

Contagious Diseases and Gold: Over 700 Years of Evidence from Quantile Regressions[#]

Elie Bouri^{*}, Rangan Gupta^{**}, Jacobus Nel^{***} and Sisa Shiba^{****}

Abstract

We investigate the effect of the probability of fatality due to contagious diseases on real gold returns over the period 1258 - 2020. To this end, we use a predictive quantile-regression model, which is justified by the features of non-normality, nonlinearity and structural breaks in the data involving real gold returns and the probability of fatality resulting from outbreaks of contagious diseases. The results show that real gold returns can hedge the risks of the probability of fatality due to contagious diseases primarily when the gold market is bullish. However, the effect is negative when the gold market is bearish, suggesting no hedging ability. These results are important for investors seeking refuge in gold during rare disaster events.

Keywords: Real gold returns; Contagious Diseases; COVID-19 outbreak; Probability of fatality; Predictive quantile-regression model

JEL Codes: C22, Q02

1. Introduction

In line with the literature on rare disaster risks and the gold market (Barro and Mishra, 2016; Salisu et al., forthcoming), a few recent studies have related gold price movements with the number of global infections, fatalities, and metrics of macroeconomic uncertainties resulting from the spread of the COVID-19 pandemic (see for example, Ali et al. (2020), Ji et al. (2020), Salisu et al. (2021), Tanin et al. (2021), Wang (2021); Zhang et al. (2022)). In general, these studies tend to suggest that gold returns are affected positively in a statistically significant manner by infections, fatalities, or uncertainties, whereas an insignificant effect is found when the downside risks of the gold

[#] We would like to thank an anonymous referee for many helpful comments. However, any remaining errors are solely ours.

^{*} School of Business, Lebanese American University, Beirut, Lebanon; Email: elie.elbouri@lau.edu.lb.

^{**} Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: rangan.gupta@up.ac.za.

^{***} Corresponding author. Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: neljaco380@gmail.com.

^{****} Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: u20810939@tuks.co.za.

market are considered. This suggest that gold can act as a safe haven or even a hedge against the risks produced by the recent Coronavirus pandemic.

In this paper, we aim to build on this line of research from a historical perspective by analyzing the predictive impact of the global probability of fatality (i.e., number of deaths relative to the population) due to contagious diseases on real gold log-returns. . In the process, we go beyond just the COVID-19 episode like most of the existing studies have done so far by considering a long sample period from 1258 to 2020 covering as many as 62 outbreaks of contagious diseases starting with the Black Death in 1331.

From an econometric perspective, we use a quantile regression approach in extension of the benchmark linear model. We show in overwhelming fashion that our dataset exhibits non-linearity and non-normality patterns, which makes a linear regression approach inadequate for examining the ability of the probability of fatality due to an outbreak of contagious diseases in predicting real gold returns. The standard linear regression approach only considers the conditional mean of real gold returns, it is likely to “hide” interesting characteristics and valuable information for certain parts of the conditional distribution of real gold returns. Thus, it might lead us to conclude that the probability of fatalities due to rare disasters events, i.e., outbreaks of contagious diseases, has poor explanatory power while it actually has a strong one. Alternatively, a quantiles-based method, 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. Another benefit of the quantile-based method is that unlike the Markov-switching and the smooth threshold models, it does not require us to specify number of regimes of real gold returns (for instance, bear and bull) in an ad hoc fashion. This is because, bear periods in the gold market will correspond to the low quantiles or the left tail of the returns distribution, while bull periods will be reflected via the high quantiles or right tail of the same. Notably, the quantile regression studies the entire conditional distribution, which captures various states of the gold market, and thus it adds an inherent time-varying component to the estimation process.

