Volatility Spillovers in the Foreign Exchange Market

by

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Abstract

I analyze the volatility spillovers among the six major exchange rates vis--vis US Dollar (namely, Euro, British pound, Japanese yen, Swiss franc, Canadian dollar and Australian dollar) over the period from January 1, 2002 to February 28, 2009. Using exchange rate data for $5-$minute intervals, I compute daily realized volatility and related daily continuous component and jump component as well as the daily range volatility as alternative measures of foreign exchange volatility. I obtain FX market volatility spillover indices from a generalized VAR (following the methodology developed by Diebold and Yilmaz, 2009, 2010) analysis. Although the spillover indices based on different volatility measures, in general, follow similar pattern over the sample period, they behave differently in certain periods. While the spillover indices fluctuate during the sample, there is an upward trend in the spillover indices in 2003-2005 and 2007-2008 periods, and during the recent financial crisis the indices stay at higher levels. In particular, I find that although the exchange rate volatilities increase tremendously during the recent financial crisis period, there was only a modest increase in volatility spillovers. Moreover, the directional volatility spillovers results suggest that the Euro/Dollar exchange rate is the net volatility transmitter over the sample period and the Japanese yen becomes net volatility transmitter in $\text{post}-2006$ period for all volatility measures.

Keywords: Foreign exchange market, Realized return, Realized volatility, Jump component, Continuous component, Range volatility, Financial crisis, Contagion, Vector autoregression, Variance decomposition, Spillover index

Özet

Bu tezde altı temel döviz kuru arasındaki oynaklık yayılmasını 1 Ocak 2002 – 28 Şubat 2009 tarihleri arası için inceledim (Avro/ABD Doları, İngiliz Sterlini/ABD Doları, Japon Yeni/ABD Doları, İsviçre Frangı/ABD Doları, Kanada Doları/ABD Doları ve Avustralya Doları/ABD Doları). Beşer dakikalık döviz kuru kapanış değerlerini kullanarak günlük gerçekleşen oynaklığı, bu oynaklığın sürekli bileşenini, sıçrama bileşenini ve ayrıca günlük aralık oynaklığını alternatif ölçütler olarak hesapladım. Döviz kuru piyasasında oynaklık yayılmasını genelleştirilmiş VAR modeli (Diebold ve Yilmaz, 2009 ve 2010 yöntemi) kullanarak elde ettim. Farklı oynaklık ölçümlerine göre hesapladığım yayılma endeksleri genel olarak benzer bir yol izlese de bazı dönemlerde farklılıklar göstermektedir. Oynaklık endeksleri dönem boyunca dalgalanma gösterse de 2003-2005 ve 2007-2008 dönemlerinde yukarı yönlü eğilim göstermekte ve son finansal kriz döneminde aşağı yönlü hareket göstermemektedir. Özellikle son finansal kriz döneminde döviz kurları oynaklığı aşırı derece artsa da yayılma endeksinde sınırlı miktarda artış görülmektedir. Ayrıca yönsel oynaklık yayılması analizleri Avro/ABD Doları döviz kurunun dönem boyunca ve Japon Yeni'nin de 2006 sonrasında tüm oynaklık ölçütleri için net oynaklık vericileri olduğunu gözlemledim.

Anahtar Kelimeler: Döviz kuru piyasası, Gerçekleşen getiri, Gerçekleşen oynaklık, Sıçrama bileşeni, Sürekli bileşen, Aralık oynaklığı, Finansal kriz, Yayılma, Vektör otoregresif (VAR) modeli, Varyans ayrıştırması, Yayılma endeksi

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Abbreviations

USD	**US D**ollar
EUR	**E**uro
GBP	**B**ritish **P**ound
JPY	**J**apanese **Y**en
CHF	**S**wiss **F**ranc
CAD	**C**anadian **D**ollar
AUD	**A**ustralian **D**ollar

R	**R**ealized **R**eturn
RV	**R**ealized **V**olatility
JC	**J**ump **C**omponent
C	**C**ontinuous **C**omponent
RNV	**R**ange **V**olatility

To my loving family. . .

Chapter 1

Introduction

In the financial economics literature, the volatility is often related to the rate of flow of information to the market (e.g., French and Roll, 1984; Ross, 1989; French and Roll, 1993). Thus, one can understand the dynamics and the direction of the information flows across the markets or the financial variables by analyzing the volatility spillovers. The volatility literature until the early 2000s was based highly on parametric volatility methods. As the high frequency data became easily accessible, starting with Andersen and Bollerslev (1998b); Andersen et al. (2001, 2003), and Barndorff-Nielsen and Shephard (2002a) and followed by many others, the non−parametric volatility models has been standing out in the volatility literature in 2000s, and realized volatility gains popularity.

In this study, I will focus on the analysis of the volatility spillovers in the foreign exchange (FX) market which is the world's largest financial market. Therefore a deeper inspection of this market is useful for analysis. The Bank of International Settlements' (BIS) latest report[1] indicates that the average daily volume in the FX market reaches as high as \$3.2 trillion in 2007 survey (Table 1). Compared to the same period average of \$80 billion daily trading volume of the world's largest equity market, the New York Stock Exchange, at the same period one can understand how large the FX market trading volume is. Moreover, the total daily turnover in the world equity markets is one-tenth of that of the FX market (Bali and Yilmaz, 2009). The FX market is not only the most

[1] BIS coordinates triennial survey of foreign exchange and derivatives market activity. Although the latest survey is done in April 2010, in my analysis I use April 2007 survey results since the 2010 survey results will be announced in September.

liquid financial market throughout the world but also it is unique in nature in terms of operating 24−h a day, 7 days a week.[2] In addition, a large number of and variety of traders including central banks, large commercial and investment banks, governments and other financial institutions as well as small investors and speculators trade in the over−the−counter (OTC) market.[3] The FX market activity has increased dramatically in the last two decades. The global FX market turnover rises from $880 billion to $1.42 trillion and $3.21 trillion in 1992, 2001 and 2007, respectively.[4] The corresponding growth rates from 1992 to 2001 and 2001 to 2007 of 61% and 125%, respectively, cast higher levels of turnovers in the future.

In this study I use four nonparametric volatility measures, namely the realized volatility, its related jump component and continuous component, as well as the range based volatility proposed by Parkinson (1980). These methods will be applied to the spot exchange rates of the US dollar (USD) vis−à−vis six major currencies, namely Australian dollar (AUD), Euro (EUR), British pound (GBP), Canadian dollar (CAD), Swiss franc (CHF), and the Japanese yen (JPY) (Table 1), which consist of the 67% of the total turnover in the FX market. In order to obtain a measure of volatility spillovers among the exchange rates I use the spillover index methodology introduced by Diebold and Yilmaz (2009) and further developed by Diebold and Yilmaz (2010), hereafter DY09 and DY10.

The volatility spillovers analysis for different asset markets at inter− and intra−market levels has long been an important topic in financial economics (e.g., Baillie and Bollerslev, 1991; Engle et al., 1990; Engle and Susmel, 1993; King et al., 1994; Lin et al., 1994; Schwert, 1989; Diebold and Nerlove, 1989; Dungey and Martin, 2004; Diebold and Yilmaz, 2009, 2010). In particular, the intra−market volatility spillovers in the FX market literature dates back to 1990s. Parallel to the volatility literature, the parametric volatility measure based volatility spillovers analysis has been prominent in the analysis of FX market volatility spillovers until recent years. In their early work, Diebold and Nerlove (1989) propose a latent factor model of foreign exchange rate volatility and their daily exchange rate data based results emphasize the commonality of the volatility movements of the exchange rates. Baillie and Bollerslev (1991) analyze the volatility spillovers in the

[2]In this sense, considering also the huge turnover rate, it is one of the closest analog to the continuous time process models.

[3]OTC is the market where the trading occurs over the telephone or electronic network instead of a physical trading floor.

[4]See the BIS 2007 survey report for detailed statistics.

FX market in detail, and cannot find sufficient evidence in favor of systematic volatility spillovers among the exchange rates. Contrary to Baillie and Bollerslev (1991), Hong (2001) find strong evidence in favor of the strong simultaneous interaction and cross correlation between Deutsche mark and Japanese yen where the direction of the volatility spillovers are from Deutschemark to Japanese yen. Following Diebold and Nerlove (1989), Dungey and Martin (2004) propose a multifactor model of exchange rates in order to measure the contagion during the 1997−98 East Asian currency crisis and their model implies strong statistical evidence of volatility spillovers. In a recent study, Kitamura (2009) examines the intraday interdependence and the volatility spillovers among the euro, the pound and the Swiss franc by applying a varying coefficient MGARCH model for the period July 2008 thru July 2009. He finds that there is a significant volatility spillover transmitted from the euro to the pound and to the Swiss franc. Inagaki (2007) apply a residual−correlation approach to examine the spillovers among the pound and the euro exchange rates, vis−à−vis the US dollar, for the period from January 1999 thru December 2004. He finds uni−directional volatility spillovers such that the euro Granger−causes the pound in variance. Nikkinen et al. (2006) examine the expected volatility linkages among the exchange rates of euro, the pound and the Swiss franc against the US dollar based on implied volatility for the period January 2001 thru September 2003. They find high linkages among these major European currencies where the euro is the dominant volatility transmitter. All of these works rely on the parametric volatility models in analyzing the volatility spillovers.

Besides the studies summarized above, a few recent papers use non-parametric volatility measures in order to analyze the volatility spillovers in the FX market. Melvin and Melvin (2003) examine volatility spillovers of the exchange rates of the Deutsche mark and the yen against the US dollar across regional markets, consisting of Asia, the Asia-Europe overlap, Europe, the Europe-America overlap, and America, by using non−parametric volatility measures.[5] Their results provide evidence for both the intra− and inter−regional spillovers for both exchange rates, where the effects of the former are observed ro be more prominent in volatility dynamics. McMillan and Speight (2009) apply Diebold and Yilmaz (2009) spillover index methodology in order to examine the volatility spillovers among the three major exchange rates of the euro vis−à−vis three major currencies consisting of the US dollar, the Japanese yen and the pound for the

[5] Melvin and Melvin (2003) base their analysis on Engle et al. (1990). Also, Cai et al. (2008) study the same issue and their results are very close to the results of Melvin and Melvin (2003).

period from January 2002 to April 2006. Their results suggest that there are strong volatility spillovers from US dollar to others in the whole sample. Moreover, Bubàk et al. (2010) investigates the volatility spillovers in the Central European FX market[6] by using non-parametric volatility measures for the period January 2003 thru June 2009. Their results suggest that there are significant volatility spillovers among Central European currencies whereas EUR does not significantly affect the volatility of these exchnage rates. They also use DY09 Diebold and Yilmaz (2009) spillover index methodology to capture the dynamic pattern of the spillovers. They illustrate that the spillover plot tend to increase with the market uncertainty.

This study differs from the previous studies in various aspects. First, this is one the first studies to use the realized volatility as well as its jump component and the continuous component and range volatility (as alternative measures) in measuring the spillovers in the FX market, whereas almost all of the previous studies rely solely on parametric volatility estimation. Although Melvin and Melvin (2003); McMillan and Speight (2009); Bubàk et al. (2010) base their analysis on the realized volatility, they do not consider the effects of the jump component. Indeed, Andersen et al. (2003) suggests that the realized volatility based simple models produce more successful forecasts than the GARCH and the related stochastic volatility models. Since my spillover methodology is based on the forecast error variance decompositions[7], non−parametric volatility measures are expected to yield better results.

Second, I use a new spillover measure proposed by DY09 and DY10 which is based on variable vector autoregression forecast error variance. By applying rolling window vector autoregression estimation, the Diebold-Yilmaz index allows us to observe not only the dynamic behavior of the gross volatility spillovers in the FX market, but also the time-varying directional volatility spillovers among different exchange rates. The previous works of McMillan and Speight (2009); Bubàk et al. (2010) use the DY09 methodology that relies on the orthogonalized error terms which is highly sensitive to ordering. Moreover, McMillan and Speight (2009) analyze the spillovers only for the whole sample which cannot capture the dynamic pattern of the volatlity spillovers. Bubàk et al. (2010) apply rolling window estimation (as proposed in Diebold and Yilmaz, 2009) and capture the time varying behavior of the spillovers. However, they use another methodology,

[6]The exchange rates are the Czech koruna (EUR/CZK), the Hungarian forint (EUR/HUF),and the Polish zloty (EUR/PLN). Also they use EUR/USD exchange rate volatility for inter-regional spillovers.
[7]See section 2.2 for detailed description of the spillover methodology.

Granger-causality test, in order to test the bi-directional spillovers. Diebold and Yilmaz (2010) eliminate the sensitivity problem in McMillan and Speight (2009) by proposing a generalized variance decomposition based spillover index which enables to analyze the directional spillovers.

The paper is organized as follows. In chapter 2, I summarize the Diebold-Yilmaz volatility spillover index methodology. Chapter 3 describes the data and discusses the covariance stationarity of the data. In chapter 4, I discuss the results and compare the spillover indices obtained by using different volatility measures. In chapter 5, I check the sensitivity of the VAR-based results to different assumptions about the VAR specification. Chapter 6 I summarize the results and discuss possible directions to future research.

Chapter 2

The Model

In this paper, the foreign exchange market volatility spillovers analysis is based on recently developed four non-parametric volatility measures: Realized Volatility, RV, its related Jump Component, JC, and Continuous Component, C, and the Range Volatility, RNV. I measure the volatility spillovers among the six exchange rates[1] via the VAR based econometric model proposed by Diebold and Yilmaz (2009, 2010).

2.1 The Volatility Measure

I consider the logarithmic relative price of a currency, $p(t)$, follows a continuous-time jump diffusion process:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \zeta(t)dq(t), \qquad 0 \leq t \leq T \tag{2.1}$$

where $\mu(t)$ and $\sigma(t)$ are drift and instantaneous volatility, respectively, $W(t)$ is a standard Brownian motion, $q(t)$ is a Poisson process uncorrelated with $W(t)$ and governed by the jump intensity $\lambda(t)$. That is, $Pdq(t) = 1 = \lambda(t)dt$, where $\lambda(t)$ positive and finite, and $\zeta(t)$ represents the size of the discrete jumps. This price process specification is superior to the standard diffusive process in the sense that it captures the effects of the unexpected news.

[1] Namely Australian dollar, Euro, British pound, Canadian dollar, Swiss franc, and Japanese yen vis–à–vis US dollar.

The cumulative quadratic exchange rate return variation process over the interval 0 to t, $0 \le t \le T$, is the sum of the diffusive integrated volatility and the cumulative discrete squared jumps

$$QV(t) = \int_0^t \sigma(s)ds + \sum_{0<s\le t} \kappa^2(s) = IV(t) + \sum_{0<s\le t} \kappa^2(s), \tag{2.2}$$

where $\kappa(t) = \zeta(t)dq(t) \ge 0$ for all t, and non-zero if there is a jump at time t.

I divide each time interval, t , into $1/\Delta$ equal parts. The $\Delta-$period returns is

$$r_{t,\Delta} = p(t) - p(t-\Delta). \tag{2.3}$$

Thus, the cumulative return at time t, R_t, is obtained by

$$R_{t+1}(\Delta) = \sum_{j=1}^{1/\Delta} r_{t+j\bullet\Delta,\Delta}. \tag{2.4}$$

Based on the realized return equation the realized volatility formula is

$$RV_{t+1}(\Delta) = \sum_{j=1}^{1/\Delta} r^2_{t+j\bullet\Delta,\Delta}, \tag{2.5}$$

where $r_{t+j\bullet\Delta,\Delta}$ is $\Delta-$period foreign exchange return and $RV_{t+1}(\Delta)$ is the daily realized volatility corresponding $1/\Delta$ high frequency intra$-$day squared returns. Andersen and Bollerslev (1998b); Andersen et al. (2001); Barndorff-Nielsen and Shephard (2002a,b), with many others, show that the Realized Variance, RV, is the consistent estimator of the Quadratic Variation, QV, (defined in equation 2.2), as $\Delta \to 0$, $RV(t) \to QV(t)$.

Barndorff-Nielsen and Shephard (2004) distinguishes the effects of the jump component from the quadratic variation by introducing a new volatility measure, the Bi-power Variation BV, which is

$$BV_{t+1}(\Delta) = \mu_1^{-2} \sum_{j=2}^{1/\Delta} |r_{t+j\bullet\Delta,\Delta}||r_{t+(j-1)\bullet\Delta,\Delta}| \tag{2.6}$$

where $\mu_1 = \sqrt{2/\pi} = E(|Z|)$[2], Z is a standard normally distributed random variable. Barndorff-Nielsen and Shephard (2004) shows that the BV is the consistent estimator

[2]For more detailed information about the Realized Power Variation, see Barndorff-Nielsen and Shephard (2004, 2005); Huang and Tauchen (2005).

of the IV (equation 2.2), as $\Delta \to 0$, $BV(t) \to IV(t)$.

Since the RV is the consistent estimator of the QV and the BV is the consistent estimator of the IV, the consistent estimator of the Jump Component, $JC_{t+1}(\Delta)$, is $RV_{t+1}(\Delta) - BV_{t+1}(\Delta)$ and thus as $\Delta \to 0$

$$RV_{t+1}(\Delta) - BV_{t+1}(\Delta) \to \sum_{0<s\leq t} \kappa^2(s) = JC_{t+1}(\Delta).$$

For some sample estimates squared jumps can possibly be negative. To ensure that all elements of the JC are non-negative, following Barndorff-Nielsen and Shephard (2004) and Andersen et al. (2007), I make an adjustment such that

$$JC_{t+1}(\Delta) = \max[RV_{t+1}(\Delta) - BV_{t+1}(\Delta), 0]. \tag{2.7}$$

Although the JC is consistent for $\Delta \to 0$, in finite samples it takes large number of positive values where one can reasonably treat the very small values as measurement errors. To distinguish the significant jump components Huang and Tauchen (2005) improves the methodology introduced by Barndorff-Nielsen and Shephard (2004) and proposes the test statistics

$$Z_{t+1}(\Delta) = \Delta^{-1/2} \frac{[RV_{t+1}(\Delta) - BV_{t+1}(\Delta)]RV_{t+1}(\Delta)^{-1}}{[(\mu_1 + 2\mu_1^{-2} - 5)\max\{1, TQt + 1(\Delta)BV_{t+1}(\Delta)\}]^{1/2}}, \tag{2.8}$$

which is well approximated by the standard normal distribution. Here, TQ, the standardized Realized Tripower Quarticity, is measured as

$$TQ_{t+1}(\Delta) = \Delta^{-1}\mu_{4/3}^{-3} \sum_{j=3}^{1/\Delta} |r_{t+j\bullet\Delta,\Delta}|^{4/3} |r_{t+(j-1)\bullet\Delta,\Delta}|^{4/3} |r_{t+(j-2)\bullet\Delta,\Delta}|^{4/3},$$

where $\mu_{4/3} = 2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1}$, and Γ represents the gamma function.

Thus, the test statistics in equation 2.8 suggests that for the significant jumps at some critical value corresponding to α percent significance level, Φ_α is

$$JC^{\circ}_{t+1,\alpha}(\Delta) = \mathrm{I}[Z_{t+1}(\Delta) > \Phi_\alpha][RV_{t+1}(\Delta) - BV_{t+1}(\Delta)],$$

where I[•] is the indicator function. To ensure that the jump component and the continuous part sum up to realized variance, one should define the continuous part as

$$C^{\circ}_{t+1,\alpha}(\Delta) = \mathrm{I}[Z_{t+1}(\Delta) \leq \Phi_\alpha]RV_{t+1}(\Delta) + \mathrm{I}[Z_{t+1}(\Delta) > \Phi_\alpha]BV_{t+1}(\Delta),$$

where both C° and JC° are non-negative and sum up to RV.

Although the test statistics in equation 2.8 is consistent, in the presence of market microstructure noise it is biased against finding jumps.[3] Huang and Tauchen (2005) propose a modified realized BV and the realized TQ measures based on staggered absolute returns which produce more accurate finite sample estimates and mitigate the effects of market microstructure noise. The modified realized bi-power variation measure is

$$BV_{1,t+1}(\Delta) = \mu_1^{-2}(1-2\Delta)^{-1}\sum_{j=3}^{1/\Delta}|r_{t+j\bullet\Delta,\Delta}||r_{t+(j-2)\bullet\Delta,\Delta}|, \tag{2.9}$$

and the modified realized tripower quarticity measure is

$$TQ_{1,t+1}(\Delta) = \Delta^{-1}\mu_{4/3}^{-3}(1-4\Delta)^{-1}\sum_{j=5}^{1/\Delta}|r_{t+j\bullet\Delta,\Delta}|^{4/3}|r_{t+(j-2)\bullet\Delta,\Delta}|^{4/3}|r_{t+(j-4)\bullet\Delta,\Delta}|^{4/3}, \tag{2.10}$$

where these modified BV and TQ measures are consistent estimators of their integrated counterparts. Corresponding to the new BV and TQ measures defined in equations 2.9 and 2.10 the related modified test statistics for the significant jump is

$$Z_{1,t+1}(\Delta) = \Delta^{-1/2}\frac{[RV_{t+1}(\Delta) - BV_{1,t+1}(\Delta)]RV_{t+1}(\Delta)^{-1}}{[(\mu_1 + 2\mu_1^{-2} - 5)\max\{1, TQ_{1,t+1}(\Delta)BV_{1,t+1}(\Delta)\}]^{1/2}}, \tag{2.11}$$

which converges in distribution to standard normal distribution as $\Delta \to 0$. Analogously, the modified significant JC at α percent significance level is

$$JC_{1,t+1,\alpha}(\Delta) = \mathrm{I}[Z_{1,t+1}(\Delta) > \Phi_\alpha][RV_{t+1}(\Delta) - BV_{1,t+1}(\Delta)], \tag{2.12}$$

and the modified C is

$$C_{1,t+1,\alpha}(\Delta) = \mathrm{I}[Z_{1,t+1}(\Delta) \leq \Phi_\alpha]RV_{t+1}(\Delta) + \mathrm{I}[Z_{1,t+1}(\Delta) > \Phi_\alpha]BV_{1,t+1}(\Delta). \tag{2.13}$$

[3] see Huang and Tauchen (2005) and Barndorff-Nielsen and Shephard (2004, 2005).

In the empirical analysis below I use RV and related JC and C as defined in equations 2.5, 2.12 and 2.13 which produce more accurate finite sample estimates and mitigate the effects of market microstructure noise.

Lastly, by following the large literature based on Parkinson (1980) I compute the Range Variation, RNV, for the time interval t from the intra−period high−low FX quotas.[4] The RNV for the time interval t is

$$RNV_t = 0.361(p_t^{\max} - p_t^{\min})^2, \tag{2.14}$$

where $p_t^{\max}$ and $p_t^{\min}$ represent the logarithm of the maximum and the minimum of the intra−period exchange rate data for the time interval t.

2.2 The Spillover Index

I measure the volatility spillovers among the foreign exchange rates by using the spillover index methodology proposed and developed by DY09 and DY10. I model the foreign exchange rate return volatilities as an $N-$variable vector autoregression (VAR). Consider a covariance stationary p^{th} order $K-$variable VAR process

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_i, \tag{2.15}$$

where $x_t = (x_{1,t}, x_{2,t}, \ldots, x_{K,t})'$ is a Kx1 endogenous variable matrix,[5] Φ is KxK coefficient matrix and $\varepsilon \sim (0, \Sigma)$ is a reduced form error term where Σ does not required to be diagonal, i.e., the error terms are allowed to be correlated. Since I assume that the VAR system defined above is covariance stationary, the moving average representation of the system exists and represented as

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \tag{2.16}$$

where A_i is NxN coefficient matrix such that $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 an NxN identity matrix and $A_i = 0$ for $i < 0$.

[4] Alizadeh et al. (2002); Brandt and Diebold (2006) show that the RNV estimates are both robust against market micro−structure noise and highly efficient. For the detailed discussion of the properties of the RNV see section 4.2 below.

[5] In my analysis x_t stands for foreign exchange rate volatilities matrix.

Then, I obtain the forecast error variance decompositions based on the the moving average representation (equation 2.16) which distinguishes the effects of *own* shocks versus shocks to *other* variables on the movements of each series. My VAR model defined in equation 2.15 is allowed to be correlated, thus over identified. To obtain unique moving average representation we have to impose restrictions on the model parameters. Cholesky factorization is one way of obtaining unique representation by orthogonalizing the VAR innovations. But the moving average equation coefficients, thus the resultant variance decompositions, depend highly on the ordering. To mitigate the order−dependency problem in this study I rely on the forecast error variance decompositions based on the Koop et al. (1996) and Pesaran and Shin (1998), hereafter KPSS, generalized VAR framework which does not require the orthogonalized error terms and produces variance decompositions invariant to ordering.[6]

Now, let me describe the variance shares of the foreign exchange return volatilities. I distinguish the forecast error variance into two components: *own variance shares* and *cross variance shares*. First, *own variance shares* is defined as the fractions of $H-$step$-$ahead error variance in forecasting x_i due to shocks to x_i, $i = 1, \ldots, K$. And the *cross variance shares* is defines as the fractions of $H-$step$-$ahead error variance in foerecasting x_i due to shocks to x_j, $j = 1, \ldots, K$ and $i \neq j$.[7] Then the $(i,j)^{th}$ element of the KPSS $H-$step$-$ahead variance decomposition matrix is

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \tag{2.17}$$

where σ_{ii} is the standard deviation of the error term of the i^{th} equation, Σ is the covariance matrix of the error vector ε defined in equation 2.16, and e_i is the selection vector with one in the i^{th} row and zero otherwise. Here, θ_{ij}^{g} is the contribution of a one-standard deviation shock to x_j to the variance of the $H-$step$-$ahead forecast error of x_i. Since in the KPSS framework the shocks to each variable are not orthogonalized, the sum of contributions to the forecast error variance is not necessarily equal to one. That is, the sum of the row elements in the variance decomposition table needs not to be equivalent to 1, $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. To obtain the spillover index, I should normalize

[6]The KPSS methodology requires the multivariate normality of the errors in order to use the historical distribution of the error terms.

