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The Forward Rate Premium Puzzle: A Resolution*

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Abstract

Empirical studies report that there is a negative relationship between the spot difference and forward premium. This result violates the forward rate unbiasedness theory. Using standard regression we found that recent samples give mixed results with both positive and negative coefficients. One possibility is that the negative coefficients could arise due to the non-linearities in the series and misspecification. To overcome these problems we employed a relatively novel technique. As an alternative to the standard regression we used a time-varying coefficient technique. This methodology estimates bias-free coefficients and thus should provide better estimates of the link between spot and forward rates. The findings of the time-varying coefficient model strongly support the forward rate unbiasedness hypothesis. All the parameters are very close to unity and significant. At the same time our results do not violate the efficient market theory.

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1. Introduction

Since the seminal paper of Fama (1984) the forward rate premium puzzle has been an abiding conundrum in finance and applied econometrics. The premium puzzle is the very robust result that if a standard regression is performed with the dependent variable being exchange rate depreciation and the independent variable being the appropriately defined forward rate premium the coefficient which results is almost always negative and often substantially so. We would of course expect that this coefficient would be unity if market participants are rational. This result of a negative coefficient has puzzled many researchers who, while they may be prepared to accept that markets are not fully rational in the strong form of the assumption, cannot accept a negative relationship between the expected exchange rate as measured by the forward rate and the actual future outcome for the exchange rate.

In this paper we apply a new econometric technique to the standard forward rate premium equation. This technique can give consistent parameter estimates in the face of omitted variables, measurement error and misspecified functional form. In particular we are arguing here that if the market has weak form rational expectations, so that on average expectations are correct in the long run but that over the short term agents do not know the true model and therefore have to engage in a learning process. Then the parameters of the forward rate premium equation should be time varying. If this is the case then we show that ordinary least squares (OLS) will not produce the average value of the time-varying coefficient, as one might hope, but instead will be biased. Further this bias can be substantial and can explain the negative coefficient usually found. We then go on to apply the new consistent technique and uncover a systematically varying coefficient which is indeed unity on average.

The remainder of this paper is divided into three sections. Section 2 briefly summarizes the theoretical derivation of the forward premium equation. It then goes on to outline our novel estimation strategy, building on the work of Swamy, Tavlas, Hall and Hondroyiannis (2010).[1] Section 3 presents empirical results using ten exchange rates using monthly data over a one month, three month, six month and one year forward horizon. We demonstrate that standard OLS produces the usual result of a negative coefficient or a very small coefficient, while our estimation approach

[1] Swamy, Tavlas, Hall and Hondroyiannis (2010) in turn draw on papers by Swamy and Tavlas (2001), Chang, Hallahan and Swamy (1992) and Chang, Swamy, Hallahan and Tavlas (2000).

reveals the average coefficient to be very close to one as theory would suggest. Section 4 concludes.

2. Theoretical considerations and empirical methodology

2.1 The Forward Rate Premium Puzzle

Under the assumption of rational expectations we would expect that the future actual realization for the log of the exchange rate should be equal to the expected log of the rate plus an unforecastable white noise error.

$$s_{t+k} = E({}_t s_{t+k}) + \varepsilon_{t+k} \tag{1}$$

Where s_{t+k} is the log of the actual exchange rate in period t+k and $E({}_t s_{t+k})$ is the expectation of s_{t+k} formed at period t. The literature then assumes that in the absence of a risk premium the log of the forward rate for k periods ahead (f_t) will be a direct measure of market expectations. Thus we re-write (1) as

$$s_{t+k} = f_t + \varepsilon_{t+k} \tag{2}$$

Finally because of potential problems with non stationarity (e.g. Bilson, 1981) the current exchange rate is subtracted from both sides to give.

$$s_{t+k} - s_t = f_t - s_t + \varepsilon_{t+k} \tag{3}$$

And so we may test this by following Fama (1984) and running the following regression

$$s_{t+k} - s_t = \alpha + \beta(f_t - s_t) + \varepsilon_{t+k} \tag{4}$$

Where we expect to find that $\alpha = 0$ and $\beta = 1$. The essence of the forward rate puzzle then is that in almost all circumstances β turns out to be negative, often with a substantial value and significantly different from zero. See for example Hodrick and Srivastava (1986), Froot and Frankel (1989), Baillie and Kilic, (2006), Maynard (2006), Sarno, Valente and Leon (2006), Frankel and Poonawala, (2010) or the many papers surveyed in Engel(1996) or Lewis(1995).

In this paper we argue that this result essentially comes about because of a basic misspecification in (4) which is that the coefficient β is assumed to be constant. This amounts to a strong form of the rational expectations assumption where we assume that agents know the full economic model and therefore make only completely random errors. However if we were to assume that agents are only weakly rational so that on average they get things right but they have to learn about the true economic system then we would expect the parameter β to vary systematically around 1 as the learning takes place (see Chakraborty (2007) for a formal analysis of how learning may affect the parameter). If this is the case then we would need to amend (4) in the following way to allow for variation in the coefficient.

$$s_{t+k} - s_t = \alpha + \beta_t (f_t - s_t) + \varepsilon_{t+k} \tag{5}$$

Now one might hope that if β_t actually is moving around 1 then a fixed coefficient estimate given by OLS would take on the average value. However this is not the case as we can easily see if we impose a fixed coefficient on (5)

$$s_{t+k} - s_t = \alpha + \overline{\beta}(f_t - s_t) + (\beta_t - \overline{\beta})(f_t - s_t) + \varepsilon_{t+k} \tag{6}$$

Now when we estimate a fixed coefficient model of the form of (4) the error term actually comprises of the last two terms in (6). For OLS to be consistent we require of course that the independent variables are orthogonal to the error process. But this can not be the case here because part of the error process actually is $f_t - s_t$. Hence OLS will give biased estimates of the parameter and will not give the average value of β_t. Given this correlation between the error term and the regressor we might think of using an instrumental method of estimation, (Hausman, 1975; Stock and Yogo, 2001; Chao and Swanson, 2003; Greene, 2003; Stock and Watson, 2003). However again from (6) we can see why this can not work. In order to perform instrumental variable estimation we require an instrument which is well correlated with the endogenous regressor but uncorrelated with the error term. But in this case as (6) makes clear the regressor and the error term contains the same term so no valid instrument can exist (e.g. Hall, Swamy and Tavlas, 2009).

In this section we have explained the forward rate puzzle and by simply allowing a learning process to exist we have shown why OLS will give a highly biased value for β rather than a sensible average. In the next section we will outline an estimation strategy which should provide a consistent estimate of the average value.

