Hedging precious metals with impact investing

Abstract
Our study examines the role of impact investing to hedge the risk against precious metals (i.e., palladium, platinum, gold, and silver) in tranquil and turmoil periods. The results demonstrate that the hedging effectiveness increases for the portfolios containing impact investing and precious metals. Our study provides evidence that the hedging effectiveness improves during the COVID–19 pandemic for the gold and impact investing portfolio. Further analysis demonstrates that investors across the risk aversion spectrum gain higher utility after considering the transaction cost while investing in portfolios of impact investing and precious metals. These results are new additions to extant literature that may interest investors, fund managers, and policymakers.

Keywords: Impact investing; greenness; hedge ratio; hedging effectiveness

JEL Classification: G11, G12, G14, G15; G23

1. Introduction

Building upon the years of activism of championing environmental, community development, and sustainable finance, impact investing (II), a term coined at the Rockefeller Foundation (Bugg-Levine and Emerson, 2011), has been a new advent in the foray of investment gaining impetus (Arjaliès and Durand, 2019; Geczy et al., 2021). It makes its presence felt by bridging the age-old institutional logic that philanthropy and finance are two ends of a bipolar world, never to meet (Freireich and Fulton, 2009; Agrawal and Hockerts, 2019). Impact investing made it feasible by blending both to address some of the intractable challenges that the world is allegedly facing by harnessing the substantial sources of the financial markets (Jackson, 2013).

Impact investing is now carving its own space in the development finance world. It is serving as a potential game-changer given the increasing motive towards financialisation both at policy and practice underpinned by the conviction that greater financial commitment is critical for world development by building a complex web of affiliation amid different financial actors and philanthropic organisations (Clapp, 2014; Gabor and Brooks, 2017). Thus set to realise the dual goal of social benefit alongside financial metrics, which sets it apart from other conventional financings like private equity (PE) or venture capital (VC) (Brest et al., 2018). Though the idea that money should be invested to generate financial returns, desirable social outcomes are not new, the notable precursors being the Quaker movement (Bugg-Levine and Emerson, 2011).

Unanimity lesser felt among different actors in milieu to defining impact investing and its coverage; however, Global Impact Investing Network (GIIN) defined impact investing as an "investment made with the intention to generate positive, measurable social and environmental impact alongside a financial return." (GIIN, 2017). Regardless of the actors' diverse motivations

and expectations, the II sector is cohesive and expected to create positive social impacts for intended beneficiaries.

With over two decades of presence and over 13000 deals (GIIN, 2019), II created a niche realm in sustainable finance. Currently, over USD 502 billion of impact investing assets are managed with a further allocation of USD 48 billion to 12,534 newer investments in 2020, which saw a 2% hike in terms of capital invested and 28% in the number of projects over the previous year (GIIN, 2019 and 2020) and the market to reach USD 1 trillion by 2020 (GIIN, 2018). This sudden surge in impact investing has drawn growing interest in gauging the overall influence of impact investing, which is one of the key attributes of any performance metrics (Evans, 2013; Molecke and Pinkse, 2017; Mersland et al., 2019; Vivian and Maurel, 2019). Given the proliferation of funds and actors in II, critical scholarship on II is still embryonic (e.g., Barber et al., 2020; Chowdhury et al., 2021).

One of the recurring themes in research in this area has been the impact assessment looking through the lens of a dualistic attempt to financial and social/environmental aims as both come from different schools of thought (Pache and Santos, 2010; Agarwal and Hockerts, 2019). Classical asset pricing theories' reinforces investing objectives as utility gained as a function of wealth creation (a common goal among investors). However, given the difference in logic, friction stems between financial aspirations and positive societal externalities among investors as it sets a trade-off between profit and purpose. However, there is an attempt to innovate the utility functions by factoring in societal externalities besides wealth. But the implications differ in numerous settings with a demerit that these models remain untested following a notion that non-pecuniary motifs affect capital allocation reflecting a readiness to recompense for impact (Laibson, 1997; Hart and Zinglaes, 2017; Niehaus, 2014). Though challenges arise because of non-standardisation

measuring the financial impact of impact investing, unlike the standardised metrics in the case of traditional funding mechanisms, such as return on assets (ROA), no such exists for gauging the social impact fuzziness continues around impact investing (Thornley, 2016). They are mostly attributed to the relatively recent advent of sustainable financing against mainstream funding and the diverse utilisation for the context-specific domain.

The current literature focuses on measuring the impact of sustainable financing as past performance can reflect future investments decisions. As Lall (2017) asserts, assessing social impact for measuring to prove and improve will drive further rationalisation in this sector. Moreover, looking to business considerations, II covering grounds reveals synchronisation of business models with ethical code of conduct reflecting the feasibility to building more ethical economies grounded on the fact to benefit the lives of the disadvantaged and marginalised. The strength of impact investing lies in facilitating capitalism to "do good", which stems from the notion of ethical capitalism, and the last two decades witnessed vigour in this direction to reduce the negative externalities of capitalistically oriented business models into more vibrant settings to tackle the social and eco-diversity issues through ethical consumption and under the head of corporate social responsibilities (Carrier, 2010; Scales, 2014).

Though the shift is apparent on the surface, concerns are raised about the broader implications of II for inclusiveness and sectoral development. The risk of illusionary hype created around II to single out as a solution for all intractable problems can still permeate, but as the World Economic Forum stated that corporates need to 'reframe the problems' by 'finding ways to leverage them into business opportunities (World Economic Forum, 2009, Schwab, 2009, 2016). Profitability amalgamated with financial discipline may fall short of reaching the poorest of the

poor, but improvisation to adapt to newer standards that prevent enforcing social mission creates a business environment that holistically believes in doing for purpose.

This paper looks into a completely different dimension of impact investing, i.e. the hedging abilities of II given the dynamic change in the financial markets brought by the pandemic situation of COVID-19. The void in traditional financial assets was glaring visible, including the commodities market falling victim to this sudden development. We largely explore whether impact investing can serve as a hedge during turmoil and tranquil periods.

Traditionally oil and gold served as strategic commodities for hedging against unwarranted instabilities in financial markets, inclusive of the commodities (Fernandez, 2015). Gold has been known as a store of value, medium of exchange and inflation hedge, and literature supporting the further notion of its hedging and safe-haven both on and off financial crises (Baur and McDermott, 2010; Baur and Lucey, 2010; Baur and McDermott, 2016; Shahzad et al., 2020; Akhtaruzzaman et al., 2021a; Banerjee and Pradhan, 2021). Against gold, oil prices show heterogeneous changes with other commodity markets (Baffes, 2007), serving hedging and diversification purposes. Despite the hedging and safe-haven potential of gold and oil, there is a contrarian perspective that gold and oil fall short as a hedge during extreme market movements (Reboredo, 2013; Selmi et al., 2018, Ji et al., 200). Extant literature has even experimented with green bonds as an option to hedge during the COVID-19 crises (Dutta et al., 2021).

Interestingly, there is little evidence regarding sustainable investing used as a hedge against metals and agricultural commodities, even though both commodity classes have witnessed enormous price swings (Liu et al., 2014). Studies link precious metals like gold or oil to examine either co-movement or spillovers against other asset classes (Mensi et al., 2013; Narayan et al., 2013; Silvennoinen and Thorp, 2013; Kang et al., 2017; Akhtaruzzaman et al., 2021), paying lesser

specific attention to the hedging qualities of impact investing on precious metals. Overall, the literature exhibits a dearth of empirical studies on the hedging potential of impact investing on precious metals. However, given the dynamic changes and the focus on climate change, exploring the hedging potential of impact investing would be interesting.

