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Volatility Episodes and Patterns in Currency Returns

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Abstract

Portfolio management under episodes of high volatility spurs difficult decision-making for asset managers in the pursuit of risk minimization as benefits from international diversification become less relevant. Dynamics of currencies under such developments add a new layer of risk. A clear description of the reaction of currencies to volatility shocks perceived in capital markets is therefore important for the success of risk management undertakings. Our paper studies the persistence of the impact of volatility changes on currencies, to enhance the prediction needed for international portfolio risk management. Our analysis focuses on the highest ranked currencies in terms of over-the-counter (OTC) foreign exchange turnover according to the latest Triennial Central Bank Survey of the Bank of International Settlements (2019). We use daily bilateral rates of 29 currencies against the US dollar collected from FRED (Federal Reserve Economic Data) and Pacific Exchange Rate Service. Our approach identifies high-volatility episodes in financial markets based on VIX, which is a widely used indicator of global financial market volatility, between January 1999 and December 2019. Specifically, we investigate the behaviour of exchange rates against the US dollar during these episodes of volatility in financial markets, by considering the first four moments of currency return distribution in a Statistical Clustering methodological framework. We find that, overall, currency returns have a rather homogeneous behaviour in turbulent times, which generates difficulties in distinguishing separate asset classes in the foreign exchange market. We cannot distinguish separate asset classes in the foreign exchange market based on currency return distributions, but knowing that currency returns exhibit similar patterns may prove to be useful for portfolio managers for designing their active investing and/or hedging strategies in a highly correlated world.

Keywords: Volatility, currency returns, cluster analysis.

JEL Classification: C38, G11, G15

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1. Introduction

Portfolio management under episodes of high volatility spurs difficult decision-making for asset managers in the pursuit of risk minimization as benefits from international diversification become less relevant. Dynamics of currency returns under such developments add a new layer of risk. A clear description of the reaction of currencies to volatility shocks perceived in capital markets is therefore important for the success of risk management undertakings. Our paper studies the persistence of the impact of volatility changes on currencies, to enhance the prediction needed for international portfolio risk management.

2. Problem Statement

The patterns of risk variations in stock and currency return dynamics are a widely explored feature in academic papers. Various studies address stylized facts such as volatility clustering, time dependence of returns, significant asymmetries, or spillover effects. Moreover, the connection between equity markets and currency reactions to regime shifting in either volatility or mean dynamics is a direction that was also investigated.

Among the seminal papers that investigated episodes of volatility shocks, we mention Schwert (1989), whose paper investigates the connection between the volatility of stock returns and macroeconomic variables; he also notes that previous research has highlighted the significant equity prices volatility during the Great Depression. The author continues the investigation of financial market volatility – see Schwert (1990) – using daily data and implied volatility applied to the October 1987 crash, considered an abnormal jump in the volatility dynamics. The unexpected nature of such shocks, together with the realm of calmness that usually quickly settles in the aftermath, beclouds the comprehension of underpinnings for volatility spikes in the framework of continuous financial market dynamics. Various following studies focused on deciphering this puzzle.

As such, Maheu and McCurdy (2002) explain the nonlinear characteristics of volatility for currency pairs under double stochastic frameworks, while Gaunersdorfer and Hommes (2007) use regime shifting techniques to investigate sudden changes in volatility and conclude that clustering is a feature that is embedded into market dynamics, i.e. an endogenous phenomenon emerging in the trading process. In the same research direction, Wang and Moore (2009) analyse the shifts in volatility mainly in European Union stock markets before the 2007 crisis, but also investigate a series of sizeable volatility changes during regional stock market crashes. They conclude that these "sudden changes" in volatility are the result of special dynamics in financial emerging markets, of unexpected changes in exchange rate policies, but also of market crashes.

From the international perspective, Edwards and Susmel (2001) investigated the cross-country correlation between episodes of high market volatility in Latin American stock markets. The regime-shifting models and co-dependence of volatility regime methodologies employed by them lead to the conclusion that high-volatility episodes were rather short-lived, but they manifest simultaneously in Mercosur countries. Similarly, Kaminsky and Reinhart (2002) identify the mostly synchronized markets internationally in an analysis covering the 1997-1999 period. The two authors find interesting the spillover effects particularly in periods of interest rate peaks and high negative changes in stock market returns.

