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Financial crises and estimation bias in international bond markets

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Abstract

This paper analyses the impact of estimation bias on various international bond markets during recent financial crises, using a unique empirical design. We estimate the Kalman filter over the period 2004-2014 using weekly data from the US and its main trading partners and construct measures of model forecasts, term premia, and risk premia in the presence of estimation bias, and in its absence. We find that the impact of estimation bias was the strongest for all sampled countries during the Global Financial Crisis of 2007-2010, and the ongoing eurozone sovereign debt crisis.

Keywords Financial Crises; Affine term structure model; International bond markets; Estimation bias

JEL Classification G01, G12, E43

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1. Introduction

The past couple decades saw an admittedly large number of crises including the Russian Default Crisis of autumn 1998, Y2K in 2000, the Dot Com Bubble spanning the period 1997-2000, the recent Global Financial Crisis of 2007-2010 and the Eurozone sovereign debt crisis that began in October of 2009 (Bussiere and Fratzscher 2006; Juneja and Pukthuanthong 2015). It is not surprising that much recent work documenting their consequences for financial markets has emerged in the extant literature (e.g., Bowe and Doumta 2001; Forbes and Rigobon 2002; Corsetti, Pericoli, and Sbracia 2005; Inyeob Ji and In 2010; Ivashina and Scharfstein 2010; Kenourigos, Samitas, and Paltalidis 2011; Wang 2014). Recently, authors have also begun to explore consequences for international bond markets (e.g., Dungey, Fry, Gonzάlez-Hermosillo, and Martin 2006; Beetsma, Guiliodori, de Jong, and Widijanto 2013; Philippas and Siriopoulos 2013). Concurrent with this literature, scholars have examined the impact of estimation bias on the empirical performance of models for the dynamics of bond markets (e.g., Dempster and Tang 2011; Bauer, Rudebusch, and Wu 2012; Bauer, Rudebusch, and Wu 2014; Wright 2014; Juneja 2016). Based upon these studies, there is reason to believe that the impact of estimation bias on the dynamics of international bond markets is exacerbated during financial crises. Such bias likely creates patterns of elevated volatility in measures of empirical performance associated with international bond markets and those crisis periods.

The primary focus of this research is to study the impact of estimation bias on the dynamics of international bond markets during recent financial crises. We focus on the US and its main trading partners, Canada, China, the eurozone, Japan, and Mexico; due to the fact that countries that are intimately involved with each other from the perspective of international trade would presumably be characterized by similarities in bond market dynamics.[1] To provide motivation for this selection, we run principal components analysis on zero coupon yields corresponding to each country in our data sample over the period under investigation in the current study; March 5, 2004 through December 12, 2014. Carrying out principal components analysis enables us to extract the

[1] Please see http://www.census.gov/foreign-trade/statistics/highlights/toppartners.html for more information on the total trade between the US and these countries and Eurozone.

main factors driving the variation in interest rates for each country. For each country, only one factor explains the majority of variation in interest rates. 97.73% of the variation in US interest rates can be explained by the first factor. 97.42% of the variation in Mexican interest rates can be explained by the first factor. 97.95% of the variation in interest rates in the eurozone can be explained by the first factor. 94.68% of the variation in Japanese interest rates can be explained by the first factor. 93.03% of the variation in Chinese interest rates can be explained by the first factor, and finally 93.06% of the variation in Canadian interest rates can be explained by the first factor. In Figure 1, we present a time-series plot of the first factor for the US and its main trading partners. Patterns in co-movements across the first principal component of the US and its main trading partners appear to be quite strongly related as the first factor generally has the same shape. In the case of Mexico, its first principal component moves inversely with that of the US. In fact, the correlation coefficient between the first principal component of the US and Mexico is -0.861, while the correlation coefficients between the first principal component and the remaining countries are 0.855 for the eurozone, 0.841 for Japan, -0.064 for China, and 0.897 for Canada. With the exception of China, the time series dynamics of the main factor driving variation in interest rates between the US and its main trading partners are very strongly interrelated. Indeed, the main factor influencing China's interest rates also exhibits similar patterns in co-movements. Byrne, Fazio, and Fiess (2012) study the co-movement in long-term interest rates for eight industrialized countries, including the US, Canada, and Japan, over the period January 1988 through July 2006. They find that yields on government debt at the 10-year maturity for the eight nations included in the sample display a remarkable degree of co-movement that increases toward the end of their sample period, which coincides with the beginning of our sample period. Taken together, Figure 1 and this prior finding suggest that co-movements across factors were especially pronounced during the Global Financial Crisis of 2007-2010 and the ongoing eurozone sovereign debt crisis that began in October 2009. Additionally, these remarkable patterns in co-movements support the notion that the US and its main trading partners are quite similar from the standpoint of bond market dynamics and this provides motivation for the inclusion of these countries in the study.

We carry out our assessment of model accuracy by constructing estimates of three measures; model forecast error, long maturity term premia, and long maturity risk premia and follow the implementation of Juneja (2016) in our empirical design. Therefore, our analysis relies on the data which we believe represents an advantage relative to prior approaches (e.g., Yang and Wang, 2010, Juneja, 2014, Juneja, 2015) which rely on observation or theory (e.g., Dempster and Tang 2011; Bauer, Rudebusch, and Wu 2012). Additionally, we focus exclusively on the class of affine term structure models because it received a large amount of attention in the literature (e.g., Dai and Singleton, 2000, Dejong, 2000, Collin-Dufresne, Goldstein, and Jones, 2008, Christensen, Diebold, and Rudebusch, 2011, Duffee and Stanton, 2012, Hamilton and Wu, 2014).[2]

[2] See Juneja (2014) or Juneja (2016) for an extensive list of studies that focus exclusively on this class of models.

Within the class of affine term structure models, we study the Joslin, Singleton, and Zhu (hereafter, JSZ) normalization, which, due to its formulation in discrete-time, is characterized by ease of implementation, relative to its continuous time, observationally equivalent specifications (e.g., Joslin, Le, and Singleton, 2013, Joslin, Priebsch, and Singleton, 2014). Moreover, it retains all the essential properties of the class of affine term structure models. We begin by reporting the serial correlation in the JSZ normalization, estimated using data from each country, and then proceed with our empirical design. We begin the implementation of our empirical design by pre-whitening each dataset and we compute out-of-sample forecasts, long maturity term premia, and long maturity risk premia using these data. To examine the impact of estimation bias on our three measures of empirical performance, we assume that serial correlation in yields comes from serial correlation in the factors, and use them to introduce serial correlation to the pre-whitened data. Finally, we compute out-of-sample forecasts, long maturity term premia, and long maturity risk premia using these new data. To compute long maturity term premia, we follow Rudebusch, Sack, and Swanson (2007) and for the computation of long maturity risk premia, we follow Cochrane and Piazzesi (2005).

Our results demonstrate that the impact of estimation bias on our measures of empirical performance of the dynamic term structure model of JSZ applied to data from various international bond markets was the strongest during the Global Financial Crisis of 2007-2010. Across each country and for the majority of maturities, percent differences in root mean squared forecast error (RMSFE) are small, but these differences were the largest during the aforementioned crisis. Results were similar for term premia and risk premia. To learn more about the patterns in the magnitudes of such differences, we present plots of the above differences from which we confirm our main finding. We also find that the eurozone displayed the largest and most dramatic changes in their term premia and risk premia in 2013 and 2014. We believe these dramatic changes reflect instability in the eurozone and owe to a lack of confidence about the future of its stability stemming from the eurozone crisis that began at the end of 2009. Finally, we find that among the countries studied, China and Japan are the least impacted by estimation bias from the perspective of term premia and risk premia over the sample period under investigation and this reflects regulatory changes experienced by these countries' financial systems during our sample period.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 describes the empirical analysis and presents the main findings. Finally, Section 4 concludes.

2. Data

Our data derives from end of week EURIBOR, government bills, and swap contracts spanning the period December 31, 1998 through March 6, 2015. Weekly government bills for the US, Mexico, Canada, Japan, and China along with EURIBOR rates were collected at the six-month maturity. End of week swap quotes for each country and the euro were obtained at maturities of 1 year, 2 years, 3 years, 5 years, 7 years, and 10 years. Our initial datasets were collected from Bloomberg database via Wells Fargo Financial Markets Laboratory at San Diego State University. Using exclusively US data, Juneja (2016) finds that estimation bias is an issue at the daily, weekly, and monthly frequencies, although it is least impactful for the monthly frequency, followed by the weekly frequency. For this reason, initially, we considered using data at the monthly frequency; however, employing data at the monthly frequency would have led us to around 100 observations for each country. Thus, we chose to study data at the weekly frequency. After merging the data and eliminating missing observations, each final dataset consisted of 476 weekly observations spanning the period March 5, 2004 through December 12, 2014. From our swap quotes and Government Bills (or EURIBOR in the case of the eurozone), we extrapolated zero coupon yields assuming constant forward rates between maturities. Means for extrapolated zero coupon yields are displayed in Table 1.[3]

As mentioned above, the focus of our study is on differences in the impact of estimation bias, as assessed through the serial correlation in measurement errors, on the empirical performance of the dynamic affine term structure model of JSZ applied to data from various countries and the Eurozone. As such, we begin by documenting serial correlation coefficients obtained from estimating the JSZ normalization of affine term structure models using the data described in Section 2 above. Our approach for extracting serial correlation coefficients follows directly from Dempster and Tang (2011) who estimate first order vector auto-regressive coefficients corresponding to the residuals constructed as the difference between the actual yield and the model-implied yield. We refer the interested reader to that study for more details. Serial correlation coefficients for each maturity and country are displayed in Table 2. Serial correlation coefficients are quite large for each country and so serial correlation is an issue for each group in our sample.

3. Empirical Analysis

In Section 2, we documented that serial correlation is an issue for each country. Here, we examine the economic implications of serial correlation for the model accuracy of the JSZ normalization estimated using the data described in Section 2 beginning with a brief overview of the JSZ normalization.

[3] For brevity, we only report the mean. Other descriptive statistics are available upon request from the author.

3.1 An Overview of the Model Used in this Study

Within the Gaussian setting, JSZ develop a normalization of the class of affine term structure models of Duffie and Kan (1996) in which pricing factors are taken to be portfolios of yields instead of latent factors consistent with the original specification. To provide an overview of the development of their representation, we start with the following discrete-time characterization of the factors (state vector) $C_t \epsilon R^N$:

$$\Delta C_t = \kappa_{OC}^{\mathbb{P}} + \kappa_{1C}^{\mathbb{P}} C_{t-1} + \Sigma_C \epsilon_t^{\mathbb{P}}, \quad \text{Eq. (1)}$$

$$\Delta C_t = \kappa_{OC}^{\mathbb{Q}} + \kappa_{1C}^{\mathbb{Q}} C_{t-1} + \Sigma_C \epsilon_t^{\mathbb{Q}}, \quad \text{Eq. (2)}$$

$$r_t = \rho_{OC} + \rho_{1C} C_t. \quad \text{Eq. (3)}$$

Here, r_t is the one-period spot rate, $\Sigma_C \Sigma_C^T$ is the conditional covariance matrix of C_t, and $\epsilon_t \sim N(0, I_N)$. Given the system in Eq. (1) to Eq. (3), prices for a zero coupon yield of maturity m are given by

$$D_{t,m} = E_t^Q \left[e^{-\sum_{i=0}^{m-1} r_{t+i}} \right] = e^{A_m + B_m C_t} \quad \text{Eq. (4)}$$

Taking the natural logarithm of Eq. (4) enables us to obtain an expression for zero-coupon yields as shown in Eq. (5) below

$$y_t = A_m + B_m C_t \quad \text{Eq. (5)}$$

where, (A_m, B_m) satisfy the well-known Riccati difference equations

$$A_{m+1} - A_m = \kappa_0^{\mathbb{Q}'} B_m + \frac{1}{2} B_m' H_o B_m - \rho_0 \quad \text{Eq. (6)}$$

$$B_{m+1} - B_m = \kappa_1^{\mathbb{Q}'} B_m - \rho_1, \quad \text{Eq. (7)}$$

subject to the initial conditions $A_0 = 0$ and $B_0 = 0$. The loadings for the corresponding bond yields are $a_m = -A_m/m$ and $b_m = {}^{-B_m}/_{m}$. The parameters used for pricing are

$\Theta_C^{\mathbb{Q}} = \left(\kappa_0^{\mathbb{Q}}, \kappa_1^{\mathbb{Q}}, \Sigma_C, \rho_0, \rho_1\right)$.

