

Do Terror Attacks Predict Gold Returns? Evidence From A Quantile-Predictive-Regression Approach

Rangan Gupta^a, Anandamayee Majumdar^b, Christian Pierdzioch^c, and Mark E. Wohar^d

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Abstract

Much significant research has been done to study how terror attacks affect financial markets. We contribute to this research by studying whether terror attacks, in addition to standard predictors considered in earlier research, help to predict gold returns. To this end, we use a Quantile-Predictive-Regression (QPR) approach that accounts for model uncertainty and model instability. We find that terror attacks have predictive value for the lower and especially for the upper quantiles of the conditional distribution of gold returns.

JEL classification: C22; C53; Q02

Keywords: Gold returns; Terror attacks; Forecasting model; Quantile regression

Addresses:

^a *Corresponding author.* Department of Economics, University of Pretoria, Pretoria, 0002, South Africa; E-mail address: rangan.gupta@up.ac.za.

^b Center for Advanced Statistics and Econometrics, Soochow University, Suzhou, China; E-mail address: anandamayee.majumdar@gmail.com.

^c Department of Economics, Helmut Schmidt University, Holstenhofweg 85, P.O.B. 700822, 22008 Hamburg, Germany; Email address: c.pierdzioch@hsu-hh.de.

^d College of Business Administration, University of Nebraska at Omaha, 6708 Pine Street, Omaha, NE 68182, USA, and School of Business and Economics, Loughborough University, Leicestershire, LE11 3TU, UK. Email: mwohar@unomaha.edu.

1 Introduction

In recent years, significant research has been done to trace out how financial markets respond to terror attacks. The majority of this research has focused on how terror attacks affect stock markets (Chuliá et al. 2007, Arin et al. 2008, Karolyi and Martell 2010, Balcilar et al. 2016a, among others) and exchange rates (Eldor and Melnick 2004, Balcilar et al. 2016b). We contribute to this research by studying whether terror attacks help to predict gold returns. The motivation for our study stems from the observation that investors and commentators often recommend gold as a safe-haven investment in times of market jitters. Market jitters, in turn, may be the result of terror attacks. In consequence, terror attacks may have direct relevance as a predictor of gold returns.

When studying the predictive power of terror attacks for gold returns it is important to control for other variables that have been studied in earlier research as determinants of gold returns, including determinants like exchange-rates movements, interest rates, stock-returns, and oil-price changes (Zhang and Wei 2010, Pukthuanthong and Roll 2011, Reboredo, 2013a, 2013b, to name just a few). As with terror attacks, it is likely that not all of the determinants considered in earlier research are relevant to the same extent for predicting gold returns at all times (Pierdzioch et al. 2014, Aye et al. 2015). For example, the determinants for predicting gold returns in a bull market may be different from the determinants relevant in a bear market. Similarly, the informational content of interest rates for predicting gold returns in periods of high interest rates may differ from their predictive value when interest rates hover around the zero-lower bound. Hence, we use in our research an approach that accounts for model uncertainty and model instability to study the predictive value of terror attacks for gold returns.¹

The specific approach that we use in our research is the quantile-predictive-regression (QPR) approach recently proposed by Pierdzioch et al. (2015) for studying gold returns. Quantile

¹Our approach captures in a simple way that a potential regime dependence of the links between gold returns and their predictors can give rise to instability of a prediction model. Bhar and Hammoudeh (2011) emphasize in a recent study the regime dependence of the links between gold returns and financial variables like interest rates and exchange rates. Beckmann and Czudaj (2015) show that a smooth transition model captures important aspects of the safe-haven property of gold investments with respect to stock-market fluctuations.

regressions have become popular in recent research on gold-price fluctuations (Ma and Patterson 2013, Baur 2013, Zagaglia and Marzo 2013, Ciner 2015, Pierdzioch et al. 2016, among others). The QPR approach that we use in this research is more informative relative to any linear model because it is not restricted just to target the conditional mean of the conditional distribution of gold returns. Rather, the QPR approach is tailored to study the ability of terror attacks to predict different segments of the entire conditional distribution of gold returns. As we show in this research, looking at just the conditional center of the distribution of gold returns would lead us to conclude that terror attacks have poor predictive performance for gold returns, while they are actually valuable for predicting certain parts of the conditional distribution of gold returns. In fact, we find that terror attacks have predictive value for the lower and especially for the upper quantiles of the conditional distribution of gold returns. In other words, terror attacks have predictive power for large movements of the price of gold, and this predictive power is strong when large gold returns are positive. Our finding is consistent with the notion that terror attacks give rise to market jitters which, in turn, lead market participants to invest in gold as a safe-haven investment.

