Similarity Measures between Buying and Selling Prices of Various Exchange Rates with the inclusion of Multidimensionality and Multicollinearity

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Abstract: - This paper introduces a new statistical model, the multidimensional measurement error model with multicollinearity, to study the relationship between buying and selling prices of foreign exchange rates of various currencies. Such a model is needed due to the possible rise in multidimensionality and multicollinearity issues that may occur due to the movement of the financial markets towards stock market integration of various countries since the occurrences of the financial crisis as well as the part result of globalization. As this integration involves the participation of various countries, it will affect the foreign exchange rate. Hence, the analyses are performed on seven currencies against the Malaysian Ringgit where four models' performances are compared. From this research, it can be concluded that the proposed model comparatively performs better than the other models in representing the relationship of the stationary prices and performs as well as existing models towards non-stationary prices. It can also be seen that the Japanese Yen is the currency that has the strongest influence and closer similar trends towards other currencies while the Great British Pound showed otherwise.

Key-Words: - measurement error model, similarity measures, multidimensionality, multicollinearity, foreign exchange rate, currencies.

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1 Introduction

Stock market integration was found to exist in the emerging market especially in Asia since the 1997 Asian financial crisis. In the beginning, numerous researchers' attention had been centered on examining the integration among five ASEAN emerging stock markets (Malaysia, Thailand, Indonesia, Singapore, and the Philippines). [1], summarizes that the five ASEAN stock markets are moving towards enhanced integration among themselves. Based on the recent market cap, the two largest stock markets in the world are NYSE and NASDAQ followed by the Shanghai Stock Exchange (SSE), EURONEXT, and the Japan Stock Exchange (JPX). Hence, [2], focused on examining the long-run co-movements between the Malaysian stock market and the two largest stock markets in the world, the United States and Japan, and was extended by [3], by adding China, one of the largest trading partners of Malaysia. The findings stated that in the long run, Malaysia's stock market is significantly influenced by its major trading partners' stock markets.

As such integration will affect various countries, we would like to analyze the relationship of an index that could be directly impacted by such an event, which is the fluctuations in foreign exchange rates. Before any integration could take place, a better understanding of the trend and performance of the exchange rates needs to be studied on both the buying and selling prices. As described by [4], the relationship between the exchange rate and stock returns exists as postulated by the flow-oriented theory of exchange rate behavior. Also, it is common knowledge that foreign exchange trading is a risky financial instrument due to its volatility, where even in recent events, the Central Bank of Malaysia would need to intervene in the market to stabilize the currency, [5]. In addition, it should not only at a one-currency basis, but also on a combination of currencies as the rise and fall of the currencies among various countries usually occur concurrently due to various reasons such as foreign direct investments, international trading, demand, and supply in the foreign exchange market, and common financial regulations. However, performing such a study will normally give rise to two common issues, which are multidimensionality and multicollinearity.

The occurrence of multidimensionality where the presence of multiple *x* and multiple *y* are considered as well as multicollinearity where the variables studied are related or influenced by one another in finance have always been a study of great interest. As multicollinearity can only exist when there is multidimensionality, they normally co-exist with one another. Much research managed to show evidence of its presence in various financial applications. In terms of multidimensionality, [6], studies ten different types of commodities listed on ASEAN's five stock markets. On Bursa Malaysia's website, there is a list of thirteen commodities' indices that are being categorized. Regarding foreign exchange rates, Bank Negara Malaysia (BNM) recorded four different trading times as well as twenty-seven exchange rates with the Malaysian Ringgit (MYR), [7]. Hence, it can be observed that the involvement of multidimensionality is important, especially in the application context of this study.

On multicollinearity, multicollinearity tests were performed in studies such as [8], that modeled the Indonesian Composite Index and performed the multicollinearity tests using the VIF (Variance Inflation Factor) approach where it was proven that multicollinearity exists among the predictor variables. From [9], the Apple Inc. stock returns and two tests on multicollinearity were performed, which are the VIF and condition index. From his study, both test results concluded that multicollinearity exists due to a strong correlation among the explanatory variables. Adding on, [10], compared two classical methods in detecting multicollinearity in a time series data for finance as well as economic sectors where both methods showed that multicollinearity exists. Besides that, foreign exchange rates also seem to contain multicollinearity between the bank forecast, univariate time series forecast along with the forward price for exchange rates, [11], between the various countries, [12], as well as between the opening, opening low, and closing prices of stock indices, which is similar to the foreign exchange rate, [9].

Though the presence of multicollinearity can be observed in various financial applications, a common assumption where the variables are independent or are not correlated to one another is posited in many regression models. However, the assumption of independence could be violated in some cases and lead to issues in constructing the model. Firstly, the estimated coefficients of the model can be unstable and will vary greatly from one sample to the next. Secondly, it undermines the statistical significance of independent variables since it might increase the standard errors of the estimated coefficient as stated in [13], which might result in inaccurate statistical analyses. It is evident in [14], where two Monte Carlo simulations were performed, and it was shown that the presence of multicollinearity is capable of causing theory testing problems with different levels of impact depending on its severity. [15], also stated that the relationship direction between explanatory variables has the biggest impact on the variance inflation factor especially when the variables are prone to errors and the measurement error influences multicollinearity in all circumstances.

Hence, to resolve the issue of multicollinearity needs, the multidimensional measurement error model with multicollinearity (MMEMc) was developed. As the name implies, the MMEMc model can cater to multidimensional data that also contains multicollinearity where it functions in measuring the similarity or dissimilarity between two sets of data. To better understand the relationship and trend of the foreign exchange rates, we would need to study the gap between the buying and selling prices of the foreign exchange rates along with combinations of various currencies where the similarity or dissimilarity measure could be performed. Hence, we can apply the MMEMc model in fitting the buying (*x*) and selling (*y*) prices of the foreign exchange data which may potentially contain the presence of multicollinearity among the various countries. Through this study, the results may assist financial investors in maximizing their profits through foreign exchange trading and be prepared for possible stock market integration shortly.

Aside from the introduction in Section 1, Section 2 introduces the proposed MMEMc model along with its closed-form equations and properties. Section 3 presents the results and discussion of the foreign exchange rate application. Conclusions and comments on future research are drawn in Section 4.

2 Research Methodology

In this section, the data collection and data massaging procedure will be listed in section 2.1. In section 2.2, assumptions along with the closed-form equation of the MMEMc model will be stated.

2.1 Data Collection and Massaging

The foreign exchange rate data is obtained from the Central Bank of Malaysia (Bank Negara Malaysia) website, [7], where all exchange rates are in terms of the Malaysian Ringgit (MYR). From the website, the data available for both the buying and selling prices are at 0900 hours, which is the opening price, 1130 hours as the best price, 1200 as the midday price, and 1700 hours as the closing price. In this example, the selected data are with the best price, which are at 1130 hours as it is mentioned that the rates at 1130 are the best counter rates offered by selected merchant banks from the website. The best counter rates at 1130 hours are the only rates where the buying price is generally higher than the selling price while prices from the other trading times showed otherwise. To obtain the highest returns possible from investing in the foreign exchange market, we would, hence, analyze the trading time that offers the best price. However, only seven currencies' data are available, comprising of the United States Dollar (USD), Great British Pound (GBP), European Euro (EUR), 100 Japanese Yen (JPY100), Australian Dollar (AUD), Canadian Dollar (CAD) and Singapore Dollar (SGD), which will be used in this study. These currencies are selected because all except the SGD are the six most popular currencies traded in the world as documented in [16], while SGD is selected due to its historical relationship with Malaysia and is also one of the most traded Asia's currencies just after JPY100, [17].