We can apply invariant transformations to the system given by Eq. (1) to Eq. (3) (See, e.g., Dai and Singleton (2000), Joslin, Singleton, Zhu (2011)), to replace the original risk factors with portfolios of yields P_t, and the $\mathbb{Q}$-distribution (risk-neutral) of P_t can be fully characterized by $\Theta_{\mathrm{P}}^{\mathbb{Q}} = \left(k_\infty^{\mathbb{Q}}, \lambda^{\mathbb{Q}}, \Sigma_{\mathrm{P}}\right)$.[4] The parameters of the $\mathbb{P}$-distribution (historical) are $(\kappa_{OP}^{\mathbb{P}}, \kappa_{1P}^{\mathbb{P}})$ and Σ_{P}. The system is given by

$$\Delta P_t = \kappa_{OP}^{\mathbb{P}} + \kappa_{1P}^{\mathbb{P}} P_{t-1} + \Sigma_P \epsilon_t^{\mathbb{P}}, \qquad \text{Eq. (8)}$$

$$\Delta P_t = \kappa_{OP}^{\mathbb{Q}} + \kappa_{1P}^{\mathbb{Q}} P_{t-1} + \Sigma_P \epsilon_t^{\mathbb{Q}} \qquad \text{Eq. (9)}$$

$$r_t = \rho_{OP} + \rho_{1P} P_t; \qquad \text{Eq. (10)}$$

where, $\left(\kappa_{OP}^{\mathbb{Q}},\ \kappa_{1P}^{\mathbb{Q}},\ \rho_{OP},\ \rho_{1P}\right)$ are analytical (i.e. closed-form) functions of $\left(k_\infty^{\mathbb{Q}}, \lambda^{\mathbb{Q}}, \Sigma_{\mathrm{P}}\right)$ owing to the invariant transformations. If we define $P_t = \mathrm{w}y_t$, then using Eq. (5),

$$P_t = wA_m + wB_m C_t \qquad \text{Eq. (11)}$$

We can express Eq. (11) in terms of C_t by solving for it

$$wB_m C_t = P_t - wA_m$$

$$C_t = (wB_m)^{-1}(P_t - wA_m)$$

Using this form for Eq. (11) will allow us to substitute the original risk factors with portfolios of yields. Taking differences of both sides of Eq. (11), substituting in Eq. (2), and simplifying,

$$\Delta P_t = wB_m \Delta C_t$$

$$= wB_m\left(\kappa_{OC}^{\mathbb{Q}} + \kappa_{1C}^{\mathbb{Q}} C_{t-1} + \Sigma_C \epsilon_t^{\mathbb{Q}}\right)$$

[4] If C is stationary under $\mathbb{Q}$, then r_∞^Q and k_∞^Q are related in the following way: $r_\infty^Q = k_\infty^Q \left[\sum_{i=1}^{m_1}\left(-\lambda_1^{\mathbb{Q}}\right)^{-i}\right]$. If m_1=1, then λ_1^Q is not a repeated root of the Jordan form of κ_{1G}^Q and r_∞^Q is simply $\frac{-k_\infty^Q}{\lambda_{\mathbb{Q}}^1}$ for any stationary model. For the purposes of the current study, as this is the case, we follow JSZ (2011) and estimate their model using r_∞^Q because of its intuitive economic meaning.

$$= wB_m\left(\kappa_{OC}^{\mathbb{Q}} + \kappa_{1C}^{\mathbb{Q}}\left((wB_m)^{-1}(P_{t-1} - wA_m)\right) + \Sigma_C\epsilon_t^{\mathbb{Q}}\right)$$

$$= wB_m\kappa_{OC}^{\mathbb{Q}} - wB_m\kappa_{1C}^{\mathbb{Q}}(wB_m)^{-1}wA_m + wB_m\kappa_{1C}^{\mathbb{Q}}(wB_m)^{-1}P_{t-1} + wB_m\Sigma_C\epsilon_t^{\mathbb{Q}}$$

$$= wB_m(\kappa_{OC}^{\mathbb{Q}} - \kappa_{1C}^{\mathbb{Q}}(wB_m)^{-1}wA_m) + wB_m\kappa_{1C}^{\mathbb{Q}}(wB_m)^{-1}P_{t-1} + wB_m\Sigma_C\epsilon_t^{\mathbb{Q}}$$

$$= -wB_m\kappa_{1C}^{\mathbb{Q}}(wB_m)^{-1}wA_m + wB_m\kappa_{1G}^{\mathbb{Q}}(wB_m)^{-1}P_{t-1} + wB_m\Sigma_C\epsilon_t^{\mathbb{Q}}$$

$$= \kappa_{OP}^{\mathbb{Q}} + \kappa_{1P}^{\mathbb{Q}}P_{t-1} + \Sigma_P\epsilon_t^{\mathbb{Q}}$$

The last line is Eq. (9) and within this expression $\kappa_{1P}^{\mathbb{Q}} = wB_m\kappa_{1C}^{\mathbb{Q}}(wB_m)^{-1}$, $\kappa_{OP}^{\mathbb{Q}} = -wB_m\kappa_{1C}^{\mathbb{Q}}(wB_m)^{-1}wA_m = -\kappa_{1P}^{\mathbb{Q}}wA_m$, and $\Sigma_P = wB_m\Sigma_C$. JSZ set $\kappa_{OC}^{\mathbb{Q}}$=0 within their normalization and this fact is used to arrive at Eq. (9) above. To write Eq. (3) in terms of portfolios of yields as presented in Eq. (10), we would follow steps similar to those provided above. Beginning from Eq. (3), following definitions made by JSZ for their normalization, and substituting in Eq. (11)

$$r_t = \rho_{OC} + \rho_{1C}C_t$$

$$= r_\infty^{\mathbb{Q}} + 1'C_t$$

$$= r_\infty^{\mathbb{Q}} + 1'((wB_m)^{-1}(P_t - wA_m))$$

$$= r_\infty^{\mathbb{Q}} - 1'((wB_m)^{-1}\, wA_m + 1'((wB_m)^{-1}P_t$$

$$= \rho_{OP} + \rho_{1P}P_t$$

The last line is Eq. (10) and within it $\rho_{OP} = r_\infty^{\mathbb{Q}} - 1'((wB_m)^{-1}\, wA_m$ and $\rho_{1P} = 1'((wB_m)^{-1}$. Finally, model implied yields are given by

$$y_t = A_P + B_pP_t, \qquad \text{Eq. (13)}$$

where, $\left(A_p, B_p\right)$ are explicit functions of (A_m, B_m). To see this, we begin from Eq. (5),

$$y_t = A_m + B_mC_t$$

$$= A_m + B_m\left((wB_m)^{-1}(P_t - wA_m)\right)$$

$$= A_m - B_m(wB_m)^{-1}wA_m + B_m(wB_m)^{-1}P_t$$

$$= A_P + B_p P_t$$

Again, we substitute Eq. (11) and define $A_P = A_m - B_m(wB_m)^{-1}wA_m$ and $B_p = B_m(wB_m)^{-1}$. As implied above, to implement this normalization, we also need to estimate $r_\infty^{\mathbb{Q}}$, the long-run mean of the short-term interest rate under $\mathbb{Q}$; λ^Q, the speed of mean reversion of the factors under $\mathbb{Q}$; and Σ_P, the conditional covariance matrix of factors. While these are considered to be "free" parameters, fairly precise initial conditions for a full-blown maximum likelihood estimation of Σ_P can be obtained using ordinary least squares. For more details on the background of the JSZ normalization, see JSZ (2011a; 2011b; 2011c).

3.2 Overview of Empirical Design

To assess the effects of estimation bias on our measures of model accuracy, we devise an empirical design in which we begin by pre-whitening each dataset through conducting the following steps. We begin by applying an Akaike information criterion to determine the optimal lag length for each country, which is one. Then, we run a vector auto regression of order one for each yield and take the pre-whitened yield to be the residual component from each regression. The reason we pre-whiten the data is to obtain a baseline dataset, which is free of serial correlation bias. The pre-whitening procedure has been used by several authors (e.g., Engle, 2011, Qu, 2011, Chau, Deesomsak, and Wang 2014; Müller, 2014).[5] To introduce the effects of serial correlation, we assume that serial correlation in the yields obtains from serial correlation in the factors and employ principal components analysis to construct factors. Then, we run a first order vector auto

[5] Prewhitening has also been used quite extensively in the natural sciences (e.g., Yue and Wang, 2002, Rodionov, 2006, Bayazit and Onoz, 2009, Hamed, 2009).

regression using ordinary least squares for each factor and keep the fitted residual. Finally, we add the fitted residual to the pre-whitened yields to obtain the dataset contaminated with serial correlation bias.

3.2 Root Mean Squared Forecast Error

We examine the impact of estimation bias on the root mean squared forecast error (RMSFE) constructed using the data described in Section 2. An accurate computation of out-of-sample forecasts of interest rates is of great interest to economists, investors, and policymakers, because among other things, it can enable them to predict major economic events-including financial crises (e.g., Ghysels and Wright, 2009, Rudebusch and Williams, 2009). However, estimation bias can contribute to our inability to obtain accurate forecasts for interest rates and such biases would create disparity in the forecasts of these variables. The empirical design we present here detects resultant differences in interest rate forecasts in order to uncover patterns in such disparities around financial crises.

We present out-of-sample forecast errors for the JSZ normalization estimated using data from the US and its main trading partners described in Section 2 in Table 3. The column headed "Absence of Serial Correlation" in Table 3 presents the RMSFE in basis points corresponding to the estimation of data that are free of serial correlation. The column headed "presence of serial correlation" in Table 3 below presents the RMSFE in basis points corresponding to the dataset with serial correlation. For each country and bond maturity, the results in Table 3 indicate that absolute differences in out-of-sample forecasting error are quite small. The majority of differences in RMSFE in Table 3 are less than five basis points.[6]

[6] We also follow Joslin, Singleton, and Zhu (2011) and compute percentage differences in RMSFE. From these computations, we find that 2/3 of the entries in Table 3 are below 10%. These differences are available upon further request.

All of the RMSFEs presented in Table 3 are obtained from a Kalman filter based estimation of the JSZ normalization. To form the state vector, we run principal components analysis on all seven yields to extract factor loadings. Then, we take the 6-month government bill (or EURIBOR in the case of the Eurozone), 2-year government bond, and 10-year government bond for the formation of the portfolios of yields. These portfolios are taken to be the state vector. Our assessment of serial correlation on RMSFE begins with the division of the dataset into two parts. We estimate the JSZ normalization using the first half of the dataset. This corresponds to the period March 5, 2004 through February 6, 2009. We leave the second half of the dataset for the construction and evaluation of out-of-sample forecasts and this corresponds to February 27, 2009 through December 12, 2014.