Our analysis shows that gold can only serve as a hedge against rare disaster risks stemming from the probability of fatality due to contagious diseases in its bullish-state, but not so in its bearish-phase, to the extent that extremely low (conditional) real gold returns are negatively impacted by our metric of rare disaster risks. To the best of our knowledge, this result presents the first empirical evidence on the hedging ability of gold while considering the probability of fatality due to contagious diseases spanning the longest possible available history. This nicely complements Salisu et al. (2021) and Tanin et al. (2021) and avoids any sample selection bias, while providing a complete picture of the evolution of the gold market in the wake of deaths from outbreaks of contagious diseases. Furthermore, it extends Wang (2021) who considers a shorter sample period covering January 23, 2020 to July 10, 2020 and a daily dataset.

Understandably, our findings should be of immense value to portfolio allocation decision of investors, if we detect evidence of quantile-specific impact of the probability of fatality resulting from contagious diseases, especially given that waves of COVID-19 continue to raise the global death toll on a daily basis.

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

For the price of gold, we use annual data of nominal prices (in British pounds) starting in 1257, and is retrieved from MeasuringWorth.¹ 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” till 2016,² and then for the remainder of the period, i.e., 2017-2020, we rely on the Main Economic Indicators (MEI) of the Organisation for Economic Co-operation and Development (OECD).³ We then compute the log-returns of real gold prices (r) over the period of 1258 to 2020.

We construct a time-series measure of the probability of fatality (pf) from a data set created by Cirillo and Taleb (2020). They provide the start- and end-dates, (lower, average and upper) estimates of fatalities, and the population at the time of major pandemics and epidemics spanning from 429 BC, involving events with more than an estimated 1000 victims. We use the average estimate of fatalities and distribute them equally across the years of the event (pandemic or epidemic) to create a time series of fatalities over time. We then divide the fatalities by the population estimate at the time of the particular event, which we keep the same in the case the pandemic or epidemic spans multiple years, to obtain the pf over the period of 1258 to 2020, i.e., the same sample size as r . Table 1 provides complete details of the events considered in this study.

¹ <https://www.measuringworth.com/>.

² <https://www.bankofengland.co.uk/statistics/research-datasets>.

³ <https://www.oecd.org/sdd/oecdmaineconomicindicatorsmei.htm>.

Table 1. Details of the contagious diseases considered

Pandemic or Epidemic	Start	End	Average Fatality Estimate (x10³)	Population (x10⁶)
Black Death	1331	1353	137500	392
Sweating Sickness	1485	1551	10	461
Smallpox Epidemic in Mexico	1520	1520	6500	461
Cocoliztli Epidemic of 1545-1548	1545	1548	10000	461
1563 London Plague	1562	1564	20	554
Cocoliztli Epidemic of 1576	1576	1580	2250	554
1592-1593 London Plague	1592	1593	20	554
Malta Plague Epidemic	1592	1593	3	554
Plague in Spain	1596	1602	650	554
New England Epidemic	1616	1620	7	554
Italian Plague of 1629-1631	1629	1631	280	554
Great Plague of Sevilla	1647	1652	150	554
Plague in the Kingdom of Naples	1656	1658	1250	603
Plague in the Netherlands	1663	1664	24	603
Great Plague of London	1665	1666	100	603
Plague in France	1668	1668	40	603
Malta Plague Epidemic	1675	1676	11	603
Great Plague of Vienna	1679	1679	76	603
Great Northern War Plague Outbreak	1700	1721	192	603
Great Smallpox Epidemic in Iceland	1707	1709	18	603
Great Plague of Marseille	1720	1722	100	603
Great Plague of 1738	1738	1738	50	814
Russian Plague of 1770-1772	1770	1772	50	814
Persian Plague	1772	1772	2000	990
Ottoman Plague Epidemic	1812	1819	300	990
Caragea's Plague	1813	1813	60	990
Malta Plague Epidemic	1813	1814	5	990
First Cholera Pandemic	1816	1826	100	990
Second Cholera Pandemic	1829	1851	100	990
Typhus Epidemic in Canada	1847	1848	20	990
Third Cholera Pandemic	1852	1860	1000	1263
Cholera Epidemic of Copenhagen	1853	1853	5	1263
Third Plague Pandemic	1855	1960	18500	1263
Smallpox in British Columbia	1862	1863	3	1263
Fourth Cholera Pandemic	1863	1875	600	1263
Fiji Measles Outbreak	1875	1875	40	1263
Yellow Fever	1880	1900	125	1263
Fifth Cholera Pandemic	1881	1896	9	1654
Smallpox in Montreal	1885	1885	3	1654
Russian Flu	1889	1890	1000	1654
Sixth Cholera Pandemic	1899	1923	800	1654

