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Jumps Across Asset Classes and Their Diversification Benefits: Evidence from Vietnamese Asset Markets

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Abstract

This study considers the jump correlations across gold, imported crude oil, the Ho Chi Minh stock exchange (VN-Index), the Ha Noi stock exchange index (HNX-Index), and their impacts on diversification benefits. Understanding jumps is critical for investors because cross-asset diversification is reduced when jumps occur often and are correlated. Results indicate the presence of jumps in all assets. The average correlation between the asset classes is –0.025, indicating that diversifying across asset classes reduces the jump risk to which an investor is exposed. The findings highlight the downside of assessing the advantages of diversification across asset classes solely on the basis of returns. While this can seem to be of little importance, diversification is likely to result in a substantial reduction in jump risk. An analysis of the domestic oil price surge, the gold ban as a payment vehicle under Government Resolution No: 11/NQ-CP, and the Covid-19 pandemic show the benefits of cross-asset diversification from a jump risk standpoint. According to the results, jump correlations do not always have a negative impact on diversification benefits. A return shift in one asset and a transition in the other asset in the same direction are common characteristics of co-jumps between assets.

Keywords: Asset Classes, Asset Correlations, Jump Risk, Portfolio Diversification Benefits

JEL Classification Code: G11, G12, G23, C30

1. Introduction

Diversification is a risk management strategy that mixes a wide variety of investments within a portfolio. A diversified portfolio contains a mix of distinct asset types and investment vehicles in an attempt at limiting exposure to any single asset or risk (Nasdaq, 2020). The rationale behind this technique is that a portfolio constructed of different kinds of assets will, on average, yield higher long-term returns and lower the risk of any individual holding or security. Diversification is defined as the practice of spreading investments in different asset classes and securities to control overall investment risks and averting portfolio performance by a poor run of a single asset, industry, or country This increases the likelihood that even if one market is risky, the other is still profitable enough to cover losses. The availability of various investments has drawn more and more attention. Even so, as economies become more interconnected, the benefits of diversification tend to be diminishing (Zaremba et al., 2021).

This study investigates whether extreme returns or jumps are correlated across VN-Index returns, HNX-Index returns, imported crude oil, and gold. The absence of jump correlation would imply that investment portfolio expansion lowers jump risk. When market volatility spikes or other major market swings affect particular investments, this is called jump risk. This risk particularly affects investments with a high amount of leverage or hedging activity that is dependent on an assumption of lower volatility. Jump risk is a critical concern for investors because, although jumps are uncommon, their effect on returns may be significant. Noussair and Popescu (2021) investigated whether co-movement can emerge between two risky assets, despite their fundamentals not being correlated. The 'Two trees' asset pricing model guided their experimental design and its predictions served as the source of hypotheses.

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The model makes time-series and cross-section return predictions following a shock to one of the two assets' dividend distributions. They observed (1) a positive contemporaneous correlation between the two assets, (2) positive autocorrelation in the shocked asset, and (3) time-series and cross-sectional return predictability from the dividend-price ratio. In line with the rational foundations of the model, the model's predictions have stronger support in markets with relatively sophisticated agents.

This research employs an indicative series for each asset class that provides the longest data time series. For equities, I use separately the VN-Index and HNX-Index because HNX-Index includes firms with lower capital requirements than firms listed on VN-Index. The correlation between HN-Index returns or jumps and other asset classes provides different perspectives on diversification benefits than VN-Index returns or jumps. Gold is represented by the Vietnamese gold mid-price. The Vietnamese imported crude oil price is used for the calculation of oil proxies.

The findings show that there are jumps in each asset class. The cross-asset jump correlations, on the other hand, are weak. Over rolling 36-month windows, I calculate jump correlations for each combination of asset groups. According to the findings, the average correlation between the six asset groups is –0.025, with five pairs having negative correlations and one having positive correlations (VN-Index-HNX-index). There is no one asset class that offers the greatest security against jump risk for investors. To demonstrate - while the pairs of VN-Index-Gold and HNX-Index-Oil are statistically significant and negative, the combinations of VN-Index-Oil and HNX-Index-Gold are not.

The effects of jump correlations differ from those of return correlations. The overall return correlation for all asset classes is positive (0.173), with positive correlations seen in five of the six asset class pairs. This emphasizes the disadvantage of evaluating the benefits of diversifying through asset groups purely based on returns. Although this can seem to be of little value, it is likely that diversification does lead to a significant decrease in jump risk.