The period of our evaluation contains both the Global Financial Crisis (2007-2010) and the ongoing eurozone sovereign default crisis. Thus by evaluating patterns in the difference in interest rate forecasts across the aforementioned bond markets during these periods, we attempt to obtain insight into patterns in the impact of estimation bias across these markets during recent financial crises. We present plots of the RMSFE differences for the 10-year yield in Figure 2.[7] Panel A of Figure 2 contains these differences for the US. The largest RMSFE difference for the US is 117.01 basis points and it occurred on July 17, 2009. The smallest difference for the US is -165.6 basis points and it occurred on August 14, 2009. Both of these dates were during the Global Financial Crisis of 2007-2010. On the whole, the plot supports the conclusion that the largest differences in

[7] We also plot these differences for the other maturities studied in this paper. The plots provide similar economic implications. For brevity, we exclude these plots from our final reported results. They are available upon request.

RMSFE were during the Global Financial Crisis of 2007-2010 implying that the impact of serial correlation on RMSFE for the US was the strongest over this period. Panel B of Figure 2 contains the RMSFE differences for China. The largest RMSFE difference for China is 74.58 basis points and it occurred on May 29, 2009, which was during the Global Financial Crisis of 2007-2010. The smallest RMSFE difference is -72.3 basis points, and it occurred on June 28, 2013 during the European Crisis, which started at the end of 2009. Just as was the case with the US, on the whole, these results support the notion that the impact of serial correlation on RMSFE for China was strongest during the Global Financial Crisis of 2007-2010. Panel C of Figure 2 contains the RMSFE differences for the eurozone. The largest RMSFE difference for the eurozone is 208.37 basis points and this occurred on November 7, 2014 during the European Crisis. The smallest RMSFE difference occurred the week before, on October 31, 2014, and this also occurred during the European Crisis. Unlike the US and China, this plot supports the idea that the impact of serial correlation on RMSFE has been quite strong not only during the Global Financial Crisis of 2007-2010 but also between February 2011 and February 2012 and during the months of October and November 2014. These facts taken together speak to the instability of the eurozone as a group over much of our sample period. Panel D of Figure 2 contains the RMSFE difference for Japan. The largest RMSFE difference for Japan is 68.43 basis points and this occurred on November 7, 2014. The smallest RMSFE difference occurred the week before this date with a value of -56.3 basis points. Overall, the impact of serial correlation on the RMSFE for Japan was not as strong as it was for the other groups in our sample in regards to the magnitude of impact, but it was strongest during the European Crisis, which started at the end of 2009. Panel E of Figure 2 contains the RMSFE for Mexico. The largest RMSFE difference for Mexico is 182.54 basis points and this occurred on July 3, 2009, while the smallest difference is -225.8 basis points and this occurred on

June 28, 2013. Overall, the impact of estimation bias was very strong during both the Global Financial Crisis of 2007-2010 and the European Crisis. Finally, in Panel F of Figure 2, we plot the RMSFE for Canada. The largest and smallest RMSFE difference of 116.73 basis points and -177.2 basis points occurred on October 9, 2009 and October 31, 2014. The first date occurred during both the Global Financial Crisis of 2007-2010 and the Eurozone Crisis, while the second date was during the Eurozone crisis only. These findings support the notion that the impact of serial correlation on RMSFE was the strongest during these crises. The plot supports these findings.

Overall, the impact of estimation bias was the strongest for all sampled countries, except Japan, during the Global Financial Crisis of 2007-2010. The impact of estimation bias during the Global Financial Crisis was just as strong during the Eurozone crisis for Mexico and Canada. For Japan, it was the strongest during the Eurozone crisis.

3.3 Estimation of Term Premia

In this section, we construct long maturity term premia. Term premia contain important information about the expected path of future short rates (Adrian, Crump, and Moench 2013). Startz (1982) finds that for the one-month Treasury bill rate between one- third and two-thirds of the variation in the difference between forward rates and realized spot rates is due to the variation in term premia. Please see Duffee (2002), Kim and Orphanides (2007) or Jardet, Monfort, and Pegoraro (2013) for additional studies that discuss the importance of estimating term premia in regards to computing and assessing interest rate forecasts. In Table 4, we present some descriptive statistics for the differences in term premia due to estimation bias across bond markets. The results presented in Table 4 are measured in basis points. Figure 3 displays plots of the term premia for each country, over the sample period under study. Our construction of long maturity term premia follows Rudebusch, Sack, and Swanson (2007). Specifically, we calculate the long maturity term premia as the difference between the model-implied 10-year yield and the expected mean of the six-month government bill over the same period.

The results in Table 4 indicate that average differences in term premia for each country are small. For all countries, average differences (in absolute value) are under a basis point. Implications are similar for median differences. Standard deviations are largest for the US, Mexico, and the Eurozone. Indeed, as we can see from Figure 2, the differences in term premia are the most extreme for these countries during the Global Financial Crisis (2007-2010). For the US, the largest difference is 163.745 basis points and this corresponds to October 10, 2008, while the smallest difference is -164.826 basis points and this occurred on August 14, 2009. Both of these values are associated with the Global Financial Crisis of 2007-2010. For China, the differences in term premia are quite large during the Global Financial Crisis. However, the differences are comparably small during the remainder of the sample period. The largest difference in term premia is 94.27 basis points and this occurred on December 7, 2007, while the smallest difference in term premia is -135.182 basis points and this occurred on December 12, 2008. A quick glance at Table 4 tells us that the 95th percentile for the difference in term premia is 37.38 basis points and the 5th percentile is -34.25 basis points. These numbers are arguably smaller than the minimum and maximum. The eurozone has a very large change in term premia between August 2013 and October 2014.[8] Additionally, in 2014, the differences in the term premia corresponding to the Eurozone are very volatile implying that the effects of the serial correlation have recently been substantially exacerbated perhaps owing to the recent increase in the instability of the Eurozone. As was the case with the term premia estimates from China, the 95th and 5th percentiles are much smaller in

[8] When, we merged the datasets from each country and the Eurozone, we lost several data points between August 2013 and October 31, 2014.

magnitude. The largest difference in term premia corresponding to the term premia estimates using data from the eurozone is 186.29 basis points and this occurred on November 7, 2014, while the smallest difference is -237.29 basis points and this occurred on October 31, 2014. From Table 4, the 95th percentile of the difference in term premia is 47.55 basis points while the 5th percentile is -45.06 basis points. Japan displays the smallest standard deviations in the difference between term premia. The largest difference in term premia for Japan is 59.64 basis points and this occurred on November 7, 2014, while the smallest difference is -60.57 basis points and this occurred on May 2, 2008. For Mexico, the largest difference in term premia is 329.24 basis points and this occurred on April 2, 2004. This date is during the Mexican crisis that occurred in 1994-1995 (Bowe and Domuta 2001; Orlov 2009). The smallest difference in term premia is -532.76 basis points and this occurred on October 31, 2008. While only the minimum value occurred during the Global Financial Crisis of 2007-2010 the plot of differences in term premia for Mexico that is displayed in Figure 3 implies that the Global Financial Crisis represents a period over which the impact of estimation bias on the term premia was quite strong for several weeks. Finally, for Canada, the largest difference in term premia is 63.84 basis points and this occurred on May 18, 2007, while the smallest difference in term premia is -83.32 basis points and this occurred on October 31, 2014.

Just as was the case with Mexico, the plot of term premia differences for Canada taken together with this information imply that the impact of estimation bias on the term premia estimates was the strongest over the course of several weeks during the Global Financial Crisis.

Collectively, these results support the conclusions we drew from the estimation of the RMSFE in Section 3.2. Bias in estimates of long maturity term premia caused by serial correlation was not very strong over our sample period. However, during the Global Financial Crisis of 2007-2010 and, to a lesser extent, the ongoing eurozone crisis that started at the end of 2009, the effects of such biases were exacerbated.

3.4 Estimation of Risk Premia

Investigating risk premia across our sample bond markets is useful because they will provide information regarding compensation required for various risks assumed when examining economic fundamentals of international bond markets associated with the countries in our study. The magnitude and impact of risks on economic fundamentals can change during financial crises periods (Beirne and Fratzscher 2013).[9] In this section, we assess how the impact of estimation bias on the risk premia from various international bond markets changes during recent financial crises. We follow Cochrane and Piazzesi (2005) in our construction of long maturity risk premia.[10] Specifically, long maturity risk premia are computed in the same manner as the calculation of long maturity term premia described in the previous sub-section but through the construction of holding period returns over the same time horizons.

[9] Please see Bansal, Tauchen, and Zhou (2004), Cochrane and Piazzesi (2005), or Ludvigson and Ng (2009) for other studies that highlight the importance of studying risk premia.
[10] We adopted the Matlab code from Monika Piazzesi's website http://web.stanford.edu/~piazzesi/ to our data and risk premia construction. Please see Piazzesi (2010) for additional information on the construction of risk premia.

We begin by presenting, in Table 5, descriptive statistics for differences in risk premia measured in basis points. The mean and median differences are quite small for all countries; they are generally much smaller than a basis point. In Figure 4, we present a plot of these risk premia over time. For the US, the largest difference in risk premia is 15.58 basis points and this occurred on October 10, 2008, while the smallest difference of -68.51 basis points occurred on December 12, 2014. The largest difference in risk premia occurred on the same day as the largest difference in term premia, and this date was during the Global Financial Crisis of 2007-2010. The smallest difference in risk premia is associated with the eurozone crisis that has been plaguing the eurozone since the end of 2009. For China, the largest difference in risk premia occurred on July 16, 2004 and is 12.48 basis points, and the smallest difference is -16.90 basis points and this occurred on June 25, 2004. Overall, the plot of the differences in risk premia, which is displayed in Panel B of Figure 4, demonstrates that overall differences in risk are greater during the Global Financial Crisis. For several weeks during this time period, there are large differences in risk premia and the impact of serial correlation on the risk premia was its strongest over this period. For the eurozone, the largest difference in risk premia is 25.99 basis points and it occurred on November 7, 2014, while the smallest difference in risk premia is -31.73 basis points and it occurred on October 31, 2014. The extreme values for the differences in risk premia occur on the same dates as the term premia. Analysis of the risk premia supports analysis of the term premia that the impact of estimation bias is greatest during the eurozone crisis that began at the end of 2009. For Japan, the largest difference in risk premia is 1.69 basis points and it occurred on December 29, 2006. The smallest difference of -6.65 basis points occurred on December 12, 2014. Although the minimum difference is associated with the eurozone crisis, the plot in Panel D of Figure 4 shows that the impact of serial correlation was strongest during the Global Financial Crisis. For Mexico, the largest difference in risk premia is 23.74 basis points and it occurred on April 2, 2004 while the smallest difference in risk premia is -39.02 and it occurred on October 31, 2008. Finally, for Canada, the largest difference in risk premia of 47.22 basis points occurred on October 9, 2009 and the smallest difference in risk premia of -52.23 basis points occurred on October 31, 2014.

Overall, the results from the estimates of risk premia support those associated with the estimates of term premia. The differences in risk premia were strongest during the Global Financial Crisis and to a lesser extent the Eurozone crisis. Furthermore, these differences are especially pronounced in recent years for the US, Mexico, Canada, and the Eurozone. The pronounced differences faced by these countries may be reflecting interrelated risks stemming from instabilities resulting from the current crisis in the Eurozone which began at the end of 2009. China and Japan have the most stable risk premia over the entire sample period, while Canada is characterized by the highest standard deviation, although it is still not very high at only 13 basis points. Figure 4 shows that the high standard deviation in the differences in risk premia associated with Canada reported in Table 5 are not really reflecting any single financial event. The fact that China and Japan have the smallest differences in the presence of serial correlation could be reflecting changes in their respective banking systems occurring during our sample period and how they are regulated. Konishi and Yasuda (2004) find that regulatory changes that took place in the Japanese banking system in the 1990s reduced risk taking by commercial banks. The implication of such regulatory changes is smaller compensation due to the reduction in risky behavior on part of the commercial banks. Garćia-Herrero, Gavilá, and Santabárbara (2009) and Jia (2009) document comprehensive banking system reforms that began in China in 1997 and continue to have an impact on their financial system. Jia (2009) uses data spanning the period 1997-2004 to conclude that such reforms have led to behavior that is more prudent on part of banks within China and that their behavior will continue to become more prudent due, in part, to increased incentives that came about as a result of the banking reform. Observed prudent behavior in a banking system tends to be associated with stable and reduced compensation afforded by affiliated assets.

