. Moss and Price (2012) explain 55.7% their portfolio variance, while Chau (2012) explains 56.6% of the variance of the HUI index, and 58.7% of the variance of the XAU index.

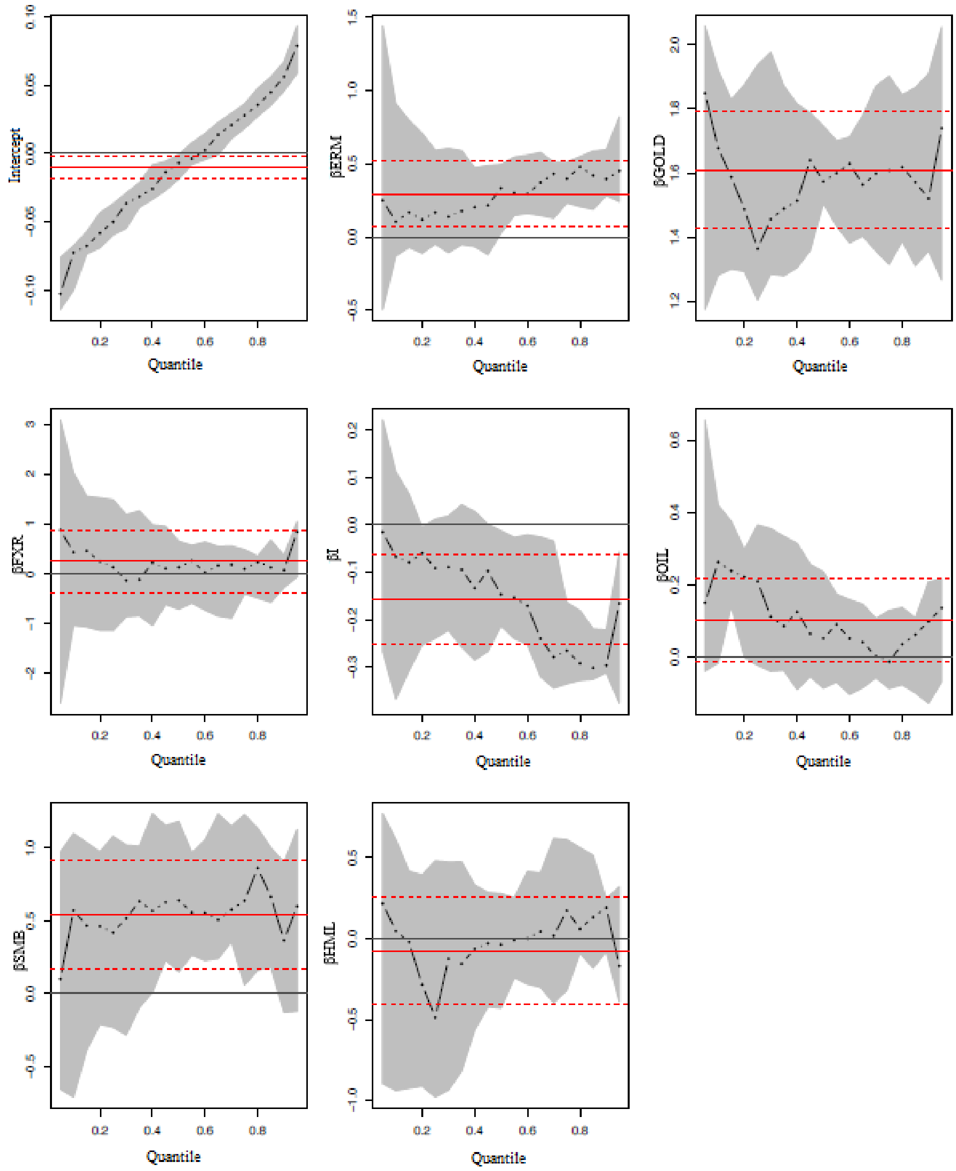

Figure 2: Graphical illustration of the OLS and quantile regression coefficients for the gold stock portfolio

Note: The solid red line shows beta coefficients for the OLS regression, and the stippled red lines are the corresponding 90%-confidence band. The stippled black line shows the beta coefficients from the quantile regression. The shaded area is the corresponding 90% confidence interval. The figure presents the estimates for the intercept, market return, change in gold price, the change in the USD, the change in the interest rate and oil price, as well as the SMB and HML portfolios.

From the OLS regression we see that the gold price and interest rate variables are significant at the 1%-level, while the market and SMB portfolio are significant on 5% and 10% levels, respectively. However, only the gold price factor is significant across the entire conditional distribution, as shown by the quantile regression.

5.1 The dependency between gold stocks and the market return

The OLS regression estimates a market beta at 0.294, indicating a positive relationship between the market return and our gold stock portfolio. In unreported results, we regress the gold price on the other macroeconomic factors, estimating a negative coefficient for the market. This shows that the gold price and gold stocks react opposite to changes in the market return, suggesting that gold stocks do not possess the same market hedging properties as gold in our sample period. However, a positive beta estimate is in accordance with Faff and Chan (1998), Moss and Price (2012) and Chau (2012), all reporting similar estimates when testing how the market affects gold stocks. The quantile regression reveals a slight increasing trend in the market betas across the quantiles, indicating the impact of the global economy to be higher in bullish gold stock markets. However, we cannot conclude that the coefficients at the different quantiles are significantly different from the OLS estimate when looking at the confidence intervals.

5.2 The dependency between gold stocks and the gold price

The OLS regression estimates a gold beta at 1.642, showing that our gold stock portfolio is more sensitive to fluctuations in the gold price than fluctuations in the market. This is contrary to Faff and Chan (1998), who estimate higher market betas than gold betas in five out of six sub periods in the Australian market. However, both Moss and Price (2012) and Chau (2012) estimate higher gold betas than market betas. A high gold beta was expected, as previous studies find the gold beta to often range in the interval between 1.5 and 2. In unreported results, we find that the gold price alone explains 73,4% of the variance of gold stock returns. The high estimated beta and explanatory power of the gold price suggest that it is the main driver for the returns of gold stocks. In addition, the quantile regression shows that gold is the only coefficient significant over the entire distribution. The coefficient estimates display a “u-shaped” form, with the highest exposures at both end quantiles. This could indicate tail dependency. However, the confidence intervals show that we cannot draw the conclusion that the gold price exhibits different betas throughout the distribution.