2.2 A new estimation strategy

In this sub-section, we outline an estimation strategy which can estimate some of the structural parameters of a relationship without specifying either the true or complete model.[2]

When studying the relation of a dependent variable, denoted by y_t^*, to a hypothesized set of $K-1$ of its determinants, denoted by $x_{1t}^*, \ldots, x_{K-1,t}^*$, where $K-1$ may be only a subset of the complete set of determinants of y_t^*, a number of problems may arise. Any specific functional form may be incorrect and may therefore lead to specification errors resulting from functional-form biases. Another problem that can arise in investigating the relationship between the dependent variable and its determinants is that $x_{1t}^*, \ldots, x_{K-1,t}^*$ may not exhaust the complete list of the determinants of y_t^*, in which case the relation of y_t^* to $x_{1t}^*, \ldots, x_{K-1,t}^*$ may be subject to omitted-variable biases. In addition to these problems, the available data on y_t^*, $x_{1t}^*, \ldots, x_{K-1,t}^*$ may not be perfect measures of the underlying true variables, causing errors-in-variables problems. In what follows, we propose the correct interpretations and an appropriate method of estimation of the coefficients of the relationship between y_t^* and $x_{1t}^*, \ldots, x_{K-1,t}^*$ in the presence of the foregoing problems.

Suppose that T measurements on y_t^*, $x_{1t}^*, \ldots, x_{K-1,t}^*$ are made and these measurements are in fact, the sums of "true" values and measurement errors: $y_t = y_t^* + v_{0t}$, $x_{jt} = x_{jt}^* + v_{jt}$, $j = 1, \ldots, K-1$, $t = 1, \ldots, T$, where the variables y_t, $x_{1t}^*, \ldots, x_{K-1,t}^*$ without an asterisk are the observable variables, the variables with an asterisk are the unobservable "true" values, and the v's are measurement errors. Also, given the possibilities that the functional form we are estimating may be misspecified

[2] The discussion below draws on Swamy, Tavlas, Hall and Hondroyiannis (2010).

and there may be some important variables missing from x^*_{1t}, ..., $x^*_{K-1,t}$, we need a model which will capture all these potential problems.

It is useful at this point to clarify what we believe is the main objective of econometric estimation. In our view, the objective is to obtain unbiased estimates of the effect on a dependent variable of changing one independent variable holding all others constant. That is to say, we aim to find an unbiased estimate of the partial derivative of y^*_t with respect to any x^*_{jt}. This interpretation of course is the standard one usually placed on the coefficients of a typical econometric model, but validity of this interpretation depends crucially on the assumption that the conventional model gives unbiased coefficients, which, of course, is not the case in the presence of model misspecification.

One way to proceed is to specify a set of time-varying coefficients which provide a complete explanation of the dependent variable y. Consider the relationship

$$y_t = \gamma_{0t} + \gamma_{1t} x_{1t} + ... + \gamma_{K-1,t} x_{K-1,t} \tag{7}$$

which we call "the time-varying coefficient (TVC) model". (Note that this equation is formulated in terms of the observed variables). As this model provides a complete explanation of y, all the misspecification in the model, as well as the true coefficients must be captured by the time-varying coefficients. Note that, if the true functional form is non-linear, the time-varying coefficients may be thought of as the partial derivatives of the true non-linear structure and so they are able to capture any possible function. These coefficients will also capture the effects of measurement error and omitted variables. The trick is to find a way of decomposing these coefficients into the biased and the bias-free components.

It is important to stress, that while we start from a time varying coefficient model, and this technique is sometimes referred to as TVC estimation, the objective here is not to simply estimate a model with changing coefficients. We start from (4) because this is a representation of the underlying data generation process, which is correct. This is the case simply because, if the coefficients can vary at each point in time, they are able to explain 100 percent of the variation in the dependent variable. In the case of the TVC procedure followed in this paper, however, we then decompose these varying coefficients into two parts, a consistent estimate of the true structural partial derivative and the remaining part which is due to biases from the various misspecifications in the model. If the true model is linear, we would get back to a constant coefficient model. If the true model is non-linear, the partial derivative will be varying with the models variables and parameters and the coefficient will then vary over time to reflect this circumstance. The key point is that the TVC technique used here produces consistent estimates of structural relationships in the presence of model misspecification.

For empirical implementation, model (7) has to be embedded in a stochastic framework. To do so, we need to answer the question: What are the correct stochastic assumptions about the TVC's of (4)? We believe that the correct answer is: the correct interpretation of the TVC's and the assumptions about them must be based on an understanding of the model misspecification which comes from any (i) omitted variables, (ii) measurement errors, and (iii) misspecification of the functional form. We expand on this argument in what follows.

Notation and Assumptions Let m_t denote the total number of the determinants of y_t^*. The exact value of m_t cannot be known at any time. We assume that m_t is larger than *K*-1 (that is, the number of determinants is greater than the determinants for which we have observations) and possibly varies over time.[3] This assumption means that there are determinants of y_t^* that are excluded from equation (7) since equation (7) includes only *K*-1 determinants. Let x_{gt}^*, $g = K, \ ,..., \ m_t$, denote these excluded determinants. Let α_{0t}^* denote the intercept and let both α_{jt}^*, $j = 1, \ ..., \ K-1$, and α_{gt}^*, $g = K, \ ,..., \ m_t$, denote the other coefficients of the regression of y_t^* on all of its determinants. The true functional form of this regression determines the time profiles of α^*s. These time profiles are unknown, since the true functional form is unknown. Note that an equation that is linear in variables accurately represents a non-linear equation, provided the coefficients of the former equation are time-varying with time profiles determined by the true functional form of the latter equation. This type of representation of a non-linear equation is convenient, particularly when the true functional form of the non-linear equation is unknown. Such a representation is not subject to the criticism of misspecified functional form. For $g = K, \ ,..., \ m_t$, let λ_{0gt}^*

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[3] That is, the number of determinants is itself time-variant.

denote the intercept and let λ^*_{jgt}, $j = 1, \ ,..., \ K-1$, denote the other coefficients of the regression of x^*_{gt} on x^*_{1t}, ..., $x^*_{K-1,t}$. The true functional forms of these regressions determine the time profiles of λ^*s.

