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Portfolio recallocation and exchange rate dynamics

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Introduction and Relevancy

This empirical paper aims to review a previous literature entitled "Portfolio Reallocation and Exchange Rate Dynamics". The literature stated that including financial market structure can provide a micro-foundation to complement other macro-based models for exchange rate dynamics which typically are meaningful for the medium and long terms but not satisfactory for the short run. The model in the literature offers another way to look at exchange rate dynamics that is significant in the short run and more practical in nature. Undoubtedly, many investors in the financial market, such as traders, dealers, fund managers, and speculators who adjust their portfolio components more frequently relative to other investors, are interested in their short-run performance and value any strong models in explaining relationships among different financial variables. Reviewing the previous findings done several years ago is to ensure the validity of the proposed model and is needed as the financial market and economic conditions change from time to time, particularly in the current era.

Therefore, this paper tries to replicate the approach adopted in the literature and covers the period subsequent to it. As this is a short empirical paper, however, some of the operations will be cut down and simplified with a few assumptions while maintaining the principal concept as much as possible.

Literature/Paper Review

Liang DING and Jun MA, authors of the paper "Portfolio Reallocation and Exchange Rate Dynamics", had been inspired by certain international portfolio rebalance studies, such as Pavlova and Roberto in 2007, Hau and Rey in 2004 and 2006, and Dunne et al. in 2010. They describe the relationship among exchange rate movements, stock prices and returns, and portfolio rebalancing, with a model linking exchange rate dynamics and foreign exchange transactions due to portfolio reallocation by financial institutions and their clients among the concerned financial markets including the US, the UK, Canada, the Eurozone, and Japan. The model is supported byevidence that is currency- and period- specific. The major regression specification of this paper is showed in as follows:

$$\Delta e_{t+1} = \beta_1 IDC_t + \beta_2 RPC_t + \beta_3 RAC_{t+1} + \beta_4 EquityC_{t+1} + \beta_5 RiskC_t + \epsilon_{t+1}$$

where the dependent variable Δe_{t+1} is the exchange rate return calculated by taking a log differential of two consecutive spot exchange rates between USD and one of the other countries' currencies. In order to align with the theoretical base, all exchange rates were converted into the dollar prices of foreign currencies. IDC_t is the 1-period-lagged change in the interest rate differential equal to $\Delta(i_t^* - i_t)$ in which i_t^* is the foreign and i_t is the domestic (the US) interest rates on respective bonds that are assumed to be risk-free. The interest rates used in the paper were monthly short-term interest rates with a maturity of 3 months. RPC_t is the 1-period-lagged change in expected stock market cross risk premium depending on the Stock Market High-Return-Currency (HRC) status of the two countries concerned (the US and another). The authors adopted this concept to determine the direction of foreign exchange order flows and identify various scenarios for conducting regime switches analysis that at the time of this paper was under-explored by researchers. The Stock Market HRC status is determined by the higher average return on the stock index of a particular country relative to that of another. Therefore, if $\bar{r}_t^* > \bar{r}_t$ is true, the foreign currency is the HRC and $RPC_t = \Delta(\bar{r}_t^* - i_t)$, or otherwise $RPC_t = -\Delta(\bar{r}_t - i_t^*)$. 12-month exponential moving averages were applied to the expected stock returns in the paper. Similarly, the concept of the HRC status was also applied in the bond market where the Bond Market HRC status is simply determined by the sign of the interest rate differential $(i_t^* - i_t)$. RAC_{t+1} is the change in risk appetite measured by a log differential of leverage or outstanding Repo of financial institutions which pledge their assets, for example on-hand treasury securities, for obtaining additional funds to invest overseas when they have a risk-on attitude so that their risk appetite increases. The value of RAC_{t+1} is either ΔRA_{t+1} or $-\Delta RA_{t+1}$ depending on the relative dominances of bond and stock reallocation within the portfolio. The detailed explanation of this determination can be found at Equation (46) on Page 3106 of the paper. $EquityC_{t+1}$ is the change in equity. The authors substituted the growth of non-farm payroll as an instrumental variable for actual changes in equity to avoid the endogeneity problem. Although it was not mentioned in the paper, the possible endogeneity problem could arise from the effect of changes in exchange rates on the decision of capital structure. Moreover, multicollinearity problem might also exist as changes in asset prices affecting their returns can cause changes in equity. The rationale of the substitution is that when income rises people will invest more and vice versa. The value of $EquityC_{t+1}$ is either $\Delta Payroll$ or $-\Delta Payroll$ also depending on the relative reallocation between bonds and stocks in the portfolio. $RiskC_t$ is the 1-period-lagged change in expected stock risk measured by VIX. Its value is determined by the Stock Market HRC status where $RiskC_t = \Delta\mathrm{VIX}$ if $\bar{r}_t^* > \bar{r}_t$ and $RiskC_t = -\Delta\mathrm{VIX}$ if otherwise. For a possible variable of exchange rate risk, the authors decided not to include it in the model because of the existence of another endogeneity problem with GARCH estimated exchange rate risk as well as the data unavailability of expected exchange rate risk derived from currency options.