3. Research Questions

Our paper continues the previous research of Horobet et al. (2009), Horobet et al. (2010), and Horobet and Belascu (2015) on the relevance of high-volatility episodes for the behaviour of currency and interest rates. The approach proposed here represents a useful tool for institutional investors confronted with the issue of risk diversification in volatile times. We use cluster analysis to identify homogeneities and dissimilarities in the behaviour of exchange rates during volatile periods, which may support managers' decisions to protect returns and/or to diversify risk in their portfolios in turbulent periods. This tool should be seen as a natural addition to decisions in the mean-variance framework proposed by the modern portfolio theory (Markowitz, 1952) or in a dynamic view, by taking into account the higher moments of return distributions, based on the models proposed by Fabozzi et al. (2006), Harvey et al. (2010), and Mhiri and Prigent (2010).

4. Research Methods

Our analysis focuses on the highest ranked currencies in terms of over-the-counter (OTC) foreign exchange turnover in 2019, according to the Triennial Central Bank Survey of the Bank of International Settlements (BIS 2019). The de facto exchange rate and monetary arrangements for these currencies vary from floating to administered arrangements, conventional pegs, or stabilized arrangements, depending on the degree of flexibility of exchange rates and the intervention of monetary authorities (i.e. central banks) in the process of exchange rate determination. It is interesting to note that for the overwhelming majority of these currencies, the monetary policy rule is inflation targeting that focuses on price stability as the main objective of a country's monetary policy – see IMF, 2019.

We use 29 exchange rates as exchange rates with no volatility over periods covering at least one of the identified high-volatility episodes have been excluded – these are the Chinese yuan, the Malaysian ringgit, the Taiwan new dollar, the Saudi Arabia riyal –, but also the Danish krone, in whose case the fixed exchange rate against the Euro after 1999 generates the same pattern in returns as the EUR/USD exchange rate. We use daily bilateral rates against the US dollar collected from FRED (Federal Reserve Economic Data) and Pacific Exchange Rate Service. Of the 29 exchange rates, two – the Singapore dollar and the Czech koruna – have a stabilized arrangement, and the remaining 27 have floating exchange rate regimes.

Volatility in financial markets is a reality that cannot be ignored; but although it tends to be noticed during turbulent periods, the presence of volatility is more pervasive, as intervals of increased turbulence in financial markets may be spotted rather frequently. Our approach identifies high-volatility episodes in financial markets based on daily VIX values, an indicator of U.S. equity market volatility, widely used as a proxy for global financial market volatility. We employ the methodology used in Horobet and Belascu (2015), i.e., the start of a high-volatility episode is the day when there is a

10 percentage point change in VIX above its 60-day backward-looking moving average; similarly, a high volatility episode is considered closed the day when VIX is below the value recorded at start of episode. The minimum length of a high-volatility episode is twenty days, needed for the subsequent work on daily currency return distributions. Our analysis covers the period January 4th, 1999 - December 31st, 2017. Data on VIX was collected from the Chicago Board of Trade website. Figure 1 shows the VIX evolution between 1999 and 2017, allowing us to notice the presence of ten high volatility episodes, most manifested in 2001, 2002, 2007, 2008 and 2011. Table 2 shows the episodes identified and the number of days included in each of them. The longest episode is found in 2008 - Episode 6 (74 days), and the shortest in 2015 - Episode 10 (30 days). Besides these episodes of minimum 20 days length, we spot 182 shorter episodes that include 1 to 18 observations days each.

We apply a smachine-learning based k-means Statistical cluster analysis (SCA), proposed by Hartigan and Wong (1979) and discussed in Witten et al. (2011), whose objective resides in assigning cases to identified clusters with or without a priori setting a specific number of clusters. Thus, the means of the variables included in the amalgamation are as different as possible between them. SCA's objective, in our case, is the identification of homogeneous groups of currency returns (cases) across the ten high-volatility episodes mentioned above based on the first four moments of return distributions – mean, standard deviation, skewness and kurtosis (variables), using the Euclidian distances and the Ward amalgamation method applied on standardized values.