5.3 The dependency between gold stocks and the remaining macroeconomic factors

The USD exchange rate index does not provide any significant explanatory power to our model. The OLS regression estimates a beta of 0.253 which is contrary to previous findings. Loudon (1993), Khoo (1994), Moss and Price (2012), and Chau (2012) all estimate negative beta values for their foreign exchange rate factor when examining gold stocks. Capie et al. (2005) find gold to be a hedge against the dollar, implying that an inverse relationship between gold mining stocks and the dollar could exist. A positive estimated beta implies that an appreciation of the USD will have a positive effect on the return of gold stocks. Even though the estimated beta is insignificant, it seems gold stocks would not have been a good exchange rate hedge in our sample period. These results are surprising considering previous findings and the negative correlations (-0.465) between the exchange rate and the gold stocks. Interestingly, we observe high beta estimates at the 0.05 and 0.95 quantiles. This could indicate a stronger impact of changes in the USD on the gold stock portfolio in extreme gold market conditions. The results are, however, not significant.

Interest rate risk, measured by 10-year U.S. Treasury rate, has a negative effect on the gold stock portfolio (-0.157). Both Faff and Chan (1998) and Chau (2012) estimate negative beta coefficients when examining interest rate risk on gold stocks, but their estimates are insignificant. This paper is the first to our knowledge to find a significant relationship between interest rates and gold stocks. A negative estimated beta shows that our gold stock portfolio reacts negatively to increasing interest rates in our sample period. When examining the entire distribution, we observe that the interest rate factor is significant only at the 0.75 and 0.90 quantile, additionally showing an increasing negative beta coefficient. An upper tail dependency seems to be the case, indicating a stronger negative dependency in bullish gold stock markets. This is similar to Jareño (2016), who finds a stronger impact of interest rate on stocks in extreme market conditions.

The oil factor is insignificant in the OLS regression with a positive estimated coefficient at 0.102. As oil is a major input in the production of gold, a negative relationship between oil prices and gold stock seems logical. However, both Elysiani et al. (2011) and Moss and Price (2012) find a positive oil coefficient when examining its effect on metal stocks. Similarly, Arouri and Nguyen (2010) find that oil input industries have positive sensitivities to the oil price, arguing higher production and transportation costs is offset by periods of high economic growth when the oil price is increasing. When looking at the entire conditional distribution we observe slightly higher dependency in the lower tail of the distribution, with significant estimates at the 0.10 and 0.25 quantile.

5.4 The dependency between gold stocks and the fundamental factors

When regressed at the mean, the SMB factor is significant at a 10% level with an estimated beta at 0.545. A positive beta implies that a size premium exists for our gold stock portfolio. Intuitively, this means that small gold mining companies outperformed big gold mining companies, regarding returns, during our sample period. Faff (2004) reports similar results as he finds that the gold mining industry is more exposed to the SMB factor than other Australian industries. When looking at the entire distribution, we see only slight fluctuations around the OLS estimate. In other words, there are small differences between the sensitivities to the SMB portfolio across the quantiles.

For the HML-factor we have insignificant coefficient estimates both for the mean and the different quantiles, as the factor adds little explanatory power to our model. The data suggests that there is no value premium for our gold stock portfolio. This is contrary to the findings of Faff (2004), as he estimates a positive value premium for his examined portfolios.

Symptomatic for the quantile regression is that even though we see certain differences across the quantiles, we have too few observations in the tails of the distribution of gold stock returns. Consequently, the model suffers from low t-statistics for the coefficients, giving low p-values and high confidence intervals. Thus, we are often unable to conclude that the factors are significantly different from OLS over the quantiles.

5.5 Analysis of the differences between big and small market cap gold stocks

In this section, we present an analysis and comparison of different gold stock portfolios sorted by size. When weighting the stocks in the original portfolio, the 20 biggest gold mining companies constitute, on average, 82% of the total market capitalisation, consequently being responsible for the majority of the results in the previous section. To study the differences between the stocks, we divide the original portfolio into three sub-portfolios, called *Big*, *Med* and *Small*.[27] Table 5 shows the estimates from a standard OLS regression for the three sub-portfolios.[28] Table 6 displays the descriptive statistics for the sub-portfolios.

Table 5: Estimated OLS coefficients for the Big, Med and Small portfolios

ERP	α	βERM	βGOLD	βFXR	βI	βWTI	βSMB	βHML	R^2
Big	-0.011**	0.370*	1.631*	0.471	-0.159*	0.118***	0.342	-0.083	0.782
	(-2.124)	(2.682)	(14.780)	(1.240)	(-2.768)	(1.698)	(1.512)	(-0.417)	
Med	-0.014**	0.734*	1.552*	1.229*	0.096	0.157***	0.090	-0.194	0.673
	(-2.301)	(4.402)	(11.637)	(2.678)	(1.375)	(1.880)	(0.330)	(-0.806)	
Small	-0.021*	0.631*	1.171*	0.570	0.107	0.081	0.185	-0.181	0.618
	(-3.669)	(4.128)	(9.580)	(1.355)	(1.686)	(1.057)	(0.737)	(-0.819)	

Note: The table presents the estimates from the OLS regression for the three size portfolios, *Big*, *Med* and *Small*. The t-statistic for the coefficients are denoted in the parenthesis.

* Denotes statistical significance at 1% level.

** Denotes statistical significance at 5% level.

*** Denotes statistical significance at 10% level.

Table 6: Descriptive statistics for the Big, Med, Small portfolios

ERP	Mean (%)	St.Dev (%)	Max (%)	Min (%)	Sharpe Ratio (%)
Big	-0.129	9.893	29.266	-37.946	-1.303
Med	0.278	13.490	36.405	-38.958	2.060
Small	0.238	10.695	41.167	-36.388	2.230

Note: The table presents the descriptive statistics for the three size portfolios *Big, Med and Small.* Numbers in percentage.

[27] The *Big* portfolio includes the gold mining companies with a market cap over USD1600m.
The *Med* portfolio includes the gold mining companies with a market cap between USD20m and USD1600m.
The *Small* portfolio includes the gold mining companies with a market cap under USD20m.

[28] For the quantile regression estimates, see Appendix F.

We observe similarities between the *Big* portfolio and our original portfolio, both in coefficient estimates and its descriptive statistics. Interestingly, we find higher market beta estimates for the *Med* (0.370) and *Small* (0.734) portfolio, than for the *Big* portfolio (0.631). All significant at the 1% -level. The results indicate that small gold mining companies are more sensitive to changes in the market return than big gold mining companies. When looking at the gold beta estimate, we find an opposite trend. The small companies have lower estimated gold betas than the big companies. These findings are similar to those of Tufano (1998), who finds that large gold mining firms are more sensitive to changes in the gold price. He proposes that a possible explanation could be a faster incorporation of gold shocks into the returns of big companies. When examining the stock details of our portfolios, we find huge differences in trading volumes for the big and small companies[29], where many of the small companies aren't even traded on a weekly basis. Consequently, the effects from a change in the gold price could have a lower impact on small gold mining stocks, as they are not continuously traded.