China Plague	1910	1912	40	1654
Encephalitis Lethargica Pandemic	1915	1926	1500	1654
American Polio Epidemic	1916	1916	7	1654
Spanish Flu	1918	1920	58500	2307
HIV/AIDS Pandemic	1920	2020	30000	3712
Poliomyelitis in USA	1946	1946	2	2948
Asian Flu	1957	1958	2000	2948
Hong Kong Flu	1968	1969	1000	3637
London Flu	1972	1973	1	3866
Smallpox Epidemic of India	1974	1974	15	4016
Zimbabwean Cholera Outbreak	2008	2009	4	6788
Swine Flu	2009	2009	364	6788
Haiti Cholera Outbreak	2010	2020	10	7253
Measles in Democratic Republic of Congo (DRC)	2011	2018	5	7253
Ebola in West Africa	2013	2016	11	7176
Indian Swine Flu Outbreak	2015	2015	2	7253
Yemen Cholera Outbreak	2016	2020	4	7643
2018-19 Kivu Ebola Epidemic	2018	2020	2	7643
2019-20 COVID-19 Pandemic	2019	2020	133.5	7643
Measles in DRC	2019	2020	5	7643
Dengue fever	2019	2020	2	7643

Note: Sourced from Table 1 of Cirillo and Taleb (2020).

2.2. Methodologies

In the Appendix, the variables have been plotted in Figure A1, while Table A1 summarizes the main statistics of the data and highlights the existence of non-normality of the variables – a preliminary motivation to consider a quantiles-based approach to address our research question.

The classical linear predictive mean-regression model is given by:

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{t+1} \quad (1)$$

where r_{t+1} is the observed real gold log-returns over time period t to $t+1$, $x_{i,t}$ is a specific predictor at time t , which in our case is the probability of fatality (pf), and ε_{t+1} is the error term, that is assumed to be independent with zero mean and variance σ^2 . The ordinary least squares (OLS) estimators, $\hat{\alpha}_i, \hat{\beta}_i$, of the parameters in the predictive mean-regression model are estimated by minimizing the quadratic expected loss, $\sum_{t=0}^{T-1} (r_{t+h} - \alpha_i - \beta_i x_{i,t})^2$, with respect to the parameters, α_i, β_i .

The aforementioned model is primarily devised to predict the mean of r_{t+1} , and not its entire conditional distribution. Koenker and Bassett (1978) show that quantile-regression estimators are more efficient and robust than mean regression estimators when nonlinearities and deviations from

normality exist. Given that both of these features exist in our data, we consider the predictive quantile-regression model as follows:

$$r_{t+1} = \alpha_i^{(\tau)} + \beta_i^{(\tau)} x_{i,t} + \varepsilon_{t+1}, i = 1, \dots, N, \quad (2)$$

where $\tau \in (0,1)$, and ε_{t+1} is assumed independent derived from an error distribution $g_\tau(\varepsilon)$ with the τ -th quantile equal to 0. Eq. (2) implies the τ -th quantile of r_{t+1} given $x_{i,t}$, is $Q_\tau(r_{t+1}|x_{i,t}) = \alpha_i^{(\tau)} + \beta_i^{(\tau)} x_{i,t}$, where the intercept and the coefficients depend upon τ . The estimators of the parameters of the predictive quantile-regression model in Eq. (2), $\hat{\alpha}_i^{(\tau)}, \hat{\beta}_i^{(\tau)}$, are obtained by minimizing the sum $\sum_{t=0}^{T-1} \rho_\tau(r_{t+1} - \alpha_i^{(\tau)} - \beta_i^{(\tau)} x_{i,t})$, where the so called check function is being used, $\rho_\tau(u) = u(\tau - I(u < 0)) = \frac{1}{2}[|u| + (2\tau - 1)u]$.