Foreign exchange rate data is known to be a time series data. However, the models that are applied and compared are mostly meant for stationary data or in other words, data that do not contain time series properties. Hence, the Augmented Dickey-Fuller (ADF) test by [18], will be used to identify the data whether it is stationary data or non-stationary data. The test statistic used in the approximate calculation of the p-value by [19] and [20], where a table of values can be referred to for various sample sizes, will be tested at a 5% significance level. If the test shows that data is non-stationary, the differencing procedure will be performed repetitively and tested with the ADF test until it is converted into a stationary one.

From the data differencing procedure, the non-stationary foreign exchange rate data is now converted into stationary data. The conversion changes the prices of foreign exchange rate data to the increase or decrease in prices of foreign exchange rate. Hence, the slope and intercept parameters now represent the gap between the increase or decrease of the buying and selling prices.

2.2 The MMEMc Model

The MMEMc model is a model extended from [21]'s multidimensional unreplicated linear functional relationship (MULFR) model to include multicollinearity. The proposed model contains the following assumptions. $\boldsymbol{Y_i} = (Y_{1i}, Y_{2i}, \cdots, Y_{pi})'$ and $\boldsymbol{X_i} = (X_{1i}, X_{2i}, \cdots, X_{pi})'$ are two linearly related unobserved true values of vector variables with p dimensions and n observations such that:

$$\boldsymbol{Y_i} = \boldsymbol{\alpha} + \beta \boldsymbol{X}_i,\ i = 1,2,\cdots,n \tag{1}$$

where $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \cdots, \alpha_p)'$ are the intercepts and β is the single slope of the linear function. The term dimension refers to the number of variables that are being studied in vector variable $\boldsymbol{x}$ and vector variable $\boldsymbol{y}$. Two corresponding random vector variables $\boldsymbol{y_i} = (y_{1i}, y_{2i}, \cdots, y_{pi})'$ and $\boldsymbol{x_i} = (x_{1i}, x_{2i}, \cdots, x_{pi})'$ are observed and subjected with errors $\boldsymbol{\delta}_i = (\delta_{1i}, \delta_{2i}, \cdots, \delta_{pi})'$ and $\boldsymbol{\varepsilon}_i = (\varepsilon_{1i}, \varepsilon_{2i}, \cdots, \varepsilon_{pi})'$ such that:

$$\left.\begin{aligned} x_i &= X_i + \delta_i \\ y_i &= Y_i + \varepsilon_i \end{aligned}\right\} i = 1,2,\cdots,n. \tag{2}$$

For all $h, k = 1,2,\cdots,p$ and $i, j = 1,2,\cdots,n$, both error vectors are normally distributed with

1. $E(\delta_i) = E(\varepsilon_i) = \mathbf{0}$,
2. $Var(\delta_{ki}) = \sigma^2$ and $Var(\varepsilon_{ki}) = \tau^2$,
3. $Cov(\delta_{ki}, \delta_{hi}) = \omega$ and $Cov(\varepsilon_{ki}, \varepsilon_{hi}) = \varphi$ for all $h \neq k$ (errors among dimensions),
4. $Cov(\delta_{ki}, \varepsilon_{hj}) = 0$,
5. $Cov(\delta_{ki}, \delta_{kj}) = 0$ and $Cov(\varepsilon_{ki}, \varepsilon_{kj}) = 0$ for all $i \neq j$ (errors among observations).

Therefore, the error vectors follow a multivariate normal distribution that $is\ \boldsymbol{\varepsilon}_i \sim N(\mathbf{0}, \Omega_{11})$ and $\boldsymbol{\delta_i} \sim N(\mathbf{0}, \Omega_{22})$ where:

$$\boldsymbol{\Omega_{11}} = \begin{pmatrix} \tau^2 & \varphi & \varphi & \varphi \\ \varphi & \tau^2 & \varphi & \varphi \\ \varphi & \varphi & \ddots & \vdots \\ \varphi & \varphi & \cdots & \tau^2 \end{pmatrix}$$

and

$$\boldsymbol{\Omega_{22}} = \begin{pmatrix} \sigma^2 & \omega & \omega & \omega \\ \omega & \sigma^2 & \omega & \omega \\ \omega & \omega & \ddots & \vdots \\ \omega & \omega & \cdots & \sigma^2 \end{pmatrix}$$

Let $\boldsymbol{v}_i = \begin{pmatrix} \boldsymbol{\varepsilon_i} \\ \boldsymbol{\delta_i} \end{pmatrix}$. Then $Cov(\boldsymbol{v}_i, \boldsymbol{v}_i) = \boldsymbol{\Omega} = \begin{pmatrix} \boldsymbol{\Omega}_{11} & \boldsymbol{\Omega}_{12} \\ \boldsymbol{\Omega}_{21} & \boldsymbol{\Omega}_{22} \end{pmatrix}$ are variance-covariance where $\boldsymbol{\Omega}_{12} = \boldsymbol{\Omega}_{21} = \mathbf{0}$.

Using the MLE method and the assumption of

$$\boldsymbol{\Omega}_{11} = \lambda \boldsymbol{\Omega}_{22}$$

$$\begin{pmatrix} \tau^2 & \varphi & \varphi & \varphi \\ \varphi & \tau^2 & \varphi & \varphi \\ \varphi & \varphi & \ddots & \vdots \\ \varphi & \varphi & \cdots & \tau^2 \end{pmatrix} = \lambda \begin{pmatrix} \sigma^2 & \omega & \omega & \omega \\ \omega & \sigma^2 & \omega & \omega \\ \omega & \omega & \ddots & \vdots \\ \omega & \omega & \cdots & \sigma^2 \end{pmatrix}$$

we have the following parameters closed-form equations:

$$\hat{\alpha} = \bar{y} - \hat{\beta}\bar{x} \qquad (3)$$

where $\overline{\boldsymbol{y}} = \begin{bmatrix} \overline{y}_1 & \overline{y}_2 \cdots \overline{y}_p \end{bmatrix}'$ and $\overline{\boldsymbol{x}} = \begin{bmatrix} x_1 & x_2 \cdots x_p \end{bmatrix}'$.

$$\hat{\beta} = \frac{b}{4a} + \frac{\pm_s\sqrt{B+2\gamma} \pm_t \sqrt{-\left(3B+2\gamma \pm_s \frac{2C}{\sqrt{B+2\gamma}}\right)}}{2} \qquad (4)$$

for $p > 1$ dimensions and $B = \frac{c}{a} - \frac{3b^2}{8a^2}$, $C = \frac{bc}{2a^2} - \frac{b^3}{8a^3} + \frac{d}{a}$ and $D = \frac{b^2c}{16a^3} + \frac{bd}{4a^2} - \frac{3b^4}{256a^4} - \frac{e}{a}$,

with $a = S_{\boldsymbol{xJx}}S_{\boldsymbol{xy}} - \frac{1}{p-1}\left(S_{\boldsymbol{xJx}} - S_{\boldsymbol{xx}}\right)S_{\boldsymbol{xJy}}$,