A study of the domestic oil price spike, the gold ban as a payment vehicle according to Government Resolution No: 11/NQ-CP, and the Covid-19 pandemic confirms the advantages of cross-asset diversification from a jump risk perspective. Specifically, the effect of Covid-19 is clearly seen in the jump correlation months, beginning in March of 2020 and continuing in March of 2021 onwards, in the correlation between VN-Index, HNX-Index, gold, and oil. The majority of asset classes have very different time ranges where the highest correlation exists, but the year with the highest correlation months is 2013 when the Government Resolution No: 11/NQ-CP on stabilizing macroeconomy was close in effect. From a return standpoint, the oil boom, gold ban, and Covid-19 pandemic have all had a major effect on correlations. The domestic price increases in oil and gold price fluctuations in 2013 stand out, with 13 of the 30 asset class pairs showing their highest return correlations between May and November 2013.

This study also looks at how return correlations and jump correlations affect diversification benefits. Following Bekaert and Urias (1996) and Branger et al. (2019), we measure the economic importance of diversification benefits as the difference between the Sharpe ratio for a two-asset portfolio and the highest Sharpe ratio of each included assets. The Sharpe ratios for the past 36 months are then regressed on the return and jump correlations of the two assets for the same time span. According to the findings, jump correlations do not necessarily have a negative effect on the gains of diversification. Co-jumps between assets frequently entail a return movement in one asset and a change in the other asset in the same direction

2. Overview of the Research Context

2.1. Vietnamese Financial Market

The government heavily regulates the financial sector, and half of the top ten largest banks are state-controlled, comprising 42% of the sector's assets (Reuters, 2017). Loans to state-owned enterprises (SOEs) take up to one-third of bank loans of the total market while the number of SOEs is only 1% of total registered firms. SOEs generally have higher debt ratios and non-performance loans than private and foreign firms, but their returns are lower (Cuong Pham & Xuan, 2019).

The equity market has been an important channel of corporate financing since 2000. Foreign investors are considered the main player of market movements (Le & Phan, 2017). Foreign shareholders also increase their presence in listed firms and play a large role in corporate financing decisions (Tran & Hoang, 2021). Vietnamese stock exchanges include the Ho Chi Minh Stock Exchange (HOSE) and Hanoi Stock Exchange (HNX) as well as the over-the-counter (Upcom) market. The firms listed on the HOSE and HNX vary in size due to each market's listing requirements. In Vietnam, Government Decree 58/2012/ND-CP mandates that firms have at least one year of operations as a joint-stock firm (HNX) or two years of operations (HOSE) before submitting a listing application. The minimum capital requirement to be listed on the HNX is a book value of VND 30 billion (= USD 1.27 million) at the time of application, while the requisite for HOSE is at least VND 120 billion (= USD 5.1 million). The applicants' minimum return on equity (ROE) is at least 5% (Nguyen et al., 2020).

2.2. The Government Resolution No: 11/NQ-CP On Stabilizing Macro Economy

Resolution No: 11/NQ-CP gives information to six economic stimulus packages - to tighten monetary policies, to tighten the fiscal policies, public investments and reduce state budget deficit, to boost production and curtail trade deficit, to increase electric prices along with support the poor and implement a more market-driven pricing mechanism for petroleum products, to safeguard the social security, and to promote propaganda activities on government policies (Goverment, 2011).

To implement this resolution in the banking system, the State bank of Vietnam (SBV) issued a decision to curtail the credit growth target from 23% to 20% and the M2 supply target from 21%–24% to 15%–16%. These goals are also a large reduction from the 2010 numbers – 32.4% of credit growth and 33.3% of M2 supply growth. SBV also made a credit restriction request to financial intermediaries for non-manufacturing activities such as real estate and securities investments to under 16% of the total lending amount.

Credit institutions are required to satisfy the above requisites by doubling the required reserves. SBV also restricts loans in foreign currency with regulated imports. Gold trade is allowed for selected firms to prevent speculative traders and stabilize Vietnam Dong. Ministry of Industry and Trade also implemented a plan to reduce trade deficits, improve the manufacturing standards to better export performance.

