Rare Disaster Risks and Gold over 700 Years: Evidence from Nonparametric Quantile Regressions

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Highlights

- We show the presence of nonlinearity and regime changes in the relationship between gold and rare disaster risks.
- We use a nonparametric quantile regression model to investigate gold's ability to hedge against such risks.
- We find that gold can only hedge against these risks if it is in its bullish-state.
- Gold is negatively impacted in its bearish-phase.

Abstract

Using annual data on real gold returns and measures of rare disaster risks over the period of 1280 to 2016, we provide evidence of nonlinearity and regime changes in the relationship between the two variables of concern, over and above the existence of non-normality in the data. In light of these issues, we rely on a nonparametric quantile regression model to show that real gold returns can hedge against such risks, but only when the market is in its bullish-state, with it being negatively impacted in its bearish-phase. Understandably, our results have important implications for investors seeking refuge in the safe haven of gold during rare disaster events. In addition, our findings, would require theoreticians to develop new asset pricing models, which would incorporate the state-specific impact of rare disaster risks on gold.

Keywords: Real gold returns; Rare disaster risks; Quantile regressions
JEL Codes: C22, Q02

1. Introduction

Following the early works of Baur and Lucey (2010), and Baur and McDermott (2010), a large literature has emerged that has investigated the role of gold as a "safe haven" in times of extreme jitters and disruptions in financial (bonds, (crypto-)currencies, and equities) markets (see, Boubaker et al. (2020) for a detailed review). In general, these studies find that investors are often attracted to this precious metal due to its ability to offer portfolio diversification and/or hedging benefits during periods of turmoil in (traditional) financial markets. At the same time, there is also a corresponding literature (see for example, Reitz (1988), Barro (2006, 2009), Watcher (2013), Berkman et al. (2011, 2017), Gabaix (2012), Farhi and Gabaix (2016), Gupta et al. (2019a, b))

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which tends to provide theoretical and empirical support to the fact that financial market downturns are a result of risks emanating from rare disaster events, which in turn, in this line of work, is identified as involving a cumulative decline in output of at least 10% over one or more years. In light of this, and given gold's relatively well-established safe haven characteristic, one can hypothesize that rare disaster risks would lead to an increase in (real) gold price and or returns, as also observed, in particular, during the early stages of the ongoing COVID-19 pandemic (Ji et al., 2020; Lahiani et al., 2021), before the financial markets started to settle down (in the wake of vaccinations).

Against this backdrop, the objective of our paper is to try and empirically validate the hypothesis that there exists a positive and statistically significant relationship between real gold returns and rare disaster risks over the year period of 1280 to 2016. In this regard, we apply linear and nonparametric quantile regressions, besides the benchmark linear model. We argue that, due to non-linearity and non-normality patterns, which we show to exist in an overwhelming fashion in our dataset based on formal statistical tests, a linear regression approach might not be adequate for exploring the ability of rare disaster events in predicting real gold returns. In fact quantiles-based approaches, as originally developed by Koenker and Bassett (1978), enables us to have a more complete characterization of the entire conditional distribution of real gold returns through a set of conditional quantiles, rather than only its conditional mean, as is the case with the standard linear regression approach. Looking at just the conditional mean of real gold returns is likely to "hide" interesting characteristics, and can lead us to conclude that a covariate, in our case rare disaster events, has poor explanatory power, while it actually contains valuable information for certain parts of the conditional distribution of real gold returns. Furthermore in terms of modelling non-linearity, unlike the Markov-switching and the smooth threshold models, we do not need to specify number of regimes of real gold returns (for instance, bear and bull) in an ad hoc fashion with the quantiles-based approach. This is because, weak periods in the gold market will correspond to the low quantiles or the left tail of the returns distribution, while the strong periods will be captured via the high quantiles or right tail of the same. Note that, since the quantile regression studies the entire conditional distribution, which captures various states of the gold market, it adds an inherent time-varying component to the estimation process. Having said this, when shapes of quantile curves are nonlinear, and also possibly depend on the quantile parameter, the linear quantile regression model does not always suffice to adequately express the relationship between covariates (rare disaster risks) and quantile functions of the response variable, i.e., real gold returns. Hence, we also resort to a nonparametric quantile model, which is expected to provide more reliable and robust inferences.

To the best of our knowledge, this is the first paper to study formally the empirical relationship between real gold returns and rare disaster events using quantiles-based econometric methods spanning the longest possible available history of these two variables, and hence in the process avoiding any sample selection bias, while providing a complete picture of the evolution of the gold market in the wake of large economic crises. Since silver is also considered as a possible safe haven (Salisu et al., forthcoming), we also conduct a comparative analysis involving historical real silver returns and rare disaster risks over 1688-2016.

Understandably, our findings should be of immense value to portfolio allocation decision of not only investors, but should carry lot of academic value. The latter is particularly the case in the context of the work done by Barro and Mishra (2016), which is perhaps the only available related paper to our study. These authors, based on correlation and covariance analyses, found that changes in real gold prices co-vary negligibly with growth rates of Gross Domestic Product (GDP), as well as consumption, of the United States (US) over the period of 1836 to 2011. More importantly, they also found that gold's mean real rate of price change for 14 Organisation of Economic Cooperation and Development (OECD) countries during 56 identified macroeconomic disasters (based on 10% or more decline in GDP growth data of 19 countries) was not statistically significantly different from the overall mean over 1880-2011.[1] Next, Barro and Misra (2016) develops an asset-pricing model with rare disasters and a high elasticity of substitution between gold services and ordinary consumption to explain these observations. Naturally, if we are able to detect quantiles-based significant correlation between gold returns and rare disaster risks, based on relatively more sophisticated econometric methods and an elaborate data set, then one would need to build state-specific models as part of future academic research to understand better the nexus between gold returns and rare disaster events. The remainder of the paper is organized as follows: Section 2 outlines the data and the methodologies, while Section 3 presents the empirical results, with Section 4 concluding the paper.

2. Data and Methodologies

2.1. Data

As far as measuring rare disaster risks are concerned, we use the dataset created by Ćorić (2021), which extends the work of Barro and Ursúa (2008, 2012) to include a larger sample of countries (compared to 42 over 1870-2009). In particular, the maximum number of countries for which data can be used is 77 before from 1820 to the end of World War II, and 169 after it. Ćorić (2021) uses the National Bureau of Economic Research (NBER)-style of measuring peak-to-trough of macroeconomic contractions to identify economic disasters. More specifically, he uses cumulative declines of output of at least 10% over one or more years. He obtains the underlying data from the Maddison Project Database 2018 (MPD) and the Penn World Table (PWT) 9.0. Ćorić (2021) then creates four datasets, as the output data from the MPD and the PWT do not entirely overlap, with the first one (DS1) created using per capita real GDP (in 2011 US dollars), the second dataset (DS2) includes population data to construct overall real GDP (in 2011 dollars). These first two datasets are created using the MDP, while the third (DS3) and fourth (DS4) datasets are based on data from the PWT. DS3 uses real GDP data (in 2011 national prices), and DS4 uses population from PWT to calculate per capita real GDP (in 2011 national prices). DS1 is available from 1280, DS2 from 1820 (limited by the data availability of population), while DS3 and DS4 start from 1950, with the end date for all the datasets being 2016.

We use DS1 to create RDR1, which is the number economic disasters in a specific year as experienced by the countries for a particular year weighted by the inverse of the total number of countries for which data is available (given that the sample size is not constant over time), and RDR11 is just the number of economic disasters, i.e., the total number of countries in disaster in a particular year. We then create RDR2 and RDR22, which has the same definition as RDR1 and RDR11 but using DS2 as the underlying dataset. The sum of the number of rare disasters identified

[1] The calculated average annual real rate of price change for gold in each country during a disaster was based on the time paths of the world dollar price of gold, the nominal exchange rate between the home currency and the US dollar and the consumer price index for the home country.

involving RDR1 (over 1280-2016) and RDR2 (covering 1820-2016) is 2227 and 977 respectively.[2] Since RDR1 and RDR2 are weighted by the inverse of the number of countries for which data is available for real GDP and per capita real GDP, these two measures basically capture the worldwide probability of a rare disaster event taking place in a certain year. With quantile regressions requiring relatively large number of observations to draw appropriate inference, we do not use DS3 and DS4 for our analyses.

For the price of gold, we use annual data of nominal prices (in British pounds) of gold starting in 1279, and is retrieved from MeasuringWorth.[3] The nominal price of gold is transformed into its real counterpart by deflating with the Consumer Price Index (CPI) of the UK derived from a database maintained by the Bank of England called: "A Millenium of Macroeconomic Data for the UK".[4] We then compute the log-returns of real gold prices over the period of 1280 to 2016, to match our longest possible rare disaster risk metrics of RDR11 and RDR1. As a robustness check, we also analyze the impact of rare disaster risks on real silver returns (with underlying data obtained from the same sources involving real gold prices), with the sample period covering 1688 to 2016.

The variables have been plotted in Figure A1 in the Appendix of the paper, while Table A1 in the Appendix summarizes the data, and highlights the existence of non-normality of the variables – a preliminary motivation to use a quantiles-based approach for our question in hand.

