

Nominal Exchange Rates and Prices: Evidence from TaiwanDavid Iheke Okorie¹, Dak-Adzaklo Cephass Simon-Peter², Manu Adasi Sylvester³¹Wang Yanan Institute for Studies in Economics (WISE), Xiamen University, China.²Institute for Financial and Accounting Studies (IFAS), Xiamen University, China³Wang Yanan Institute for Studies in Economics (WISE), Xiamen University, China.***Corresponding Author:**

David Iheke Okorie

Email: okorie.davidiheke@gmail.com

Abstract: Economic theories postulate that the nature of relationship between the Nominal Exchange Rate and Prices (domestic and foreign) are linearly related. We investigate this using information from Taiwan and adopted data driven methods in establishing the true nature of the relationship that exists between the Nominal Exchange Rate and the Domestic Prices and we discovered a nonlinear relationship and a 0.25% foreign price pass-through effect on the Nominal Exchange Rate of Taiwan.

Keywords: Economic theories, Nominal Exchange Rate, Prices, Taiwan.

INTRODUCTION

Moving from a closed economy to an open economy is basically to trade internationally with the rest of the world economies. This had been shown to foster rapid growth and development in economies; it is the building block for theoretical facts like Comparative Advantage [10], Absolute Advantage [11], Heckscher-Ohlin model, etc. For trade to take place, there has to be an established price system, this serves as a mechanism which regulates the market and in this platform, it's called the exchange rate. The Nominal Exchange Rate is the relative price of domestic currency in terms of foreign currency, simply put is the amount of domestic currency to purchase a unit of a foreign currency. In general, dollar has always served as the basis on which exchange rate of a country's currency is defined. For example, 10RMB/Dollar, 12NGN/Dollar, 0.34Euro/Dollar, etc. Directly from this definition, prices in the United States affects the exchange rates since the exchange rate is expressed jointly in terms of a country's currency and the dollar. The Exchange Rate model is defined as:

$$e = \frac{\varepsilon P^*}{P} \quad (1)$$

e denotes the nominal exchange rate, ε is the real exchange rate, defined in terms of quantities of domestic good required to purchase a unit of foreign good. P is the domestic price while P^* is foreign prices (prices in the United States). A priori denotes that while domestic prices inversely affect the nominal exchange rates, foreign prices directly affects it. For a given Real Exchange Rate, the growth rate of the nominal exchange rate is the difference between foreign and

domestic inflation rates; this is show from the equation above as:

$$\frac{1}{e} \Delta e = \frac{1}{\varepsilon} \Delta \varepsilon + \pi^* - \pi \quad (2)$$

Where π^* the price growth rate (inflation rate) is in the foreign economy, π is the domestic price growth rate (inflation rate), ε is the real exchange rate, and e is the nominal exchange rate. This connotes that the monetary authorities both domestic and abroad, play a significant role in managing the exchange rates by understanding the dynamics and adjusting monetary policies to affect prices so as to establish a stable economy. Alternatively, we also establish the pass-through effect, which is the effect of foreign prices on the exchange rate.

RESEARCH OBJECTIVE AND TESTABLE HYPOTHESES

The objective of this work therefore follows from the picture created above, we set out to establish a data driven form of relationship between the domestic prices and the nominal exchange rate without any form of restrictions (linear or nonlinear). Next we examine how the nominal exchange rate changes for changes in the domestic and foreign prices, therefore, the hypotheses are stated thus:

H_{01} : *there is no form of relationship between exchange rates and prices*

H_{02} : *there is no price pass – through on the exchange rates*

In capturing these objectives, the Consumer Price Index will be used as the measure of prices both domestically (Taiwan) and abroad (the U.S.) and the Nominal

Exchange Rate (Taiwan) data will be used to establish the empirical results.

EMPIRICAL LITERATURE

Examining the pass-through effects of exchange rate changes on East Asian domestic prices using Vector Auto-Regressive analysis, discovered that the pass-through effect from exchange rate to domestic prices is generally low [1]. Goldberg & Campa [2], decomposed the source of stability for 21 OECD countries and discovered that border prices of traded goods are highly sensitive to exchange rates, but the CPI and the retail prices of the goods are stable. Following this, Philippe Bacchetta [3], tried to explain the reason behind pass-through effect of exchange rates to consumer prices being lower relative to import prices and discovered that that the local distribution costs is a significant reason the pass-through effect is small on Consumer Prices. Goldberg & Knetter [4], noted that common-currency relative prices are highly correlated with exchange rates between those markets which implies that incomplete pass-through is a result of third-degree price discrimination and distance matters for segmentation of markets across borders. Campa & Goldberg [5] showed there exists an evidence of partial pass-through in the short run while in the long run; producer currency pricing is more prevalent. Analyzing the dynamic composition of the pass-through effect, it was discovered that there is a big difference in the