4. Conclusion

Much recent work has focused on consequences of recent financial crises. In this paper, we have examined how the impact of estimation bias on various measures of model accuracy changes during recent financial crises using data from the US and its main trading partners—Canada, China, the Eurozone, Mexico, and Japan. Our motivation for selecting the US and its main trading partners stems from similarities in the bond market dynamics of these countries. Our objective is to examine the extent to which patterns in the impact of estimation bias on model accuracy are altered in the face of important global economic events or crisis periods. We estimate model forecasts, long maturity risk premia, and long maturity term premia as measures of model accuracy. Motivation for the importance of studying these three measures and their relevance to financial crises were provided in the body of the paper.

Our main findings can be summarized as follows. We find that the impact of estimation bias, as assessed through serial correlation in the measurement errors, on aforementioned accuracy measures was exacerbated during the Global Financial Crisis of 2007-2010 and to a lesser extent the eurozone crisis that began at the end of 2009. While these results were applicable for all countries in our study, we noted that the impact of estimation bias was especially pronounced in recent years for the US, Mexico, Canada, and the eurozone. We believe that this also is due to economic events related to the instability of the eurozone that have been occurring since the end of 2009 with the inception of the eurozone crisis. China and Japan seem to be the least affected by such events. This finding is reflecting that, owing to recent regulatory reform, Japan and China are characterized by different financial systems and relevant regulation channels than the US and the eurozone. Such differences can lead to a diminished impact of events in the eurozone on Asian markets. Overall, our results suggest that the impact of estimation bias on model accuracy is especially pronounced during periods of crisis or important economic events.

In contrast to most studies on this topic, our design relies on the data and not theory or observation and we believe that this represents an advantage of our approach relative to previously completed works. We decided to focus exclusively on the class of affine term structure models due to its wide popularity and usage in the relevant literature. Additionally, our decision to study the discrete-time JSZ normalization of affine term structure models stems from the ease of its implementation relative to its continuous-time, observationally equivalent counterparts. It also retains all of the essential properties of affine term structure models and converges to a global optimum quite quickly.

Finally, our findings leave some important issues unresolved. Our results suggest that the interest rate structures of China and Japan are not as correlated with those interest rate structures affiliated with Western economies. It would be interesting to compare such structures for the ultimate purpose of determining if this lack of correlation in such markets is in fact due to differences in banking and regulatory systems across countries and regions. We leave these ideas to future research.

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Figure 1: Plot of first principal component of the US and its main trading partners

This figure plots the first principal component of the term structure of interest rates for the US and its main trading partners. Principal components are estimated using the data described in Section 2 of the body of the paper.

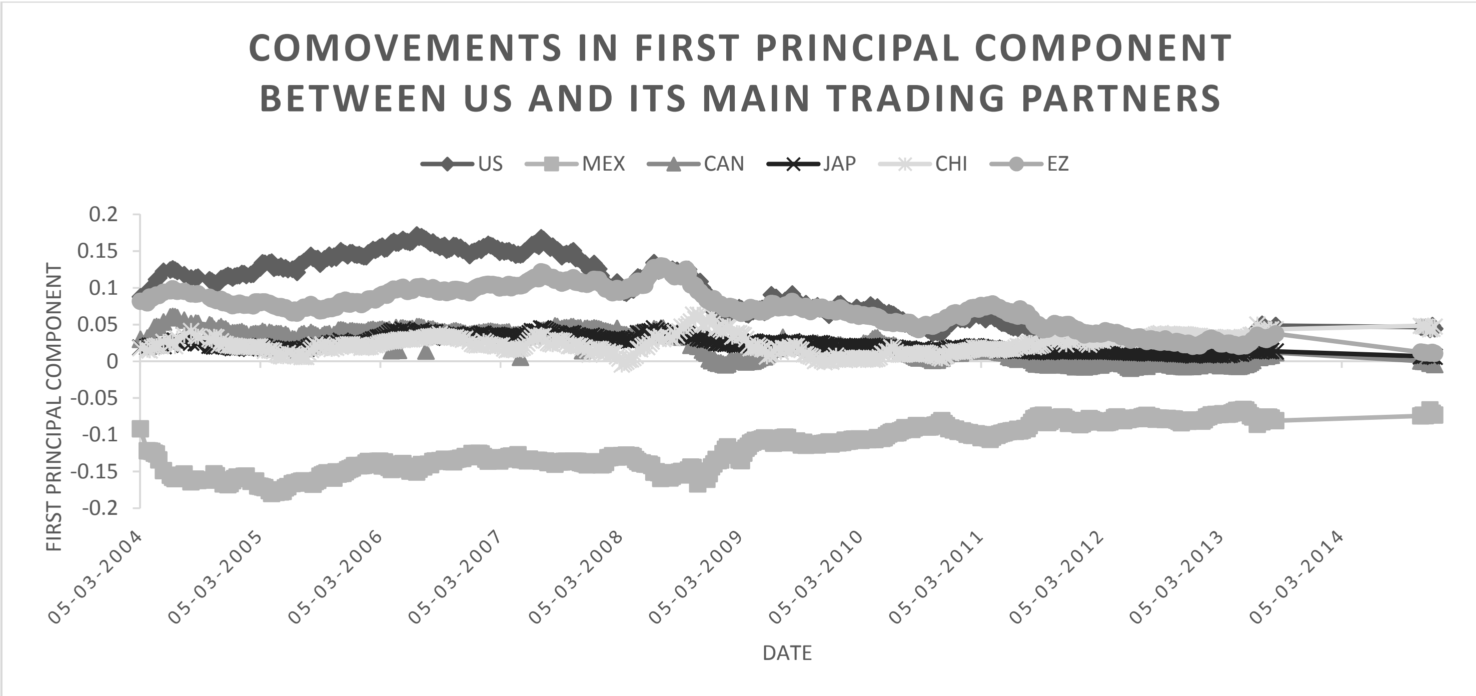
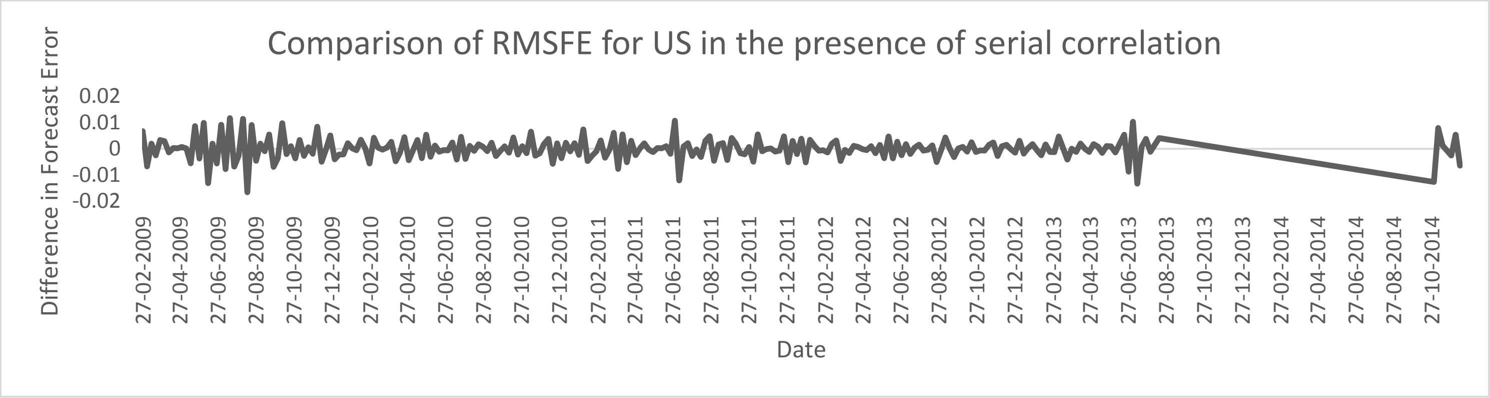


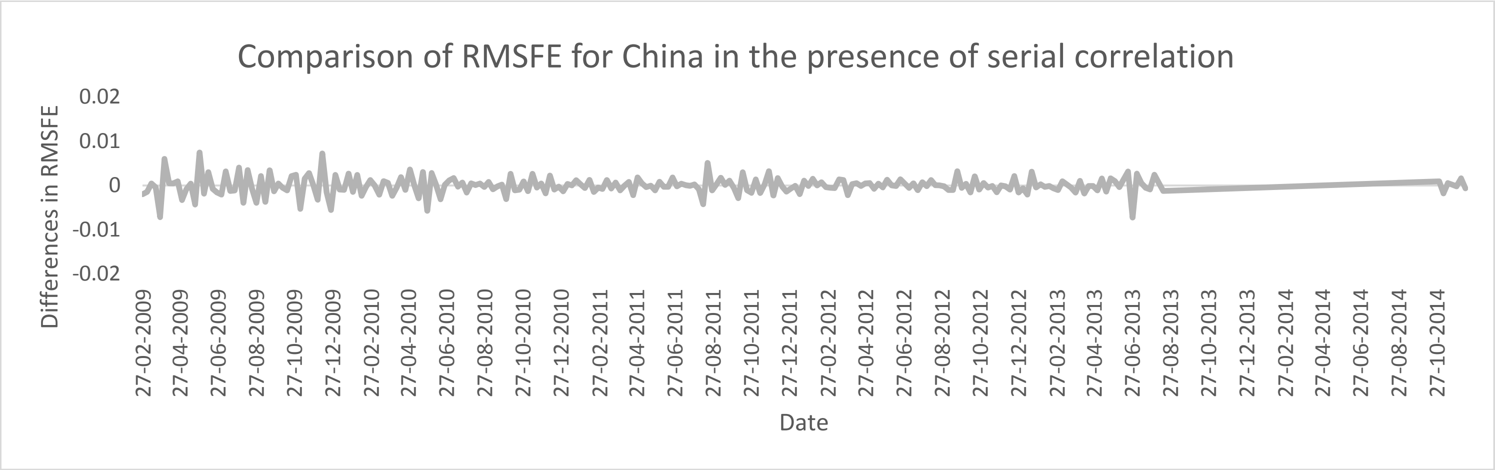
Figure 2: Plot of differences in forecast error for US and its main trading partners

This figure plots differences in root mean squared forecast error (RMSFE) implied by the JSZ normalization. Estimation of differences in RMSFE are computed in regards to before and after the addition of serial correlation and are carried out using the data described in Section 2 of the body of the paper.