We contribute to a different strand of finance literature. First, we contribute to a smaller but growing literature on impact investing (e.g., Barber et al., 2020; Chowdhry et al., 2019; Geczy et al., 2021) as prior research is practically silent regarding the hedging effectiveness of impact investing. Literature has corroborated the safe-haven property of sustainable finance like green bonds against tail risks (Jin et al., 2020; Yi et al., 2021), especially during the upsurge of the COVID-19 period (Uddin et al., 2021), not on impact investing. This paper first investigates the hedging effectiveness between impact investing and precious metals (gold, silver, platinum and palladium), as little empirical evidence exists about the hedging effectiveness of impact investing. We focus on the US market as it forms the core holding for investment for domestic and international investors. Further, we used gold and other precious as gold is widely known for its hedging abilities against inflation and adverse economic times (Bekiros et al., 2017; Junttila et al., 2018; Akhtaruzzaman et al., 2021; Banerjee and Pradhan, 2021).

We have taken the prices data from the Datastream for two different impact investing indexes and that of the precious metal of gold, silver, platinum and palladium for this study to estimate the time-varying correlation using a multivariate GARCH model in line with Engle (2002). First, the study uses the asymmetric dynamic conditional correlation (ADCC) Generalized Autoregressive Conditional Heteroscedasticity (GARCH) framework to capture the time-varying correlation between II and precious metal. Second, we calculate the hedge ratios as ADCC

GARCH models better adapt to capture the time-varying correlation (Cappiello et al., 2006; Banerjee, 2021; Banerjee and Pradhan, 2021).

We used the time-varying hedge ratios estimated from the asymmetric dynamic conditional correlation (ADCC), Generalized Autoregressive Conditional Heteroscedasticity (GARCH) framework to determine the hedging effectiveness for the period from 30 November 2015 to 18 February 2022. We have several interesting findings. The results demonstrate that the hedging effectiveness increases for the portfolios containing impact investing and precious metals. Our study provides evidence that the hedging effectiveness improves during the COVID–19 pandemic for the portfolio of gold and impact investing. The results also show that investors across the risk aversion spectrum gain higher utility in portfolios of impact investing and precious metals after considering the transaction cost. The results are robust to the use of alternative specifications and impact investing indices. These results are of interest to investors, fund managers, and policymakers.

The organisation of the rest of the paper is as follows. Section 2 develops the methodology while section 3 presents the data and descriptive statistics. Section 4 presents empirical results and section 5 checks the robustness. Section 6 concludes.

2. Methodology

This paper used a dynamic conditional correlation (DCC) GARCH model proposed by Engle (2002) to generate the time-varying variance and covariance matrices and optimal design portfolios containing the proxy for impact investing and precious metals like gold, silver, platinum and palladium. The model details are specified in the subsections as follows:

2.1 ADCC–EGARCH model

A vector autoregressive (VAR) structure is adapted to model the returns. Then the VAR structure is extended to the dynamic conditional correlation (DCC) GARCH structure to investigate the time-varying volatility as developed by Engle (2002).[1] The conditional mean using a bivariate VAR structure is expressed as follows:

$$r_t = \alpha_0 + \sum_{i=1}^{n} \beta_i r_{t-i} + \varepsilon_t \tag{1}$$

Where r_t is the $n \times 1$ vector of daily returns of the Impact Investing Index (hereafter II index) and the precious metals. α_0 the vector of the constant term, r_{t-i} are the lagged returns and β_i are the corresponding lag coefficients. ε_t is the vector of error terms with zero mean and constant variance $\left(\varepsilon_t \middle| \Omega_{t-1} \sim \mathrm{N}(0, H_t)\right)$with (i, j) lag order. The optimal lag length is selected using the Akaike Information Criterion (AIC) and Likelihood ratio (LR). The VAR model is elaborated to a conditional heteroscedastic error structure to deduce the conditional variance-covariance matrix. Further, Cappiello et al. (2006) proposed that the ADCC GARCH model is found superior against DCC GARCH to capture the time-varying correlation and the leverage effect of the news. The vector of errors vector is specified as: $\left(\varepsilon_t \middle| \Omega_{t-1} \sim Studentized\ t\ (0, H_t, \kappa)\right)$ where $H_t = D_t R_t D_t$ with $D_t = dia\left(\sqrt{h_{11,t}}, \ldots\ldots \sqrt{h_{nn,t}}\right)$ are the time-varying standard deviations obtained from the GARCH model and $R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$ and $Q_t = (1 - a - b)\bar{Q} + a u_t u'_{t-1} + bQ_{t-1}$ where Q_t is the covariance of the standardised residuals u_t, $\bar{Q}$ is the unconditional covariance matrix of u_t ($\bar{Q} = Cov(u_t u'_{t-1})$) and a and b are the non-negative scalars sufficing the inequality $a + b < 1$ to ensure stationarity and positive definiteness of $\bar{Q}$.

Further, the error term ε_t is assumed to follow Student's t distribution to accommodate excess kurtosis (Baillie and Bollerslev, 1989), which aids in robust estimates for normality

[1] Extant literature uses the VAR structure to model returns (Banerjee, 2021).

deviations (Tse, 1999). For this study, we allowed the conditional heteroscedastic $h_{i,t}$ to follow an EGARCH process in line with Nelson (1991) and is presented as follows:

$$log(h_{i,t}) = \omega_i + \alpha_i \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] + \beta_i log(h_{i,t-1}) + \gamma \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) \quad (2)$$

where $\alpha_i's$ and $\beta_i's$ captures the ARCH and the GARCH effects, and γ is the coefficient term for asymmetry in conditional volatility. Besides calibrating the asymmetric volatility and the time-varying conditional correlation, the DCC GARCH model is extended to an ADCC EGARCH framework following Cappiello et al. (2006) with the dynamics of Q_t expressed as follows:

$$Q_t = (\bar{R} - A'\bar{R}A - B'\bar{R}B - G'\bar{S}G) + A'u_{t-1}u'_{t-1}A + B'Q_{t-1}B + G'k_{t-1}k'_{t-1}G \quad (3)$$

where A, B, and G $(A = a^2, B = b^2, G = c^2)$ are the $N \times N$ parameters matrices, u_t denotes the standardised residuals, $\bar{R}$ and $\bar{S}$ the unconditional matrices of u_t, $k_t = I[u_t < 0]$ is equal to 1 and 0 otherwise. To have Q_t positive-definite the intercept term $(\bar{R} - A'\bar{R}A - B'\bar{R}B - G'\bar{S}G)$ must be positive semidefinite along with the initial covariance matrix Q_0 should be positive definite.