[7]I assess the FX market volatility spillovers based on six exchange rates namely Euro, British pound, Japanese yen, Swiss franc, Canadian dollar and Australian dollar vis−à−vis US dollar. Thus, in this framework, i, j stands for the volatility measures of these exchange rates which are computed as in section 2.1.

either the row sum or the column sum to 1. Following the DY10, I normalize the row sum. The normalized variance decomposition is

$$\tilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)}. \tag{2.18}$$

Now, by construction $\sum_{j=1}^{N} \tilde{\theta}^g_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H) = N$.

2.2.1 Total Spillovers

In equation 2.18, $\tilde{\theta}^g_{ij}$ represents the contribution of a one-standard deviation shock to x_j to the variance of the $H-$step$-$ahead forecast error of x_i, in normalized terms. Based on the variance decompositions from variable j to variable i, $\forall i, j$, given in equation 2.18, I now define the *Total Spillovers* as the measure of spillovers in percentage terms:

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}^g_{ij}(H)}{N} \times 100. \tag{2.19}$$

In sum, the spillover index is the sum of all the off-diagonal elements in the $H-$step$-$ahead forecast error variance matrix normalized by the number of the endogenous variables in a VAR system.

2.2.2 Directional Spillovers

The *Total Spillovers* defined in equation 2.19 gives information about the aggregate volatility contributions among the exchange rates. I also interested in the direction of the volatility spillovers across the exchange rates. Based on the variance decompositions given in equation 2.18 from variable j to variable i, $\forall i, j$ in equation I define the *Directional Spillovers* "received by" exchange rate i from all other exchange rates j in the VAR system in percentage terms:

$$S^g_{i\bullet}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}^g_{ij}(H)}{N} \times 100, \tag{2.20}$$

where "$\bullet$" represents all exchange rates j in the VAR system such that $j \neq i$. Analogously, I define the *Directional Spillovers* "transmitted by" exchange rate i to all other exchange rates j in the VAR system in percentage terms:

$$S^g_{\bullet i}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^N \tilde{\theta}^g_{ji}(H)}{\sum_{i,j=1}^N \tilde{\theta}^g_{ji}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^N \tilde{\theta}^g_{ji}(H)}{N} \times 100. \tag{2.21}$$

2.2.3 Net Spillovers

Directional Spillovers defined in equations 2.20 and 2.21 measure the volatility contribution of an exchange rate *FROM* and *TO* all other exchange rates, respectively. Now, it is useful to define the net volatility spillovers from the exchange rate i to the all other exchange rates j in the VAR system as

$$S^g_i(H) = S^g_{\bullet i}(H) - S^g_{i\bullet}(H). \tag{2.22}$$

Lastly, in order to obtain the net volatility transmission between each pair of the exchange rates I define *Net Pairwise Spillovers* between each dual combination of the exchange rate i, j, $\forall i \neq j$, in a VAR system as

$$S^g_{ij}(H) = \left[\frac{\tilde{\theta}^g_{ji}(H)}{\sum_{i,k=1}^N \tilde{\theta}^g_{ki}(H)} - \frac{\tilde{\theta}^g_{ij}(H)}{\sum_{k,j=1}^N \tilde{\theta}^g_{jk}(H)}\right] \times 100 = \left[\frac{\tilde{\theta}^g_{ji}(H) - \tilde{\theta}^g_{ij}(H)}{N}\right] \times 100, \tag{2.23}$$

where S^g_{ij} represents the gross volatility shocks transmitted from exchange rate i *TO* exchange rate j minus the volatility shocks transmitted from exchange rate j *TO* exchange rate i.

Chapter 3

Data and Summary Statistics

3.1 Data

I analyze the exchange rate volatility spillovers among the six major exchange rates vis−à−vis US dollar consisting of Australian dollar, AUD, Euro, EUR, British pound, GBP, Canadian dollar, CAD, Swiss franc, CHF, and the Japanese yen, JPY. I use 5−min exchange rate data for the period January 1, 2002 and February 28, 2009, compiled by Olsen&Associates. My data set contains a total of 753,408 5−min observations for each exchange rates.

I compute "daily" realized return, R, realized volatility, RV, related jump component, JC, and continuous component, C, and range volatility, RNV, from 5−min exchange rates, as described in Section 2.1, as a result I have 2616 daily observations. Consistent with the literature[1], as the transaction volume decline after $9:00$ pm in Friday and increase after $9:00$ pm in Sunday, I construct that the day starts at $9:00$ pm and ends at $9:00$ pm next day.

In the weekends and the national holidays[2] the transaction volume in the FX−market is very low, i.e., there are lots of missing intra−day observations. Since the RV defined in section 2.1 is simply the sum of the squared daily returns, as number of the missing observations increases the RV estimate biased downward. Analogously, other three

[1] e.g., Müller et al. 1990; Bollerslev and Domowitz 1993; Andersen and Bollerslev 1998b; Andersen et al. 2001.

[2] Those consist of Good Friday, Easter Monday, Memorial day, July 4$^{\text{th}}$, Labor day, Thanksgiving day, Christmas and New Year's day.

volatility measures become biased. Thus, I omit those weekends and national holidays, which consists of 829 days. Also I omit the days, consisting of 15 days, that the number of the intra−day 5−minute zero returns exceeds 80. After these adjustments, I am left with 1772 daily volatility estimates for each four volatility measures.

3.2 Summary Statistics

Table 2 presents the summary statistics of the daily realized returns defined in equation 2.3 for the sample period 2002 − 2009. On average, all six currencies appreciated against the US dollar[3] where the daily average return of the EURO is 0.00018 which is followed by CHF(0.00017), CAD(0.00009), JPY(0.00007), AUD (0.00005) and GBP(0.00002). Considering the variations of the returns, AUD is the most volatile currency (0.009) whereas the standard deviation of the other currencies are around 0.006 over the period 2002−2009 (Table 2).

Tables 3, 5, 7 and 9 show the summary statistics of the daily RV, RNV, JC and C, respectively. On average, in terms of all volatility measures AUD is the most volatile currency for 2002 − 2009 period. The average volatilities of the other currencies are close to each other. The average daily RV and C almost coincide and the average RNV is very close to these, but the average JC is quite low.

All four volatility measures have large skewness and kurtosis values where the skewness takes values within the [4, 13] band and the kurtosis within the [32, 284] band, which are far away from the Gaussian counterparts, 0 and 3, respectively. For the natural logarithm of these volatility measures, however, both the skewness and kurtosis decline considerably (Tables 4, 6, 8 and 10) and approach to the normal distribution parameters, 0 and 3, respectively.

In order to illustrate the significant difference between the distribution of the log−volatility measures and level−volatility measures I present the kernel density estimates of both the level and the log of the six exchange rate volatilities in Figures 2−to−5. For all four volatility measures and all six exchange rates, the log of the volatilities are almost coincide with the Normal distribution whereas the level−volatility distributions are far

[3]The positive values corresponding to the exchange rates which is denoted as •/USD represent the appreciation of the currency "•" against the US dollar, whereas the positive values of the exchange rate that is denoted as USD/• represents the depreciation of the currency "•" against the US dollar.

from being Gaussian. Thus, consistent with Andersen et al. (2001, 2003), I can safely say that the unconditional distributions of the natural logarithm of the realized volatility measures are closer to the normal distribution. However, although the Jarque−Berra statistics for all volatility measures decline sharply for log volatilities, they are still very high, thus there is no sufficient statistical evidence supporting normality of the volatility series at 5% significance level. Despite the fact that I should reject the normality of the log−volatility measures, since their distributions are close to Gaussian compared to level-volatility measures using the log−measures are more appropriate in standard time series models (see Andersen et al., 2007).[4]

Figure 1 shows the 5−minute exchange rates of EUR, GBP, JPY, CHF, CAD and AUD vis−à−vis USD for the period 2002 – 2009. From the beginning of 2002, until the last quarter of 2008, all currencies appreciated in nominal terms against the USD, except JPY. From this point to the end of the sample the US dollar appreciated against all currencies except the Japanese yen. Japanese yen has unique pattern by appreciating until the end of 2004, and depreciating from 2005 thru mid−2007. From this point on it again appreciated against USD until 2009.

I plot the daily volatility series in Figures 6−to−10. Overall, all volatility measures follow very similar patterns over the sample period 2002 – 2009, except JC. In 2003 and 2004, the volatilities increased significantly, especially for EUR and CHF, and then declines and stay at low levels until mid−2007. In mid−2007, when the mortgage crisis deepened and the credit crunch hit the climax, the volatilities increased again. The most severe increase in volatilities, however, took place when the global financial crisis hit the climax in the last quarter of 2008. In this period, the volatility measures of AUD increased most compared to other exchange rates for all volatility measures (reached more than 40% higher levels than its whole sample average).

Figures 8 and 9 shows the JC and the significant JC at 5% significance level, respectively (see equations 2.7 and 2.12). The behavior of these two series close to each other. The pattern of the JC for some exchange rates deviate from the other three volatility measures. For EUR, CHF and CAD the JC takes highest values in 2003 – 2004 and

[4] The Ljung−Box test results assert that all of the volatility measures are strongly persistent (see Tables 3−to−10). Thus, it is reasonable to use their lags in modeling and forecasting these series. This persistence property is crucial for my analysis since my spillover methodology based on VAR which relies on the lags of the endogenous variables in obtaining the forecast error variance, and thus spillovers.

especially for GBP and EUR the JC do not increase much during the most intense period of the recent financial crisis.

3.3 Sampling Frequency

Before presenting the empirical results, I explain the choice of 5−minute sampling frequency in my analysis.[5] There is a trade−off between choosing sampling interval. On the one hand, as the sampling frequency increases, or Δ declines, RV converges to QV, sampling error declines. On the other hand, due to the market microstructure noise (such as bid/ask spread, discreteness, etc.), at higher frequencies the estimates become more biased. However, since the exchange rate data I used are very liquid, the microstructure effects alleviated.

I use an intuitive tool, so called "volatility signature plot", introduced by Andersen et al. (2001), to determine the optimal sampling frequency. The signature plot simply depicts the sample average of the volatility measure against the sampling frequency. I compute the volatility signatures for the RV. Figure 11 plots the average RV against 5, 10, 15 and 20 minute frequencies.[6] There is almost no difference in the plot between 5−min and 10−min frequencies. Although there are a declines in the plots for 15−min frequency for all exchange rate volatilities, the size of the declines are very small, it is around 5% for all volatilities. Thus, the volatility signature plot suggests that using 5−min sampling frequency does not yield biased estimates. Also, 5−min frequency appears to have emerged as a popular choice to compute daily return and variance estimates(e.g., Andersen et al., 2001, 2003, 2007; Bandi and Russell, 2008, and Andersen, Bollerslev, Diebold, and Vega, 2007).

[5] There are a number of studies in the literature to mitigate the effects of the microstructure noise and produce unbiased and efficient return and volatility estimates by choosing the sampling frequency optimally such as Ait-Sahalia et al., 2005; Bandi and Russell, 2006, 2008.

[6] Since the data that I used is in 5−min interval I can obtain estimates for only multiples of 5−min frequencies.

Chapter 4

Empirical Results

The results presented below based on the second-order VARs, $p = 2$, where the number of endogenous variables $N = 6$[1] and the forecast horizon $h = 10$. The spillovers are measured as defined in section 2.2. I present the results under three subsections: *a*) full sample analysis, *b*) gross spillovers and *c*) directional spillovers.

4.1 Full Sample Analysis

In order to understand the mechanics and the intuition of the gross spillovers as well as directional and net spillovers methodology in detail, I estimate the VAR model defined above for the four volatility measures for the full sample (2002-2009) and report the resultant generalized variance decompositions and spillovers in Tables 11−to−14. In terms of realized volatility spillovers (Table 11) the diagonal values representing the own variance share is quite low compared to the off-diagonal values. 72.6% of the forecast error variance of the CHF is explained by shocks to the other currencies (Contribution *FROM* others column). This is followed by EURO and GBP with values 71.7% and 60.8%, respectively. CAD is the least spillover receiver with 60% level. In terms of the directional spillovers *TO* others, regarding the *RV* spillovers, EURO and GBP are the currencies which contribute to others' forecast error variance most, their contributions adds up to 83.4 and 83.9 points (which constitute 13.9% and 14% of the total forecast error variance), respectively (Table 11). AUD and the CHF follow with values 73.4

[1]The six endogenopus variables are the daily volatility measures of the six exchange rates: EUR, GBP, JPY, CHF, CAD, and AUD vis−à−vis USD.

and 68.8. CAD is appeared to be the least volatility transmitter (46), followed by JPY (50.9).

I obtain the *spillover index* by summing up the "Contribution TO Others" row, or similarly by adding the entries of the"Contribution $FROM$ Others" column, and then dividing by the total forecast error variance, in my case $6 \times 100 = 600$. For the realized volatility, the index is 67.74% suggesting that around 68% of forecast error variance is explained by the shocks to the other exchange rates. These high values of the spillover index, directional spillovers and the total spillovers indicate the high interdependence and contagion of the shocks among the exchange rates.

Lastly, I compute the net volatility spillovers by extracting "Contribution $FROM$ Others" column from the "Contribution TO Others" row (equation 2.22). Considering the RV, GBP, EURO and AUD are the net transmitters of the shocks to the other exchange rates whereas JPY, CAD and CHF are the net receivers of the shocks on the volatilities.

Considering the other three volatility measures, RNV, JC and C, the results of the C are almost coincides with the RV spillovers results where the C spillover index is 67.84. Whereas the RNV spillovers take values a handful level below the RV and C with the 57.4% spillover index. The RNV directional spillovers, however, follow a similar pattern, in terms of being recipient or transmitter, to the RV and C spillovers, except CHF (becomes net volatility transmitter).

The JC spillovers results, however, are quite different. JC spillover index is 37.1%, which is much lower compared to the other measures. In terms of net volatility spillovers, GBP is still the net transmitter of the shocks (16.6) but the EURO and AUD become net receivers (-1.8, -0.6 respectively) and the JPY turn into slightly net transmitter (0.08).

4.2 Gross Volatility Spillovers

Although the full sample analysis describes the average interdependence of the forecast error variance among the exchange rate volatilities, it cannot capture the time varying pattern of the interdependence. In order to capture the behavior of the spillover index over time I apply 100−day rolling window sub−sample estimation. The estimation procedure follows these steps: 1) I take first 100−day sub−sample, estimate my VAR model and obtain the spillover index, 2) I add one more observation to the previous sub−sample and drop the first observation, then estimate VAR and obtain the spillover index. This process continues until the last 100−day sub−sample. I illustrate the rolling−window spillover plots for the RV, RNV, JC and C for the period 2002 − 2009 in Figures 13−to−16. The spillover plots of all the volatility measures do not follow a clear trend but excessively fluctuate over time. First, I analyze the RV spillover plot in detail and then compare with the other volatility measures spillover plots.

The RV spillover index (Figure 13) fluctuates within 40% band (40%−to−80%) over the 2002−2009 period. One can divide the spillover plot into five cyclic periods. The first period started in mid−2002 where the level of the index was around 45%.[2] There was a 10% level jump in the spillover plot (from 48% to 58%) in June 26, 2002 following the news of a \$3.8 billion fraud of WorldCom.[3] Following the Enron scandal in 2001, the WorldCom fraud led the investors loose confidence in the global financial markets, thus France's CAC 40, Germany's Dax and Japan's Nikkei fell by over 4%, US dollar depreciated against major currencies, especially against Euro, and the realized volatility of the six exchange rates jump around 200% in June 26^{th}[4]. After this initial jump of the spillover plot, the index stayed at higher levels for six months. The index increased 10% in late−July 2002, during the 2002 stock market turmoil, and reached its sub−sample peak in late−August 2002 at 71% level. During the stock market turmoil US stock markets as well as continental Europe and England stock markets fell by over half since peaking in 2000-2001. Also, during this period US dollar depreciated steadily against all other currencies, especially against Euro. Until the end of November 2002 the index stayed above 65%, after the beginning of December 2002 the index declined sharply and within three months fell below 47%. Starting from mid−March 2003, there was little recovery and the index was pushed up above 55% in July. But the index continued to decline and fell down its sample minimum, 41%, in December 2003.

The second period, the longest one, started in January 2004 and ended in January 2006. Starting at the beginning of 2004 there had been a gradual build up in the volatility

[2] Although the data sample starts in June 1^{st} 2002, since I use rolling−window estimation first 100 daily observations are used for the initial spillover index measure. Thus, the spillover plot starts in June 20, 2002.

[3] WorldCom was the America's second−biggest long−distance phone company after AT&T in 2002. WorldCom had exaggerated its profits by recording its operating expenses as capital expenses consisting of \$3.8 billion over five quarters starting from the first quarter of 2001.

[4] See Economist (2002) for detailed discussion about the effects of the WorldCom fraud as well as Enron and others.

spillover plot until the end of August 2004, where the index became stable around 73% until June 2005 and reached the whole period peak in mid−March 2005 at 76% level. In June there was a 10% decline and the index stay around 66% until mid−December. In December 2005, the spillover index declined to 58%. After the 2002 stock market crash, until the 2007 credit crunch, global financial markets did not face with a significant turmoil, instead it is a relatively tranquil period for the financial markets. In mid−2004, the Federal Reserve (Fed) reversed its target rate policy and increased the target rate gradually until mid−2006 (Figure 12). Over this period the Bank of England (BoE) slightly changed its policy rate. On the other hand, the ECB's target rate was quite stable until the beginning of 2006. Fed policy rate, which was 1 percent at the time, was below both the BoE and ECB target rates (respectively 4.50 and 2) in mid−2004. But by mid−2006, the Fed target rate reached 5.25 percent and exceeded both BoE's and ECB's target rates (4.50 and 2.75, respectively). In addition, the Bank of Japan (BOJ) applied zero interest rate policy for almost 6 years until June 2006. Thus, the interest rate differentials between Fed, ECB, BoE and BOJ increased until mid−2006 and stayed above mid−2004 level until late 2007. This policy shift corresponded to a sharp increase in volatility spillovers after mid−2004 (by around 20%). Over this long last positive interest rate differentials period the RV spillover plot stayed at higher levels (above 70% for more then three quarters).

The third period began in February 2006 and lasted until July 2007 where the spillover index were 58% and 55%, respectively. After March 2006 the BOJ altered its "quantitative easing" policy and intended to withdraw excess Yen which has been pumped into the system since March 2001.[5] In May 9, 2006 BOJ started to withdraw excess liquidity[6] and in June 14 it abandoned zero interest rate policy by increasing operational short term interest rate to 0.25% which was followed by a second 0.25% increase in February 2007. Following the BOJ's reversal of the easy monetary policy, there has been large amount of carry trade unwinding throughout May (Gagnon and Chaboud, 2007). In addition, Fed decided to increase the target rate by 25 basis point to 5.00% in May 9^{th} meeting. This target rate increase led the investors to expect further increase

[5]Quantitative easing is a form of monetary policy used to increase the money supply by, such as, buying government securities or other securities from the market when the interbank interest rate, or target rate, is close to, or at, zero. Bank of Japan set their operational short term interest rate virtually equal to zero from February 1999 to June 2006. In order to increase the money supply, in March 19, 2001 BOJ started to apply quantitative easing policy.

[6]In May 9 by 12.2 trillion yen excess liquidity was withdrawn.

in the target rate in June meeting. After the policy shift of BOJ and Fed's further tightening monetary policy decision, realized volatility of all exchange rates jumped, on average, 250% and the spillover plot increased around 9% within one week and hit its sample−peak of 67% in late−May 2006.

The fourth period started in July 2007 with the beginning of the credit crunch and continued until May 2008. [7] First, in the early summer 2007 fixed income markets and then in July 2007 the equity markets faced with huge losses and finally, in August 9, a sudden liquidity squeeze happened. The crisis in the FX market came just after the stock market downturn by means of huge unwinding of the carry trade in August 16, 2007 (see Melvin and Taylor 2009). The currency carry trade is usually defined as taking short position in low interest rate currencies and long position in high interest rate currencies in order to take advantage of interest rate differentials. This strategy is profitable as long as the gains from the interest rate differentials are not offsetted by the exchange rate movements.[8] Starting from the beginning of July, until August 16 the spillover index increased only 8%, from 56% to 64%. The huge unwinding of the carry trade, however, created a dramatic jump in the *RV* spillover plot in 16 August 2007. The daily realized volatility of the exchange rates compared to previous day jumped as high as 500% (JPY 488%, AUD 410%, CAD 130%, CHF and GBP 109%, and EUR 77%) and did not die out quickly. These huge responses resulted in 6.3% (from 63.9% to 70.2%) jump in the gross spillover plot in one day (August 16) which is followed by another 2.5% jump in August 17.

Until December 2007 the spillover plot stayed around 70% and in December 2007 the spillover index declined to 66% and stayed around this level until March 2008 (Bear Stern's takeover by JP Morgan Chase). By March 14, in the last trading day of the week, concerns about the Bear Stern, US's fifth largest investment bank, are peaked and fears over the potential failure of big firms deepened. As a result the spillover index jumped by 2.5% to 68% in Monday March 17. JP Morgan offered to buy Bear Stern for $2 per share in March 17 and finally took over Bear in March 24 for $10 per share, and Fed cut fed funds rate by three−quarters of a percentage point to 2.25% on March

[7] The detailed analysis of the 2007−2008 liquidity and the credit crunch can be found in Brunnermeier (2009).

[8] The interest rate parity argues that the gains from high interest rate currency is offsetted by the appreciation in the low interest rate currency. But, in most cases the reverse happened and the low interest rate currency depreciates (Melvin and Taylor 2009). In addition, due to the leverage effects the gains, or losses, are very sensitive to the exchange rate movements.

18. Following these event market fear was calmed and the spillover plot declined to 64% within two weeks.

Finally, the last period started in May 2008 and lasted until the end of the sample, February 27^{th} 2009 where the level of the spillovers were 64% and 70%, respectively. Until the end of August the spillover plot reached up to 71% and was at 66% level in the beginning of September 2008. The situation turned into uglier in September. The realized volatility of all six exchange rates doubled within 2 weeks and in September 15, with the bankruptcy of Lehman Brothers and Merrill Lynch's rapid sale to Bank of America, the volatilities tripled on average and stayed at higher levels (with reaching peak in October) until the end of the sample. The daily volatility of AUD reached as high as 0.37%, followed by JPY(0.16%), GBP(0.097%), CHF(0.065%), CAD(0.064%) and EUR(0.055%). Compared to the average daily realized volatility over the whole period (Table 3)[9], it is clear that the volatilities in this climax of the crisis jump tremendously. In spite of these huge volatility jumps the response of the spillover plot was modest. The spillover plot increased merely 2.5% in September 15, to the level of 72% and reached sample peak of 74%[10] in late−October. During this period, the global financial system became more interacted[11] and the shocks to the FX market were mostly simultaneous, thus these shocks affected the own variances rather than the off diagonal entries of the forecast error variance decomposition matrix. As a result, the spillover plot increased mildly. The spillover plot stayed above 70% until the end of January 2009 and falls slightly to 69% in February 2009.

Until this point I discuss the realized volatility, RV, gross spillover plot. Among the other three volatility measures, first, the Continuous Component, C, spillover plot (Figure 16) almost coincides with its RV counterpart. Second, the RNV spillover plot (Figure 14) has similar shape (almost always below, yet close) to RV spillover plot. When the latter increases the former increases and vice versa. The RV spillover plot fluctuates in 41% − 76% band, whereas the RNV counterpart fluctuates within 35% − 65% band. Although the RNV and RV spillover plots behave correspondingly, the pattern of the former diverges in two sub−periods: in 2003−2004 period and in the recent financial crisis period (last quarter of 2008). First, in 2003−2004 period, the RV spillover plot declined from 70% to 41% (29% decline) and increased above 75% in 2004, while the

[9] AUD(0.009%); JPY, CHF and CAD(0.005%); EUR and GBP(0.005%).

[10] 2% lower than the whole sample maximum of 76% in March 2005.

[11] The central banks as well as the governments of the major countries apply coordinated policies.

RNV spillover plot declined from 60% to 43%(17% decline) and reached slightly above 60% in 2004. Second, after the 2007 credit crunch the RNV spillover plot declined around 20% (from 55% to 35%) and increased above 25% (reached above 60%) within 1 month whereas the movement of the RV was less than 10% in the same period.[12]

In section 2.2, I emphasized that the errors' distribution has to be multivariate normal in order to apply generalized VAR methodology. As I will show in section 5.2 the distribution of the errors of the RNV based VAR are closer to the multivariate gaussian than that of the RV based VAR.[13] Therefore, considering the distributions of the errors the RNV may yield more accurate forecast error variances, and thus better spillover measures. However, the accuracy of the RNV estimates are only as good as the RV estimates based on 2− or 3−hour returns (Andersen and Bollerslev, 1998a).[14] As the measurement error declines, or the efficiency or the accuracy increases, with higher−frequency sampling intervals, the RV estimates are more consistent which in turn should result in more accurate spillover estimates.[15]

The JC spillover plot (Figure 15), however, behaves quite different. First, although the spillover plots of the other three volatility measures fluctuates within the 35 percentage band the JC spillover plot's variation band is 55%, (between 15% and 70%). Second, the JC spillover plot's responses to the shocks are very high. For instance, during the August 2007 credit crunch, in 16 August the JC spillover plot jumps from 24% to 44% (20% jump) while this level is much lower for RV(6.3%), RNV(6.5%) and C(5.2%). Moreover, the JC spillover plot moves well below the RV spillover plot except 2004−2005 period

[12]The cholesky based spillover plots of the RV and the RNV follow quite similar pattern over the sample and especially the RV spillover plot increase dramatically during the recent financial crisis (Figures 17 and 18).

