Geopolitical risk and precious metals

Debojyoti Das[i]

Woxsen School of Business, India

M. Kannadhasan[ii]

Indian Institute of Management Raipur, India

Puja Bhowmik[iii]

St. Xavier's College, India

Abstract

We empirically examine the impact of Geopolitical Risk (GPR) on tradable precious metal returns for a period spanning over January 1985 to December 2017. We report the evidence of: (a) increase in GPR of 100 units increases Gold returns by 0.0029 percent. (b) For a 100 unit increase in GPR the returns of Silver, Platinum and Palladium falls by -0.0008, -0.0057 and -0.0343 percent respectively. (c) Gold returns are higher (and positive) under threat conditions rather than actual occurrence of any risk events. (d) Palladium is found to be most vulnerable to GPR and (e) we also find positive and significant sensitivity of Gold at normal market conditions.

Keywords: Geopolitical risk, Precious metals, Gold, Quantile regression

JEL Classification: G11, G17, G19

i) Woxsen School of Business, Kamkole, Sadasivpet, Medak District, Hyderabad, Telangana 502 345, India. E-mail: debojyoti.d@outlook.com
ii) Indian Institute of Management Raipur, Atal Nagar, P. O. - Kurru (Abhanpur), Raipur 493 661, Chhattisgarh, India. E-mail: mkdhasan@iimraipur.ac.in
iii) St. Xavier's College, 30, Park St, Mullick Bazar, Park Street area, Kolkata, West Bengal 700 016, India. E-mail: puja_bhowmik@yahoo.com

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HIGHLIGHTS

- The relationship between Geopolitical risk (GPR) and precious metals is studied for the first time.
- Gold is positively associated with GPR shocks. Increase in GPR of 100 units increases Gold returns by 0.0029 percent.
- Silver, Platinum and Palladium returns fall by -0.0008, -0.0057 and -0.0343 percent respectively with 100 units rise in GPR.
- Gold returns exhibit positive sensitivity mostly at normal market conditions. Silver depicts positive sensitivities at bullish market state.

1 Introduction

Risk is an important factor in planning strategies to diversify portfolios aiming to enhance returns over time. Political events like elections, changes in political ideologies, terrorist attacks, trade negotiations, domestic tensions, nuclear programs and so on (Drakos and Kallandranis, 2015) influence the business cycles, equity market, the correlation between assets and decisions to diversify portfolios (Omar et al., 2017). In this article, we assess the effect of Geopolitical Risk (GPR) on the price of precious metals. Such that, they could be used as a hedging instrument against volatile stock market returns. When instability in the political scenario of an economy affects macroeconomic variables, business environment and profit objectives of a firm and in turn investors perceive the variation through fluctuations in portfolio returns, the risk is termed as political or geopolitical risk (Caldara and Iacoviello, 2017). Foreign Direct Investments and investment returns have the possibility of being impacted by the changing relationships between nations owing to the alterations in the economic and political scenario (Sottilotta, 2013). Although this risk may be presented here in lucid terms, the concept of political risk has undergone evolution and still remains ambiguous to a certain extent. With the passage of time and increased comprehension of the term, additions and alteration were made to the existing meaning, only to broaden the horizon of the term and view it as a global activity. The noteworthiness of the risk is easier to understand than to quantify and assess it, since risk in itself is a fuzzy concept (Caldara and Iacoviello, 2017). Sottilotta (2013) classifies the political risk assessment into two categories: (a) macro political risk assessment and (b) micro political risk assessment. The paper utilizes the news based geopolitical risk index GPR by Caldara and Iacoviello (2017) to evaluate the safe haven property of precious metals against the backdrop of uncertainty in geopolitical events. GPR comprises of two components: (a) geopolitical threats (GPRT) and b) geopolitical acts (GPRACT). The threats predict future adverse scenario, which creates negative impacts on economic activity, prices of assets and risk premia. The geopolitical act, on the other hand, refers to the occurrences of actual undesirable political events such as outbreak or escalation of war; air strikes etc. (opposed to just risk).