The following theorem gives the correct interpretations of the coefficients of equation (7):

Theorem 1 *The intercept of (7) satisfies the equation,*

$$\gamma_{0t} = \alpha^*_{0t} + \sum_{g=K}^{m_t} \alpha^*_{gt}\lambda^*_{0gt} + v_{0t} \tag{8}$$

and the coefficients of (7) other than the intercept satisfy the equations,

$$\gamma_{jt} = \alpha^*_{jt} + \sum_{g=K}^{m_t} \alpha^*_{gt}\lambda^*_{jgt} - \left(\alpha^*_{jt} + \sum_{g=K}^{m_t} \alpha^*_{gt}\lambda^*_{jgt}\right)\left(\frac{v_{jt}}{x_{jt}}\right) \qquad \left(j = 1, \ ..., \ K-1\right) \tag{9}$$

Proof See Swamy and Tavlas (2001, 2007).

Thus, we may interpret the TVC's in terms of the underlying correct coefficients, the observed explanatory variables and their measurement errors. It should be noted that, by assuming that the λ^*s in equations (8) and (9) are possibly nonzero we do not require that the determinants of y^*_t included in (7) be independent of the determinants of y^*_t excluded from (7). Pratt and Schlaifer (1988, p. 34) show that this condition is "meaningless". By the same logic, the usual exogeneity assumption of independence between a regressor and the disturbances of an econometric model is "meaningless" if the disturbances are assumed to represent the net effect on the dependent variable of the determinants of the dependent variable excluded from the model. The real culprit appears to be the interpretation that the disturbances of an econometric model represent the net effect on the dependent variable of the unidentified determinants of the dependent variable excluded from the model. In other words, if we make the classical econometric assumption that the error term is an i.i.d. process, then standard techniques go through in the usual way. If however we interpret the error term as a function of the misspecification of the model, then it becomes impossible to assert its conditional independence from the included regressors and standard techniques such as instrumental variables are no longer consistent.

By assuming that the α^*s and λ^*s are possibly time-varying, we do not *a priori* rule out the possibility that the relationship of y_t^* with all of its determinants and the regressions of the determinants of y_t^* excluded from (7) on the determinants of y_t^* included in (7) are non-linear. Note that the last term on the right-hand side of equations in (9) implies that the regressors of (7) are correlated with their own coefficients.[4]

Theorem 2 *For* $j=1, \ ..., \ K-1$, *the component* α_{jt}^* *of* γ_{jt} *in (9) is the direct or bias-free effect of* x_{jt}^* *on* y_t^* *with all the other determinants of* y_t^* *held constant and is unique.*

Proof It can be seen from equation (9) that the component α_{jt}^* of γ_{jt} is free of omitted-variables bias $\left(=\sum_{g=K}^{m_t}\alpha_{gt}^*\lambda_{jgt}^*\right)$, measurement-error bias $\left(=-\left(\alpha_{jt}^*+\sum_{g=K}^{m_t}\alpha_{gt}^*\lambda_{jgt}^*\right)\times\left(v_{jt}/x_{jt}\right)\right)$, and of functional-form bias, since we allow the α^*s and λ^*s to have the correct time profiles. These biases are not unique being dependent on what determinants of y_t^* are excluded from (7) and the v_{jt}. However, the γ_{jt} are unique when their correct interpretations given by (8) and (9) are adopted (see Swamy and Tavlas 2007, p. 300). Note that α_{jt}^* is the coefficient of x_{jt}^* in the correctly specified relation of y_t^* to all of its determinants. Hence α_{jt}^* represents the direct, or bias-free, effect of x_{jt}^* on y_t^* with all the other determinants of y_t^* held constant. The direct effect is unique because it represents a property of the real world that remains invariant against mere changes in the language we use to describe it (see Basmann 1988, p. 73; Pratt and Schlaifer 1984, p. 13; Zellner 1979, 1988). In effect the direct effect is a consistent estimator of the derivative of x_{jt}^* with respect to y_t^*, it is essentially simply a number and is therefore unique.

[4] These correlations are typically ignored in the analyses of state-space models. Thus, inexpressive conditions and restrictive functional forms are avoided in arriving at equations (8) and (9) so that Theorem 1 can easily hold; for further discussion and interpretation of the terms in (8) and (9), see Swamy and Tavlas (2001), Swamy, Tavlas and Mehta (2007) and Hall, Hondroyiannis, Swamy and Tavlas (2010).

The direct effect α^*_{jt} is constant if the relationship between y^*_t and all of its determinants are linear; alternatively, it is variable if the relationship is non-linear. We often have information from theory as to the right sign of α^*_{jt}. Any observed correlation between y_t and x_{jt} is spurious if $\alpha^*_{jt} = 0$ (see Swamy, Tavlas and Mehta 2007). [5]

A key implication of (8) and (9) is that, in the presence of a misspecified functional form and omitted variables, the errors in a standard regression will contain the difference between the right-hand side of (7) and the right-hand side of the standard regression with the errors suppressed. So the errors will contain the included *x* variables. This means that the independence condition between an error term and instrumental variables underlying the GMM and instrumental variables method cannot be met as the errors contain exactly the same variables that we require the instruments to have a strong correlation with. In effect, if the instruments are highly correlated with the *x* variables, they cannot be uncorrelated with the errors as these errors contain exactly the same *x* variables.

Swamy, Tavlas, Hall and Hondroyiannis (2010) go on to show how a TVC model may be estimated and then the time-varying coefficients decomposed to give consistent estimators of the bias-free direct effects in a model which is misspecified in terms of its functional form, its excluded variables and measurement error. The key to this decomposition is to use a set of observable variables, called coefficient drivers, which explain the time variation in the coefficients. This set of coefficient drivers can be split into two subsets so that one subset, say the first subset, *should be correlated* with any true variation in the direct effect while the other subset, say second subset, *should be correlated* with the biases that are present. Once this is achieved we can estimate the biases which come from the second subset of coefficient drivers. We remove the estimates of biases from the estimates of total coefficients and obtain a consistent estimator of the underlying direct effect. This second subset of coefficient drivers then acts rather like the dual of conventional instruments. The key difference however is that some of these drivers should be correlated with the misspecifications rather than uncorrelated with an error term, as in

[5] We use the term spurious in a more general sense than Granger and Newbold's (1974), where it strictly applies to linear models expressed in terms of integrated variables. Here we mean any correlation which is observed between two variables when the true direct effect of one on the other is actually zero.

the case of instruments, and this should be much easier to achieve in a real world situation.

3. Data and empirical results

In this paper we used monthly data for ten spot and forward exchange rates with one-, three-, six-, and twelve-month maturity. The data for the spot exchange rates were obtained from IMF International Financial Statistics (IFS), (ESDS database). The data for the forward rates were extracted from Thomson Reuters, GTIS/Thomson Reuters and WM/Reuters, (DataStream database). The timeline spans from the month 1990:M5 to the month 2009:M7. The exception is the Chinese Yuan. The time series for this currency starts at 2002:M1 and ends at 2009:M7. All rates are given as US dollar against national currencies of respective countries.