To the best of our knowledge, this research is the first attempt to analyse the forecastability of gold returns based on terror attacks, utilizing a QPR approach. We organize the remainder of this research as follows. In Section 2, we briefly describe the QPR approach. In Section 3, we lay out our data and our empirical findings. In Section 4, we offer some concluding remarks.

2 The QPR Approach

We consider the financial variables $x_{j,t}, j = 1, \dots, n$ as predictors of the returns, r_{t+k} , of the gold price between period of time t and $t+k$, where k denotes the forecast horizon. The forecasting model is of the format $r_{t+k} = \beta_0 + \beta_1 x_{1,t} + \dots + \beta_n x_{n,t} + u_{t+k}$, where u_{t+k} = disturbance term and β_j = regression coefficients. Because an optimal forecasting model does not necessarily feature all n predictor variables we account for model uncertainty by estimating in every period a large number, m , of forecasting models, where every model features a different combination of the n predictors (Pesaran and Timmermann 1995, 2000). Furthermore, because the effect of terror attacks on gold returns may differ across the conditional distribution of gold returns, we use quantile-regression techniques (Koenker and Basset 1978, Koenker 2005) to estimate

the forecasting models. The following period-loss function forms the foundation of the QPR approach:

$$\mathcal{L}(\alpha, \hat{u}_{t+k,m,\alpha}) = \hat{u}_{t+k,m,\alpha}(\alpha - \mathbf{1}(\hat{u}_{t+k,m,\alpha} < 0)), \quad (1)$$

where $\mathbf{1}(\cdot)$ = indicator function, and $\hat{u}_{t,m,\alpha}$ = forecast error for model m in period of time t , given the quantile parameter, $\alpha \in (0, 1)$. The forecast error is defined as actual gold returns minus the forecast. For a quantile parameter of $\alpha = 0.5$ the period-loss function is symmetric in the absolute forecast error, and a forecaster should target the median of the conditional distribution of gold returns. For $\alpha < 0.5$ ($\alpha > 0.5$) the period-loss function implies that a negative (positive) forecast error exceeds the loss of a positive (negative) forecast error. Equipped with the period-loss function, we compute for every given quantile parameter the total loss and choose for every model, m , the quantile-specific parameters, β_α , to minimize

$$\mathcal{L}(\alpha, m, t) = \min_{\beta_\alpha} \sum_{j=0}^t \mathcal{L}(\alpha, \hat{u}_{j+k,m,\alpha}), \quad (2)$$

where the summation is carried out until the latest period of time is reached for which data are available, and $\hat{u}_{j+k,m,\alpha}$ = in-sample prediction error.

We select in every period of time, t , an optimal forecasting model by comparing the m estimated models with a benchmark model, b . Like Pierdzioch et al. (2015), we use the model-selection criterion $\min c_{\alpha,m,t}$, with $c_{\alpha,m,t} = \gamma_{m,\alpha} \mathcal{L}(\alpha, m, t) / \mathcal{L}^b(\alpha, t)$, where $\gamma_{m,\alpha} = (t - 1) / (t - l_{\beta,m,\alpha})$ penalizes model complexity, $l_{\beta,m,\alpha}$ = length of the vector of regression parameters (neglecting the constant) for model m given the quantile parameter, α , and \mathcal{L}^b = loss under a benchmark model. In addition, we use a forecast-combination approach to forecast gold returns (for applications of forecast-combination approaches, see Aiolfi and Timmerman 2006, Rapach et al. 2010, Pierdzioch et al. 2014, among others). The specific forecast-combination approach that we use is the simple average of the forecasts of all m estimated forecasting models. Moreover, because the optimal forecasting model may change over time when the links between gold returns and the predictors vary, we recursively reestimate all m models in every period of time. The QPR approach, thus, accounts for both model uncertainty and potential model instability.

We evaluate forecasts using the out-of-sample R_{oos}^2 statistic studied by Pierdzioch et al. (2015), which resembles the goodness-of-fit criterion for quantile regressions studied by Koenker and

Machado (1999). The R_{oos}^2 statistic evaluates forecasts using the same loss function (see Eq. (1)) that is used to compute forecasts. For the QPR approach, we define $R_{oos}^2(\alpha, b) = 1 - \mathcal{L}(\alpha)/\mathcal{L}^b(\alpha)$, where $\mathcal{L}(\alpha)$ = sum of the out-of-sample losses, and $\mathcal{L}^b(\alpha)$ = sum of the out-of-sample losses for a benchmark model. If $R_{oos}^2(\alpha, b) > 0$ ($R_{oos}^2(\alpha, b) < 0$), the QPR approach outperforms a benchmark model.