3. Empirical findings

3.1. Main results

Preceding the presentation of the result from the quantiles-based model, we present in Table 2 the predictive-effect of the first-lag of pf on the conditional mean of real gold returns (r) based on standard OLS regression (with Newey and West (1987) Heteroskedasticity and Autocorrelation corrected (HAC) standard errors). The corresponding estimate of β_l in Eq. (1) is positive (53.6788), but statistically insignificant (p -value of 0.6379). This result tends to suggest that gold can indeed serve as a safe haven, as it is unaffected by the probability of fatality associated with contagious diseases, but cannot be used to hedge such risks, since the increase in real gold returns is not significantly different from zero.

Table 2. Slope parameter estimates from OLS regressions: real gold returns (r) on lagged probability of fatality (pf) due to contagious diseases

Sample	β_l
1258-2020	53.679 (0.729)
1258-1352	12.26710 (0.955)
1353-1548	640.3753 (0.102)
1549-1648	-3384.998** (0.045)
1649-1744	-9317.334 (0.112)
1745-1919	-434.1782 (0.596)
1920-2020	329.5397 (0.845)

Note: Entries are coefficient values of the OLS regression i.e., Eq. (1), with p -values given in parentheses, while ** indicates significance at the 5% level.

To examine whether the statistically insignificant coefficient of β_l under the linear model is due to model misspecification, we conduct the Brock et al. (1996, BDS) test of nonlinearity and the powerful *UDMax* and *WDMax* tests of multiple structural breaks of Bai and Perron (2003). As shown in Table 3, the null hypothesis of *iid* residuals of Eq. (1) is overwhelmingly rejected across the various dimensions considered, which is indicative of uncaptured nonlinearity. As far as regime-changes are concerned, the results from the tests of multiple structural breaks, indicate the presence of five structural breaks at: 1353, 1549, 1649, 1745, and 1920, which correspond to the periods in and around the Black Death, Sweating Sickness and the Cocoliztli Epidemic of 1545-1548, the Great Plague of Sevilla, the Great Plague of 1738, the Spanish Flu and the HIV/AIDS pandemic, respectively. Besides the non-normal distributions of the variables involved (see Table A1), these results from the nonlinearity and structural instability analyses point to the inappropriateness of the linear predictive regression model and the necessity to employ a quantiles-based approach. In other words, the linear predictive regression model does not tell the whole story, implying that there might be valuable information “hidden” elsewhere in the conditional distribution, say, the upper- and lower tails.

Table 3. BDS test

	Dimension (m)				
	2	3	4	5	6
<i>z</i> -statistic	6.6924***	9.9933***	11.5245***	12.5632***	13.5673***

Note: The test is applied on the residuals recovered from the linear regression of real gold returns (r) as the dependent variable and one lag of the probability of fatality (pf) as the independent variable; *** indicates rejection of the null-hypothesis of *iid* residuals at the 1% level of significance.