2.2. Methodologies

In a linear model specification, rare disasters only impact conditional real returns of gold (or silver). Such a model can be specified as follows:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t = \beta' z_t + \varepsilon_t \tag{1}$$

where $t = 1,2,\dots,T$ is the time index in months, y_t is the real gold (or silver) returns, x_t is the rare the indicator of rare disaster risk, the vector z_t is defined as $z_t = (1, x_t)'$, and ε_t is an independently and identically distributed error term with zero mean and constant variance σ^2, $\varepsilon_t \sim iid(0, \sigma^2)$. The model in equation (1) can be usually estimated using ordinary least squares (OLS), and statistical inference is made by making a parametric distributional assumption for ε_t. Frequently, one appeals to a normal distribution assumption for ε_t.

Under OLS, equation (1) can be specified in the normal fashion, where the rare disaster risk only effects the conditional mean $E(y_t|x_t) = \beta' z_t = \xi(\beta, z_t)$ of the returns. However, modeling the conditional mean, as is done with OLS, could obscure other features in the data. Precious metal returns display large variations in level and variance (as seen from Figure A1), due to effect of

[2] If we count only the beginning year of a crises, and not its duration, then the corresponding numbers of rare disaster risks are 621 and 330, which is way more than the 183 identified by Barro and Ursúa (2008, 2012).
[3] https://www.measuringworth.com/.
[4] https://www.bankofengland.co.uk/statistics/research-datasets.

important economic events such as, rare disasters. These events can change both the central tendency (mean) and the variance of returns. Central tendency changes imply variation in the intercept β_0 ('location model') while changes in the variance imply variations in the slope parameter β_1 ('scale model'). Even the shape of the distribution of returns could change over time, implying changes in both β_0 and β_1 ('location-scale model'). The changes in β_0 and β_1 over support of the distribution of the returns implies different values of these parameters at different quantiles of the distribution of returns. Let the cumulative distribution of a random variable y be given by: $F(y_t) = P(y \leq y_t)$ for any value y_t. Then, for any $\tau \in (0,1)$, $Q_\tau(y_t) = F^{-1}(\tau) = \inf\{y_t: F(y_t) \geq \tau\}$ is called the τ-th quantile of y. When an additional random variable x is informative of y, we can define the conditional quantile of y given $x = x_t$ as $Q_\tau(y_t|x_t) = F^{-1}(\tau|x_t) = \inf\{y_t: F(y_t|x_t) \geq \tau\}$. When y_t displays location-scale effect, this can be represented by a model with parameters displaying change at different quantiles of y_t. In this case, we can estimate the conditional quantile of y_t $Q_\tau(y_t|x_t)$ instead of the conditional mean $E(y_t|x_t)$, which leads to following quantile regression model of Koenker and Bassett (1978):

$$y_t = \beta_0(\tau) + \beta_1(\tau)x_t + \varepsilon_t(\tau) = \beta(\tau)'z_t + \varepsilon_t(\tau) \tag{2}$$

where the quantile-specific linear effects are enforced by the parameters $\beta(\tau) = (\beta_0(\tau), \beta_1(\tau))'$. In a time series context, the model in equation (2) can be viewed as time-varying parameter model (Koenker and Xiao, 2006). The conditional quantiles of y_t are, then, given by

$$Q_\tau(y_t|x_t) = \beta_0(\tau) + \beta_1(\tau)x_t = \xi\big(x_t, \beta(\tau)\big) \tag{3}$$

with the parametric function ξ denoting the quantile regression predictor.

Quantile regression, which models the outcome variable's conditional quantile, may be more useful than the OLS. It enables variation in the effects of an explanatory variable (on the dependent variable) across quantiles of the distribution. As an alternative to standard least squares regression, it provides a more thorough framework for examining how covariates affect not just the location but also the entire conditional distribution (Koenker, 2005). The basic objective of quantile regressions is to build a regression function that reveals the relationship between the τ-th quantile of the response y_t and the covariate x_t. Often, a parametric version of the regression function is assumed for ease of comprehension and computational efficiency. In general, quantile regression is favorable when the form of the response variable's distribution is dependent on other variables, i.e., when the error terms are not iid, or when the response does not follow a well-known distribution, for example, when it is asymmetric or has heavy tails or outliers.

For modelling the impact of rare disaster risks, quantile regression can be useful to account for the reality that gold (and silver) commodity markets are segregated into bad (receding returns) and good (rising returns). Rare disaster risks might change when markets are in a crash or when markets are experiencing positive growth. The bad periods correspond to the low quantiles or the left tail of the returns distribution, while the good periods are captured by the high quantiles or right tail of the same. The effect might be different in these periods since market participants react differently in bad and good times, and these are separated from each other since the market cannot be in both bad and good states at the same time. Thus, market segregation is implicit in a quantile model. Clearly, if the coefficients are constant across quantiles, the normal linear representation is appropriate.

In equation (2), $\beta(\tau)$ denotes the vector of quantile regression coefficients and is interpreted as the marginal change in the conditional quantile τ caused by a marginal change in the vector coefficients on z_t. The conditional quantile of the unobserved error is supposed to vanish in quantile regression. Thus, $Q_\tau(\varepsilon_t(\tau)|z_t) = 0$; nevertheless, the error terms' distribution is not specified.

Following Koenker and Bassett (1978), we can estimate the conditional quantiles using the parametric function ξin equation (3) by minimizing the weighted sum of absolute deviances:

$$\min_{\beta\in\mathbb{R}^2} \sum_{t=1}^{T} \rho_\tau[y_t - \xi(\beta, z_t)] \tag{4}$$

where ρ_τ is the check function defined as $\rho_\tau(u) = (\tau - I(u < 0))$ with I denoting the indicator function. Koenker and Basset (1978) propose minimizing the asymmetrically weighted absolute sum of the errors in order to solve the minimization problem in equation (4). As a result, the τ-th $(0 < \tau < 1)$ regression quantile solves the following:

$$\min_{\beta\in\mathbb{R}^2} \{\sum_{t:\, y_t \geq \beta' z_t} \tau\, |y_t - \beta' z_t| + \sum_{t:\, y_t < \beta' z_t} (1-\tau)|y_t - \beta' z_t|\} \tag{5}$$

The minimization problem in equation (5) involves a linear objective function on a polyhedral constraint set. This constrained minimization problem can be solved using linear programming (Koenker and Basset, 1978; Koenker, 2005). The solution yields the "regression quantiles", which are determined by the solution parameters: $\beta(\tau)$. The properties of $\beta(\tau)$ follow immediately from the well-known properties of solutions of linear programs. However, the estimated standard errors are potentially heteroskedastic, so the wild bootstrap method of Feng et al. (2011) is used to avoid understating the standard errors.

When the shapes of quantile curves are nonlinear, and even depend on the quantile parameter, the linear quantile regression model in equation (2) does not always suffice to adequately express the relationship between covariates and quantile functions of the response variable. While parametric assumptions lead to a simple model structure and low implementation cost, it is not flexible enough for complex problems, and thus runs the risk of model misspecification. Nonparametric quantile regression has emerged as a viable alternative to parametric assumptions that are too restrictive. Koenker et al. (1994) pioneered nonparametric quantile regression in spline models for single predictor models, in which the quantile function is found by solving the minimization problem.

Nonparametric quantile regression involves estimating the presumably smooth function $g(x_t)$, defined as the conditional τ-th quantile of y_t conditional on x_t , given a value $\tau \in (0,1)$. As in the standard quantile regression, a common approach involves obtaining an estimate $g(x) = \hat{g}_{\tau,\lambda}(x)$ by solving the following minimization:

$$\min_{g\in\mathcal{G}} \sum_{t=1}^{T} \rho_\tau[y_t - g(x_t)] + \lambda H(g) \tag{6}$$

over a suitable function space $\mathcal{G}$. Here, $H(g)$ is a roughness functional, and λ is a smoothness tuning parameter that determines how much roughness is penalized. Various alternatives are proposed for the specific form of $H(g)$. Koenker et al. (1994) take $H(g) = V(g'(x))$, with $V(g')$ denoting the total variation penalty on the derivative g', for which linear programming can be used to find the minimizer of equation (6) over an appropriately chosen function. Some subsequent work has retained the objective function in the form equation (6), but differed from Koenker et al. (1994) in one or both of the penalty function or function space for g. Koenker et al. (1994) show that when $H(g) = V(g')$, the minimizer is a linear spline with knots at design points x_t, $t = 1, 2, \ldots, T$. Bloomfield and Steiger (1983) and Nachka et al. (1995) consider a problem similar to equation (6), but with the roughness penalty $H(g) = \int_0^1 [g''(x)]^2 dx$, which may impose a more visually appealing form of "smoothness" than alternative functionals. We use regression smooth splines for (x_t) , are matching curve processes, as recommended by Koenker et al. (1994).

The nonparametric quantile regression model requires the selection of the smoothness parameter λ. We choose the smoothing parameter λ using k-fold CV algorithm of Lin et al. (2013).