composition of the pass-through effect. Conditioned on price changes between the average dollar prices on the exchange rate against the average non-dollar prices, there pass-through effect is significantly different and they are 25% and 95% respectively [6]. Campa & Goldberg [7], argued that retail prices affect the exchange rates which is significantly felt for traded goods than non-traded goods. Studying the transmission rates from the exchange rate movements to import prices over 15 years reveals a high transmission in the short run, although incomplete and differs across industries, the effect is high while in the long run, it's also high and close to one [8]. There also exists a co-integration relationship between stock prices and the exchange rate studying the Asian economies. This was observed using South Korean data while data from Hon Kong, Malaysia, Singapore, Taiwan and Thailand indicates a strong feedback relationships [9].

DATA DESCRIPTIVE STATISTICS

The Data set is sourced from the Journal of Applied Econometrics as used by Kul B. Luintel in his work titled Real Exchange Rate Behaviour: Evidence from Black Markets. The variables of interest to us are the Consumer Price Index (Taiwan & USA) and the Nominal Exchange rate for the periods of 1959 January to 1989 June. These variables are examined using their plots and the summary statistics is shown below:

Table-1: Summary Statistics

Variables	limits		Mean	Median	SD
	Min	Max			
EXR	25.85	53.20	40.57	40.90	4.28
CPI	15.00	92.68	48	44.25	27.57
CPIus	23.04	98.76	48.47	38.13	24.93

Source: Computation using R.

EXR is the Nominal Exchange Rate, CPI is the Consumer Price Index for Taiwan, and CPIus is the Consumer price Index for the United States. The summary statistics of the variables are shown above containing the maximum and minimum values, mean, medians, and standard deviations of the variables. Mostly for the nominal exchange rate, its mean is approximately same with the median with small standardized deviations from the mean. The cases for the other variables are some worth similar to that of the nominal exchange rate.

THE MODEL

To model this relationship parametrically with linear restriction is to transform equation (1) into a linear form by taking natural log and applying logarithmic principles to get:

$$e = \frac{\epsilon P^*}{P} \tag{1}$$

$$\ln Y_t = \alpha + \beta \ln X_t + \gamma \ln Z_t + \phi \ln W_t + \epsilon_t \tag{3}$$

Where $Y_t = e$, $\alpha = \epsilon$, $X_t = P$, $Z_t = P^*$, ϕ is a vector containing the estimates of the control variable, and W_t is a vector of control variables. The control variables are the CPI or neighboring economies to Taiwan in Asia, they include India, Sri Lanka, Malaysia, Myanmar, Pakistan, Philippines, and Thailand. Alternatively, one could also model the growth rate equation which is the equation (2):

$$\frac{1}{e} \Delta e = \frac{1}{\epsilon} \Delta \epsilon + \pi^* - \pi \tag{2}$$

recall that $\frac{1}{\theta} \Delta \theta \approx \Delta \ln \theta$

$$\Delta \ln Y_t = \alpha + \beta \Delta \ln X_t + \gamma \Delta \ln Z_t + \phi \Delta \ln W_t + \epsilon_t \tag{4}$$

Where π^* is the price growth rate (inflation rate) in the foreign economy represented by $\Delta \ln Z_t$ in our model, π is the domestic price growth rate (inflation rate) represented by $\Delta \ln X_t$ in our model, ϵ is the real

exchange rate which is assumed to be given and thus represented by α , $\Delta \ln W_t$ is the growth vector of the control variables, and e is the nominal exchange rate represented by $\Delta \ln Y_t$ in our model with ϵ_t as the residual term. This is basically a linear-log transformation because double log models are linearly restricted models. However, this work will adopt a semi-parametric model which has the combined advantages of both parametric and nonparametric models. It is a model which its form or nature of relationship is partly data driven and partly restricted (linearly or nonlinearly). The estimation of this model is free from the curse of dimensionality inherent in nonparametric model estimation with large dimension. Also the relationship between the variables of interest is not restricted whether linearly or nonlinearly. This model is stated as:

$$Y_t = g(X_t) + \beta Z_t + \phi W_t + \epsilon_t \tag{5}$$

X is the Consumer Price Index of Taiwan, Z is the United States Consumer Price Index, and the response variable Y is the Nominal Exchange rate of Taiwan. Given the nature of the dataset (i.e. time series) we will have to establish that the series are stationary, having constant mean and variance using rigorously established methods like the Phillips-Perron [12] and Augmented Dickey-Fuller stationarity tests. Then we can proceed to the estimation of the model which could be done using the Spline method or the Kernel method [13] for the nonparametric component of the model while the parametric component will be estimated using the Ordinary Least Squares (OLS). For the purpose of robustness we will estimate the nonparametric component using both the kernel and spline estimation methods. To estimate the nonparametric component requires smoothing parameter. This is the Bandwidth for Kernel estimation and the Knots (turning parameters) for spline estimation. For Spline estimation, equation three (3) above can be rewritten as:

$$Y_t = P_x u + \beta Z_t + \phi W_t + \epsilon_t \tag{6}$$

$$Y_t = \gamma_1 X_t + \sum_{k=1}^K \gamma_{1,k} (X_t - z_k)_+ + \beta Z_t + \phi W_t + \epsilon_t \tag{7}$$

Where P_x is the spline basis function of X and u is the vector of spline coefficients. In order to further simplify the model such that its relationship with piecewise linear regression is shown clearly, we rewrite the model as shown in equation (6) into equation (7) and $(X_t - z_k)_+ = [X_t - z]$ if $X_t \geq z, [0]$ otherwise. At this point, the smoothing parameter k (Knots) can be equally placed at the intervals of the series or using a data driven method like placing the knots equally according to the sample quantiles or use adaptive knot placements or use large number of knots and introduce penalty. Dues to the

trade-off between variance and bias with respect to the degree of flexibility of a model, we don't want to under-fit (over-smooth) or over-fit (under-smooth) the true relationship therefore we will select the choice of large number of knots with penalty which will shrink the irrelevant estimates close to zero and at the same time, reduce the variability of the fitted curve. The choice of penalty in this work is based on the differentiability of the penalty thus Ridge Regression. Using Ridge penalty, the minimization of the objective function requires a smoothing parameter λ^2 , which maintains balance between the fidelity to data and wiggleness of the curve. It is important to note that the higher order spline will be used to counter the drawback of linear splines in which the fitted curve being continuous but not differentiable at each knot *thus*

$$Y_t = \gamma_1 X_t + \sum_{k=1}^K \gamma_{1,k} (X_t - z_k)_+^p + \beta Z_t + \phi W_t + \epsilon_t \tag{8}$$

$p = \text{selected using the Equivalent Degree of Freedom (polynomial order)}$

Since the smoothing parameter is one dimensional, we could use the Cross Validation (CV), Generalized Cross Validation (GCV), Mallow's C_p , and Information Criterion (AIC & BIC) in selecting the smoothing parameter while estimating our model. On the other hand, estimating the nonparametric component using the Kernel Regression is all about estimating the conditional expectation of the response variable given the predictor. The estimated function is thus given as

$$\hat{g}(X_t) = \sum_{i=1}^n Y_i w_t(X_t) \tag{9}$$

where $w_t(X_t) = \frac{K\left(\frac{X_t - x}{h}\right)}{\sum_{i=1}^n K\left(\frac{X_t - x}{h}\right)}$

$K\left(\frac{X_t - x}{h}\right)$ is the kernel density estimator and h (Bandwidth) is the smoothing parameters which is not a function of the response variable but its selection is based on the response and predictor variables. To select this smoothing parameter, could be by the normal Rule of Thumb (RT) on the assumption that the predictor is distributed normal, Least Square Cross Validation (LSCV), and Information Criterion (AIC). We will consider all these smoothing parameter selection criterion while selecting the bandwidth and estimations. In estimating the multivariate distribution, we will try to capture the dependence structure among the variables thus, using the copula density function approach while selecting the optimal bandwidth considering the performance of the Rule of Thumb techniques, and Cross Validation. This approach is preferred mostly because it captures the dependency structure between variables unlike the normal density

which is most times used and it assumes independence of the variables. Copula approach is like a generalized approach which in the face of independence between or among variables, their joint distribution copula function takes a unit value one, reducing the joint distribution to an independent distribution, otherwise, the copula function takes on values which are data driven with respect to the nature of the dependency structure between or among the variables. Sklar’s theorem (1959) through change of variables showed that we can represent the joint distribution as

$$= C(F_1(x_1), F_2(x_2), \dots, F_k(x_k)) \quad F(x_1, x_2, \dots, x_k) \quad (10)$$

$F(x_1, x_2, \dots, x_k)$ is the joint distribution for $x = [x_1, x_2, \dots, x_k]$ with density $f(x_1, x_2, \dots, x_k)$ and distribution $F_j(x_j)$, where $C(F_1(x_1), F_2(x_2), \dots, F_k(x_k))$ is the copula function taking any value between 0 and 1 with both limits included. Partially differentiating equation (14) with respect to x_1 and x_2 gives:
 $f(x_1, x_2)$
 $= f_1(x_1)f_2(x_2) \dots f_k(x_k)c(F_1(x_1), F_2(x_2), \dots, F_k(x_k))$ (11)

