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Using Precious Metals to Reduce the Downside Risk of FinTech Stocks

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Abstract: FinTech stocks are an important new asset class that reflects the rapidly growing FinTech sector. This paper studies the practical implications of using gold, silver, and basket-of-precious-metals (gold, silver, platinum, palladium) ETFs to diversify risk in FinTech stocks. Downside risk reduction is estimated using relative risk ratios based on CVaR. The analysis shows that gold provides the most downside risk protection. For a 5% CVaR, a 30% portfolio weight for gold reduces the downside risk by about 25%. The minimum variance and minimum correlation three-asset (FinTech, gold, and silver) portfolios (with portfolio weights estimated using a TVP-VAR model) have the highest risk-adjusted returns (Sharpe ratio, Omega ratio) followed by the fixed-weight FinTech and gold portfolio. These results show the benefits of diversifying an investment in FinTech stocks with precious metals. These results are robust to weekly or monthly portfolio rebalancing and reasonable transaction costs.

Keywords: FinTech stocks; downside risk; minimum variance portfolio; gold; portfolio analysis

JEL Classification: G1; G11; G15

1. Introduction

In the past ten years, financial technology (FinTech) has evolved to create some amazing new financial products and services. Examples of FinTech include mobile payments via smartphones, securing transactions through blockchain, peer-to-peer lending, robo-investment advising, cybersecurity, cloud computing, and crowdfunding [1]. FinTech can increase efficiency in the financial sector [2,3] and promote financial inclusion [4–7]. The growth of FinTech has been accompanied by a rapid growth in investing in FinTech stocks. For example, in July 2023, publicly traded FinTech companies had a market capitalization of USD 550 billion, which is a two-time increase versus 2019 [8].

The growing interest in FinTech stocks has inspired a literature looking at the dynamic connectedness between FinTech stocks and other assets. To date, there is research looking at the relationship between FinTech stocks and other financial assets like Bitcoin, green bonds, and AI [9], robotics and AI stocks [10], conventional finance [11–15], renewable energy [16], green bonds [17], and related FinTech assets [18–20].

While the abovementioned studies provide important perspective on the relationship between FinTech stocks and other financial markets, the risk management of FinTech stocks is understudied. The risk management of FinTech stocks is important because investors need to identify and measure downside risk and either accept the impact these downsides have on risk-adjusted returns or mitigate downside risk in order to achieve higher risk-adjusted returns. One way to mitigate the downside risk associated with FinTech stocks is to combine FinTech stocks with another unrelated (uncorrelated) asset class—a tactic referred to as portfolio diversification. According to modern portfolio theory, an investment portfolio experiences two types of risk: systematic risk and unsystematic risk or specific risk [21]. Systematic risk is the risk associated with the volatility in the entire capital market and cannot be diversified away. Specific risk is the volatility associated with a specific

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security and can be diversified away by investing in other securities. In the context of FinTech stocks, Henriques and Sadorsky [22] find that combining FinTech stocks with clean energy stocks produces higher risk-adjusted returns than an investment only in FinTech stocks. They do not, however, investigate the role of precious metals in reducing FinTech downside risk.

The purpose of this research is to examine the ability of precious metals to reduce the downside risk for an investment in FinTech stocks. In this paper, risk reduction is measured using risk ratios [23,24]. A risk ratio is constructed where the numerator is the risk of a portfolio that mixes FinTech with precious metals and the denominator is the risk of an investment in FinTech. The value of this ratio shows the share of portfolio risk remaining after diversifying with precious metals. Lower values of this ratio indicate greater risk reduction. Risk ratios are often used by practitioners because they are easy to calculate and easy to interpret. The analysis in this paper uses conditional value at risk (CVaR) as the risk measure. CVaR, also referred to as expected shortfall (ES), is a risk measure that quantifies tail risk in the return distribution. More explicitly, CVaR is computed by taking a weighted average of the loses below the value at risk (VaR) value. VaR measures how much an investment will lose (with given probability α) over a specific time period [25]. CVaR is often preferred in practice over VaR because CVaR is a coherent measure of risk, while VaR is not [26]. A comparison is made between fixed-weight two-asset portfolios and three-asset (FinTech, gold, silver) changing-weight minimum-variance, minimum-correlation, and minimum-connectedness portfolios where the portfolio weights are estimated using a TVP-VAR model.

Precious metals are chosen as the financial assets to reduce FinTech downside risk because of the long history of using these assets as diversifiers. Gold is often used by investors as a hedge against inflation or adverse economic times [27–44]. For example, gold prices increased during the 2008–2009 global financial crisis (GFC) and during the COVID-19 pandemic as investors sought safe-haven investments. In addition to gold, there is research showing that other precious metals like silver, platinum, and palladium also have diversification and hedging properties [40,45–49].

For the purposes of this research, a FinTech company is defined to be a small, technology-enabled, new entrant to financial services that disrupts the incumbents [50]. FinTech stock prices and the prices of gold, silver, and a basket of precious metals are measured using exchange-traded funds (ETFs). ETFs are collections of traded securities used by individual and institutional investors to build portfolios. ETFs have low management fees and are widely traded. The daily data set covers the time period 16 September 2016 to 28 June 2024. In addition to estimating and comparing downside risk ratios for different weights of precious metals, risk and return analysis is provided by comparing an investment in FinTech stocks with portfolios that combine FinTech and precious metals.