As the three independent variables IDC, RPC, and RiskC may incur endogeneity problem should the dependent variable Δe is regressed on them in a contemporaneous manner, 1-period-lagged values of them were chosen rather than the same period data. Except $RiskC_t$, all other regression coefficients were expected to be positive that (i) a positive $i_t^* - i_t$ with a positive change, namely a larger interest rate differential with the foreign country belonging to the Bond Market HRC status, (ii) a larger difference between the foreign stock return and the domestic interest rate attracts more overseas financial purchases of stocks, (iii) increased risk appetite leads to larger foreign financial investment, and (iv) higher income implies larger financial investment. The negative relationship between Δe and RiskC can be interpreted in the way that investment funds will flow to foreign markets if the risk of local stock increases when the local stock index generates a higher return that might lead to more severe drop when the market slows down relative to the counterparty country.

The whole causality mechanism for the relationship between exchange rate dynamics and portfolio reallocation consists of two principal sections – how foreign exchange order flows are induced by portfolio reallocation and how such order flows affect exchange rate dynamics. This paper focuses on the former while the latter was examined by Evans and Lyons in 2002. The portfolio rebalancing process in the model follows the mean-variance optimization approach for capital allocation which maximizes the utility to investors given the expected return, the risk measured by the variance of the portfolio, as well as the degree of risk aversion. The mechanism bases on the profit-seeking orientation of financial investors who try to maximize their profits via carry trade, i.e. taking advantage of interest rate and/or return differentials in hopes of gaining profits from less than expected depreciation of the HRC (Uncovered Interest Rate Parity does not hold.). According to the HRC statuses, the authors identified different scenarios in which the values of independent variables were adjusted as explained above, and then ran separate regressions for different periods of time (regime switches) within 02/1991 to 09/2009. The entire period was divided into an in-sample period of 02/1991-12/2007 and an out-of-sample period of 01/2008-09/2009 in which the authors claimed that the model exhibited a random walk. For the latter, the authors predicted the exchange rate return one period ahead by the rolling regression method. As for scenario identification, it involves determining the Stock Market and Bond Market HRC statuses and picking the dominant market if the status are conflicting. Possible scenarios are the money market scenario, the stock market downturn scenario, the HRC in the stock market scenario, and the dominating market scenario.

The result of the empirical study shows that IDC_t, RPC_t, and $RiskC_t$ were consistently and significantly relevant to exchange rate dynamics in the tested period suggesting exchange rate dynamics is not only based on traditional macroeconomic factors in the medium and long run, but also the financial market microstructure which is deemed as powerful in explaining exchange rate dynamics in the short run and can extend a micro-foundation to expectation-based macro models. The regression coefficients were time-varying. The dominance of independent variables differed in different regimes. They also argued that the critical reason for a HRC to appreciate is a larger interest rate differential instead of simply the sign of the differential.

This model is subject to certain restrictions. It does not apply to the countries or regions with regulations of capital flows, intensive government intervention in the foreign exchange market, a pegged currency policy where the government will maintain the exchange rate with a specified band by intervention, and/or with little financial speculation that the effect of the financial-transaction-driven foreign exchange flows on the exchange rate movement is minimal.

In addition, the disconnect puzzle arising from information asymmetry, human psychology, and irrational behavior has certain impact on predicting exchange rate returns by using only financial market and macroeconomic factors.