3 Empirical Analysis

Gold returns are measured in terms of the first-differenced natural log of the gold fixing price at 3:00 P.M. (London time) in the London Bullion Market, based in U.S. Dollars, which is obtained from the FRED database of the Federal Reserve Bank of St. Louis. We use weekly (end-of-week) data. The gold fixing price is available at a daily frequency, but studying weekly data allows one to have sufficient information to reflect accurately the dynamics of the data (Álvarez-Díaz et al. 2014). Additionally, studying weekly data helps alleviate possible biases related to daily data such as, for example, a weekend effect or day-of-the-weeks effects. Similarly, Reboredo (2013a) argues that drifts and noise present in daily data may complicate modeling gold returns.² Studying gold returns, in turn, ensures that our dependent variable is stationary, a standard requirement in classical estimation methods. The sample period starts in January 1986 and ends in December 2009. The start of the sample period is governed by the availability of data on the determinants of gold returns other than terror attacks. The end of the sample period is purely driven by availability of data on terror attacks.³

Figure 1 plots the gold price (index starts at 100 at the beginning of the sample period) and gold returns. Based on the Jarque-Bera test statistic (not reported), we can reject normality

²As a robustness check, we studied a recursively estimated bivariate quantile regression model estimated on daily data of gold returns and the world terror index. Because we excluded all other standard predictors we could estimate the model dating back to 1968. Results (not reported, but available from the authors upon request) corroborated the findings we report in this research.

³The effective sample period ends in November 2009 rather than in December because we shall present results for both one-week-ahead and four-week-ahead (that is, monthly) returns, and both results were obtained by estimating the QPR approach on the same sample period. See Figure 7.

Figure 1: Gold Price and Returns

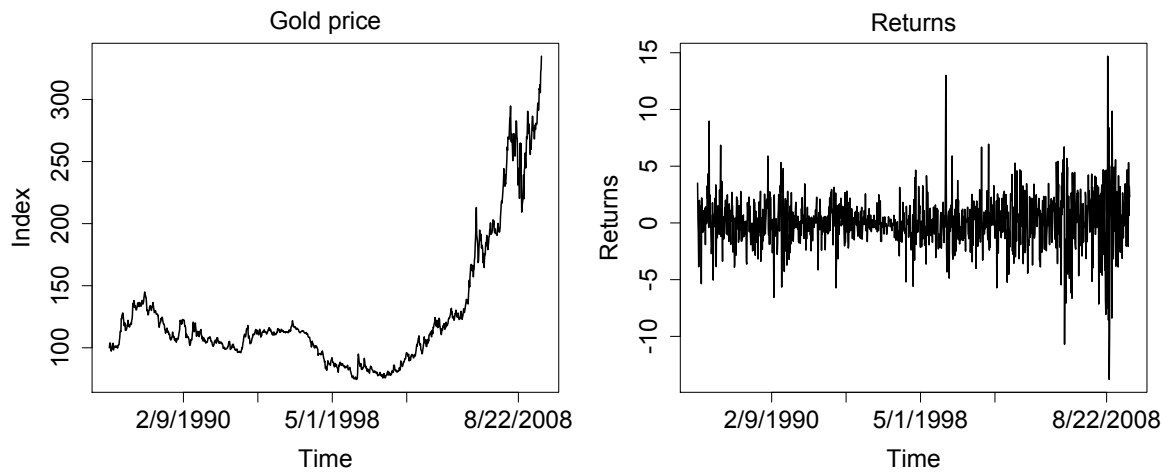
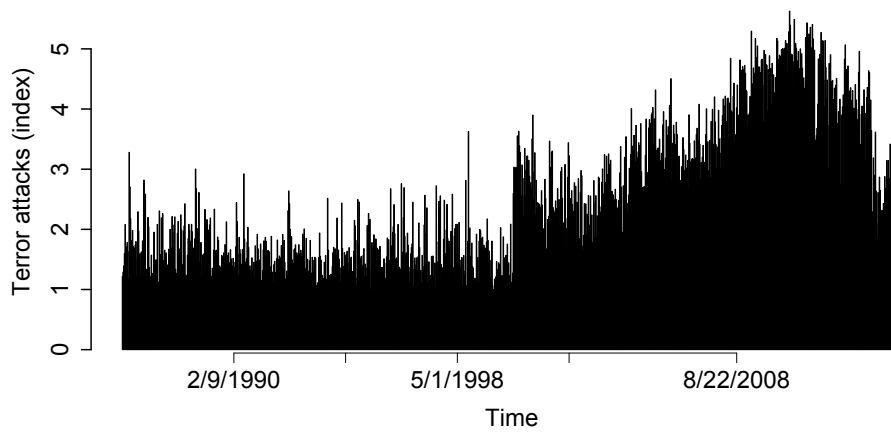