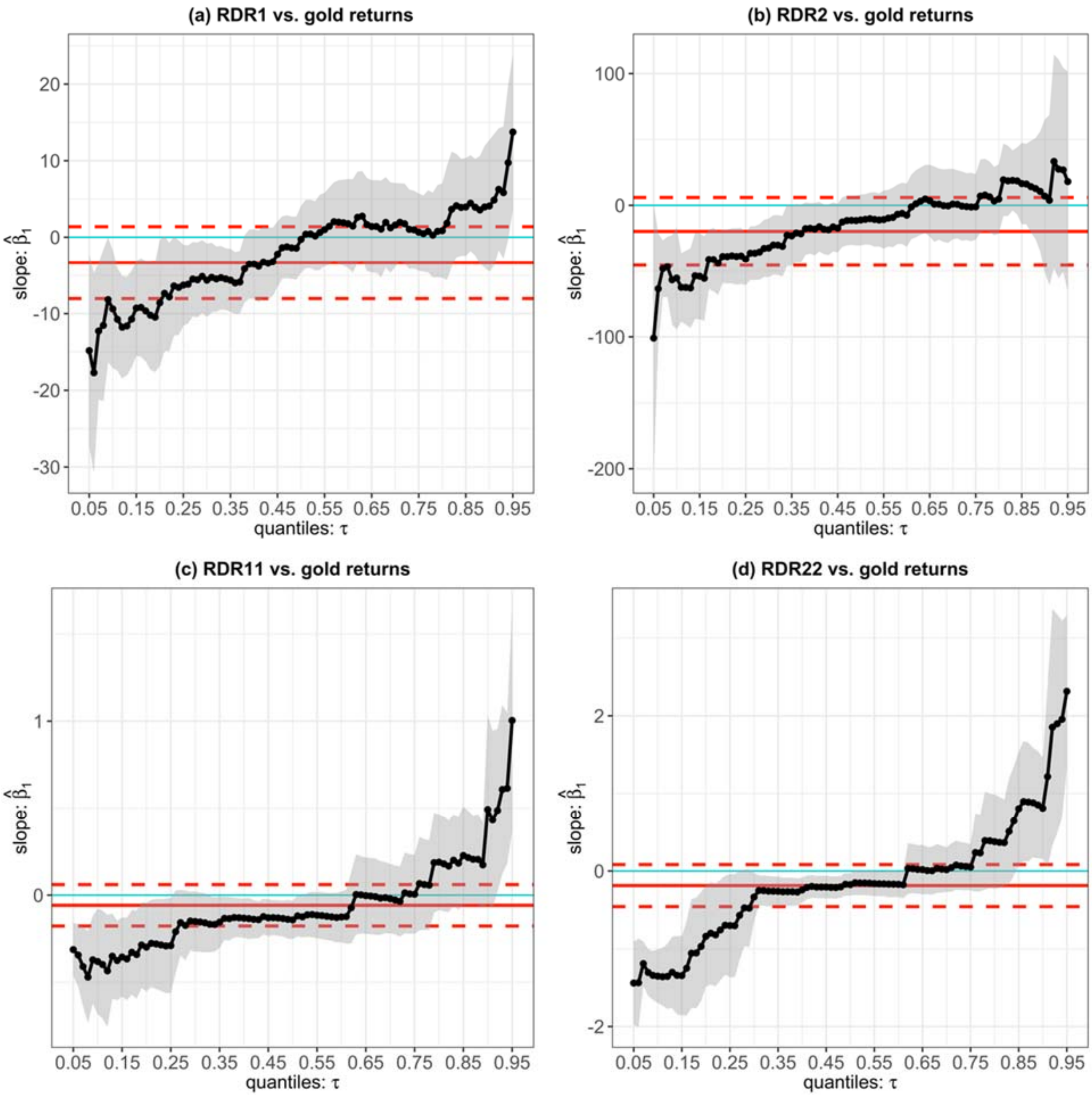
3. Empirical findings

3.1. Main results

Though our main focus are the results from the quantiles-based models, we also first investigated the effects of the rare disaster risks variables on the conditional mean of real gold returns based on standard OLS regressions (with Newey and West (1987) Heteroskedasticity and Autocorrelation corrected (HAC) standard errors) involving RDR1, RDR2, RDR11, and RDR22 as the covariates. The corresponding estimates of β_1 in equation (1) are respectively (with *p*-values in parenthesis): -3.366 (0.130), -19.987 (0.369), -0.058 (0.417), and -0.187 (0.166), i.e., we find negative and statistically insignificant effects (see also Figures 1 and 2) – a finding in line with Barro and Misra (2016).

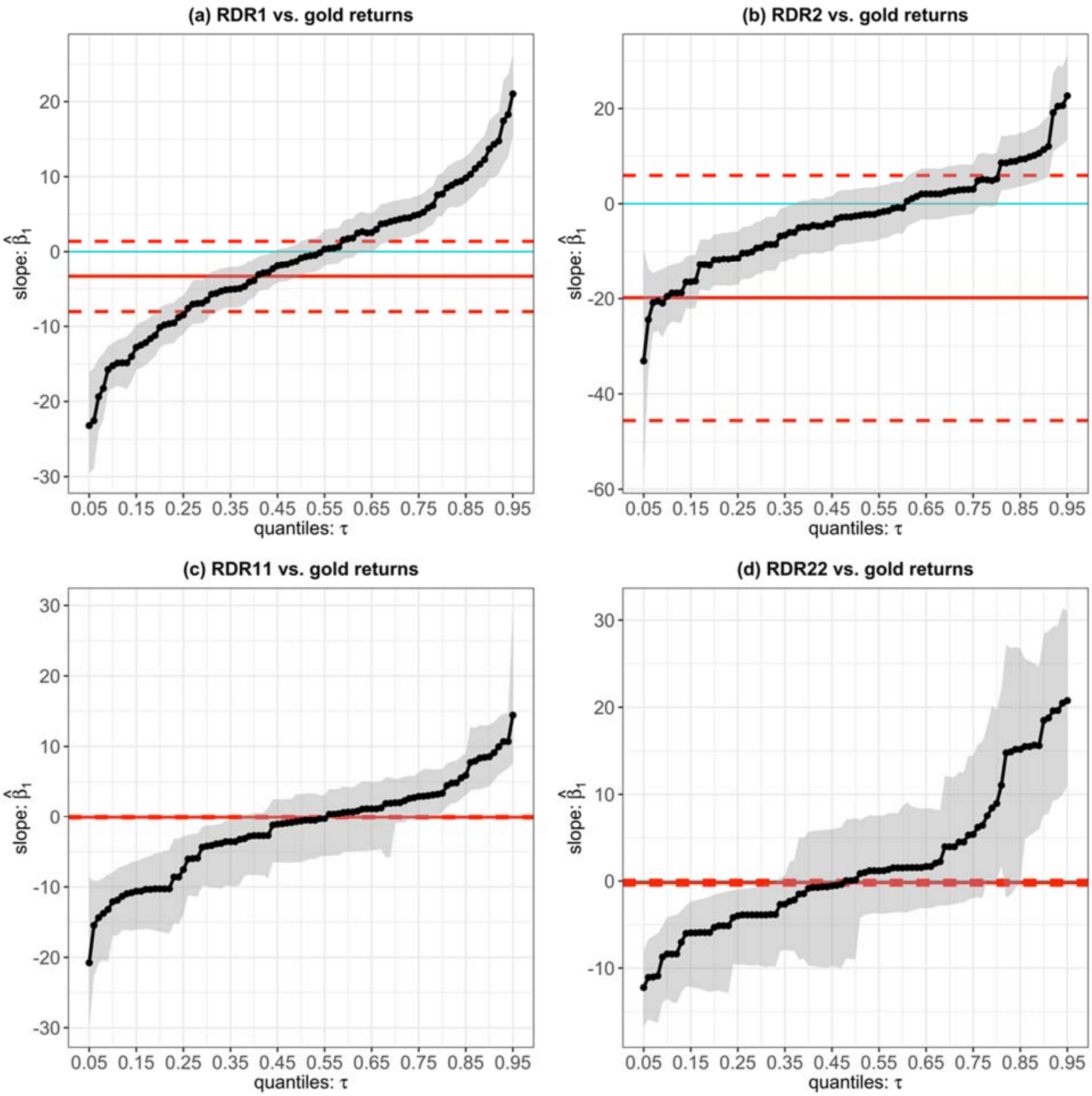
Given the statistically insignificant results of the effects of the rare disaster risks covariates under the linear model, we wanted to check if this is because of the fact being misspecified. In this regard, we conducted the Brock et al. (1996, BDS) test of nonlinearity, as well as the powerful *UDMax* and *WDMax* tests of multiple structural breaks of Bai and Perron (2003). As can be seen from Table A2 in the Appendix, the null hypothesis of *iid* residuals of equation (1) is overwhelmingly rejected across various dimensions considered, and is indicative of uncaptured nonlinearity. While structural breaks could not be detected under RDR1, a minimum of 4 breaks were obtained between the relationship of real gold returns with RDR2, RDR11 and RDR22, as reported in Table A3 in the Appendix. Over and above the non-normal distributions of the variables involved, these results from the nonlinearity and structural instability analyses, highlight, on the one hand, the inappropriateness of the linear predictive regression model and, on the other hand, indicate the necessity to employ a quantiles-based approach.