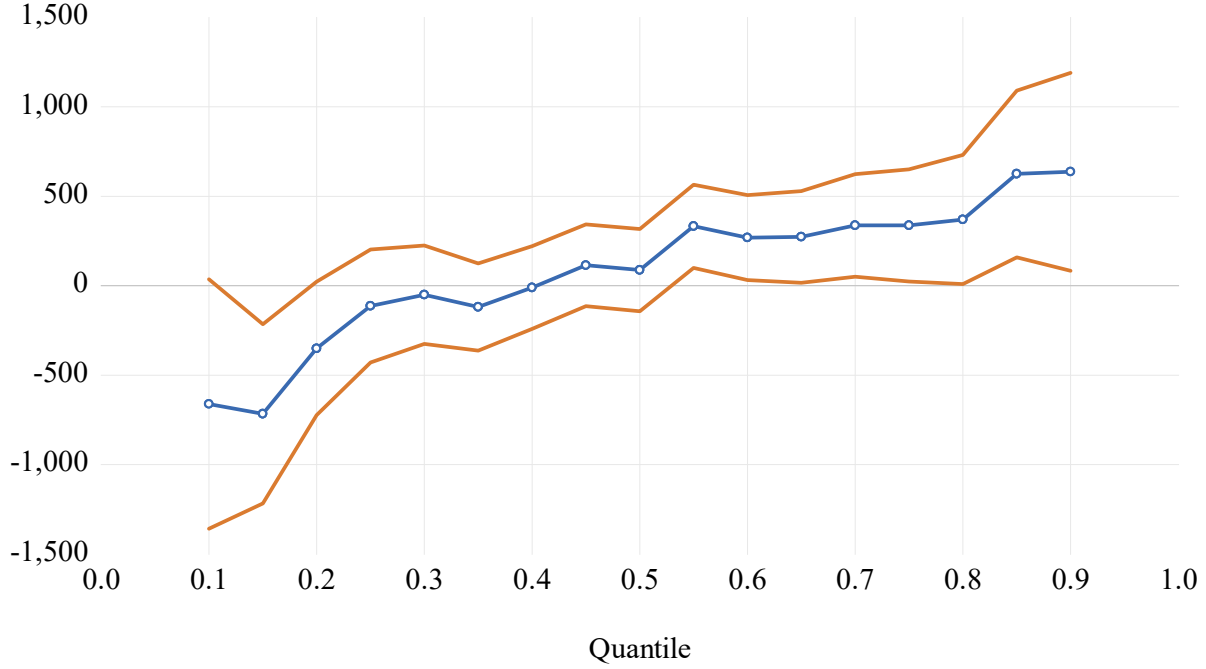
Accordingly, we consider the effect of the lagged pf on real gold returns, i.e., r , under the quantile regression approach reported in Figure 1. We find that pf tends to negatively predict r over the quantile range of 0.10 to 0.40, though the effect is only statistically significant at the 5% level at $\tau=0.15$ (and at the 10% level for $\tau=0.10$ and 0.20). The predictive impact of pf on the conditional distribution r turns positive over $\tau=0.45$ to 0.90, but the effect is statistically significant at the 5% level only beyond the median, i.e., $\tau=0.55$ to 0.90. In sum, our findings suggest that gold cannot serve as a hedge against fatality risks emanating from contagious diseases in its bearish-phase. However, gold turns into a safe haven just around the normal-state of its market i.e., the median, and a hedge beyond it.⁴ Alternatively put, the evidence in favor of gold serving as a hedge against rare disaster risks, involving probability of death due to contagious diseases, exist when real gold returns tend to be generally high, i.e., beyond its normal-state and into its bullish-phase.^{5, 6}

⁴ Comparatively, by using real silver returns over the period of 1688 to 2020, with the underlying data derived from the same sources, we found that lagged pf negatively and significantly impacted real silver returns over the quantile range of 0.15-0.30, and insignificantly beyond it till 0.90. This finding, complete details of which are available upon request from the authors, we see that silver cannot act as a hedge against risks associated with deaths due to contagious diseases.

⁵ A similar observation related to cases and deaths associated with COVID-19 was also drawn by Wang (2021), who too relied on a quantiles-based approach.