Figure 2: Terror Attacks



of the sampling distribution of returns at the highest levels of significance, which provides some preliminary justification for using the QPR approach.⁴

In order to measure terror attacks, we use a global terror-attacks index that accounts for terror attacks across the entire world. Data on the terror attacks were collected from the RAND Database of Worldwide Terrorism Incidents (RDWTI).⁵ The RDWTI database integrates data from many important terrorism resources. As in Eckstein and Tsiddon (2004) and Arin et al., (2008), the terror index on a specific date across countries (in case there are terror attacks on the same day in multiple countries) is defined as $\ln(e + \text{number of human casualties} + \text{number of people injured} + \text{number of terrorist attacks})$. As in Arin et al., (2008), terror attacks which occurred during a weekend are summed up to the previous Friday's figure. Because we study weekly data, we compute the weekly average of the terror-attacks index. Figure 2 plots the terror-attacks index.

Figure 3 depicts the results of a simple bivariate quantile-regression model of one-week-ahead gold returns (that is, $k = 1$) on terror attacks (and a constant), estimated on the full sample of data. The main message to take home from this figure is that the coefficient of terror attacks is insignificant for intermediate quantile parameters, but that it becomes significant for the lower and especially for the upper quantile parameters. The coefficient is negative for the lower quantile parameters and positive for the upper quantile parameters.⁶

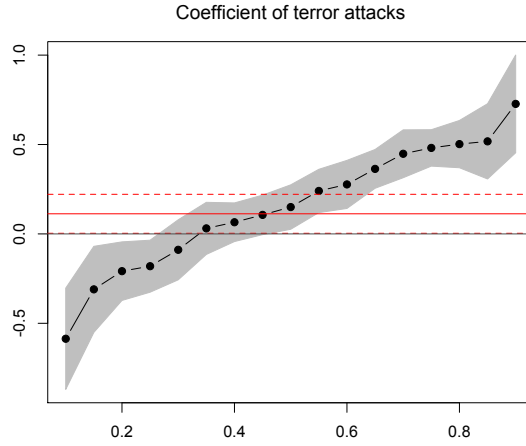
The full-sample results for the bivariate quantile-regression model indicate that terror attacks have predictive power for subsequent gold returns. This predictive power, however, reflects

⁴Results of the BDS test (Brock et al. 1996) indicated, for various embedding dimensions, the presence of nonlinearity in gold returns and also in the residuals of a least-squares regression of gold returns on terror attacks, lending further support to the QPR approach. Results for the BDS test are available from the authors upon request.

⁵Available freely for download at <http://www.rand.org/nsrd/projects/terrorism-incidents.html>.

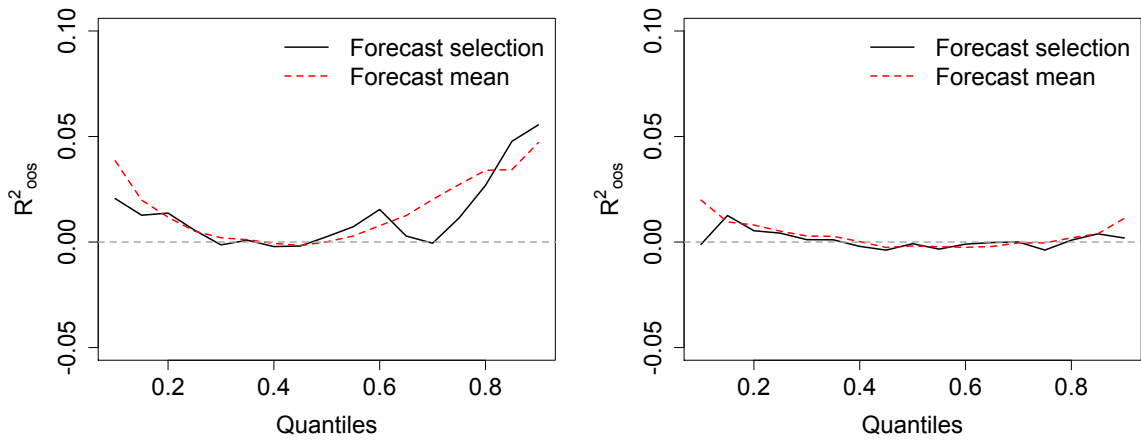
⁶All empirical results reported in this research were computed using the free R programming environment (R Development Core Team, 2014). The quantile regressions were estimated using the `quantreg` package developed by Koenker (2013).