Figure 1. Slope parameter estimates from linear quantile regression: real gold returns vs. rare disasters



Note: The figure plots the slope estimates $\hat{\beta}_1$ at the 91 equally spaced quantiles from the 0.05-th quantile to 0.95-th quantile. The parameter estimates are plotted against the quantiles with a dotted bold line. A point-wise 95% confidence interval is indicated (gray shaded regions) around the quantile regression parameter estimates. The confidence intervals are obtained using the wild bootstrap method of Feng *et al*. (2011) with 2000 bootstrap draws. Superimposed on the graphs are the OLS parameter estimates (solid horizontal line) and their 95% confidence intervals (two dashed horizontal lines). A horizontal line is drawn at zero (thin light line) to indicate $\beta_1 = 0$, the null effect.

Figure 2. Slope parameter estimates from nonparametric quantile regression: real gold returns vs. rare disasters



Note: The figure plots the nonparametric slope estimates $\hat{\beta}_1$ at the 91 equally spaced quantiles from the 0.05-th quantile to 0.95-th quantile. The nonparametric quantile regressions are estimated using the method of Koenker *et al*. (1994). The reported slope estimates are obtained at the median value of the independent variable. The slope estimates are plotted against the quantiles with a dotted bold line. A point-wise 95% confidence interval is indicated (gray shaded regions) around the quantile regression parameter estimates. Superimposed on the graphs are the OLS parameter estimates (solid horizontal line) and their 95% confidence intervals (two dashed horizontal lines). A horizontal line is drawn at zero (thin light line) to indicate $\beta_1 = 0$, the null effect.

Given the issue of misspecification of the linear model, we turn next to effects of RDR1, RDR2, RDR11 and RDR22 on real gold returns under linear and nonparametric quantile regressions reported in Figures 1 and 2 respectively. Concentrating first on the results from the linear quantile regressions in Figure 1, we find that the four rare disaster risks related variables tend to produce significant negative effects on real gold returns at extreme-low to moderate-low quantiles under the global probabilities of the occurrence of rare disaster events: RDR1 and RDR2, but the effect stretches to the median under RDR11 and RDR22, i.e., for the cases involving number of countries facing rare disaster events. Comparatively, at times intermittent significant positive effects are only detected at extreme upper quantiles of gold returns, particularly under RDR22, and to some extent for RDR1 and RDR11 as well. Overall, rare disaster events seem to affect real gold returns negatively, except when the market is characterized by an exceptional bullish-phase. Alternatively put, evidence in favor of gold serving as a hedge against rare disaster risks is, at best, weak, and is associated when gold returns are extremely high.

In Figure 2, we now focus our attention on the results from the relatively robust nonparametric quantile regression in light of the evidence of nonlinearity and regime changes. While the significant negative impact below the median is still observable as in Figure 1 under the linear quantile regressions, but now, we also detect significant increases in gold returns under all four measures of rare disasters beyond the quantile of 0.75. In other words, we obtain evidence supporting our hypothesis that gold acts as a hedge against risks associated with rare disaster events, but for this to happen the market must be at its moderately-high to extremely-high conditional quantiles, i.e., in its bullish-state.

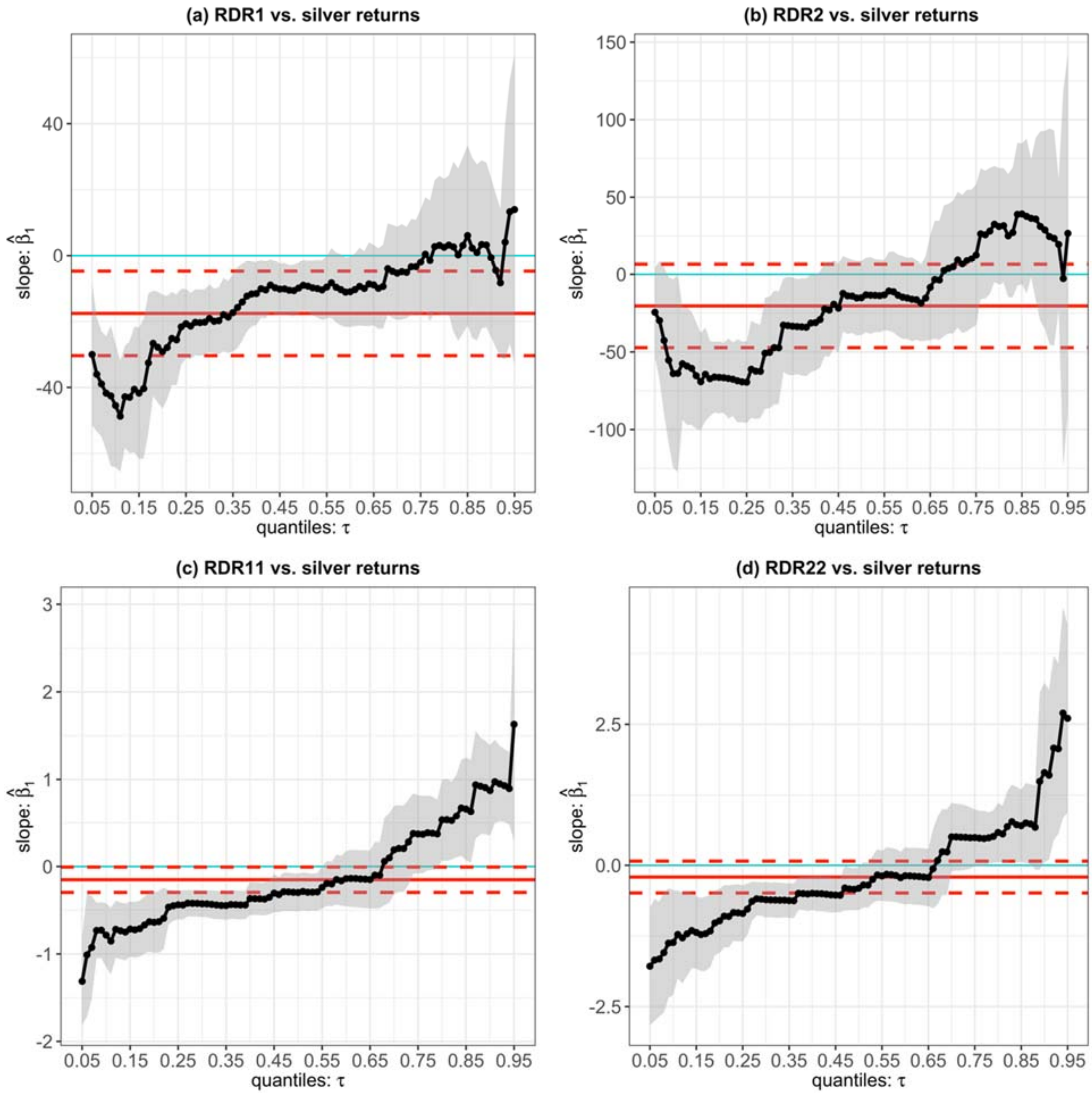
At this stage, our finding that gold can act as a hedge against rare disaster risks when its returns are in a good-state, warrants a bit of discussion. Our result tend to suggest that, while negative output effects can indeed increase real gold returns, but for that to happen the market must be soaring already, i.e., financial markets are possibly already in turmoil. This is likely to happen if gold prices and or returns are also affected by relatively faster moving behavioral variables, such as economic sentiment, evidence of which can be found in Balcilar et al. (2017) and Bonato et al. (2018), before a rare disaster event fully manifests. In other words, as output starts declining, and that period can be categorized as a rare disaster, negative sentiments are likely to have already set-in to adversely impact the conventional asset markets (see, Da et al. (2015) for a detailed discussion on the link between sentiment and asset prices), and drive gold prices and or returns higher.

3.2. Additional results

Just like real gold returns, we also consider the impact of our rare disaster risks variables on real silver returns using the linear and nonparametric quantile regressions, with results reported in Figures 3 and 4. As with gold, the four rare disaster risk variables have a significantly negative impact at the lower conditional quantiles of real silver returns, while the effect is positive and significant at the upper end, with this effect particularly noticeable under the relatively robust nonparametric quantile regression.[5] In other words, just like gold, silver too seems to act as a hedge against risks associated with rare disaster events during its bullish phase wherein real silver returns increases following rise in the global probability and number of countries facing such risks, but not so during its bearish-state, at which real silver returns is negatively impacted.