International diversification of portfolios through less than perfectly integrated markets reduces chances of suffering losses (Francis et al., 2008). But since the markets across nations co-move strongly during periods of volatility, such as economic crises due to the contagion effect (Forbes and Rigobon, 2002; Markwat et al., 2009; Ranta, 2013; Samarakoon, 2011). Thus, attaining diversification benefits are difficult during economically turbulent conditions (Ibragimov and Walden, 2007). Gold has been an eminent metal for safe investment (Baur and Lucey, 2010; Baur and McDermott, 2010). Nevertheless, the safe haven phenomenon of Gold occurs only at moderate levels of risk since at higher or extreme levels of volatility the market co-moves with the stock market (Baur and McDermott 2010). Thus, owing to this hedging limitation of Gold, recently the focus has been expanded to include other metals like Silver, Platinum, Palladium and other industrial metals (Agyei-Ampomah et al., 2014; Bhatia et al., 2017; Hillier et al., 2006). Precious metals like platinum, silver and palladium have better safe haven effect than gold. As pointed out during 1996's equity return slow down, silver served as a better safe haven than gold (Lucey and Li, 2015). Nevertheless, there could be channels through which the adverse influences of GPR may be transmitted to the prices of the alternative precious metals such as Silver, Platinum, and Palladium. Besides commodity trading, these metals also serve an important role in industrial production. The GPR and allied risks is expected to dampen the propensity to consume for an economy and hence firms are expected to curb production volume. Consequently, the demand for the alternative precious metals is expected to fall and so the prices.

Caldara and Iacoviello (2017) highlight the fact that rise in GPR leads to decline in real activity, global stock returns and capital flows to emerging markets and increase in Volatility Index (VIX). However, we for the first time, attempt to empirically examine the impact of GPR on precious metals. Caldara and Iacoviello (2017) report that increase in GPR of 100 units decreases world stock returns by 1.23 percent. We report that increase in GPR of 100 units increases Gold returns by 0.0029 percent. For a 100 unit increase in GPR the returns of Silver, Platinum and Palladium fall by -0.0008, -0.0057 and -0.0343 percent respectively. Though the returns for Silver, Platinum and Palladium are negative, however, the values are relatively smaller compared to the fall in world stock returns (i.e. 1.23). In addition, we also find that Gold returns are higher (and positive) under threat conditions rather than actual occurrence of any risk events. Palladium is found to be most vulnerable to GPR among all other precious metals. Further, we also find positive and significant sensitivity of Gold at normal market conditions (and Silver to some extent) to the GPR measures.

The rest of the paper is structured as follows: Section 2 describes the estimation methodology in brief. Section 3 discusses the data characteristics. The main results are reported in Section 4 and Section 5 concludes.

2 Estimation Methodology

2.1 Geopolitical Risk and precious metals returns

To examine the reaction of precious metals returns to the shocks in the GPR we adopt a method similar to Caldara and Iacoviello (2017). We run the following regression model for each of the metal returns individually as:

$$R_{i,t} = \mu_i + \alpha_i GPRSHOCK_t + \varepsilon_{i,t} \quad (1)$$

where $R_{i,t}$ represents the precious metal returns for metal i in month t and *GPRSHOCK* is computed as the residual of an AR(1) process, which is estimated for GPR and is divided by 100.[2] Thus, the coefficient measures the percentage impact on stock returns from an innovation in GPR of 100 units. To correct the standard errors for autocorrelation, the Newey-West method is considered.

2.2 Sensitivity analysis using Quantile Regression

The traditional regression models establish symmetric linear relationship between the variables of interest. In general, to establish a relationship between an independent variable and a set of variables a model with linear specification is formulated which is conditional upon its mean. Thus, the results essentially focus upon the mean value relationship. However, the relationship at different levels of conditional distribution of dependent variables remains unexplored. To captivate the complex dependence of time-series Quantile Regression (QR) technique was introduced by Koenker and Bassett (1978). To captivate the asymmetric and non-linear dependence structure, the recent studies advocate the use of QR (Baur, 2013; Mensi et al., 2014; Nusair and Al-Khasawneh, 2017).