[13]See Alizadeh et al. (2002) about the properties of the RNV estimates.

[14]Parkinson (1980) shows that the daily RNV estimates, based on daily high−low observations as defined in equation 2.14, are five times more efficient than that of RV based on close−to−close daily returns. Similarly, Andersen and Bollerslev (1998a) and Brandt and Diebold (2006) find that the daily RNV estimates are as efficient as the RV estimates based on 3− or 6−hour returns. In my analysis I use 5−minute sampling interval, rather than 3−hourly or daily, which increases the efficiency (see Andersen and Bollerslev, 1998a). Although the market microstructure effects yield biased estimates, I mitigate this problem by distinguishing jump component from the RV and use staggered measures of continuous component (see section 2.1). According to Andersen and Bollerslev (1998a), the measurement error of the RV based on 5−min returns are **30−times** lower than daily RNV measure. Lastly, the RNV measures requires specific distributional assumptions which are avoided in RV measures (see Andersen et al., 2003). Recent works of Martens and Van Dijk (2007) and Christensen and Podolskij (2007) proposes realized range−based measure of volatility which may well be both more efficient and accurate than that of RV.

[15]As Alizadeh et al. (2002) and Brandt and Diebold (2006) argue, the RNV estimates are robust to micro−structure noise. But, in my analysis I use micro−structure−noise−robust RV estimates by introducing jump component and using staggered returns (see section 2.1).

where both became very close.[16] The lower levels of the *JC* spillover plot during the 2007 credit crunch and recent financial crisis (Figure 15) in spite of the higher *JC* values (Figures 8 and 9) may be a result of the commonality of the shocks to the exchange rates which in turn do not affect the spillover index significantly.

4.3 Directional Volatility Spillovers

Gross spillover plot illustrates the time varying average interdependence among the exchange rates. Now, to analyze the roles of the each exchange rate in the transmission of the effects of the shocks to the others I discuss the results of the directional and pairwise spillovers defined in section 2.2.2 and 2.2.3. Figures 21, 25, 29 and 33 plot the directional spillovers *FROM* each exchange rate to the others. Similarly, Figures 22, 26, 30 and 34 illustrate the directional spillovers *TO* each exchange rate from the others. I illustrate the *net spillovers*, obtained by subtracting the directional *TO* from directional *FROM*, in Figures 23, 27, 31 and 35 among six exchange rates for the four volatility measures *RV*, *RNV*, *JC* and *C*, respectively. First, I discuss the results of the *RV* directional spillovers and then compare these results to that of other volatility measures.

The *RV* directional volatility spillovers *FROM* (*TO*) each exchange rate does not exceed 20% (14%) (Figure 21 and 22).[17] EUR, GBP and CHF both transmit and receive volatility at higher levels over the whole period (Figures 21**a**, **b**, **d** and 22**a**, **b**, **d**), JPY started to give and receive volatility at higher levels after mid−2004 (Figures 21**c** and 22**c**), while CAD and AUD receives volatility at higher levels but transmit less volatility to the others throughout whole sample (Figures 21**e**, **f** and 22**e**, **f**). In terms of *net volatility spillovers*, the EUR/USD exchange rate is the dominant net volatility transmitter over the period 2002−2009. One can detect three major episodes of net volatility spillovers taking place *FROM* EUR to other exchange rates: from 2002 until mid−2006, late−2006 through mid−August 2007 and from mid-August 2008 thru end of

[16] The sharp decline in the *JC* spillover plot is due to my rolling window size selection (100−day). I apply my VAR model on simulated data. The simulation results show that a coordinated one−time shock to the error terms creates a permanent jump in the spillover plot where the the spillover plot declines slightly over the rolling window and at the end of the rolling window sub−sample the spillover plot declines sharply. To mitigate the effect of the rolling window size I apply my model under various rolling window sizes and check the sensitivity of the results in section 5.3.

[17] Note that the directional *FROM* or directional *TO* entries sum up to spillover index for each time t.

the sample (Figure 23). In the first period, the *RV* spillovers transmitted *FROM* EUR to the others reached as high as 7%. During the 2002 stock market downturn the direction of the volatility spillovers took place *FROM* EUR to first CHF and CAD and then to GBP (Figure 24**a**, **b**, **c**). In this period, although EUR received significant amount of volatility from JPY, this amount is offsetted by volatility transmission *TO* others. Later in this period the bulk of the volatility spillovers from EUR were transmitted to GBP and JPY (Figure 24**a**, **b**).

The second period of EUR's net volatility transmission status started in late−2006 lasts until mid−August 2007, just before the climax of the credit crunch. Throughout this period the gross spillover plot declined from 70% to 55%. The spillovers transmitted mostly *TO* GBP and slightly *TO* CAD and AUD (Figure 24**a**, **d**, **e**). Similar to the first period, EUR was the net recipient of the volatility in this period following the effects of Bank of Japan's huge intervention in mid−2006.[18]

Finally, the last period started in the last quarter of 2008 thru the end of the sample. In this period the global financial crisis hit the global financial markets and the spillover plot stayed above 71%. The net volatility spillovers *FROM* EUR reached as high as 7% where the spillovers mostly took place *TO* CAD and CHF as well as JPY (Figures 23**a** and 24**c**, **d**, **d**). Overall, EUR is the major vehicle currency that transmits its own shocks to the other currencies throughout the whole sample.

The GBP net spillovers folllowed an oscillating pattern in pre−2004 and post−2006 periods whilst turned into a net volatility transmitter from 2005 thru mid−2006 (Figure 23**b**). CHF and CAD were the net receivers of the bulk of the volatility spillovers transmitted *FROM* GBP over the whole period, and especially in the crisis periods: 2002 stock market downturn, 2007 credit crunch and 2008 global financial crisis (Figure 24**g**, **h**). The behavior of JPY is same except mid-2006 and 2007 credit crunch period when GBP became net receiver of the volatility spillovers transmitted *FROM* JPY (Figure 24**f**). It is also noteworthy that GBP was the net volatility transmitter in the crisis periods where the volatility transmitted *FROM* GBP jumped above 5 percent level.

[18] I will show that JPY became net volatility transmitter after this intervention until the last quarter of 2008.

The Japanese yen was the net volatility receiver until May 2006. After Bank of Japan's May 9, 2006 huge market intervention and reversing its long lasting zero target rate policy[19] in the following month JPY became an important volatility transmitter until August 2008 except January and December 2007 (Figure 23**c**). The net spillovers transmitted *FROM* JPY had three peaks which corresponds to post−policy shift of BOJ in August 2006 (7%), huge carry trade unwind occurred in August 16−17, 2007 following the collapse of the global stock and equity markets (8.5%) and just before the climax of the global financial crisis in July 2008 (5.3%). In terms of net pairwise spillovers *FROM* JPY the major recipients were AUD, GBP and EUR in both during 2006 and 2007, and CHF and CAD only throughout 2006 (Figure 24**b**, **f**, **j**, **k**, **l**).

The CHF is the net volatility transmitter throughout the whole sample except during 2003 and the crisis periods: 2002 stock market downturn, 2007 credit crunch and 2008 global financial crisis. Although it is the net transmitter of the volatility spillovers the size of the volatility spillovers *FROM* CHF does not exceed 3% level (Figure 23**c**).

The CAD and the AUD are the net receivers of the volatility spillovers except third quarter of 2003 and late−2007 for the former and during 2002, mid−2006 and post−2007 for the latter (Figures 23**e** and 23**f**). It is striking that during the recent financial crisis the volatility spillovers transmitted *FROM* AUD reached as high as 7.3% where all exchange rates were the net receivers of volaitlity from AUD (e.g., higher than 2% for GBP) (Figures 23**f** and 24**i**).

Up to this point I have presented the results of the *RV* net and pairwise directional spillovers. The *C* directional spillovers results are rather similar to that of the *RV* (Figure 35). The *RNV* directional spillovers results are quite similar to the *RV* results for CHF, CAD and AUD (Figure 27**d**, **e**, **f**) whilst they are quite different in certain periods for the most actively traded currencies EUR, GBP and JPY (Figure 27**a**, **b**, **c**). First, considering EUR, the net directional spillovers pattern of *RNV* and *RV* are similar except 2007 credit crunch and recent financial crisis periods (Figure 27**a**). In 2007 credit crunch period, *RV* net spillovers took large negative values (fell below -4.7%) for five months starting on August 16. The *RNV* net spillovers, however, did not follow a clear pattern, oscillated around zero (within [-1,1.4] band). Similarly, the period after the beginning os September 2008, the financial crisis hit climax, the *RV* net spillovers

[19]BOJ increased the operational short term interest rate to 0.25% in both June 14, 2006 and February 2007.

took large positive values (above 6%) while that of the RNV oscillates within [-2, 2] band.

Second, the RNV GBP net directional spillovers is mostly net volatility recipient throughout the sample whereas the reverse is the case for that of the RV (Figure 27**b**). In particular, in the 2007 credit crunch and 2008 financial crisis periods the net volatility transmitter pattern of GBP for the RV turned into net volatility receiver for the RNV. Lastly, The behavior of JPY net spillovers were almost same for 2002−2006 and 2007-2008 periods for both RNV and RV. The JPY RNV net spillovers became less negative after BOJ policy reversal and huge market intervention in mid−2006 but JPY did not turn into a net volatility transmitter (Figure 27**c**). Similarly, while the JPY for the RV was mostly a net volatility recipient (lower than -4.5%) when the recent financial hit climax, it turned into a net transmitter (higher than 3%) for the RNV. Overall, the RNV and RV net spillovers do not act accordingly for the most−actively traded currencies[20] during the turmoil periods (Figures 23**a**, **b**, **c** and 27**a**, **b**, **c**).

Finally, the JC net spillovers behave quite different compared to other three volatility measures. The EUR as well as the CHF become the dominant net volatility transmitters yet the size of the spillovers transmitted $FROM$ CHF does not exceed 3% except the recent financial crisis (reached 5% in mid−2008). The net volatility transmitter pattern of the GBP for the RV in the crisis periods were preserved for the JC. The JPY directional spillovers, however, did not respond to the 2006 policy reversals of the BOJ by remaining as net volatility receiver. Although the JPY net spillovers pattern turned into positive (jump from -2.5% to 2.1%) in August 16, 2007, it reverted back to the net receiver position in August 20. In addition, especially in the 2007 credit crunch period, for the JC, the behavior of the net spillovers for the EUR as well as CHF, CAD and AUD took place in the same direction yet died out rapidly compared to the RV. By construction, the JC consists of only the significant jumps and zeros otherwise (see equation 2.12). Thus, the higher jumps may well be followed by insignificant jumps (zero values) which supports the short−lived−responses of the net volatility spillovers.

[20]Which are EUR, JPY and GBP consisting of the 52% of the total FX market turnover (see Table 1)

Chapter 5

Robustness Check

In this chapter I will check the assumptions of the VAR model defined in section 2.2 as well as the sensitivity of my results to different VAR specifications.

5.1 Stationarity

The spillover index methodology used in this study is based on VAR which requires the covariance stationary of the endogenous variables. I use four different volatility measures RV, RNV, JC and C. Since the Philips$-$Perron test, for the rest of the paper $PP{-}test$, is robust against different forms of the heteroskedasticity in the error term, and does not require lag length selection, I apply $PP - test$ and allow for constant for all tests.

I report the $PP{-}test$ statistics for each volatility measures for the whole sample period, $2002-2009$, in Table 15. All the test statistics given in the table are considerably below the critical value at even 1% significance level (-2.86). Thus, the test results indicate that we should reject the null of unit root for all series even at 1% significance level.

Although at full sample level there no evidence against the stationarity, since I apply rolling window estimation in order to compute the VAR based spillover index I have to check the covariance stationarity of each series for each rolling window. This constitutes $4 \times 6 \times 1670 = 40080$[1] test statistics. Thus instead of using tables, I graphically illustrate the test results. Figures 37$-$to$-$40 depict the $PP - test$ statistics for each 100$-$day

[1] I use 4 voaltility measures, 6 exchange rate series and 1772 daily observations ($1772 - 102 = 1670$).

rolling window sub−samples for the RV, RNV, JC and C, respectively. Considering the RNV and the JC, all volatility measures for all of the rolling window sub−samples are stationay at 5% significance level, except 1 sub−sample for the JC.

Considering the RV and the C, however, for 95 and 103 of the sub−samples I cannot reject the null of the unit root at 5% significance level, respectively. The Figures 37 and 40 illustrate that for the RV and the C, during the global financial crisis, especially the crisis hit the climax in the last quarter of 2008, the volatility measures of almost all exchange rates became non-stationary.

5.1.1 Vector Error Correction

In section 5.1, I show that for some of the rolling window sub−samples the volatility series are non-stationary for the RV and the C. Thus, I can not apply VAR model for these nonstationary sub−samples. Thus, I use the VEC model to measure the spillover index.[2]

First, since VEC model requires cointegration among non-stationary series I apply Johansen cointegration test for the non−stationary sub−samples and plot the p−values of the corresponding test statistics in Figures 41−to−44. I do not allow for the deterministic trend in the cointegrating equation but intercept. For the RV and C, both the trace test and max-eigenvalue test indicate that at 5% significance level there is at least one cointegrating equation for 3/4 and 5/6 of the nonstationary sub−samples, respectively.[3]

The VAR based and VEC based spillover plots for the non−stationary rolling window sub− ssamples for the RV and the C are given in Figures 45 and 47. The spillover plots follow similar paths and are very close to each other for both the RV and the C.[4]

[2] In order to measure the spillovers Yilmaz (2009) uses VEC model.

[3] Which consists of 70 out of 95 sub−samples for the RV and 86 out of 103 for the C.

[4] There may well be some undetected nonstationary in the sub−samples. In order to include the effects of these sub−samples I plot the VEC based spillover plots for the RV and the C for all the sub−samples and compare these plots with the VAR based spillover plots (Figures 46 and 48). The results show that VAR based and VEC based spillover indices have similar shapes and moves within a narrow area band.

5.2 Normality of the Residuals

Although the VAR model defined in section 2.2 does not assume normality of the residuals, the generalized variance decompositions requires multivariate normally distributed residuals (Pesaran and Shin 1998). It also has many applications in financial time series models (see Demiroglu and Kilian, 2000). For example Lütkepohl and Schneider (1989) use normality of the residuals in detecting the normality of the endogenous variables in the autoregressive models. I choose Jarque-Berra methodology since it is consistent for the stationary autoregressive processes (see Lütkepohl, 1993) and use the modified Jarque-Berra test, hereafter $JB - test$, introduced by Urzúa (1996) which is more appropriate for small- and medium-sized samples.

Figures 57−to−64 plots the p−values of the $JB - tests$. The p−values of the joint normality test for the log volatility measures are considerably higher than the level counterparts (Figure 57). Considering the log RV, the residuals are jointly Gaussian for around half of the rolling window sub−samples at 5% significance level. This ratio is 3/4 for the log C and around 1 for the log RNV. Considering the level volatility measures this ratio is around zero for all of the four measures. Also, almost all of the VAR error terms based on log volatility measure are individually Gaussian (Figures 58−to−60) whereas for the level volatility measures the result is exactly opposite. These results provide evidence for preferring the log volatility over the level measures.[5]

5.3 Lag Length, Forecast Horizon Length and Rolling Window Size

In my spillover measures I use VAR(2) model. Here, I relax this assumption and estimate the VAR equation for different lag lengths (from 2 to 6 lags, see Figures 49−to−52). In addition I obtain the spillover indices for different forecast horizon lengths (from 5 to 10 days, see Figures 53−to−56). For all four volatility measures, the spillover plots for different forecast horizons almost coincides.[6] The spillover plots, however, are more sensitive to the different lag length selection where the sensitivity increases for the lower

[5] I also plot the log volatility vs. level volatility measures based spillovers for the RV, RNV and C (Figures 69−to−71). Although the fluctuations of the spillover plots are very small for log vs. level measures, the resultant error term distributions differ substantially.

[6] I also check the results under 12, 16, 24 days forecast horizons. The results do not vary significantly.

level of the spillovers. The highest deviations occur in the JC and RNV spillover indices (Figure 49 and 51).

I also select the optimal lag length in each rolling window sub−sample based on the information criteria and likelihood ratio statistic. The optimal lag length is around 2 for all volatility measures, whereas for the last quarter of 2008, the optimal length rise up to 5 indicating the higher serial dependence of the volatility during the financial crisis period.

Lastly, I check the sensitivity of the results to the rolling window sub−sample size by estimating my VAR model (equation 2.15) for the 75−, 100−, 150− and 200−rolling windows (Figures 65−to−68). The spillover plots fluctuate within the 14% band where the responsiveness increases with the level of the spillover index. This result suggests that my results are not very sensitive to the rolling window size.

Chapter 6

Summary and Concluding Remarks

In this paper, I apply the DY10 (building on DY09) spillover index methodology to six major exchange rates in order to make a comparative analysis of the volatility spillovers in the FX market for the period 2002-2009 by using recently developed four non−parametric volatility measures, namely RV, RNV, JC and C. I results can be summarized in two parts.

First, the rolling window sub−sample VAR estimation based volatility spillover indices fluctuate over time for all volatility measures and move around 65% for RV and C, 45% for RNV and JC. The high levels of the spillovers over time are consistent with the results of Diebold and Nerlove (1989); Dungey and Martin (2004); Bekiros and Diks (2008) in which there are high linkages among the exchange rates. The RV and C spillover plots move very close over time, which indicates that the results are robust to the jumps. The RNV and especially the JC spillover plots, however, behave quite different at certain time periods. Although the volatilities of the exchange rates reach as high as 40 times higher than their corresponding sample means during the recent financial crisis period, the spillover plots do not increase much. These results provide evidence for the concurrency of the shocks during these global turmoil periods.

Second, I analyze the direction of the volatility spillovers among the exchange rates over time. The volatility spillovers transmitted $FROM/TO$ exchange rates almost always stay above the 12% for the RV and C, and 8% for the RNV and JC. Moreover, the net volatility spillovers fluctuates within [-8%, 8%] band for all volatility measures. These high levels of directional spillovers as well as the high levels of the gross spillovers illustrate the higher interdependence of the volatility movements in the FX market. The direction of the volatility spillovers are mostly *FROM* EUR to other exchange rates during 2002-2009 period and *FROM* JPY to others after BOJ's policy reversal in mid−2006 for all volatility measures. These results are consistent with that of Kitamura (2009); Inagaki (2007); Nikkinen et al. (2006) who find that the EUR is the major net volatility transmitter over time. Nevertheless, similar to the gross spillovers, the behavior of the directional volatility spillovers based on different volatility measures differ a lot, particularly during the turmoil periods.

My results suggest for various avenues for future research. First, in my analysis, I apply an intuitive tool, rolling window sub−sample VAR estimation in order to obtain the time varying pattern of the volatility spillovers. Instead, one may use recently developed "time-varying-coefficient" VAR model that relies on the Bayesian methods (see Canova, 2007) which proposes an "econometric model" based measurement of the time varying pattern of the impulse responses and variance decompositions, and thus spillovers.

Second, I obtain spillovers based on daily volatility measures. Considering the tremendous volume of trade in the FX market and the high level of interaction among the financial markets, the daily volatility measures might fail to capture the directional movement (spillovers) of the intra−day shocks and presume them as common shocks which results in downward bias of the spillover measures. Thus, instead of daily volatility measures, using 3−, 6− or 12−hourly volatilities might yield more accurate spillovers. On the contrary, the non−parametric volatility measures tend to be biased as the number of the underlying return data decreases. Taking this trade off into account, higher frequency estimates may result in better spillover measures in the FX market.

Lastly, the economists have long been interested in the effects of the macroeconomic news on the return and the volatility of the assets (see, for example, Hardouvelis, 1988, Andersen and Bollerslev, 1998b, Andersen et al., 2003 and Andersen et al., 2007). It would be interesting to analyze the effects of the macroeconomic news on the return and volatility spillovers in the FX market.

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A. Descriptive Statistics

Table 1: **Reported FX Market Turnover by Currency Pair**
(Daily averages in April 2007, in billions of US dollars and per cent)

	2001		**2004**		**2007**	
	Amount	% share	Amount	% share	Amount	% share
US dollar/euro	354	30	503	28	840	27
US dollar/yen	231	20	298	17	397	13
US dollar/British pound	125	11	248	14	361	12
US dollar/Australian dollar	47	4	98	5	175	6
US dollar/Swiss franc	57	5	78	4	143	5
US dollar/Canadian dollar	50	4	71	4	115	4
US dollar/other	195	17	295	16	628	21
Euro/yen	30	3	51	3	70	2
Euro/sterling	24	2	43	2	64	2
Euro/Swiss franc	12	1	26	1	54	2
Euro/other	21	2	39	2	112	4
Other currency pairs	26	2	42	2	122	4
All currency pairs	1173	100	1794	100	3081	100

Source: BIS April 2007 triennial central bank survey.
* Adjusted for local and cross-border double-counting.

Table 2: **Daily Realized Return Summary Statistics**

	EUR/ USD	**GBP/ USD**	**USD/ JPY**	**USD/ CHF**	**USD/ CAD**	**AUD/ USD**
Mean	0.00018	0.00002	-0.00007	-0.00017	-0.00009	0.00005
Median	0.00011	0.00024	0.00007	0.0000	-0.00022	0.00059
Maximum	0.03069	0.02979	0.05752	0.03025	0.03266	0.06369
Minimum	-0.0265	-0.03764	-0.03424	-0.04247	-0.0404	-0.07346
Std. Dev.	0.00629	0.00602	0.00658	0.00686	0.00613	0.00906
Skewness	0.02975	-0.53364	0.11384	-0.16211	0.13471	-0.91684
Kurtosis	4.704	7.032	8.094	4.742	6.402	13.933
LB$_{15}$	19.324	36.377^{a*}	46.147^{a}	30.146^{a}	32.148^{a}	39.295^{a}
JB	214.59^{a}	1284.24^{a}	1919.77^{a}	231.71^{a}	859.78^{a}	9072.98^{a}

* The superscript “a” and “b” stand for the rejection of the null at 1% and 5% significance levels, respectively.