⁶ Based on the suggestion of an anonymous referee, since physical gold is not easily tradeable, we analyzed the relationship between the log-returns of gold futures and the first lag of an index of equity market volatility due to infectious diseases as developed by Baker et al. (2020). Based on daily data covering the period of 2nd January, 1985 to 15th July, 2022, our results were qualitatively similar. In other words, gold returns were negatively impacted at

Figure 1. Slope parameter estimate from quantile regression: real gold returns (r) on lagged probability of fatality (pf) due to contagious diseases



Note: The figure plots the slope estimates 18 equally spaced quantiles of real gold returns from the 0.10-th quantile to 0.90-th quantile (blue-line with circles). A point-wise 95% confidence interval is indicated (brown line) around the quantile regression parameter estimates of Eq. (2).

At this stage, the superiority of using the quantile regression over the linear model can be further highlighted by reporting the sub-samples-based results of the OLS regressions. Note that, the sub-samples: 1258-1352, 1353-1548, 1549-1648, 1649-1744, 1745-1919 and 1920-2020 are determined by the 5 identified break dates (discussed above). As can be seen from Table 2, barring the case of the third sub-sample, i.e., 1549 to 1648, where the effect of lagged pf on real gold returns is negative and statistically significant at the 5% level, there is no evidence of any significant impact of our metric of rare disaster risks on real gold returns. In other words, the underlying time-varying nature of quantile regressions, as it captures the various states of real gold returns, allows us to obtain more reliable results in terms of the hedging ability of gold, without having to conduct sub-sample estimations, given the existence of nonlinearity and regime-changes in the relationship between real gold returns and the lagged probability of fatality due to contagious diseases.

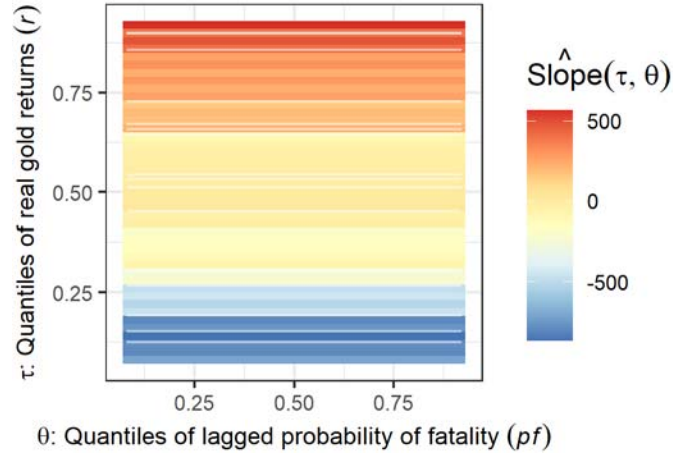
3.2. Additional results

As a further analysis, we first use the quantile-on-quantile regression approach of Sim and Zhou (2015), to investigate if the quantile (τ)-specific impact on real gold returns is dependent on the size of the probability of fatality, i.e., its quantiles (θ). As Figure 2, the size of the lagged probability of fatality does not tend to alter our existing results obtained from the quantile regression. That is, the hedging strength of gold at its upper conditional quantiles is unaffected by

extremely lower quantiles, then it served as a safe-haven till the median, and as a hedge beyond it. Complete details of these results are available upon request from the authors.

the magnitude of the probability of death due to contagious diseases. This is possibly an indication that, once the world witnesses such rare disaster risks, the size of the associated probability of fatality does not necessarily change the behavior of gold returns.