The dependency structure captured by copula density is scale free and invariant to monotone transformations, capturing both linear and non-linear dependency structures. In cases of independence, then $c(F_1(x_1), F_2(x_2), \dots, F_k(x_k)) = 1$ and the copula decomposition of the joint density is reduced to $f(x_1, x_2) = f_1(x_1)f_2(x_2) \dots f_k(x_k)$. The copula density function will be estimated using kernel method which is

data driven instead of the parametric methods like Gaussian copula, Frank copula, Clay copula, etc. which are to an extent not flexible enough relative to data driven methods like kernel. Also, to reduce the boundary bias drawback of kernel method, we will use the boundary kernel method while adopting the two step estimation strategy to mitigate curse of dimensionality. Generally, to estimate a semiparametric model involves by intuition two basic steps. The first step is to estimate the parametric part using the OLS method as we minimize the objective function:

$$MSE = \frac{1}{n} \sum_{t=1}^n (Y_t - \beta Z_t - \phi W_t)^2 \quad (12)$$

And get the estimates that will minimize the Mean Squared Error (MSE) then proceed to calculating $Y_t^* = Y_t - \beta Z_t - \phi W_t$ then proceed to the second step which is the estimation of the nonparametric component stated below using the appropriate estimation methods.

$$Y_t^* = g(X_t) + u_t \quad (13)$$

This is in fact, the estimation procedure of a semi-parametric model and will rigorously be adopted in carrying out the analysis of this research work so as to make inference on the nature of the relationship between the nominal exchange rate and prices in Taiwan as well as the exchange rate pass-through effects with respect to domestic and foreign prices.

**RESULTS OF MODEL ESTIMATIONS
STATIONARITY TEST**

Table-2: Test of Unit-Root

Variable	Level	lags	P-value	Level	lags	P-value	Conclusion
TAWEX_t	I(0)	7	0.5984	I(1)	7	0.0100	Stationary
TAWCPI_t	I(0)	7	0.5505	I(1)	7	0.0100	Stationary
CPIus_t	I(0)	21	0.5772	I(1)	21	0.0968	Stationary
lnTAWEX_t	I(0)	7	0.9348	I(1)	7	0.0100	Stationary
lnTAWCPI_t	I(0)	6	0.6918	I(1)	6	0.0100	Stationary
lnCPIus_t	I(0)	25	0.4531	I(1)	25	0.0909	Stationary

Source: Computation using R.

The above table shows the Augmented Dickey Fuller test of the variables used in this analysis. Times Series are expected to be at statistical equilibrium to be fit for analysis. All the variables are not stationary at the level form $I(0)$ but became stationary after the first difference $I(1)$, judging from their p-value. The variables are stationary at 5% size of test, except for the United States CPI, which is stationary at 10% test size. The logarithmic variables will be used in estimating the transformed parametric model equation (3) instead of equation (4) because our interest is not on the percentage change but on the form of relationship and unit effect of the predictors, then take anti-log of the estimates so as to get the natural effect. Whereas the original series will be use to estimate the semi-

parametric model. Since all the variables (interest and control variables) are stationary at first difference, we will proceed to testing for Engel-Granger Co-integration test in other to establish if the linear combination (for parametric model) of the original series produces a robust result. It is important to note that the Co-integration work of Engel and Granger is basically for a linear combination, moreover, the nonparametric part of the semiparametric model is not linear, thus making it in appropriate to use the Engel and Granger Co-integration test on the residual values of the semi-parametric model, therefore, we use the differenced stationary series for estimating the semi-parametric model.