Table 3: **Daily Realized Volatility Summary Statistics**

	EUR/ USD	GBP/ USD	USD/ JPY	USD/ CHF	USD/ CAD	AUD/ USD
Mean	0.00004	0.00004	0.00005	0.00005	0.00005	0.00009
Median	0.00003	0.00003	0.00004	0.00004	0.00003	0.00005
Maximum	0.00055	0.00097	0.00157	0.00065	0.00064	0.00372
Minimum	0.00001	0.00001	0	0.00001	0.00001	0.00001
Std. Dev.	0.00004	0.00006	0.00007	0.00004	0.00005	0.00019
Skewness	4.477	6.11	9.443	4.763	4.827	9.203
Kurtosis	32.101	58.204	146.798	45.455	36.797	124.47
LB$_{15}$	12406.7^a	14281.3^a	5998.9^a	7438.1^a	14097.8^a	10745.5^a
JB	67327^a	232670^a	1528975^a	138329^a	90367^a	1097087^a

Table 4: **Daily Log Realized Volatility Summary Statistics**

	EUR/ USD	GBP/ USD	USD/ JPY	USD/ CHF	USD/ CAD	AUD/ USD
Mean	-10.29	-10.458	-10.148	-10.075	-10.261	-9.733
Median	-10.327	-10.559	-10.234	-10.1	-10.315	-9.88
Maximum	-7.51	-6.942	-6.456	-7.333	-7.358	-5.593
Minimum	-11.942	-12.126	-12.416	-11.788	-12.182	-11.118
Std. Dev.	0.64371	0.68011	0.65272	0.58581	0.6889	0.74622
Skewness	0.676	1.513	1.061	0.43886	0.72876	1.688
Kurtosis	4.204	6.645	5.656	3.765	4.308	7.041
LB$_{15}$	13287.5^a	14980.9^a	8978.8^a	10729.6^a	15059.6^a	14674.1^a
JB	234.9^a	1648.6^a	835.8^a	97.17^a	297.6^a	2016.6^a

Table 5: **Daily Range Volatility Summary Statistics**

	EUR/ USD	GBP/ USD	USD/ JPY	USD/ CHF	USD/ CAD	AUD/ USD
Mean	0.00004	0.00004	0.00004	0.00004	0.00004	0.00007
Median	0.00002	0.00002	0.00002	0.00003	0.00002	0.00003
Maximum	0.00054	0.00161	0.00196	0.00079	0.00122	0.00416
Minimum	0.000001	0.000001	0.000000	0.000002	0.000002	0.000003
Std. Dev.	0.00005	0.00007	0.00008	0.00005	0.00006	0.00021
Skewness	4.818	10.153	13.495	5.332	8.599	11.412
Kurtosis	37.141	181.91	284.289	53.644	122.798	172.995
LB$_{15}$	4563.4^a	5564.26^a	1785.38^a	1765.02^a	5445.4^a	5202.03^a
JB	92916^a	2393224^a	5895650^a	197786^a	1081429^a	2172092^a

Table 6: **Daily Log Range Volatility Summary Statistics**

	EUR/ USD	GBP/ USD	USD/ JPY	USD/ CHF	USD/ CAD	AUD/ USD
Mean	-10.74	-10.86	-10.63	-10.49	-10.78	-10.30
Median	-10.75	-10.94	-10.64	-10.48	-10.79	-10.43
Maximum	-7.53	-6.43	-6.24	-7.14	-6.71	-5.48200
Minimum	-13.51	-13.44	-14.84	-13.37	-13.31	-12.87
Std. Dev.	0.961	0.99094	0.96128	0.91877	0.98027	1.04000
Skewness	0.184	0.48003	0.23288	0.00504	0.33747	0.83188
Kurtosis	2.990	3.669	3.589	3.033	3.337	4.42
LB$_{15}$	3910.3^a	4931.9^a	2672.4^a	2337.9^a	5311.4^a	6455.9^a
JB	9.9^a	101.1^a	41.5^a	0.091	42.0^a	353.2^a

Table 7: **Daily Jump Component Summary Statistics**

	EUR/ USD	**GBP/ USD**	**USD/ JPY**	**USD/ CHF**	**USD/ CAD**	**AUD/ USD**
Mean	0.00000	0.00000	0.00000	0.00000	0.00001	0.00001
Median	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Maximum	0.00017	0.00018	0.00031	0.00016	0.00012	0.00019
Minimum	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Std. Dev.	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001
Skewness	9.075	9.283	11.029	6.774	4.968	4.822
Kurtosis	144.3	142.244	198.42	68.961	41.42	39.955
$\mathbf{LB}_{15}$	25^b	581^a	361^a	28^b	561^a	502^a
JB	1498466^a	1457001^a	2855574^a	334793^a	116273^a	107701^a

Table 8: **Daily Log Jump Component Summary Statistics**

	EUR/ USD	**GBP/ USD**	**USD/ JPY**	**USD/ CHF**	**USD/ CAD**	**AUD/ USD**
Mean	-12.05	-12.16	-11.86	-11.75	-11.93	-11.44
Median	-12.08	-12.25	-12.00	-11.78	-12.02	-11.50
Maximum	-8.67	-8.61	-8.07	-8.77	-9.07	-8.59
Minimum	-13.98	-14.19	-14.12	-13.62	-13.90	-13.17
Std. Dev.	0.77	0.74	0.81	0.75	0.76	0.76
Skewness	0.476	0.956	0.998	0.658	0.583	0.539
Kurtosis	3.796	4.817	4.58	4.304	3.661	3.308
$\mathbf{LB}_{15}$	268.43^a	452^a	203^a	117^a	1161^a	350^a
JB	48.87^a	241.76^a	193.35^a	101.70^a	72.15^a	42.83^a

Table 9: **Daily Continuous Component Summary Statistics**

	EUR/ USD	**GBP/ USD**	**USD/ JPY**	**USD/ CHF**	**USD/ CAD**	**AUD/ USD**
Mean	0.00004	0.00004	0.00005	0.00005	0.00004	0.00009
Median	0.00003	0.00002	0.00003	0.00004	0.00003	0.00005
Maximum	0.00055	0.00079	0.00126	0.00065	0.00059	0.00373
Minimum	0.00001	0.00000	0.00000	0.00001	0.00000	0.00001
Std. Dev.	0.00004	0.00006	0.00006	0.00004	0.00005	0.00019
Skewness	4.767	5.696	8.291	5.14	4.972	9.43
Kurtosis	36.231	47.232	111.066	54.501	38.817	129.413
$\mathbf{LB}_{15}$	13284^a	14995^a	7109^a	8557^a	14704^a	10513^a
JB	88246^a	154035^a	882546^a	203632^a	102019^a	1206141^a

Table 10: **Daily Log Continuous Component Summary Statistics**

	EUR/ USD	GBP/ USD	USD/ JPY	USD/ CHF	USD/ CAD	AUD/ USD
Mean	-10.38	-10.55	-10.23	-10.16	-10.38	-9.83
Median	-10.42	-10.66	-10.31	-10.19	-10.42	-10.00
Maximum	-7.51	-7.15	-6.68	-7.33	-7.43	-5.59
Minimum	-11.99	-12.25	-12.42	-11.79	-12.46	-11.25
Std. Dev.	0.65	0.69	0.65	0.58	0.70	0.76
Skewness	0.724	1.539	1.052	0.46	0.657	1.814
Kurtosis	4.333	6.77	5.613	3.828	4.337	7.486
LB15	14245^a	15449^a	9599^a	11592^a	15631^a	15043^a
JB	286^a	1749^a	831^a	113^a	259^a	2458^a