$b = 2S_{\boldsymbol{xy}}S_{\boldsymbol{xJy}} - \frac{2}{p-1}\left(S_{\boldsymbol{xJy}} - S_{\boldsymbol{xy}}\right)S_{\boldsymbol{xJy}} + S_{xJx}\left(S_{\boldsymbol{yy}} - \lambda S_{\boldsymbol{xx}}\right) - \frac{1}{p-1}\left(S_{\boldsymbol{xJx}} - S_{\boldsymbol{xx}}\right)\left(S_{\boldsymbol{yJy}} - \lambda S_{\boldsymbol{xJx}}\right)$,

$c = \frac{p+1}{p-1}\left(S_{\boldsymbol{yJy}} - \lambda S_{\boldsymbol{xJx}}\right)S_{\boldsymbol{xy}} - \frac{3}{p-1}\left(S_{\boldsymbol{yJy}} - \lambda S_{\boldsymbol{xJx}}\right)S_{\boldsymbol{xJy}} + \frac{2p-1}{p-1}\left(S_{\boldsymbol{yy}} - \lambda S_{\boldsymbol{xx}}\right)S_{\boldsymbol{xJy}}$,

$d = 2\lambda S_{\boldsymbol{xJy}}S_{\boldsymbol{xy}} - \frac{2\lambda}{p-1}\left(S_{\boldsymbol{xJy}} - S_{\boldsymbol{xy}}\right)S_{\boldsymbol{xJy}} - \left(S_{\boldsymbol{yy}} - \lambda S_{\boldsymbol{xx}}\right)S_{\boldsymbol{yJy}} + \frac{1}{p-1}\left(S_{\boldsymbol{yJy}} - S_{\boldsymbol{yy}}\right)\left(S_{\boldsymbol{yJy}} - \lambda S_{\boldsymbol{xJx}}\right)$,

$e = \lambda\left[S_{\boldsymbol{yJy}}S_{\boldsymbol{xy}} - \frac{1}{p-1}\left(S_{\boldsymbol{yJy}} - S_{\boldsymbol{yy}}\right)S_{\boldsymbol{xJy}}\right]$.

where the subscript, *s* represents that the operations have to be the same for both the expressions while the sign with subscript t is independent. From Equation (4), we observe that there are four possible solutions where due to the presence of the negative sign, there is a possibility of obtaining a complex number. Hence, only the real part of the solution and the one that returns the highest log-likelihood will be selected.

For the case of $p = 1$, we have the following closed-form after the derivations.

$$\hat{\beta} = \frac{S_{\boldsymbol{yy}} - \lambda S_{\boldsymbol{xx}} \pm \sqrt{\left(S_{\boldsymbol{yy}} - \lambda S_{\boldsymbol{xx}}\right)^2 + 4\lambda S_{\boldsymbol{xy}}^2}}{2S_{\boldsymbol{xy}}} \qquad (5)$$

Equation (5) has two solutions. The solution that returns the highest log likelihood is selected.

$$\hat{\sigma}^2 = \frac{1}{(n-2)p}\frac{1}{\hat{\beta}^2+\lambda}\left[\sum_{i=1}^{n}\left(\boldsymbol{y}_i - \hat{\boldsymbol{\alpha}} - \hat{\beta}\boldsymbol{x}_i\right)'\left(\boldsymbol{y}_i - \hat{\boldsymbol{\alpha}} - \hat{\beta}\boldsymbol{x}_i\right)\right] \quad (6)$$

$$\hat{\omega} = \frac{1}{(n-2)p(p-1)}\frac{1}{\hat{\beta}^2+\lambda}\left[\sum_{i=1}^{n}\left(\boldsymbol{y}_i - \hat{\boldsymbol{\alpha}} - \hat{\beta}\boldsymbol{x}_i\right)'J\left(\boldsymbol{y}_i - \hat{\boldsymbol{\alpha}} - \hat{\beta}\boldsymbol{x}_i\right) - \sum_{i=1}^{n}\left(\boldsymbol{y}_i - \hat{\boldsymbol{\alpha}} - \hat{\beta}\boldsymbol{x}_i\right)'\left(\boldsymbol{y}_i - \hat{\boldsymbol{\alpha}} - \hat{\beta}\boldsymbol{x}_i\right)\right] \quad (7)$$

$$R^2 = \frac{1}{\hat{\beta}+1}\left(\frac{1}{S_{\boldsymbol{yy}}}\right)\left[\hat{\beta}^2\left(S_{\boldsymbol{yy}} - S_{\boldsymbol{xx}}\right) + 2\,\hat{\beta}S_{\boldsymbol{xy}}\right] \qquad (8)$$

The estimated parameters of the MMEMc model are proven to be unbiased, consistent, and asymptotically normal distributed and they are able to provide explanations for the data. The estimated parameters of β and α represent the size of the gap between the two vector variables under study. The estimated error-variance parameter of σ represents the errors that occur among the daily data within the same dimension while the error-covariance, ω represents the errors that occur among the different dimensions. The R^2 value measures the similarity or dissimilarity between two vector variables which assist in providing the strength of the relationship between them. Stronger relationships allow more accurate estimations while weaker ones will be harder to predict.

3 Results and Discussion

The MMEMc model can assist in measuring the relationship between the buying (*x*) and selling (*y*) prices of the foreign exchange data which may potentially contain the presence of multicollinearity among the various currencies. In this study, we will be analyzing the scenario where the dimensions of the vector variables are represented by the various currencies as there is a possibility of multicollinearity to occur between them.

Relating the parameters to this application, the MMEMc model estimated parameters of β and α represent the size of the gap between the buying and selling prices which will help investors to estimate the potential returns that may be gained from this investment through the prediction of the buying and selling prices. On the other hand, the values of σ represent the errors that occur among the daily data within the same currency while ω represents the errors that occur among the different dimensions. The R^2 estimated represents the strength of relationship between the buying and selling prices where large values that are close to 1 represent strong relationship or high similarity while smaller values close to 0 represent weak relationship or low similarity. The results obtained will represent the currencies and the combinations of currencies that have the strongest or weakest relationship between the buying and selling prices which will assist in obtaining the highest returns assuming that there is severe multicollinearity among the currencies.

To compare the performance of the MMEMc model, the MULFR, linear regression, and canonical correlation analysis models will be used. The slope and error parameters will be compared between the MMEMc and MULFR model while the R^2 coefficient will be compared across all the four models mentioned. For the linear regression, the R^2 will be calculated by obtaining the average value of the R^2 from each of the dimensions.

In this section, the correlation matrices of the Malaysian currency with other countries will be displayed in section 3.1. The results and discussions of the estimated parameters will be explained in section 3.2 for seven countries as an overall view of all the combinations, section 3.3 for one country analysis, and section 3.4 for six countries analyses. For the intercept parameter, α, the number of values follows the number of dimensions under study. Due to the larger number of values, only the value that has the highest magnitude will be displayed in this manuscript.

3.1 Correlation Among Currencies

To determine whether multicollinearity is present among the dimensions under study, the correlation coefficients are calculated. In [22], study, it was mentioned that a correlation coefficient between 0.637 and 0.771 by [23], might indicate a significant relationship among the dimensions. However, [22], stated a general rule of thumb with a correlation coefficient threshold of 0.8 where any value more than 0.8 implies a serious multicollinearity problem. Hence, we would set a benchmark of 0.63 where any values greater than 0.63 imply that multicollinearity exists in the study while 0.8 will be the benchmark for a high level of multicollinearity.