Let y be a dependent variable, which is assumed to be dependent on x linearly. Thus, the τ^{th} conditional quantile of function y may be specified as below:

$$Q_y(\tau|x) = \inf(b|F_y(b|x) \geq \tau) = \sum_k \beta_k(\tau)x_k = x'\beta(\tau) \quad (2)$$

where the conditional distribution function of $(y|x)$ is represented by $F_y(b|x)$. The relationship of dependence between vector x and the τ^{th} conditional quantile of function y is determined by $\beta(\tau)$. The dependence is conditional if the exogenous variables added to x, while the dependence is unconditional if the exogenous variables are excluded from x. The complete dependence structure of y is determined by $\beta(\tau)$ for $\tau \in [0,1]$. There could be three possible dependence structures between y and vector of independent variables x: (a) where the value of $\beta(\tau)$ for different values of τ is similar (dissimilar) the relationship is symmetric

[2] The conversion into 100 units is performed merely to express the value of coefficients in percent. By stating 100 units we do not necessarily mean a higher value of risk.

(asymmetric) for lower and higher quantiles, (b) where the value of $\beta(\tau)$ does not change, the relationship is constant and (c) where the values of $\beta(\tau)$ increases (decreases) with the values of τ, the relationship is monotonically increasing (decreasing).

For a given τ, the coefficients of $\beta(\tau)$ are estimated by minimization of the weighted absolute deviations between y and x:

$$\hat{\beta}(\tau) = \arg\min \sum_{t-1}^{T} (\tau - 1_{[y_t < x'_t \beta(\tau)]}) \left| y_t - x'_t \beta(\tau) \right| \tag{3}$$

where the usual indicator function is denoted by $1_{[y_t < x'_t \beta(\tau)]}$. The solution to this problem is arrived by using linear programming algorithm (Koenker and D'Orey, 1987). To obtain the standard error for the estimated coefficients the pair-bootstrapping procedure proposed by Buchinsky (1995) is used. The asymptotically valid standard errors under heteroskedasticity and misspecifications of the QR function are obtained by this pair-bootstrapping procedure.

To capture the sensitivity of precious metals returns to GPR shocks we adopt a two-factor linear regression model. The model of this kind was first developed by Stone (1974), which is an extension to the standard market model of assets returns and can be traced in recent literature, for instance refer to (Jareño et al., 2016). We adopt a similar model that includes two explanatory variables: (a) the precious metals markets returns[3] and (b) the shocks in GPR. Thus, our model is expressed as:

$$R_{it} = \alpha_i + \beta_1 R_{mt} + \beta_2 GPR_t + \varepsilon_{it} \tag{4}$$

where R_{it} denotes the returns for metal i at time t. R_{mt} indicate the market returns. GPR_t represents the shock components in GPR and its constituents. The random error is denoted by ε_{it}. As mentioned earlier, to capture the sensitivity across different conditional quantiles and tails of the distribution, we reframe the model in Eq. (4) as:

$$R_{it} = \alpha_i^{\theta} + \beta_1^{\theta} R_{mt} + \beta_2^{\theta} GPR_t + \varepsilon_{it} \tag{5}$$

[3] We have constructed an equal weighted index to proxy for precious metals markets returns.

where α_i^θ , β_1^θ , β_2^θ corresponds to the QR estimated coefficients. We have split the data into 9 regression quantiles (0.1 to 0.9).

3 Data

We empirically examine the relationship between GPR and precious metals using monthly data for a period spanning from January 1985 to December 2017.[4] The period of study is constrained by the availability of GPR data. 'GPR Benchmark' represents the composite GPR index, which aggregates: (a) Geopolitical threats and (b) Geopolitical acts. The impact of each of the GPR measures on each of the precious metals is studied individually. As a proxy for precious metals we have considered tradable (which may also be used as a hedge instrument) precious metals i.e. Gold, Silver, Platinum and Palladium. The statistical properties of the precious metals are exhibited in Table 1. The price data for precious metals is converted into returns by taking logged differences as: $R_t = (\ln(P_t) - \ln(P_{t-1}))$. Among the precious metals group, Palladium yields the highest mean returns followed by Gold and Silver. Volatility in terms of standard deviation (SD) is also the highest for Palladium, however the lowest for Gold. The skewness coefficient is positive only for Gold; the other metals bear negative coefficients. For the investor community a positive skewness coefficient is desirable since it indicates more frequent occurrences of positive returns than negative returns and vice-versa. The Kurtosis coefficients shows all the returns distributions are more peaked than usual i.e. leptokurtic. The Jarque-Bera test statistic shows the returns significantly depart from the assumption of normality. Table 2 provides the results of Augmented Dickey Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) tests. The results clearly show that the variables are non-stationary at level. Nevertheless, they become stationary at their respective first differences. The series plot for both GPR