Even though the gold price increased in the sample period, it seems that the small gold mining companies outperformed the big companies (with higher gold price exposures). This is indicated by a higher mean return for the *Med* and *Small* portfolios, as reported in table 6. The Sharpe ratio is lowest for the *Big* portfolio, and highest for the *Small* portfolio. This is accordance with the significant size premium on the full sample portfolio, which also suggests that smaller companies performed better than big companies during our research period.

5.6 Fama-MacBeth regression results

Table 7 shows the results from the two-step Fama-MacBeth regression. The test studies the hypothesis of whether the independent factor exposures have non-zero risk premiums.

[29] For example, the biggest company in the *Big* portfolio, Barrick Gold Corporation, had trading volumes at 394 366 500 in December 2016. While the biggest company in the *Small* portfolio, Antioquia Gold Inc., had trading volumes at 455 900 the same month.

Table 7: Fama-MacBeth regression estimates

	Fama-MacBeth regressions				
	γ_0	γ_{ERM}	γ_{GOLD}	γ_{Size}	γ_{BM}
Model (7)	-0.0357***	0.0137	0.0145***		
	(-1.86)	(0.94)	(1.76)		
Model (8)	0.006	-0.0314	0.0259**	-0.0071*	
	(0.23)	(-1.58)	(2.57)	(-3.48)	
Model (9)	0.0187	-0.0265	0.01995**	-0.0095*	-0.0308*
	(0.71)	(-1.30)	(2.00)	(-4.80)	(-8.25)

Note: The table presents the estimated gamma-coefficients from the FMB regression for model 7,8 and 9. Each gamma represent the risk premium of its associated factor, calculated as the time series average of the month-by-month regressions divided by its time-series standard error. The t-statistic of the risk premium is given in parentheses beneath the coefficient. *, ** and *** denotes statistical significance at 1%, 5% and 10% level, respectively.

The estimated market risk premium is insignificant in all three models, suggesting that the market return is not a priced factor for gold mining stocks. Though we did find the market return to have a significant explanatory power on our dependent variable in the time-series regressions, both at the mean and at different quantiles of the return distribution, the market exposures of gold mining stocks do not seem to help explain the cross-sectional differences in average returns. These results contradict the theory of the well-known capital asset pricing model, while supporting the studies of Fama and French (1992, 1993).

The premium for gold price risk is significantly positive at 10% in model 7, and at 5% in model 8 and 9. This indicates that the gold price is a priced factor for gold mining stocks through our sample period, even when including company size and book-to-market equity to the regression. The premium of gold price risk is therefore robust for gold mining stocks during the sample period. The interpretation of the positive gamma-coefficient for gold price, is that firms with a higher exposure to changes in the gold price have, on average, higher returns than those with lower exposure. Hence, investors require higher returns for such high gold beta stocks.

Model 8 shows a significant negative premium to size in the cross-section of gold stock returns. This is in accordance with the results of Fama and French (1992). The results suggest that small gold mining companies have, on average, higher returns than big gold mining companies, confirming our findings from section *5.5*. When controlling for size, the estimated gold premium and the corresponding t-statistic increase. This suggests that even though big gold mining companies on average have higher betas, their lower average returns could be attributed to the size effect.

When we include book-to-market equity to the regression, the results reveal a significant negative value premium on a 1% level. It also strengthens the test statistics of size (from -3.48 to -4.8), while weakening the test statistics on the premium for gold risk (from 2.57 to 2.0). The interesting part, when compared with previous studies, is that the book-to-market equity premium is negative. The interpretation of a negative book-to-market equity exposure is that growth stocks have, on average, higher returns than value stocks in the gold mining industry. Fama and French (1992) find the opposite relationship between the returns of nonfinancial firms and book-to-market equity in the 1963-1990 returns on NYSE, NASDAQ and AMEX stocks. Our results could imply that the relationship between returns and the book-to-market equity of gold mining stocks have a different relationship than that of general stocks. However, as we also find that the HML portfolio factor has a negative mean average[30], it seems that the results are unique for our sample period rather than our sample of stock data.

6. Conclusion

This paper studies the risk profile of gold mining stocks, with the gold price exposure as the main focus. Specifically, we use the quantile regression methodology to examine the dependency between different risk factors and gold stock returns over the entire conditional return distribution. The Fama-MacBeth regression is applied to study the cross-section of gold mining stocks. This enables us to check if the market is pricing gold price risk for the gold mining industry. We fill a gap in existing literature, as previous studies on the determinants of gold stock returns have examined the time series effect of different risk factors, using ordinary least squares.

[30] See table 2: Descriptive statistics.

In this study, we find that gold stocks do not possess all the same properties as gold. In the OLS regression, we estimate positive betas for the market return and foreign exchange rate, indicating that gold stocks do not function as a hedge against the two. In addition, our portfolio performed badly during the financial crisis, while gold itself produced positive returns.

This paper finds that the gold price is the main driver for gold stock returns. When regressing at the mean, we find that the market return, gold price, interest rate and SMB significantly explain the return of gold stocks. However, it is the gold price factor which constitutes most of the explanatory power of the model. As the gold mining companies mainly produce and sell gold, the high dependency between their returns and gold prices is not surprising. Yet, it is interesting to see that the gold price has such strong impact, in comparison to the market, on the returns of gold stocks. This is further confirmed by the quantile regression. We find that the gold price is the only risk factor that significantly explains the return of gold stocks over the entire return distribution, having higher estimated betas than the market at all quantiles. While a strong gold beta sensitivity seems to be the case for gold stocks, we find it to vary both through time and companies. Moreover, when we divide the gold stocks into portfolios based on size, we find differences between big and small gold mining companies both in average returns and their sensitivities towards changes in the market return and the gold price. This indicates that there are cross-sectional differences between the gold mining companies.

Interestingly, when studying the cross-section using the FMB regression, we find that there is a premium associated with gold price risk. In other words, gold mining companies with high gold betas have higher average returns than companies with low gold betas. The same analysis reveals that both company size and book-to-market equity explain the cross-section of gold stock returns. However, the FMB regression reveals no significant market premium for gold stocks, suggesting that the market factor does not explain the cross-section of gold stock returns. These findings indicate that the market prices gold risk, but not market risk.

Our findings have implications for investors who want to invest in gold mining stocks. We provide insight to which factors affect the returns of gold mining stocks, both generally and when considering the state of the industry. Most importantly, we show that there is a premium associated with gold price risk, company size and book-to-market equity. However, there seems to be no such premium for market risk. This insight can be useful for portfolio managers and investors in asset allocation and portfolio optimisation.