2.2 Optimal portfolio design and hedging ratios

Following Kroner and Sultan (1993), the optimal hedge ratio, $\beta_t^{i/II}$ is calculated as:

$$\beta_t^{i/II} = \frac{h_t^{i/impact}}{h_t^{II}} \quad (4)$$

Where $h_t^{i/II}$ is the conditional covariance between II and the precious metals h_t^{II} is the conditional variance of II at day *t*, from the ADCC–EGARCH model. A long position of 1 dollar in precious metals must be hedged by shorting $\beta_t^{i/II}$ dollars in II fund to minimise the portfolio risk. Extant literature used Kroner and Sultan's (1993) model to design optimal portfolios (see Akhtaruzzaman et al., 2021). For this paper, we estimated the hedged portfolio return as:

$$r_{h,t} = r_{i,t-}\beta_t^{i/impact} r_{II,t} \tag{5}$$

Where $r_{h,t}$ is a hedged portfolio return, $r_{i,t}$ is the return of the precious metals, $r_{II,t}$ is II's returns and $\beta_t^{i/II}$ is an optimal hedge ratio on given day *t*. The conditional variance of $r_{h,t}$ is calculated as:

$$var(r_{h,t}|I_{t-1}) = var(r_{impact,t}|I_{t-1}) - 2\beta_t^{i/II} cov(r_{impact,t}, r_{i,t}|I_{t-1}) + \beta_t^{i/impact^2} var(r_{i,t}|I_{t-1}) \tag{6}$$

2.3 Hedging Effectiveness

We estimate the hedging effectiveness (HE) index to check the performance of the hedging strategy. Following Dale (1981) and Batten et al. (2021), we calculate the HE index as below:

$$HE_{i,t} = \beta_t^{i/II^2} \frac{h_t^{impact}}{h_t^i} \tag{7}$$

If HE is 1, it results in a perfect hedge; if 0 occurs, there is no hedge effectiveness.

3. Data and descriptive statistics

Data are obtained from Datastream for the period from 30 November 2015 to 18 February 2022. The sample period corresponds with the launch date of the MSCI All Country World Index (ACWI) Sustainable Impact Index (hereafter the impact investing index). Data further include the prices of precious metals in USD per troy ounce. Figure 1 presents the prices of the impact investing index, palladium, platinum, gold, and silver. Figure 1 reveals that the prices of the impact investing and precious metals significantly dropped during the second of half of March 2020 when the financial markets experienced significant negative returns during the COVID–19 crisis (Akhtaruzzaman et al., 2021a). After the low points in March 2022, prices recovered significantly as the effects of the COVID–19 pandemic on the financial markets subsided due to the economic stimuli by governments across the world.

<Insert figure 1 about here>

The returns are presented in Figure 2. The daily returns are calculated from the prices as: $r_t = ln\left(\frac{P_t}{P_{t-1}}\right)$ where P_t is the index's closing price at the time *t*. Most of the return indices reflected high volatility mainly attributed to the sudden spread of the COVID–19 infections, which created larger swings in returns at the first quarter of 2020 at the onset of the COVID–19 outbreak and caused widespread uncertainty in the global financial markets (See Figure 2)). Table 1 presents the descriptive statistics. Palladium exhibits the highest mean return and variation measured by standard deviation. The return series distribution for all indices is negatively skewed and distinctly non-Gaussian due to high values of kurtosis, which is validated by the Jarque-Bera test at a 1% significance level.

Further, all the return series are stationary using the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests. The presence of non-normality and data being stationary aids us to continue our empirical analysis based on a multivariate GARCH framework.

<Insert table 1 about here>

<Insert figure 2 about here>

4. Empirical results

4.1 Asymmetric Dynamic Conditional Correlation

Table 3 presents the results of the ADCC (1,1) EGARCH (1,1) model. We used Hosking (1980) test to check for serial correlation, and we found negative evidence of serial correlation. Li and McLeod's (1981) was used to model misspecification, and they revealed no evidence of misspecification. The ADCC EGARCH is estimated on the VAR's residuals after estimating the

VAR model. The model analysis shows that α and β, the ARCH, and GARCH parameters are mostly found significant at the 1% level, except platinum and palladium, where the ARCH effect was found insignificant. Besides, the sum of ARCH and GARCH parameters are less than one, sufficing the necessary condition of the finiteness of the conditional variances. The higher values of β over α indicate that past variances tend to dominate the recent ones. The coefficient capturing the asymmetric impact (γ) is positive and significant at 1%, indicating the asymmetric impact of news, i.e., negative shocks have a higher impact against the positive ones. While the ADCC parameters a and b are non-negative and suffice the inequality $a + b < 1$ to ensure stationarity and positive definiteness. The parameters (a and b) are significant except platinum and palladium, where coefficient a was found insignificant.

Further, the high values of b indicate long-term persistence and volatility spillover between the impact investing and precious metals. The shape coefficient m is significant, supporting that the studentized-t distributed ADCC EGARCH is the best fit model for marginal and joint distribution, reflected in lower values of Akaike's Information Criterion (AIC) information criterion and Bayes Information Criterion (BIC). Figure 3 presents the dynamic conditional correlations (DCCs) between impact investing and precious metals. The DCCs significantly increased onset the COVID–19 pandemic in March 2020. The DCC between gold and impact investing rose to 0.4957 on 13 March 2020, implying that gold lost its safe-haven asset property in the earlier phase of the pandemic. This result is consistent with the literature (for example, Akhtaruzzaman et al. (2021b) find that gold lost it safe-haven property from March 17 to April 20, 2020).

<Insert table 2 about here>

<Insert figure 3 about here>

4.2 Optimal portfolio design and hedge ratios

The optimal hedge ratios are estimated from Eq. (4) using the ADCC–EGARCH model. Table 3 shows the time-varying optimal hedge ratios. The results provide interesting insights for portfolio design. Optimal hedge ratios for gold and silver changed from positive to negative during the first quarter of 2020 when the financial markets experienced the largest negative returns during the COVID–19 pandemic (see Figure 4). However, the hedge ratios for palladium and platinum remained positive during the COVID–19 pandemic. Literature shows that negative hedge ratios exist during crisis periods (Akhtaruzzaman, et al., 2021; Iglesias-Casal et al., 2020). The conversion of optimal hedge ratios for gold and sliver from negative to positive after the first quarter of 2020 could be due to the implementation of monetary and fiscal stimulus packages to revive economies (Batten et al., 2021). The significant increase in optimal hedge ratios after the first quarter of 2020 implies that the hedging cost significantly increased after the first quarter, associated with increased DCCs between impact investing and gold and silver.

<Insert Table 3 about here>

<Insert Figure 4 about here>

4.3 Hedging Effectiveness

Optimal hedge ratios provide a general understanding of how a hedge is constructed to minimise risk. However, they do not help us decide whether the hedge is effective. The HE index helps us examine the performance of hedging strategies. This index is calculated using Eq. (7) and shows whether the hedge is effective by comparing the variance of the hedged portfolio with that of the unhedged portfolio. Figure 5 shows that the evolution of the HE index over time. The results demonstrate that the hedging effectiveness increases for all precious metals, with platinum having the highest average HE. The positive HE is consistent with the literature (Hussain Shahzad et al.,

2020). To further examine whether the hedging effectiveness improves during the pandemic, we use the following model:

$$HE_{i,t} = \alpha_0 + \alpha_{i,t} D_{COVID} + \varepsilon_{i,t} \tag{8}$$

Where D_{COVID} is a dummy variable that equals 1 during the first quarter of 2020 when the financial markets suffered the most during the pandemic and 0 otherwise. The results demonstrate that the hedging effectiveness increases (decreases) for gold (silver) during the pandemic. The improvement in the hedging effectiveness of gold during the pandemic demonstrates the safe-haven asset property of gold. These results provide practical implications for investors, policymakers, and regulators.