[4] Monthly frequency is adopted since the GPR data is available monthly, which is sourced from (http://www.policyuncertainty.com/gpr.html). The data for Gold and Silver is available for the full sample i.e. 01/1985-12/2017. However, the data for Platinum and Palladium is available from 01/1987-12/2017 and 10/1993-12/2017 respectively. The data for precious metals is extracted from Bloomberg.

and precious metals groups are presented in Figure 1 and 2 respectively.

Table 1. Statistical properties of precious metals returns

	Gold	**Silver**	**Platinum**	**Palladium**
Mean (×100)	0.3631	0.2455	0.1475	0.7199
SD	0.0440	0.0786	0.0602	0.1001
Maximum	0.1557	0.2536	0.2162	0.4010
Minimum	-0.1850	-0.3285	-0.3855	-0.4294
Skewness	0.0843	-0.0775	-0.8979	-0.1631
Kurtosis	4.0675	4.3532	7.7664	5.5354
JB	2545000*	2537300*	2541800*	2533100*

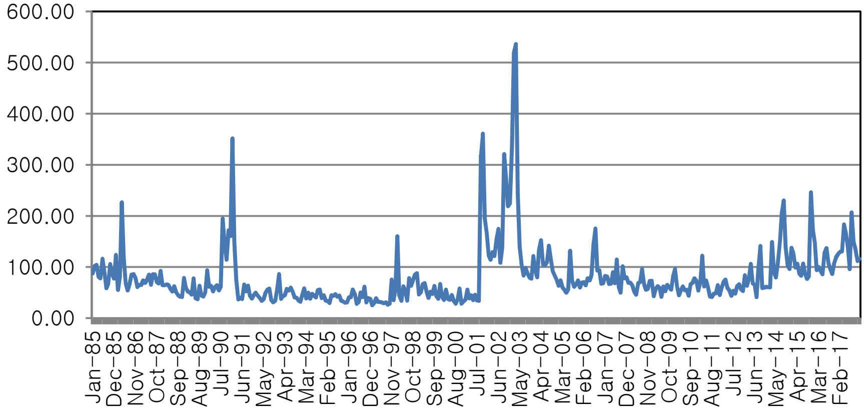
Note: The empirical statistic of the Jarque-Bera test of normality is given by *JB*. The asterisk represents the rejection of the null hypothesis at 1% level. * $p<0.1$. The distribution of precious metal returns is presented in appendix.

Table 2. Stationary test results

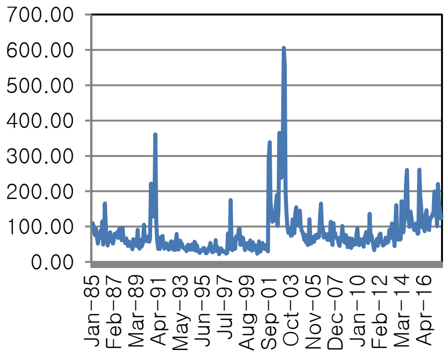
	ADF		**PP**	
	Level	*Δ*	*Level*	*Δ*
Gold	-0.33	-15.69***	-0.40	-22.01***
	(0.92)	(0.00)	(0.91)	(0.00)
Silver	-1.54	-15.57***	-1.63	-22.03***
	(0.51)	(0.00)	(0.47)	(0.00)
Platinum	-1.64	-12.79***	-1.54	-18.24***
	(0.46)	(0.00)***	(0.52)	(0.00)
Palladium	-0.85	-11.35***	-0.89	-16.72***
	(0.80)	(0.00)	(0.79)	(0.00)

Note: The delta (Δ) denotes the first difference operator. (a) The critical values for the ADF at 1%, 5% and 10% levels of significance corresponds to -3.457, -2.878 and -2.570 respectively. (b) The critical values for the PP at 1%, 5% and 10% levels of significance corresponds to -3.457, 2.878 and -2.570. The MacKinnon approximate p-values are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