Risk ratios computed using CVaR show that gold provides the most downside risk reduction. For a 5% CVaR, a 30% portfolio weight for gold reduces the downside risk by about 25%. Silver has the least downside risk reduction. Portfolio analysis shows that combining FinTech stocks with either gold, silver, or a precious metals basket in a fixed-weight two-asset portfolio produces higher risk-adjusted returns and lower maximum drawdowns than an investment solely in FinTech stocks. Overall, the three-asset (FinTech, gold, silver) minimum-variance portfolio (MVP) and minimum-correlation portfolio (MCP) have the highest risk-adjusted returns and lowest drawdown. The MVP and MCP portfolio weights are estimated using a TVP-VAR model. These results are robust to weekly or monthly rebalancing of portfolios and transaction costs.

This study proceeds as follows. Section 2 describes the methodology, while Section 3 details the data. The results are presented in Section 4. Section 5 presents a discussion and conclusion.

2. Methods

This section describes the empirical methods used in the analysis. There are two main empirical methods of analysis used in this paper—relative risk ratios and investment portfolio performance.

2.1. Relative Risk Ratios

Relative risk ratios are computed as the ratio $CVaR_{mix}/CVaR_{ft}$, where "*mix*" is a portfolio that mixes FinTech stocks with precious metals and "*ft*" is the investment in FinTech stocks. The $CVaR_p$ is the average expected portfolio loss larger than a VaR_p for a confidence interval of $(1-\alpha)$:

$$CVaR_p(1-\alpha) = E(R_p \middle| R_p < VaR_p(1-\alpha) \tag{1}$$

Rp is the portfolio return and VaR_p is the portfolio VaR_p calculated at the α level. *VaR* quantifies an investment loss for a specific time period and probability (α). Typical values for α are 0.01 (1%) and 0.05 (5%). The expression for VaR_p is:

$$Prob\left(R_p \leq VaR_p(1-\alpha)\right) = \alpha \tag{2}$$

VaR can be calculated parametrically or non-parametrically [26]. The analysis in this paper uses a historical *VaR* (non-parametric) and a modified VaR (parametric) [51]. The historical *VaR* is the α percentile value of the return distribution. The modified *VaR* uses a Cornish–Fisher expansion to modify the Gaussian *VaR* to account for skewness and kurtosis [51].

2.2. Portfolio Construction

Portfolios were constructed for two-asset portfolios and three-asset portfolios. The two-asset portfolios (FinTech and one precious metal) are estimated using fixed weights and do not require econometric techniques.

The three-asset portfolios (FinTech, gold, and silver) are estimated with changing portfolio weights and require econometric techniques. Three portfolios are estimated, (1) minimum-variance portfolio (*MVP*) [52], (2),minimum-correlation portfolio (*MCP*) [53], and (3) minimum-connectedness portfolio (*MPC*) [54].

The *MVP* minimizes total variance where $\sum_t$ is the 3×3 variance–covariance matrix of the asset returns at time period t. The portfolio weights for the *MVP* are:

$$w_{MVPt} = \frac{\sum_t^{-1} I}{I \sum_t^{-1} I} \tag{3}$$

The matrix I is the 3×3 identity matrix.

The objective of *MCP* is to determine portfolio weights by minimizing the portfolio correlation. The portfolio weights for the *MCP* are:

$$w_{MCPt} = \frac{CC_t^{-1} I}{CC_t^{-1} I} \tag{4}$$

where CC_t = diag$(\sum_t)^{-0.5} \sum$ diag$(\sum_t)^{-0.5}$ is the conditional correlations of asset returns.

The portfolio weights for the *MPC* are:

$$w_{MPCt} = \frac{PCI_t^{-1} I}{IPCI_t^{-1} I} \tag{5}$$

Here, PCIs are pairwise correlations estimated from a TVP-VAR(1) connectedness model. The Antonakakis et al. [55] TVP-VAR approach to estimating connectedness has several advantages over the VAR approach first proposed by Diebold and Yilmaz [56,57].

The TVP-VAR captures the time-varying nature in the data, taking into account changing dynamics over different periods and assessing the extent and direction of market spillovers [58]. This approach also avoids the problem of arbitrarily selecting a rolling window size. The SIC selected one as the order of the TVP-VAR lag length. The TVP-VAR connectedness was estimated using 20-step-ahead generalized forecast error variance decompositions.

2.3. Portfolio Comparison

The risk-adjusted returns of portfolios are compared using the Sharpe ratio and the Omega ratio. The Sharpe ratio divides the average portfolio return (net of a risk-free rate) by the portfolio standard deviation. Higher Sharpe ratios indicate higher risk-adjusted returns. The Omega ratio is the probability weighted ratio of gains versus loses relative to a threshold target. While the Sharpe ratio takes mean and standard deviation into account, the Omega ratio also accounts for skewness and kurtosis. A higher Omega ratio indicates higher risk-adjusted returns.

In addition to the Sharpe ratio and Omega ratio, maximum drawdown, value-at-risk (VaR), and expected shortfall (ES) are calculated. A discussion of these measures can be found in Cogneau and Huber [59].