Research Methodology

Regression Specification and Data Description: In this empirical paper, the regression specification is actually a simplified version of that of the reference literature. The period covered is 06/2010-09/2015.

$$\Delta e_t = \alpha_1 IDC_t + \alpha_2 RPC_t + \alpha_3 RAC_t + \alpha_4 EquityC_t + \alpha_5 RiskC_t + \epsilon_t$$

Six variables are included with the dependent variable being Δe_{t+1} representing the log differential of two successive spot exchange rate between the US and the UK. The exchange rates are monthly average rates measured in a USD-per-GBP term and extracted from the OECD database. The first independent variable IDC_t is the change in interest rate differential by subtracting the US interest rate from the UK interest rate $(i_t^* - i_t)$ for each period and then taking the differences between any two consecutive periods. The interest rate data is extracted from the OECD database. During the whole period, the interest rate data indicates that GBP was the HRC in the bond market.

The second independent variable RPC_t is the change in stock market expected cross risk premium. Instead of the exponential moving average method adopted in the reference literature, a 12-month simple moving average method is used to calculate the expected stock index returns for the US and the UK markets and then determination of the Stock Market HRC status was conducted. USD in most of the time was the HRC in the stock market and therefore it is assumed that USD is the HRC for the whole period and the values of RPC_t are $\Delta(\bar{r}_t^* - i_t)$. Although this assumption renders certain observations improper, it allows this study to have only one scenario and therefore only one final regression should be run, i.e. regime switches are not considered in this empirical paper -since one of the two main purpose is to test the general problems in econometric analysis. The stock index data is extracted from the OECD database.

The third independent variable RAC_t is risk appetite measured by the change in average Repo collateral value of 18 parties obtained from the New York Fed. The reference literature used both leverage and Repo for this variable but the former is dropped in this paper due to failure to collect data for leverage. By the assumption of USD as the Stock Market HRC, the values of RAC_t are $-\Delta RA_{t+1}$., It is also assumed that the stock market is dominant. This assumption is reasonable because in the reference literature the stock market was always dominant when conflicts existed. As the data of Repo is only available for the period of 05/2010-09/2010, the initial intention to include the period of 10/2009-05/2010 is infeasible.

The fourth independent variable $EquityC_t$ is the change in equity. This variable follows the reference literature to use the growth of non-farm payroll as a proxy. The values of it are $-\Delta Payroll$ decided by the same assumptions as in RAC_t. Data of the total non-farm payroll is extracted from Federal Reserve Bank of St. Louis.

The fifth independent variable $RiskC_t$ is the change in expected stock risk measured by the change in VIX of S&P 500. The values of $RiskC_t$ is either ΔVIX if $\bar{r}_t^* > \bar{r}_t$ and −ΔVIX if $\bar{r}_t^* < \bar{r}_t$. Data of VIX of S&P 500 is extracted from Yahoo! Finance. All data is monthly data where the units of interest rates and expected stock returns are in percentage.

Econometric Approaches: This empirical paper covers various methods to detect whether heteroscedasticity and/or autocorrelation problems exist in the data set and the regression model.

For heteroscedasticity, residual plots serve as an informal method to have the first glance of determining any existence of heteroscedasticity. If any scatter plot illustrates a particular pattern, it can be subjectively considered that the problem exists. However, this method highly depends on personal subjective judgement. There is no a specific and clear-cut criterion to justify the existence. In view of this drawback, the White's Heteroscedasticity Test is conducted. This is a formal test of heteroscedasticity suitable under the situation where the form of the variance function is unknown. In applying this test, squares of estimated residuals are regressed on all independent variables, the squares of them, and all interacting terms.

For autocorrelation, similarly, plotting of the no-lag value of a variable against the 1-period-before value of the same variable is done to see whether there exists any pattern suggesting the possible existence of the autocorrelation problem. This method also suffers from the personal subjective judgement bias and lack of deterministic criterion. Another test is constructing correlograms for each variable and determining existence of autocorrelation for different periods of lag of each variable by comparing the z scores of the results with the critical z. The third method is the Lagrange Multiplier Test with two alternative ways applied. The first way is directly regressing the dependent variable on the other independent variables and the lagged residual (let the regression coefficient of this lagged variable be ρ) with a hypothesis test of $H_0: \rho = 0$ and $H_1: \rho \neq 0$. If the null hypothesis is rejected, serial correlation exists. The second way is regressing the estimated residual on the other independent variables and the estimated residual with 1 lag. If the null hypothesis $H_0: \rho = 0$ is true, the value of $\mathrm{T} \cdot R^2$ has an approximate $\chi^2_{(1)}$ distribution and otherwise serial correlation exists.