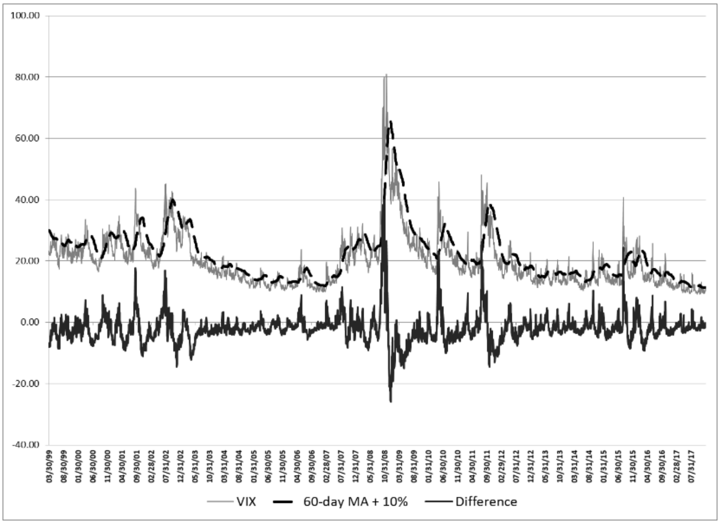

Figure 1. VIX versus 60-days moving average, 1999-2017

Source: Authors' development based on data from Chicago Board of Trade

Table 1. High-volatility episodes, 1999-2017

Episode number	Interval	Number of days
1	October 6th, 2000 –November 16th, 2000	30
2	August 30th, 2001 – October 23rd, 2001	34
3	June 3rd, 2002 – August 13th, 2002	51
4	May 12th, 2006 – June 20th, 2006	27
5	July 20th, 2007 – August 23rd, 2007	25
6	September 12th, 2008 – November 25th, 2008	52
7	May 4th, 2010 – June 14th, 2010	29
8	July 26th, 2011 – October 5th, 2011	51
9	May 11th, 2012 – June 14th, 2012	24
10	August 20th, 2015 – September 18th, 2015	21

Source: Authors’ development

5. Findings

5.1. Brief analysis of currency return frequency distributions

The study of currency return properties across the ten high volatility episodes allows us to uncover preliminary behavioural patterns of these returns. Figure 2 shows the boxplots of currency return distribution moments for each volatility episode.

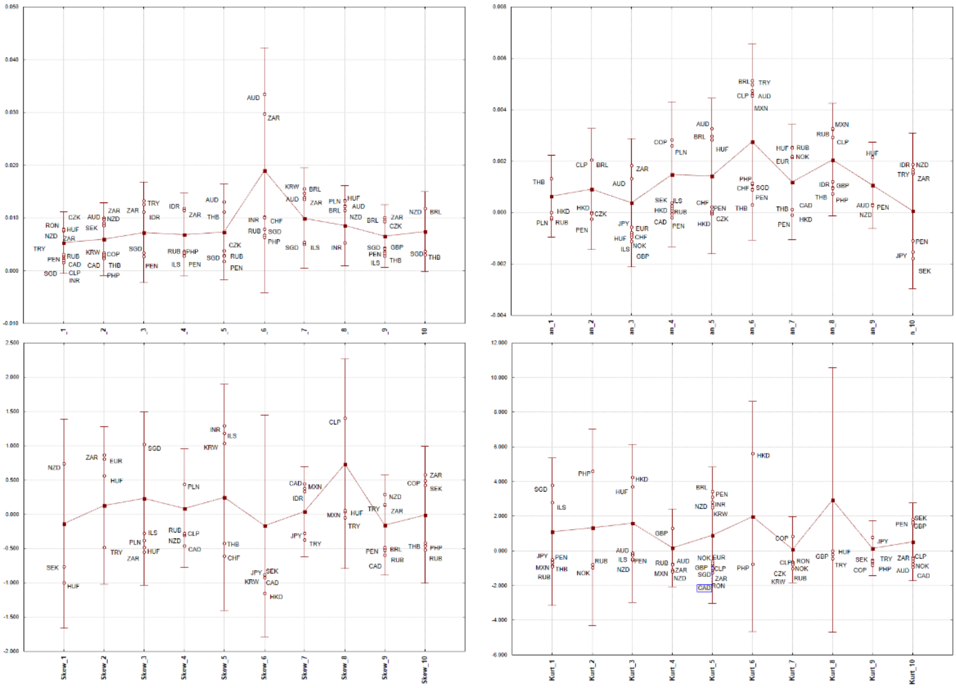

Figure 2. Boxplots of currency return means (up left), standard deviations (up right), skewness (down left), and excess kurtosis (down right), 1999-2017

Note: Squares indicate means and circles indicate outliers, defined as “observation > UBV +1.5 × (UBV – LBV)” or “observation < LBV – 1.5 × (UBV – LBV)”; UBV - upper value of the box in the boxplot, LBV - lower value of the box in the boxplot

Source: Authors’ development based on data from Chicago Board of Trade

The averages of mean returns of exchange rates are variable from one episode to the other, but they are always positive; the highest mean is recorded in episode 6, which covers the Global Financial Crisis, and the lowest in episode 10. Across episodes and exchange rates, negative return means dominate, with the notable exception of episode 10, where 19 mean returns are positive and only 10 are negative. The range of means across the sample is variable from one episode to another, with the smallest values in episode 1 and episode 9. Episode 6 shows the highest mean standard deviation of currency returns, but also the highest range of all episodes. Rather curious, the mean standard deviations seem to increase as we move from episode 1 to episode 6 and afterwards decline until episode 9, but increase again in episode 10. In skewness terms, the means are positive for six episodes and negative for four episodes, without a clear pattern; the highest mean skewness is in episode 8 and the lowest in episode 6. Excess kurtosis values have positive means for all episodes, which indicates leptokurtic currency return distribution on average, but across episodes the number of distributions with positive excess kurtosis is variable – episodes 8, 6 and 3 show the highest number of leptokurtic return distributions (27, 25 and 24, respectively).