Figure 2. Slope parameter estimates from quantile-on-quantile regression: real gold returns (r) on lagged probability of fatality (pf) due to contagious diseases

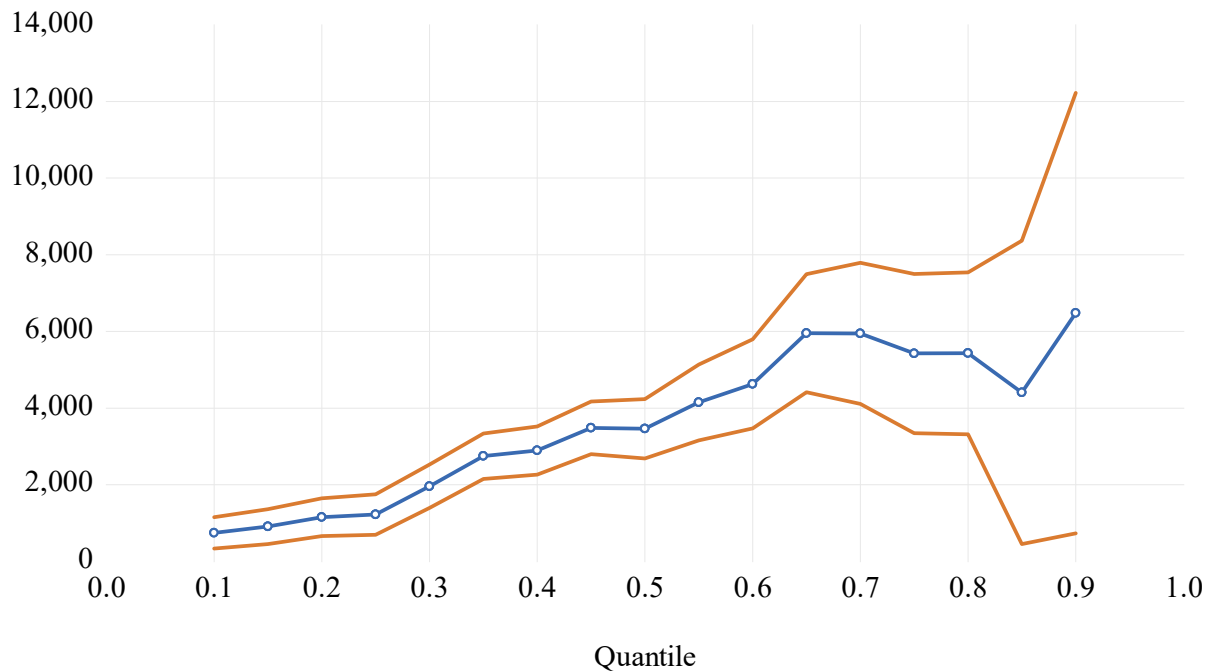


Note: See Sim and Zhou (2015) for complete technical details associated with the estimation of the model.

Second, given that the literature discussed in the introduction suggests that fatalities associated with COVID-19, which is a rare disaster, can lead to an increase in macroeconomic uncertainty, it is likely that pf can also predict volatility of gold returns. Given this, we obtain the conditional volatility of real gold returns (vr) by fitting a standard Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, and then regressed it on lagged pf using the quantile regression model specified in Eq. (2). The findings have been plotted in Figure 3. They show a positive impact of lagged pf over the entire conditional distribution of vr .⁷ On one hand, the positive impact on volatility at the lower quantiles of vr can be associated with the well-known leverage effect in the gold market (Asai et al., 2020), whereby the negative effect on gold returns in its bearish-state due to pf , enhances volatility being bad news. On the other hand, higher gold returns during its bullish-phase resulting from increased pf is possibly driving up the vr due to higher trading in the gold market (Bouri et al., 2021).

⁷ The conditional mean estimate of the lagged effect of pf on vr was 2394.0780, with a p -value of 0.0821.

Figure 3. Slope parameter estimate from quantile regression: real gold returns volatility (vr) on lagged probability of fatality (pf) due to contagious diseases



Note: See Notes to Figure 1.

4. Conclusion

In this paper, we analyze the predictive effect of the probability of fatality due to 62 outbreaks of contagious diseases on real gold returns over the period of 1258 to 2020. While, standard linear (conditional mean) predictive regression fail to show any significant effect of the rare disaster risks variable, i.e., the probability of fatality due to contagious diseases, on real gold returns, the quantile regression method 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, the quantile regression result emerges as more reliable relative to that of the linear predictive model. Our finding tends to suggest that gold serves as a hedge during its bullish-state against associated risks of the probability of death due to outbreaks of contagious diseases.