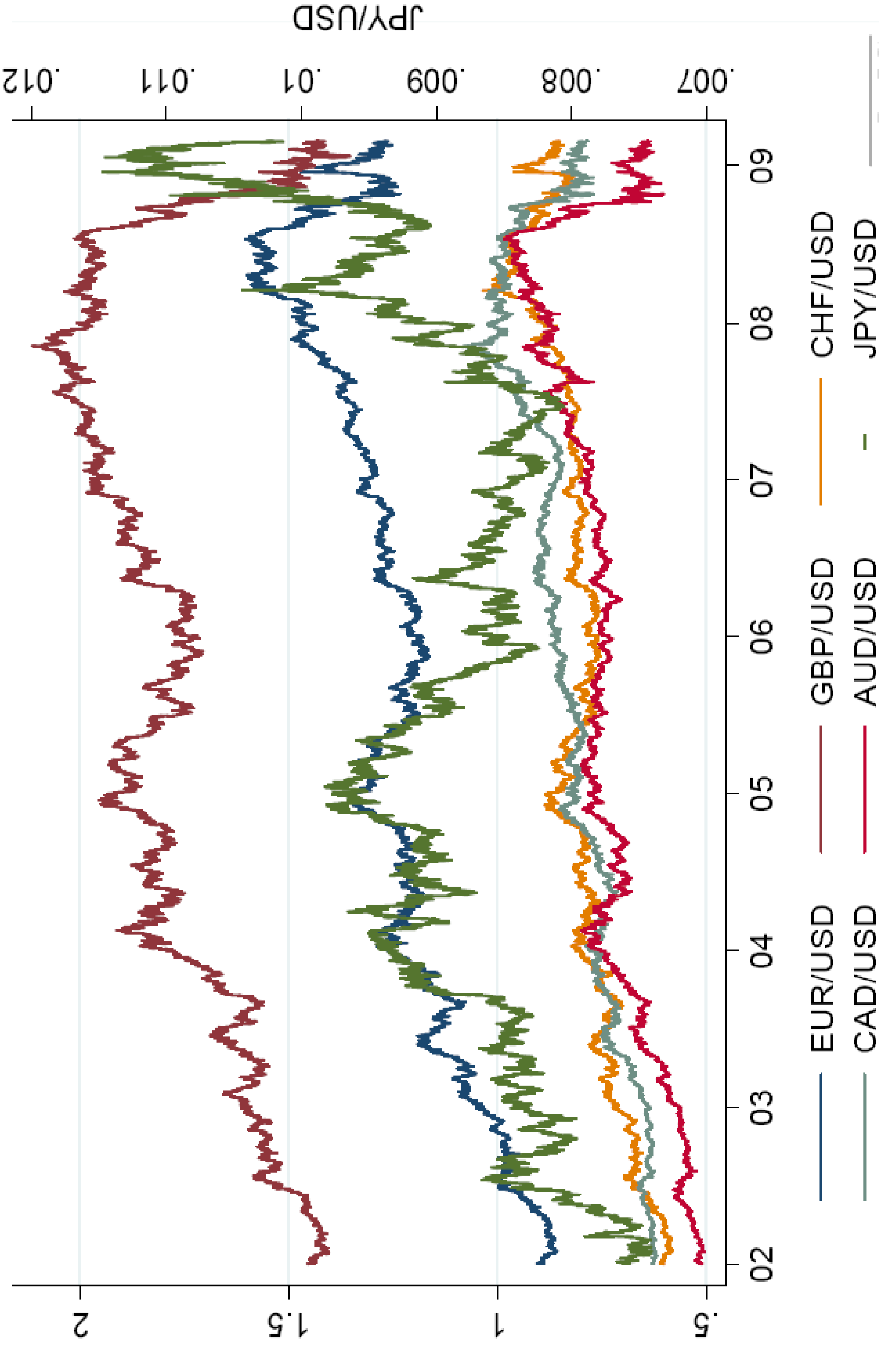


FIGURE 1: **Exchange Rates**

Figure 2: **RV Kernel Density**

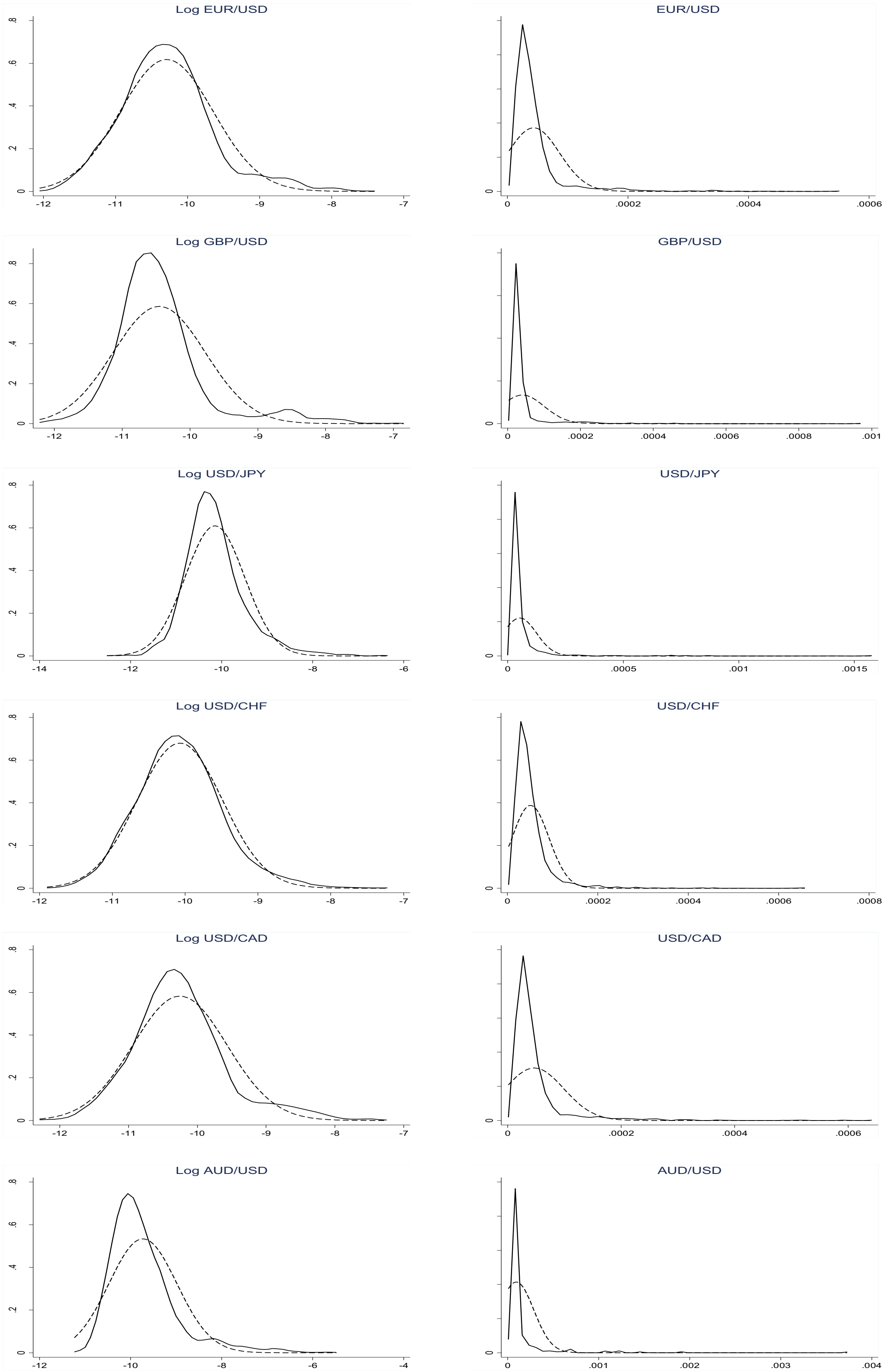


Figure 3: **RNV Kernel Density**

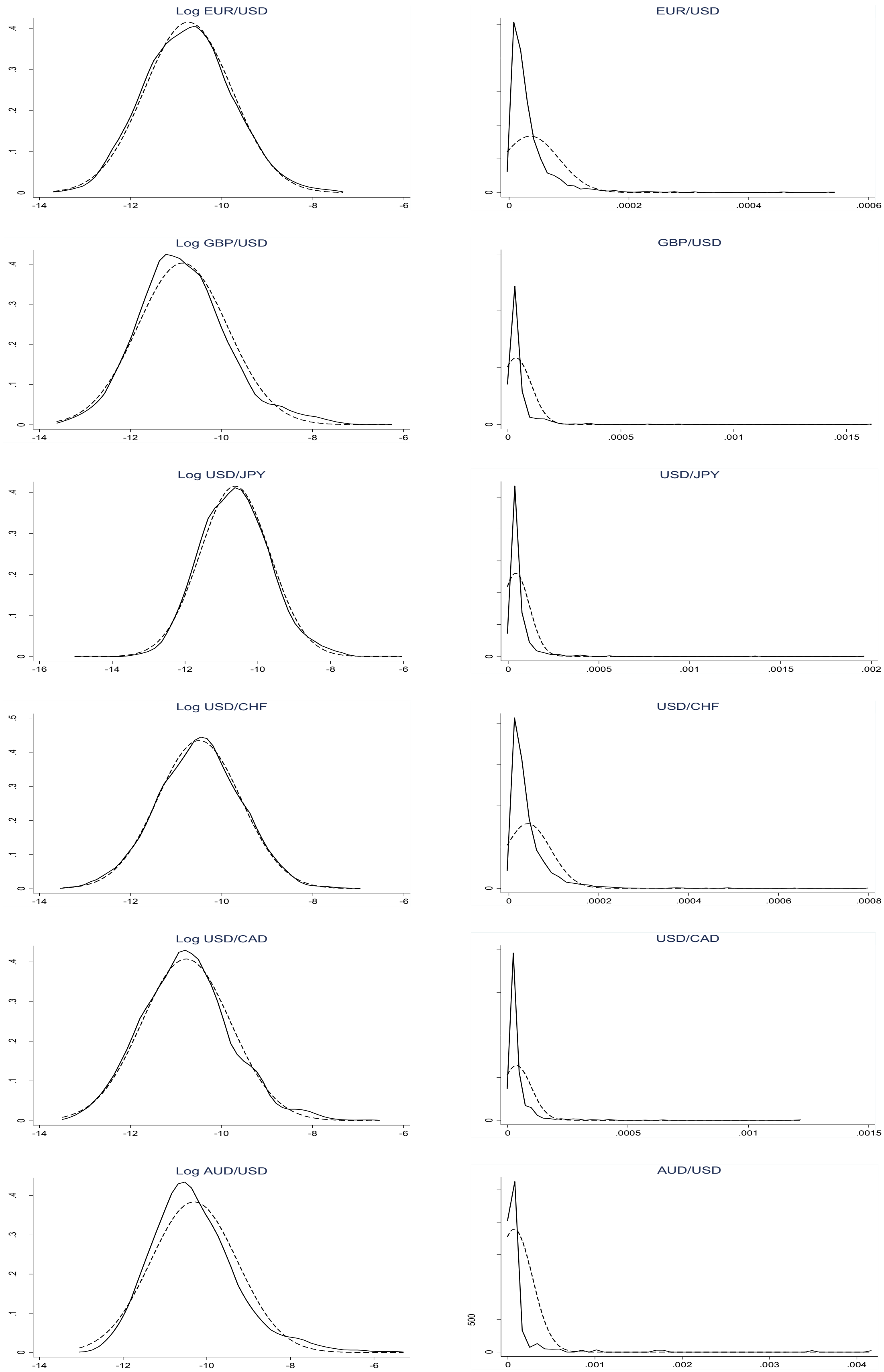


FIGURE 4: **JC Kernel Density**

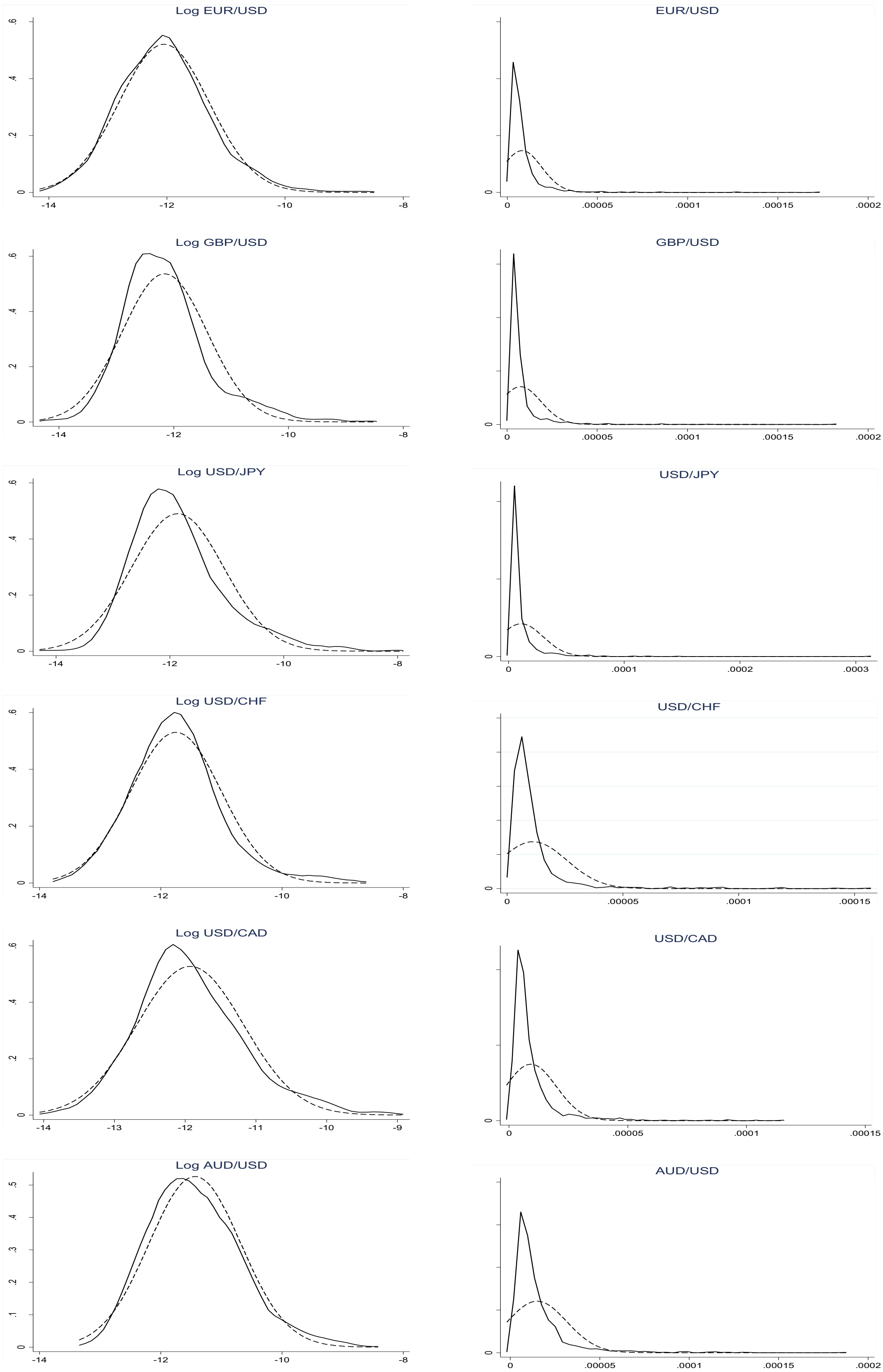


FIGURE 5: **C Kernel Density**

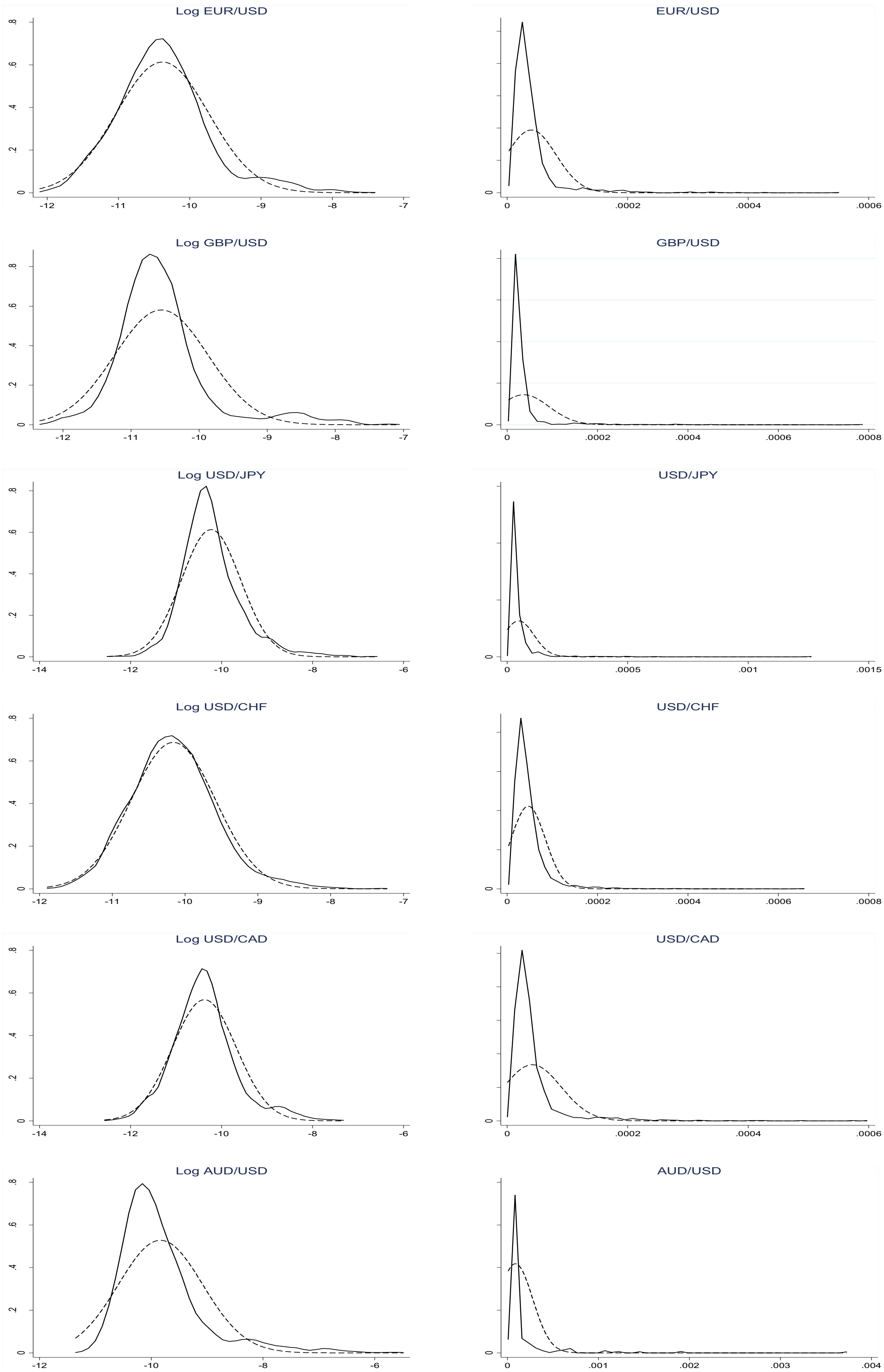


Figure 6: **Realized Volatility**

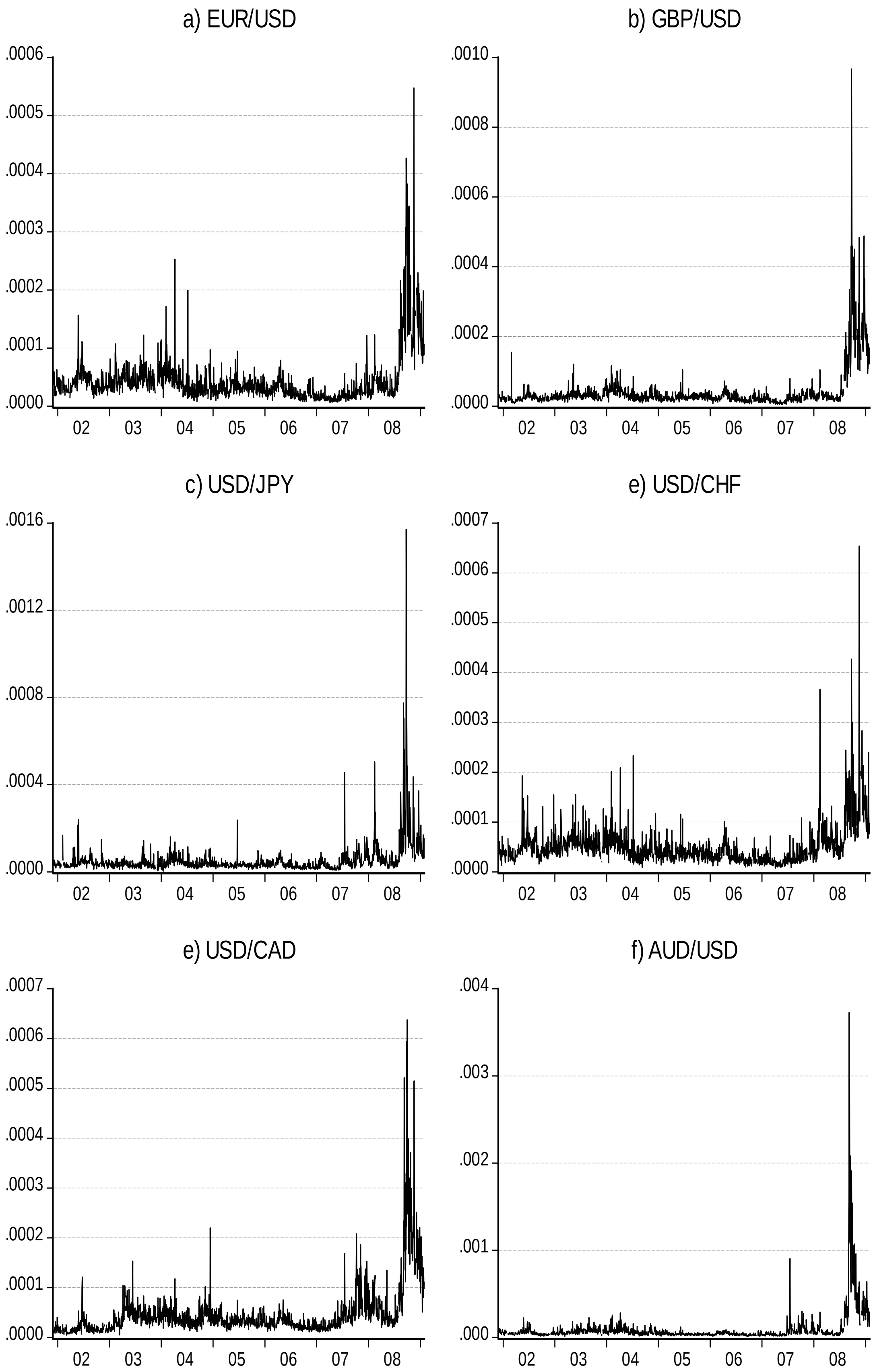


Figure 7: **Range Volatility**

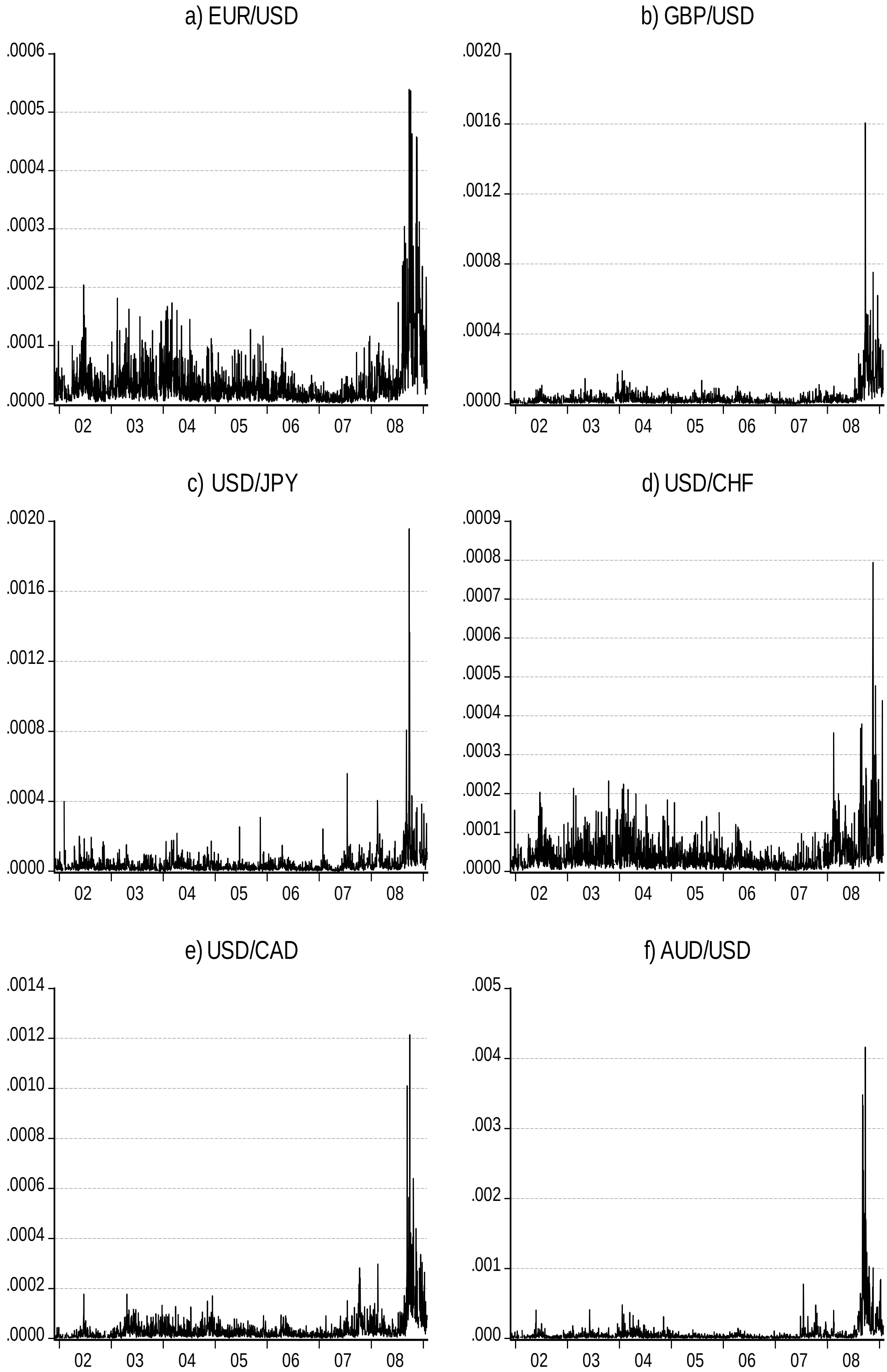


Figure 8: **Jump Component**

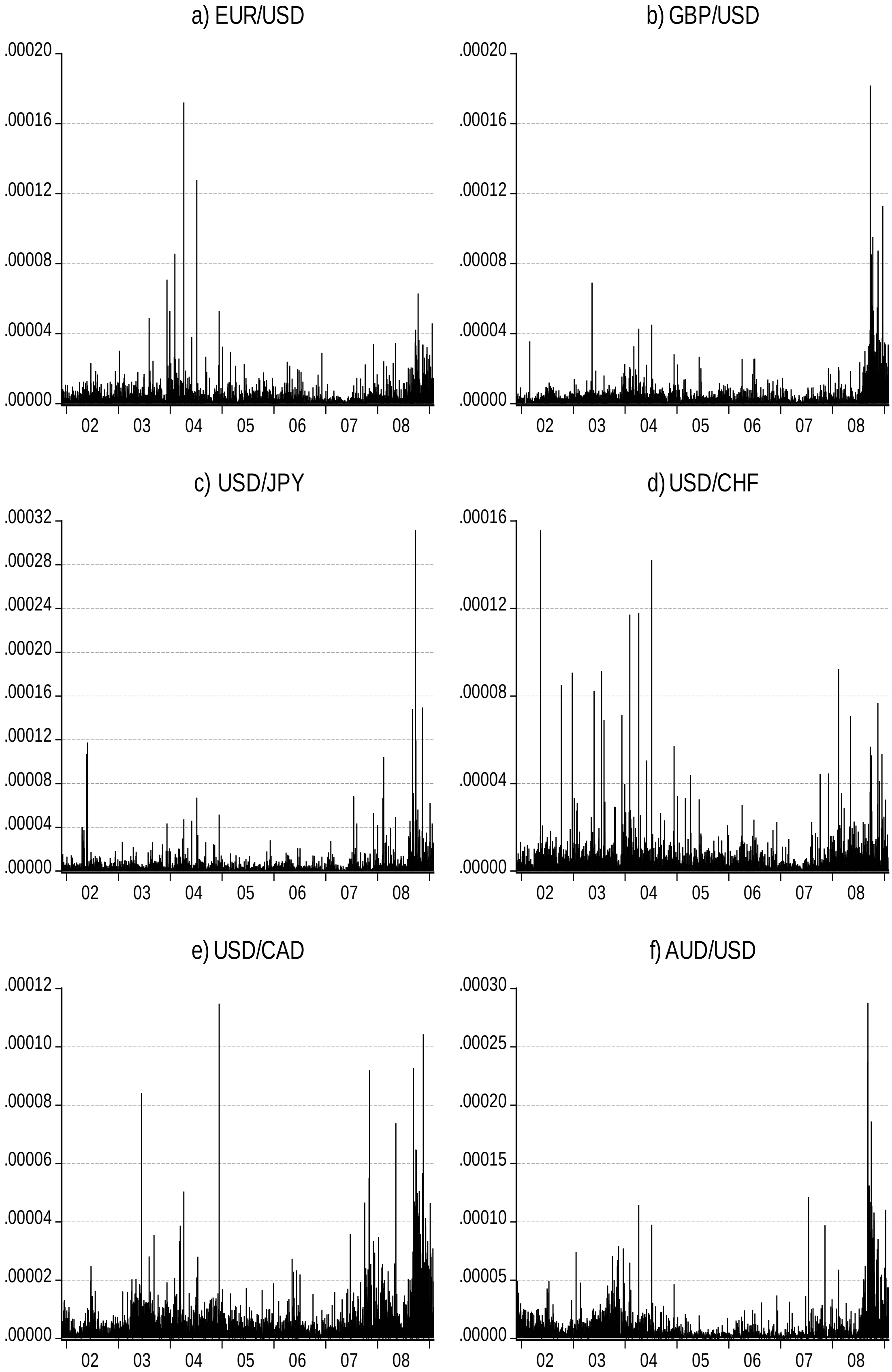


Figure 9: **Significant Jump Component (5% Significance Level)**

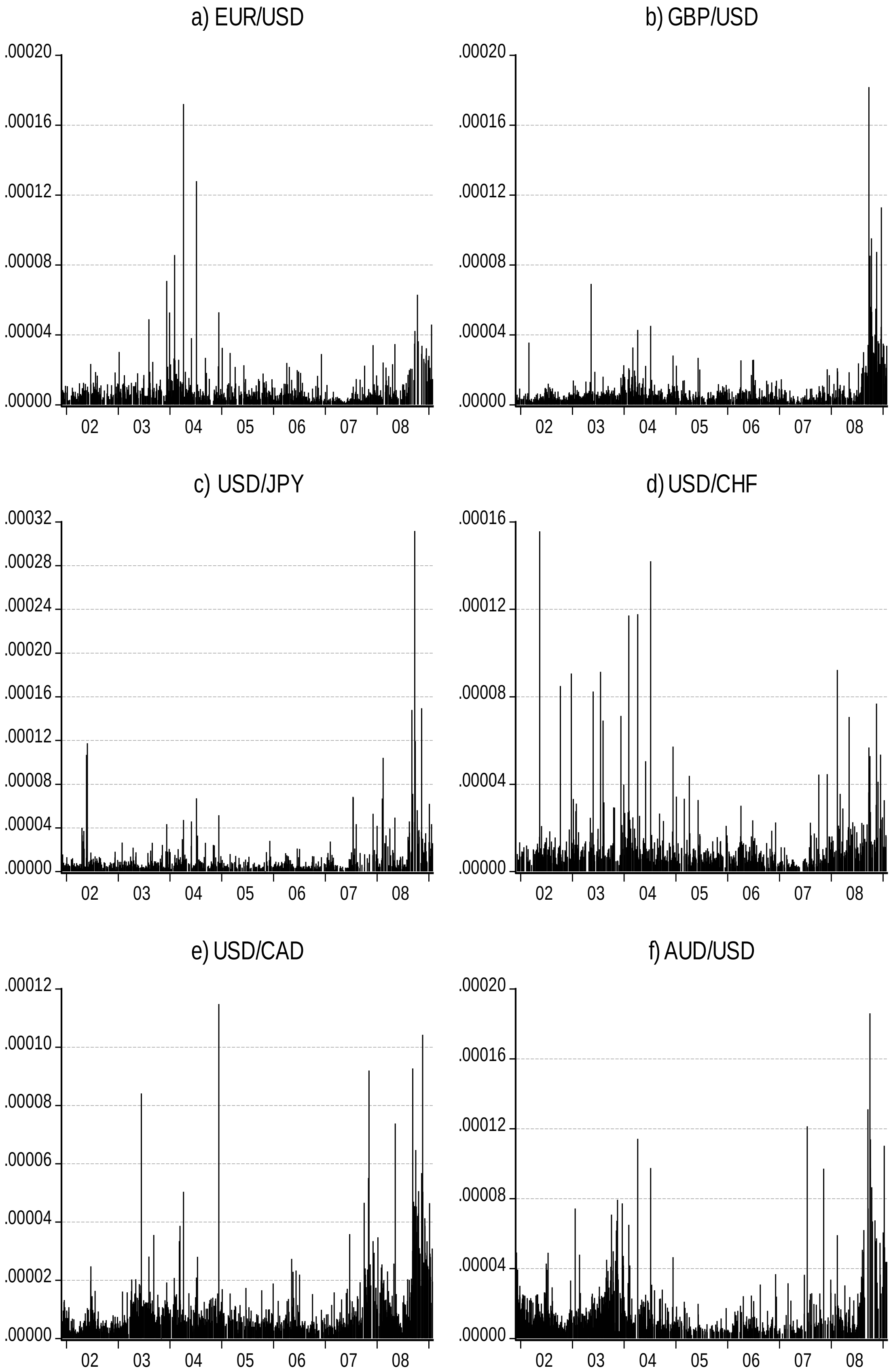


Figure 10: **Continuous Component**

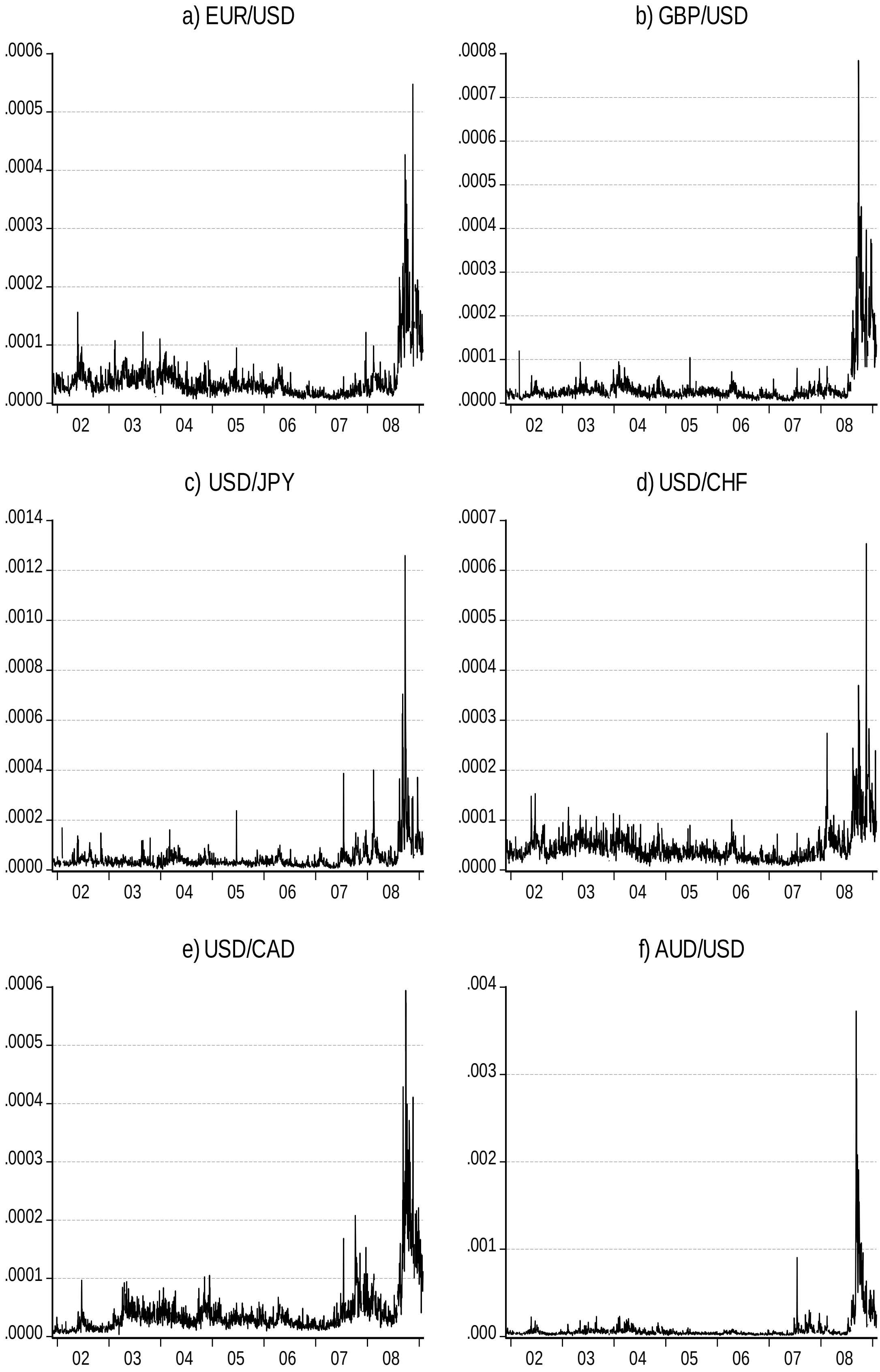
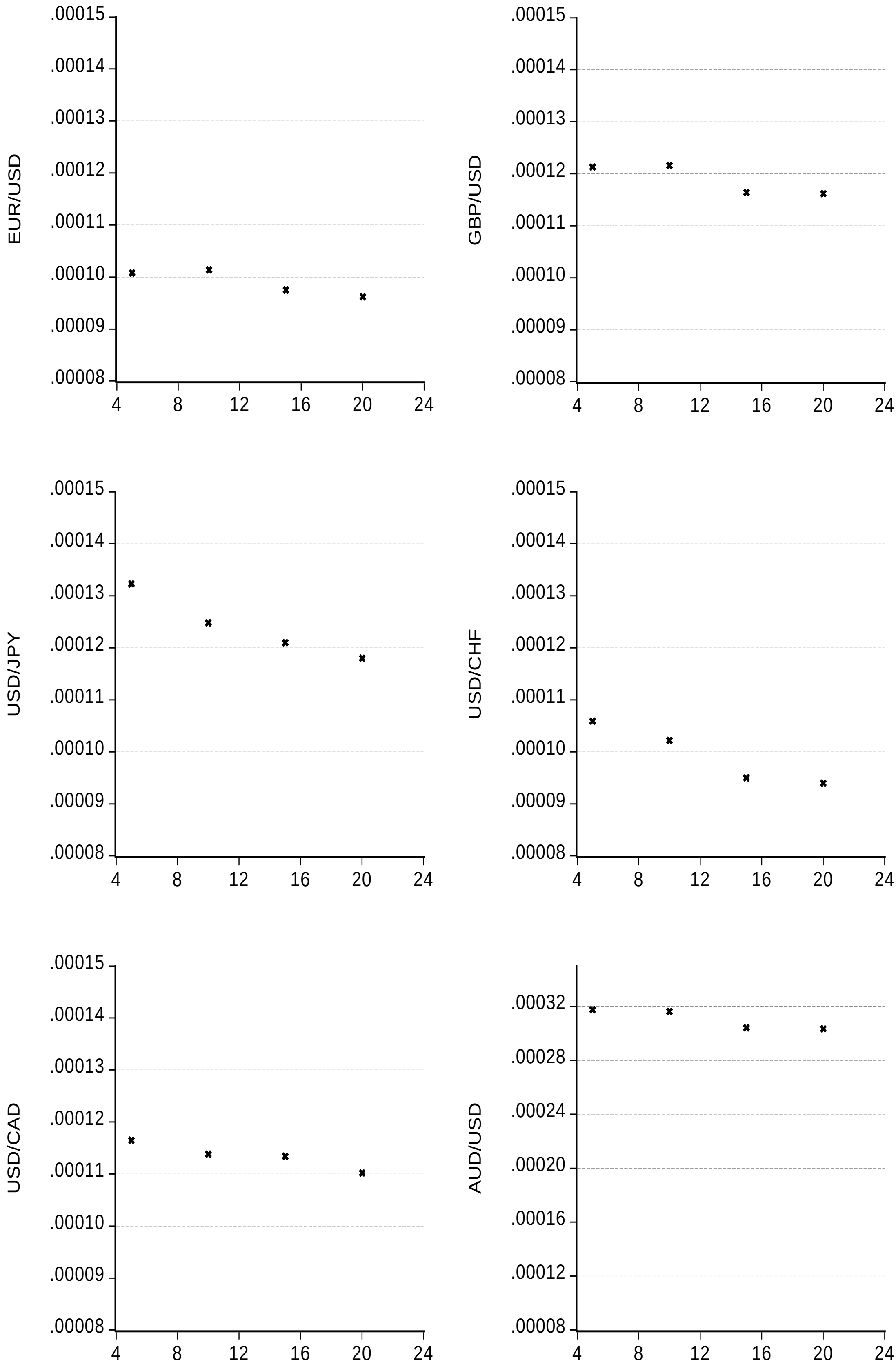


FIGURE 11: **RV Volatility Signature Plot**



B. Spillovers

Table 11: **Realized Volatility Spillover Table**

	EUR/ USD	**GBP/ USD**	**USD/ JPY**	**USD/ CHF**	**USD/ CAD**	**AUD/ USD**	**Directional *FROM* Others**
EUR/USD	28.31	19.53	9.77	21.11	7.13	14.16	71.69
GBP/USD	19.11	29.18	10.33	14.45	11.21	15.72	70.82
USD/JPY	14.56	15.87	32.47	13.65	8.00	15.46	67.53
USD/CHF	25.02	17.24	10.48	27.39	7.80	12.07	72.61
USD/CAD	10.26	15.40	8.59	9.35	40.45	15.95	59.55
AUD/USD	14.47	15.89	11.73	10.21	11.94	35.76	64.24
Directional *TO* Others	83.42	83.93	50.90	68.76	46.09	73.35	406.40
Directional Including Own	111.70	113.10	83.37	96.15	86.54	109.10	Total Spillover Index (406/6) = 67.74

Table 12: **Range Volatility Spillover Table**

	EUR/ USD	**GBP/ USD**	**USD/ JPY**	**USD/ CHF**	**USD/ CAD**	**AUD/ USD**	**Directional *FROM* Others**
EUR/USD	35.09	15.24	6.73	25.20	5.88	11.87	64.91
GBP/USD	17.73	38.17	7.67	13.50	8.35	14.58	61.83
USD/JPY	10.78	10.18	49.23	10.65	5.22	13.94	50.77
USD/CHF	28.90	13.37	7.53	37.41	4.87	7.92	62.59
USD/CAD	8.06	10.83	6.41	6.05	50.67	17.98	49.33
AUD/USD	11.57	12.38	11.23	7.30	12.37	45.14	54.86
Directional *TO* Others	77.05	62.00	39.56	62.70	36.69	66.28	344.30
Directional Including Own	112.10	100.20	88.79	100.10	87.36	111.40	Total Spillover Index (344/6) = 57.38

Table 13: **Jump Component Volatility Spillover Table**

	EUR/ USD	GBP/ USD	USD/ JPY	USD/ CHF	USD/ CAD	AUD/ USD	Directional *FROM* Others
EUR/USD	60.99	5.19	3.63	23.96	1.39	4.83	39.01
GBP/USD	5.67	68.04	12.95	6.05	4.70	2.58	31.96
USD/JPY	3.63	14.07	73.96	4.77	3.01	0.56	26.04
USD/CHF	23.86	4.49	4.36	60.36	2.81	4.11	39.64
USD/CAD	2.00	7.12	4.37	4.54	79.47	2.50	20.53
AUD/USD	6.24	2.82	1.04	5.52	2.67	81.71	18.29
Directional *TO* Others	41.40	33.69	26.35	44.86	14.58	14.59	175.50
Directional Including Own	102.39	101.70	100.30	105.21	94.06	96.29	Total Spillover Index (176/6) = 29.25

Table 14: **Continuous Component Volatility Spillover Table**

	EUR/ USD	GBP/ USD	USD/ JPY	USD/ CHF	USD/ CAD	AUD/ USD	Directional *FROM* Others
EUR/USD	29.17	19.49	9.11	21.40	7.21	13.62	70.83
GBP/USD	19.19	28.72	10.01	14.51	11.59	15.98	71.28
USD/JPY	14.16	15.63	32.52	13.67	8.53	15.50	67.48
USD/CHF	25.07	17.05	10.02	27.93	8.33	11.60	72.07
USD/CAD	10.03	15.10	8.35	9.15	40.44	16.94	59.56
AUD/USD	14.23	16.55	11.67	10.26	13.10	34.20	65.80
Directional *TO* Others	82.68	83.82	49.16	68.99	48.76	73.64	407.00
Directional Including Own	111.80	112.50	81.67	96.91	89.19	107.80	Total Spillover Index (407/6) = 67.84