2.3. The Covid-19 Pandemic

The Vietnamese government released the first COVID-19 diagnostic guidance on January 16, 2020, well ahead of the first case of SARS-CoV-2 in the world (Ozturk & Cavdar, 2021). The recommendations included guidance for tracing connections and isolating direct contacts (F1) of a reported case for 14 days (Van Tan, 2021). On Thursday, January 23, Vietnam's health ministry confirmed the country's first two cases of a novel coronavirus (2019-nCoV), which originated in Wuhan (Hubei province, China) in December 2019. Because the outbreak enters its second year, phase 1 clinical studies of domestically sourced vaccine products are being conducted in Vietnam, and 30 million shots of the Oxford–AstraZeneca vaccine were requested for 2021. Before that, the country will seek to enforce the policies that helped it maintain such outstanding regulation of COVID-19 in 2020.

3. Literature Review

3.1. Diversification Across Asset Classes

This study contributed in a variety of ways. To begin, it contributes to research on asset class diversification in the context of a transition economy. According to Malceniece et al. (2019), liquidity proxies play an important role in understanding heterogeneity in stock-bond co-movements, while Nguyen et al. (2020) discovered that implicit uncertainty has an effect on the stock-bond return relationship. Mo et al. (2018) stated that commodity futures returns are inversely correlated with bond and stock returns. Based on this, considerable research effort has been drawn toward recognizing the hedging capacity of commodities, especially oil. According to Avdulaj and Barunik (2015), Oil is perceived as a good diversification tool for stock markets. Their findings have important implications for asset allocation, as the benefits of including the oil in stock portfolios may not be as large as perceived. Pal and Mitra (2019) explored possible co-movement between oil price and automobile stock return in a joint time-frequency domain. The co-movement was found to be more pronounced in the long-term and stock return is sensitive to the higher oil price emanating from the demand shock. This contravenes the conventional wisdom that crude oil is always counter-cyclical to automobile stocks. For investors, this weakens the probable gain from including oil assets in a portfolio of automobile stocks as crude oil does not offer a cushion against bearish automobile stock markets during the crisis period. Du and He (2015) found proof of a positive relationship between the S&P 500 stock index and West Texas Intermediate (WTI) crude oil futures returns, and Kisswani and Elian (2017) found support for a positive relationship between oil prices (Brent and WTI) and Kuwait Stock Exchange (KSE) prices at in downturns and price declines. However, as Tiwari et al. (2020) pointed out, little has been understood about diversifying through investment vehicles including gold and oil (Dhanraj & Pragati, 2021).

3.2. Jump Spillover Across Asset Classes

Second, and more importantly, this study adds to the jump spillover literature, which has, to the best of my understanding, been limited to foreign stock markets. Asgharian and Bengtsson (2006) found significant evidence of jump spillover. In addition, they found that jump spillover seems to be particularly large between countries that belong to the same regions and have similar industry structures. Kshatriya and Prasanna (2021) stated that negative jumps from the USA and Europe are transmitted to the domestic Asian markets, while positive jumps are majorly from the regional markets. They also stated that the cross-market linkages vary with respect to markets and regimes. Cha and Jithendranathan (2009) revealed that if the total investment in emerging markets is restricted, a minimum investment of 20% in emerging markets is required to obtain significant diversification benefits. With investments in each of the emerging markets restricted to less than 3%, there was no significant diversification benefit. Das and Uppal (2004) find signs of linked jumps in emerging stock markets as well. Pukthuanthong and Roll (2015) investigated using returns on broad equity indexes from eighty-two countries and modern statistical measures of jumps. They found that jumps are weakly correlated internationally, except within Europe. Although the variation in ordinary returns seems to reflect systematic global factors, jumps are more idiosyncratic.

3.3. Hypothesis Development

Pukthuanthong and Roll (2015) stated that jumps are prevalent in most countries, but their cross-country comovements have not been extensively documented. This is important because international diversification is less effective if jumps are frequent, unpredictable, and strongly correlate in the context of cross-asset diversification, Marshall et al. (2017) found that the advantages of cross-asset diversification from a jump risk viewpoint are further reinforced by an examination of the global financial crisis (GFC) timeline. The highest return correlations exist in 21 of the 45 asset pairs over the 36-month cycle ended in October 2008. In the context of Vietnam, Nguyen and Tran (2015) used the Heston-Cox-Ingersoll-Ross model to account for jump volatility and jump-diffusion in forecasting commodity prices in Vietnam. They found a negative relationship between market volatility and product price shifts. However, research on the cross-asset jumps and their impacts on portfolio diversification advantages is lacking in the Vietnamese context. As a result, the following is the research hypothesis:

***H1:** The extreme returns or jumps are correlated across asset classes.*

***H2:** The cross-asset return and jump correlations have effects on the diversification benefits of each cross-asset portfolio pair.*