There are some possible extensions of this study. First, the quantile regression reveals certain fluctuations over the return distribution. However, the general findings from the quantile regression are that few of the risk factors exhibit estimates which are significantly different from the OLS. A reason is that, with monthly data and a period of ten years, we get few observations at the end quantiles, yielding weaker t-statistics. Consequently, a natural extension of the research is to study the return distribution of gold stocks using weekly or daily data, and a longer sample period. Additionally, it could be interesting to study the cross-section of stock returns in different sub-periods. The beta estimations for our FMB regressions include the financial crisis, a period where the market was in an extreme condition. As such, there could be diverging results for different sub-periods.

List of references

Allen, D. E. and S. R. Powell (2011). Asset Pricing, the Fama—French Factor Model and the Implications of Quantile-Regression Analysis. Financial Econometrics Modeling: Market Microstructure, Factor Models and Financial Risk Measures, Springer**:** 176-193.

Arouri, M. E. H. and D. K. Nguyen (2010). "Oil prices, stock markets and portfolio investment: evidence from sector analysis in Europe over the last decade." Energy Policy **38**(8): 4528-4539.

Babyak, M. A. (2004). "What you see may not be what you get: a brief, nontechnical introduction to overfitting in regression-type models." Psychosomatic medicine **66**(3): 411-421.

Badshah, I. U. (2013). "Quantile regression analysis of the asymmetric return-volatility relation." Journal of Futures Markets **33**(3): 235-265.

Bampinas, G. and T. Panagiotidis (2015). "On the relationship between oil and gold before and after financial crisis: linear, nonlinear and time-varying causality testing." Studies in Nonlinear Dynamics & Econometrics **19**(5): 657-668.

Barnes, M. L. and A. T. W. Hughes (2002). "A quantile regression analysis of the cross section of stock market returns."

Baur, D. G. and B. M. Lucey (2010). "Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold." Financial Review **45**(2): 217-229.

Black, F. (1972). "Capital market equilibrium with restricted borrowing." The Journal of Business **45**(3): 444-455.

Blose, L. E. and J. C. P. Shieh (1995). "The impact of gold price on the value of gold mining stock." Review of Financial Economics **4**(2): 125-139.

Blume, M. E. (1970). "Portfolio theory: a step toward its practical application." The Journal of Business **43**(2): 152-173.

Buchinsky, M. (1995). "Estimating the asymptotic covariance matrix for quantile regression models a Monte Carlo study." Journal of econometrics **68**(2): 303-338.

Capie, F., et al. (2005). "Gold as a hedge against the dollar." Journal of International Financial Markets, Institutions and Money **15**(4): 343-352.

Chau, M. (2012). "Macroeconomic Determinants of Gold Industry Stock Returns."

Chen, N. F., Roll, R. & Ross, S.A. (1986). "Economic forces and the stock market." Journal of business **59**(3): 383-403.

Dickey, D. A. and W. A. Fuller (1979). "Distribution of the estimators for autoregressive time series with a unit root." Journal of the American statistical association **74**(366a): 427-431.

Elyasiani, E. and I. Mansur (1998). "Sensitivity of the bank stock returns distribution to changes in the level and volatility of interest rate: A GARCH-M model." Journal of Banking & Finance **22**(5): 535-563.

Elyasiani, E., et al. (2011). "Oil price shocks and industry stock returns." Energy Economics **33**(5): 966-974.

Faff, R. (2004). "A simple test of the Fama and French model using daily data: Australian evidence." Applied Financial Economics **14**(2): 83-92.

Faff, R. C., H. (1998). "A multifactor model of gold industry stock returns: evidence from the Australian equity market." Applied Financial Economics **8**(1): 21-28.

Fama, E. F. and K. R. French (1992). "The cross-section of expected stock returns." The Journal of Finance **47**(2): 427-465.

Fama, E. F. and K. R. French (1998). "Value versus growth: The international evidence." The Journal of Finance **53**(6): 1975-1999.

Fama, E. F. and J. D. MacBeth (1973). "Risk, return, and equilibrium: Empirical tests." Journal of political economy **81**(3): 607-636.

Fama, E. F. F., K.R. (1993). "Common risk factors in the returns on stocks and bonds." Journal of financial economics **33**(1): 3-56.

Fin, D. E. A. F., et al. (2009). "Quantile regression: its application in investment analysis." Jassa(4): 7.

Flannery, M. J. and C. M. James (1984). "The effect of interest rate changes on the common stock returns of financial institutions." The Journal of Finance **39**(4): 1141-1153.

Ghosh, D., et al. (2004). "Gold as an inflation hedge?" Studies in Economics and Finance **22**(1): 1-25.

Gilmore, C. G., McManus, G.M, Sharma, R & Tezel, A (2009). "The Dynamics of Gold Prices, Gold Mining Stock Prices and Stock Market Prices Comovements." Research in Applied Economics **1**(1): 1-19.

Jaffe, J. F. (1989). "Gold and gold stocks as investments for institutional portfolios." Financial Analysts Journal: 53-59.

Jagannathan, R. and Z. Wang (1996). "The conditional CAPM and the cross-section of expected returns." The Journal of Finance **51**(1): 3-53.

Jareño, F., et al. (2016). "US stock market sensitivity to interest and inflation rates: a quantile regression approach." Applied Economics **48**(26): 2469-2481.

Khoo, A. (1994). "Estimation of foreign exchange exposure: an application to mining companies in Australia." Journal of International Money and Finance **13**(3): 342-363.

Koenker, R. and G. Bassett Jr (1978). "Regression quantiles." Econometrica: journal of the Econometric Society: 33-50.

Koenker, R. and J. A. F. Machado (1999). "Goodness of fit and related inference processes for quantile regression." Journal of the American statistical association **94**(448): 1296-1310.

Lewellen, J. and S. Nagel (2006). "The conditional CAPM does not explain asset-pricing anomalies." Journal of financial economics **82**(2): 289-314.

Lintner, J. (1965). "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets." The review of economics and statistics: 13-37.

Loudon, G. (1993). "The Foreign Exchange Operating Exposure of Australian Stocks." Accounting and Finance Association of Australia and New Zealand **33**(1): 19-32.

Martin, J. D. K., A.J. (1977). "Interest Rate Sensitivity and Portfolio Risk." Journal of Financial and Quantitative Analysis **12**(2): 181-195.

Mensi, W., et al. (2014). "Do global factors impact BRICS stock markets? A quantile regression approach." Emerging Markets Review **19**: 1-17.

Moss, J. D. and D. I. Price (2012). "VARIABLES EXPLAINING THE PRICE OF GOLD MINING STOCKS." Southwestern Economic Review **39**: 81-88.