Figure 12: **Target Rate Differentials (FED-ECB and FED-BoE)**

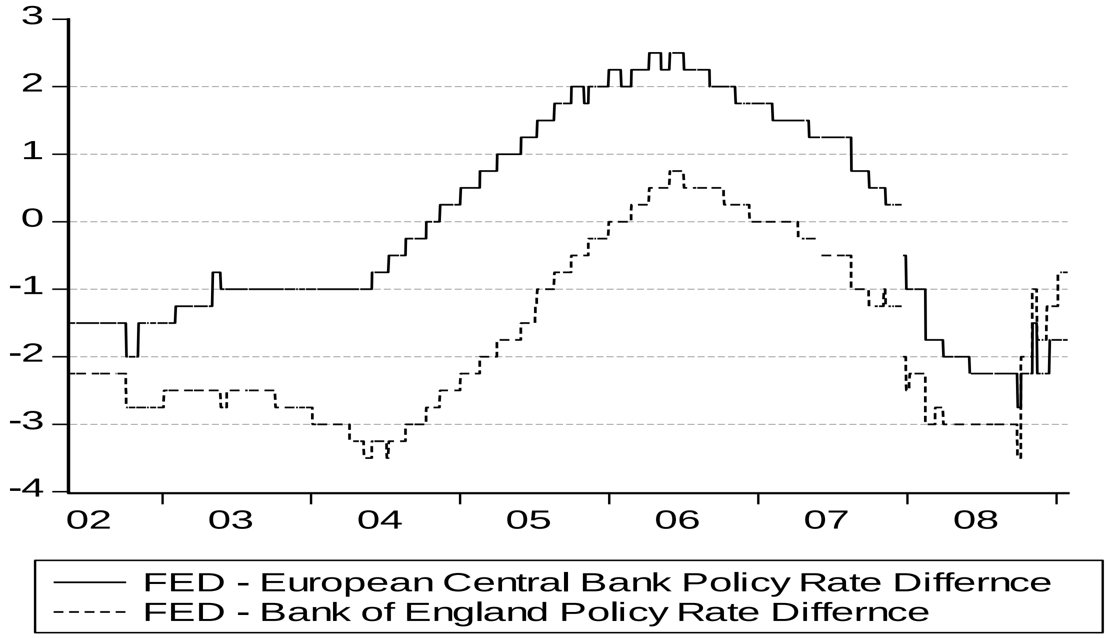


FIGURE 13: **Realized Volatility Spillover Plot (Generalized VAR)**

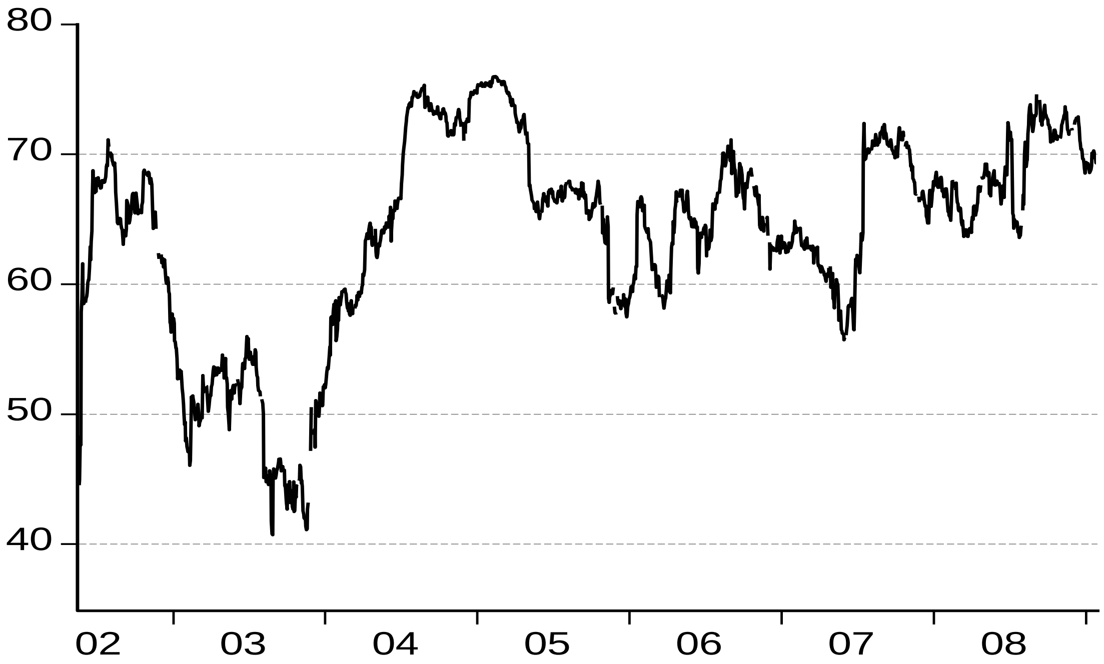


FIGURE 14: **RNV vs RV Spillover Plots (Generalized VAR)**

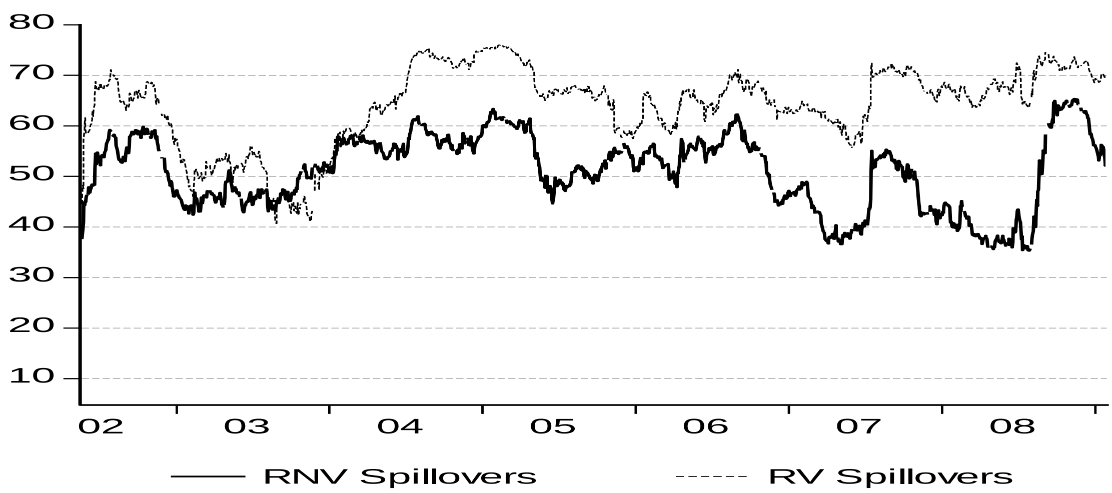


FIGURE 15: **JC vs RV Spillover Plots (Generalized VAR)**

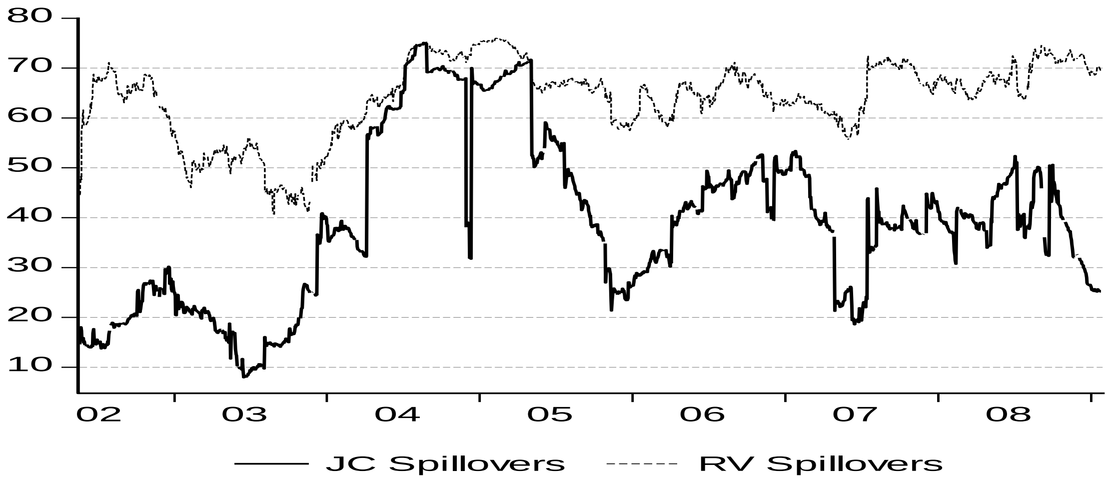


FIGURE 16: **C vs RV Spillover Plots (Generalized VAR)**

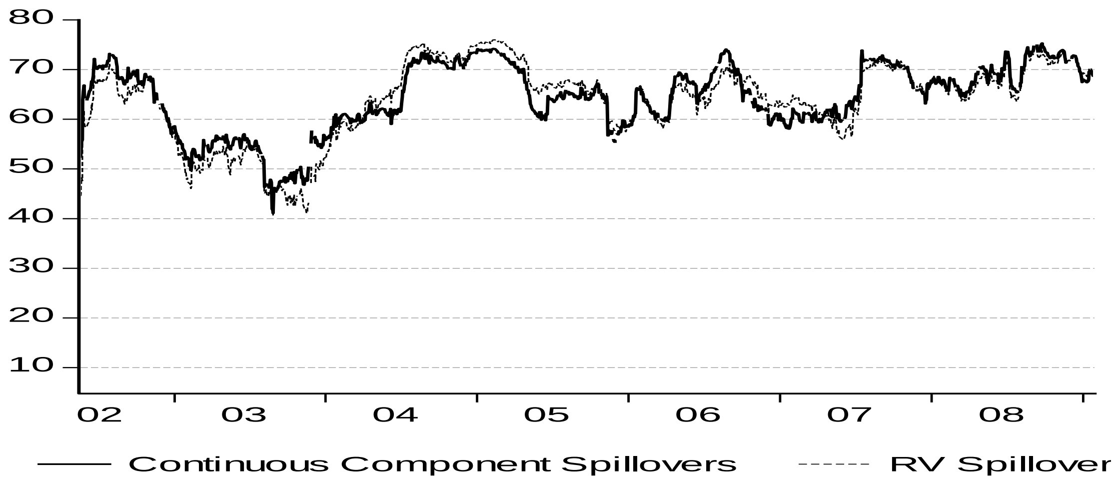


FIGURE 17: **RV Spillover Plot (Cholesky Based VAR)**

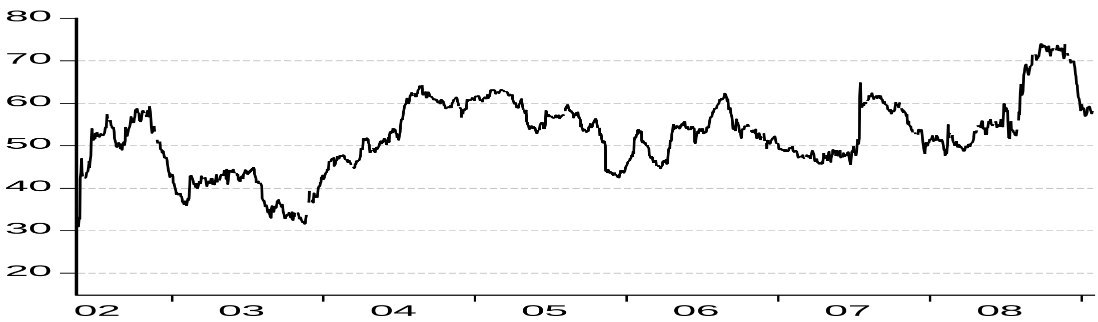


Figure 18: **RNV Spillover Plot (Cholesky Based VAR)**

Figure 19: **JC Spillover Plot (Cholesky Based VAR)**

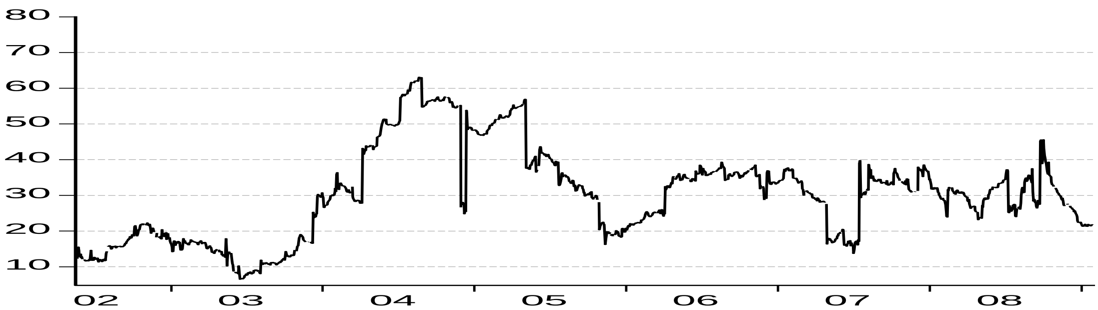


Figure 20: **C Spillover Plot (Cholesky Based VAR)**