Our findings have important implications for investors. Understandably, in the wake of the outbreaks of contagious diseases, gold market players 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. However, for this information to be available to investment decisions, investors and analysts must be aware that they need to rely on an underlying quantiles-based econometric model.

As far as future research is concerned, it would be interesting to extend our in-sample predictive analyses to an out-of-sample forecasting one involving both gold returns and its volatility.

References

- Ali, M., Alam, N., and Rizvi, S.A.R. (2020). Coronavirus (COVID-19) - An epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*, 27, 100341.
- Asai, M., Gupta, R., and McAleer, M. (2020). Forecasting Volatility and Co-volatility of Crude Oil and Gold Futures: Effects of Leverage, Jumps, Spillovers, and Geopolitical Risks. *International Journal of Forecasting*, 36(3), 933-948.
- Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 1-22.
- Barro, R.J., and Misra, S. (2016). Gold Returns. *The Economic Journal*, 126 (594), 1293-1317.
- Bouri, E., Gkillas, K., Gupta, R., and Pierdzioch, C. (2021). Forecasting power of infectious diseases-related uncertainty for gold realized variance. *Finance Research Letters*, 42, 101936.
- Cirillo, P., and Taleb, N.N. (2020). Tail risk of contagious diseases. *Nature Physics*, 16(6), 606-613.
- Brock, W., Dechert, D., Scheinkman, J., and LeBaron, B. (1996). A test for independence based on the correlation dimension. *Econometric Reviews*, 15, 197-235.
- Ji, Q., Zhang, D., and Zhao, Y. (2020). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis*, 71, 101526.
- Koenker, R., and Bassett, G. (1978). Regression Quantiles. *Econometrica*, 46(1), 33-50.
- Newey, W.K., and West, K.D. (1987). A simple positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3), 703-708.
- Salisu, A.A., Gupta, R., Nel, J., and Bouri, E. (Forthcoming). The (Asymmetric) Effect of El Niño and La Niña on Gold and Silver Prices in a GVAR Model. *Resources Policy*.
- Salisu, A.A., Raheem, I.D., and Vo, X.V. (2021). Assessing the safe haven property of the gold market during COVID-19 pandemic. *International Review of Financial Analysis* 74 (2021) 101666.
- Sim, N., and Zhou, H. (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking & Finance*, 55, 1-8.
- Tanin, T.I., Sarker, A., Hammodeh, S., and Shahbaz, M. (2021). Do volatility indices diminish gold's appeal as a safe haven to investors before and during the COVID-19 pandemic? *Journal of Economic Behavior and Organization*, 191, 214-235.

Wang, K-M. (2021). Can gold be a safe haven during the COVID-19 pandemic? A quantile causality analysis. *Journal of Statistics and Management Systems*, 24(5), 1113-1125.

Zhang, H., Hong, H., Guo, Y., and Yang, C. (2022). Information spillover effects from media coverage to the crude oil, gold, and Bitcoin markets during the COVID-19 pandemic: Evidence from the time and frequency domains. *International Review of Economics and Finance*, 78, 267-285.

Appendix:

Table A1. Summary statistics: 1258-2020

Statistic	Variable	
	Real Gold Returns (<i>r</i>)	Probability of Fatality (<i>pf</i>)
Mean	-0.2865	0.0006
Median	-0.4400	0.0000
Maximum	137.9596	0.0153
Minimum	-41.5800	0.0000
Std. Dev.	11.5959	0.0027
Skewness	2.1510	5.0134
Kurtosis	30.4436	26.6599
Jarque-Bera	24532.3500***	20992.9400***
Observations	763	763

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

Figure A1. Data plots: 1258-2020