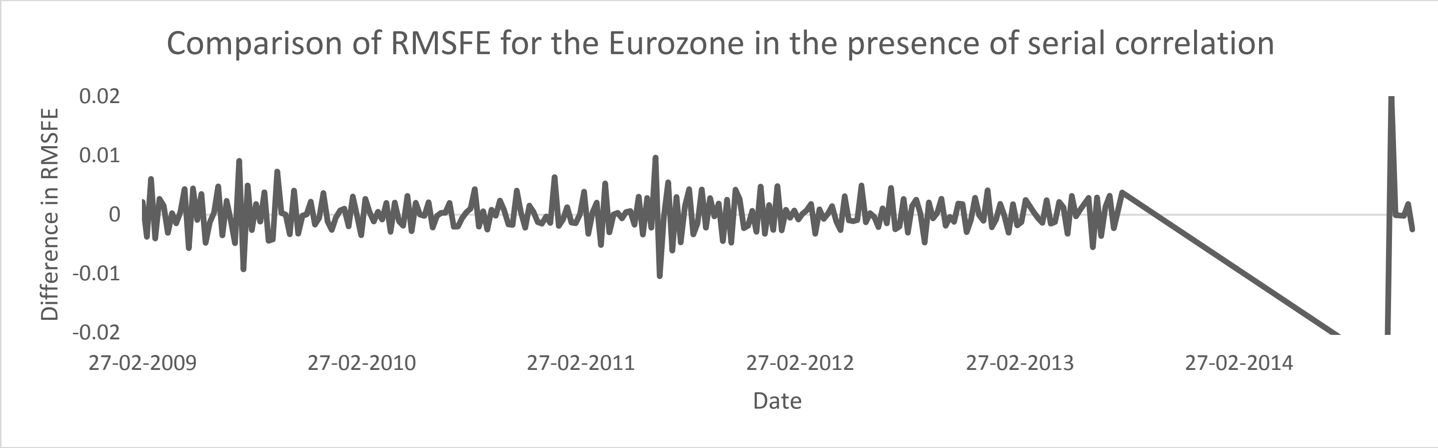
Panel A: US



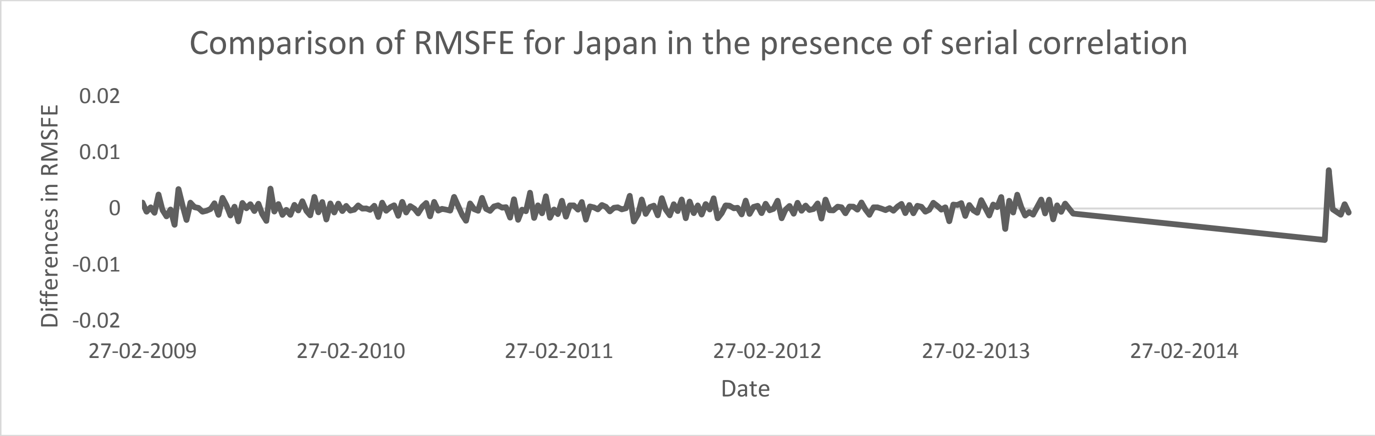
Panel B: China



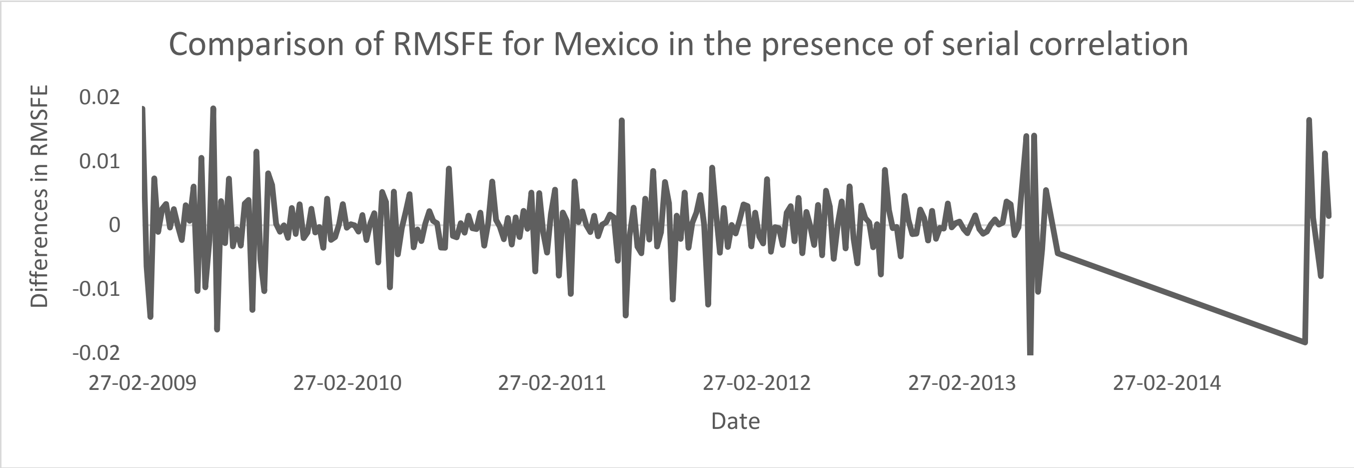
Panel C: Eurozone



Panel D: Japan



Panel E: Mexico



Panel F: Canada

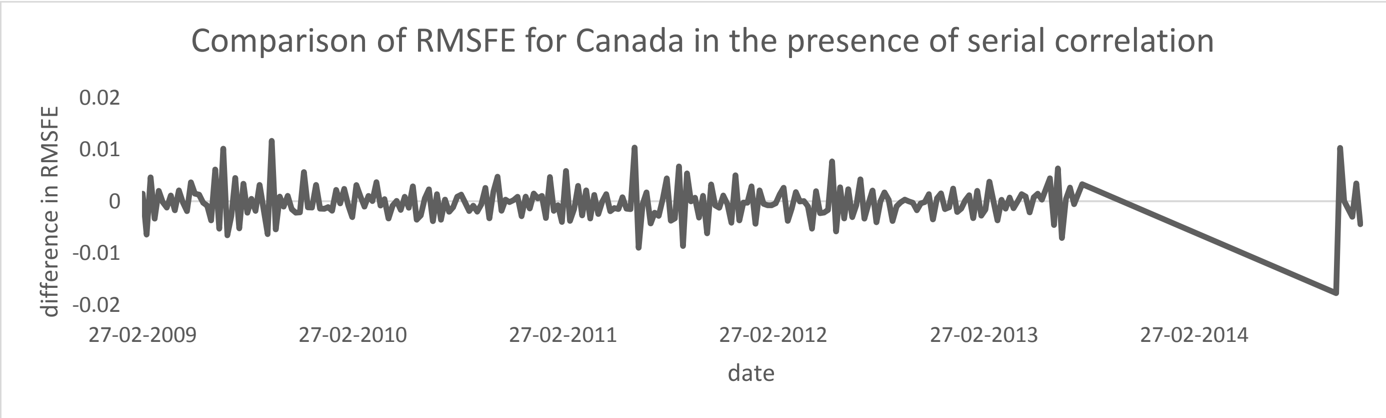
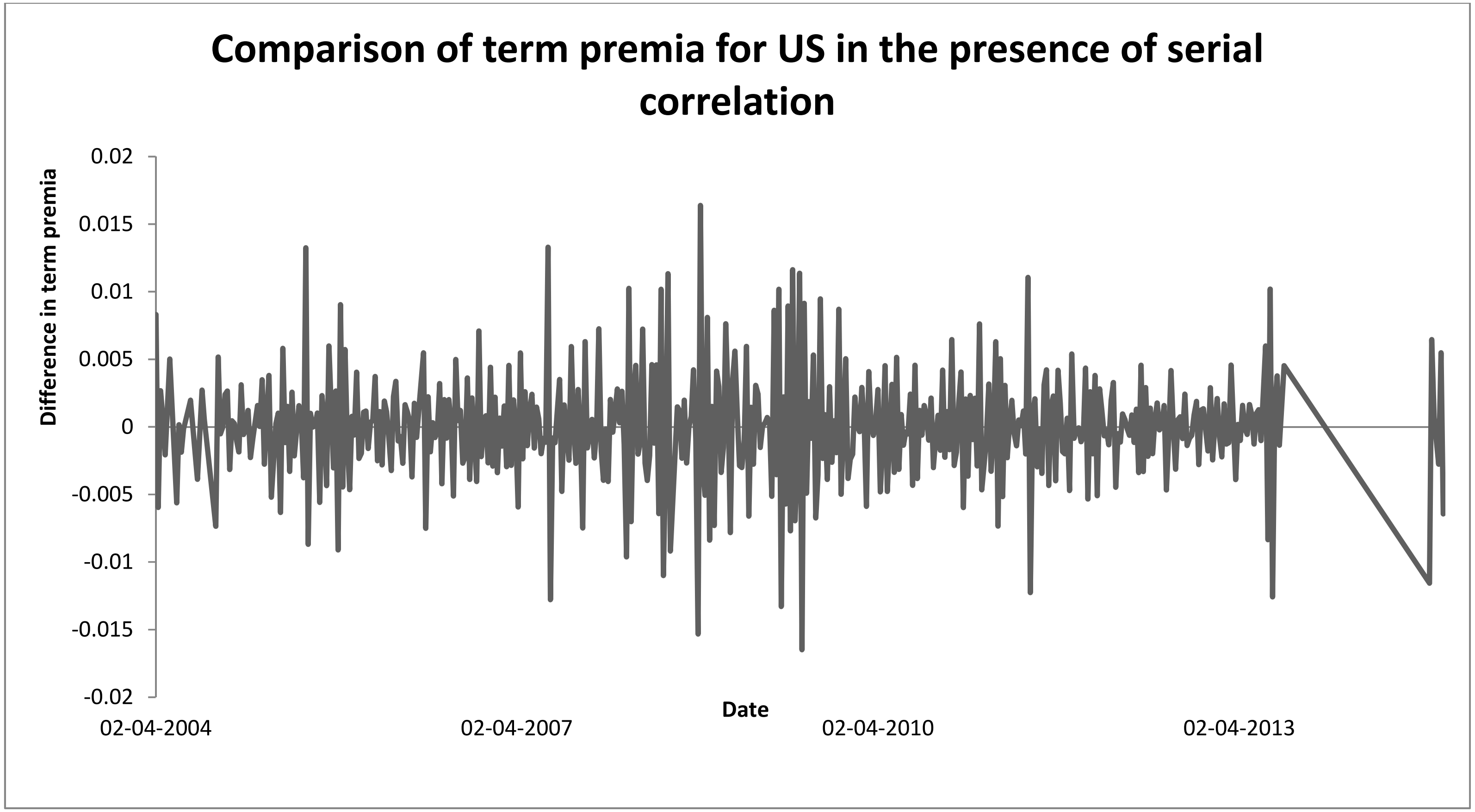


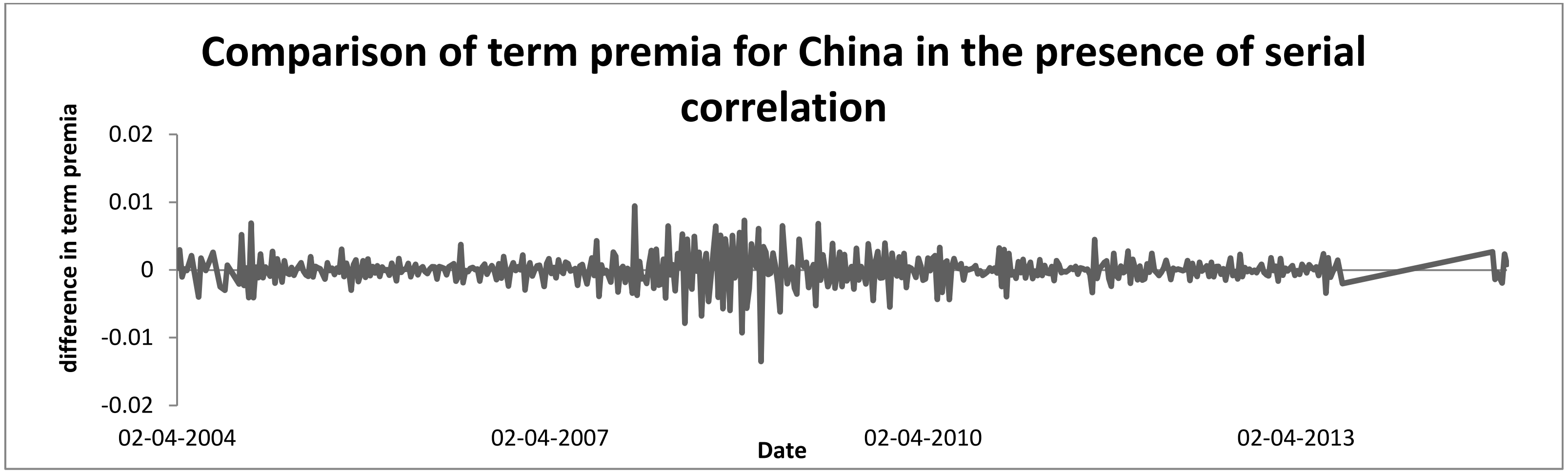
Figure 3: Plot of differences in term premia for US and its main trading partners

This figure plots differences in term premia implied by the JSZ normalization. Estimation of differences in term premia are computed in regards to before and after the addition of serial correlation and are carried out using the data described in Section 2 of the body of the paper. Term premia are computed as described in Section 3 of the body of the paper.