From Table 1, the country that shows the highest level of multicollinearity among the other countries in the stationary buying price is the SGD which it correlates to the USD, JPY100, and CAD with 0.6107, 0.6380 and 0.7085, respectively. On the stationary selling prices, it can be seen from Table 2 that there is a low correlation among the countries. Combining the two sets of data, the correlation values based on Table 3 are now much lower than 0.63, and hence the presence of multicollinearity towards the data is relatively small.

Table 1. Correlation of the Stationary Buying Prices among Currencies

Currency	USD	GBP	EUR	JPY100	AUD	CAD	SGD
US	1.00	0.27	0.31	0.47	0.16	0.46	0.61
GBP	0.27	1.00	0.23	0.27	0.14	0.35	0.42
EUR	0.31	0.23	1.00	0.13	0.25	0.36	0.45
JPY100	0.47	0.27	0.13	1.00	0.11	0.44	0.64
AUD	0.16	0.14	0.25	0.11	1.00	0.31	0.30
CAD	0.46	0.35	0.36	0.44	0.31	1.00	0.71
SGD	0.61	0.42	0.45	0.64	0.30	0.71	1.00

Table 2. Correlation of the Stationary Selling Prices among Currencies

Currency	USD	GBP	EUR	JPY100	AUD	CAD	SGD
US	1.00	0.35	0.22	0.13	0.26	0.24	0.10
GBP	0.35	1.00	0.25	0.06	0.32	0.20	0.05
EUR	0.22	0.25	1.00	0.07	0.24	0.12	0.04
JPY100	0.13	0.06	0.07	1.00	0.08	0.04	0.01
AUD	0.26	0.32	0.24	0.08	1.00	0.32	0.15
CAD	0.24	0.20	0.12	0.04	0.32	1.00	0.13
SGD	0.10	0.05	0.04	0.01	0.15	0.13	1.00

Table 3. Correlation of the Stationary Buying and Selling Prices among Currencies

Currency	USD	GBP	EUR	JPY100	AUD	CAD	SGD
USD	0.31	0.11	0.09	0.03	0.05	0.04	0.04
GBP	0.09	0.29	0.08	0.00	0.08	0.05	0.02
EUR	0.11	0.14	0.03	0.03	0.08	0.05	0.01
JPY100	0.21	0.12	0.14	0.10	0.07	0.03	0.02
AUD	0.05	0.12	0.07	0.02	0.19	0.09	0.00
CAD	0.19	0.21	0.14	0.00	0.21	0.25	0.04
SGD	0.25	0.21	0.16	0.04	0.16	0.10	0.01

On non-stationary data based on Table 4 and Table 5, except for GBP, the other currencies have some correlation among the countries in the exchange rate. For instance, multicollinearity is present in the USD currency with EUR, JPY100, CAD, and SGD in both the buying and selling prices though the multicollinearity with the SGD can be seen as severe in the buying price. Multicollinearity also exists in EUR with USD, JPY100, CAD, and SGD where the buying price in relation to SGD shows severe multicollinearity. JPY100, has multicollinearity with currencies like USD, EUR and SGD with SGD showing severe multicollinearity in the buying price. AUD only has multicollinearity with CAD in both the buying and selling prices. Multicollinearity can also be seen in CAD with USD, EUR, AUD, and SGD in both the buying and selling prices. For SGD, it has generally multicollinearity with most of the other currencies except for GBP and AUD with severe multicollinearity found in the relation with USD, EUR, and JPY100 of the buying price. Combining both the buying and selling prices to calculate the correlation results in a similar observation as can be seen in Table 6.

Table 4. Correlation of the Non-Stationary Buying Prices among Currencies

Currency	USD	GBP	EUR	JPY100	AUD	CAD	SGD
USD	1.00	0.14	0.64	0.75	0.45	0.67	0.89
GBP	0.14	1.00	0.06	-0.30	0.24	0.23	0.03
EUR	0.64	0.06	1.00	0.70	0.51	0.70	0.84
JPY100	0.75	-0.30	0.70	1.00	0.30	0.49	0.84
AUD	0.45	0.24	0.51	0.30	1.00	0.73	0.54
CAD	0.67	0.23	0.70	0.49	0.73	1.00	0.79
SGD	0.89	0.03	0.84	0.84	0.54	0.79	1.00

Table 5. Correlation of the Non-Stationary Selling Prices among Countries

Currency	USD	GBP	EUR	JPY100	AUD	CAD	SGD
USD	1.00	0.11	0.68	0.74	0.45	0.68	0.79
GBP	0.11	1.00	0.07	-0.27	0.21	0.20	0.02
EUR	0.68	0.07	1.00	0.68	0.53	0.72	0.74
JPY100	0.74	-0.27	0.68	1.00	0.31	0.49	0.69
AUD	0.45	0.21	0.53	0.31	1.00	0.71	0.52
CAD	0.68	0.20	0.72	0.49	0.71	1.00	0.70
SGD	0.79	0.02	0.74	0.69	0.52	0.70	1.00

Table 6. Correlation of the Non-Stationary Buying and Selling Prices among Countries

Currency	USD	GBP	EUR	JPY100	AUD	CAD	SGD
USD	0.98	0.15	0.62	0.71	0.48	0.65	0.76
GBP	0.09	0.98	0.02	-0.29	0.21	0.17	-0.01
EUR	0.68	0.11	0.96	0.68	0.56	0.73	0.73
JPY100	0.77	-0.30	0.69	0.94	0.34	0.50	0.72
AUD	0.42	0.23	0.47	0.27	0.98	0.67	0.47
CAD	0.68	0.24	0.68	0.47	0.76	0.97	0.68
SGD	0.91	0.05	0.84	0.80	0.59	0.79	0.86

From the observations described, we would like to compare with the results of the models to check on their consistency with the correlation results.

3.2 Overview of the Seven Countries

From the correlation results, it is now of great interest to observe how does the proposed MMEMc model, its previous MULFR model, and along with other existing models fit the foreign exchange rate data. Looking at the results modeled based on all the seven currencies, we have the results of parameter estimates in Table 7 and results of R^2 in Table 8 and Table 9 for stationary and non-stationary data, respectively.

Focusing on the stationary data, we have the estimated parameters of the MMEMc model with 6.5893 for β, value with the largest magnitude for α at -0.0023, 0.0522 for σ as the error variance, 0.0005 for ω as the error covariance and R^2 at 0.3592. For the MULFR model, we have 4.6308 for β, -0.0015 for α, 0.0521 for σ and 0.03592 for R^2. Comparing these two models, it shows that the presence of the error covariance value, though small, causes a significant impact on the estimated parameters especially on the slope and intercept parameters while the impact on the error variance as well as the R^2 is quite minimal. The meaning of the estimated parameters represents that for every RM 1 in the increase or decrease of the buying price, the increase or decrease in the selling price rises by β value of RM 6.5893 adds with the α values where -RM 0.0023 is the value with the largest magnitude. For the σ value, it implies that the errors among the observations within the same dimension or currency of the increase and decrease in foreign exchange will deviate at about 5% around the mean of zero which is relatively small. The covariance value implies the errors among the observations between the different dimensions or currencies of the increase and decrease in foreign exchange will deviate at about 0.05% around the mean of zero which is also relatively small.