4. Data

Every asset class is represented by one series. For each case, we choose data for an instrument that has the widest possible coverage and longest time series. The required data samples for this study are the index of the Ho Chi Minh stock exchange (VN-Index), the index of Ha Noi stock exchange (HNX-Index), the imported crude oil price, and the Vietnamese Gold price. The VN-Index series begins in March 2002, when continuous automatic trading is permitted, while the HNXI timeline starts in June 2006. The imported crude oil series commenced in March of 2010. The gold index commenced in March of 2010. Furthermore, this analysis intends to add to the domestic output costs of oil suppliers as well as the volatility of oil prices. The monthly average of imported crude oil prices obtained from Vietnam customs is in US dollars. The series is then deflated using monthly US CPI data from the Federal Reserve Bank of St. Louis, with March 2010 as the base month, to obtain the actual import price of crude. The indexes for the Ho Chi Minh stock exchange, Ha Noi stock exchange, and Vietnam's gold price are taken from the Thompson Eikon database. They are also deflated with Vietnam CPI, which is obtained from the General Statistics Office of Vietnam (GSO), to arrive at the actual index values. The ending month of the data is March of 2021.

5. Research Methods

5.1. Jump Measurement

Bollerslev et al. (2008) supported BNS's G statistics, proposed by Barndorff-Nielsen and Shephar (2006) (BNS) as by far the most evolved and commonly used of the various approaches. The BNS's G is not only applicable for international equity data (Pukthuanthong & Roll, 2015), but also to different assets such as Bitcoin (Bouri et al., 2020), gold (Demirer et al., 2019), and oil (Ma et al., 2019). The BNS bipower variation is computed as follows:

$$\beta_{i,k} = \frac{1}{T_k - 1} \sum_{t=2}^{T_k} \left|R_{i,t,k}\right| \left|R_{i,t-1,k}\right| \tag{1}$$

The BNS squared variations, $S_{i,k}$ is stated as follows:

$$S_{i,k} = \frac{1}{T_k} \sum_{t=1}^{T_k} R_{i,t,k}^2 \tag{2}$$

Where, t denotes a day

T_k is the number of day in a sub-period k

$R_{i,t,k}$ means the log return for asset i on day t in sub-period k

According to Pukthuanthong and Roll (2015), the quadratic versus bipower variance measure has both ratio and difference variants. This study employs the ratio variant, with the null hypothesis with no jumps, according to $\left(\frac{\pi}{2}\right)\beta_{i,k} - S_{i,k}$, tested. In the null hypothesis, the standard deviations of this difference are determined by the application's "quarticity," which can be calculated as follows:

$$Q_{i,k} = \frac{1}{T_k - 3} \sum_{t=4}^{T_k} \left|R_{i,t,k}\right| \left|R_{i,t-2,k}\right| \left|R_{i,t-3,k}\right| \tag{3}$$

If the constant $\vartheta = \left(\frac{\pi^4}{4}\right) + \pi - 5$, the BNS G statistics is measured as follows:

$$G_{i,k} = \frac{\left(\frac{\pi}{2}\right)\beta_{i,k} - S_{i,k}}{\sqrt{\vartheta\left(\frac{\pi}{2}\right)^2 Q_{i,k}}} \quad (4)$$

The BNS's G metric is unit normal asymptotically. If the variation is smooth, the squared variation ($S_{i,k}$) should be low, as with the normal distribution. The existence of a jump is shown by a sufficiently significant deviation of the BNS's G statistic from zero (either positive or negative). The value of the BNS's G statistic, on the other hand, does not mean the sign of the return jump. Specifically, the direction of the jump is not shown by the sign of the jump statistic. A positive correlation means that two assets have jumps simultaneously, while a negative correlation implies that a jump in one asset coincides with "smooth returns" in another.

5.2. Model Specification for Diversification Benefit Determinants

This study looks at how return correlations and jump correlations affect diversification benefits. Following Bekaert and Urias (1996) and Branger et al. (2019), the economic importance of diversification benefits (Diversification) is measured as the difference between the Sharpe ratio for a two-asset portfolio and the highest Sharpe ratio of each included assets. The risk-free rate in use for the Sharpe ratio calculation is the Vietnamese 3-year bond yield minus the inflation rate. Sharpe ratios are computed over a 36-month time period, as are the return correlation (Return_Corr) and jump correlation (Jump_Corr). The following equation is estimated over 36-month rolling windows with 12 lags using Newey-West standard errors.

$$\text{Diversification}_t = \beta_{1t}\text{Return\_Corr} + \beta_{2t}\text{Jump\_Corr} + \beta_{3t}\text{Diversification}_{t-1} + \varepsilon_t \quad (5)$$

6. Results and Discussion

6.1. Summary Statistics of Returns and Return Correlations

Table 1 shows monthly return overview figures. The VN-Index, HNX-Index, and Oil all have at least one month with a return decrease of more than 0.25 while Gold experiences a maximum decline of 0.133. Based on standard deviations, Gold and the HNX-Index are the least risky, while Oil is the riskiest. As compared to other asset groups, Gold has the highest kurtosis.