3.1. OLS regressions

We start our results by analyzing the outcomes of equation (4). The standard regression results are reported in Table 1. The output of this table gives mixed results for the beta coefficients of the regressions. Some currencies have positive coefficients while others have negative coefficients. The t-test shows that the β's range from cases when they are significantly different from zero, and quite substantially in some instances, to the cases when they are practically not distinguishable from 0. For example, for the Australian dollar β estimate is very close to unity, (for three- and six-month forward rates), or practically identical to unity, (for one-month forward rate).[6] The t test statistics for these β's show significance at 1% level for all four forward rates. Figure 1 shows movement of the spot rate difference and forward premium for one-month forward rate. While the outcome of the standard regression for the Australian dollar supports the hypothesis of the forward rate unbiasedness; this result implies strong predictability of the future returns within one-month range. Thus, violation of the efficient market theory (EMT), which states that the best prediction of the future spot rate is current rate itself, is evident.

Comparable outcomes are obtained for the coefficients of the British pound and New Zealand dollar. They are positive and non-zero. Somewhat similar results for the Norwegian and Swedish currencies, with mostly positive β's. However, as opposed

[6] Contrasting results are obtained by Frankel and Poonawala (2010). One of the reasons is probably due to the small sample the authors used in their research. See for example, Chakraborty (2009) regarding properties of the small sample.

to the previous two currencies, in almost all instances the t-ratios indicate that they are not significantly different from zero. The only exception is the β estimate of the one-month forward premium for the Swedish currency, which is negative, but nonetheless, it is also statistically not significant. Denmark, Japan, South Africa and Singapore have forward premiums with negative coefficients that generally ascend with the increase of the forward rate horizon.[7] However, even for these currencies the β estimates significantly vary from currency to currency. For instance, the Danish currency indicates β estimates which are not significant while the Singaporean currency has statistically significant β estimates.

On the other hand, the Japanese Yen has both significant and not significant β estimates. It has a negative β estimate for the one-month forward rate but it is very close to zero, -0.08. The result of the t-test confirms this, -0.456. Nevertheless, the rest of the forward rates have coefficient values which are close to one, (three- and six-month horizons) and close to two (twelve-month horizon) in absolute values. The visual inspection of the one year spot difference and forward premium for Japan show interesting pattern, see Figure 2. There are clear signs that, in the short run, market agents are not able to predict the future exchange rate. Nevertheless, it seems that they engage in learning process. When the forward premium indicated appreciation of the Yen, the actual exchange rate depreciated and quite substantially in the late 90s. The market participants made wrong forecast in that period. In 2001, they expected that the currency continue to depreciate but their expectations were not realized. And finally, in 2006, the market agents already had past experience that the Yen could move either way. As a result, they adjusted their expectations accordingly.

The outcomes indicate that the coefficients of the forward premium are time varying. Time-varying coefficient methodology was implemented to explore this issue.

[7] This is also true for the other currencies.

3.2. TVC regressions

Coefficient drivers play a significant role in removing the non-linearity present in the model. Following Hall, Hondroyiannis, Swamy and Tavlas (2010), seven coefficient drivers were used.[8] Along with a constant term (Z_{0t}), coefficient drivers in this paper include lagged variables of the spot and forward rates. Three lags of the spot rate were utilized: $Z_{1t}=S^{n}_{t-1}$, $Z_{2t}=S^{n}_{t-2}$ and $Z_{3t}=S^{n}_{t-3}$, and similarly for the forward rate: $Z_{4t}=F^{n}_{t-1}$, $Z_{5t}=F^{n}_{t-2}$ and $Z_{6t}=F^{n}_{t-3}$. The superscript n represents the maturity of the forward rates, (*i.e.*, one-, three-, six- or twelve-month horizon), and spot rates for these periods. The bias-free component α^{*} was computed by separating the total effect from measurement error and omitted-variable bias, (see Swamy, Tavlas, Hall and Hondroyiannis; 2010) and this gives bias-free estimate for β.

The averages of the estimates of the total and bias-free components of β coefficients are presented in Table 2 and 3, respectively. The total effect shows that the most of the coefficients are close to zero. Removing biases from the coefficients given by the total effect give results which are identical to unity for all currencies and forward rates. The t-tests conducted on the bias-free coefficients indicate that they are not significantly different from unity. This is in line with the forward rate unbiasedness theory.

As in the previous subsection, our discussion here starts from the Australian dollar. The bias-free estimates for the forward premium of this currency vary within a very small margin around one. The corresponding test statistics indicate significance at less than 1% level. Figure 3 presents the movement of the bias-free and total coefficients of the forward premium for the one-month forward rate. This figure reveals that the total effect varies around the bias-free coefficient. However, there is a clear pattern in the evolution of the forward rate. Starting from 1998 most of the total coefficients are below the bias-free coefficients and after 2005 - above the bias-free coefficients. Interestingly, the movement of the bias-free coefficient shows a steady increase followed by a sharp depreciation in the value of the Australian dollar in 2008 as opposed to the relatively high fluctuation reported by the total effect. All these patterns strongly suggest that there are signs of the non-linearity presented in the model. Nevertheless, the average values of the bias-free and total coefficients are close to unity, in line with the theory.

[8] This paper can be seen as an application of Hall, Hondroyiannis, Swamy and Tavlas (2010).

The coefficients representing the bias-free and total effects for the Yuan also show signs of non-linearity. As in the case of the Australian dollar the bias-free coefficients are close to unity with insignificant divergence from one, this is particularly relevant for the forward premium with the twelve-month maturity. The bias-free coefficient for this forward rate is 0.999 with zero as its t-ratio, as can be seen in Table 3. However, as opposed to the Australian currency, the movement of the bias-free and total effects for the Yuan is close to being flat, see Figure 4. In addition, while the total effect indicates some volatility and the average value is close to zero, the bias-free effect is practically unchanged from one during the whole period. We can possibly explain this by the fact that the monetary authorities in China kept the currency fixed during the analyzed period and the bias-free coefficient indicates this.

Finally, analysis of the forward rate for the British pound with one-month horizon is reported. Again as in the previous cases the coefficients of the bias-free effect are close to one; the t-ratios show significance at less than 1% level. Figure 5 reveals an interesting pattern, when the biases associated with this currency for one-month forward rate are removed. First, one can discern that the total effect indicate volatility clustering during turbulent periods. Second, the bias-free effect in this case is given by the constant of the coefficient drivers and close to the mean of the total effect.