In an attempt to eliminate the serial correlation problem in the regression specification, the values of Akaike Information Criterion (AIC) and Schwarz Criterion (SC) are acquired for a model without lag, and models with 1 lag to 12 lags respectively in all independent variables except RPC_t where this independent variable and the dependent variable are showed to have no autocorrelation problem by the plotting and the correlograms. Although doing so saves lots of time for completing all the combinations of lags among the variables, it is likely that the most desirable combination is not found.

Finally, after choosing an appropriate combination, a robust regression will be conducted to obtain the α regression coefficients in case existence of heteroscedasticity is confirmed.

Empirical Results

The first task of the empirical study is to test the Heteroscedasticity problem. As can be seen in the figures contained in the Heteroscedasticity Test – Residual Plots section (available upon request) , the independent variables do not show any concrete pattern, while the dependent variable has a weak pattern that the estimated residual shrinks as the estimated exchange rate return increases.

Furthermore, the White's test is performed. The resulting χ^2 value obtained from Stata is 22.57 with a p-value of 0.3105. This evidence does not justify the existence of heteroscedasticity in the data se t. The manual White's Test also shows the same χ^2 value as by the direct command of testing heteroscedasticity with a critical χ^2 of 31.41.

The second task is to detect autocorrelation. According to the Autocorrelation Test – Plots (available upon request), six figures in which the no-lag values of each variable are plotted against the values with 1 lag of the same variable, it is obvious that the independent variables IDC_t, RAC_t, and $EquityC_t$ show either positive- or negative- related pattern and thus autocorrelation is possible for these variables.

According to the correlograms, not only the three variables are statistically significant for autocorrelation testing with 1 lag, but the independent variable $RiskC_t$ is also marginally significant with 1 lag. Although the z score of the 12-period-lagged RPC_t is just larger than the critical value, it is too remote and ignorable, given the relatively small z scores in other lags.

To confirm the autocorrelation problem, the Lagrange Multiplier Test is executed. The p-value of the regression coefficient of estimated residuals in the direct regression of exchange rate returns provides evidence to reject the null hypothesis and suggests the existence of Autocorrelation. By the alternative way, the regression of estimated residuals on other independent variables and estimated residuals with 1 lag has an identical result as in the aforementioned way. In addition, an analogous regression with 1 to 12 lagged estimated residuals is also run and the result indicates L5 is marginally statistically significant while L11 and L12 are obviously statistically insignificant suggesting the current exchange rate return may be traced from the past 9 periods.

To select a regression specification in order to eliminate the autocorrelation problem, AICs and SCs are calculated. The table in the Appendix lists the calculation results for a no lag model and models in which independent variables IDC_t, RAC_t, $EquityC_t$, and $RiskC_t$ has 1 to 12 lags. The smallest AIC and SC values appear when 11 lags are contained in each of the four independent variables. However, this selection approach might be incorrect. Therefore, it is decided that the final estimation includes three regressions with no lag, 1 lag, and 11 lags for the four independent variables, based on the correlogram analysis. The regressions are conducted in a robust manner to correct the heteroscedasticity problem.

In the no lag regression, the regression coefficients of independent variables IDC_t, RPC_t, and RAC_t have a zero p-value and are statistically significant with a positive sign, while $EquityC_t$ has a positive sign and $RiskC_t$ has a negative one but both are statistically insignificant.

In the 1-lagged regression, the overall result is quite similar to the no lag regression. The remarkable points are (i) the 1-lagged RPC_t is marginally statistically insignificant and (ii) the sign of $RiskC_t$ is now positive.

In the 11-lagged regression, only the independent variable IDC_t has a sign consistent with the expectation. Many lagged regressors are statistically insignificant.

The three regressions are run in the robust manner for avoiding operation mistake in detecting heteroscedasticity, although heteroscedasticity is not justified and this may not create the best result.