The β estimated showed a value that is greater than 1 and very small values of α which may imply that the increase or decrease in the buying price is relatively directly proportional to that of the selling price. The error variance and covariance values are also relatively small which represent those minimal errors exist between the observations within and among the dimensions. However, the low values of the R^2 showed otherwise due to the values of the observation. Hence, it is evident that the relationship between the increase or decrease in the buying price and the selling price is not strong in both the models. Comparing with the other two models, linear regression and canonical correlation analysis, the linear regression model tends to show an R^2 value that is way smaller that the proposed model while the canonical correlation analysis mode showed a value similar to the proposed model. Therefore, it is conclusive to say that the linear regression model may have underestimated the relationship strength between the variables while the other models have somewhat similar estimation strength.

On the non-stationary data, the β values of both the MMEMc and MULFR model are somewhat similar which is around 1. The α magnitudes are larger than those from the stationary data, but they are relatively small with only values between 1 and -1. The σ values are also similar to those of the stationary data at approximately 0.0426 for both the models. The error covariance estimated is also small at 0.0003. The small values of the estimated error parameters also showed that minimal errors exist between the observations within and among the dimensions. On the R^2 values for all the models, they are relatively large with values above 0.9 with canonical correlation showing the largest, followed by the proposed models and finally the linear regression models.

Table 7. Table of MMEMc and MULFR parameter estimates for all Seven Currencies' (USD GBP EUR JPY100 AUD CAD SGD) Stationary and Non-Stationary Foreign Exchange Rate Data

Parameters	Stationary		Non-Stationary	
	MMEMc	MULFR	MMEMc	MULFR
β	6.5893	4.6308	1.0078	1.0113
α	-0.0023	-0.0015	-0.1133	-0.1330
σ	0.0522	0.0521	0.0426	0.0426
ω	0.0005	*N/A*	0.0003	*N/A*

**N/A implies Not Available*

Table 8. Table of MMEMc, MULFR, Linear

Currencies	Stationary			
	MMEMc	MULFR	Lin. Reg.	Can. Cor.
USD GBP EUR JPY100 AUD CAD SGD	0.3577	0.3592	0.0419	0.3548

Regression and Canonical Correlation Analysis models' R^2 estimates for Seven Countries' Stationary Foreign Exchange Rate Data

Table 9. Table of MMEMc, MULFR, Linear

Currencies	Non-Stationary			
	MMEMc	MULFR	Lin. Reg.	Can. Cor.
USD GBP EUR JPY100 AUD CAD SGD	0.9609	0.9609	0.9097	0.9909

Regression and Canonical Correlation Analysis models' R^2 estimates for Seven Countries' Non-Stationary Foreign Exchange Rate Data

In summary, the proposed model, MMEMc and its prior model, MULFR are able to perform as well as the canonical correlation analysis model with the linear regression model and then underestimate its estimation based of the stationary data. However, the presence of the error covariance parameter which caused a slight difference in the estimated parameters between the MMEMc and MULFR model showed that it is important to have a parameter that can represent multicollinearity. Therefore, the MMEMc model may be a better performed model in the foreign exchange rate stationary data. On the non-stationary data, the four models showed a strong relationship between the buying and selling prices for all the countries combined with the canonical correlation analysis showing the highest values, followed by the proposed models and finally the linear regression model.

Nevertheless, this case only shows the overall value for the combination of all the seven currencies, and not much information can be obtained from it. Reasons behind the small R^2 values even though the β values are greater than 1 could not be determined via this case. Therefore, the relationship between the buying and selling prices is also studied at a single currency basis which will be analyzed in the next section.

3.3 Single Currency

Looking at the results modeled based on a single country perspective, we have the results of β in Table 10, results of α in Table 11, results of σ in Table 12, and results of R^2 in Table 13 and Table 14 for stationary and non-stationary data, respectively. For this study, we are looking at a one-dimensional study. Hence, the estimates and results for both the MMEMc and MULFR are the same with the error covariance, ω, to be zero which will not be displayed.

Focusing on the stationary data, SGD seems to have the highest β value of 422.2836 followed by JPY100 at 29.4816 and CAD at 5.5084. The rest of the currencies have β values lesser than 1. A β value of 1 is placed as a benchmark as it normally shows a strong relationship between the two variables as can be seen through the non-stationary data results. On the α parameter, the magnitude of the values for all the currencies are relatively small and are lesser than 1. The σ parameter values are also small with the largest value being 0.0542. This implies that the errors among the observations within the same dimension of the increase and decrease in foreign exchange will deviate at about 5% around the mean of zero which is relatively small. The values of the MMEMc and MULFR R^2 reflect the values of the β parameter. Hence, it is observed that the highest value goes to SGD with a value of 0.9658 followed by JPY100 at 0.9109 and CAD at 0.7390. The next highest value calculated is 0.1302 which is the USD R^2. The rest of the R^2 values are lesser than 0.1. However, the R^2 values for the other two models, the linear regression and canonical correlation, are very much smaller in general than the MMEMc and MULFR models, especially for currencies such as the JPY100, CAD, and SGD where their R^2 tend to be larger. For smaller values of the MMEMc and MULFR R^2, the R^2 values for the canonical correlation model are slightly larger which can be seen in the currencies of USD, GBP, EUR, and AUD.

On non-stationary data which represents the actual price, the β values of the MMEMc and MULFR models are generally around 1 with the highest value being 1.2786 for the SGD. The α values have generally small magnitudes with the largest value being 0.8906. Also, the error variance largest value can be seen to be 0.0625 which is relatively small as well. This implies that the errors among the observations within the same dimension in foreign exchange will deviate at about 6% around the mean of zero which is relatively small. On the R^2, they are all generally close to one with the smallest being 0.8876. However, compared with the β values, the R^2 values do not fully reflect them as the β value of the SGD is the largest but its R^2 value is the smallest. This occurs because of the buying and selling prices which affect the ***Sxx***, ***Sxy*** and ***Syy*** values that is present in the calculation of the R^2. Comparing the R^2 results with the linear regression and canonical correlation models, the values are very close to one another with the MMEMc and MULFR models showing the highest values followed by the canonical correlation model and finally the linear regression model.

Table 10. Table of MMEMc and MULFR β estimates for a Single Country's Stationary and Non-Stationary Foreign Exchange Rate Data

Currencies	Stationary Data		Non-Stationary Data	
	MMEMc	MULFR	MMEMc	MULFR
US	0.2247	0.2247	0.9924	0.9924
GBP	0.1359	0.1359	0.9530	0.9530
EUR	0.0470	0.0470	1.0451	1.0451
JPY100	29.4816	29.4816	1.0542	1.0542
AUD	0.2974	0.2974	0.9660	0.9660
CAD	5.5084	5.5084	1.0330	1.0330
SGD	422.2837	422.2837	1.2786	1.2786

Table 11. Table of MMEMc and MULFR α estimates for a Single Country's Stationary and Non-Stationary Foreign Exchange Rate Data

Currencies	Stationary Data		Non-Stationary Data	
	MMEMc	MULFR	MMEMc	MULFR
US	0.0003	0.0003	-0.0094	-0.0094
GBP	0.0001	0.0001	0.1924	0.1924
EUR	0.0003	0.0003	-0.2732	-0.2732
JPY100	-0.0117	-0.0117	-0.2521	-0.2521
AUD	0.0001	0.0001	0.0504	0.0504
CAD	-0.0006	-0.0006	-0.1608	-0.1608
SGD	-0.1059	-0.1059	-0.8906	-0.8906