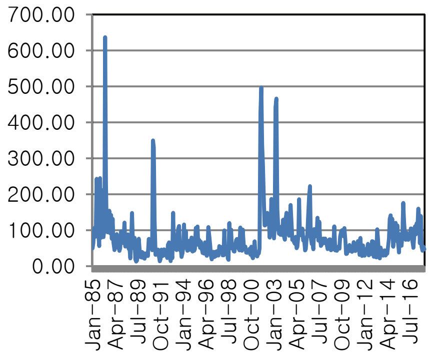
Figure 1. Series plot for Geopolitical risk, threats and acts



(a) Geopolitical risk- Benchmark

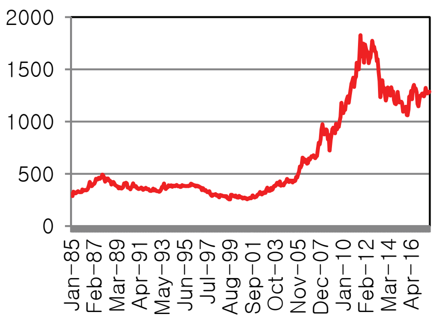


(b) Geopolitical threats

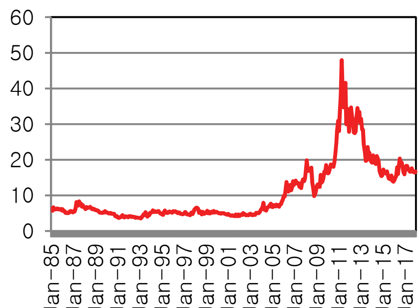


(c) Geopolitical acts

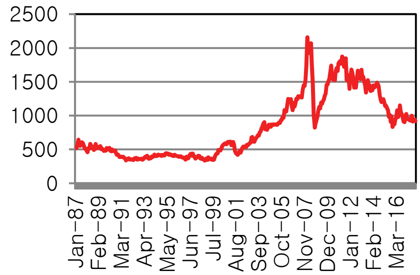
Figure 2. Series plot for precious metals



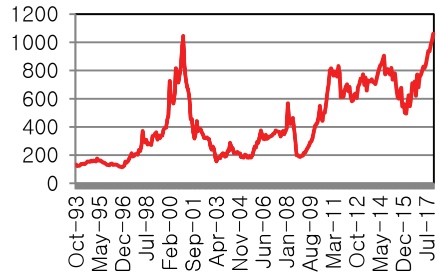
(a) Gold



(b) Silver



(c) Platinum



(d) Palladium

4 Main Results

In this section of the study we briefly discuss the implications of the empirical results. In Table 3 we report the results of the reaction of precious metals returns to changes in GPR. All the three measures of GPR are taken into account for the examination. Panel A of Table 3 reports the results of the composite GPR index i.e. GPR Benchmark. The result clearly shows that the rise in risk enhances the returns for Gold. This safe haven property of Gold is well established in the earlier literature (Baur and Lucey, 2010; Baur and McDermott, 2010). Silver does not depict a positive return however, and among the other metals, it bears the lowest negative value of the coefficient.

Table 3. GPR and precious metals returns

	Coefficient	**Std. Error**	**Sample**
Panel A: GPR Benchmark			
Gold	0.0029	0.0059	01/1985-12/2017
Silver	-0.0008	0.0094	01/1985-12/2017
Platinum	-0.0057	0.0079	01/1987-12/2017
Palladium	-0.0343	0.0177	10/1993-12/2017
Panel B: GPR Threat			
Gold	0.0024	0.0054	01/1985-12/2017
Silver	-0.0018	0.0084	01/1985-12/2017
Platinum	-0.0040	0.0074	01/1987-12/2017
Palladium	-0.0254	0.0164	10/1993-12/2017

Panel C: GPR Act			
Gold	0.0015	0.0036	01/1985-12/2017
Silver	-0.0006	0.0072	01/1985-12/2017
Platinum	-0.0072	0.0053	01/1987-12/2017
Palladium	-0.0442	0.0130	10/1993-12/2017

Note: Table 2 exhibits the estimation for effects of global GPR on precious metal returns on individual metals. The estimated $\alpha's$ for the model: $R_{i,t} = \mu_i + \alpha_i GPRSHOCK_t + \varepsilon_{i,t}$, where $R_{i,t}$ represents the precious metal returns for metal i in month t and $GPRSHOCK$ is computed as the residual of an AR(1) process, which is estimated for GPR divided by 100. Thus, the coefficient measures the percentage impact on stock returns from an innovation in GPR of 100 units. Using the Newey-West method the standard errors are corrected for autocorrelation. Similar process is adopted for assessing the impact of GPR threats and acts on precious metals returns.