Mossin, J. (1966). "Equilibrium in a capital asset market." Econometrica: journal of the Econometric Society: 768-783.

Mulyadi, M. S., et al. (2012). "Gold versus stock investment: An econometric analysis." International Journal of Development and Sustainability **1**(1): 1-7.

Nathan, L. J. (2002). "Modelling the impacts of interest rate and exchange rate changes on UK stock returns." Journal of Derivatives & Hedge Funds **7**(4): 306.

Roll, R. and S. A. Ross (1980). "An empirical investigation of the arbitrage pricing theory." The Journal of Finance **35**(5): 1073-1103.

Ross, S. A. (1976). "The arbitrage theory of capital asset pricing." Journal of economic theory **13**(3): 341-360.

Sharpe, W. F. (1964). "Capital asset prices: A theory of market equilibrium under conditions of risk." The Journal of Finance **19**(3): 425-442.

Šimáková, J. (2011). "Analysis of the relationship between oil and gold prices." Journal of Finance **51**(1): 651-662.

Stone, B. K. (1974). "Systematic Interest-Rate Risk in a Two-Index Model of Returns." Journal of Financial and Quantitative Analysis **9**(5): 709-721.

Tsai, I. C. (2012). "The relationship between stock price index and exchange rate in Asian markets: A quantile regression approach." Journal of International Financial Markets, Institutions and Money **22**(3): 609-621.

Tufano, P. (1998). "The determinants of stock price exposure: Financial engineering and the gold mining industry." The Journal of Finance **53**(3): 1015-1052.

Zhang, Y. J. W., Y.M. (2010). "The crude oil market and the gold market: Evidence for cointegration, causality and price discovery." Resources Policy **35**(3): 168-177.

Appendix

A. Companies included in the data sample

Company names		**Ticker**
Barrick Gold		ABX
Newmont Mining		NEM
Goldcorp		GG
Newcrest Mining		NCM.AX
Anglogold Ashanti		ANGJ.J
Franco-Nevada		FNV.TO
Fresnillo		FRES.L
Agnico-Eagle Mining		AEM
Randgold Resources		RRS.L
Kinross Gold (Nys)		KGC
Royal Gold		RGLD.O
Yamana Gold		YRI.TO
B2gold		BTO.TO
Gold Fields		GFIJ.J
Eldorado Gold		ELD.TO
Detour Gold		DGC.TO
Evolution Mining		EVN.AX
Endeavour Mining		EDV.TO
Centamin		CEY.L
Alamos Gold		AGI.TO
Iamgold		IMG.TO
		PVG.TO
Oceanagold		OGC.TO
Torex Gold Resources		TXG.TO
Novagold Resources		NG.TO
Centerra Gold		CG.TO
New Gold		NGD.TO
Regis Resources		RRL.AX
Mcewen Mining		MUX
Semafo		SMF.TO
Harmony Gold		HMY
St Barbara		SBM.AX
Guyana Goldfields		GUY.TO
China Gold Intl.Res		CGG.TO
Nevsun Resources		NSU.TO
Resolute Mining		RSG.AX
Saracen Mineral Hdg.		SAR.AX
Alacer Gold		ASR.TO
Richmont Mines		RIC.TO
Seabridge Gold		SEA.TO

Continental Gold		CNL.TO
Premier Gold Mines		PG.TO
Roxgold		OSK.TO
Belo Sun Mining		ROXG.TO
Gold Road Resources		BSX.TO
Gold Resource		GOR.AX
Argonaut Gold		GORO.K
Golden Star Res. (Ase)		AR.TO
Pan African Resources		GSS
Beadell Resources		PAFR.L
Silver Lake Resources		BDR.AX
Petropavlovsk		SLR.AX
Wesdome Gold Mines		POG.L
Teranga Gold		WDO.TO
Dalradian Resources		TGZ.TO
Tribune Resources		DNA.TO
Sabina Gold & Silver		TBR.AX
Victoria Gold		SBB.TO
Ramelius Resources		VIT.V
Perseus Mining		RMS.AX
Ngex Resources		PRU.AX
Lydian International		NGQ.TO
Ascot Resources		LYD.TO
Alkane Resources		AOT.V
Primero Mining		ALK.AX
Jaguar Mining		P.TO
Gabriel Resources		JAG.TO
Avocet Mining		GBU.TO
Timmins Gold		AVM.L
Midas Gold		TMM.TO
Gascoyne Resources		MAX.TO
Barkerville Gold Mines		GCY.AX
Vista Gold		BGM.V
Hummingbird Resources		VGZ.TO
Doray Minerals		HUMR.L
Harte Gold		DRM.AX
Greenland Minerals.& Energy		HRT.TO
Exeter Resource		GGG.AX
West African Resources		XRC.TO
Rye Patch Gold		WAF.AX
Probe Metals		RPM.V
Marathon Gold		PRB.V
Golden Queen Mining		MOZ.TO
International Tower Hill Mines		GQM.TO
Rupert Resources		ITH.TO
Majestic Gold		RUP.V

Goldquest Mining		MJS.V
Caledonia Mining Corp.		GQC.V
Dynacor Gold Mines		CAL.TO
Eastmain Resources		DNG.TO
Tanzanian Royalty Exploration		ER.TO
Terrax Minerals		TNX.TO
Lion One Metals		TXR.V
Medusa Mining		LIO.V
Focus Minerals		MML.AX
Trans Siberian Gold		FML.AX
Pilot Gold		TSG.L
Tanami Gold		PLG.TO
Talisman Mining		TAM.AX
Golden Arrow Resources		TLG.AX
Kingsgate Consolidated		TLM.AX
Balmoral Resources		GRG.V
Dgr Global		KCN.AX
Banro Corporation		BAR.TO
Atac Resources		DGR.AX
Corvus Gold		BAA.TO
Treasury Metals		ATC.V
Troy Resources		KOR.TO
Serabi Gold		TML.TO
Merrex Gold		TRY.AX
Lexam Vg Gold		SRB.L
Moneta Porcupine Mines		LEX.TO
Heron Resources		ME.TO
Cb Gold		HRR.AX
Red 5		RED.AX
Gowest Gold		GWA.V
Golden Reign Resources		GRR.V
Robex Resources		RBX.V
Mawson Resources		MAW.TO
Chalice Gold Mines		CHN.AX
Bassari Resources		BSR.AX
Hastings Technology Metals		HAS.AX
Antioquia Gold		AGD.V
Skeena Resources		SKE.V
Emmerson Resources		ERM.AX
Abm Resources Nl		ABU.AX
Kingsrose Mining		KRM.AX
West Kirkland Mining		WKM.V
Goldstrike Resources		GSR.V
St. Augustine Gold & Copper		SAU.TO
Angkor Gold		ANK.V
Tristar Gold		TSG.V