All computations were performed using R [60] with the help of the following packages-- ConnectednessApproach [61], quantmod [62], and PerformanceAnalytics [63].

3. Data

FinTech stock prices are measured using the adjusted closing prices of the Global X FinTech ETF (FINX). FINX is one of the largest (in terms of assets under management) ETFs specializing in FinTech stocks and has the longest trading history. Gold prices are measured by the GLD ETF and silver prices are measured by the SLV ETF. The ETF GLTR is a basket of precious metals (gold, silver, platinum, and palladium). The daily data set covers the period 13 September 2016 to 28 June 2024. GLD, SLV, and GLTR are the three largest precious metal ETFs in terms of assets under management. As of 1 August 2024 GLD, SLV, and GLTR had USD 55 billion, USD 10 billion, and USD 930 million, respectively, in assets under management (data sourced from Yahoo Finance). The starting date of the analysis is determined by the inception of FINX. The data are in USD and were downloaded from Yahoo Finance.

The time series pattern of FINX displays considerable variability (Figure 1). Between March 2018 and March 2020, FINX increased from USD 20 to USD 50. Most of this increase occurred during the onset of the COVID-19 lockdowns as consumers shifted more of their economic activity online [64]. The price appreciation was short lived and by September 2022, FINX was trading around USD 20.

The time series plots of the precious metals display a similar pattern of price appreciation from January 2019 to June 2020, although gold appreciated the most. Afterwards, gold and GLTR show the strongest performance. Over the sample period studied, gold has the strongest upwards trend followed by GLTR.

FINX, measured in continuously compounded daily percent returns, had a small positive average daily value of 0.03% over the sample period (Table 1). For the precious metals, GLD had the largest average daily return (0.027%) and SLV had the smallest (0.020%). Notice that while the variables have similar mean values, they display considerable variability. According to the coefficient of variation, SLV is the most variable while GLD is the least. The distribution of each variable is lightly skewed to the left and has heavier tails than a normal distribution. Each variable is stationary because the KPSS unit root test statistics are below the 5% critical value. Each variable is non-normally distributed.

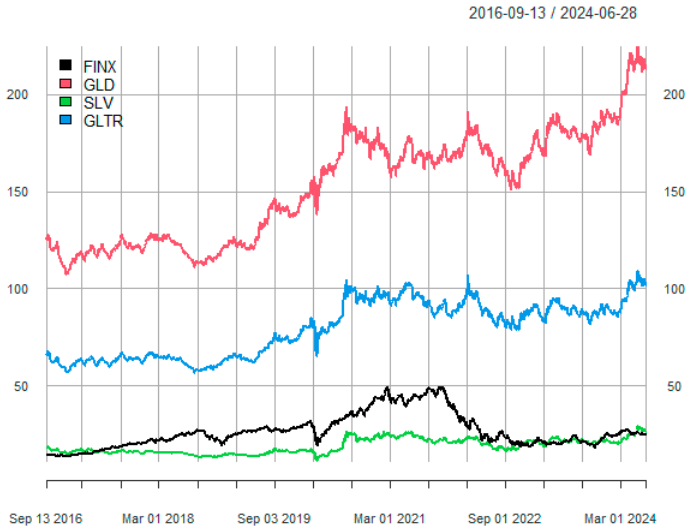

Figure 1. Time series plot of FINX, GLD, SLV, and GLTR adjusted closing prices.

Table 1. Summary statistics.

	Median	Mean	Std.dev	Coef.var	Skewness	Kurtosis	KPSS	W	W(p)
FINX	0.145	0.030	1.804	60.532	−0.490	5.600	0.287	0.938	0.000
GLD	0.055	0.027	0.865	31.595	−0.314	3.275	0.098	0.966	0.000
SLV	0.040	0.020	1.708	85.116	−0.418	7.627	0.080	0.924	0.000
GLTR	0.066	0.023	1.098	48.471	−0.486	5.513	0.053	0.949	0.000

Notes. All variables measured in continuously compounded daily percent returns. W is the Shapiro–Wilk test for normality and W(p) is the associated probability value. KPSS is the Kwiatkowski–Phillips–Schmidt–Shin test for unit roots (5% critical value is 0.463).

The Pearson correlation coefficients indicate that FINX is positively correlated with each precious metal (Table 2). The lowest correlation is between FINX and GLD while the highest correlation is between GLTR and SLV. Pearson correlation analysis indicates that GLD may be the best diversifier for FINX.

Table 2. Pearson correlation coefficients.

	FINX	GLD	SLV	GLTR
FINX	1.000	0.105	0.239	0.223
GLD	0.105	1.000	0.783	0.902
SLV	0.239	0.783	1.000	0.909
GLTR	0.223	0.902	0.909	1.000

Notes: See Table 1.

4. Results

The relative risk ratio plots show how relative risk varies by the precious metal portfolio weight (Figure 2). The top panel of Figure 2 shows relative risk ratios computed for 5% CVaR coverage (α value), while the lower panel shows ratios for 1% coverage. CVaR ratios are computed using either the historical or modified approach. Looking first at the top panel of Figure 2, gold has the greatest risk reduction. A 30% portfolio weight for gold reduces the downside risk by about 25% (relative risk ratio value is 0.75). Notice also that both GLD and GLTR show a smooth decline in relative risk as their portfolio weights increase until a weighting of 80%—after which higher weights add little to reducing downside risk. Silver is different in that relative risk is never reduced below 0.75. It is also important to point out that for each precious metal, the risk ratio computed using the historical method is similar to that using the modified method.