Table 12. Table of MMEMc and MULFR σ estimates for a Single Country's Stationary and Non-Stationary Foreign Exchange Rate Data

Currencies	Stationary Data		Non-Stationary Data	
	MMEMc	MULFR	MMEMc	MULFR
US	0.0204	0.0204	0.0247	0.0247
GBP	0.0353	0.0353	0.0475	0.0475
EUR	0.0542	0.0542	0.0475	0.0475
JPY100	0.0371	0.0371	0.0625	0.0625
AUD	0.0276	0.0276	0.0245	0.0245
CAD	0.0192	0.0192	0.0219	0.0219
SGD	0.0156	0.0156	0.0443	0.0443

Table 13. Table of MEMMc, MULFR, Linear Regression and Canonical Correlation R^2 estimates for a Single Country's Stationary Foreign Exchange Rate Data

Currencies	Stationary Data			
	MMEMc	MULFR	Lin. Reg.	Can. Cor.
USD	0.1302	0.1302	0.0973	0.3120
GBP	0.0979	0.0979	0.0836	0.2892
EUR	0.0021	0.0021	0.0011	0.0325
JPY100	0.9109	0.9109	0.0106	0.1029
AUD	0.0770	0.0770	0.0374	0.1933
CAD	0.7390	0.7390	0.0631	0.2511
SGD	0.9658	0.9658	0.0002	0.0124

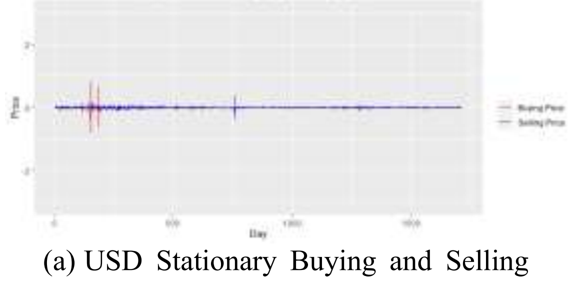
Table 14. Table of MEMMc, MULFR, Linear Regression and Canonical Correlation R^2 estimates for a Single Country's Non-Stationary Foreign Exchange Rate Data

Currencies	Non-Stationary Data			
	MMEMc	MULFR	Lin. Reg.	Can. Cor.
USD	0.9833	0.9833	0.9671	0.9834
GBP	0.9764	0.9764	0.9555	0.9775
EUR	0.9627	0.9627	0.9237	0.9611
JPY100	0.9460	0.9460	0.8896	0.9432
AUD	0.9774	0.9774	0.9567	0.9781
CAD	0.9704	0.9704	0.9399	0.9695
SGD	0.8876	0.8876	0.7354	0.8576

The above observations discussed can be explained via the graphs plotted. Stationary prices for the seven countries can be seen in Fig. 1 with subfigures 1a, 1b, 1c, 1d, 1e, 1f and 1g representing USD, GBP, EUR, JPY100, AUD, CAD, and SGD. From the graphs, those with only the blue color are values where the increase or decrease in the selling price is larger than the buying price while the red color represents that the increase or decrease in the buying price is larger than the selling price. As it is common knowledge that the increase or decrease in selling price must be higher than the increase or decrease in buying price in every business, hence the blue color lines are seen more frequently in the graphs.

Looking closer, currencies with higher R^2 values tend to have fewer red lines observed whereas currencies with low R^2 values tend to have more red lines observed. Hence, it means that the relationship of the increase or decrease in selling price in comparison with those of the buying price is relatively stronger which allows a more accurate estimation of the prices. When there are more frequent red spikes, the increase or decrease in the prices is much harder to estimate as the prices are not following the usual trend, hence, lower R^2 values are estimated. Therefore, the value of the R^2 can assist in a more reliable prediction of the increase or decrease in the selling price given that the increase or decrease in the buying price is known or vice versa.

Comparing with the linear regression and canonical correlation model, they show relatively lower and smaller R^2 values in all the currencies which cannot be justified from the graphs. This shows that the models have relatively lower predictive power in estimating the increase or decrease of the prices. Thus, it can be concluded that the MMEMc and MULFR models perform better than the linear regression and canonical correlation models in the single currency scenario. It can also be concluded that the currencies of JPY100, CAD, and SGD are more predictable currencies which can be represented by the MMEMc and MULFR model.



(a) USD Stationary Buying and Selling Prices at 1130

(b) GBP Stationary Buying and Selling Prices at 1130

(c) EUR Stationary Buying and Selling Prices at 1130

(d) JPY100 Stationary Buying and Selling Prices at 1130

(e) AUD Stationary Buying and Selling Prices at 1130

(f) CAD Stationary Buying and Selling Prices at 1130

(g) SGD Stationary Buying and Selling Prices at 1130

Fig. 1: Comparison of 7 countries 1130 Stationary Buying and Selling prices of Foreign Exchange Rate

On the non-stationary data, the trend of prices for the seven currencies can be seen in Fig. 2 with subfigures 2a, 2b, 2c, 2d, 2e, 2f, and 2g representing USD, GBP, EUR, JPY100, AUD, CAD, and SGD. From the graphs, two colors can be seen obviously. The buying price is represented by the red color while the selling price is blue. At the 1130 price, it is known to be the best price offered by merchant banks. Hence, it can be observed that the buying price is generally higher than the selling price which is quite consistent throughout the seven years though there are certain prices that show a different trend on certain days which can be seen from the crossovers of the two lines. Therefore, this trend contributes to the relatively high R^2 for all the currencies as observed by all the four models compared.

(a) USD Non-Stationary Buying and Selling Prices at 1130

(b) GBP Non-Stationary Buying and Selling Prices at 1130

(c) EUR Non-Stationary Buying and Selling Prices at 1130

(d) JPY100 Non-Stationary Buying and Selling Prices at 1130

(e) AUD Non-Stationary Buying and Selling Prices at 1130

(f) CAD Non-Stationary Buying and Selling Prices at 1130

(g) SGD Non-Stationary Buying and Selling Prices at 1130

Fig. 2: Comparison of 7 countries 1130 Non-Stationary Buying and Selling prices of Foreign Exchange Rate

However, looking deeper into the graphs, it can be observed that there are a few large spikes seen in the graphs which show a sudden drop or increase in the buying or selling prices. Comparing with the R^2 values, currencies with fewer number of spikes regardless of the buying or selling price tend to have higher R^2 values while currencies with more spikes tend to have lower R^2 values. This supports the results where the SGD graph which reflects the highest number of spikes showing the lowest R^2 values compared to the other currencies.

Comparing among the models, most of the R^2 values are relatively close to one another especially the MMEMc, MULFR and canonical correlation models with the linear regression model showing the lowest value in all the currencies. Therefore, it can be concluded that the MMEMc, MULFR and canonical correlation models perform better in estimating the selling price given that the buying price is known while the linear regression has slightly lower estimation capability. Also, it can be evident that the SGD prices are slightly more difficult to predict compared to the other currencies.