Spanish Mountain Gold		SPA.V
Orvana Minerals		ORV.TO
Monument Mining		MMY.V
Echo Resources		EAR.AX
Bonterra Resources		BTR.V
Sarama Resources		SWA.V
Otis Gold		OOO.V
Aurvista Gold		AVA.V
Dynasty Metals & Mining		DMM.TO
Orex Minerals		REX.V
Giyani Gold		WDG.V
Macphersons Resources		MRP.AX
Atacama Pacific Gold		ATM.V
Alexandria Minerals		AZX.V
Amarillo Gold		AGC.V
Haoma Mining		HAO.AX
Matsa Resources		MAT.AX
Gme Resources		GME.AX
Metanor Resources		MTO.V
Dragon Mining		DRA.AX
Sihayo Gold		SIH.AX
Crusader Resources		CAS.AX
Ariana Resources		ARNR.L
Rio Novo Gold		RN.TO
Riverside Resources		RRI.V
Goldgroup Mining		GGA.TO
Citigold		CTO.AX
Terraco Gold		TEN.V
Azumah Resources		AZM.AX
Intrepid Mines		IAU.AX
Rugby Mining		RUG.V
Cartier Resources		ECR.V
Strategic Minerals		SMC.AX
Intermin Resources		IRC.AX
Canarc Resource		CCM.TO
Ressources Min Radisson 'A'		RDS.V
Corex Gold		CGE.V
Nevada Exploration		NGE.V
Helix Resources		HLX.AX
Carbine Resources		CRB.AX
Goldplat		GLDP.L
African Gold Group		AGG.V
Predictive Discovery		PDI.AX
Red Pine Exploration		RPX.V
Anaconda Mining		ANX.TO
Scorpio Gold		SGN.V

Kilo Goldmines Canyon Resources Coral Gold Resources Inca One Gold Galantas Gold		KGL.V CAY.AX CLH.V IO.V GAL.V

B. The independent variables' sources

Table B1: The independent variables' sources

Variable	**Collected from / Datastream code**
MSCI ACWI	Datasteam/ MSACWF$
Gold Bullion Spot Price	Datasteam/ S20665
Trade Weighted Treasury Constant Maturity Rate	Datasteam/ S05966
10-Month Treasury Constant Maturity Rate	Datasteam/ Y74758
WTI Crude Oil Spot Price	Datasteam/ S71926
1-Month Risk-free Rate	Datasteam/ Y70459
SMB	http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
HML	http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

C. Assumptions for using OLS

Table C1: Test of assumptions for using OLS

Assumptions	Test	P-value

$E(u_t) = 0$		
$var(u_t) = \sigma^2 < \infty$	Breusch-Pagan test	0.412
$cov(u_i, u_j) = 0$ for $i \neq j$	Breusch-Godfrey test	0.272
$u_t \sim N(0, \sigma^2)$	Jarque-Bera test	0.5534

Note: The Breusch-Pagan test, tests for heteroskedasticity in the residuals. The null hypothesis is homoscedasticity.

The Breusch-Godfrey test, tests for autocorrelation in the residuals. The null hypothesis is no autocorrelation. The Jarque-Bera test, tests for normality in the residuals. The null hypothesis is normality.

D. Graphic illustrations of the price development of the gold stock portfolio and the risk factors

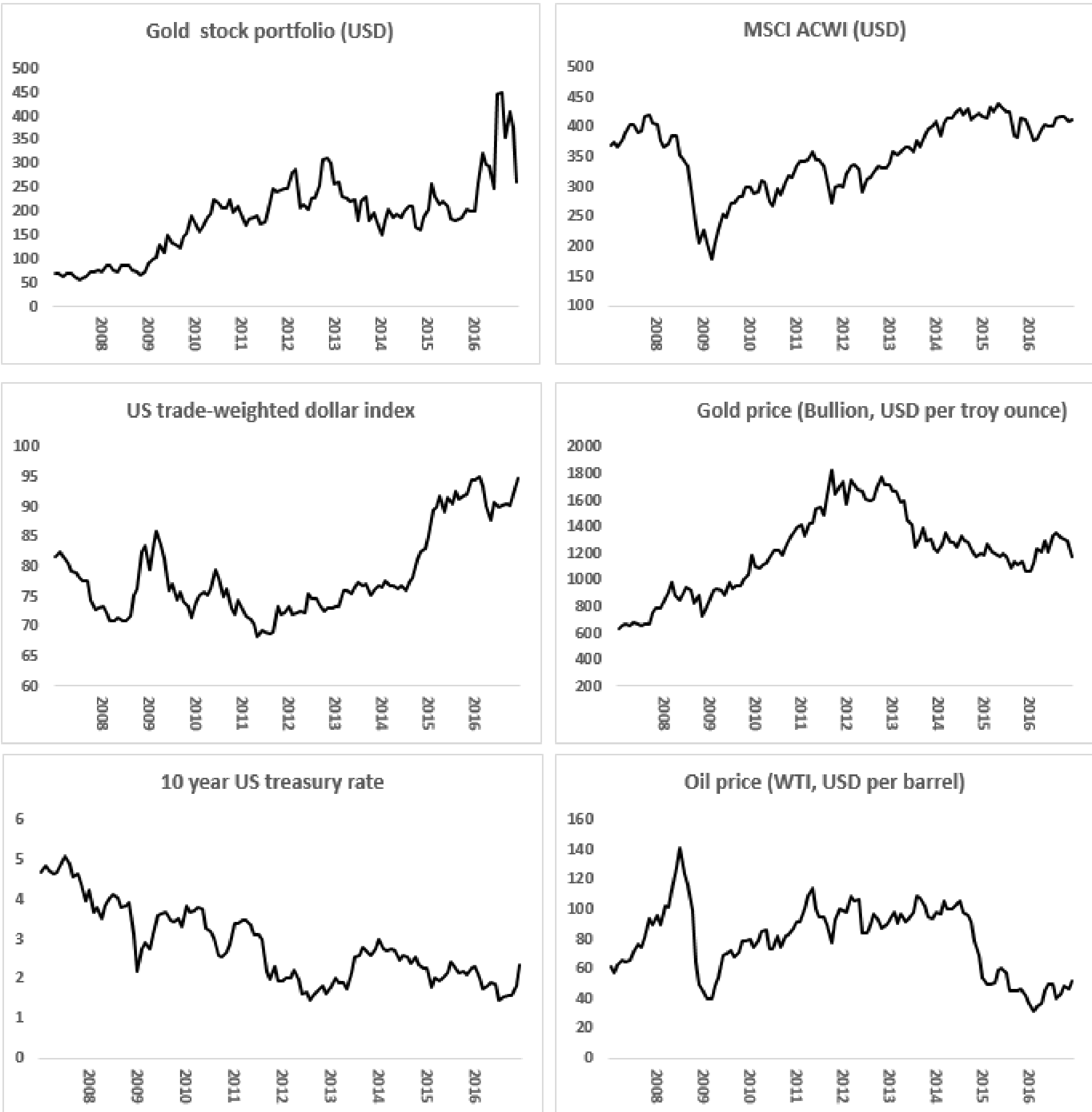

Figure D1: The figure shows the development of our gold stock portfolio, the MSCI ACWI, the gold price, the USD exchange rate, the 10-year Treasury rate and the Oil price. From January 2007 to December 2016. The USD trade weighted dollar index shows the dollar relative to a weighted set of other exchange rates.