<Insert Tables 4 and 5 about here>

<Insert Figure 6 about here>

4.4 Economic significance of hedging strategy

The HE index provides evidence for the hedging effectiveness of optimal portfolios. However, to examine the economic significance of the hedging strategies, we analyse how hedge portfolios offer utilities to investors. We follow Batten et al. (2021), Kroner and Sultan (1993), and Narayan and Sharma (2016) to calculate the change in the utility gain, $\Delta E(U)$, defined as the difference between the utility of the hedged portfolio (HP) and unhedged portfolio (UP).

$$\Delta E(U) = \left[E\left(U(HP_t|I_{t-1})\right)\right] - \left[E\left(U(UP_t|I_{t-1})\right)\right] \tag{9}$$

$$E\left(U(HP_t|I_{t-1})\right) = E\left(r_{h,t}\middle|I_{t-1}\right) - \frac{1}{2}\gamma\, var\left(r_{h,t}\middle|I_{t-1}\right) - TC \tag{10}$$

$$E\left(U(UP_t|I_{t-1})\right) = E\left(r_{i,t}\middle|I_{t-1}\right) - \frac{1}{2}\gamma\, var\left(r_{i,t}\middle|I_{t-1}\right) \tag{11}$$

Where γ is a risk aversion parameter that accounts for the different levels of risk aversion and TC is transaction cost. Since the expected utility depends on the level of risk aversion, we have considered different types of investors (i.e., low-risk aversion investors ($\gamma = 3$), medium risk aversion investors ($\gamma = 6$), and high-risk aversion investors ($\gamma = 12$)). Following Batten et al. (2021) and Narayan and Sharma (2016), we have considered the transaction cost of 0.50%. The results demonstrate that all precious metals provide higher utility gains for each type of investor. These results provide policy implications for investors where to hedge.

<Insert Table 6 about here>

5. Robustness

We apply several alternative specifications to check the robustness of our findings. Our main results are based on the MSCI All Country World Index (ACWI) Sustainable Impact Index. However, we alternatively use the STOXX Global ESG Impact Index to substantiate our findings. We find similar results using the STOXX Global ESG Impact Index. The results from STOXX Global ESG Impact Index are provided in Tables A1 to A4 and Figures A1 and A2. The use of alternative specification and STOXX Global ESG Impact Index provides robustness to the findings.

6. Conclusion

Impact investing is increasing in popularity as a key asset class for investors. Though impact investing is lending its contribution, debate continues whether impact investing is equally prone to systemic risk and how it performs during crisis and non-crisis periods. This paper is the first to

analyse the impact investing-precious metal hedge. The results show that the hedge ratios are time-varying and change during the uncertain period of the pandemic. Apart from studying hedge ratios, we have studied the hedging effectiveness when the impact investing index is used as an instrument for both tranquil and turmoil periods. The results support that impact investing are a viable risk mitigation instrument, especially during the COVID–19 pandemic. The results demonstrate that investors across the risk aversion spectrum gain higher utility after considering the transaction cost while investing in portfolios of impact investing and precious metals. Our findings are of important for the fund management industry as they can use this information to hedge their portfolios during market stress to improve portfolio performance.

Moreover, future research can use our findings to provide additional information about the usage of different indices to see how the results differ when other impact investment indices are used. Does the result remain the same? Finally, does the impact investing bonds appeal to the fund management industry? Are fund managers sensitive to the latest developments and practices in the investment industry concerning impact investing?

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Table 1: Descriptive statistics

Panel A: Descriptive statistics

	MSCI Impact Investing Index	Palladium	Platinum	Gold	Silver
Mean	0.0004	0.0009	0.0002	0.0004	0.0003
Maximum	0.0525	0.1696	0.0934	0.0497	0.1021
Minimum	-0.0892	-0.1568	-0.1442	-0.0507	-0.1959
Std. Dev.	0.0083	0.0208	0.0160	0.0086	0.0166
Skewness	-1.1911	-0.5366	-0.5151	-0.2472	-0.8681
Kurtosis	16.2961	13.1995	9.7713	7.7219	19.3865
Jarque-Bera	12346.51***	7117.23***	3174.34***	1525.29***	18373.77***
ADF	-12.03***	-36.63***	-39.36***	-39.91***	-38.49***
PP	-36.71***	-36.49***	-39.39***	-39.94***	-38.46***
Observations	1624	1624	1624	1624	1624

Panel B: Correlation Matrix

	MSCI Impact Investing Index	Palladium	Platinum	Gold	Silver
MSCI Impact Investing Index	1.0000				
Palladium	0.3422***	1.0000			
Platimun	0.3224***	0.5141***	1.0000		
Gold	0.1236***	0.4481***	0.2684***	1.0000	
Silver	0.2224***	0.5533***	0.3429***	0.4262***	1.0000

Notes: The Jarque–Bera test is used to check whether the return distribution is normal. The augmented Dickey-Fuller (ADF) and Philip- Perron (PP) tests are used to check the unit root of the return series.
*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Results of the VAR (ADCC) EGARCH model

	Gold	Silver	Platinum	Palladium
Conditional variance				
Const	-0.0046**	0.0050***	0.0021**	0.0208***
Arch (α)	0.0296**	0.0371***	-0.0004	-0.0137
Garch (β)	0.9860***	0.9936***	0.9971***	0.9841***
Leverage (γ)	0.0809***	0.0659***	0.0636***	0.1190***
Joint				
a	0.0384***	0.0163**	0.0123	0.0011
b	0.8822***	0.9636***	0.9462***	0.9517***
Shape				
m	5.4980***	6.0026***	7.6884***	4.6176***
Information Criterion				
AIC	4.4083	5.5566	5.5847	6.0662
BIC	4.5975	5.7459	5.7740	6.2555
Shibata	4.4059	5.5542	5.5824	6.0639
HQ	4.4785	5.6268	5.6549	6.1364
Log-likelihood				
LL	-3522.5100	-4454.9470	-4477.7840	-4868.7690
Model-fit				
Hosking test	130.7377	126.7919	97.6456	130.8441
Li and McLeod test	131.1892	126.4183	97.6469	130.4065

Note: 1. We reported lag 30 values for Hosking's (1980) test to check for the presence of no serial correlation.
2. The Li and McLeod test results are reported at lag 30, which checks the model misspecification.
*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Hedge Ratios

	Palladium	Platinum	Gold	Silver
Mean	0.7355	0.6171	0.1475	0.4007
Maximum	1.5848	1.5131	0.6813	1.2402
Minimum	0.2796	0.1055	-0.3349	-0.3178
Std. Dev.	0.1894	0.2132	0.1625	0.2393
Skewness	0.5240	0.5345	-0.0610	0.1245
Kurtosis	3.3565	3.5608	3.0002	3.4125

Notes:

Following Kroner and Sultan (1993), the optimal hedge ratio, $\beta_t^{i/II}$ is calculated as:

$$\beta_t^{i/II} = \frac{h_t^{i/impact}}{h_t^{II}} \tag{4}$$

Where $h_t^{i/II}$ is the conditional covariance between II and the precious metals h_t^{II} is the conditional variance of II at day *t*, from the ADCC–EGARCH model.