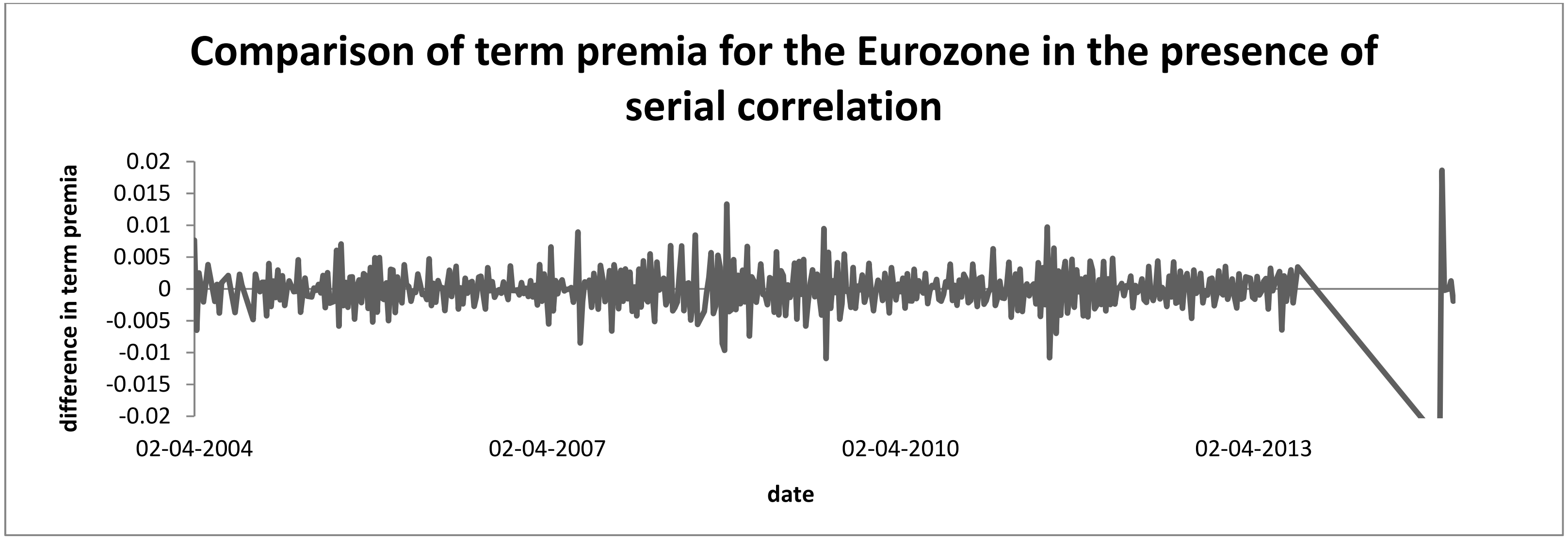
Panel A: US



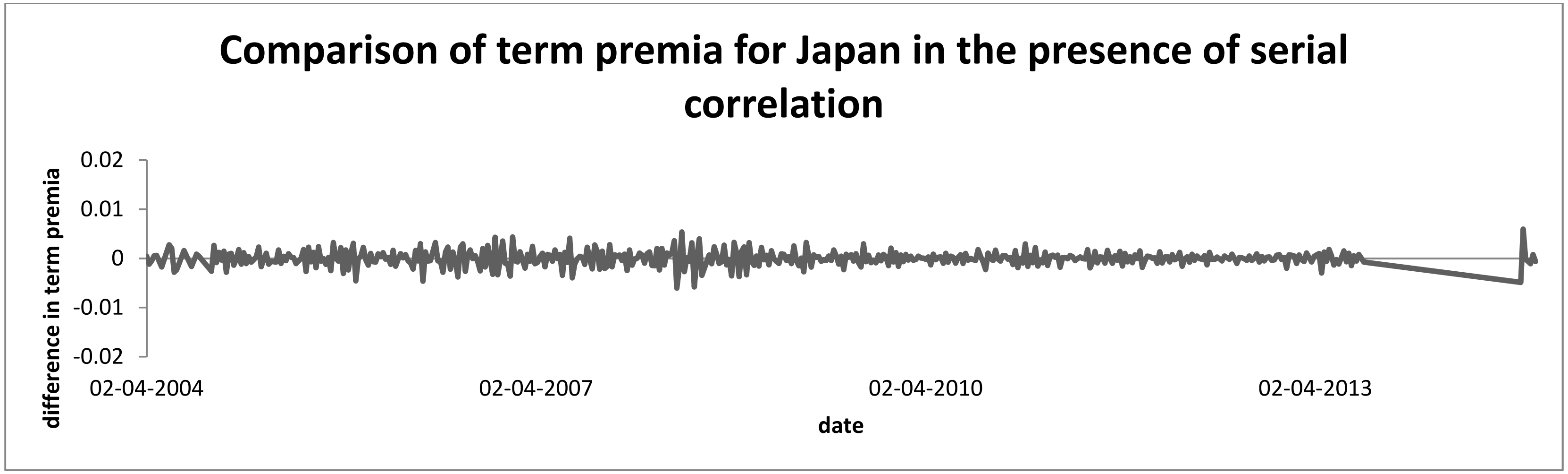
Panel B: China



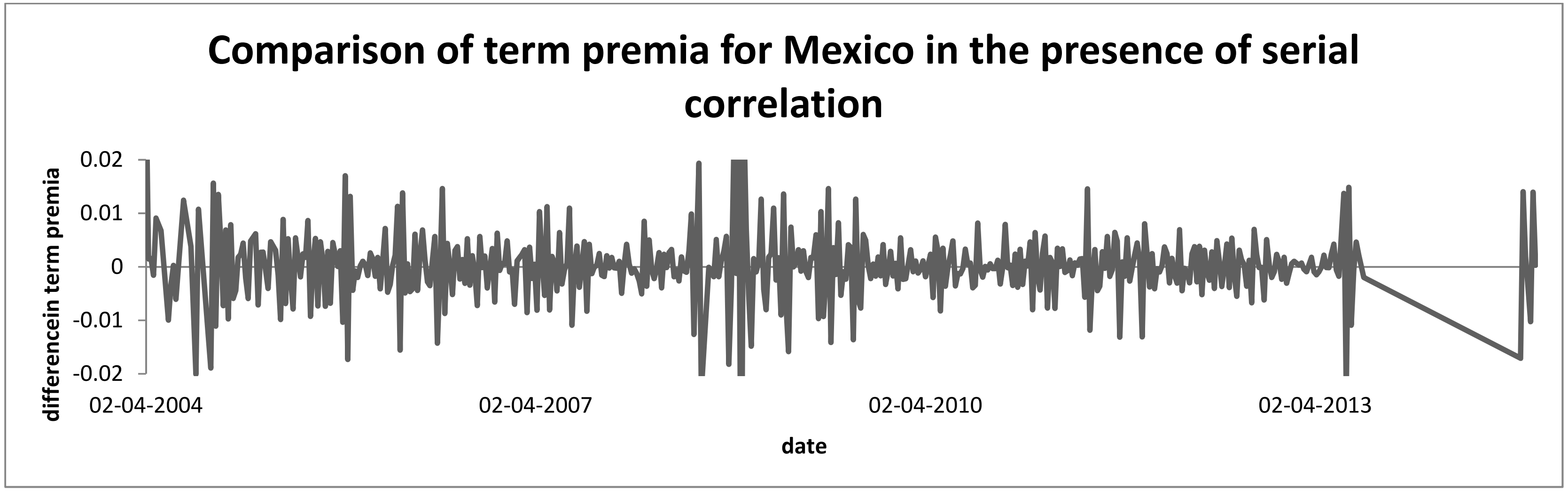
Panel C: Eurozone



Panel D: Japan



Panel E: Mexico



Panel F: Canada

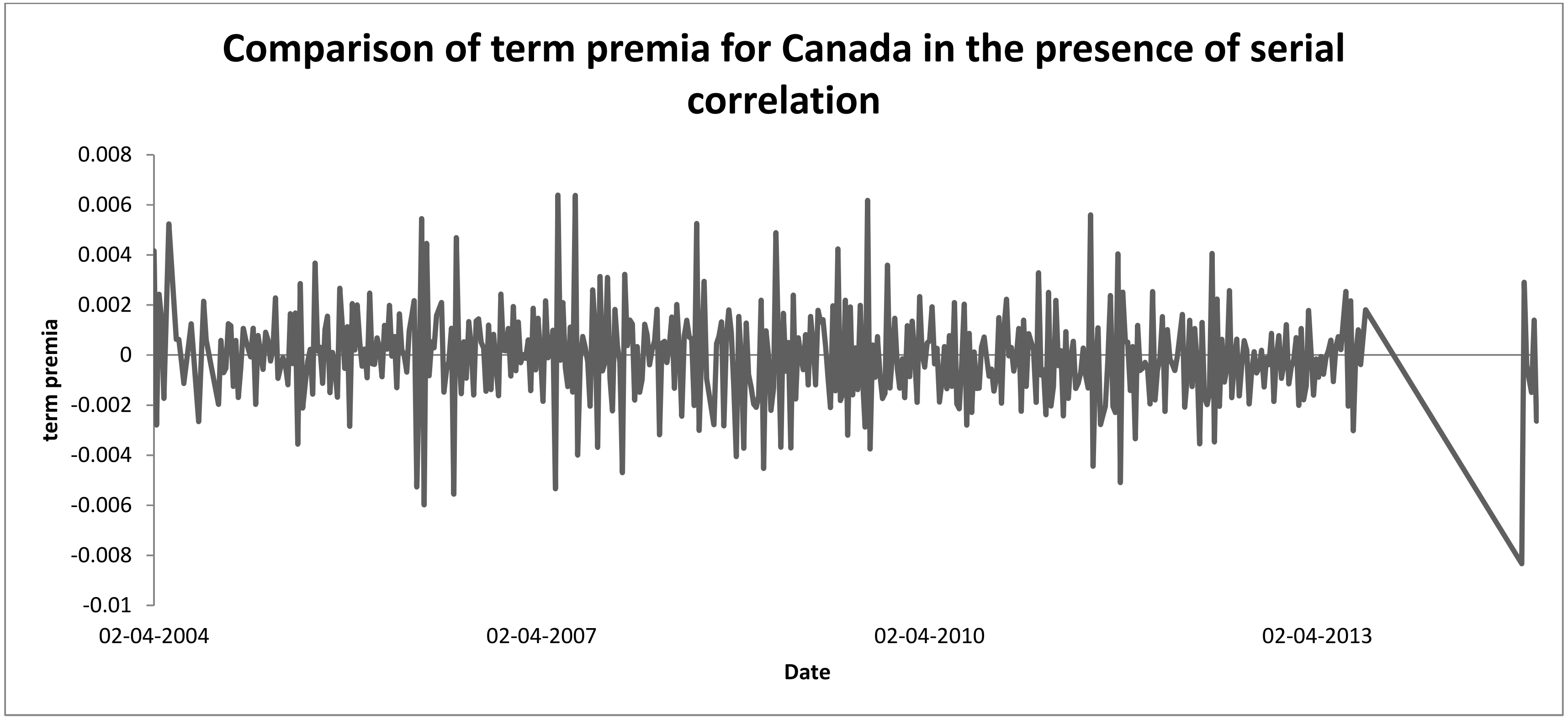
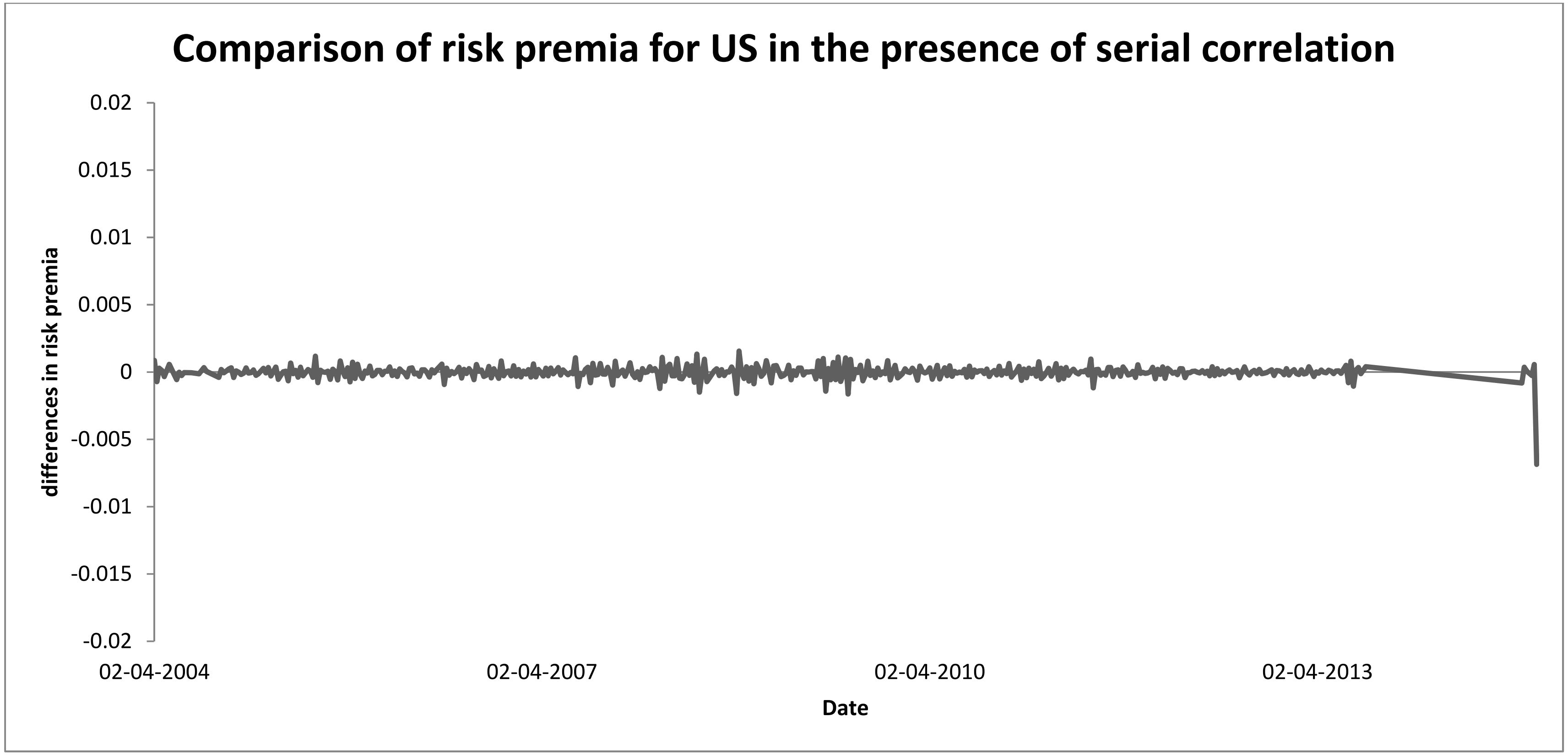


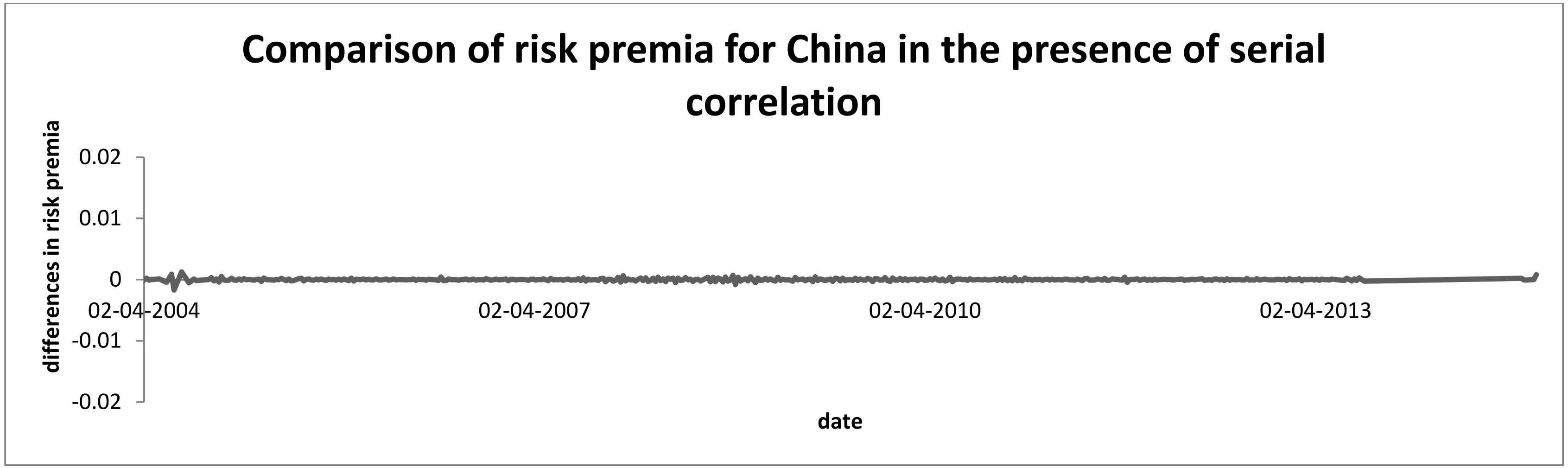
Figure 4: Plot of differences in risk premia for US and its main trading partners

This figure plots differences in risk premia implied by the JSZ normalization. Estimation of differences in risk premia are computed in regards to before and after the addition of serial correlation and are carried out using the actual data described in Section 2 of the body of the paper. Risk premia are computed as described in Section 3 of the body of the paper.