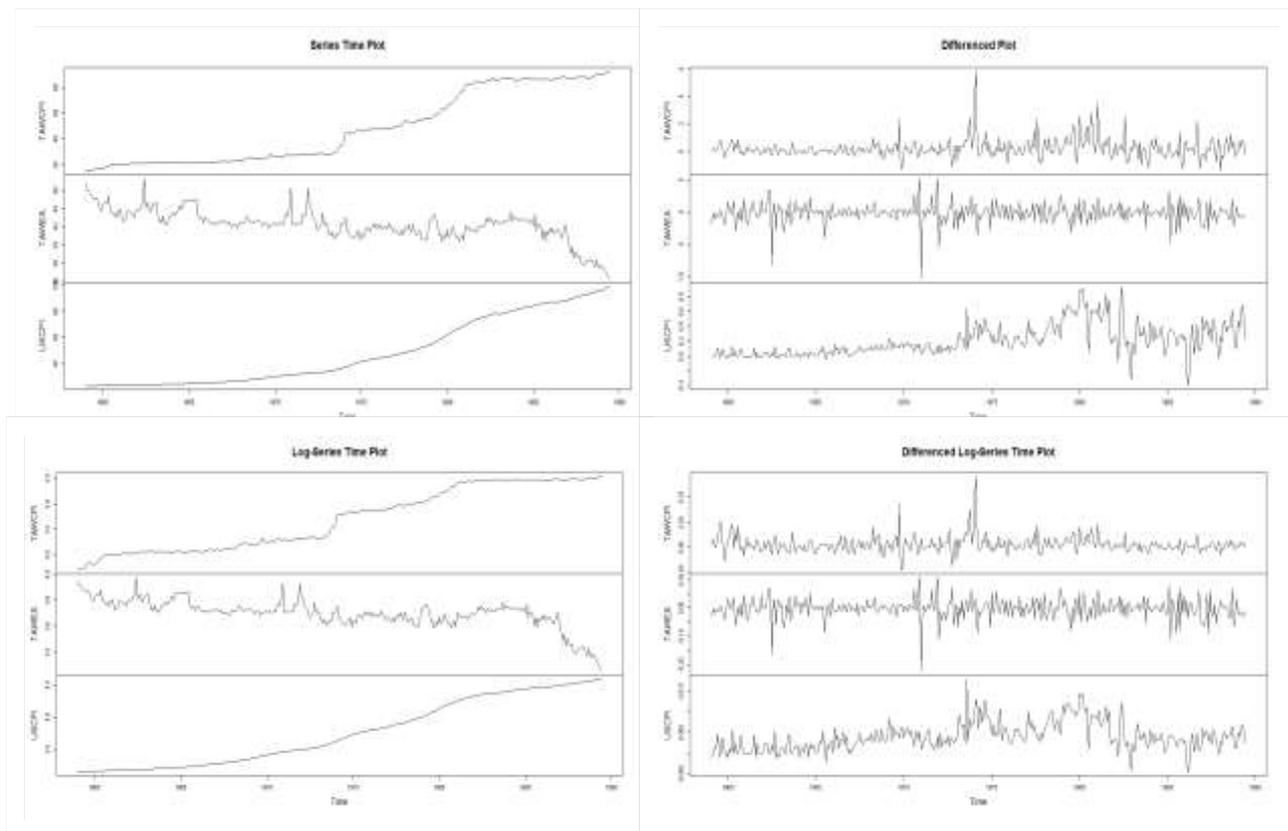


Fig-1: Time Plots

The figure above is shows the nature of the variables of interest. Panel A (top-left) shows the nature of the dependent and independent variables over time. Panel B (top-right) is the time plot of the first difference of the original series. Panel C (bottom-left) shows the

time plot of the logarithmic values of the original series, and Panel D (bottom-right) displays the time plot of the first difference logarithmic series. One can see that the series became stationary at the fist difference; therefore we proceed to Co-integration test and estimations.

CO-INTEGRATION TEST

Table-3: Test of Unit-Root

Variable	Level	lags	P-value	Conclusion
ϵ_t	I(0)	7	0.0100	Co-integrated

Source: Computation using R.

From the result of the two-step Engel-Granger Co-integration test, we then reject the null hypothesis of no co-integration and conclude that the model is co-integrated and thus will do all estimation for the parametric model using the original series in place of the first order differenced series.

**SMOOTHING PARAMETER SELECTION
SPLINE ESTIMATION**

The method used in this work to determine the spline estimation smoothing parameter which is the knots is the data driven method of introducing a very large number of knots and introduce penalty (Ridge) on it so as to shrink the irrelevant estimates to a value close or approximately zero. We also used the cubic spline

which was informed by the equivalent degree of freedom.

KERNEL ESTIMATION

The smoothing parameter selection criteria used in determining the bandwidth are Kullback-Leibler cross validation (suggesting 1.72 as bandwidth), least squares cross validation (suggesting 0.09 as bandwidth). As informed by the copula joint distribution density plot, we also estimated the Kernel using the Gaussian distribution density function, using normal rule of thumb (suggesting 0.22 as bandwidth) , optimizing the least square cross validation i.e. the leave one out function (suggesting 0.22 as bandwidth) for the bandwidth (smoothing parameter) selection. It is however, important to note that all estimation

smoothing parameters (both estimation models) we gotten using the stationary series while applying the data driven methods and we used these derived smoothing parameters to estimate the original series.

ESTIMATION RESULT PARAMETRIC COMPONENT OF THE MODEL

The parametric component of our semiparametric model will be estimated using a log-log model to capture the relationship between Taiwan Exchange rates and the United States' Consumer Price Index while involving other control variables. The relationship between the Consumer Price Index and Exchange rate of Taiwan will be captured non-

parametrically. The parametric estimate shows that the pass-through effect from foreign price to the Nominal Exchange Rate of Taiwan is 0.25% and it's statistically significant at 5% level of significance.