Table 4: Hedging Effectiveness

	Palladium	Platinum	Gold	Silver
Mean	0.0007	0.0009	0.0003	0.0004
Maximum	0.0009	0.0021	0.0026	0.0015
Minimum	0.0005	0.0001	0.0000	0.0000
Std. Dev.	0.0001	0.0003	0.0004	0.0003
Skewness	0.4370	0.4492	2.0853	0.4344
Kurtosis	2.9003	3.1651	8.3294	2.1741

Notes:
Following Dale (1981) and Batten et al. (2021), we calculate the HE as below:

$$HE_{i,t} = \beta_t^{i/II^2} \frac{h_t^{Impact}}{h_t^i} \quad (7)$$

Where $\beta_t^{i/II}$ is the optimal hedge ratio; $h_t^{i/Impact}$ is the conditional covariance between Impact Investing and precious metals and h_t^{Impact} is the conditional variance of Impact Investing at day *t*, derived from the ADCC–EGARCH model.

Table 5: Economic significance of hedging strategy

Industry and major financial assets	Risk aversion		
	$\gamma = 3$ (Low Risk Aversion)	$\gamma = 6$ (Medium Risk Aversion)	$\gamma = 12$ (High Risk Aversion)
Palladium	0.0293	0.0442	0.0886
Platinum	0.0075	0.0152	0.0306
Gold	0.0021	0.0042	0.0085
Silver	0.0149	0.0299	0.0601

Notes:

Following Batten et al. (2021), Kroner and Sultan (1993), and Narayan and Sharma (2016), we calculate the change in the utility gain, $\Delta E(U)$, defined as the difference between the utility of the hedged portfolio (HP) and unhedged portfolio (UP).

$$\Delta E(U) = \left[E\left(U(HP_t|I_{t-1})\right)\right] - \left[E\left(U(UP_t|I_{t-1})\right)\right] \quad (9)$$

Table 6: HE during the COVID–19 pandemic, 15 Oct 2014–22 Nov 2021

Industry and major financial assets	Intercept	Dummy for COVID–19
Palladium	0.0007***	-0.0000
Platinum	0.0009***	0.0001
Gold	0.0003***	0.0002***
Silver	0.0005***	-0.0002***

Notes:

To further examine whether the hedging effectiveness improves during the pandemic, we use the following model:

$$HE_{i,t} = \alpha_0 + \alpha_{i,t} D_{COVID} + \varepsilon_{i,t} \quad (8)$$

Where D_{COVID} is a dummy variable that equals 1 during the first quarter of 2020 when the financial markets suffered the most during the pandemic and 0 otherwise.

