International Review of Financial Analysis 39 (2015) 45–53

Contents lists available at ScienceDirect

International Review of Financial Analysis

Does data frequency matter for the impact of forward premium on spot exchange rate?

Paresh Kumar Narayan [1], Susan Sunila Sharma [2]

Centre for Economics and Financial Econometrics Research, Deakin Business School, Deakin University, 70 Elgar Road, Burwood, 3125, Australia

ARTICLE INFO

Article history:
Received 26 September 2014
Received in revised form 19 January 2015
Accepted 23 January 2015
Available online 13 February 2015

JEL classification:
C33
C80
G1

Keywords:
Exchange rate
Forward premium
Data frequency
Investors

ABSTRACT

In this paper we take the forward premium and exchange rate literature forward by asking whether data frequency matters in that relationship. We use four frequencies of data, namely, quarterly, monthly, weekly and daily. We find that data frequencies matter both statistically and economically. More specifically, we document that investors prefer the forward premium model over a constant returns model in most countries when models are estimated using daily, weekly, and quarterly data, but not when using monthly data.

1. Background and motivation

1.1. Background

The subject of our investigation is the popular forward premium puzzle documented in the financial economics literature. As popular as this literature is, there is one feature of the literature that motivates us to re-visit the puzzle and that is the different data frequencies used. There are some studies (see Chang, 2013; Flood & Rose, 2002; Hansen & Hodrick, 1980) that use daily data, some (see Bansal, 1997; Bansal & Dahlquist, 2000) use weekly data, while others (see Al-Zoubi, 2011; Kim, 2013) apply monthly data.[3] A feature of this literature that motivates us to undertake the present study is that none of the studies attempts to investigate the robustness of the results on the forward premium using multiple data frequencies.

We do not test the forward premium puzzle. In fact, at the outset it should be understood that the literature has accepted this forward premium puzzle and several explanations have been provided for its existence. For example, Fama (1984) and Hodrick and Srivastava (1986) associate the puzzle with time-varying risk premium; Chakraborty and Evans (2008) use the perpetual learning hypothesis to explain the puzzle; Cornell (1989) attributes this puzzle to measurement errors in the data; and the carry trade strategy role in this puzzle is proposed by Brunnermeier, Nagel, & Pedersen (2009). Therefore, based on the literature, we take this as given. Instead, we propose a different question: do data frequencies actually dictate the results on the forward premium puzzle? This question is relevant for two specific reasons. We, as applied researchers, have not cared seriously about our use of data frequencies. We have used what is "convenient" or "available" it may seem. This will not do in practice. There needs to be a clear understanding on whether different data frequencies lead to different results on the forward premium puzzle.[4] An important question that arises and needs to be dealt with at the outset is why does different data frequency matter?[5] Before we proceed to answer

E-mail addresses: paresh.narayan@deakin.edu.au (P.K. Narayan), s.sharma@deakin.edu.au (S.S. Sharma).

[1] Tel.: +61 3 9244 6180; fax: +61 3 9244 6034.

[2] Tel.: +61 3 9244 6871.

[3] In other strands of the literature where exchange rate is the main subject, different frequencies of data are also used. For example, monthly data are used in the elementary monetary (portfolio balance) model by, amongst others, Huang (1981), and Meese and Rogoff (1983).

[4] In other literature, for instance, on return predictability, a range of different data frequencies is used. For example, Zakamulin (2013) uses monthly, quarterly, semi-annual, and annual data frequencies to test for equity return predictability.

[5] Perhaps the literature that has attracted the most debate on data frequency is that relating to unit root and co-integration tests. For example, Shiller and Perron (1985) and Perron (1989) show that when data are sampled at discrete points, simply increasing the frequency of observation and keeping the data span fixed does nothing to improve the power of unit root tests. Choi and Chung (1995) find mixed results; high frequency data improves the power of some unit root tests but not all. Similarly, on co-integration, an attractive debate has emerged and is still evolving. Hooker (1993) argues that temporal disaggregation actually increases the power of co-integration tests, which has been contested by Lahiri and Mamingi (1995). They contend that the power of the co-integration test is contingent on the length of the sample period rather than on the number of observations. More recently, Otero and Smith (2000) show that there is little power gain in using the high frequency monthly data over quarterly data in finding evidence for co-integration.

http://dx.doi.org/10.1016/j.irfa.2015.01.011
1057-5219/

this question, it is perhaps imperative to highlight here that the sensitivity of econometric results to data frequency is quite extinct in many areas of financial economics, as pointed out by one referee of this journal. The exceptions are those of Narayan, Narayan, and Sharma (2013) and Narayan, Ahmed, and Narayan (2014), who show the sensitivity of commodity market profits to different data frequencies.

1.2. Motivation

There are at least three reasons why data frequencies matter. First, it is a well-known fact that relatively high frequency data provides additional information (see Bollerslev & Wright, 2001). This implies that forward premium-based models that are estimated using relatively high frequency data should forecast spot exchange rate returns much better than low frequency data. That is not all though. By virtue of the additional information in high frequency data, return forecasts based on forward premiums should evince higher investor utility and profits compared with low frequency data. However, nothing is known on these issues. It is this research gap that motivates us to revisit the literature. In fact, when one reviews the literature, which shows that forecasting performance is data frequency-dependent, the evidence is only statistical. What will be of equal, if not more, interest will be whether this superiority in a statistical sense translates into economic gains (for investors) when using different data frequencies. It would seem that this information will be relatively more important to investors. Therefore, in our empirical analysis, we take both a statistical test as well as an economic significance test of the effect of the forward premium on spot exchange rate returns.