As an overall summary, the MMEMc and MULFR models are better performed models in estimating the stationary prices of the increase or decrease in selling and buying prices for each single currency compared to the linear regression and canonical correlation models based on their consistency. From the models, SGD, JPY100, and CAD are the currencies that show better consistency in the increase or decrease in their prices. Also, the four models compared showed relatively similar estimation strength in predicting the non-stationary actual selling and buying prices of each country with the linear regression showing slightly lower capability in the estimation. This proves that the MMEMc and MULFR models are equivalent in estimation strength with the canonical correlation model in modeling single currencies. Overall, the MMEMc and MULFR models performed better if not equivalent in modeling single currency foreign exchange rates.

3.4 Combinations of Six Currencies

With the relationship studied between the buying and selling prices for both the stationary and nonstationary data on a single currency basis, we would now like to observe which currency has the largest impact on the others either positively or negatively where currencies that have similar trends tend to have stronger relationships while dissimilar trends will have weaker relationships. Thus, an analysis on the combination of six currencies will be performed where seven such combinations can be grouped. Looking at the results modeled based on a six-currency perspective, we have the results of β in Table 15, results of α in Table 16, results of σ in Table 17, results of ω in Table 18, and results of R^2 in Table 19 and Table 20 for stationary and non-stationary data, respectively.

Focusing on the stationary data, there are 6 larger β values observed that are greater than 1 with USD GBP EUR AUD CAD SGD group being lesser than it with a value at 0.3912 and 0.3917 for the MMEMc and MULFR models, respectively. From here, it can be observed that the combinations with JPY100 result in larger β values which implies that the Japanese Yen has the strongest positive influence on the seven currencies. Furthermore, it can also be seen that GBP is the currency that decreases the β values of the combinations greatly where the combination of USD EUR JPY100 AUD CAD SGD can be seen as the highest at 19.7796 and 13.3372 for the MMEMc and MULFR models, respectively. On the values of the α where only the ones with the highest magnitude will be shown, they are generally quite small with the value of the largest magnitude seen to be -0.0077 and -0.0051 by both the MMEMc and MULFR models respectively for the USD EUR JPY100 AUD CAD SGD.

Similarly, on the σ values, the values are generally small with the largest value seen in the combined currencies of USD GBP EUR AUD JPY100 at 0.0558 and 0.0557 by the MMEMc and MULFR models, respectively. On the error covariance estimated, the values seem to be relatively small as well with approximately 0.0006 from the USD GBP EUR JPY100 AUD SGD and USD GBP EUR JPY100 CAD SGD combinations as the largest value seen. These parameters imply that minimal errors exist between the observations within and among the dimensions. Regarding the R^2 values, the currencies that consist of JPY100 and also do not consist of GBP show the highest value at 0.6160 and 0.6164 by the MMEMc and MULFR models respectively. Whereas the combinations that do not consist of JPY100 but consist of GBP show the lowest R^2 value at 0.0504 for both the MULFR and MMEMc models.

Comparing across the models, the linear regression and canonical correlation analysis models show relatively smaller values in all the combined currencies with the canonical correlation analysis model showing approximately 0.33 on average and linear regression approximately lesser than 0.1. However, the MMEMc and MULFR models are seen to better represent the relationship of the increase or decrease in the prices for the six combined currencies where the estimates can be justified from the studies done at a single currency basis. Also, it can be concluded that the combined currencies of USD EUR JPY100 AUD CAD SGD is the better portfolio which has more similar trends among the currencies in their increase or decrease in the buying and selling prices using the proposed model which allows better estimations. From the study of combinations of six currencies, it can be determined that the JPY100 has the strongest influence on the seven currencies while GBP has the weakest.

On non-stationary data, the following explanations apply to both the MMEMc and MULFR models. The β values are generally the same for all the currencies combinations approximately around 1. On the largest magnitude of the α, it is still slightly larger than those of the stationary data, but they are still relatively small with values that are lesser than 1 or larger than -1. The error variances, it is similar to the stationary data with the largest value seen at approximately 0.0451 for the combined currencies of USD GBP EUR JPY100 AUD, and SGD. Similarly, the error covariance also showed small values with the largest seen at approximately 0.0003 for most of the combined currencies except USD GBP JPY100 AUD CAD SGD and USD EUR JPY100 AUD CAD SGD. The estimated error parameters imply that there are only minimal errors seen between the observations within and among the dimensions. Regarding R^2, the values are generally similar to one another where they are all larger than 0.9 for both the MMEMc and MULFR models.

Compared with other models, the canonical correlation model seems to show the largest values in all the combinations followed by the MMEMc and MULFR models which are only slightly lesser, while the linear regression is seen to be the smallest where some combinations show R^2 values that are lesser than 0.9. Therefore, it can be evident that the MMEMc and MULFR models can perform almost as well as the canonical correlation model but better than the linear regression model in estimating the actual buying or selling prices for a combination of six currencies. All the combinations of the currencies show similar strong relationships between the buying and selling prices due to their similar trends which can be seen in Figure 2.

Table 15. Table of MMEMc and MULFR β estimates for Six Countries' Stationary and Non-Stationary Foreign Exchange Rate Data

Currencies	Stationary Data		Non-Stationary Data	
	MMEMc	MULFR	MMEMc	MULFR
USD GBP EUR JPY100 AUD CAD	2.6678	1.9421	0.9980	1.0016
USD GBP EUR JPY100 AUD SGD	6.3976	4.5530	1.0070	1.0102
USD GBP EUR JPY100 CAD SGD	7.6990	5.3661	1.0117	1.0157
USD GBP EUR AUD CAD SGD	0.3912	0.3917	0.9960	1.0002
USD GBP JPY100 AUD CAD SGD	7.5983	6.1621	1.0027	1.0040
USD EUR JPY100 AUD CAD SGD	19.7796	13.3372	1.0418	1.0396
GBP EUR JPY100 AUD CAD SGD	7.6201	5.7663	1.0107	1.0139

Table 16. Table of MMEMc and MULFR largest α estimates for Six Countries' Stationary and Non-Stationary Foreign Exchange Rate Data

Currencies	Stationary Data		Non-Stationary Data	
	MMEMc	MULFR	MMEMc	MULFR
USD GBP EUR JPY100 AUD CAD	-0.0007	-0.0004	-0.0588	-0.0786
USD GBP EUR JPY100 AUD SGD	-0.0022	-0.0015	-0.1089	-0.1267
USD GBP EUR JPY100 CAD SGD	-0.0027	-0.0018	-0.1348	-0.1576
USD GBP EUR AUD CAD SGD	0.0003	0.0003	-0.0473	-0.0709
USD GBP JPY100 AUD CAD SGD	-0.0027	-0.0021	-0.0850	-0.0923
USD EUR JPY100 AUD CAD SGD	-0.0077	-0.0051	-0.2574	-0.2472
GBP EUR JPY100 AUD CAD SGD	-0.0027	-0.0020	-0.1292	-0.1471

Table 17. Table of MMEMc and MULFR σ estimates for Six Countries' Stationary and Non-Stationary Foreign Exchange Rate Data

Currencies	Stationary Data		Non-Stationary Data	
	MMEMc	MULFR	MMEMc	MULFR
USD GBP EUR JPY100 AUD CAD	0.0550	0.0549	0.0416	0.0416
USD GBP EUR JPY100 AUD SGD	0.0558	0.0557	0.0451	0.0451
USD GBP EUR JPY100 CAD SGD	0.0543	0.0542	0.0448	0.0448
USD GBP EUR AUD CAD SGD	0.0473	0.0473	0.0381	0.0381
USD GBP JPY100 AUD CAD SGD	0.0472	0.0472	0.0416	0.0416
USD EUR JPY100 AUD CAD SGD	0.0425	0.0425	0.0412	0.0412
GBP EUR JPY100 AUD CAD SGD	0.0540	0.0540	0.0449	0.0449