For the sake of brevity, we omit the discussion of the results for the other currencies, which all broadly follow a similar pattern. However, the interested reader can obtain the omitted results from the authors.

4. Conclusions

This paper addressed a question which puzzled many researchers: empirical violation of the forward rate unbiasedness theory. That is, the coefficient of forward rate premium in the regression of spot exchange rate change on forward rate premium is negative.

Using the standard regression, we found that the recent samples give mixed results as opposed to the previous studies. Some of the currencies have negative coefficients while others have positive coefficients. The latest empirical findings, as well as this paper, suggest that there are non-linearities in the model which lead to the biased outcomes.

A novel approach was used to overcome the aforementioned problem. In this research we employed time-varying coefficient methodology. This methodology enables the extraction of biases from the models, and allows for accurate results. The findings of the TVC model strongly support the forward rate unbiasedness hypothesis. All the coefficients of forward rate premium are very close to unity and significant. At the same time the results do not violate the efficient market theory.

Table 1. OLS estimation for forward-rate unbiasedness in returns

Forward rate	One month	Three months	Six months	Twelve months
Australia				
Forward premium	*1.001*	*0.974*	*1.075*	*0.702*
	[29.184]	*[8.486]*	*[5.888]*	*[2.701]*
China				
Forward premium	*0.043*	*0.728*	*0.731*	*0.632*
	[0.386]	*[6.823]*	*[7.154]*	*[6.008]*
Denmark				
Forward premium	*-0.223*	*-0.099*	*-0.105*	*-0.208*
	[-1.325]	*[-0.372]*	*[-0.357]*	*[-0.754]*
Japan				
Forward premium	*-0.080*	*-0.553*	*-0.987*	*-1.901*
	[-0.456]	*[-1.931]*	*[-3.192]*	*[-7.439]*
Norway				
Forward premium	*-0.111*	*0.179*	*0.295*	*0.339*
	[-0.673]	*[0.634]*	*[0.926]*	*[1.181]*
New Zealand				
Forward premium	*0.941*	*1.373*	*1.372*	*0.310*
	[9.834]	*[6.033]*	*[3.792]*	*[0.665]*
South Africa				
Forward premium	*-0.208*	*-0.429*	*-1.113*	*-1.765*
	[-1.213]	*[-1.454]*	*[-3.192]*	*[-5.095]*
Singapore				
Forward premium	*-0.415*	*-1.002*	*-0.640*	*-1.187*
	[-2.027]	*[-3.302]*	*[-2.018]*	*[-4.082]*
Sweden				
Forward premium	*-0.230*	*0.082*	*0.493*	*0.725*
	[-1.342]	*[0.291]*	*[1.541]*	*[2.489]*
UK				
Forward premium	*0.829*	*1.147*	*1.137*	*1.254*
	[8.372]	*[5.431]*	*[3.907]*	*[4.281]*

Notes: OLS estimation for forward-rate unbiasedness in returns, (1990:M5-2010:M7). Figures in brackets are t-ratios.
The coefficients were estimated using the following regression model:
$s_{t+k} - s_t = \alpha + \beta(f_t - s_t) + \varepsilon_{t+k}$

Table 2. TVC total effect estimation for forward-rate unbiasedness in returns

Forward rate	One month	Three months	Six months	Twelve months
Australia				
Forward premium	*1.038*	*0.101*	*1.122*	*0.098*
	[6.703]	*[0.259]*	*[0.060]*	*[0.339]*
China				
Forward premium	*-0.153*	*1.301*	*0.191*	*0.062*
	[-0.321]	*[0.487]*	*[0.556]*	*[0.924]*
Denmark				
Forward premium	*-0.439*	*0.644*	*0.543*	*0.785*
	[-0.423]	*[1.929]*	*[1.412]*	*[1.779]*
Japan				
Forward premium	*0.049*	*0.340*	*0.958*	*0.435*
	[0.146]	*[0.506]*	*[1.770]*	*[3.879]*
Norway				
Forward premium	*-0.189*	*0.680*	*0.610*	*0.539*
	[-0.260]	*[1.152]*	*[1.066]*	*[1.106]*
New Zealand				
Forward premium	*0.840*	*-0.310*	*4.195*	*-0.546*
	[2.655]	*[-0.635]*	*[0.152]*	*[-1.079]*
South Africa				
Forward premium	*-0.005*	*0.983*	*-0.686*	*0.520*
	[-0.006]	*[1.444]*	*[-0.084]*	*[1.145]*
Singapore				
Forward premium	*-0.091*	*0.060*	*0.694*	*-0.113*
	[-0.095]	*[0.039]*	*[0.814]*	*[-0.392]*
Sweden				
Forward premium	*-0.318*	*0.399*	*0.368*	*0.589*
	[-0.424]	*[0.733]*	*[0.492]*	*[1.056]*
UK				
Forward premium	*0.811*	*-0.377*	*0.675*	*-0.267*
	[2.446]	*[-1.027]*	*[0.545]*	*[-0.513]*

Notes: TVC total effect estimation for forward-rate unbiasedness in returns, (1990:M5-2010:M7). Figures in brackets are t-ratios. The t-test was conducted on $H_0 : \beta = 0$. The estimates were obtained using seven coefficient drivers: a constant term and three lags of the spot and forward rates.

Table 3. TVC bias-free estimation for forward-rate unbiasedness in returns

Forward rate	One month	Three months	Six months	Twelve months
Australia				
Forward premium	*1.005*	*0.994*	*0.983*	*0.969*
	[0.006]	*[-0.007]*	*[0.000]*	*[-0.015]*
China				
Forward premium	*0.955*	*1.312*	*0.930*	*0.999*
	[0.000]	*[0.002]*	*[-0.003]*	*[0.000]*
Denmark				
Forward premium	*0.918*	*0.871*	*1.041*	*1.035*
	[-0.002]	*[-0.010]*	*[0.002]*	*[0.002]*
Japan				
Forward premium	*1.336*	*1.101*	*0.944*	*0.809*
	[0.003]	*[0.001]*	*[-0.001]*	*[-0.007]*
Norway				
Forward premium	*1.077*	*0.969*	*1.048*	*0.995*
	[0.002]	*[-0.002]*	*[0.002]*	*[0.000]*
New Zealand				
Forward premium	*0.978*	*0.994*	*1.098*	*1.035*
	[-0.005]	*[-0.001]*	*[0.001]*	*[0.010]*
South Africa				
Forward premium	*0.897*	*1.011*	*0.831*	*1.503*
	[-0.006]	*[0.000]*	*[-0.002]*	*[0.039]*
Singapore				
Forward premium	*0.932*	*1.088*	*0.962*	*1.041*
	[-0.001]	*[0.002]*	*[-0.001]*	*[0.003]*
Sweden				
Forward premium	*1.131*	*1.035*	*0.949*	*0.967*
	[0.002]	*[0.002]*	*[-0.002]*	*[-0.004]*
UK				
Forward premium	*0.825*	*1.022*	*1.026*	*0.977*
	[-0.028]	*[0.003]*	*[0.006]*	*[-0.003]*