Platinum has a higher negative coefficient to Silver. The possible underlying causal reason that could be attributed to the fact that Platinum, which is used in jewelry as well as for industrial purposes (Bhatia et al., 2017), is much more expensive than gold,. Thus, under economically uncertain situations, it is very likely that the demand for luxury platinum items will be curbed. In turn, the prices of platinum may be impacted negatively.

Figure 3. Coefficient plot of response of precious metal returns to GPR

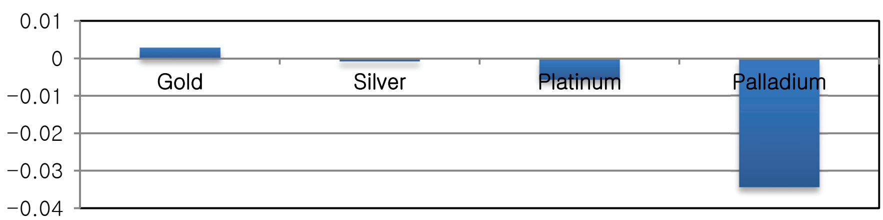
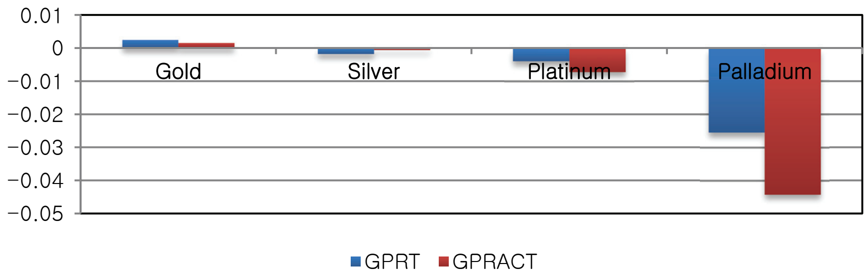


Figure 4. Coefficient plot of response of precious metal returns to GPR threats and acts



Note: The y-axis represents the value of regression coefficients

Palladium is found to be highly vulnerable to GPR shocks. Palladium is also used as jewelry in addition to its industrial uses (such as for dental fillings and also for catalytic converters in exhaust systems of cars). Caldara and Iacoviello (2017) purport that rise in GPR would lead to decline in real activity, which essentially means contraction in economic output and hence in production and demand for Palladium. The results are represented diagrammatically in Figure 2.

As can be observed Gold is positively associated with GPR shocks. Increase in GPR of 100 units increases Gold returns by 0.0029 percent. Silver, Platinum and Palladium returns fall by -0.0008, -0.0057 and -0.0343 percent respectively with 100 units rise in GPR.

The operation on GPR Benchmark is replicated with the other measures of risk, i.e. GPRT and GPRACT in Table 3 panels B and C respectively. We find that the results are identical. One interesting finding that can be observed is that the Gold returns are marginally higher in a condition of uncertainty of prevailing threat rather than actual occurrence of economically devastating episodes. Figure 3 exhibits a comparative chart for visual analysis.