E. Quantile regression details and bootstrapping procedure

Generally, the coefficient for each quantile can be found by solving the following optimisation problem developed by Koenker and Basset (1978):

$$\min_{\alpha,\beta} \sum_{t=1}^{T}(q - 1_{Y_t \leq \alpha+\beta X_t})(Y_t - (\alpha + \beta X_t)) \qquad (10)$$

where

$$1_{Y_t \leq \alpha+\beta X_t} = \begin{cases} 1 & if\ Y_t \leq \alpha + \beta X_t \\ 0 & otherwise \end{cases}$$

where Y_t is the dependent variable at time *t*, X_t is the independent variable at time *t*, α is the intercept, β is the coefficient and q is the studied quantile.

To obtain robust standard errors, we employ the pairs-bootstrapping technique suggested by Buchinsky (1995). To estimate the variance-covariance matrix of the estimates (standard errors), the procedure generates repetitive computations. Let $\hat{\beta}_i{}^q$ denote the bootstrapping coefficient estimate from a quantile regression. If the regression is repeated N times we obtain, $\hat{\beta}_i{}^q$,…, $\hat{\beta}_N{}^q$ bootstrap estimates. The variance of the coefficients is given by:

$$S^2\,(\hat{\beta}_i{}^q) = (N-1)^{-1} \sum_{i=1}^{N}(\hat{\beta}_i{}^q - \overline{\hat{\beta}_\iota{}^q}) \qquad (11)$$

where

$$\overline{\hat{\beta}_\iota{}^q} = N^{-1} \sum_{i=1}^{N} \hat{\beta}_i{}^q$$

By using this procedure, the standard errors should be consistent and can be used for hypothesis testing and confidence intervals. According to Buchinsky (1995) the errors are robust and asymptotically valid under heteroskedasticity.

F. Quantile regressions for the size portfolios

Table F1: The estimates for the *Big* market capitalisation portfolio

Quantile	α	βERM	βGOLD	βFXR	βI	βWTI	βSMB	βHML	R^2
Q(0.05)	-0.099*	0.340**	1.794*	0.208	0.082*	0.066	0.318	0.382**	0.606
Q(0.10)	-0.072*	0.369*	1.707*	0.661	-0.107	0.253*	0.441	-0.08	0.592
Q(0.25)	-0.049*	0.282***	1.475*	0.155	-0.133**	0.189**	0.201	-0.294	0.545
Q(0.50)	-0.013***	0.445**	1.573*	0.837***	-0.11	0.066	0.366	-0.235	0.497
Q(0.75)	0.026*	0.437**	1.703*	0.329	-0.221**	-0.046	0.235	0.04	0.520
Q(0.90)	0.062*	0.412**	1.550*	0.409	-0.248**	0.105	0.459	0.0574	0.576
Q(0.95)	0.075*	0.317	1.550*	0.242	-0.220**	0.152**	0.54	0.01	0.619
OLS	**-0.011****	**0.370***	**1.631***	**0.471**	**-0.159***	**0.118*****	**0.342**	**-0.083**	**0.782**

Note: The table present the coefficient-estimates from the OLS - and quantile regression from equation (1) and (2). Test statistics in parenthesis. For the quantile regression, the t-statistics are obtained using the pairs-bootstrapping technique, with 1000 replications.

* Denotes statistical significance at 1% level

** Denotes statistical significance at 5% level

*** Denotes statistical significance at 10% level

Table F2: The estimates for the *Med* market capitalisation portfolio

Quantile	α	βERM	βGOLD	βFXR	βI	βWTI	βSMB	βHML	R^2
Q(0.05)	-0.120*	1.169*	1.552*	1.535*	-0.005	0.386*	0.311	0.255**	0.550
Q(0.10)	-0.112*	1.122*	1.585*	1.658*	0.009	0.351**	0.409	-0.001	0.497
Q(0.25)	-0.054*	1.032*	1.515*	1.681*	0.05	0.161	0.023	-0.454***	0.469
Q(0.50)	-0.014***	0.811*	1.254*	1.065***	0.111	0.066	-0.067	-0.245	0.430
Q(0.75)	0.030*	0.370**	1.575*	0.713	0.0672	0.13	0.329	-0.088	0.456
Q(0.90)	0.053*	0.624***	1.800*	1.145***	0.176	0.045	0.267	-0.077	0.450
Q(0.95)	0.091*	0.305	1.985*	1.1780*	0.07	0.158*	-0.235	0.648***	0.427
OLS	**-0.014****	**0.734***	**1.552***	**1.229***	**0.096**	**0.157*****	**0.09**	**-0.194**	**0.673**

Note: See F1.

Table F3: The estimates for the *Small* market capitalisation portfolio

Quantile	α	βERM	βGOLD	βFXR	βI	βWTI	βSMB	βHML	R^2
Q(0.05)	-0.106*	0.751**	1.112*	1.48	0.019	0.322	0.128	-0.434	0.521
Q(0.10)	-0.088*	0.490***	0.910*	0.604	-0.009	0.263	0.12	-0.424	0.487
Q(0.25)	-0.058*	0.755*	1.124*	1.023**	0.055	0.141	-0.106	-0.631*	0.448
Q(0.50)	-0.024*	0.720*	1.019*	0.632	0.076	0.030	0.056	-0.230	0.393
Q(0.75)	0.013	0.412***	1.169*	0.511	0.158***	0.094	0.534	-0.441	0.375
Q(0.90)	0.054*	0.178	1.416*	-0.21	0.086	0.112	0.447	-0.181	0.388
Q(0.95)	0.078*	0.265	1.596*	-0.032	0.142***	0.13	-0.243	0.619	0.403
OLS	**-0.021***	**0.631***	**1.172***	**0.570**	**0.107***	**0.081**	**0.185**	**-0.181**	**0.618**

Note: See F1.