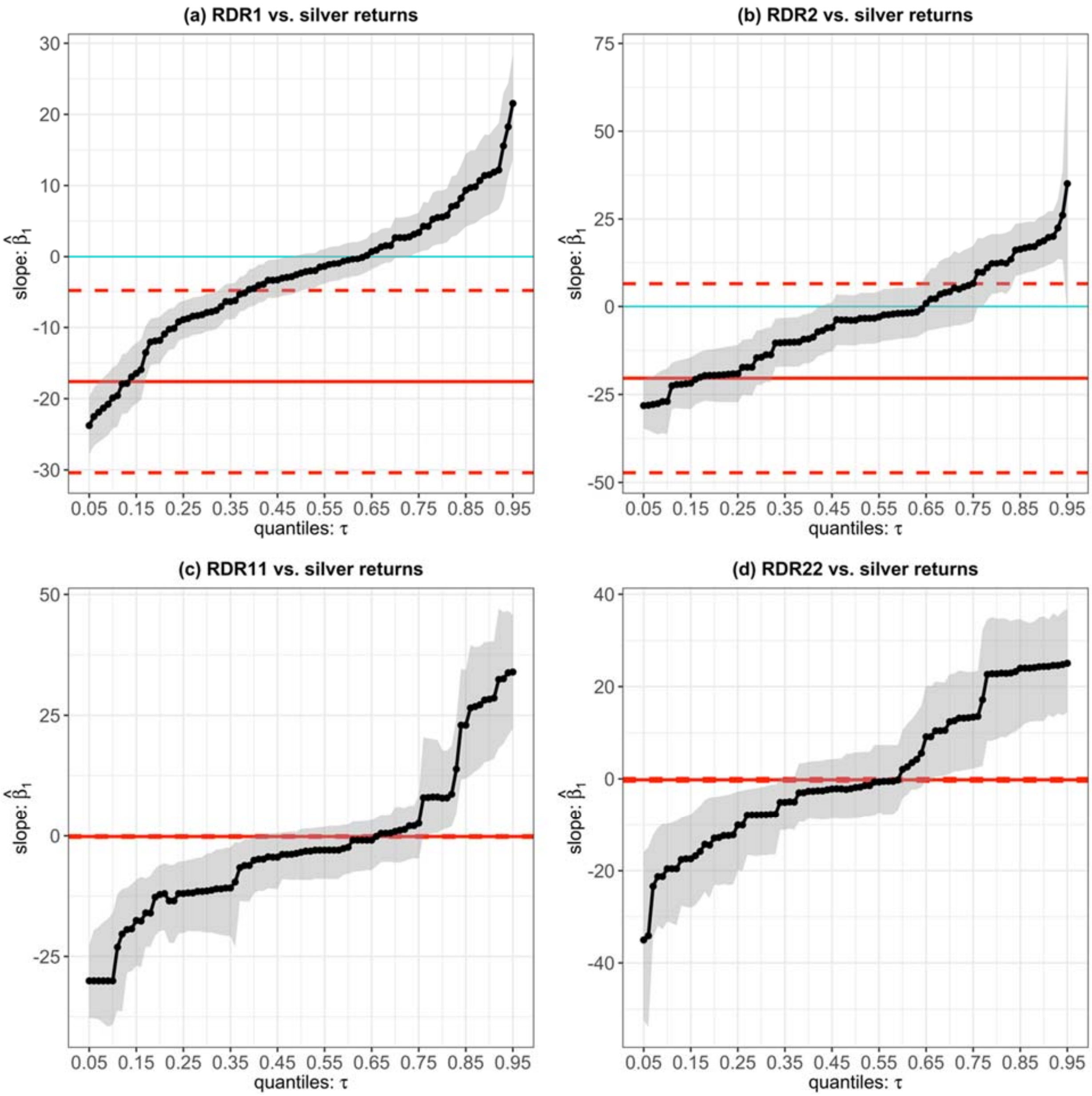
[5] The estimates of β_1 in equation (1) are respectively (with *p*-values in parenthesis): -18.067 (0.001), -20.962 (0.122), -0.150 (0.115), and -0.208 (0.204), i.e., negative and statistically insignificant effects, barring the case of RDR1 (see also Figures 3 and 4) – an observation, in general, again in line with Barro and Misra (2016).

Figure 3. Slope parameter estimates from linear quantile regression: real silver returns vs. rare disasters



Note: The figure plots the slope estimates $\hat{\beta}_1$ at the 91 equally spaced quantiles from the 0.05-th quantile to 0.95-th quantile. The parameter estimates are plotted against the quantiles with a dotted bold line. A point-wise 95% confidence interval is indicated (gray shaded regions) around the quantile regression parameter estimates. The confidence intervals are obtained using the wild bootstrap method of Feng *et al*. (2011) with 2000 bootstrap draws. Superimposed on the graphs are the OLS parameter estimates (solid horizontal line) and their 95% confidence intervals (two dashed horizontal lines). A horizontal line is drawn at zero (thin light line) to indicate $\beta_1 = 0$, the null effect.

Figure 4. Slope parameter estimates from nonparametric quantile regression: real silver returns vs. rare disasters



Note: The figure plots the nonparametric slope estimates $\hat{\beta}_1$ at the 91 equally spaced quantiles from the 0.05-th quantile to 0.95-th quantile. The nonparametric quantile regressions are estimated using the method of Koenker *et al*. (1994). The reported slope estimates are obtained at the median value of the independent variable. The slope estimates are plotted against the quantiles with a dotted bold line. A point-wise 95% confidence interval is indicated (gray shaded regions) around the quantile regression parameter estimates. Superimposed on the graphs are the OLS parameter estimates (solid horizontal line) and their 95% confidence intervals (two dashed horizontal lines). A horizontal line is drawn at zero (thin light line) to indicate $\beta_1 = 0$, the null effect.

As a further analysis, we used the quantile-on-quantile regression approach of Sim and Zhou (2015), with the technical details provided in Appendix B, to investigate if the quantile-specific impact on real gold and real silver returns are dependent on the size of the rare disaster risks variables, i.e., its quantiles. These results for real gold and real silver returns have been presented in Figures 5 and 6 respectively. As can be seen, that the size of the global probability of rare disaster events, or increase in the number of countries facing rare disaster risks does not tend to alter our existing results obtained from the nonparametric quantile regressions in particular. That is, the hedging strength of gold and silver at their respective upper conditional quantiles is unaffected by the magnitude of the covariates. This is possibly an indication that, once certain major global economies, which are also the main players in the gold and silver markets, face rare disaster risks, spillover of such risks to other economies does not necessarily have an impact on the gold and silver markets.

Figure 5. Slope parameter estimates from quantile-on-quantile regression: real gold returns vs. rare disasters