Figure 3: Full Sample Bivariate Quantile Regression



Note: The black dots denote the quantile-regression point estimates. The gray area denotes the 95% confidence band computed using 500 bootstrap simulations. The solid horizontal line denotes the OLS estimate, and the dashed horizontal lines denote the corresponding 95% confidence interval. The forecast horizon is $k = 1$.

Figure 4: Comparison of the QPR Approach With an AR(1) Benchmark Model



Note: Left-hand panel for a model with terror attacks as a potential predictor. Right-hand panel for a model without terror attacks as a potential predictor. Training period = 1986/1–1989/12. The forecast horizon is $k = 1$.

the in-sample fit of the quantile-regression model and an interesting question is whether the predictive power carries over to an out-of-sample analysis.

In an out-of-sample analysis, it is also important to control for the impact that predictors considered in earlier research may have on gold returns. Because we study weekly data, we do not consider standard macroeconomic data but instead consider in this research the following financial-market variables as predictors of gold returns:⁷

- A stochastically detrended short-term interest rate measured by means of the 3-months T-bill rate. Stochastic detrending is achieved by subtracting from the T-bill rate its one-month backward looking average (for a similar detrending approach, see Rapach et al. 2005). For recent studies that include the nominal interest rate in the list of variables determining gold returns and volatility, see Hammoudeh and Yuan (2008), Bhar and Hammoudeh (2011), and Pierdzioch et al. (2014). For a study of the link between real interest rates and fluctuations of the real price of gold, see Pierdzioch et al (forthcoming).
- The term spread as defined as the yield on 10-year government bonds minus the 3-months T-bill rate. For recent examples of studies that take the term spread into account as a determinant of gold-price fluctuations, see Pierdzioch et al. (2014) and Bialkowski et al. (2015).
- Continuously compounded exchange-rate returns as measured in terms of the returns on the dollar/pound and the yen/dollar exchange rates. Examples of recent research of the link between gold returns and exchange-rate movements are Pukthuanthong and Roll (2011), Reboredo (2013b), and Reboredo and Rivera-Castro (2014), among others.
- Continuously compounded returns on the S&P 500 index (closing prices) and financial-market volatility as measured in terms of the CBOE S&P 100 volatility index (VXO). Stock-market return often plays a key role in studies of the hedging and safe-haven property of gold investments. See, for example, Baur and Lucey (2010), Baur and

⁷All data were downloaded from the internet page of the Federal Reserve Bank of St. Louis (<https://research.stlouisfed.org/fred2/>) except for the data on the S&P 500 index, which were downloaded from Yahoo finance (<https://finance.yahoo.com/q/hp?s=%5EGSPC&a=00&b=3&c=1950.00&d=01&e=13&f=2016&g=d>).

McDermott (2011), and Beckmann et al. (2015). We use the CBOE volatility index as a measure of the expected intensity of market fluctuations.

- Continuously compounded oil-price returns (West Texas Intermediate). For recent studies of various aspects of the link between the price of gold and the price of oil, see Beckmann and Czudaj (2013), Malliaris and Malliaris (2013), and Ewing and Malik (2013), to name just a few.

Like Pierdzioch et al. (2015), we always include lagged gold returns in the forecasting model so that we can use a simple AR(1) model as our benchmark model. As is the case for the coefficients of all other predictors of gold returns, the coefficient of lagged gold returns can vary across quantiles.

Table 1 summarizes how often (in percent) the optimal forecasting model for one-week-ahead gold returns includes the predictor variables, where we use data for the training period 1986/1 to 1989/12 to initialize the QPR approach. Corroborating the full-sample results (Figure 3), the QPR approach selects terror attacks mainly for predicting the lower and the upper quantiles of the conditional distribution of gold returns. In contrast, the optimal forecasting model hardly favors terror attacks for intermediate quantile parameters in the range from 0.3 to 0.4. For a median regression ($\alpha = 0.5$), terror attacks enter approximately one-third of all optimal forecasting model.