5.2. Cluster analysis results

Figure 3 shows the final classification of currency returns in clusters for each of the ten high-volatility episodes, as well as the distance to the cluster centroids for each currency pair for all types of clusters.

Figure 3. Cluster membership and distances to centroid
Source: Authors' development

The k-means clustering algorithm indicates the presence of three clusters: 18 exchange rates in the first cluster (62.07% of cases; AUD, CHF, SEK, MXN, NZD, NOK, KRW, TRY, RUB, BRL, ZAR, PLN, HUF, CZK, CLP, IDR, COP and RON), 3 exchange rates in the second one (10.34%; JPY, HKD and PEN) and 8 in the third (27.59%; EUR, GBP, CAD, SGD, INR, THB, ILS and PHP). Table 2 shows the distance between centroids. The smallest distance is between clusters 1 and 3 and the highest between clusters 1 and 2.

Table 2. Distances between cluster centroids

	Cluster 1	Cluster 2	Cluster 3
Cluster 1	0.0000	2.0222	0.9870
Cluster 2	2.0222	0.0000	1.5667
Cluster 3	0.9870	1.5667	0.0000

Source: Authors' development

In the second clusterisation, Cluster 2, that includes only 3 exchange rates, is the most homogeneous of the three clusters – distances to centroid fall in a range between 1.028 (JPY) and 1.249 (HKD) –, while Cluster 1 is the most heterogeneous, given a range of distances to centroid between 0.819 (NOK) and 1.857 (COP). Interestingly, the ANOVA procedure on both clustering algorithms shows that means and standard deviations are the main providers of differentiation between clusters, but also that the first two volatility episodes matter less for cluster building than the other episodes.

Figure 4 presents graphically the attributes of the identified clusters. The differentiation between the three clusters is clear-cut, as the "dominance" of a cluster over the other two in terms of all or at least a significant part of the variables is not present. Still, two of the three clusters are clearly segregated by the clustering variables; Cluster 1 includes currency returns with generally high average means, high standard deviations and, to some extent, low kurtosis, Cluster 2 features on average exchange rates returns with low means, low standard deviations and high kurtosis, while Cluster 3 captures returns with low skewness and low kurtosis.

6. Conclusions

Our paper's objective resided in identifying similarities and dissimilarities in the behaviour of the most traded exchange rates during volatile periods. Our novel approach was focused on noticing whether the first four moments of exchange rate returns based on the US dollar may provide complementary information to portfolio managers' decisions to protect the returns and/or to diversify the risk of their investments in turbulent periods.

Our analysis has implications for international investors interested in forecasting currency behaviour in likely high-volatility episodes in the future; since the majority of currencies have similar return distribution properties across volatility episodes, this can be expected to continue in the future and is relevant from the perspective of international portfolio investors, who diversify their holdings across various asset classes and currencies.

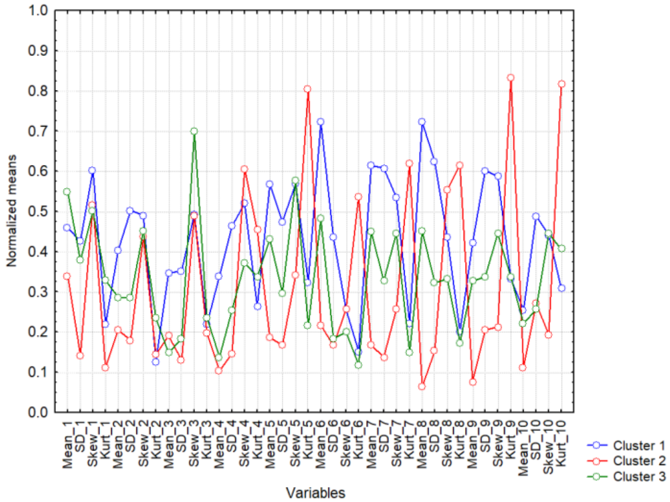

Figure 4. Cluster attributes based on variables standardized values

Source: Authors' development

Overall, we cannot distinguish separate asset classes in the foreign exchange market based on currency return distributions, but knowing that currency returns exhibit similar patterns may prove to be useful for portfolio managers for designing their active investing and/or hedging strategies in a highly correlated world. Therefore, cluster analysis may be successfully used as a natural add-on to the traditional mean-variance portfolio framework or the newer proposed portfolio selection models based on the higher moments of return distributions.

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