In the next segment, we attempt to study the sensitivity of precious metals to GPR at various market states. For this purpose, we adopt a quantile regression approach as per Jareño et al. (2016). In Table 4, panel A the QR estimates for GPR Benchmark is reported. The regression quantiles (0.1-0.3) corresponds to the bearish market state, the quantiles (0.4-0.6) relates to normal market state and quantiles (0.7-0.9) represents bullish

Table 4. Quantile regression estimates

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Panel A: GPR Benchmark									
Gold	0.0038	0.0068	0.0072	0.0111**	0.0089**	0.0079*	0.0080*	0.0061	0.0054
Silver	0.0055	0.0028	0.0031	0.0051	0.0064	0.0100	0.0041	0.0228	0.0289*
Platinum	0.0029	0.0039	0.0018	0.0015	-0.0018	-0.0054	-0.0006	0.0074	0.0038
Palladium	-0.0439	-0.0229	-0.0056	-0.0159	-0.0178*	-0.0207**	-0.0199**	-0.0277**	-0.0317**
Panel B: GPR Threat									
Gold	0.0087**	0.0048	0.002	0.0034	0.0057**	0.0048*	0.0054	0.0048	0.0128**
Silver	0.0023	0.0022	0.0027	0.0035	0.0054	0.0021	0.00153	0.0167	0.0189
Platinum	0.0028	0.0043	0.0012	0.0019	-0.0017	-0.0054	-0.000259	0.0066	0.0032
Palladium	-0.0179	-0.0104	0.00187	-0.0107	-0.0128	-0.0176*	-0.0165	-0.0230**	-0.0218*
Panel C: GPR Act									
Gold	0.0018	0.0067	0.0082	0.0098*	0.0065	0.0066	0.0069	0.0048	0.0016
Silver	0.0014	0.0036	-0.0019	0.0029	0.0008	0.0029	0.0018	0.0210*	0.0217**
Platinum	0.0077	0.0027	0.0006	0.0015	-0.0009	0.0065	0.0006	0.0045	-0.0003
Palladium	-0.0330**	-0.0316**	-0.0298*	-0.0306*	-0.0193	-0.0241*	-0.0274*	-0.0234*	-0.0262

Notes: This table exhibits the QR estimates for precious metals according to the defined empirical model in Eq. (5). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

market state. As can be observed in panel A, Gold depicts a positive relationship at lower quantiles of (0.1–0.3). However, the relationship is not statistically significant. The relationship becomes significant at middle quantiles (0.4–0.6) till quantile 0.7; after then the significance of the relationship is lost. Thus, Gold is found to be a more effective hedge instrument at normal market state. Silver depicts a weak and insignificant positive relationship. Nevertheless, at the extreme upper tail Silver depicts a significant positive coefficient. Hence, at the bullish market state/or at the extreme upper tail where Gold loses statistical significance (Baur and McDermott, 2010), Silver can be used as a potential hedging instrument. Platinum depicts insignificant relationship across all the regression quantiles. However, positive coefficients may be observed in the lower quantiles i.e. up to quantile 0.4. This could be possible since the probability of any uncertain event may induce investors to invest in platinum, when the market prices are relatively low. The result for Palladium is consistent as it depicts negative sensitivities across all the market states.

Table 3 panels B and C report the results for GPRT and GPRACT. We find under the situation of threat Gold emerges as a better hedge instrument. In fact, Gold outperforms all other precious metals in hedging GPR. The negative sensitivity of Palladium fades in the state of threat rather in actual occurrence. Silver in response to GPRACT becomes positive and significant at quantile 0.9. Thus, we can infer that Silver may also be used as a substitute for Gold at the upper tail.

5 Conclusions

We attempt to study the response of precious metals to GPR to ascertain whether precious metals can hedge the geopolitical uncertainties for the first time in literature. As Caldara and Iacoviello (2017) confirm the negative impact of rising GPR on world stock returns, identification of a potential instrument, which is insulated from global political tensions could have overwhelming implications for the investor community. Since, the potential usage of tradable precious metals with portfolio risk-return optimization is much debated, it becomes inevitable to test the robustness of precious metals against various sources of risk. We report that: (a) increase in GPR of 100 units increases Gold returns by 0.0029 percent. (b) For a 100 unit increase in GPR the returns of Silver, Platinum and Palladium fall by -0.0008, -0.0057 and -0.0343 percent respectively. (c) Gold returns are higher (and positive) under threat conditions rather than actual occurrence of any risk events. (d) Palladium is found to be most vulnerable to GPR and (e) we also find positive and significant sensitivity of Gold at normal market conditions. Our findings are in favor of Gold to be a safe haven asset.

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Appendix

Figure A1. Distribution of precious metals return with normal curve