Discussion of the Results and Conclusion

The Bond Market HRC status of the UK for the whole period is very likely because of the difference between the economic targeting of the US and the UK and the unconventional monetary policy conducted by the US after the 2008 financial crisis where the US interest rate has been maintained at a very low level for a long time. On the other hand, the Stock Market

HRC status of the US can be attributed to the quantitative easing. This empirical paper tries to replicate the mechanism in the reference literature to see whether the validity of what Liang DING and Jun MA found sustains. The regression with a 1-period lag for each of the four independent variable and the no lag regression generated results consistent with the reference literature that IDC_t, RPC_t, and RAC_t are significant in the relationship with exchange rate dynamics and the signs of regression coefficients are the same as expected in the reference literature except $RiskC_t$ in the 1-lagged regression. This can be deemed that the model proposed by Liang DING and Jun MA still has explanatory power for exchange rate dynamics after their study, at least for the US and the UK.

Along with the expectation of the US interest rate hiking, the interest rate differential between the US and the UK probably would change substantially in the next several years. Besides, given China's RMB has been included in the currency basket of IMF's Special Drawing Right, China will gradually release her capital control and let RMB flow freely. This implies the possibility of the model to cover China in the future. This is very likely to attract attention from many financial practitioners, academic scholars, policy makers, and so on.

To improve this empirical paper, much knowledge about econometrics should be acquired and applied. In fact, this work ignores a great deal of econometric concerns, such as nonlinearity and nonstationary of certain variables. The implementation of AIC and SC should also be clarified because the empirical result in this paper generated a dissatisfactory result related to selecting the number of lags. Moreover, it is desirable to test for the endogeneity problems stated in the reference literature and particularly test the validity of the growth of non-farm payroll being an instrumental variable of the change in equity.

Heteroscedasticity Test – White's Test

```
. estat imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(20)     =    22.57
         Prob > chi2  =   0.3105

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	22.57	20	0.3105
Skewness	0.50	5	0.9920
Kurtosis	0.44	1	0.5086
Total	23.51	26	0.6040

```
. reg ehat1sq IDC RPC RAC EquityC RiskC IDCsq RPCsq RACsq EquityCsq RiskCsq ///
>     IRPC IRAC IE IRiskC RPCRAC RPCEquityC RPCRiskC RACEquityC RACRiskC ///
>        EquityCRiskC
```

Source	SS	df	MS
Model	6.4188e-07	20	3.2094e-08
Residual	1.1784e-06	43	2.7404e-08
Total	1.8203e-06	63	2.8893e-08

Number of obs =	64
F(20, 43) =	1.17
Prob > F =	0.3228
R-squared =	0.3526
Adj R-squared =	0.0515
Root MSE =	.00017

```
. di "Chi-square Value = N x R^2 = " =e(N)*e(r2)
Chi-square Value = N x R^2 = 22.568301

. di "5% critical value = " invchi2tail(e(df_m),0.05)
5% critical value = 31.410433
```

```
. list zy zx1 zx2 zx3 zx4 zx5 in 1/12
```

	zy	zx1	zx2	zx3	zx4	zx5
1.	.604924	-3.772694	.416615	-2.996076	2.659734	-2.155659
2.	.1955009	-.7875294	-1.300179	-.496554	1.37273	1.570705
3.	1.230108	1.624587	-.6542755	.02489	-.3753254	-.7155604
4.	-.7259835	-.7739323	-.7185818	-1.012961	-.742848	-.6051412
5.	-1.2546	-.6714331	.1053795	1.848948	.2657039	-.8217936
6.	-.5649616	.4519352	-.7066782	-1.545318	1.985096	.0844479
7.	-.6845521	.0347016	.2923856	.5255517	1.865191	.1405267
8.	-.8739712	-.8208928	.9313979	.5105127	.9103377	-.0416713
9.	.4336086	1.290379	.0475828	-.2281106	1.150622	.2242698
10.	-.6263911	.0235327	-.1569213	.4048807	.5663084	-1.061441
11.	-1.728914	-1.367362	.0171203	-.0664354	1.668077	1.221189
12.	-.3087203	.7444343	-2.02578	-1.361198	.5212981	-.8918144