Notes: TVC bias-free estimation for forward-rate unbiasedness in returns, (1990:M5-2010:M7). Figures in brackets are t-ratios. The t-test was conducted on $H_0 : \beta = 1$. The bias-free components were computed by separating the total effect from measurement error and omitted-variable bias

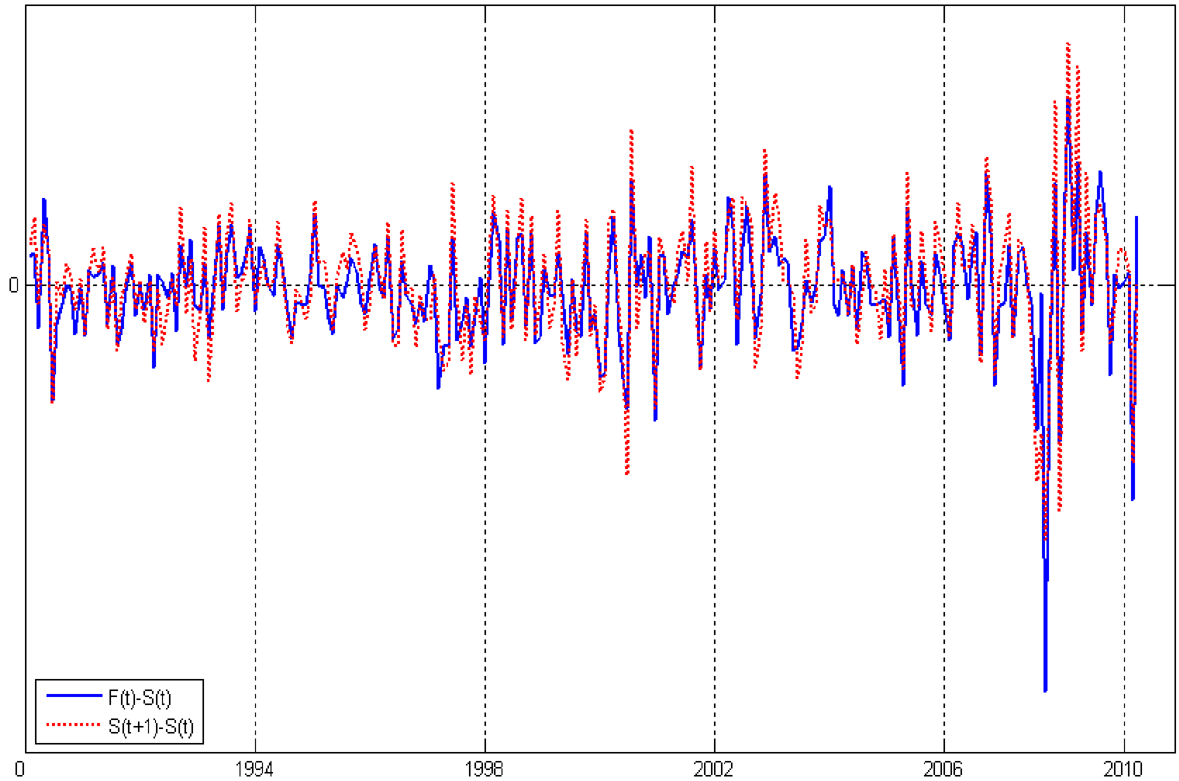

Figure 1 First differences of spot rate and one-month forward premium for Australia.

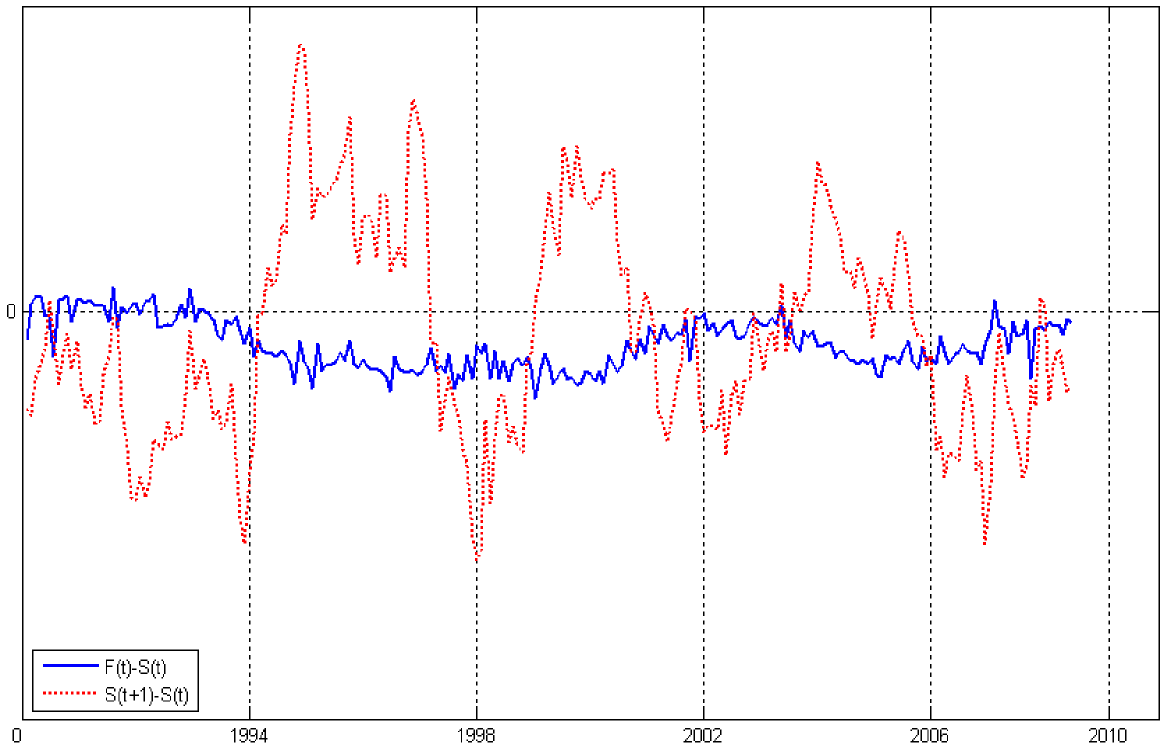

Figure 2 Differences of twelve-month apart values of spot rate and twelve-month forward premium for Japan.