NONPARAMETRIC COMPONENT OF THE MODEL

Estimating using the Kernel approach requires the use of the joint density function which we used the bivariate copula density function to estimate, the joint density function chart (plotting the Joint Density, Taiwan Nominal Exchange Rate, and Consumer Price Index) is shown below:

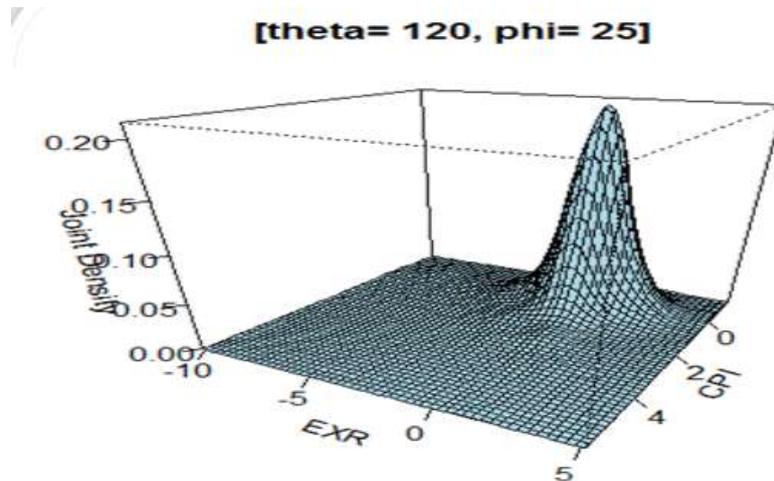


Fig-2: Joint Density plot

From the copula joint density function, there is evidence of Gaussian distribution suggesting that the true relationship between the Taiwan Nominal Exchange Rate and her Consumer Price Index can be

effectively captured using the Gaussian density for Kernel estimation. Therefore, we will estimate the relationship between these variables adopting both the copula and Gaussian joint densities as shown below:

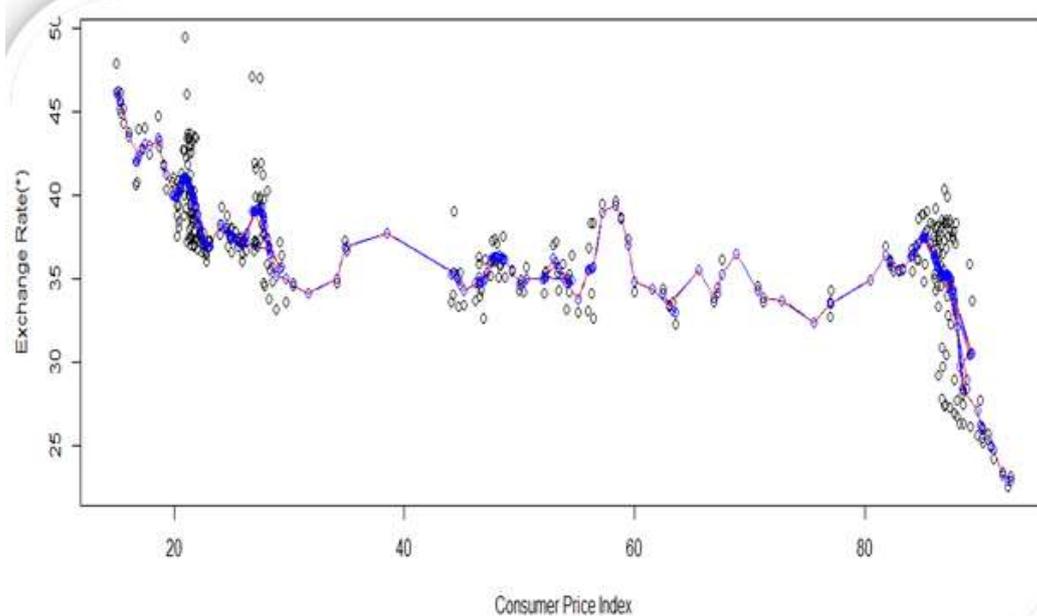


Fig-3: Kernel Estimation with Copula Density function

Exchange Rate(*) $\equiv Y_t^*$ as used in the plots is the residual of the first step estimation of the semiparametric model steps. The chart above shows the Kernel estimation fitted values on the scatter plot of the Consumer Price Index and the Exchange rate of Taiwan series, using copula density function and different bandwidths selected using Kullback-Leibler cross validation (suggested 1.7 as bandwidth), and least squares cross validation (suggested 0.095 as

bandwidth). The Red fitted line represents the Kernel estimation using the Kullback-Leibler cross validation bandwidth and the Blue fitted line is for using the bandwidth selected by the least squares cross validation. Moreover, both bandwidth selections seems to be doing approximately same as informed by the plot. The function is however; not very smooth (under-smooth) suggesting using the Gaussian joint density function to estimate the kernel. This is shown below:

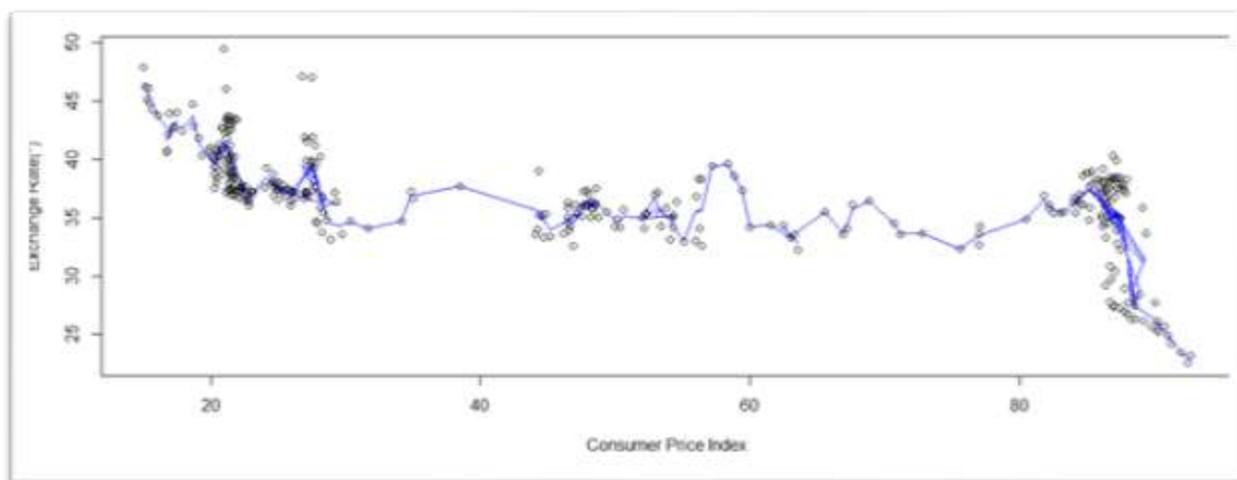


Fig-4: Kernel Estimation with Gaussian Density function

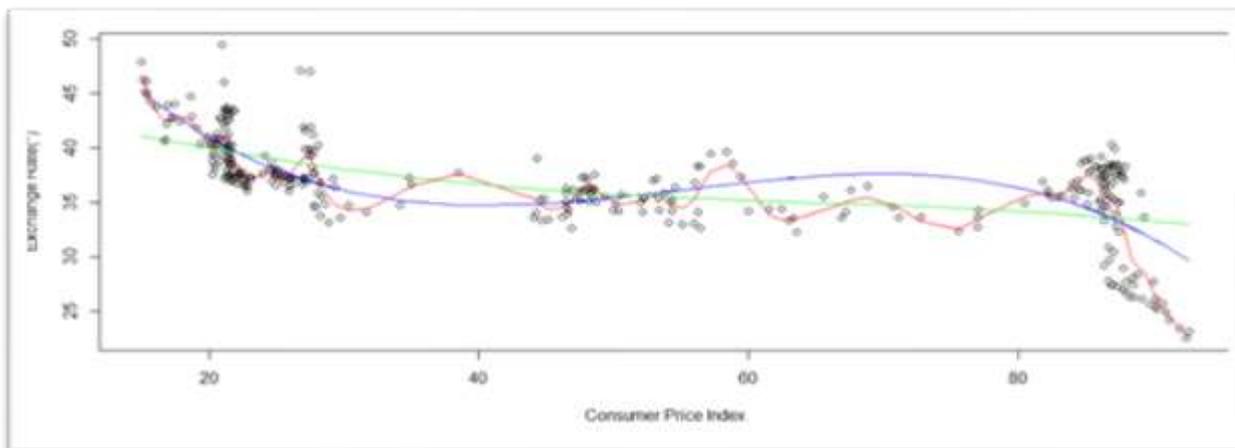


Fig-5: Spline Estimations

Basically, using the normal rule of thumb, the kernel estimation using Gaussian joint density function is shown in blue, while using the bandwidth selected by optimizing the leave one out function as the objective function to be optimized gives the same bandwidth selection with the rule of thumb and thus same fitting. Considering *fig.3* and *fig.4* it shows that the copula density did a great job in determining the joint density function between the Exchange Rate variable and the Consumer Price Index variable as it approximates the fitted line with normal joint density function. We move on to estimating this relationship using the Spline estimation as show below:

Estimating the original series (Y_t^*), using Natural Cubic Spline as suggested by the equivalent degree of freedom selection on the stationary series we derive the green fitted line. Fitting the original series (Y_t^*) and allow the equivalent degree of freedom to be selected on the original series (Y_t^*) the red fitted line was derived which is equivalent to the result from kernel estimation. However, when we tried introducing a large number of knots and penalty on the cubic spline, there were singular matrix problem for any positive number of spline term introduced but using only the global terms, the blue fitted line was derived which seems to be a smooth curve.

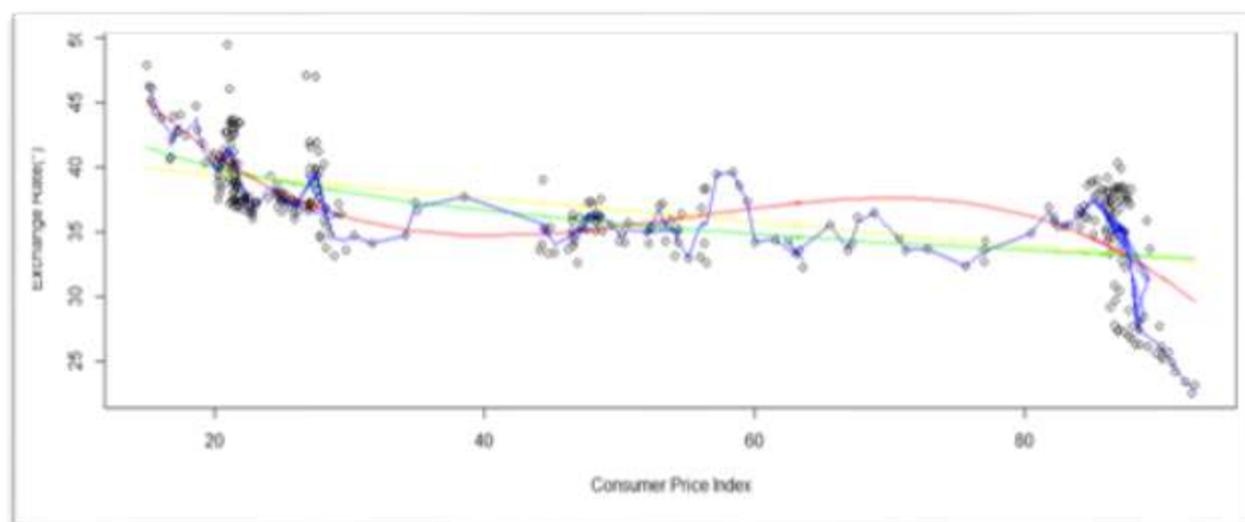


Fig-6: Parametric and Nonparametric Performance

COMPARING NONPARAMETRIC AND PARAMETRIC MODELS PERFORMANCE

At this point, we compare the fitting performance of the nonparametric component of the model $Y_t^* = g(X_t) + u_t$ as shown in equation (13) with a parametric model which fits the same relationship, this parametric model is stated as $Y_t^* = \alpha + \beta_1 X_t + u_t$, say eqn (13*). Both eqn (13) & (13*) are estimating the relationship between $Exchange\ Rate(*) \equiv Y_t^*$ and the $TAWCPI \equiv X_t$, where $Y_t^* = Y_t - \beta Z_t - \emptyset W_t$. In the above chart, the blue and red fits represents the nonparametric fitting of the relationship using Kernel Estimation and Spline Estimation respectively while the yellow and green fits represent the Linear and Log-Log Estimation respectively.

In as much as the kernel estimation shows over fitting, the Spline estimation is a smooth and good approximation of the relationship between these two variables, on the other hand the parametric models tried capturing this relationship using linear and some worth linear approach. Judging from the chart, the nonparametric model (Spline) best explains the nature of the relationship between the Nominal Exchange rate of Taiwan and her Prices (Consumer Price Index).

SUMMARY AND CONCLUSION

In nutshell, this work sets out to examine the nature of the relationship between the Nominal Exchange Rate and Prices using Taiwan as a case study and to also establish the Exchange Rate pass through effect. Theory postulates that the form of relationship between the Nominal Rate and Prices (domestic and foreign) is linear as shown in the introduction part of this work. Using a data driven method, we have established that the nature of relationship between these two variables are not linear both non-linear using

information from Taiwan. Next, we also have shown that the Nominal Exchange Rate of Taiwan as a foreign currency pass-through effect of 0.25%.

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