```
. list zehat1 in 1/12
```

	zehat1
1.	3.913836
2.	.6079925
3.	.6480213
4.	-.0275243
5.	-.4355
6.	-.1868449
7.	-.836395
8.	-.9892367
9.	-.6758378
10.	-1.945061
11.	-1.843627
12.	-.6217852

28

Autocorrelation Test – Lagrange Multiplier Test

```
. reg lndife IDC RPC RAC EquityC RiskC L.ehat1

      Source |       SS       df       MS              Number of obs =      63
-------------+------------------------------           F(  6,    56) =   20.45
       Model |  .011279093     6  .001879849           Prob > F      =  0.0000
    Residual |  .005147014    56  .000091911           R-squared     =  0.6867
-------------+------------------------------           Adj R-squared =  0.6531
       Total |  .016426107    62  .000264937           Root MSE      =  .00959

------------------------------------------------------------------------------
      lndife |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         IDC |   .6831377   .0681053    10.03   0.000     .5467064     .819569
         RPC |    1.24584   .4678728     2.66   0.010     .3085778    2.183102
         RAC |   .7785761   .3425364     2.27   0.027     .0923933    1.464759
     EquityC |   3.577655   1.859883     1.92   0.059    -.1481385    7.303449
       RiskC |  -.0001658   .0002631    -0.63   0.531    -.0006929    .0003614
             |
       ehat1 |
         L1. |   .6959405   .1245292     5.59   0.000     .4464785    .9454026
             |
       _cons |   .0060665   .0028923     2.10   0.040     .0002725    .0118606
------------------------------------------------------------------------------
```

```
. reg ehat1 IDC RPC RAC EquityC RiskC L.ehat1

      Source |       SS       df       MS              Number of obs =      63
-------------+------------------------------           F(  6,    56) =    5.32
       Model |  .002936137     6  .000489356           Prob > F      =  0.0002
    Residual |  .005147014    56  .000091911           R-squared     =  0.3632
-------------+------------------------------           Adj R-squared =  0.2950
       Total |  .008083151    62  .000130373           Root MSE      =  .00959

------------------------------------------------------------------------------
       ehat1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         IDC |   .2149479   .0681053     3.16   0.003     .0785166    .3513792
         RPC |  -.2055651   .4678728    -0.44   0.662    -1.142827    .7316968
         RAC |  -.3002347   .3425364    -0.88   0.385    -.9864175    .3859482
     EquityC |   .3929049   1.859883     0.21   0.833    -3.332889    4.118699
       RiskC |  -.0001175   .0002631    -0.45   0.657    -.0006446    .0004096
             |
       ehat1 |
         L1. |   .6959405   .1245292     5.59   0.000     .4464785    .9454026
             |
       _cons |   .0006061   .0028923     0.21   0.835    -.0051879    .0064002
------------------------------------------------------------------------------

. di "5% critical value = " invchi2tail(e(df_m),0.05)
5% critical value = 12.591587

. di "T*r2 = " e(N)*e(r2)
T*r2 = 22.884221
```

```
. reg ehat1 IDC RPC RAC EquityC RiskC L(1/12).ehat1

      Source |       SS       df       MS              Number of obs =      52
-------------+------------------------------           F( 17,    34) =    4.55
       Model |  .004318075    17  .000254004           Prob > F      =  0.0001
    Residual |  .001899502    34  .000055868           R-squared     =  0.6945
-------------+------------------------------           Adj R-squared =  0.5417
       Total |  .006217577    51  .000121913           Root MSE      =  .00747

------------------------------------------------------------------------------
       ehat1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         IDC |   .3275727   .0754852     4.34   0.000     .1741683    .4809772
         RPC |  -.4337389   .3982706    -1.09   0.284    -1.243122    .3756443
         RAC |   .2197772   .3367255     0.65   0.518    -.4645313    .9040857
     EquityC |  -3.432606   2.377751    -1.44   0.158    -8.264777    1.399566
       RiskC |  -.0001418   .0002303    -0.62   0.542    -.0006099    .0003262
             |
       ehat1 |
         L1. |   1.180432   .1668503     7.07   0.000     .8413515    1.519513
         L2. |  -.8300917   .1743685    -4.76   0.000    -1.184451   -.4757323
         L3. |   .5667075   .1739336     3.26   0.003      .213232     .920183
         L4. |  -.3964523   .1753862    -2.26   0.030    -.7528799   -.0400247
         L5. |   .3338907    .173286     1.93   0.062    -.0182688    .6860501
         L6. |  -.4207327   .1685933    -2.50   0.018    -.7633554   -.0781099
         L7. |   .3382231   .1768813     1.91   0.064     -.021243    .6976893
         L8. |  -.4170869   .1715788    -2.43   0.020    -.7657769   -.0683969
         L9. |   .4181988   .1664407     2.51   0.017     .0799505     .756447
        L10. |  -.4384509   .1506319    -2.91   0.006    -.7445716   -.1323301
        L11. |   .1935441   .1540882     1.26   0.218    -.1196008    .5066891
        L12. |   -.160714   .1305284    -1.23   0.227    -.4259796    .1045516
```