FIGURE 21: **RV Directional Volatility Spillovers, *FROM***

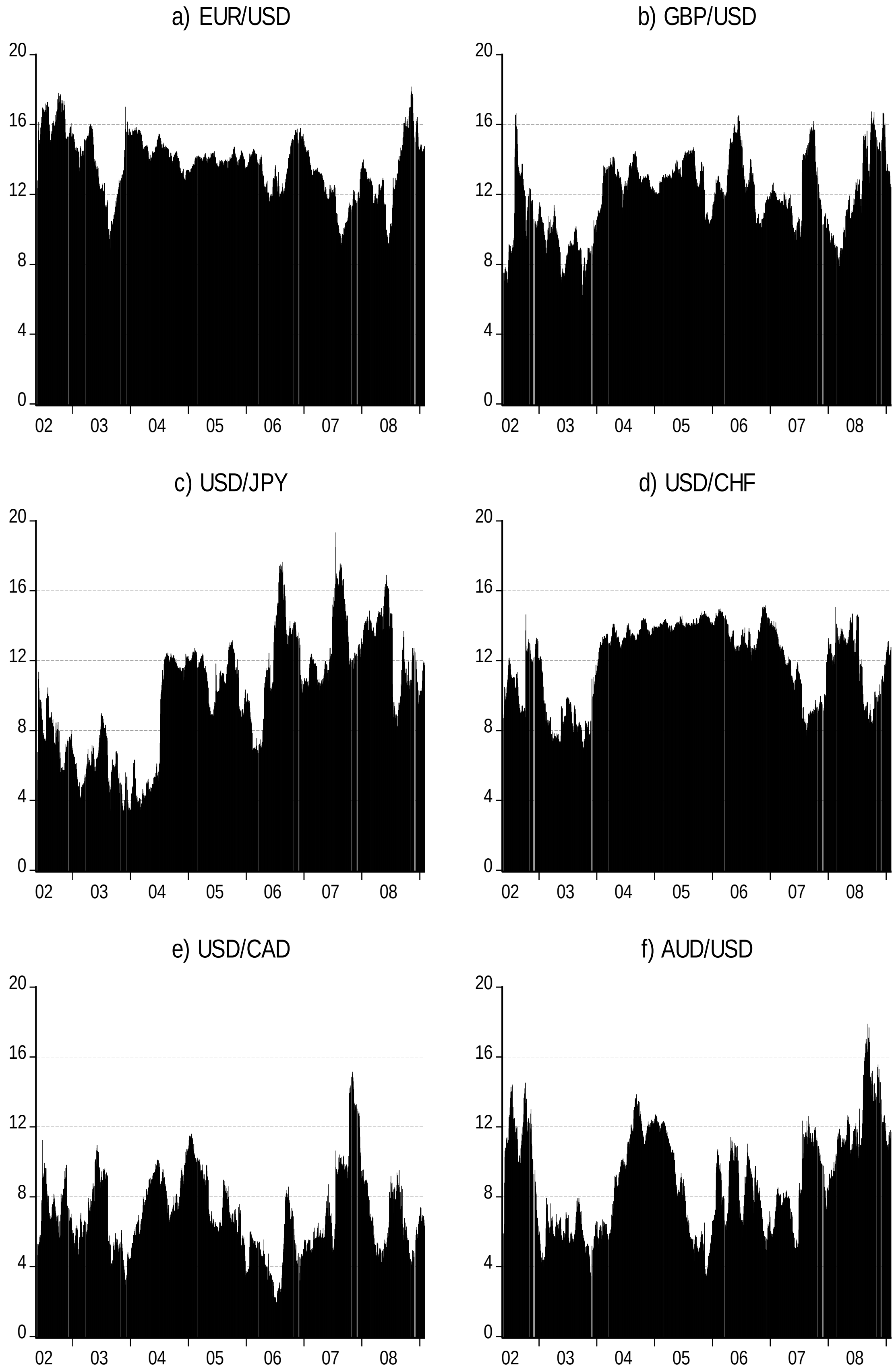


Figure 22: **RV Directional Volatility Spillovers, *TO***

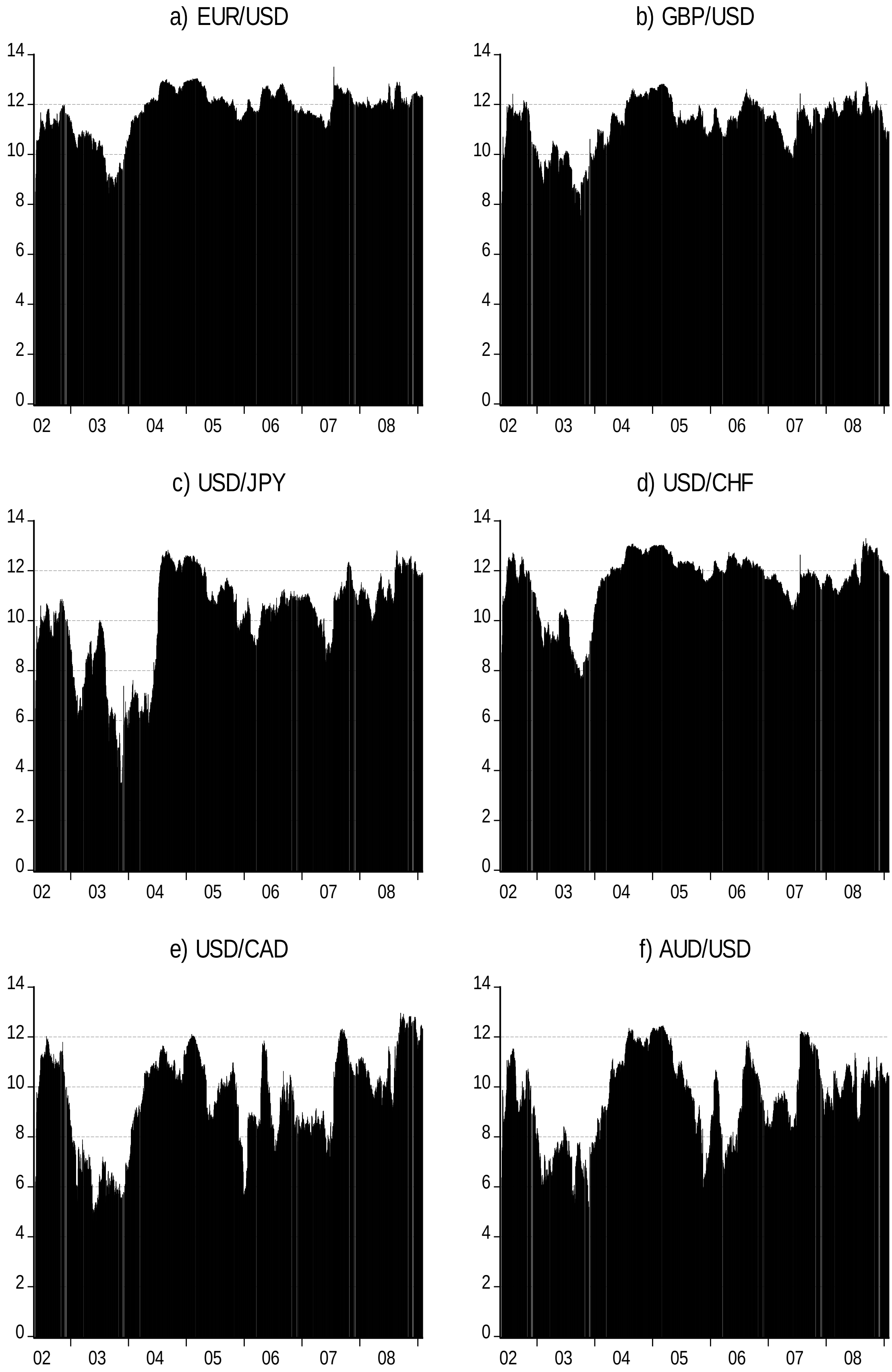


Figure 23: **RV Net Spillover Plot**

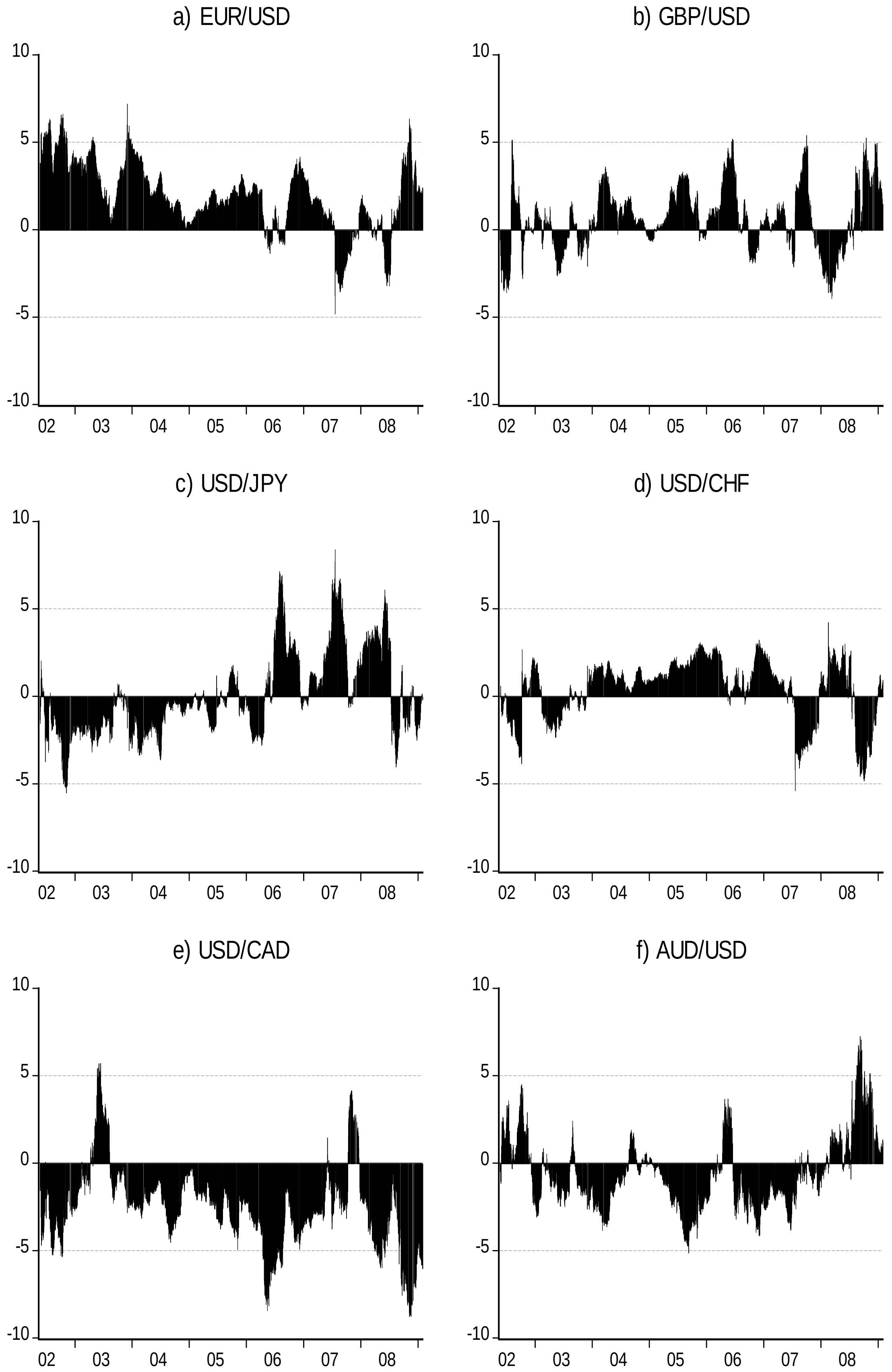


FIGURE 24: **RV Pairwise Spillover Plot**

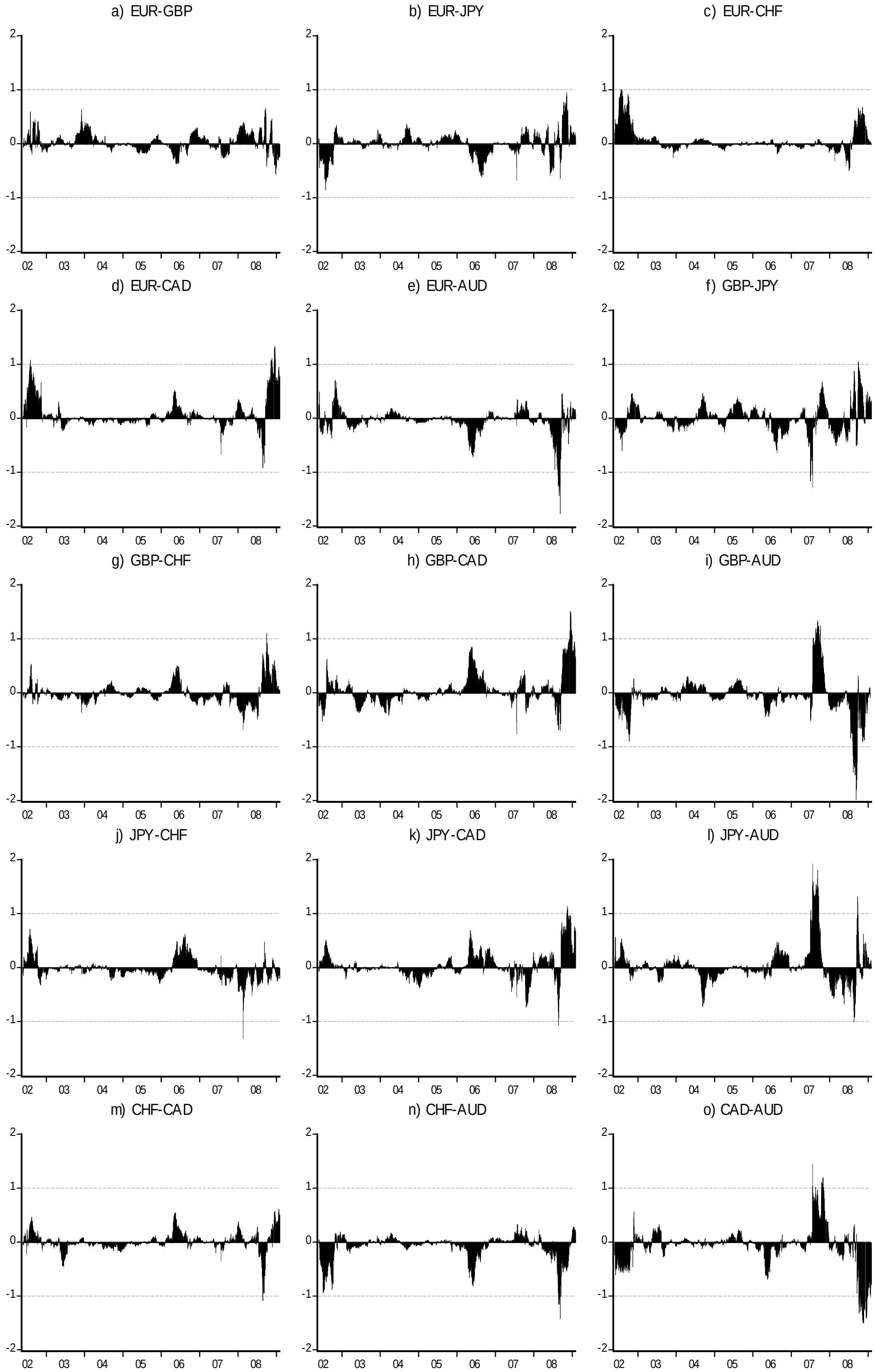


Figure 25: **RNV Directional Volatility Spillovers, *FROM***

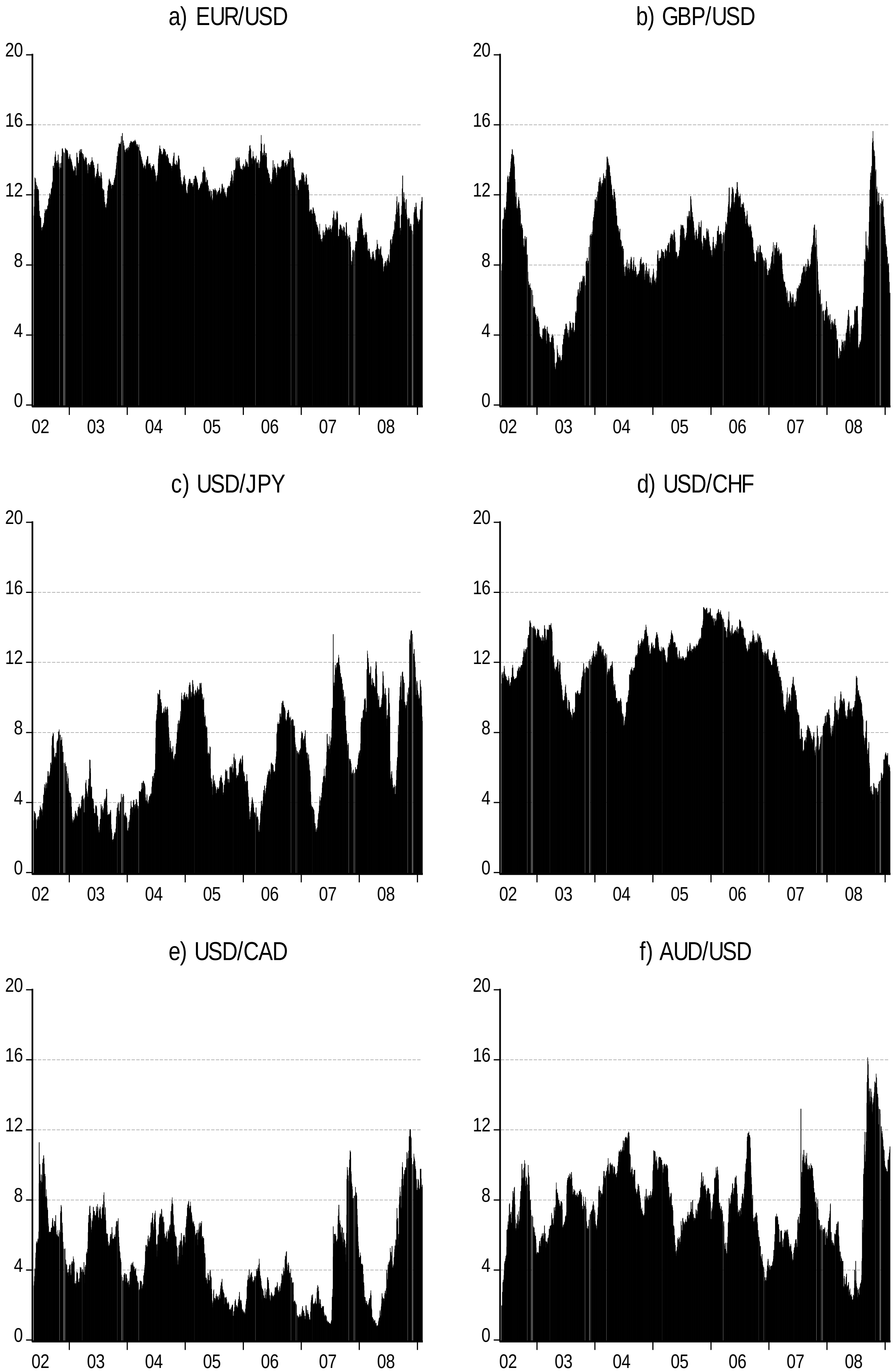


Figure 26: **RNV Directional Volatility Spillovers, *TO***

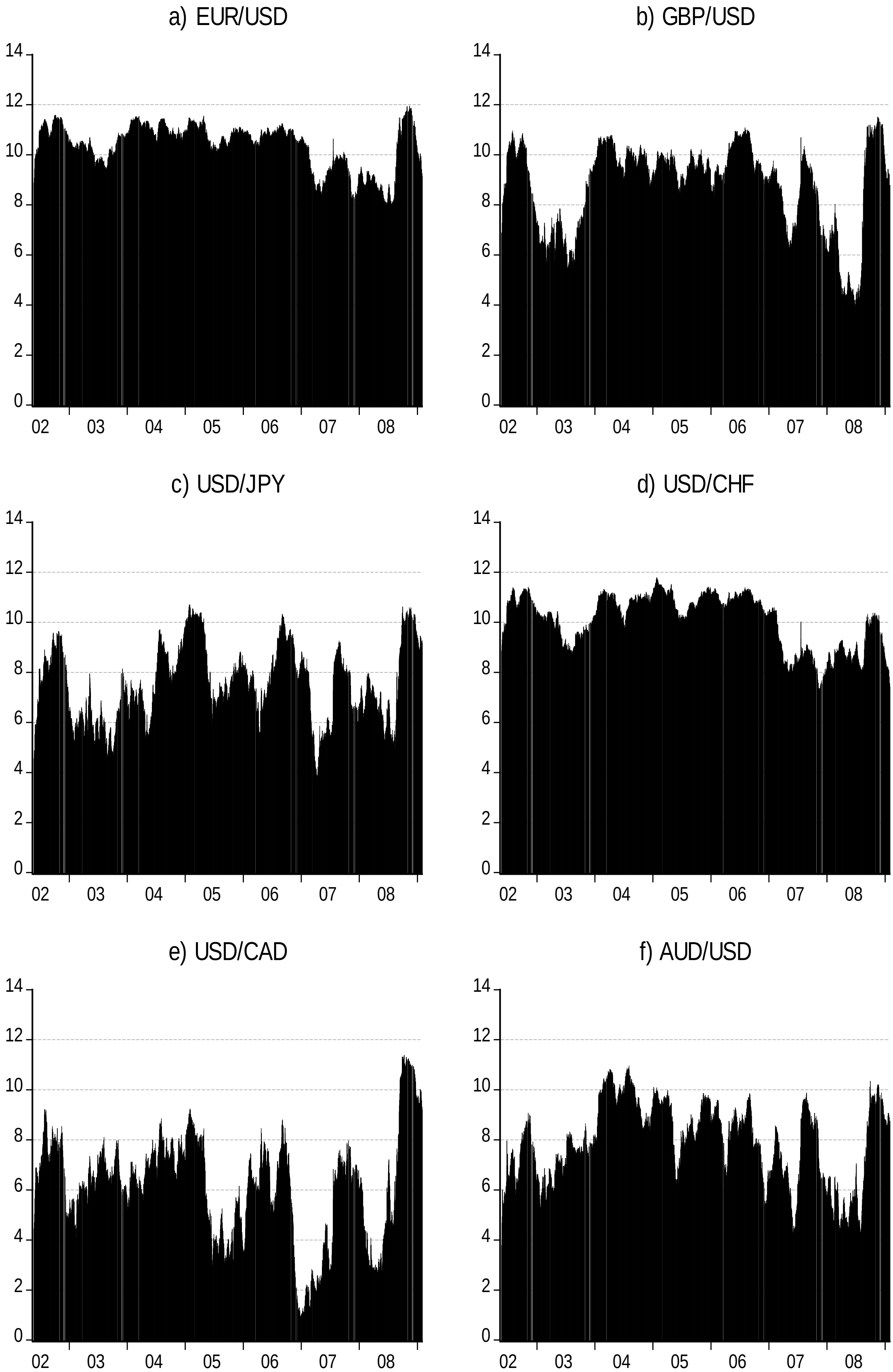


Figure 27: **RNV Net Spillover Plot**

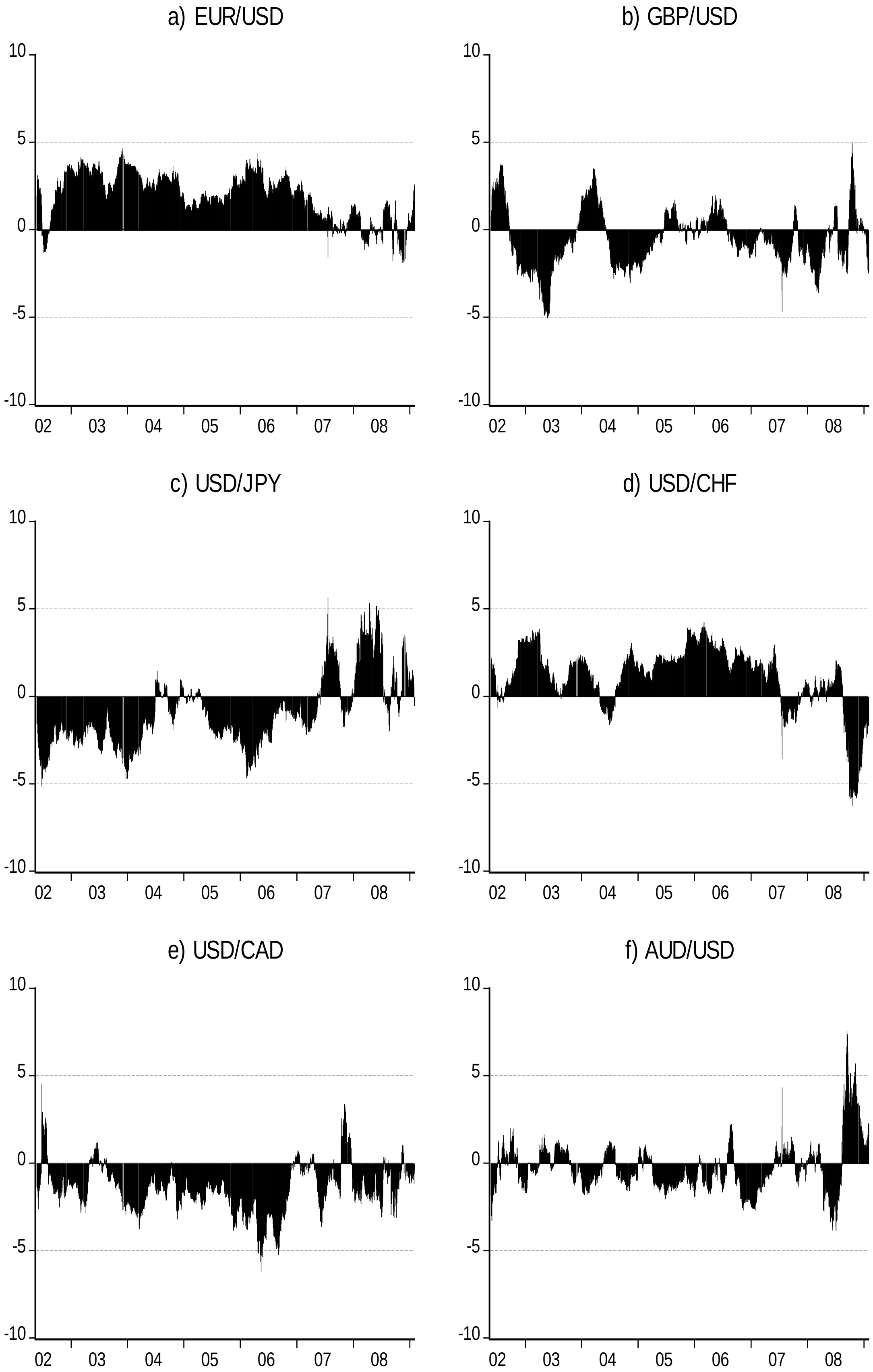


Figure 28: **RNV Pairwise Spillover Plot**

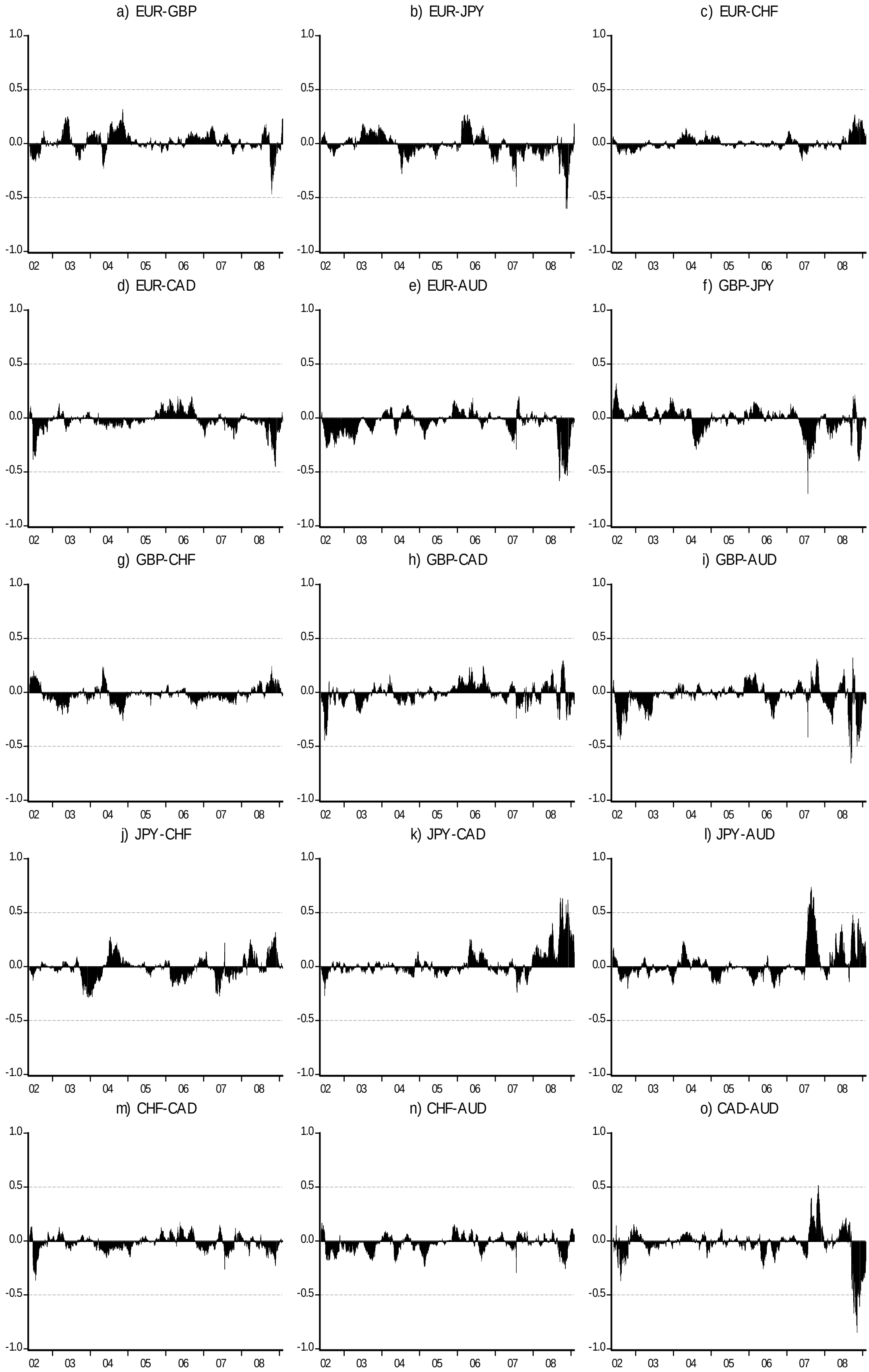


FIGURE 29: **JC Directional Volatility Spillovers, *FROM***

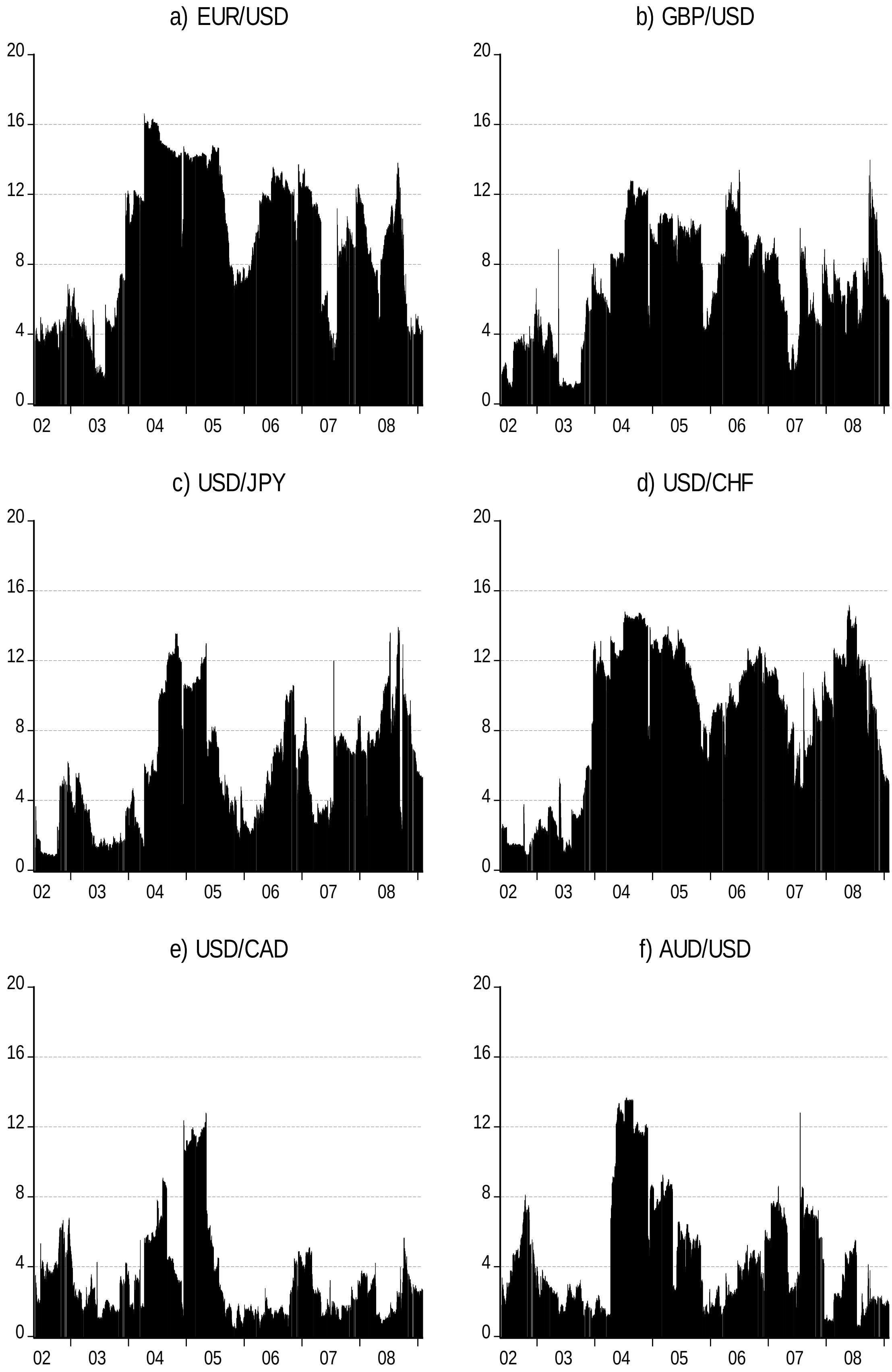