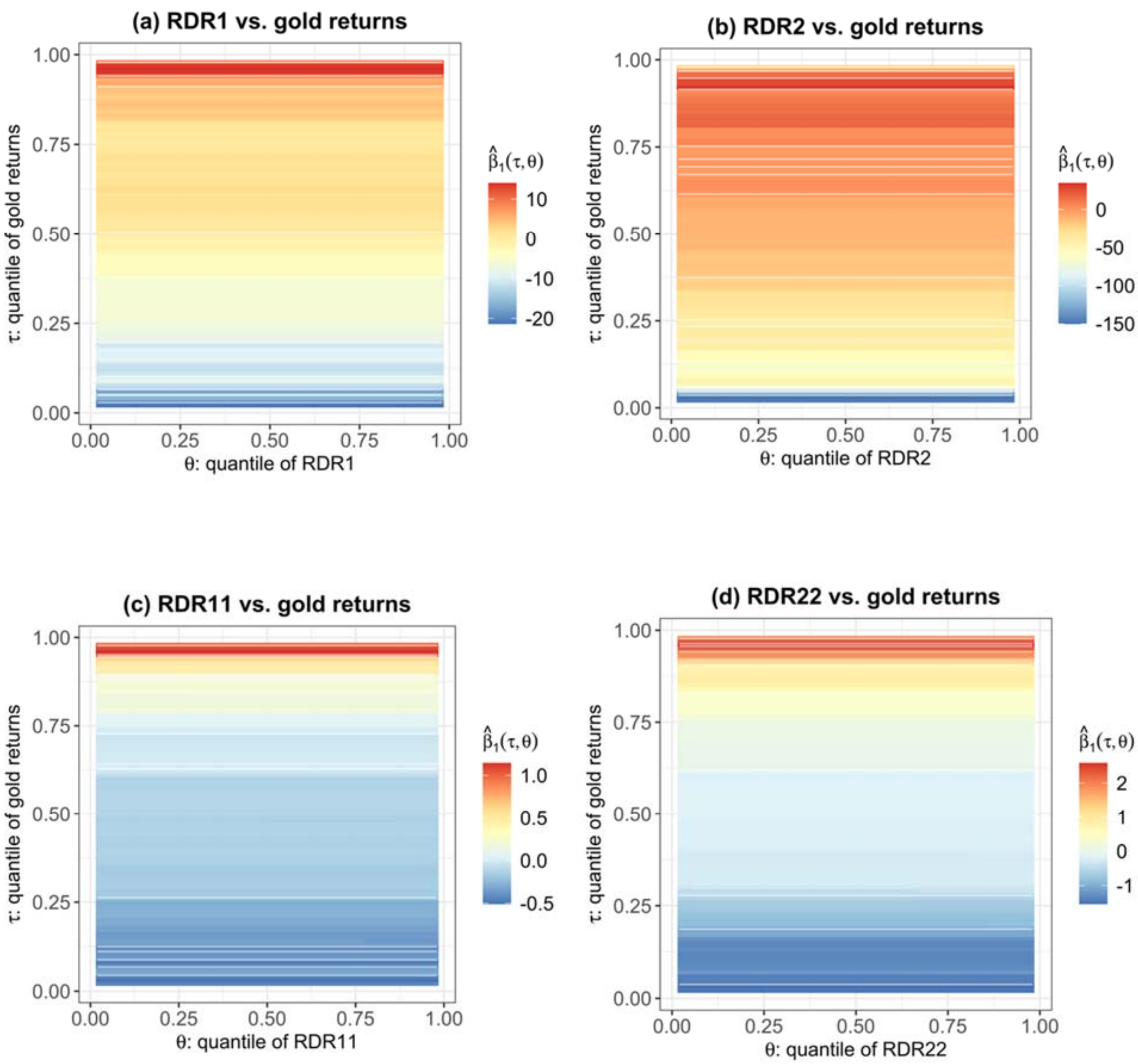
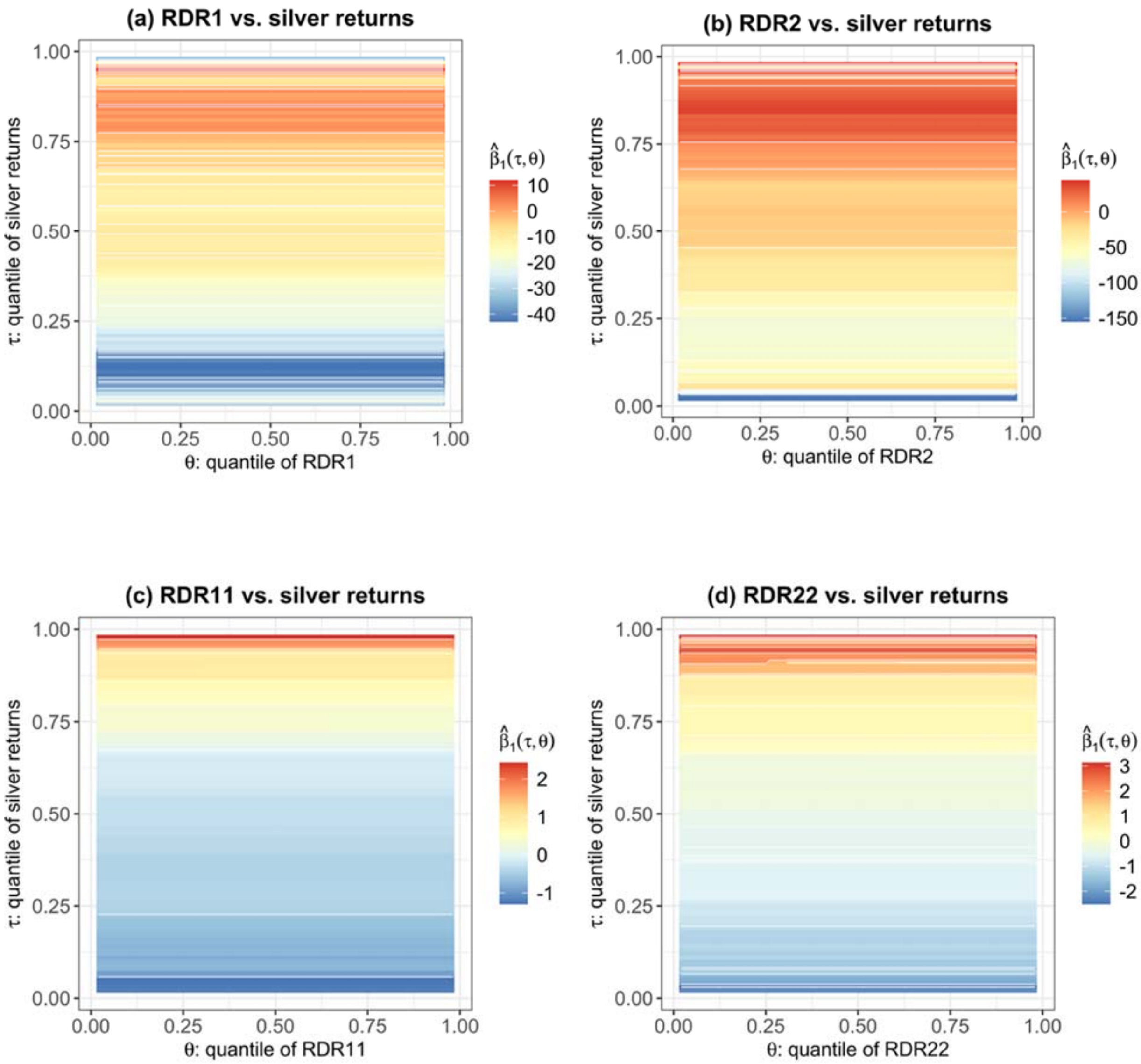


Figure 6. Slope parameter estimates from quantile-on-quantile regression: real silver returns vs. rare disasters



4. Conclusion

In this paper, we analyze the effects of rare disaster risks on real gold returns over the period of 1280 to 2016, based on linear and parametric quantile regressions. Rare disaster events are identified as the percentage of countries relative to the total number of countries for which data on output is available (i.e., global probability of the occurrence of a rare disaster event), as well as the number of countries, facing a cumulative decline of more than 10% in per capita real GDP and real GDP growth rates for a specific year. While, in line with the study of Barro and Misra (2016), standard linear (conditional mean) regressions fail to show any significant effect of the rare disaster risks variables on real gold returns, quantile regressions, and in particular nonparametric versions of the same, depict evidence of a significant negative impact at lower conditional quantiles and significant positive effect at upper conditional quantiles. Due to the existence of non-normality, nonlinearity and structural breaks in our data and relationships, quantile regression results are understandably more reliable than the non-results derived from a misspecified linear model. Our finding tends to suggest that, irrespective of the definition of rare disasters, gold serves as a hedge against associated risks of rare disaster events during its bullish-state. As a comparative analysis, real silver returns over 1688 to 2016 also provides similar observations. Furthermore, using a quantile-on-quantile approach reveals that, our results are unaffected by the size of the global probability of a rare disaster event or the number of countries facing the same.

Our findings have important implications for investors and academics. Understandably, in the wake of rare disaster events, gold traders must be aware that the safe haven property of gold is only likely to hold if the market is already performing well, since then only can gold hedge against such risks via increased real returns. But for this information to be available to the investors, they must be aware that one needs to rely on an underlying nonparametric quantiles-based econometric model. From an academic perspective, the existing rare disaster risks model involving gold of Barro and Misra (2016), which is derived to match the conditional mean-based empirical observation of insignificant statistical relationship between gold returns and rare disaster risks, needs to be modified. In particular, this asset pricing framework would require to theoretically model regime-specific movement of precious metals, such as gold and silver, to match the quantile-specific negative and positive impact of rare disasters on the returns of these commodities, as originally existing in the data.

As far as future research is concerned, besides the theoretical extension discussed above, it would be interesting to extend our analysis to a forecasting exercise for not only gold returns, but also its volatility, given that the market is not only characterized by leverage (Asai et al., 2019, 2020), i.e., good and bad news related to returns emanating from rare disasters is also likely to impact its variability.[6]

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[6] In fact, using the *k*-th order nonparametric causality-in-quantiles test of Balcilar et al. (2018), we were able to detect in-sample predictability for not only real gold (and real silver) returns, but also squared returns, i.e., volatility over majority of the conditional distributions of these two variables of interest. Complete details of these results are available upon request from the authors.

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Appendixes:
Appendix A:

Table A1. Summary statistics

	Variable					
Statistic	Real Gold Returns	Real Silver Returns	RDR1	RDR2	RDR11	RDR22
Mean	-0.354	-0.583	0.171	0.067	3.022	4.959
Median	-0.440	-1.004	0.125	0.047	1.000	2.000
Maximum	137.960	50.566	1.000	0.463	63.000	45.000
Minimum	-41.580	-65.188	0.000	0.000	0.000	0.000
Std. Dev.	11.596	13.180	0.178	0.081	7.053	7.708
Skewness	2.242	0.370	1.167	2.236	5.043	2.934
Kurtosis	31.478	7.470	4.210	9.237	32.958	13.256
Jarque-Bera	25521.05^{***}	281.38^{***}	212.286^{***}	483.37^{***}	30684.42^{***}	1146.00^{***}
Observations	737	329	737	197	737	197

Note: *** indicates rejection of the null-hypothesis of normality at the 1% level of significance.

Table A2. BDS test

	Real Gold Returns				Real Silver Returns			
Dimension	RDR1	RDR2	RDR11	RDR22	RDR1	RDR2	RDR11	RDR22
2	8.287^{***}	7.862^{***}	8.503^{***}	7.252^{***}	6.105^{***}	5.727^{***}	6.484^{***}	4.403^{***}
3	9.921^{***}	9.610^{***}	10.061^{***}	8.865^{***}	9.527^{***}	7.826^{***}	9.308^{***}	7.023^{***}
4	11.108^{***}	10.191^{***}	11.227^{***}	9.639^{***}	10.685^{***}	8.373^{***}	10.540^{***}	8.406^{***}
5	11.915^{***}	10.378^{***}	12.029^{***}	9.876^{***}	12.145^{***}	9.607^{***}	12.013^{***}	9.946^{***}
6	12.902^{***}	11.334^{***}	13.038^{***}	10.906^{***}	13.294^{***}	10.563^{***}	13.199^{***}	11.127^{***}

Note: See Notes to Table 1; The test is applied on the residuals recovered from the linear regression of real gold or real silver returns as the dependent variable and a specific rare disaster risks measure (RDR1, RDR2, RDR11, RDR22) as the independent variable.