Table 18. Table of MMEMc ω estimates for Six Countries' Stationary and Non-Stationary Foreign Exchange Rate Data

Currencies	Stationary Data MMEMc	Non-Stationary Data MMEMc
USD GBP EUR JPY100 AUD CAD	0.0005	0.0003
USD GBP EUR JPY100 AUD SGD	0.0006	0.0003
USD GBP EUR JPY100 CAD SGD	0.0006	0.0003
USD GBP EUR AUD CAD SGD	0.0002	0.0003
USD GBP JPY100 AUD CAD SGD	0.0004	0.0002
USD EUR JPY100 AUD CAD SGD	0.0004	0.0002
GBP EUR JPY100 AUD CAD SGD	0.0005	0.0003

Table 19. Table of MMEMc, MULFR, Linear Regression and Canonical Correlation R^2 estimates for Six Countries' Stationary Foreign Exchange Rate Data

Currencies	Stationary Data			
	MMEMc	MULFR	Lin. Reg.	Can. Cor.
USD GBP EUR JPY100 AUD CAD	0.1936	0.1970	0.0488	0.3544
USD GBP EUR JPY100 AUD SGD	0.3390	0.3403	0.0384	0.3312
USD GBP EUR JPY100 CAD SGD	0.3872	0.3884	0.0426	0.3397
USD GBP EUR AUD CAD SGD	0.0504	0.0504	0.0471	0.3510
USD GBP JPY100 AUD CAD SGD	0.4992	0.4997	0.0487	0.3543
USD EUR JPY100 AUD CAD SGD	0.6160	0.6164	0.0349	0.3313
GBP EUR JPY100 AUD CAD SGD	0.3993	0.4000	0.0326	0.3495

Table 20. Table of MMEMc, MULFR, Linear Regression, and Canonical Correlation R^2 estimates for Six Countries' Non-Stationary Foreign Exchange Rate Data

Currencies	Non-Stationary Data			
	MMEMc	MULFR	Lin. Reg.	Can. Cor.
USD GBP EUR JPY100 AUD CAD	0.9662	0.9662	0.9387	0.9903
USD GBP EUR JPY100 AUD SGD	0.9604	0.9604	0.9047	0.9906
USD GBP EUR JPY100 CAD SGD	0.9596	0.9596	0.9019	0.9899
USD GBP EUR AUD CAD SGD	0.9655	0.9655	0.9130	0.9903
USD GBP JPY100 AUD CAD SGD	0.9607	0.9607	0.9073	0.9906
USD EUR JPY100 AUD CAD SGD	0.9556	0.9556	0.9021	0.9896
GBP EUR JPY100 AUD CAD SGD	0.9581	0.9581	0.9001	0.9860

In summary, the MMEMc and MULFR models are better performed models in estimating the stationary prices of the increase or decrease in selling prices and the increase or decrease in buying prices for six combined currencies compared with the linear regression and canonical correlation models based on their consistency. From the better performed models, USD EUR JPY100 AUD CAD SGD combination is the portfolio that shows similar trends in the increase or decrease in their prices which may allow higher returns with some risks being hedged. For combinations that have lower R^2, the currencies' increase or decrease in prices do not move towards the same trend which shows weak relationship between the buying and selling prices with the weakest seen in the USD GBP EUR AUD CAD SGD combination. Also, it can be analyzed that the JPY100 has the strongest influence among the seven currencies while GBP has the weakest which affected the overall R^2 values.

On the non-stationary prices, the four models compared showed relatively similar strong estimation strength in predicting the actual selling and buying prices of each six currencies combinations where the values are all similar with only the linear regression showing slightly lower capability in the estimation. This proves that the MMEMc and MULFR models are equivalent in estimation strength to the canonical correlation analysis model. Also, as the error covariance estimated is relatively small, the impact on the R^2 values is minimal hence, not many differences can be seen. Overall, the MMEMc and MULFR models performed better if not equivalent to the canonical correlation analysis model in modelling combined three currencies foreign exchange rates.

4 Conclusion

From the discussions, we started with the study of correlation among the seven countries followed by an overview of the estimation results of all the seven countries. Then, we analyzed the results for each of the currencies individually to understand their relationship between the buying and selling prices. Then, a study on combinations of six currencies was also performed to analyze the currency that has the strongest positive or negative influence towards the other currencies which assists in identifying the number of possible portfolios that have better predictability for investment. From the analyses, it was determined that the MMEMc and MULFR models have similar R^2 values as the error covariance values are quite small. Though the presence of ω, is small, it also results in some differences in the estimated β, α as well as R^2 parameters. Nevertheless, among the four models compared, the MMEMc and MULFR models are able to perform better than the linear regression and canonical correlation analysis models in fitting the stationary foreign exchange rate data where the prices with similar trends are able to be captured by the two models regardless of the combinations.

From the single stationary currency analyses from the better performed models, it was mentioned that SGD has the best relationship, based on the R^2 values among the seven compared currencies, the relationship between the increase or decrease of the selling and the buying prices followed by JPY100 and CAD where they are the currencies with the better relationships. On the other currencies, the worst off is EUR followed by AUD, GBP, and USD. However, as the analysis continues with a combination of six currencies, JPY100 seems to be the currency with the strongest influence in raising the R^2 values while GBP has the strongest influence in decreasing them. Hence, it is evident to conclude that combinations that contain the currency of JPY100 and do not contain GBP are safer portfolios as they allow more accurate estimation of the increase or decrease in the prices.

On the non-stationary prices, all four models tend to show similar strength in determining the relationship between the buying and selling prices. All of them show strong relationships regardless of the number of combinations and currencies with canonical correlation analysis tend to show the largest values, followed closely by the MMEMc and MULFR models and finally linear regression model. The three models with the higher R^2 values are quite close to one another and are relatively consistent in all the cases where they are above 0.9. However, the linear regression model has R^2 values slightly lower than them with some cases being less than 0.9. Therefore, it can be said that the linear regression model tends to underestimate in calculating R^2 values while the other three models have similar performances for the non-stationary prices.

In conclusion, this study showed that multicollinearity does exist, though not severe, among the various currencies studied and it is important to include its presence in a particular model in which the MMEMc model is able to. From the model, the JPY100 is concluded as the currency with the strongest positive influence on all the seven currencies studied while GBP is the worst. On nonstationary prices, the MMEMc and MULFR models can perform as well as the canonical correlation model in the study of their relationship. All the currencies and their combinations showed a similar strong relationship between the buying and selling prices.

Nevertheless, further analyses can be extended as future work from this point. Predictive analytics studies can be conducted to test the accuracy of the predicted prices with the actual ones based on the estimated parameters. If the accuracy can be proven to be strong, financial analysts will be able to utilize this model in making more accurate predictions which will help in maximizing investors' profits through foreign exchange rate trading. Of course, this model could also be applied to other financial instruments or even another field of studies that uses primary data from surveys or experiments conducted are being used for analysis and the study of relationships is needed to better understand the data.

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