Second, consider what we learn from the use of different data frequencies in other financial economics literature and the key implications, and it is those implications that motivate us. We begin with Narayan et al. (2013), who examine commodity spot market return predictability using monthly and daily data. They argue that data frequency matters for time-series evidence on commodity market return predictability. They demonstrate that with daily data there is greater evidence of return predictability compared to the use of monthly data. Consider also Huang and Jo (1995). Their proposal is premised on the idea that the factors that determine returns may be data frequency-dependent. When they investigate this possibility using daily, weekly and monthly data, they find that the number of factors that determine returns is not at all frequency-dependent. Next, we read the mutual fund literature, where we come across Elton, Gruber, Blake, Krasny, and Ozelge (2010). They examine investment manager behaviour by using quarterly and monthly data. They find results that are data frequency-dependent and argue that the main reason is because monthly holdings data capture a large number of trades missed by quarterly data. Consider also the evidence from the volatility and return forecasting literature. In that literature, evidence suggests that high frequency data improve volatility forecasts (see Andersen, Bollerslev, & Lange, 1999) and return forecasts (see Maheu & McCurdy, 2011).

A final source of our motivation is the literature that models extreme co-movements amongst financial assets. The role and influence of data frequency in this literature have been shown by Zhang and Shinki (2007). They analyse extreme co-movements and extreme impacts amongst spot exchange rate returns. Their main finding is that extreme impacts of high frequency data are stronger than extreme impacts of low frequency data; the implication being, data frequency matters in financial economics research and is not specific to a particular strand of the literature.

From these motivations, given that the forward premium and spot exchange rate return literature are based on multiple data frequencies, as alluded to earlier, it exposes the literature to the possibility that data frequency may have a role to play. This is exactly what we investigate. We address this issue by considering 36 exchange rate markets. Motivated by the panel data approach proposed by Bansal (1997), we specify a total of 13 panels of exchange rate markets. Of these panels: (i) seven are based on income groups, namely, developed countries, developing countries, high-income panel, middle-income panel, G6 panel, high-income OECD panel, and high-income non-OECD panel; and (ii) six are based on the geographical location of countries, namely, Europe and Central Asia, Middle East and North Africa, East Asia and the Pacific, Latin America and the Caribbean, South Asia, and Sub-Saharan Africa.

2. Econometric approach

The aim of this section is to outline the empirical approach that we use to analyse the forward premium puzzle. In this regard, we follow Bansal (1997) and Bansal and Dahlquist (2000), where the spot exchange rate return is specified as a function of the forward premium and, therefore, takes the following regression form:

$$gS_{it} = \alpha_0 + \alpha_1 FP_{it} + \varepsilon_{it+1}, \tag{1}$$

where gS is the growth form of spot exchange rate which is denoted by $(SR_{it+1} - SR_{it})/SR_{it}$; SR_{it} represents the exchange rate in US dollars per unit of foreign currency i at time t; FP_{it} is the normalised forward premium, $(FR_{it} - SR_{it})/SR_{it}$; and ε_{it+1} is the projection error.

Since the expected currency depreciation (CD_{it}), the risk premium on the forward contract (FRP_{it}), and the forward premium (FP_{it}) are closely related, adding and subtracting SR_{it+1}/SR_{it} from the forward premium and taking conditional expectations gives the following equation:

$$\frac{(FR_{it}-SR_{it})}{SR_{it}} = E\left[\frac{SR_{it+1}-SR_{it}}{SR_{it}}|\gamma_t\right] + E\left[\frac{FR_{it}-SR_{it+1}}{SR_{it}}|\gamma_t\right]. \tag{2}$$

In simple terms, Eq. (2) states that the sum of the expected currency differential, CD_{it}, and the forward risk premium, FRP_{it}, gives us the forward premium, FP_{it}. Finally, γ_t denotes all the information, such as the interest rate differentials of all currencies, available to agents.

There is also the possibility that the slope coefficient may be state-dependent, which maybe a source of non-linearity. This motivation for state-dependence of the slope coefficient has roots in the work of Bansal (1997), who proposed a state-dependent regression model of the following form:

$$gS_{it} = \alpha_0 + \alpha_1^+ FP_{it}^+ + \alpha_2^- FP_{it}^- + \varepsilon_{it+1}, \tag{3}$$

where FP_{it}^+ and FP_{it}^- are defined as follows:

$$FP_{it}^+ = \begin{cases} FP_{it} & \text{if } FP_{it} > 0 \\ 0 & \text{if } FP_{it} \leq 0 \end{cases}, \tag{4}$$

$$FP_{it}^- = \begin{cases} FP_{it} & \text{if } FP_{it} \leq 0 \\ 0 & \text{if } FP_{it} > 0 \end{cases}. \tag{5}$$

The variables, FP_{it}^+ and FP_{it}^-, divide the forward premium into two regimes; a regime in which the forward premium is positive and the other in which it is negative. It should be noted that with regression (3) we are able to capture any non-linear relationship between spot returns and forward premium.

3. Data and results

3.1. Data

Our sample contains 36 countries. This choice is based purely on data availability. In choosing the countries, because our approach is based on balanced panel data models, we kept in mind the need to have the same start and end dates for all countries and for all four frequencies. Therefore, while many countries have exchange rate data, they did not meet our proposed modelling requirements. Unfortunately, as a result, these countries were not considered. We use spot exchange rate and forward rates at four frequencies, namely, daily, weekly, monthly and quarterly. This choice is representative of the