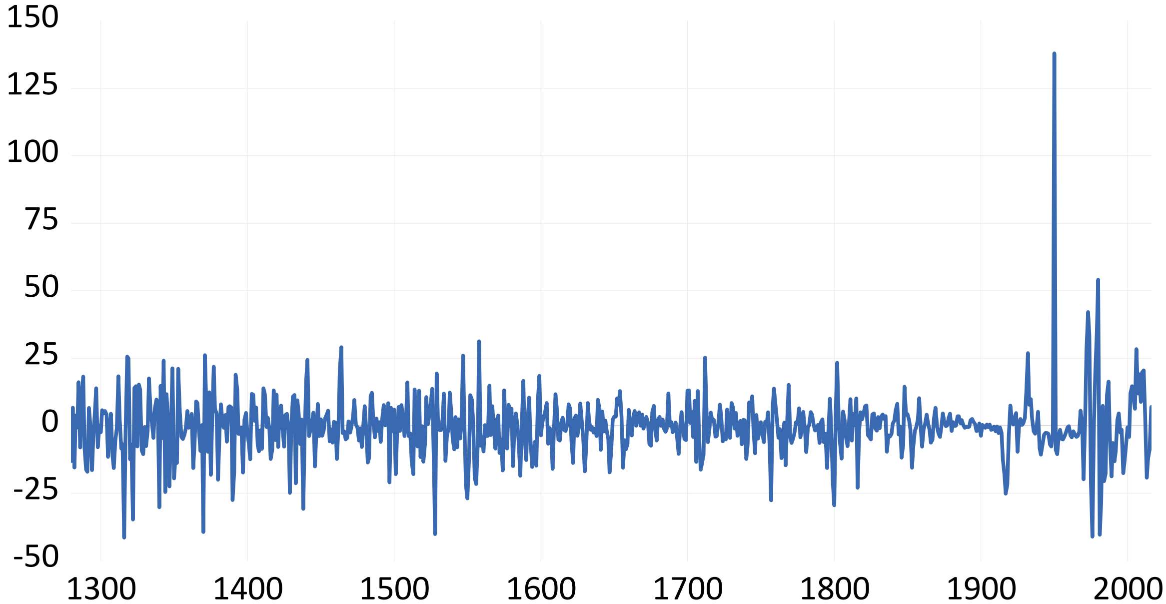
Table A3. Multiple breaks test

Dependent Variable	Independent Variable	*UDmax* test statsitic	*WDmax* test statsitic
Real Gold Returns	RDR1		
	RDR2	1879, 1919, 1952, 1981	1850, 1879, 1919, 1952, 1981
	RDR11		1423, 1595, 1706, 1817
	RDR22	1852, 1883, 1921, 1952, 1981	1852, 1883, 1921, 1952, 1981
Real Silver Returns	RDR1		
	RDR2		1884, 1916, 1949, 1981
	RDR11		
	RDR22	1916, 1950, 1986	1884, 1916, 1950, 1986

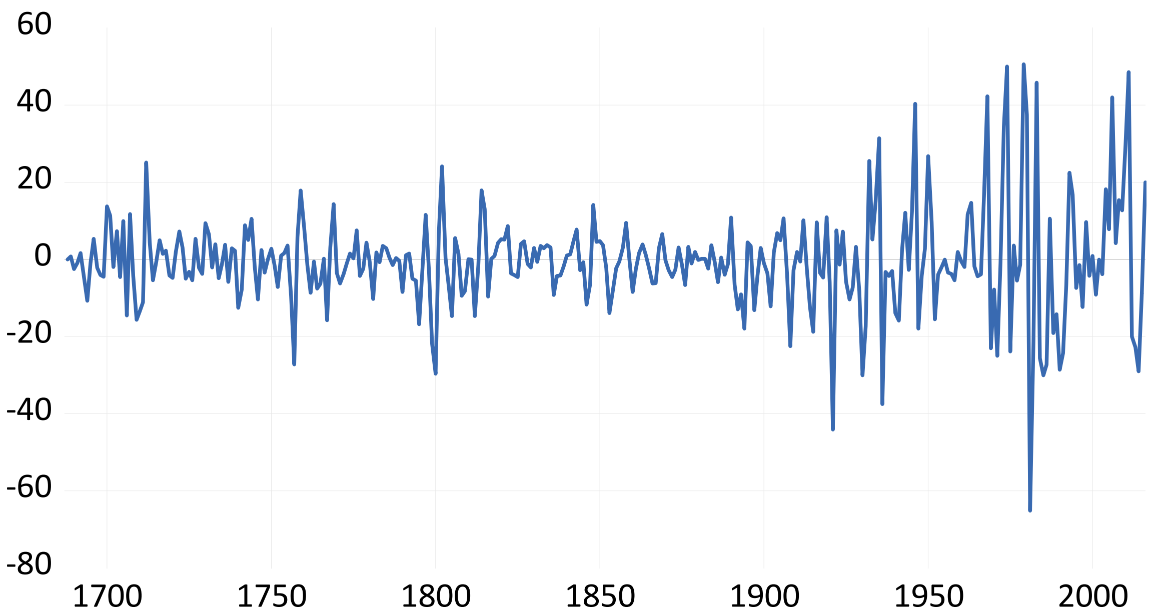
Note: The test is applied on the linear regression of real gold or real silver returns as the dependent variable and a specific rare disaster risks measure (RDR1, RDR2, RDR11, RDR22) as the independent variable.