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

Figure 1: Impact investing index and precious metal prices

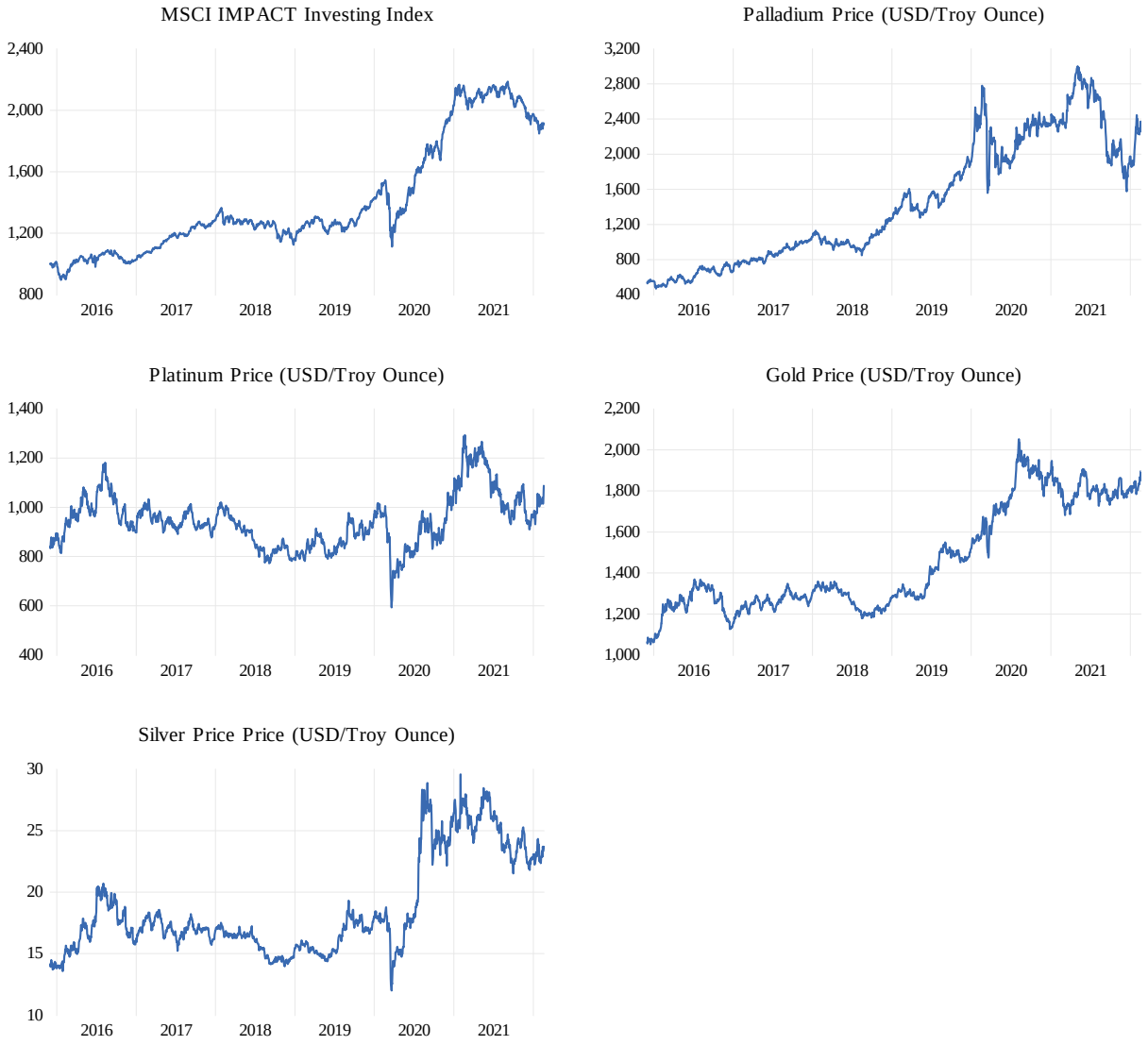


Figure 2: Returns Impact investing index and precious metals

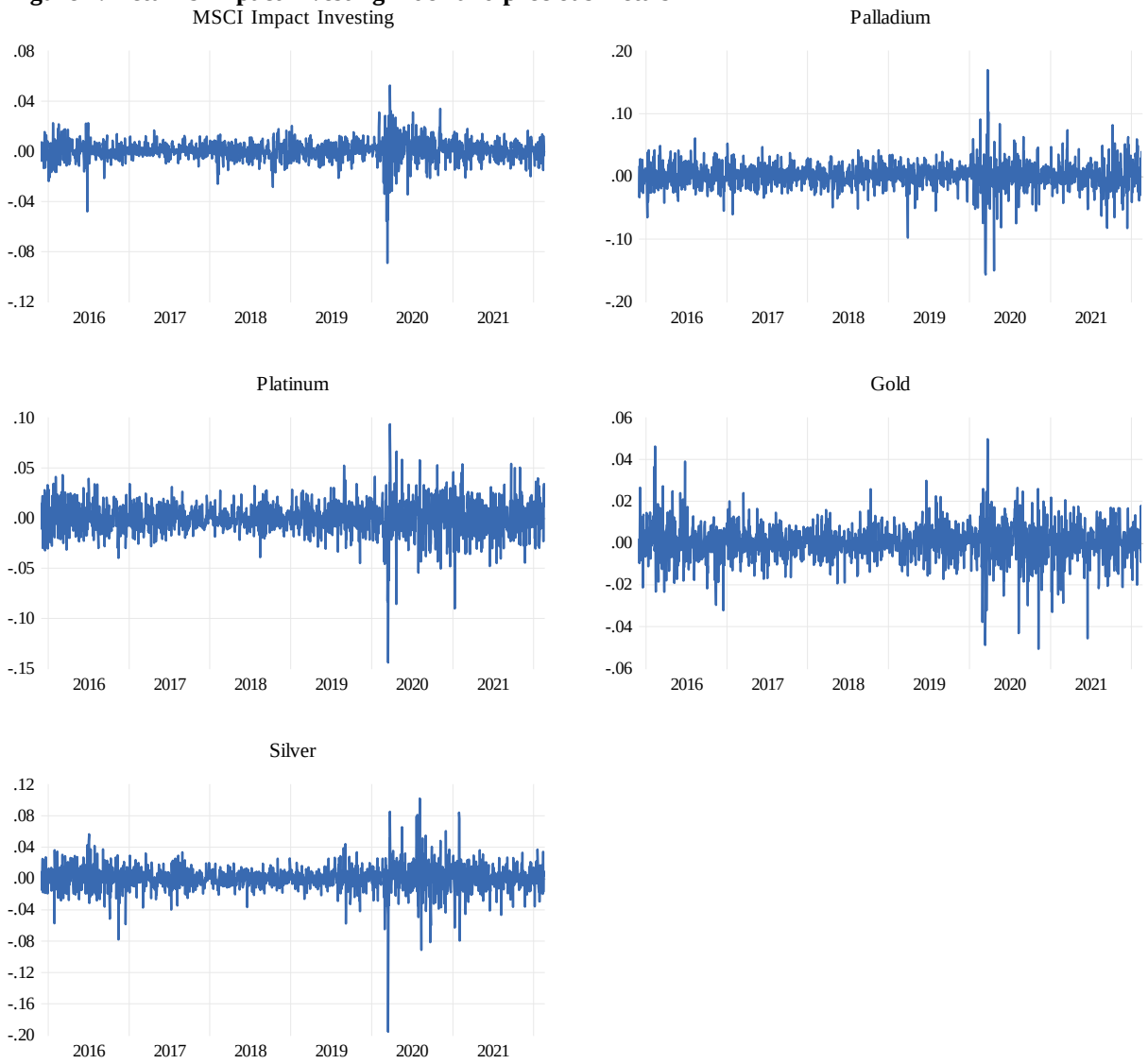


Figure 3: DCC plots between the impact investing and precious metals

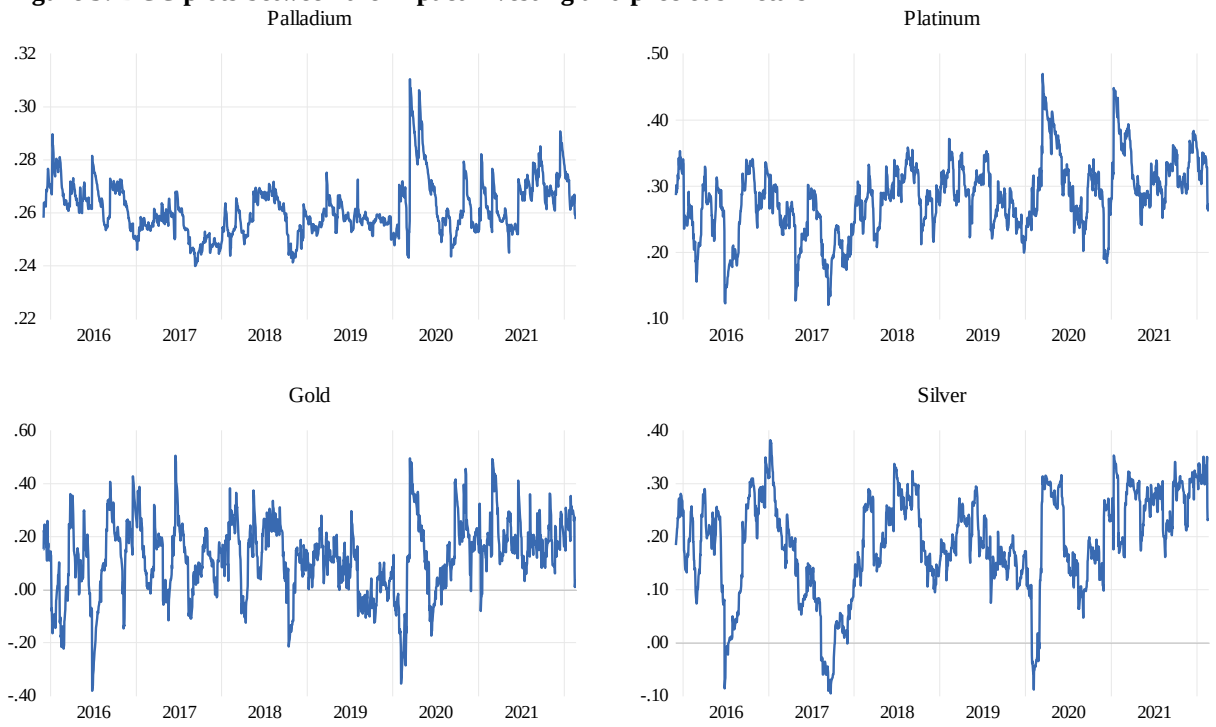


Figure 4: Hedge ratios

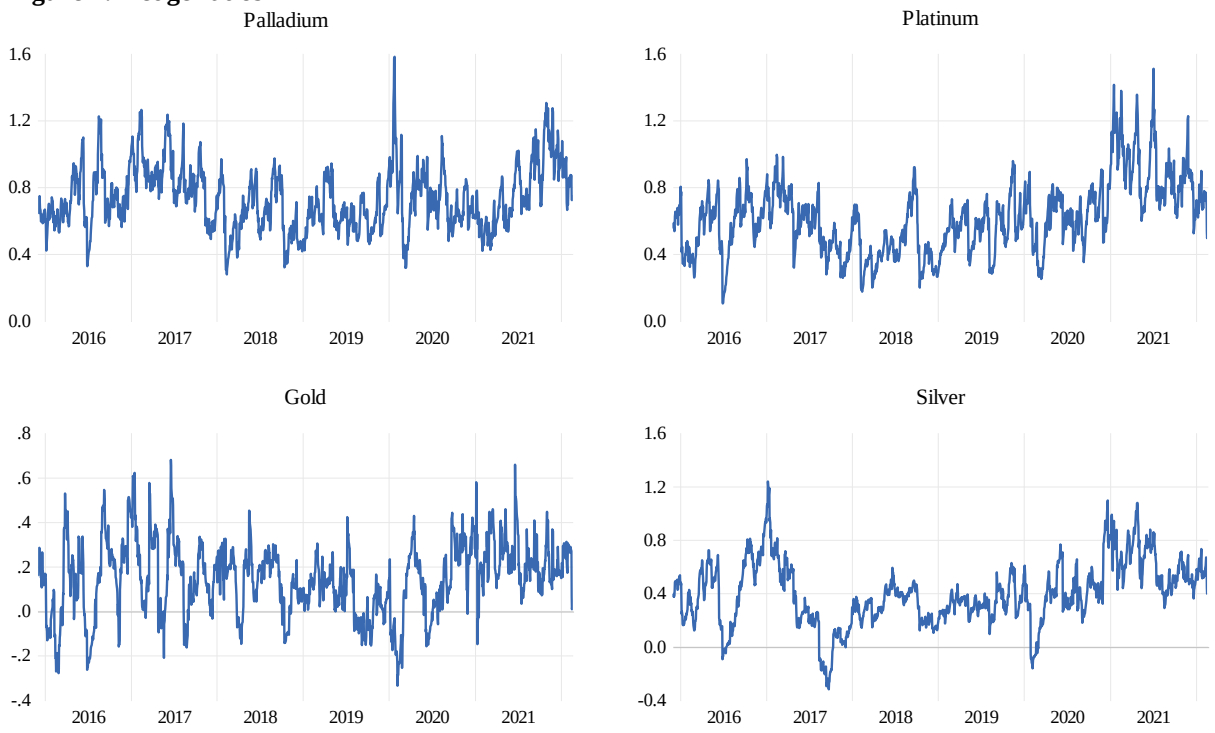
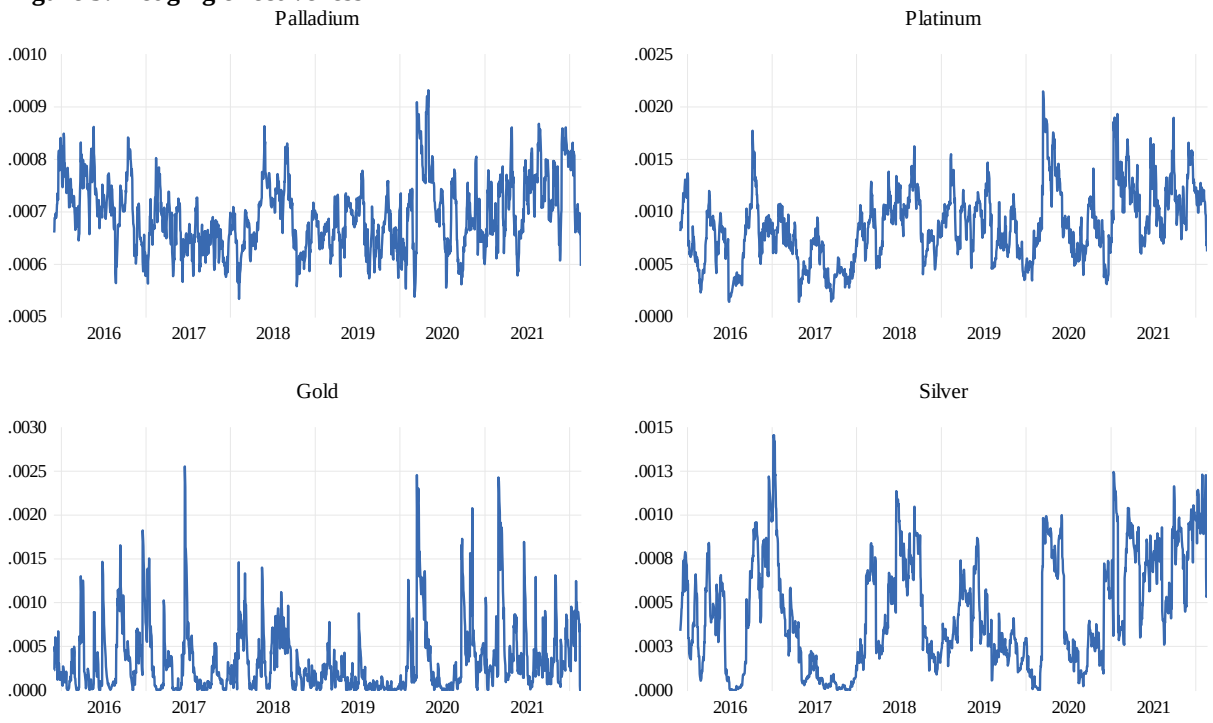


Figure 5: Hedging effectiveness



Appendices

Table A1: Results of the VAR (ADCC) EGARCH model

	Gold	Silver	Platinum	Palladium
Conditional variance				
Const	0.0023*	-0.0060***	0.0210***	-0.0306***
Arch (α)	0.0001	0.0267*	-0.0082***	-0.0855***
Garch (β)	0.9970***	0.9847***	0.9834***	0.9632***
Leverage (γ)	0.0661***	0.0847***	0.1279***	0.2074***
Joint				
a	0.0125***	0.0297***	0.0083***	0.0443***
b	0.9666***	0.9288***	0.9449***	0.8720***
Shape				
m	6.6932***	5.2162***	5.5891***	6.3701***
Information Criterion				
AIC	5.5857	4.3982	6.0513	3.0196
BIC	5.7885	4.6010	6.2541	3.2224