There are also noticeable differences across quantiles with regard to the inclusion of the control variables in the optimal forecasting model. For example, the results for the short rate resemble the results for terror attacks insofar as the short rate shows up in the optimal forecasting model relatively often when the forecasting targets are the lower and upper quantiles of the conditional distribution of gold returns. Exchange-rate movements, in contrast, seem to be relevant for predicting gold returns mainly for the lowest quantile being studied. Moreover, the yen returns are more often included on balance in the optimal forecasting model than the pound returns. Stock returns, in turn, are often included in the optimal forecasting model when we model the lower and upper quantiles of the conditional distribution of gold returns, while the inclusion of oil-price movements in the optimal forecasting model is more balanced across quantiles (the median regression being an exception).

Table 1: Variable Importance

Quantiles (α)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Terror attacks	86.05	60.12	8.06	16.63	35.12	47.00	39.26	75.93	41.53
Short rate	49.69	28.00	47.62	26.86	28.31	20.35	12.29	47.11	88.43
Term spread	52.58	76.03	20.56	15.39	7.54	5.58	18.60	23.86	45.15
Pound returns	57.54	16.53	8.26	13.64	27.89	12.50	0.00	14.88	14.05
Yen returns	61.67	18.39	23.35	35.85	27.69	16.94	11.36	21.49	49.59
VXO	25.93	65.70	70.35	2.417	0.10	0.31	0.00	23.86	60.54
Oil returns	51.55	81.10	71.07	47.42	5.79	19.32	26.24	45.25	53.93
Stock returns	90.70	84.81	26.55	13.43	0.00	1.14	4.03	31.72	78.31

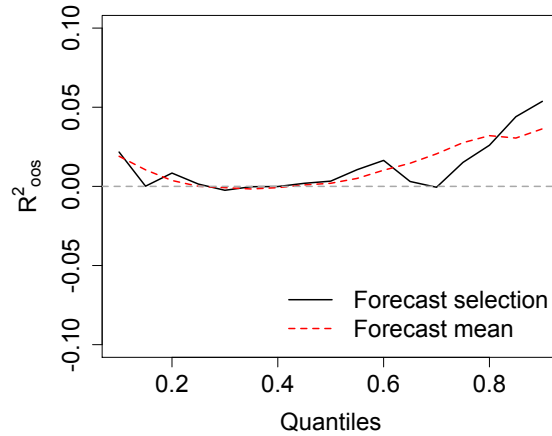
Note: Inclusion of predictors in the optimal forecasting model. Results are in percent. Training period = 1986/1–1989/12. The forecast horizon is $k = 1$.

Figure 4 compares for various quantiles the out-of-sample R_{oos}^2 statistic for the QPR approach with the R_{oos}^2 statistic for an AR(1) benchmark model. We present results for both a QPR approach that uses our model-selection criterion to compute an optimal forecast (solid line) and for a QPR approach that uses thick modeling to compute an optimal forecast (dashed line). In addition, we present the R_{oos}^2 statistic for a model that features terror attacks as a potential predictor (left panel) and for a model that excludes terror attacks from the list of potential predictors (right panel).

As one would have expected, the R_{oos}^2 statistic is a smoother function of the quantile parameter in the case of thick modeling. Model selection and thick modeling, however, yield similar results insofar as the predictive performance of the QPR approach, relative to the predictive performance of the benchmark model, increases for the lower and upper quantiles of the conditional distribution of gold returns when the list of predictors includes terror attacks. When the list of predictors excludes terror attacks, in contrast, the predictive performance of the QPR approach is close to the predictive performance of the benchmark model. Terror attacks, thus, are an important predictor as far as the lower and upper quantiles of the conditional distribution of gold returns are concerned.