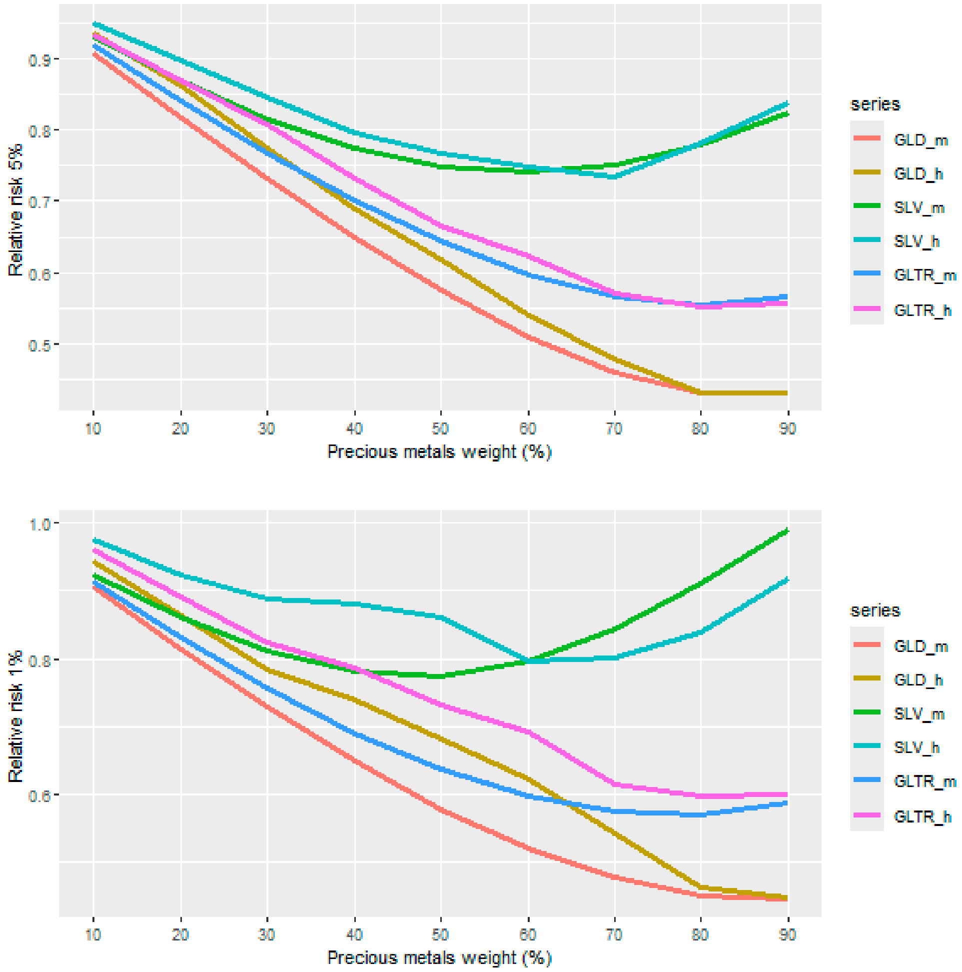

Figure 2. Relative risk ratio plots. The suffixes _m and _h denote modified and historical CVaR.

The lower panel of Figure 2 shows relative risk ratios computed using coverage at 1%. It is still the case that GLD and GLTR show the greatest risk reduction as the precious metal portfolio weight increases. Notice, however, that for each precious metal the choice of CVaR method (historical, modified) affects the pattern of the plots. This is expected because there are not many observations in the 1% tail of the return distribution, and this affects the precision of the CVaR calculation.

Since risk reduction may vary across time, it is also of interest to see how relative risk varies across time. For this analysis, the relative risk ratios are computed using a fixed rolling window of length 500 observations (two years of daily data) and a precious metals portfolio weighting of 25%. CVaR is calculated using the modified method. At a portfolio weighting of 25%, gold and precious metals show relative risk ratios of around 80%, which is enough of a risk reduction to accommodate trading costs in the portfolio analysis presented below. Regulators require that at least 250 daily observations be used for calculating VaR [65,66] and in practice 500 days is often used. The impact of the COVID-19 lockdowns on the relative risk (at 5% loss) is clear (Figure 3). All risk ratios experienced large increases during March 2020 when the COVID-19 lockdowns began. Thus, risk reduction is reduced during times of economic stress. Risk ratios remained elevated until January 2023. GLD provides the greatest amount of risk reduction across the sample period with a risk ratio that never exceeds 80%. GLTR has the next best risk reduction, while SLV provides the least amount of risk reduction.