Shibata	5.5829	4.3955	6.0485	3.0168
HQ	5.6613	4.4738	6.1268	3.0952
Log-likelihood				
LL	-4109.9460	-3224.0880	-4457.2520	-2195.6370
Model-fit				
Hosking test	120.2770	139.4796	142.7808	149.6412
Li and McLeod test	119.9999	138.8551	142.1623	148.8216

Notes:
We reported lag 30 values for Hosking's (1980) test to check for the presence of no serial correlation.
The Li and McLeod test results are reported at lag 30, which checks the model misspecification.
*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table A2: Hedge Ratios

	Palladium	Platinum	Gold	Silver
Mean	0.06	0.56	0.50	2.01
Maximum	0.37	1.44	1.45	5.57
Minimum	-0.40	0.14	0.06	0.10
Std. Dev.	0.13	0.22	0.24	1.03
Skewness	-0.52	0.73	0.83	0.83
Kurtosis	3.02	3.50	3.80	3.16

Notes:

Following Kroner and Sultan (1993), the optimal hedge ratio, $\beta_t^{i/II}$ is calculated as:

$$\beta_t^{i/II} = \frac{h_t^{i/impact}}{h_t^{II}} \tag{4}$$

Where $h_t^{i/II}$ is the conditional covariance between II and the precious metals h_t^{II} is the conditional variance of II at day *t*, from the ADCC–EGARCH model.