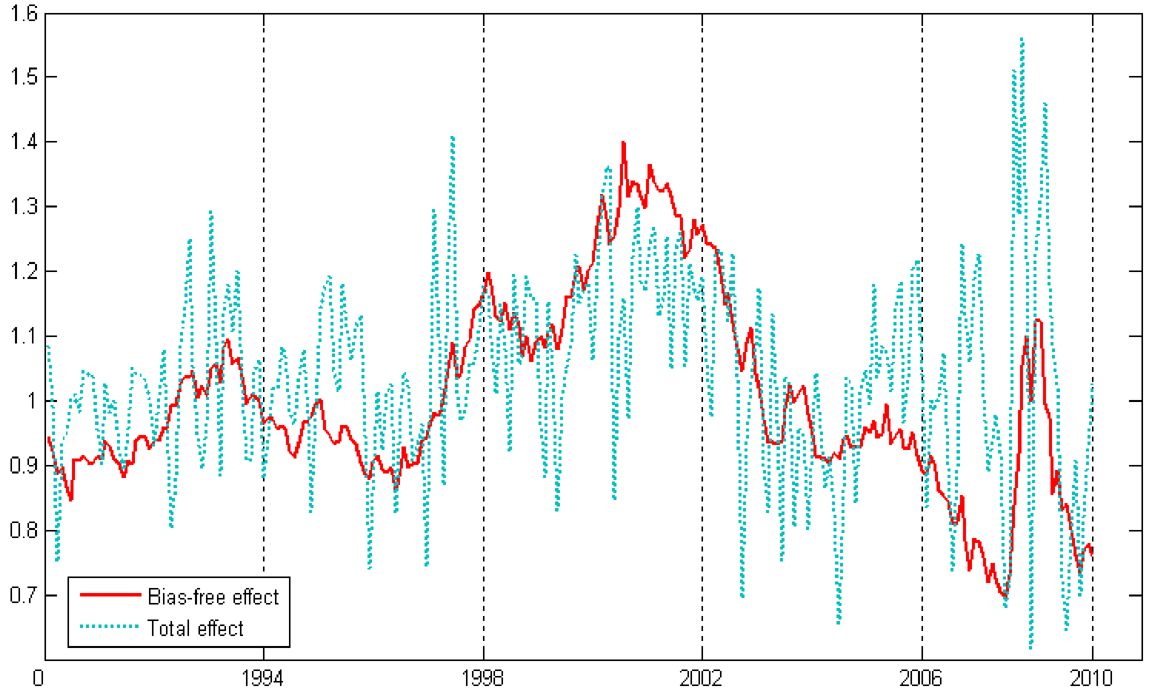

Figure 3 Bias-free and total effects of the forward premium for the Australian one-month forward rate.

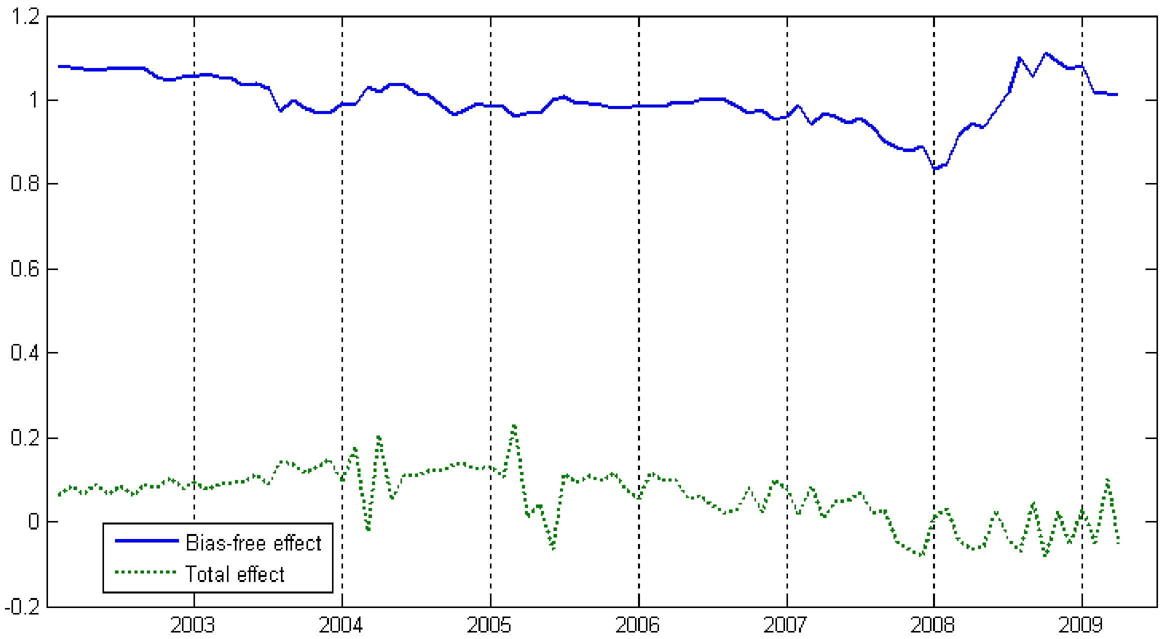

Figure 4 Bias-free and total effects of the forward premium for the Chinese twelve-month forward rate.