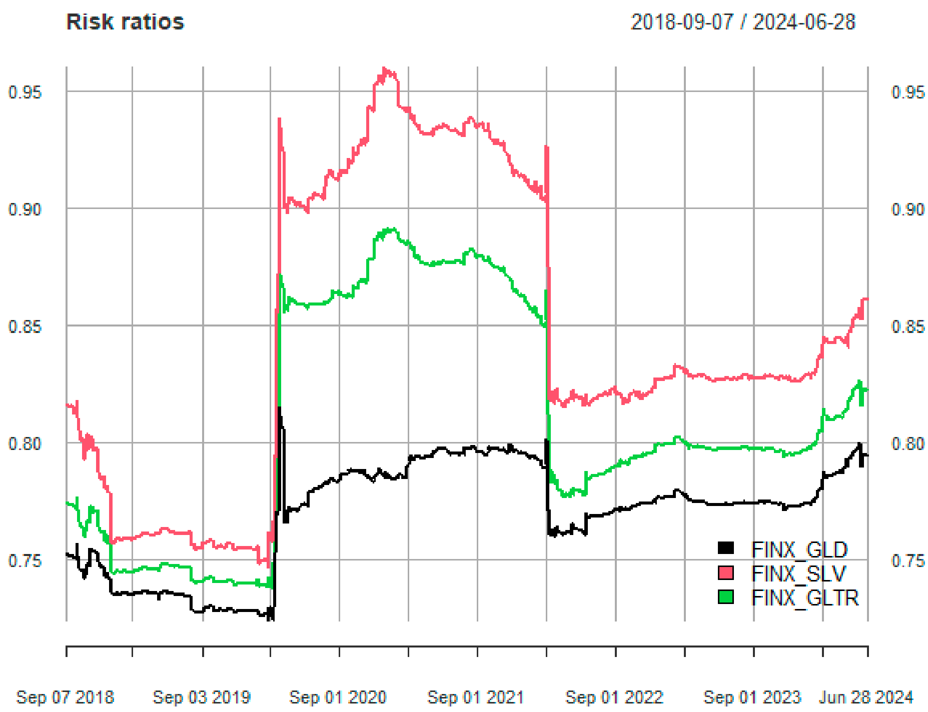

Figure 3. Risk ratios (at 5% loss) across time.

Risk ratios calculated for a 1% loss (Figure 4) show a similar pattern to those calculated for a 5% loss. GLD provides the greatest risk reduction, while SLV provides the least. Notice that gold's risk reduction during the COVID-19 period is higher than silver's risk reduction in the pre-COVID-19 period.

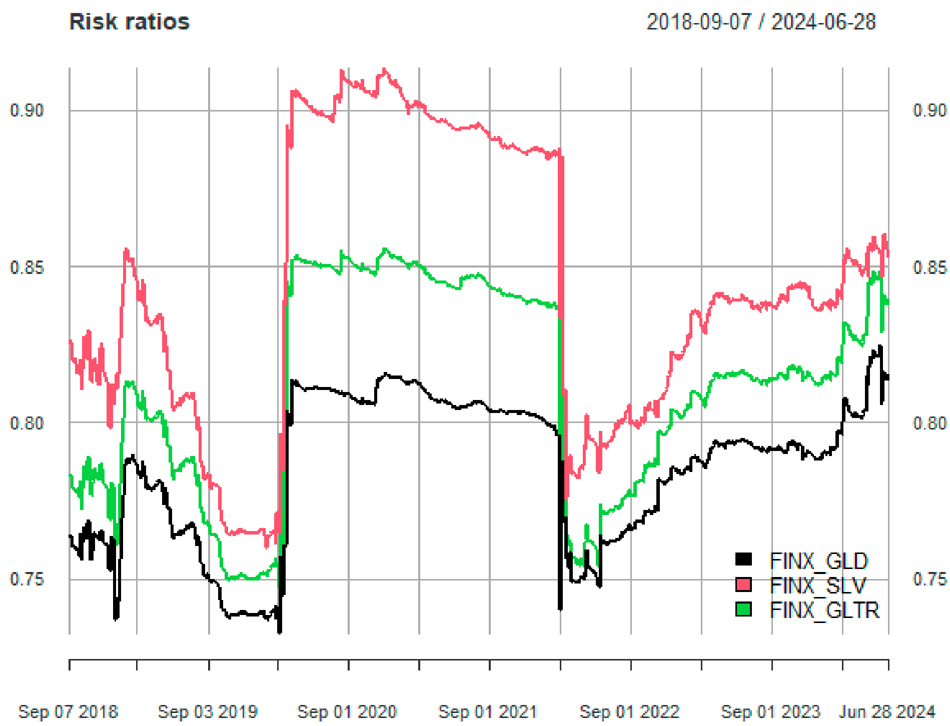

Figure 4. Risk ratios (at 1% loss) across time.

4.1. Two-Asset Portfolios

Turning now to portfolio performance comparisons, it is interesting to see how portfolios that combine FinTech stocks with precious metals compare to an investment only in FinTech stocks. For each two-asset portfolio, the precious metals weighting is 25%. Portfolio rebalancing occurs weekly and the transaction costs are 50 basis points per trade (50 cents per USD 100 transacted). A transaction cost of 50 basis points is generous as many discount brokers allow ETF trading for less than 10 basis points.

Equity curves (Figure 5) show how USD 1 in each portfolio evolves across time. The investment in FinTech stocks shows the greatest amount of variability while the portfolios that combine FinTech stocks with precious metals show less variability. At the endpoint of the time period, the FINX_GLD portfolio has a slightly higher return than the other portfolios.