Table A3: Hedging Effectiveness

	Palladium	Platinum	Gold	Silver
Mean	0.0005	0.0009	0.0021	0.0525
Maximum	0.0020	0.0053	0.0108	0.3147
Minimum	0.0000	0.0000	0.0001	0.0001
Std. Dev.	0.0001	0.0007	0.0017	0.0543
Skewness	8.6499	2.0972	1.4970	1.4991
Kurtosis	112.8627	9.9656	5.6986	4.7713

Notes:
Following Dale (1981) and Batten et al. (2021), we calculate the HE as below:

$$HE_{i,t} = \beta_t^{i/II^2} \frac{h_t^{Impact}}{h_t^i} \quad (7)$$

Where $\beta_t^{i/II}$ is the optimal hedge ratio; $h_t^{i/Impact}$ is the conditional covariance between Impact Investing and precious metals and h_t^{Impact} is the conditional variance of Impact Investing at day *t*, derived from the ADCC–EGARCH model.

Table A4: Economic significance of hedging strategy

Industry and major financial assets	Risk aversion		
	$\gamma = 3$ (Low Risk Aversion)	$\gamma = 6$ (Medium Risk Aversion)	$\gamma = 12$ (High Risk Aversion)
Palladium	0.0473	0.0947	0.1895
Platinum	0.0078	0.0160	0.0323
Gold	-0.0005	-0.0007	-0.0011
Silver	0.0363	0.0735	0.1479

Notes:

Following Batten et al. (2021), Kroner and Sultan (1993), and Narayan and Sharma (2016), we calculate the change in the utility gain, $\Delta E(U)$, defined as the difference between the utility of the hedged portfolio (HP) and unhedged portfolio (UP).

$$\Delta E(U) = \left[E\left(U(HP_t|I_{t-1})\right)\right] - \left[E\left(U(UP_t|I_{t-1})\right)\right] \quad (9)$$

Figure A1: Hedge Ratios

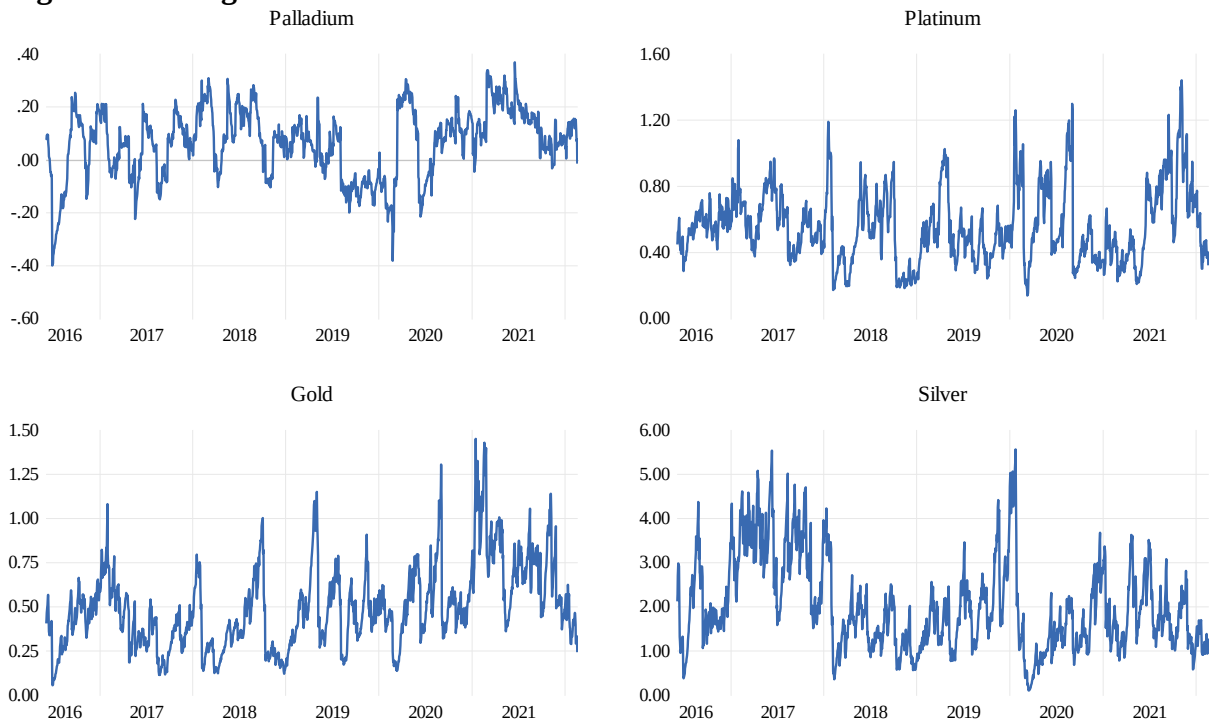
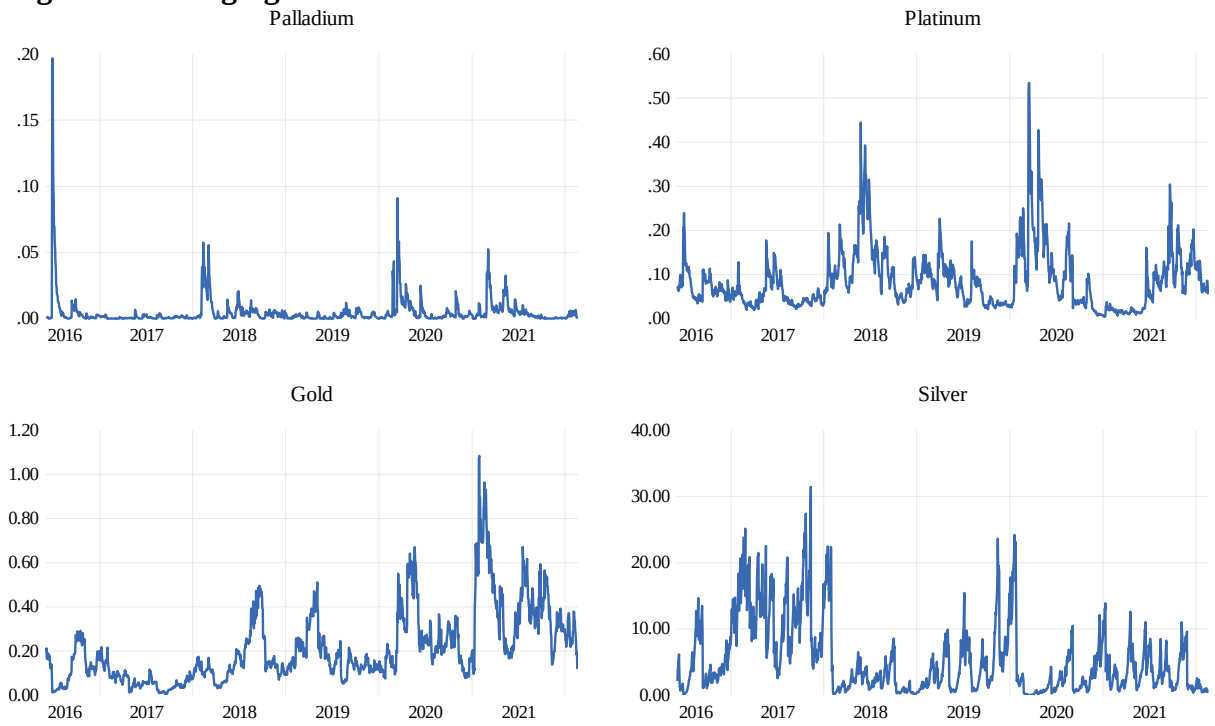



Figure A2: Hedging Effectiveness