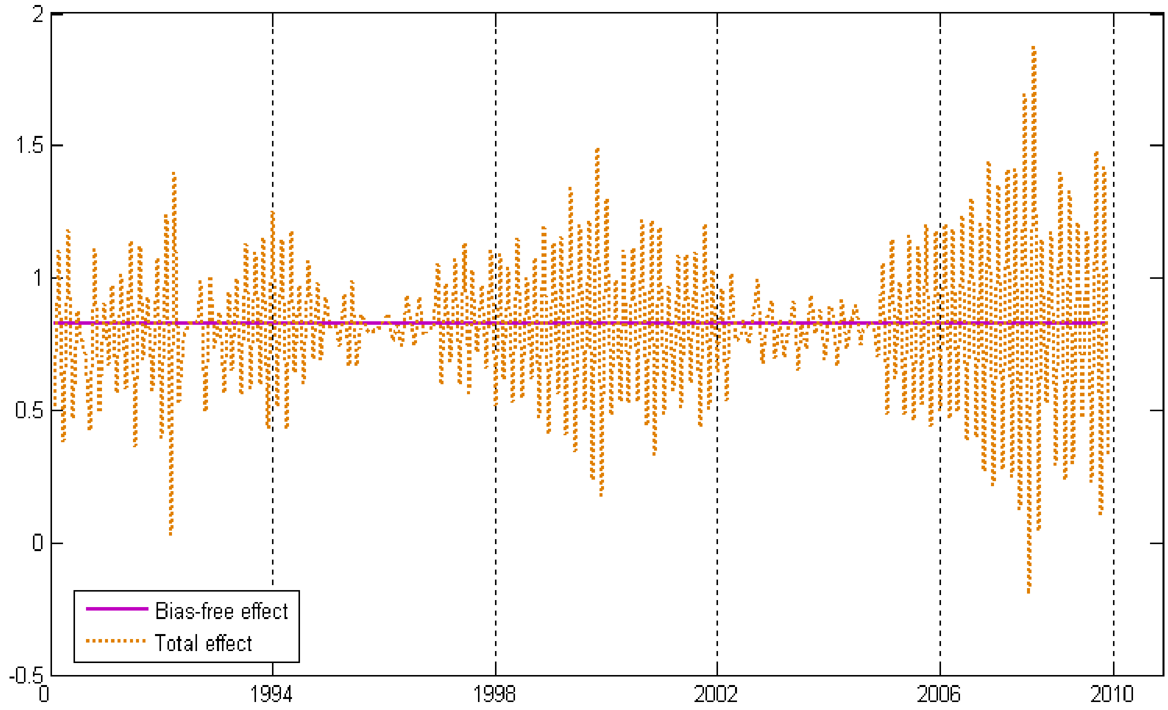

Figure 5 Bias-free and total effects of the forward premium for the British one-month forward rate.

References

Baillie, R. T., Kilic R., 2006 Do asymmetric and nonlinear adjustments explain the forward premium anomaly?, *Journal of International Money and Finance*, 25, pp. 22-47.

Basmann, R. L., 1988. Causality tests and observationally equivalent representations of econometric models, *Journal of Econometrics*. 39, 69-104.

Bilson, J. F. O., 1981. The "Speculative Efficiency" Hypothesis , *The Journal of Business*, 54, pp. 435-451.

Chakraborty A., 2007. Learning, forward premium puzzle and exchange rate fundamentals under sticky prices, *Economics Bulletin*, 34, 1-13.

Chakraborty A., 2009. Learning, the forward premium puzzle, and market efficiency. *Macroeconomic Dynamics*, 13, pp. 31-57.

Chang, I., Hallahan, C., Swamy, P. A. V. B., 1992. Efficient computation of stochastic coefficient models. In: Amman, H. M., Belsley, D. A., Pau, L. F. (Eds.), Computational Economics and Econometrics, London: Kluwer Academic Publishers.

Chang, I., Swamy, P. A. V. B., Hallahan, C., Tavlas, G. S., 2000. A computational approach to finding causal economic laws. *Computational Economics*. 16, 105-136.

Chao J.C., Swanson, N.R., 2003. Consistent estimation with a large number of weak instruments, *Econometrica*, Vol. 73, pp. 1673-1692.

Engel C., 1996. The forward discount anomaly and the risk premium: A survey of recent evidence. *Journal of Empirical Finance*. 3, 123-192.

Fama, E. F., 1984. Forward and spot exchange rates. *Journal of Monetary Economics*. 14, 319-338.

Frankel, J., Poonawala, J., 2010. The forward market in emerging currencies: Less biased than in major currencies, *Journal of International Money and Finance*, 29, pp 585-598.

Froot, K. A., Frankel, J. A., 1989 Forward Discount Bias: Is it an Exchange Risk Premium? *The Quarterly Journal of Economics*, 104, pp. 139-161.

Granger C. W. J., Newbold, P., 1974. Spurious regressions in econometrics. *Journal of Econometrics*. 2, 111-20.

Greene, W. H., 2003. Econometric analysis, 5th edition, Upper Saddle River, New Jersey: Prentice Hall.

Hall, S. G., Hondroyiannis G., Swamy, P. A. V. B., Tavlas, G. S., 2010. The Fisher effect puzzle: A case of non-linear relationship? *Open Economic Review.* 21, 91-103.

Hall, S.G., Swamy P.A.V.B., Tavlas G. S., (2009) The Nonexistence of Instrumental Variables, Discussion Papers in Economics 09/16, Department of Economics, University of Leicester.

Hausman, J. A., 1975 An Instrumental Variable Approach to Full Information Estimators for Linear and Certain Nonlinear Econometric Models, *Econometrica*, 43, pp. 727-738.

Hodrick R.J., Srivastava S., 1986. The covariation of risk premiums and expected future spot exchange rates. *Journal of International Money and Finance.* 5, 5-21.

Lewis K. K., 1995. Puzzles in international financial markets. *Handbook of International Economics.* 3, 1913-1971.

Pratt, J. W., Schlaifer, R., 1984. On the nature and discovery of structure. *Journal of the American Statistical Association.* 79, 9-22.

Pratt, J. W., Schlaifer, R., 1988. On the interpretation and observation of laws. *Journal of Econometrics.* 39, 23-52.

Sarno, L., Valente, G., Leon H., 2006. Nonlinearity in Deviations from Uncovered Interest Parity: An Explanation of the Forward Bias Puzzle. *Review of Finance*, 10, pp. 443-482.

Stock J.H., Yogo, M., 2001. Testing for weak instruments in linear IV regression. NBER working papers No. 0284.

Stock, J. H., Watson, M. W., 2003. Introduction to Econometrics. Boston:Addison Wesley.

Swamy, P. A. V. B., Tavlas, G. S., 1995. Random coefficient models: Theory and applications. *Journal of Economic Surveys.* 9, 165-182.

Swamy, P. A. V. B., Tavlas, G. S., 2001. Random coefficient models. In: Baltagi, B. H. (Ed.), A Companion to Theoretical Econometrics, Malden: Blackwell, pp. 410-428.

Swamy, P. A. V. B., Tavlas, G. S., Hall, S. G., Hondroyiannis G., 2010. Estimation of parameters in the presence of model misspecification and measurement error. *Studies in Nonlinear Dynamics & Econometrics.* 14, 1-33.

Swamy, P. A. V. B., Tavlas, G. S., Mehta, J. S., 2007. Methods of distinguishing between spurious regressions and causality. *Journal of Statistical Theory and Applications.* 1, 83-96.

Zellner, A., 1979. Causality and econometrics. In: Brunner, K. and Meltzer, A. H. (Eds.), Three Aspects of Policy and Policymaking, Amsterdam: North-Holland, pp. 9-54.

Zellner, A., 1988. Causality and causal laws in economics. *Journal of Econometrics.* 39, 7-21.