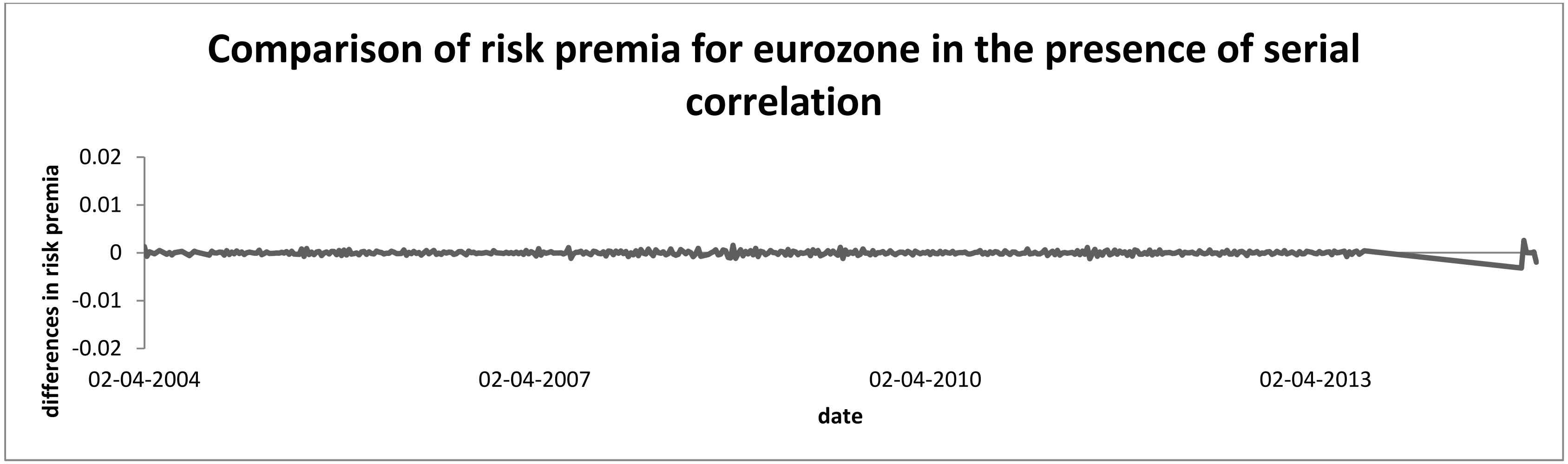
Panel A: US



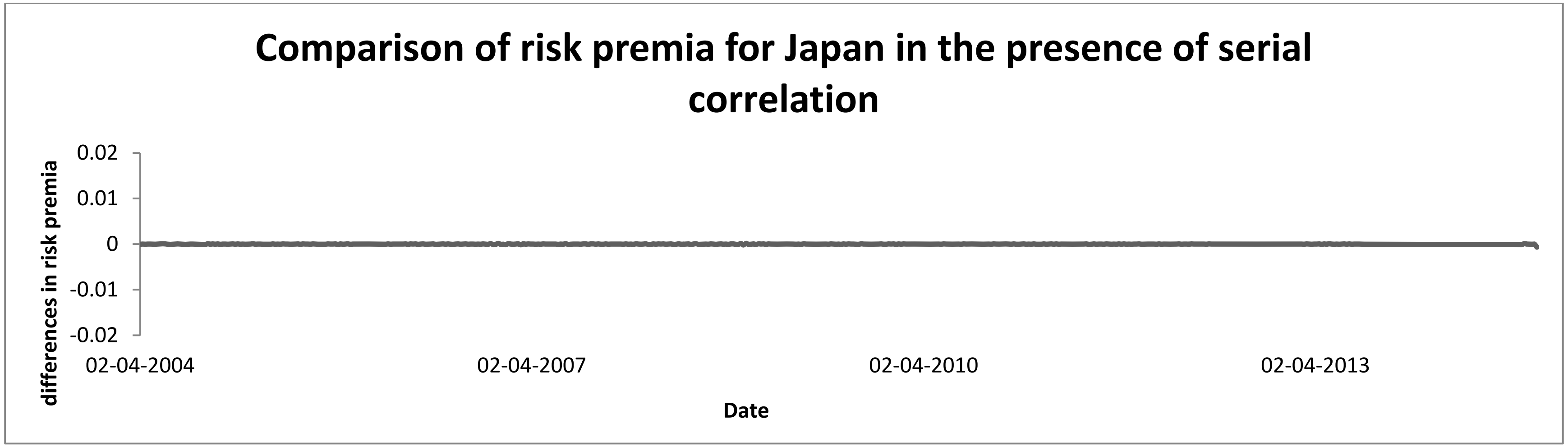
Panel B: China



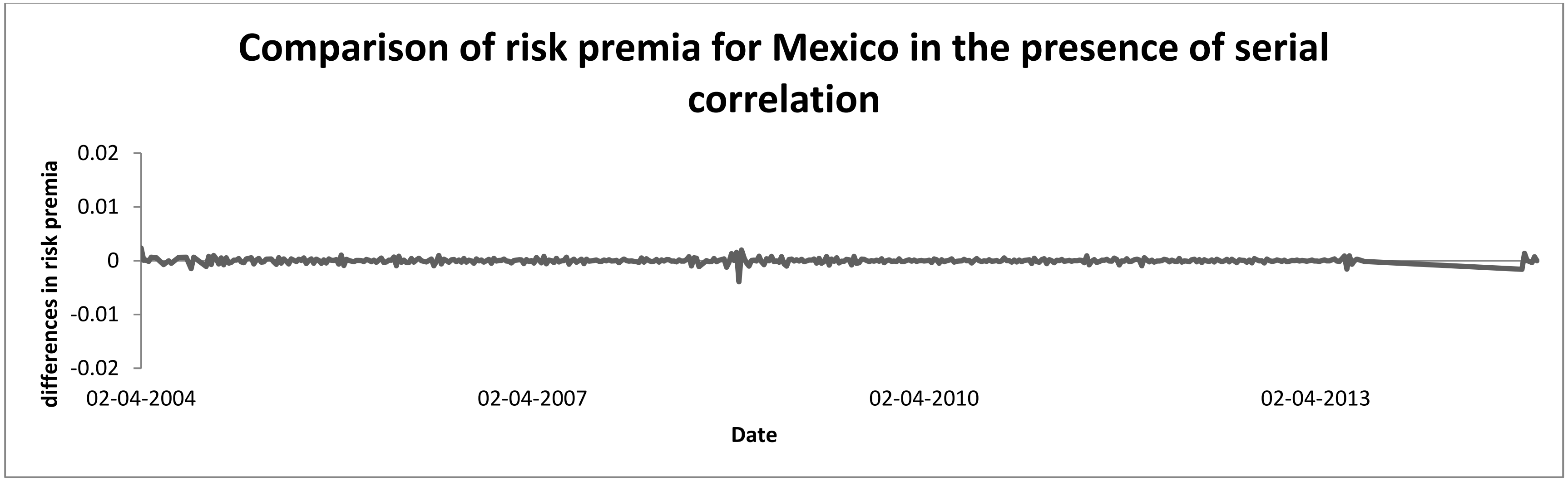
Panel C: Eurozone



Panel D: Japan



Panel E: Mexico



Panel F: Canada

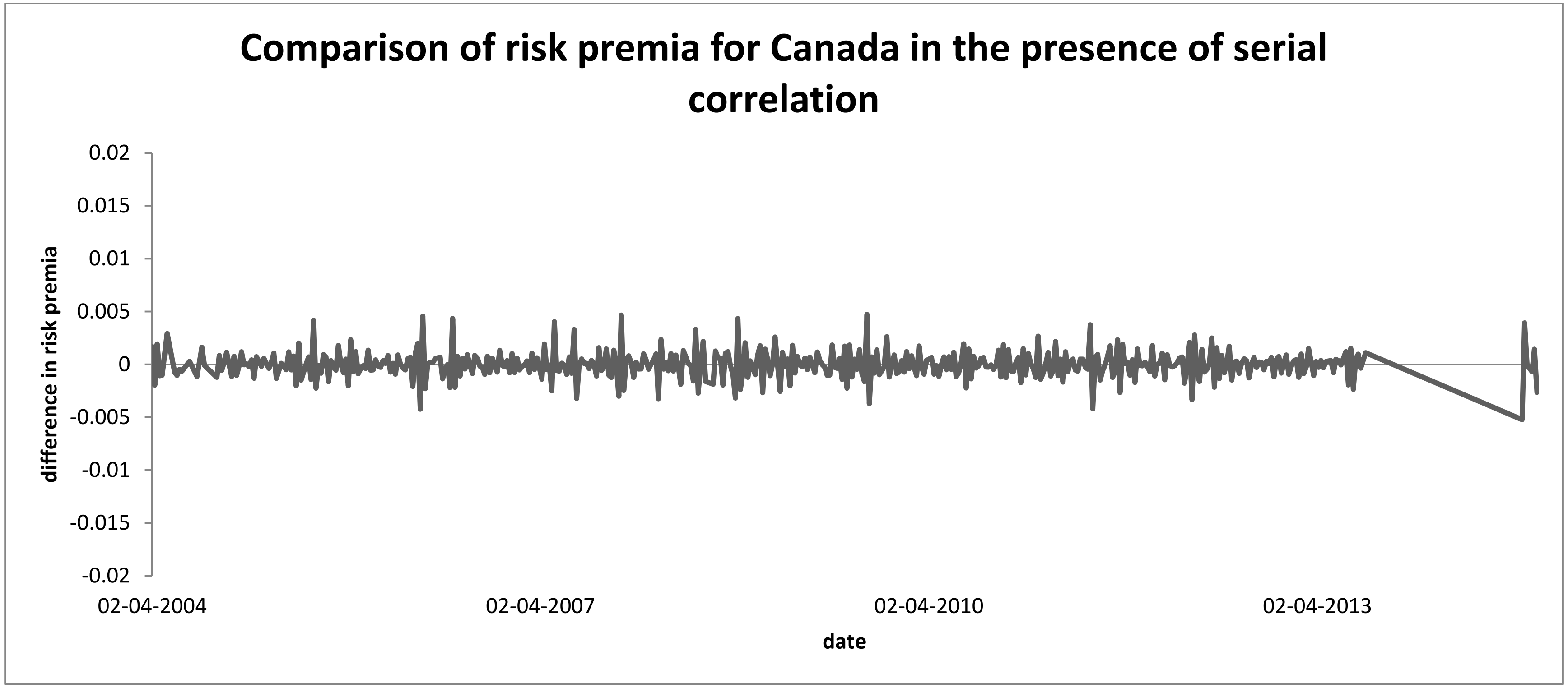


Table 1: Means of Extrapolated Zero Coupon Yields

This table reports descriptive statistics for the zero coupon yields used in this paper. For each country, zero coupon yields were extracted from data on EURIBOR, government bills, and swap contracts collected from Bloomberg over the period March 5, 2004 through December 12, 2014.

Maturities / Countries	6 month	1 year	2 years	3 years	5 years	7 years	10 years
US	0.0175	0.0175	0.0282	0.0403	0.0609	0.0703	0.0678
Canada	0.0202	0.0208	0.0342	0.0440	0.0617	0.0693	0.0656
China	0.0221	0.0213	0.0023	0.0093	0.0271	0.0158	0.0134
Euro Zone	0.0224	0.0226	0.0308	0.0410	0.0583	0.0653	0.0616
Japan	0.0022	0.0022	0.0069	0.0090	0.0144	0.0183	0.0206
Mexico	0.0627	0.0646	0.0880	0.1151	0.1583	0.1721	0.1544

Table 2: Serial Correlation Coefficients in JSZ normalization

This table reports serial correlation coefficients associated with residuals, ξ_t, obtained from the estimation of the JSZ normalization of the class of affine term structure models using the data described in Section 2 of the body of the paper. Serial correlation coefficients are estimated by applying ordinary least squares to the following equation $\xi_t = \rho\xi_{t-1} + \eta_t$ for each maturity.

Maturities / Countries	6 month	1 year	2 years	3 years	5 years	7 years	10 years
US	0.9626	0.9812	0.9419	0.9769	0.9788	0.9765	0.7598
Canada	0.9884	0.9964	0.6313	0.9119	0.9423	0.8425	0.8424
China	0.9797	0.9857	0.8775	0.7167	0.9208	0.9929	0.8064
Euro Zone	0.9694	0.9755	0.8521	0.9503	0.9127	0.8698	0.8934
Japan	0.9469	0.9870	0.9454	0.9069	0.9078	0.7260	0.8962
Mexico	0.8983	0.8835	0.8093	0.9455	0.8730	0.8605	0.6748

Table 3: Comparison of out of sample forecasting error in the presence of serial correlation

This table contains root mean squared forecast errors (RMSFEs) corresponding to yield forecasts obtained from estimating the JSZ normalization in the absence of serial correlation and in its presence using data described in Section 2 of the body of the paper. RMSFEs are measured in basis points.

Absence of Serial Correlation						
	Forecast error (US)	Forecast error (Canada)	Forecast error (China)	Forecast error (Eurozone)	Forecast error (Japan)	Forecast error (Mexico)
6 month	2.0307	4.0022	9.4877	2.6997	1.1646	10.3055
1-year	2.4723	4.4364	11.0160	3.0171	1.1692	13.3244
2-year	7.4090	32.3959	39.6201	8.8942	1.7533	19.0025
3-year	12.7174	16.2715	47.3835	12.8237	2.6961	20.0016
5-year	22.0678	21.1113	59.4228	20.7439	5.1787	30.3832
7-year	27.3950	26.6077	22.6042	25.0064	7.4419	38.2756
10-year	27.1509	24.6880	15.0938	24.3306	8.7365	38.0040
Presence of Serial Correlation						
6 month	2.6394	6.9842	8.6356	4.5193	1.3286	12.0151
1-year	2.4664	7.4105	11.2333	3.1860	1.2075	13.3545
2-year	7.5223	32.2499	40.0252	8.3041	1.4144	20.7072
3-year	11.1380	13.3700	45.2431	11.0716	2.6979	19.5691
5-year	21.3258	20.2725	57.1578	19.8088	5.3118	32.6871
7-year	24.8152	19.3535	21.6709	24.5361	7.2141	37.8726
10-year	25.5764	18.7319	14.0719	22.6353	8.8807	37.8458

Table 4: Comparison of term premia

This table reports descriptive statistics corresponding to differences in term premia. Differences are computed in regards to estimation of term premia before and after the addition of serial correlation using the data described in Section 2 of the body of the paper. Term premia are constructed following Rudebusch, Sack and Swanson (2007). For more details regarding the construction of the term premia, please see Section 3 of the body of the paper. Descriptive statistics for the differences in term premia are measured in basis points.

	mean	Std. dev.	5^{th} percentile	95^{th} percentile	median
US	-0.2157	41.7357	-66.5151	66.7812	-0.1635
Canada	-0.6347	18.7319	-29.2218	25.2530	-0.5641
China	0.0589	22.0850	-34.2455	37.3751	0.1390
Euro Zone	0.0110	33.4301	-45.0583	47.5546	-1.3245
Japan	-0.0176	15.5225	-26.2196	26.2381	0.0020
Mexico	0.9504	67.6715	-98.7483	109.6762	2.2035

Table 5: Comparison of risk premia

This table reports descriptive statistics corresponding to differences in risk premia implied by the JSZ normalization. Differences are computed in regards to estimation of risk premia before and after the addition of serial correlation using the data described in Section 2 of the body of the paper. Risk premia are constructed following Cochrane and Piazzesi (2005). For more details regarding the construction of the risk premia, please see Section 3 of the body of the paper. Descriptive statistics for the differences in risk premia are measured in basis points.

	mean	Std. dev.	5^{th} percentile	95^{th} percentile	median
US	-0.1360	5.2001	-6.5330	7.0093	0.0516
Canada	-0.0504	13.2332	-21.6581	20.2534	-0.5568
China	0.0180	1.9736	-2.5698	2.9041	-0.0513
Euro Zone	-0.0270	4.3353	-5.8792	6.2504	-0.2856
Japan	-0.0146	0.4715	-0.5577	0.5075	-0.0083
Mexico	0.0557	4.5078	-6.4931	6.5221	0.1743