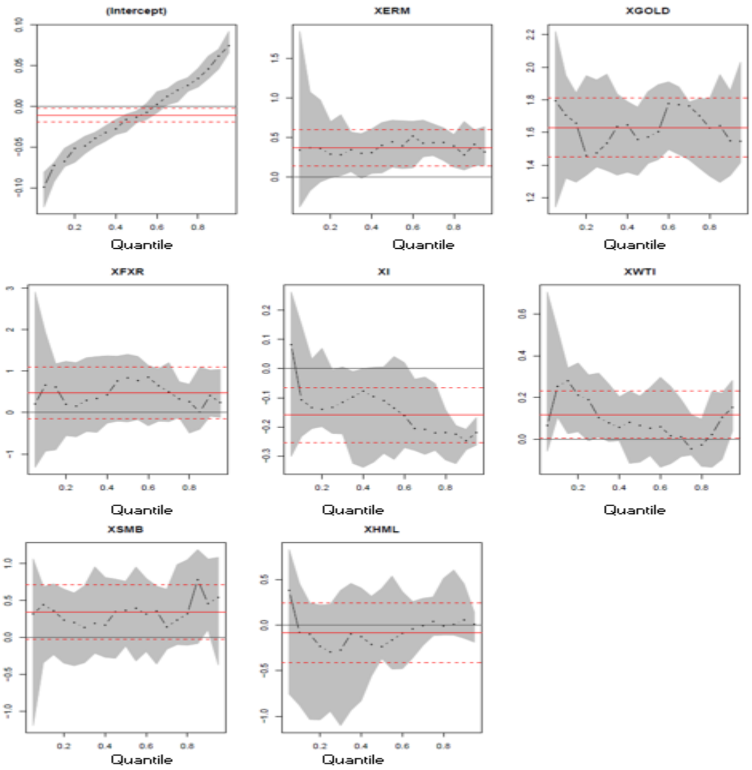

Figure F1: Graphical illustration of the OLS and quantile regression estimates for the *Big* market capitalisation portfolio.

Note: The solid red line shows beta coefficients for the OLS regression, while the stippled black line shows the beta coefficients from the quantile regression. The grey area is the 90% confidence interval. The figure presents the estimates for the intercept, market return, change in gold price, the change in the USD, the change in the interest rate and oil price, as well as the SMB and HML portfolios.

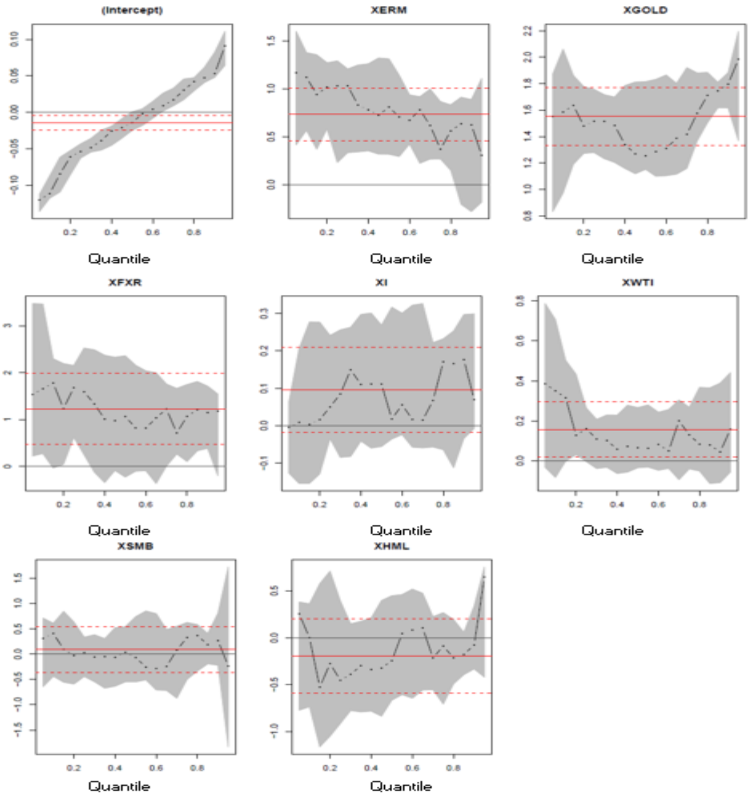

Figure F2: Graphical illustration of the OLS and quantile regression estimates for the *Med* market capitalisation portfolio.

Note: See figure F1.

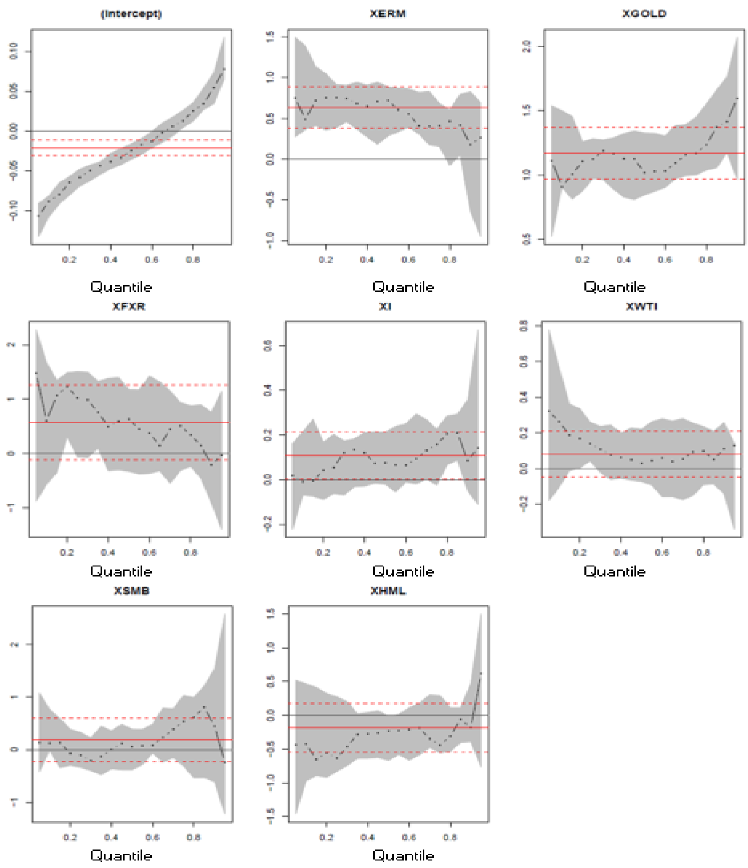

Figure F3: Graphical illustration of the OLS and quantile regression estimates for the *Small* capitalisation portfolio.

Note: See figure F1.