This table summarises the statistics for each asset class.

Table 2 displays cross-asset return correlations measured over rolling 36-month windows. Positive correlations outnumber negative correlations. In 5 of the 6 asset class

Table 1: Summary Statistics

	N	Min	p5	Median	Mean	p95	Max	Std. Dev.	Skewness	Kurtosis
VN-Index	228	–0.286	–0.124	0.003	0.008	0.158	0.326	0.088	0.023	5.127
HNX-Index	178	–0.349	–0.177	0.001	0.002	0.158	0.361	0.101	0.086	5.039
Oil	132	–0.439	–0.226	–0.005	–0.010	0.140	0.341	0.110	–0.907	7.048
Gold	132	–0.133	–0.026	–0.001	0.003	0.061	0.144	0.031	0.613	11.467

Table 2: Cross-Asset Return Correlations

Asset 1	Asset 2	*N*	Mean	Median	Std. Dev.	*t*-stat	MAD	Maximum	Minimum	Prob *t* > 2	Prob *t* < –2
VN-Index	HNX-Index	202	0.828	0.837	0.075	23.500	0.063	1.000	0.660	0.950	0.000
VN-Index	Gold	119	0.093	0.058	0.196	2.560	0.129	0.586	–0.211	0.320	0.020
HNX-Index	Gold	119	–0.060	–0.074	0.070	–2.030	0.056	0.194	–0.191	0.045	0.290
VN-Index	Oil	119	0.091	0.133	0.189	1.710	0.129	0.481	–0.628	0.110	0.012
HNX-Index	Oil	119	0.078	0.112	0.250	1.140	0.154	0.354	–0.933	0.255	0.130
Gold	Oil	119	0.009	0.000	0.122	–0.330	0.089	0.361	–0.228	0.740	0.045

This table includes a variety of statistics for return correlations measured over rolling 36-month intervals. The Newey-West t-statistic for the mean correlation with 12 lags is *t*-statistic. MAD is the mean absolute deviation.

pairs, the mean and median correlations are also positive. The mean correlations for two asset class pairs are positive and statistically significant at the 10% level or higher over the entire time series, while the mean correlations for one asset class pair are negative and statistically significant at the 10% level or higher. Statistical significance is determined in both cases using Newey-West *t*-statistics of 12 lags. Furthermore, the average percentage of 36-month periods with positive correlations with a *t*-statistic greater than 2 between asset class pairs is 33%, relative to 17% with negative correlations over 36-month periods with a *t*-statistic less than –2.

The VN-Index and Oil have positive average correlations with other asset groups, but other assets tend to have positive average correlations with others and negative average correlations with others. The mean correlation between the HNX-Index and Gold, for example, is –0.060, but the correlation between the HNX-Index and Oil is 0.078. Furthermore, no asset class pair has a stable negative relationship over time. The others, on the other hand, have a 36-month period of correlations greater than 0.009.

Table 3 reports the highest 36-month correlation and the second to fifth highest 36-month correlations with each respective asset pair. Each recorded month reflects the last month of each 36-month cycle. It is clear that the global financial crisis (GFC) period is not prominently portrayed, which is due in part to the fact that the data coverage for Gold and Oil begins in 2010, which postdates the GFC. However, the domestic price increases in oil and gold price fluctuations in 2013 stand out, with 13 of the 30 asset class pairs showing their highest association between May and November 2013. After the first Covid-19 case arrived in Vietnam from China (Van Cuong et al., 2020), the impact of Covid-19 is clearly featured in the return correlation months, starting from March of 2020 to March of 2021 in the correlation between VN-Index, HNX-Index, Gold and Oil. Overall, the correlation findings are evident in the literature, which notes a lack of reliably negative associations across investment vehicles and a strong increase in the correlation of the returns of a variety of asset classes during crises such as the oil crisis and the withdrawal of gold as a payment vehicle as stated in the Government Resolution No: 11/NQ-CP on stabilizing macroeconomy (Goverment, 2011).