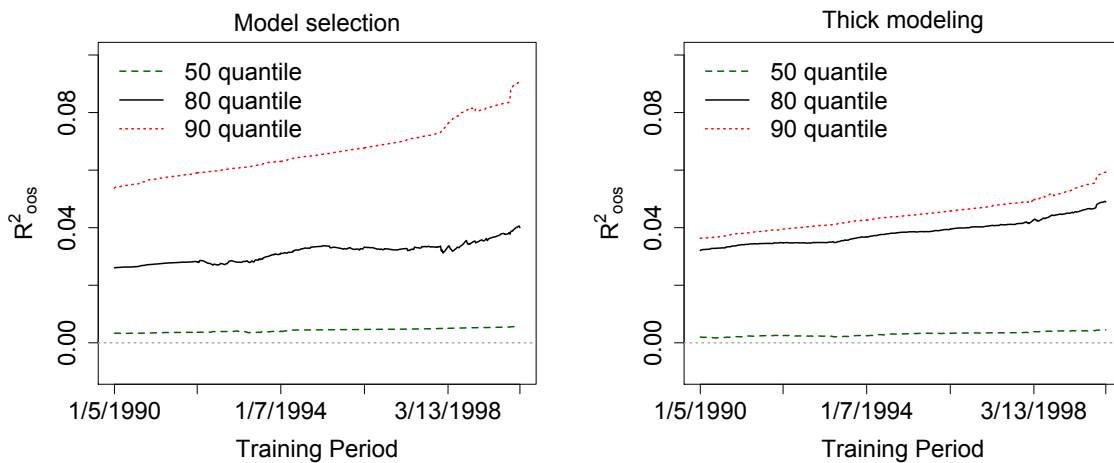
Figure 5 depicts the R_{oos}^2 statistic that we obtain when we use the QPR approach that neglects terror attacks as a predictor of gold returns as the benchmark model. As one would have expected given the results plotted in Figure 4, adding terror attacks to the list of potential predictors improves the performance of the QPR approach for the lower and particularly for the upper quantiles. Hence, while terror attacks are included relatively often in the selected optimal forecasting models for the lower and upper quantiles (Table 1), terror attacks have a more substantial value-added in terms of the predictive performance of the QPR approach for the upper quantiles of the conditional distribution of gold returns.

Figure 5: Using the QPR Approach that Never Uses Terror Attacks as the Benchmark Model



Note: The benchmark model is the QPR approach that excludes terror attacks from the list of predictors of gold returns. Thick modeling = simple mean forecast of all forecasting models. Training period; 1986/1–1989/12. The forecast horizon is $k = 1$.

Figure 6: Results for Alternative Training Periods



Note: The benchmark model is the QPR approach that excludes terror attacks from the list of predictors of gold returns. Thick modeling = simple mean forecast of all forecasting models. The forecast horizon is $k = 1$.

A natural question is whether adding terror attacks to the list of potential predictors results in statistically significant differences of the predictions implied by the QPR approach.⁸ We use Fair-Shiller regressions (Fair and Shiller 1990) to address this question.⁹ The Fair-Shiller regressions test the informational content of different forecasts by regressing actual one-week-ahead returns on a constant, the forecasts from the QPR approach that features terror attacks in the list of potential predictors of gold returns, and the forecasts computed by means of the QPR approach that neglects terror attacks. We estimate the Fair-Shiller regressions as quantile-regression models estimated separately for every quantile parameter under consideration. Table 2 summarizes the results.

The results show that, in the case of model selection, the predictive value of forecasts computed using the QPR approach that features terror attacks as a potential predictor of gold returns dominates for some lower and several upper quantiles the predictive value of the QPR approach that neglects the information that terror attacks contain for predicting gold returns. In other words, for quantile parameters exceeding approximately $\alpha = 0.75$ (i) the predictive value of the more parsimonious QPR approach that drops terror attacks from the list of predictors of gold returns is contained in the predictive value of the forecasts generated using the QPR approach that includes terror attacks in the list of predictors, and, (ii) the latter contains additional information useful for predicting gold return. For thick modeling, the results of the Fair-Shiller regressions are similar but for quantile parameters in the range $0.55 \leq \alpha \leq 0.75$ both QPR approaches produce significant regression coefficients. The p-values for the QPR approach that neglects terror attacks, however, start increasing again for larger quantile parameters. Hence, the results of the Fair-Shiller regressions suggest that including terror attacks in the

⁸Campbell and Thompson (2008) emphasize that even small R_{oos}^2 statistics can be economically significant because "... the correct way to judge the magnitude of R^2 is to compare it with the squared Sharpe ratio S^2 ." (Page 1525). Pierdzioch et al. (2015) use a simulation study to show that a R_{oos}^2 statistic of about 5% indicates a statistically significant difference between forecasting models.

⁹As an alternative test, we considered a conditional predictive ability test (Giacomini and White, 2006; see also Manzan 2015). Results (not reported, but available from the authors upon request) showed that the QPR approach that includes terror attacks in the list of potential predictor variables dominates for the upper quantile parameters and also (mainly in the case of thick modeling) for some lower quantiles the QPR approach that completely neglects terror attacks.