Figure A1. Data plots

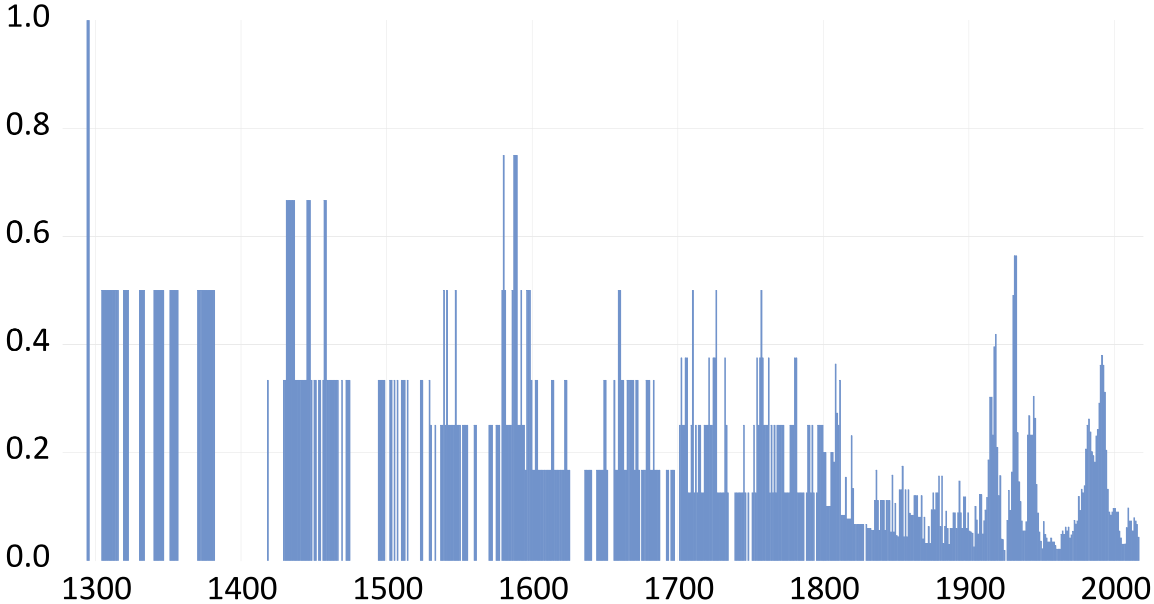
A1(a). Real Gold Returns



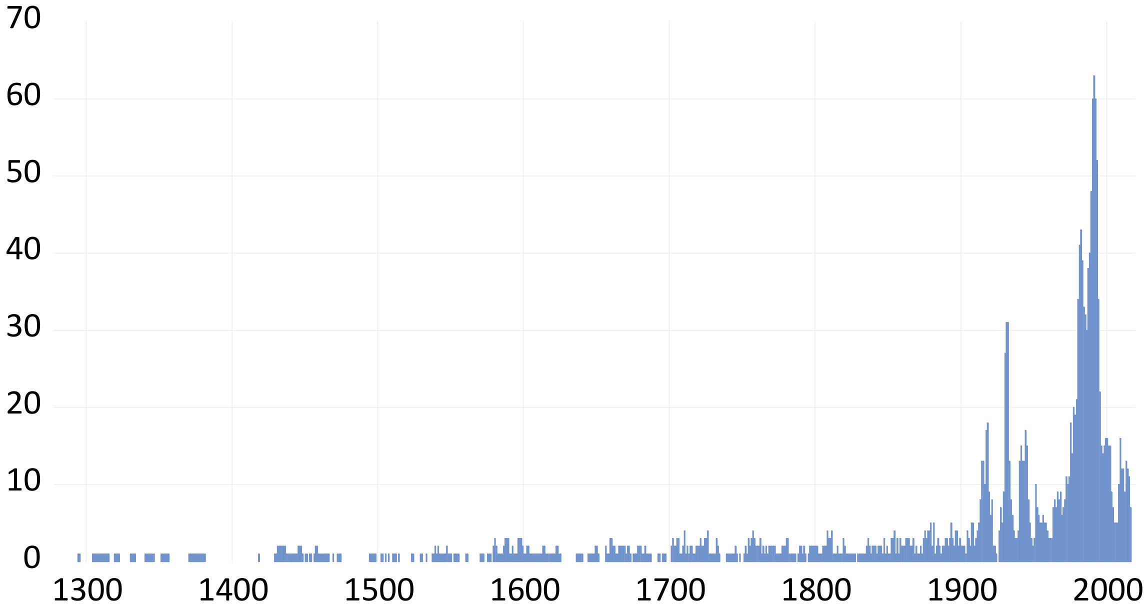
A1(b). Real Silver Returns



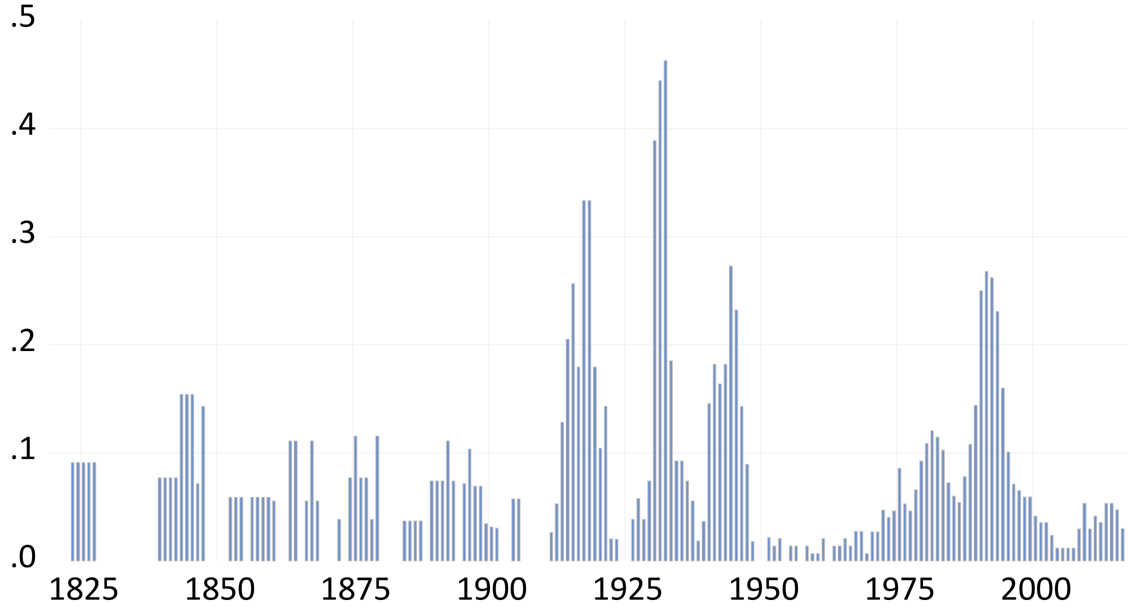
A1(c). RDR1



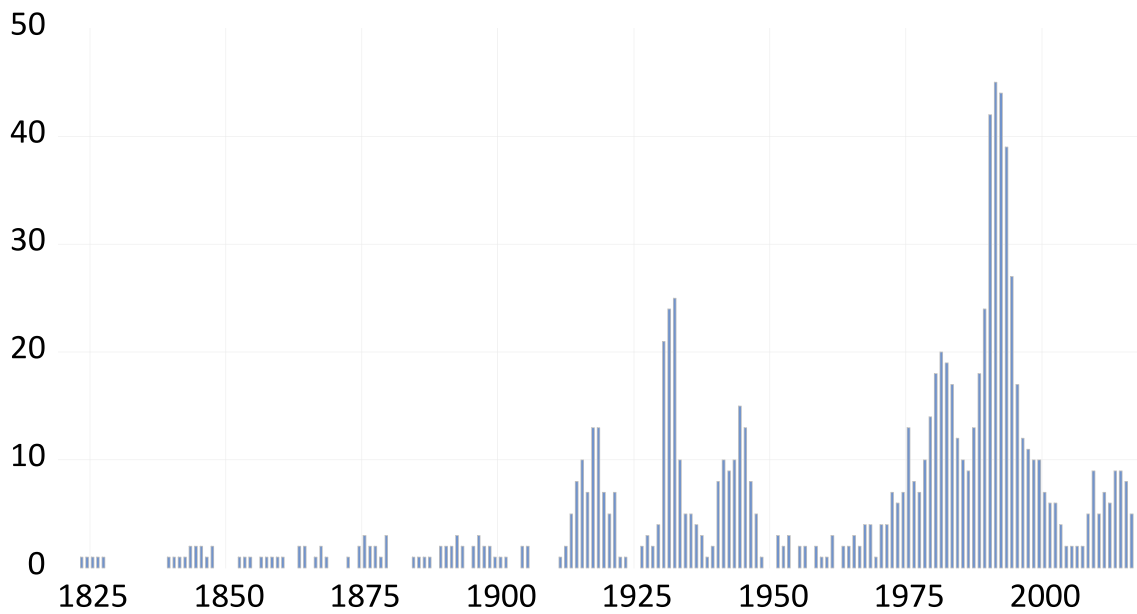
A1(d). RDR11



A1(e). RDR2



A1(f). RDR22



APPENDIX B:
Technical details of the quantile-on-quantile (QQ) regression methodology:

The linear quantile regression model in equation (2) allows the effect of rare disaster risk to vary across the different quantiles of real gold (or silver) returns. However, the response of returns may also depend on the magnitude of rare disaster risks. The standard quantile regression is unable to capture the dependence on the covariate x_t. In order to get a comprehensive insight, we focus on the relationship between the τ-th quantile of real gold (or silver) returns and the θ-th quantile of the rare disaster risk x_t, denoted by x_θ, $\theta \in (0,1)$. Sim and Zhou (2015) consider a non-parametric specification $y_t = \beta(\tau, x_t) + \varepsilon_t(\tau)$ and a first order Taylor expansion of $\beta(\tau, x_t)$ around a quantile x_θ to obtain the following quantile-on-quantile (QQ) regression model:

$$y_t = \beta_0(\tau,\theta) + \beta_1(\tau,\theta)(x_t - x_\theta) + \varepsilon_t(\tau) \tag{B1}$$

where the term $\beta_0(\tau,\theta) + \beta_1(\tau,\theta)(x_t - x_\theta)$ is the τ-th conditional quantile of the real gold (or silver) returns. Indeed, this specification obtains a linear model in doubly indexed parameter, but allows us to examine whether marginal effect of rare disaster risk varies with its magnitude within a linear specification. Unlike the standard conditional quantile function, equation (B1) captures the overall dependence structure between the θ-th quantile of rare disaster risk and the τ-th quantile of real gold (or silver) returns as the parameters β_0 and β_1 are doubly indexed in τ and θ. Sim and Zhou (2015) propose a local linear regression to estimate the parameters of the QQ model by solving the following minimization:

$$\min_{\beta \in \mathbb{R}^2} \sum_{t=1}^{T} \rho_\tau [y_t - \beta_0 \ - \beta_1(x_t - x_\theta)]\, K\left(\frac{F_T(x_t) - \theta}{h}\right) \tag{B2}$$

where $F_T(x_t) = \frac{1}{T}\sum_{k=1}^{T} I(x_k < x_t)$, $t = 1,2,\ldots,T$, is the empirical distribution function of x_t, $K(\cdot)$ denotes the kernel function and h is the bandwidth parameter of the kernel. The linear program in equation (B2) is solved analogous to the standard quantile regression in equation (5) to get the QQ estimates of parameters: $\beta(\tau,\theta) = (\beta_0(\tau,\theta), \beta_0(\tau,\theta))'$. Note that the kernel weights are inversely related to the distance between the empirical distribution function $F_T(x_t)$ of x_t and the θ.

The QQ regression model requires selections for the kernel function $K(\cdot)$ and bandwidth h. Because of its computational simplicity and efficiency, the Gaussian kernel is used to weight the observations in the neighborhood of x_θ for the QQ regression. The bandwidth parameter h is selected using the least-squares cross validation (CV) regression approach with a local linear regression based on the method of Li and Racine (2004).

At this stage, we must highlight an important issue, as indicated in the main text, when the shapes of quantile curves are nonlinear, and even depend on the quantile parameter, the linear quantile regression does not always suffice to adequately express the relationship between covariates and quantile functions of the response variable. While the QQ model is a solution to a linear model, but it too makes parametric assumptions, which in turn may not be rich enough to capture arbitrary nonlinearities. In light of this, the importance of nonparametric quantile regressions cannot be overlooked.