6.2. Within Asset Class Jumps

Table 4 shows the jump results for asset class dependent on the BNS's G statistic. This metric is dependent on daily returns over the course of a month. Assuming that the BNS's G statistic has a unit normal distribution when there are no jumps, the lack of jumps will be shown by a mean and

Table 3: Largest Return Correlation Months

Asset 1	Asset 2	Largest	2	3	4	5
VN-Index	HNX-Index	Nov-17	Nov-13	Apr-14	Sep-15	Apr-18
VN-Index	Gold	May-13	Aug-13	Sep-13	Oct-13	Jul-13
HNX-Index	Gold	Sep-14	Sep-17	Mar-17	Dec-19	Nov-18
VN-Index	Oil	Sep-13	Oct-13	Jul-13	Oct-20	Mar-21
HNX-Index	Oil	Mar-20	Jan-15	Feb-15	Mar-15	Dec-14
Gold	Oil	Aug-13	Sep-13	Oct-13	Jul-13	Mar-21

The highest 36-month return correlations for each asset pair are seen in this table, depending on the final month of the correlation cycle.

Table 4: Summary Statistics for the Barndorff-Nielsen and Shephard (2006)'s G Jump Measure

	N	Mean	Median	Std. Dev.	*t*-stat	MAD	Maximum	Minimum
VN-Index	229	–0.052	–0.037	0.061	–11.070	0.045	0.043	–0.366
HNX-Index	178	–0.061	–0.042	0.091	–8.870	0.052	0.041	–0.835
Oil	132	0.094	0.112	0.128	12.360	0.090	0.343	–0.821
Gold	132	0.079	0.085	0.049	25.750	0.039	0.204	–0.057

This table includes a variety of statistics for Barndorff-Nielsen and Shephard's (2006)' G Jump metrics, which are determined using daily returns for each month. The Newey-West *t*-statistic for the mean correlation of 12 lags is *t*-statistic. The average mean absolute deviation is abbreviated as MAD.

standard deviation of around zero and one, respectively. This is not true in any of the asset classes. Centered on Newey-West *t*-statistics of 12 lags, we are able to debunk the null hypothesis that the BNS statistic is zero in each asset category. The BNS's G mean departs from zero most in the HNX-Index and Oil, meaning that these asset groups are prone to jumps. Gold, on the other hand, has the least unfavorable BNS's G numbers. The study of the distribution based on the typical BNS's G statistic month reveals that it lacks symmetry. The minimum is often substantially different from the mean from the maximum. For example, the HNX-Index has a mean BNS's G statistic of –0.061, a maximum of 0.041, and a minimum of –0.835.

6.3. Cross-Asset Class Jumps

Table 5 shows the effects of calculating the jump correlations of every asset class duo over 36-month rolling windows. It's necessary to note that the BNS's G statistic sign does not signify the path of the jump. Rather, a statistic's divergence from zero (in any direction) implies the existence of a jump, while a number similar to zero indicates a smooth sequence with no jump. A negative jump correlation implies that jumps in one asset category are synonymous with smooth returns or a shortage of jumps in another. A positive correlation, on the other hand, indicates that jumps between two asset groups appear to occur at the same time, even though these jumps are significant positive or negative returns in both series, and a significant positive return in one series and a significant negative return in another. The discovery of low jump correlations implies that diversifying through asset classes serves the essential function of reducing jump risk. This risk is critical for investors to consider since, by default, jumps have a major effect on returns.

The average jump correlation between the five asset classes (excluding the VN-Index and the HNX-Index) is negative (–0.025), with more negative correlations (5 pairs) than positive correlations (1 pair). Furthermore, two pairs have negative correlations that are significantly different from zero, but only one pair has positive correlations that are significantly different from zero. The trend with more negative than positive correlations is also expressed in the ratio of 36-month periods with negative correlations with a *t*-statistic less than –2 relative to those with positive correlations with a *t*-statistic greater than 2. Both ratios are 33% and 17%, respectively. Although there are five 36-month cycles with return correlations greater than 0.50, there are no periods with jump correlations greater than 0.50 (except for VN-Index and HNX-Index pair). The surprising observation is that while the pairs of VN-Index-Gold and HNX-Index-Oil are statistically important and negative, the variations of VN-Index-Oil and HNX-Index-Gold are not.