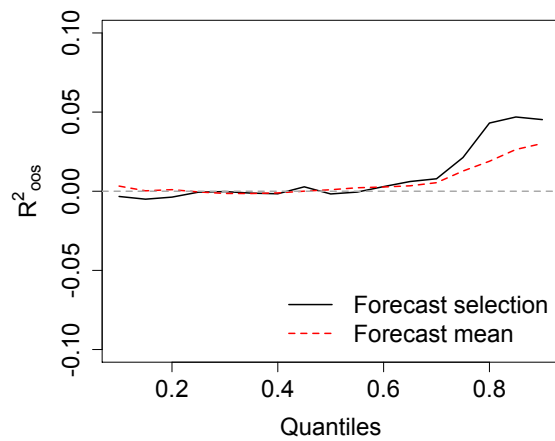
Table 2: Fair-Shiller Regressions

Panel A: QPR Approach With Terror Attacks vs. QBR Approach Without Terror Attacks (Model Selection)																	
Quantiles (α)	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9
With terror attacks	0.02	0.13	0.03	0.08	0.01	0.60	0.85	0.45	0.20	0.00	0.00	0.35	0.85	0.01	0.00	0.00	0.00
Without terror attacks	0.91	0.32	0.71	0.30	0.00	0.81	0.58	0.03	0.23	0.00	0.03	0.40	0.04	0.32	0.65	0.44	0.29

Panel B: QPR Approach With Terror Attacks vs. QBR Approach Without Terror Attacks (Thick Modeling)																	
Quantiles (α)	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9
With terror attacks	0.01	0.00	0.03	0.93	0.48	0.29	0.86	0.64	0.16	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Without terror attacks	0.10	0.07	0.13	0.80	0.33	0.14	0.97	0.34	0.08	0.01	0.00	0.00	0.01	0.00	0.06	0.04	0.17

Note: p-values (500 bootstrap simulations). Training period = 1986/1–1989/12. The forecast horizon is $k = 1$.

Figure 7: Comparing the QPR Approaches (Four-Weeks-Ahead Returns)



Note: The benchmark model is the QPR approach that excludes terror attacks from the list of predictors of gold returns. Thick modeling = simple mean forecast of all forecasting models. Training period = 1986/1–1989/12. The forecast horizon is $k = 4$.

list of predictors of gold returns tends to yield superior results for the upper and some lower quantiles, corroborating the results of our analysis based on the R^2_{oos} statistic.

The results we have described so far are obtained for a model that we train by using data for 1986/1 to 1989/12. This choice of the training period, of course, is somewhat arbitrary. In Figure 6 we show that our main results continue to hold when we extend the length of the training period. The performance of the QPR approach that features terror attacks as a potential predictor relative to the QPR approach that neglects the information of terror attacks for predicting gold returns even increases for the upper quantiles when the training period becomes longer.

Figure 7 extends the empirical analysis to four-week-ahead returns (that is, we set $k = 4$ and study the change in the price of gold during the subsequent four weeks). Adding terror attacks to the list of potential predictors does not improve the performance of the QPR approach for the lower quantiles. The findings for the longer forecast horizon, however, corroborate the results for the one-week-ahead returns in that terror attacks boost the performance of the QPR approach for the upper quantiles.

4 Concluding Remarks

The findings we have laid out in this research contribute to both the literature on the effects of terror attacks on financial markets and the literature on the determinants of the price of gold and the properties of gold as a safe-haven investment. Using a recursively estimated QPR approach that accounts for model uncertainty and model instability, we have computed out-of-sample forecasts of gold returns by means of a model-selection approach and thick modeling. We then have used an out-of-sample R^2 statistic and formal statistical tests to examine whether including terror attacks in the list of potential predictors of gold returns improves the forecasting performance of the QPR approach. We have found that terror attacks have predictive value for gold returns, where their predictive value is concentrated at the lower and especially at the upper quantiles of the conditional distribution of gold returns. We have shown that, especially with regard to the upper quantiles of the conditional distribution of

gold returns, this finding is robust to an extension of the forecast horizon to four weeks and to alternative training periods that a researcher uses to initialize the QPR approach.

While our findings suggest that gold investments have the potential to act as a safe haven against terror attacks, further research should be undertaken to study the safe-haven hypotheses in more detail. In future research, it is interesting to build on our findings and to use techniques applied in the safe-haven literature (Baur and Lucey 2010, Baur and Dermott 2010) to study further the safe-haven and hedging properties of gold investments with respect to terror attacks.

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