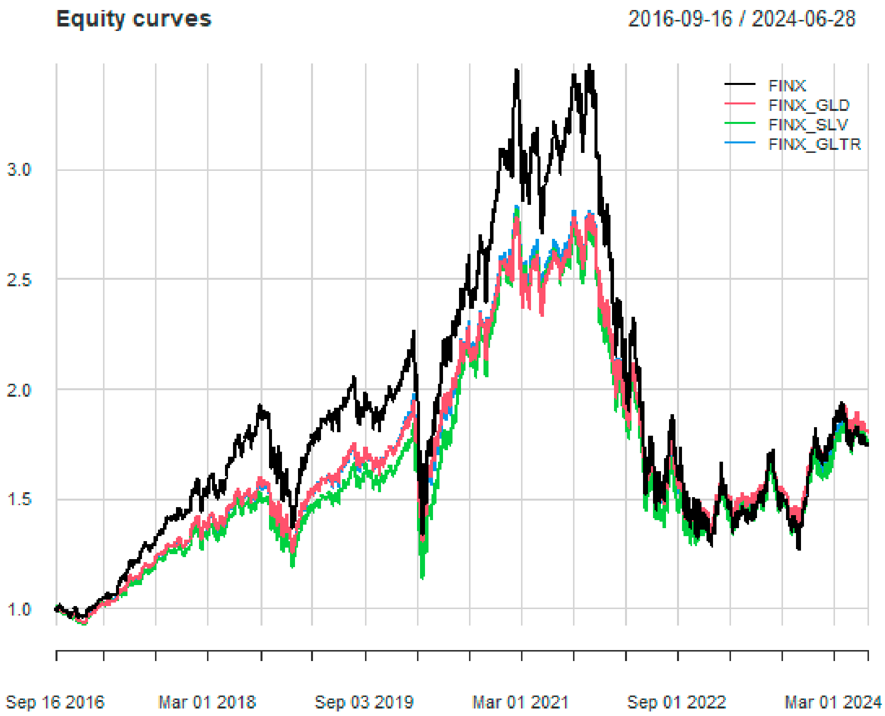

Figure 5. Equity curves—weekly rebalancing.

This figure shows how USD 1 invested in each portfolio evolves across time. For each two-asset portfolio, the precious metals weighting is 25%. Portfolio rebalancing occurs weekly and the transaction costs are 50 basis points per trade.

Portfolio summary statistics show that each of the portfolios that combine FinTech stocks with precious metals has a higher Sharpe ratio and Omega ratio and a lower standard deviation than an investment in FinTech stocks (Table 3. Portfolios that mix FinTech stocks with precious metals also have lower maximum drawdown, VaR, and ES. For example, an investment in FINX has an annualized return, Sharpe ratio, and maximum drawdown of 0.075, 0.153, and 0.635, respectively. In comparison a portfolio that combines FINX with GLD has an annualized return, Sharpe ratio, and maximum drawdown of 0.080, 0.218, and 0.521, respectively. While the annualized returns of the portfolios are similar, the risk-adjusted returns are higher for portfolios that combine FinTech stocks with precious metals. The FINX_GLD portfolio has the highest risk-adjusted returns (Sharpe ratio and Omega ratio).

Table 3. Portfolio summary statistics (two-asset portfolios).

	FINX	FINX_GLD	FINX_SLV	FINX_GLTR
Annualized Return	0.075	0.080	0.076	0.076
Annualized Std Dev	0.286	0.220	0.239	0.227
Annualized Sharpe	0.153	0.218	0.187	0.196
Maximum Drawdown	0.635	0.521	0.543	0.531
Historical VaR (95%)	−0.030	−0.023	−0.024	−0.024
Historical ES (95%)	−0.043	−0.033	−0.036	−0.034
Modified VaR (95%)	−0.029	−0.022	−0.024	−0.023
Modified ES (95%)	−0.051	−0.039	−0.047	−0.043
Omega (L = 0%)	1.074	1.086	1.080	1.082

Notes: The risk-free rate is set at 3% per year. For each two-asset portfolio, the precious metals weighting is 25%. Decimal returns reported. Portfolios rebalanced weekly. Transaction costs are 50 basis points per transaction.

4.2. Three-Asset Portfolios

The variation across time in the downside risk ratios shows that portfolio weights may need to be rebalanced and estimated frequently. This section reports results for three-asset (FINX, GLD, SLV) MVP, MCP, and MPC portfolios where the portfolio weights are estimated using a TVP-VAR model.

The total connectedness index (TCI) plot, estimated using a TVP-VAR(1) model, shows how total connectedness varies across time (Figure 6). The mean value of the TCI is 45%, indicating that on average 45% of the forecast error variance comes from spillovers. September of 2016, March of 2020, and November of 2022 exhibited periods of higher than average spillovers. Spillovers increased in 2016 as the strong performance of gold in the first half of the year (concerns over rising interest rates, Brexit, and the US presidential election) was offset by weakness in the second half of the year as concerns over these issues mitigated. Spillovers increased in March 2020 as COVID-19 was declared by the World Health Organization as a global heath pandemic. In 2022, central banks in North America and Europe began hiking interest rates to slow inflation and this led to higher spillovers and TCI.