There is really no single asset class that offers the greatest security against jump risk for investors subjected to all of the others, but empirical findings do offer a valuable guide about which asset class can be applied to current asset class exposure to minimize jump risk. VN-Index buyers, for example, may gain the most from a jump risk perspective by including Gold exposure (and vice versa). The mean jump correlation for VN-Index stock investors is –0.049, and just 2.3 percent of 36-month periods have a positive significant correlation, relative to 28.7 percent of 36-month periods with a negative significant correlation. Investors in the HNX-Index should consider adding a position in oil. The mean correlation coefficient is –0.042, with 5.9 percent of 36-month periods showing a significant positive correlation and 32.9 percent showing a significant negative correlation. Surprisingly, investors of VN-Index and HNX-Index exposure gain successful diversification through incorporating various commodities (Gold in the case of VN-Index and Oil in the case of HNX-Index). This demonstrates that there are significant variations between stock indexes.

Table 5: Cross-Asset Barndorff-Nielsen/Shephard (2006) G Jump Measure Correlations

Asset 1	Asset 2	*N*	Mean	Median	Std. Dev.	*t*-stat	MAD	Maximum	Minimum	Prob $t > 2$	Prob $t < -2$
VN-Index	HNX-Index	203	0.397	0.441	0.274	10.080	0.217	0.815	–0.374	0.970	0.010
VN-Index	Gold	119	–0.049	–0.046	0.164	–2.290	0.115	0.431	–0.739	0.023	0.287
HNX-Index	Gold	119	–0.005	–0.029	0.125	0.420	0.088	0.733	–0.189	0.075	0.044
VN-Index	Oil	119	–0.002	–0.018	0.173	–0.300	0.132	0.976	–0.319	0.061	0.090
HNX-Index	Oil	119	–0.042	–0.033	0.247	–2.010	0.182	0.369	–0.954	0.059	0.329
Gold	Oil	119	–0.029	–0.021	0.213	–1.200	0.169	0.378	–0.869	0.129	0.059

This table includes a variety of statistics for Barndorff-Nielsen and Shephard's (2006) G jump correlations, which are determined using daily returns for each month. The Newey-West *t*-statistic for the mean correlation of 12 lags is *t*-statistic. The average mean absolute deviation is abbreviated as MAD.

Table 6: Largest Barndorff-Nielsen/Shephard (2006) G Jump Measure Correlation Months

Asset 1	Asset 2	Largest	2	3	4	5
VN-Index	HNX-Index	Nov-13	Jun-13	Feb-17	May-15	Mar-17
VN-Index	Gold	Nov-19	Jan-16	Oct-13	May-20	Jan-17
HNX-Index	Gold	Aug-13	Jun-13	Aug-19	Jul-18	Jun-19
VN-Index	Oil	Nov-19	Jan-16	May-18	Oct-13	Feb-18
HNX-Index	Oil	Mar-21	Dec-15	May-20	Apr-20	Nov-19
Gold	Oil	Sep-13	Nov-13	Apr-16	Aug-19	Jun-20

The highest 36-month Barndorff-Nielsen and Shephard's (2006)'s G jump correlations for each asset pair are seen in this table, depending on the final month of the correlation cycle.

Table 7: Diversification Benefit Determinants

Asset 1	Asset 2	Constant	β_1	*t*-stat	β_2	*t*-stat	β_3	*t*-stat
VN-Index	HNX-Index	–0.081	0.194**	2.190	–0.137*	–1.830	1.008***	10.610
VN-Index	Oil	–0.053	0.232**	2.140	–0.230*	–1.640	0.992***	11.880
VN-Index	Gold	–0.043	0.082***	2.670	–0.330**	–2.010	0.977***	15.780
HNX-Index	Gold	–0.009	0.973***	2.810	0.053	0.840	0.975***	25.200
HNX-Index	Oil	0.003	0.115**	2.430	0.134**	2.380	0.902***	22.020
Gold	Oil	0.002	–0.364**	–2.400	0.171	0.830	0.894***	17.840

This table includes the outcomes of the following regressions:

$$\text{Diversification}_t = \beta_{1t}\text{Return\_Corr} + \beta_{2t}\text{Jump\_Corr} + \beta_{3t}\text{Diversification}_{t-1} + \varepsilon_t$$

Diversification is calculated as the difference between the portfolio Sharpe ratio and the portfolio's largest asset Sharpe ratio. Sharpe ratios are computed over a 36-month time period, as are the return correlation (Return_Corr) and jump correlation (Jump_Corr). The following equation is estimated over 36-month rolling windows with 12 lags using Newey-West standard errors. *, **, and ***denote the significance level of 10%, 5%, and 1% respectively.