```
. di "5% critical value = " invchi2tail(e(df_m),0.05)
5% critical value = 27.587112

. di "T*r2 = " e(N)*e(r2)
T*r2 = 36.113733
```

AIC & SC

		All 1 Lag	All 2 Lags	All 3 Lags	All 4 Lags	All 5 Lags	All 6 Lags	All 7 Lags
	No Lag	Except lndife(y variable) and RPC(x2)						
AIC	-8.776866	-9.0850022	-9.2388187	-9.3426918	-9.592262	-9.7662599	-9.9391214	-10.057167
SC	-8.574471	-8.7448221	-8.7584981	-8.719811	-8.8243357	-8.8507349	-8.873375	-8.8385053
			All 8 Lags	All 9 Lags	All 10 Lags	All 11 Lags	All 12 Lags	
			Except lndife(y variable) and RPC(x2)					
AIC			-10.311785	-10.991082	-11.590352	-15.274683	N/A	
SC			-8.9374391	-9.4582096	-9.8960326	-13.425917	N/A	

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Final Estimations

```
. reg lndife IDC RPC RAC EquityC RiskC, vce(robust)

Linear regression                                      Number of obs =      64
                                                       F(  5,     58) =   20.58
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5022
                                                       Root MSE      =  .01188
```

lndife	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IDC	.4681898	.0600224	7.80	0.000	.348042	.5883376
RPC	1.451405	.3440789	4.22	0.000	.762656	2.140154
RAC	1.078811	.2620285	4.12	0.000	.5543038	1.603318
EquityC	3.184751	2.277816	1.40	0.167	-1.374794	7.744295
RiskC	-.0000482	.0002664	-0.18	0.857	-.0005814	.0004849
_cons	.0054604	.003593	1.52	0.134	-.0017319	.0126527

```
. reg lndife  L(0/1).IDC RPC L(0/1).RAC L(0/1).EquityC L(0/1).RiskC, vce(robust)

Linear regression                                      Number of obs =      63
                                                       F(  9,     53) =   16.26
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6835
                                                       Root MSE      =   .0099
```

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lndife	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IDC						
--.	.623691	.0679436	9.18	0.000	.4874134	.7599687
L1.	.3202156	.0651039	4.92	0.000	.1896337	.4507975
RPC	1.240244	.4405845	2.81	0.007	.3565436	2.123945
RAC						
--.	1.191165	.2881072	4.13	0.000	.6132951	1.769035
L1.	.4702171	.2448948	1.92	0.060	-.0209797	.961414
EquityC						
--.	.9169102	2.416076	0.38	0.706	-3.929124	5.762944
L1.	4.038541	2.216421	1.82	0.074	-.4070358	8.484118
RiskC						
--.	.0001923	.0002301	0.84	0.407	-.0002692	.0006538
L1.	.0000217	.0003042	0.07	0.943	-.0005884	.0006319
_cons	.00791	.0031772	2.49	0.016	.0015374	.0142826

```
. reg lndife  L(0/11).IDC RPC L(0/11).RAC L(0/11).EquityC L(0/11).RiskC, ///
>     vce(robust)