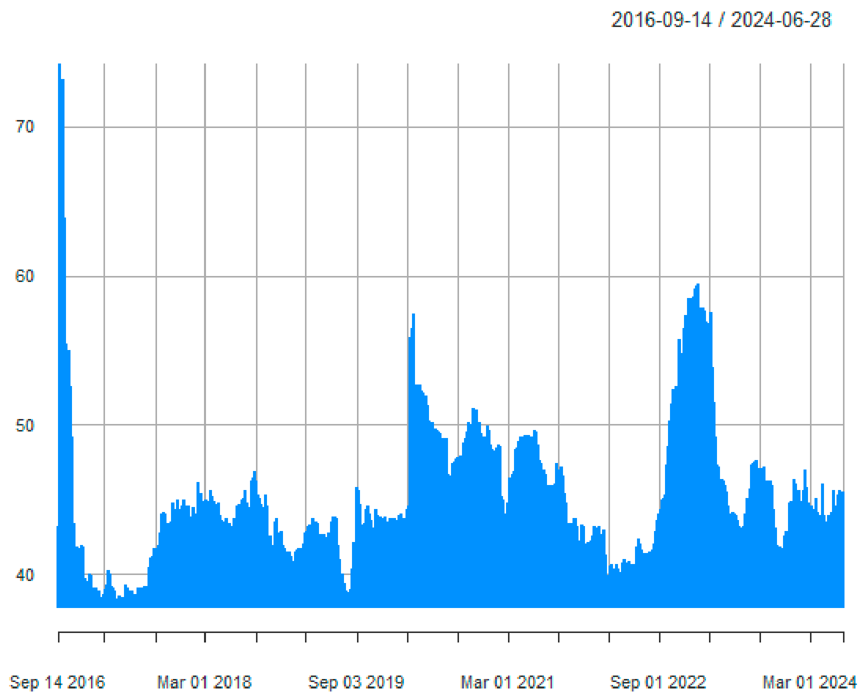

Figure 6. Total connectedness index estimated from a TVP-VAR(1) model.

The network connectedness plot shows average pairwise connectedness (Figure 7). Silver is the net contributor to spillovers, while gold and FINX are net receivers. This plot shows that gold is a better diversifier for FinTech than silver.

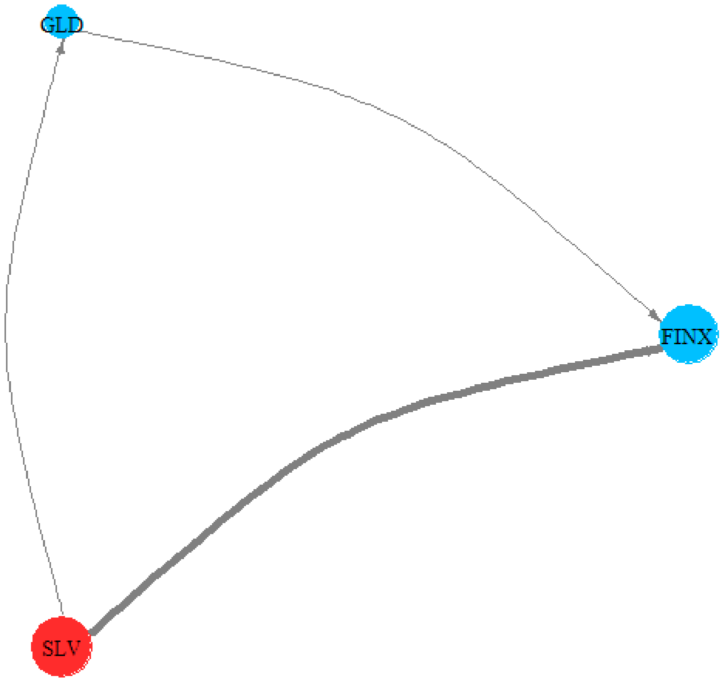

Figure 7. Network connectedness.

Equity curves for the three-asset portfolios show that the MVP has the highest end period returns, followed by the MCP and MPC (Figure 8). Notice that during the COVID-19 period, the MCP had the best performance. The MVP, which minimizes risk, underperforms during periods of high risk.