Table 6 shows the findings of a study that looked at whether co-jumps through asset classes were clustered in some time periods. The months with the highest asset class correlations, where the month corresponds to the last month of the 36-month cycle, are used to calculate correlations. The findings show that there is no consistent trend of jump correlations being higher in the same month across asset classes. Although domestic oil price increases and gold ban as a payment method are prevalent in the months with the highest return correlation, there is no equivalent trend in the jump correlations. The effect of Covid-19 is clearly seen in the jump correlation months, beginning in March of 2020 and continuing in March of 2021 onwards, in the correlation between VN-Index, HNX-Index, Gold, and Oil. The majority of asset classes have very different time ranges where the highest correlation exists, but the year with the highest correlation months is 2013 when the Government Resolution No: 11/NQ-CP on stabilizing macroeconomy was close in effect.

6.4. The Impact of Correlations on Portfolio Diversification Benefits

This study looks at how return correlations and jump correlations affect diversification benefits. Table 7 shows the regression results of the model for diversification benefits determinants. The average sensitivity of diversification gains to return correlation (β_1) is 0.21, which is statistically significant with a cross-sectional *t*-statistic of 2.51 (without Gold-Oil) but negligible with a *t*-statistic of 1.53 (with Gold-Oil) (with Gold-Oil). An increase in correlation between asset groups, in general, results in an increase in portfolio diversification gains. In comparison, the average sensitivity of the diversification advantage to the jump correlation (β_2) is just –0.04, with a cross-sectional *t*-statistic of –0.19. This implies that the diversification gain of lowering the jump correlation is six times less than the benefit of increasing the return correlation. This means that co-jumps between assets frequently entail a return movement in one asset and a change in the other asset in the same direction. A scenario like this has no negative effect on the Sharpe ratio in the same manner as simultaneous return volatilities do.

7. Conclusion

Diversification is a key principle in finance. However, research suggests that the benefits of diversification are diminishing as economies become more interconnected. This research looks at whether drastic returns (jumps) are correlated across asset groups. Jumps are noteworthy because they have a significant effect on returns. A shortage of jump correlation across the VN-Index, HNX-Index, Gold, and imported crude oil asset classes suggests that investment portfolio diversification is critical for reducing jump risk.

Diversification across asset classes appears to minimize jump risk, according to research findings. Whether there are jumps in each asset class, the correlations between asset classes are minimal. Across all asset classes, no single asset class offers the greatest jump risk security. However, investors who have exposure to one asset class will reduce their chance of a jump by applying exposure to another asset class. For example, VN-Index investors benefit from the best jump risk security by investing in Gold, while VN-Index investors gain from including HNX-Index.

The findings of jump correlations differ from those of return correlations, which appear to be more positive. This demonstrates that there is a disadvantage to evaluating the benefits of diversifying through asset groups purely based on returns. Returns can imply that there is little benefit to diversifying across asset classes. Cross-asset class diversification may appear to provide little benefit in terms of returns, but this may conceal a meaningful reduction in jump risk. To illustrate, VN-Index investors can diversify their portfolios by increasing their exposure to HNX-Index. The benefit of diversification to Gold and Oil for VN-Index investors can be minimal. The HNX-Index-Oil relationship demonstrates that an increase in jump risk can be accompanied by an increase in the return correlation between HNX-Index and Oil, implying that increasing HNX-Index investor exposure to Oil commodities offers diversification benefits. Overall, the HNX-Index investors can benefit from adding different asset classes to their portfolios.

To my surprise, the impact of 2008 global financial crisis (GFC) is not very clearly portrayed in the months with the highest correlation between months and jumps. However, the events such as the domestic oil price surge, the gold ban as a payment vehicle, according to Government Resolution No: 11/NQ-CP, and the Covid-19 pandemic are prominently displayed. The impact of Covid-19 is clearly seen in the return correlation and jump correlation months, starting from March of 2020 to March of 2021 in the correlation between VN-Index, HNX-Index, Gold, and Oil. The majority of asset groups have very different time scales where the greatest correlation occurs, but the year with the highest return and jump correlation months is 2013 when the Government Resolution No: 11/NQ-CP on macroeconomic stabilization was close to being implemented. The findings imply that macroeconomic events do impact the diversification tendency of investors who want to expose to different asset classes other than equities.

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