Linear regression                                  Number of obs =       53
                                                   F( 49,      3) =17862.80
                                                   Prob > F      =   0.0000
                                                   R-squared     =   0.9999
                                                   Root MSE      =   .00079
```

lndife	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IDC						
--.	1.121704	.0358723	31.27	0.000	1.007542	1.235866
L1.	1.257761	.047918	26.25	0.000	1.105264	1.410257
L2.	1.19167	.0468925	25.41	0.000	1.042437	1.340903
L3.	1.264381	.0581669	21.74	0.000	1.079268	1.449494
L4.	.9652162	.0329527	29.29	0.000	.8603459	1.070087
L5.	.757182	.0349862	21.64	0.000	.6458404	.8685235
L6.	.6111141	.0455692	13.41	0.001	.4660927	.7561356
L7.	.5157379	.0499128	10.33	0.002	.3568932	.6745826
L8.	.4378352	.0507304	8.63	0.003	.2763883	.599282
L9.	.3495376	.0453604	7.71	0.005	.2051807	.4938945
L10.	.2934721	.0409296	7.17	0.006	.1632157	.4237285
L11.	.055965	.028324	1.98	0.143	-.0341746	.1461047

RPC	-10.02862	.7754719	-12.93	0.001	-12.49652	-7.560722
RAC						
--.	-8.697148	.6722881	-12.94	0.001	-10.83667	-6.557627
L1.	-8.244024	.6170176	-13.36	0.001	-10.20765	-6.280398
L2.	-6.950491	.4564301	-15.23	0.001	-8.403055	-5.497927
L3.	-5.610457	.3659295	-15.33	0.001	-6.775008	-4.445905
L4.	-4.431728	.426676	-10.39	0.002	-5.789601	-3.073854
L5.	-4.389643	.4809346	-9.13	0.003	-5.920191	-2.859094
L6.	-2.545633	.4450275	-5.72	0.011	-3.961909	-1.129357
L7.	-1.325908	.3594728	-3.69	0.035	-2.46991	-.1819048
L8.	-.9550394	.3615738	-2.64	0.078	-2.105728	.1956497
L9.	-.1564447	.2670337	-0.59	0.599	-1.006265	.6933758
L10.	.3072515	.1493437	2.06	0.132	-.168027	.7825299
L11.	.1070061	.1387687	0.77	0.497	-.3346178	.54863
EquityC						
--.	-7.192802	1.022511	-7.03	0.006	-10.44689	-3.938716
L1.	2.479706	1.07908	2.30	0.105	-.9544088	5.91382
L2.	-2.861209	.8205658	-3.49	0.040	-5.472616	-.2498023
L3.	-1.638777	1.226631	-1.34	0.274	-5.542464	2.26491
L4.	-3.025752	.8269591	-3.66	0.035	-5.657505	-.3939988
L5.	2.490026	.5998247	4.15	0.025	.5811159	4.398936
L6.	3.607589	.6875755	5.25	0.013	1.419417	5.795761
L7.	7.169235	.7253468	9.88	0.002	4.860858	9.477612
L8.	8.509408	.864225	9.85	0.002	5.759059	11.25976
L9.	8.430563	.7805728	10.80	0.002	5.946432	10.91469
L10.	2.500065	.5298904	4.72	0.018	.8137175	4.186413
L11.	6.470813	.7528277	8.60	0.003	4.07498	8.866647
RiskC						
--.	-.0002427	.0000689	-3.52	0.039	-.0004619	-.0000236
L1.	.0005452	.0001598	3.41	0.042	.0000367	.0010538
L2.	.0004604	.0001236	3.72	0.034	.000067	.0008538
L3.	.000731	.0001847	3.96	0.029	.0001431	.0013189
L4.	.0011707	.0002233	5.24	0.014	.0004602	.0018811
L5.	.0016136	.0001963	8.22	0.004	.000989	.0022382
L6.	.0018502	.0001609	11.50	0.001	.0013381	.0023623
L7.	.0022875	.0001223	18.71	0.000	.0018984	.0026766
L8.	.0024424	.0001282	19.05	0.000	.0020343	.0028505
L9.	.0017292	.0001575	10.98	0.002	.0012279	.0022306
L10.	.0028678	.0003054	9.39	0.003	.0018958	.0038398
L11.	.0014422	.000234	6.16	0.009	.0006976	.0021867
_cons	.0391172	.00334	11.71	0.001	.0284879	.0497466

Reference

Liang DING and Jun Ma, 2013. Portfolio Reallocation and Exchange Rate Dynamics. Journal of Banking and Finance 37, 3100-3124.