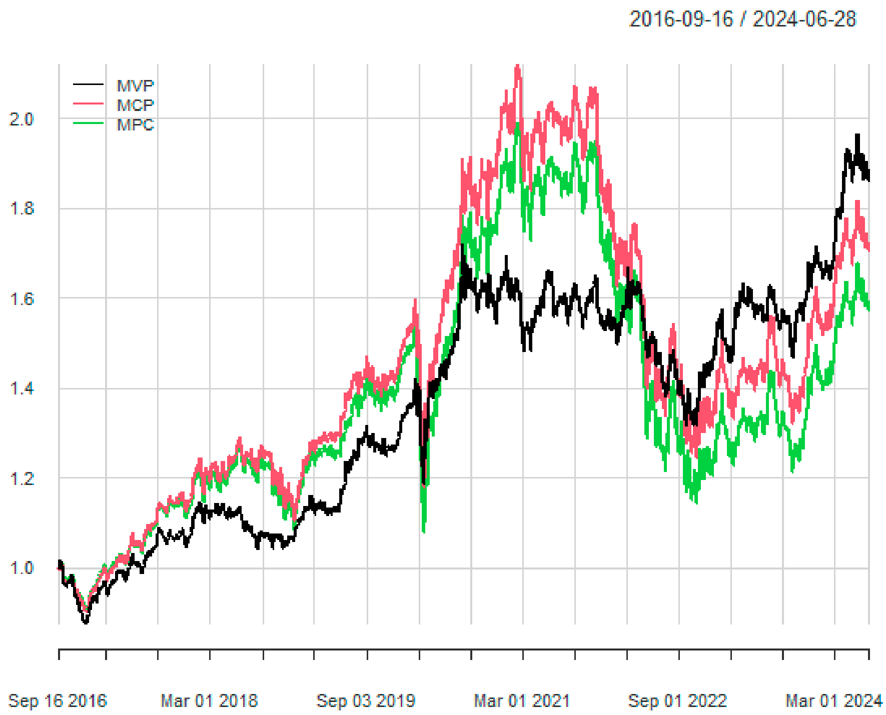

Figure 8. Equity curves for three-asset portfolios (FINX, GLD, SLV)—weekly rebalancing.

This figure shows how USD 1 invested in each portfolio evolves across time. Portfolio weights are constructed using a TVP-VAR(1) model. Portfolio rebalancing occurs weekly and the transaction costs are 50 basis points per transaction.

Portfolio summary statistics show that the MVP had the highest return, Sharpe ratio, and Omega ratio (Table 4). The MVP also had the lowest standard deviation, drawdown, value at risk, and expected shortfall. In comparing the Sharpe ratios in Table 4 with those in Table 3, notice that the MVP has the highest value overall and the MCP has the second highest value overall. The FINX-GLD portfolio has the third highest overall Sharpe ratio. All of the portfolios in Tables 3 and 4 have higher Sharpe ratios than an investment solely in FINX—illustrating the benefits of diversification.

Table 4. Portfolio summary statistics (three-asset (FinTech, gold, silver) portfolios).

	MVP	MCP	MPC
Annualized Return	0.085	0.072	0.062
Annualized Std Dev	0.127	0.171	0.177
Annualized Sharpe	0.458	0.269	0.199
Maximum Drawdown	0.235	0.412	0.425
Historical VaR (95%)	−0.013	−0.017	−0.018
Historical ES (95%)	−0.018	−0.025	−0.026
Modified VaR (95%)	−0.013	−0.017	−0.018
Modified ES (95%)	−0.021	−0.031	−0.035
Omega (L = 0%)	1.131	1.091	1.078

Notes: The risk-free rate is set at 3% per year. Decimal returns reported. Portfolios rebalanced weekly. Portfolio weights are constructed using a TVP-VAR(1) model. Transaction costs are 50 basis points per trade.

Although not reported in detail, the results in Tables 3 and 4 are robust to portfolios rebalanced monthly.

5. Discussion and Conclusions

FinTech stocks are an important new asset class that reflects the rapidly growing FinTech sector. Investors invest in FinTech stocks in the hopes of realizing large future gains. Many FinTech companies are young and emerging and FinTech stocks display considerable risk. In accordance with modern portfolio theory, investors are advised to combine FinTech stocks with uncorrelated assets to diversify the risk of an investing in only in FinTech stocks.

This paper studies the practical implications of using gold, silver, and basket-of-precious-metals (gold, silver, platinum, palladium) ETFs to diversify risk in Fintech stocks. Downside risk reduction is estimated using relative risk ratios based on CVaR. Relative risk ratios are computed using the ratio $CVaR_{mix}/CVaR_{ft}$, where mix is a portfolio that mixes FinTech stocks with precious metals and ft is the investment in FinTech stocks. The analysis shows that gold provides the most downside risk protection. For a 5% CVaR, a 30% portfolio weight for gold reduces the downside risk by about 25%. These findings add to the existing literature demonstrating the diversification benefits of gold [27–43]. Silver has the least protection for downside risk. Downside risk ratios vary across time. In the case of gold, for example, the downside risk ratio was below 75% in late 2019 and then increased rapidly to over 80% in early 2020 as the COVID-19 pandemic spread. The risk ratio for silver during this time period spiked to over 90%, offering little in downside protection.

The variation across time in the downside risk ratios indicates that portfolio weights may need to be updated and rebalanced frequently. To investigate this further, three-asset (FinTech, gold, silver) MVP, MCP, and MPC portfolios were estimated where the portfolio weights are estimated using a TVP-VAR model. The MVP and MCP portfolios with time varying weights have the highest risk-adjusted returns (Sharpe ratio, Omega ratio), followed by the fixed-weight FinTech and gold portfolio. The MVP, MCP, and MPC portfolios have lower drawdown than any of the fixed-weight two-asset portfolios—illustrating the benefits of diversification with time varying portfolio weights. This analysis is robust to portfolios rebalanced weekly or monthly and reasonable transaction costs. These results are important in adding to the literature on using gold to diversify portfolio risk.

Future research could look at comparing different measures of risk for computing downside risk ratios. For example, one could use maximum drawdown or risk measures from extreme value theory as the basis to form risk ratios. Future research could also look into how useful platinum or palladium are for reducing downside risks.

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