Figure 30: **JC Directional Volatility Spillovers, *TO***

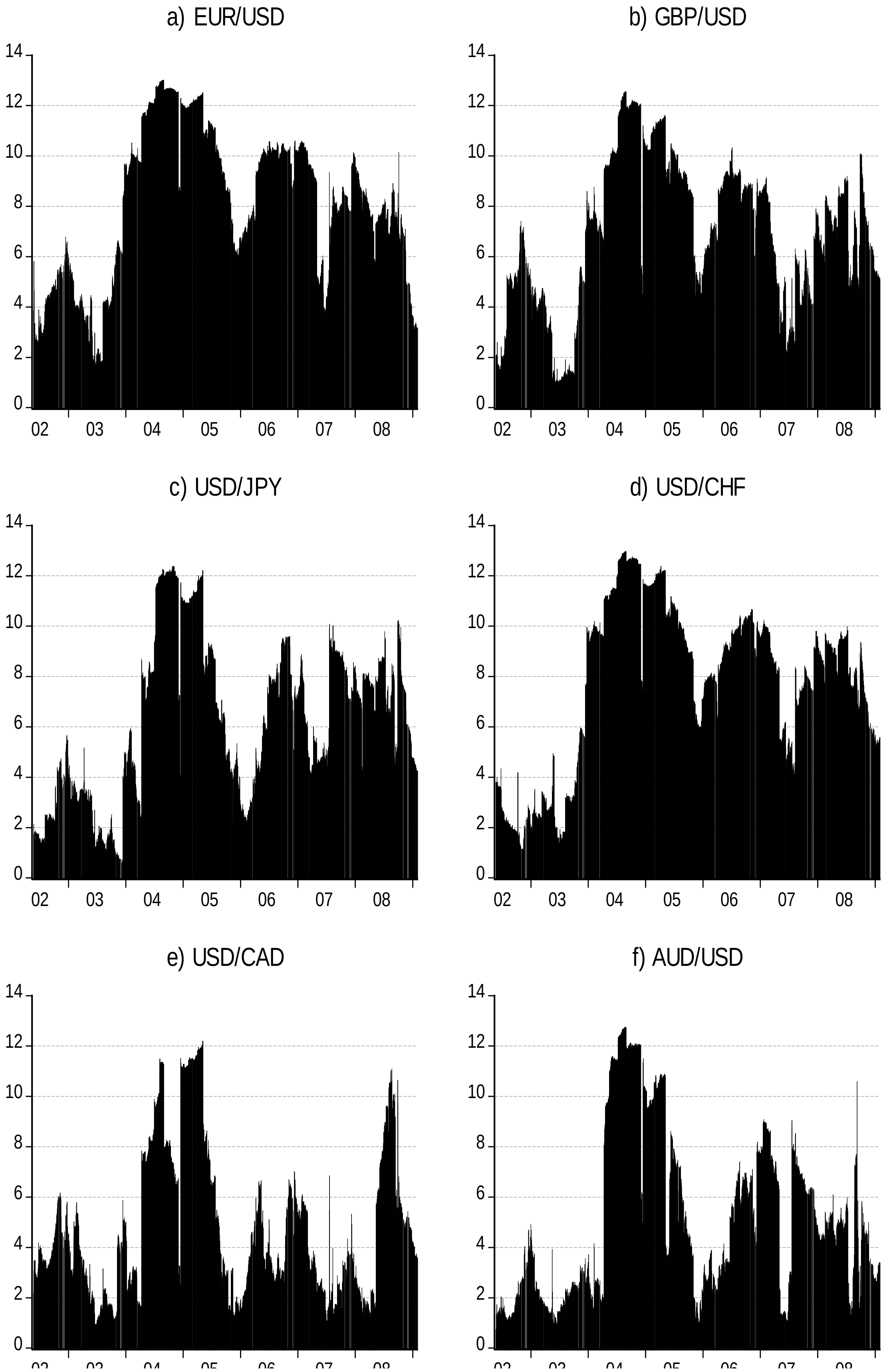


Figure 31: **JC Net Spillover Plot**

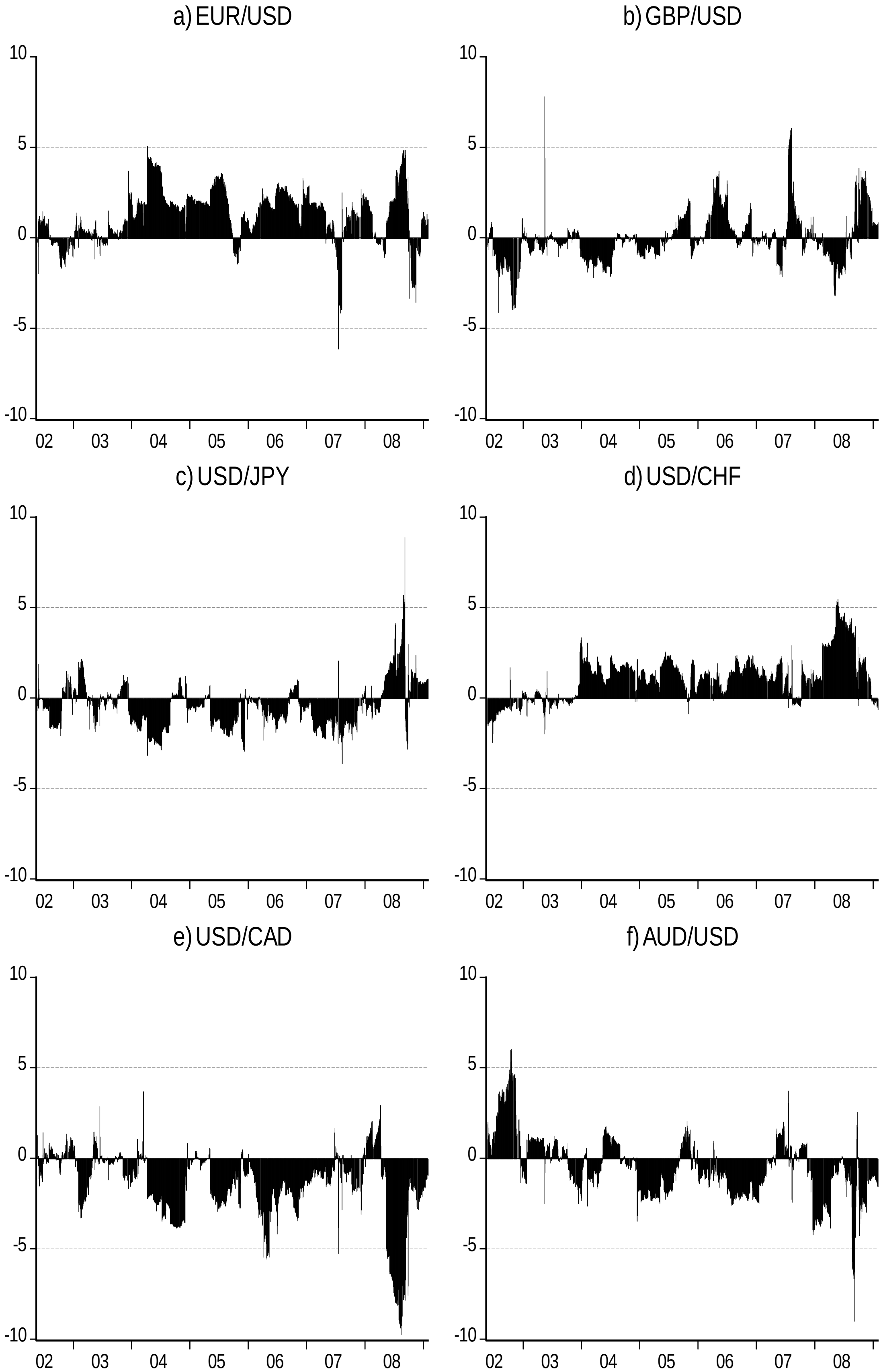


FIGURE 32: **JC Pairwise Spillover Plot**

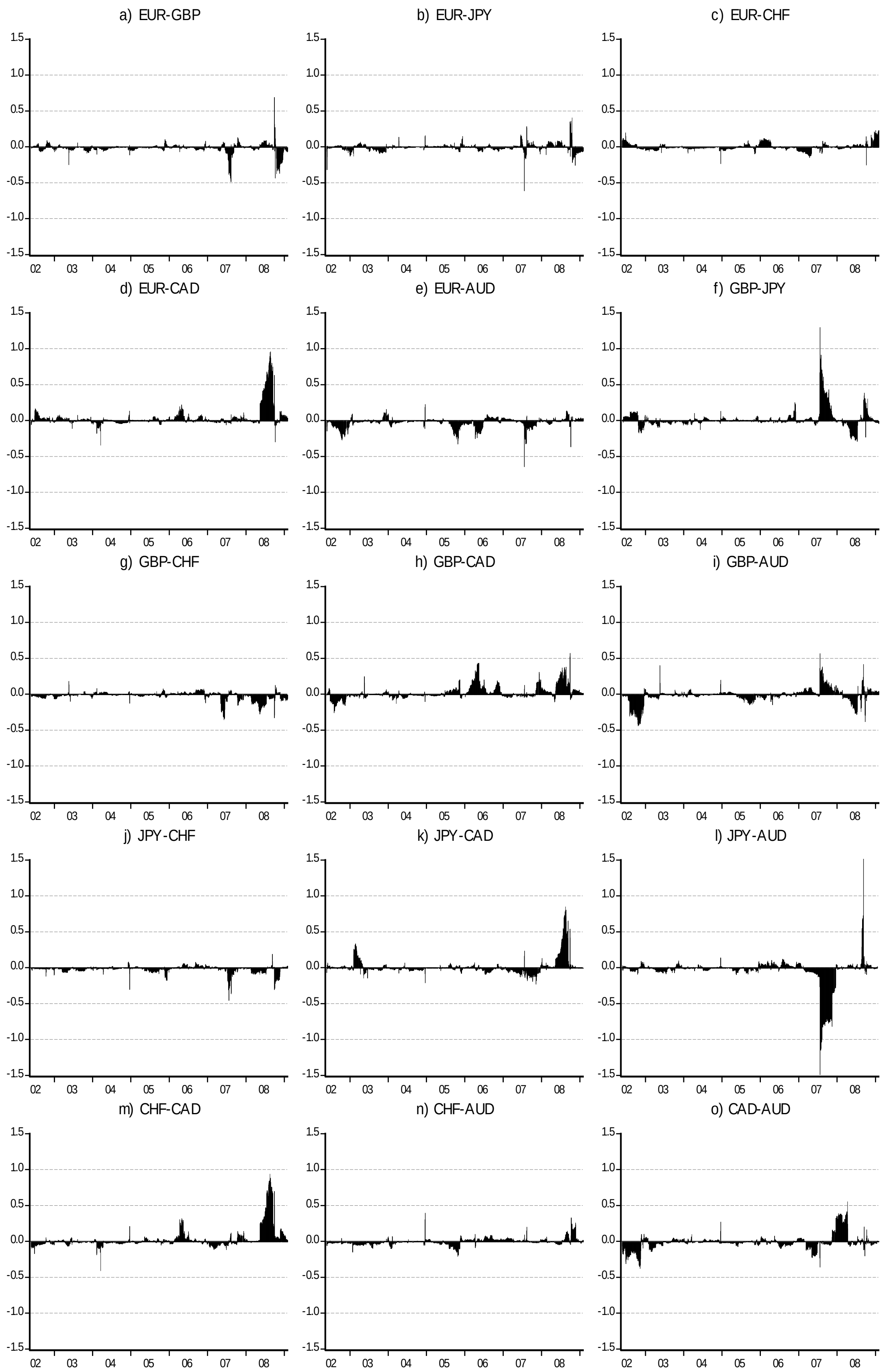


FIGURE 33: **C Directional Volatility Spillovers, *FROM***

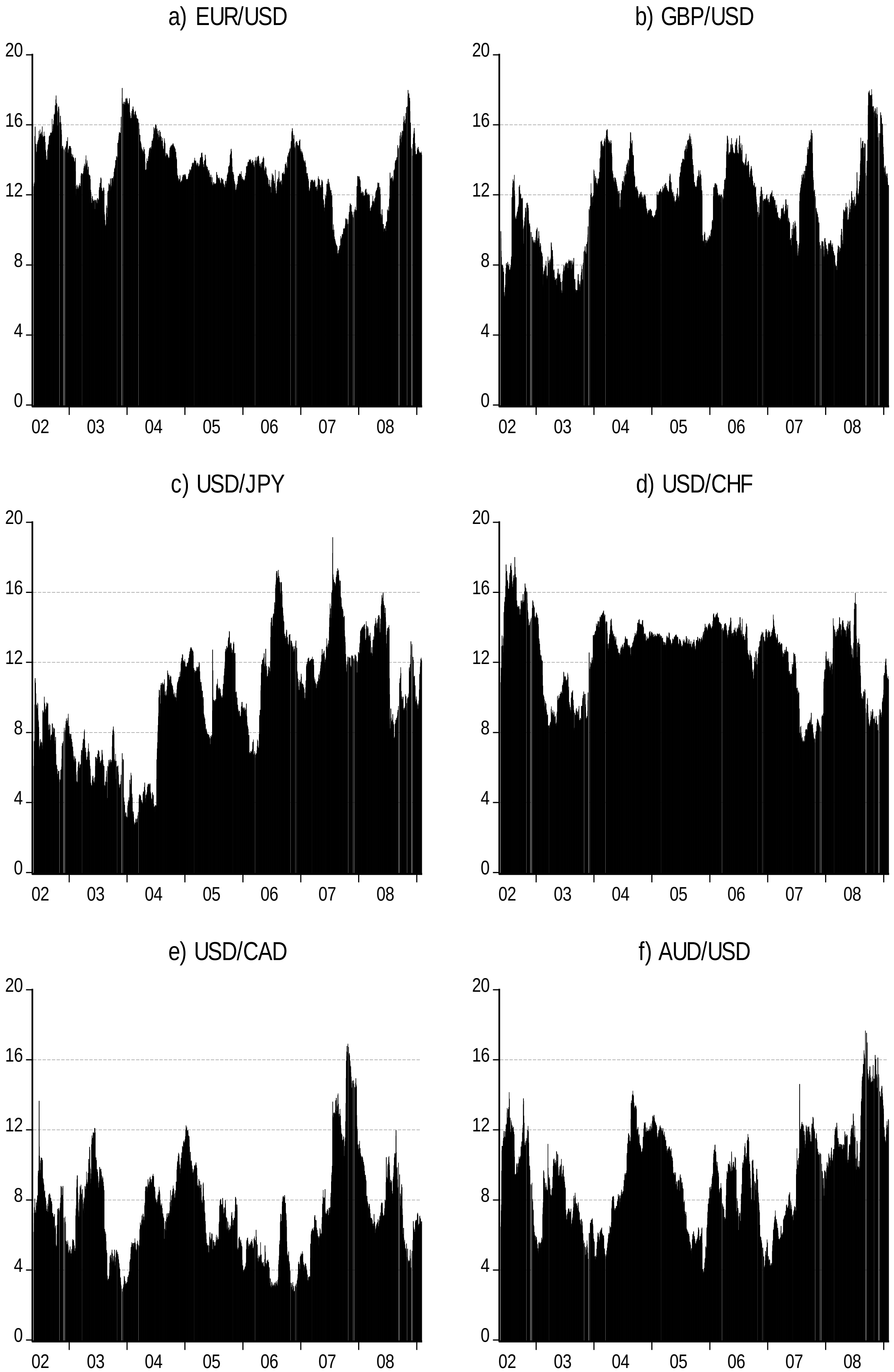


FIGURE 34: **C Directional Volatility Spillovers, *TO***

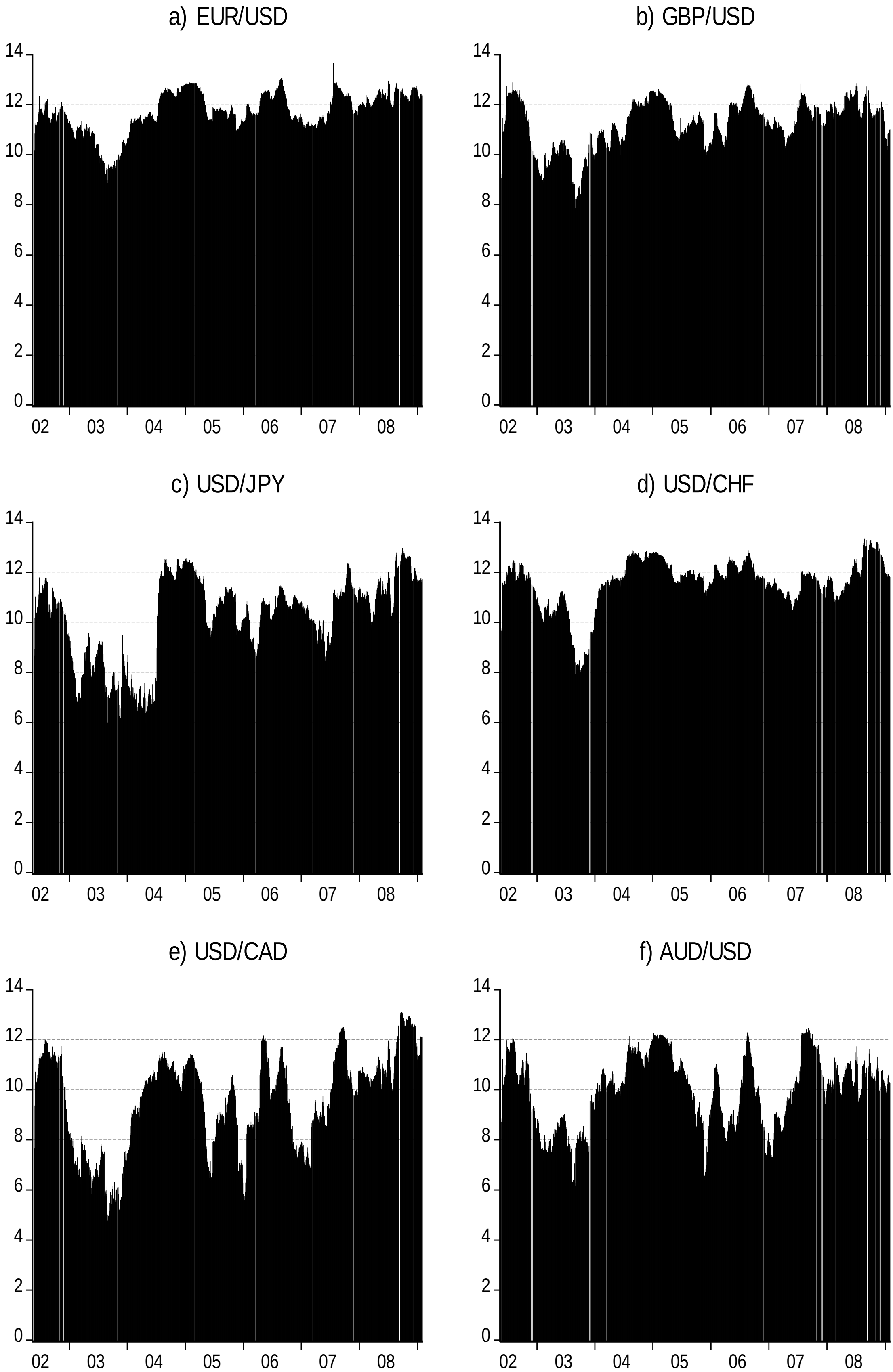


Figure 35: **C Net Spillover Plot**

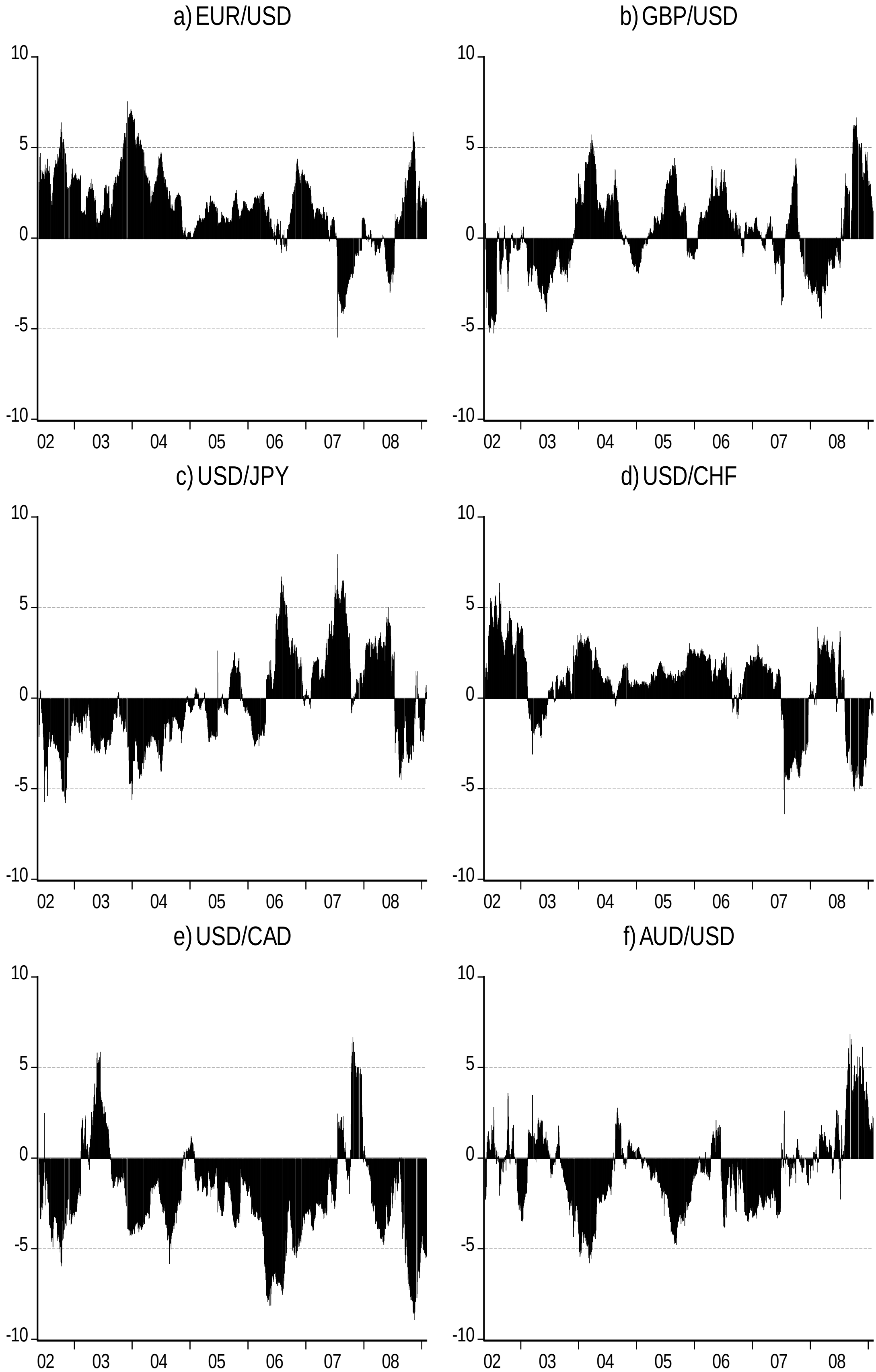
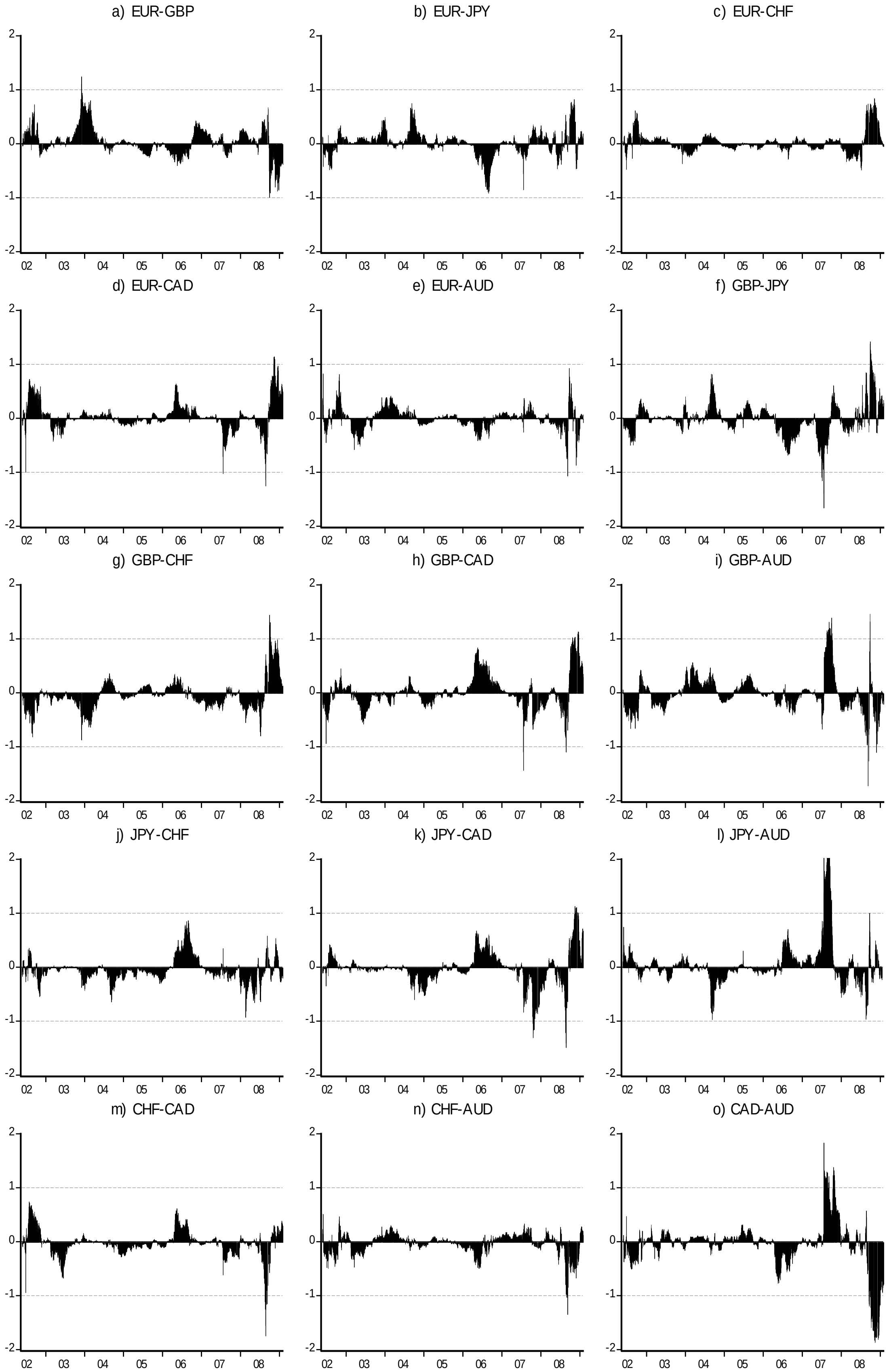


FIGURE 36: **C Pairwise Spillover Plot**



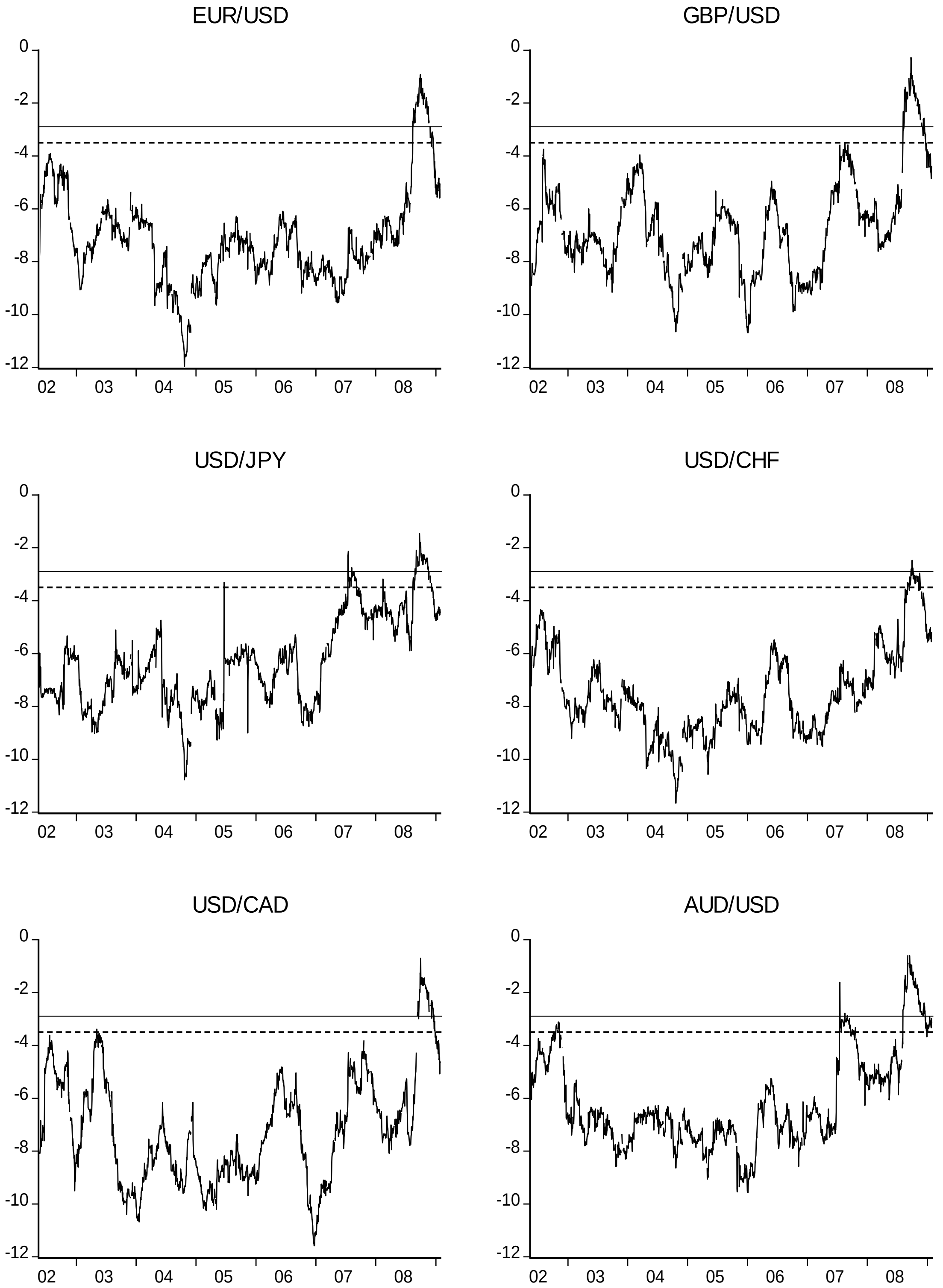
C. Robustness Check

Table 15: **Unit Root Test** ($PP - test$)

	EUR/ USD	GBP/ USD	USD/ JPY	USD/ CHF	USD/ CAD	AUD/ USD
RV	-22.9	-17.1	-24.0	-27.9	-19.3	-14.9
RNV	-53.6	-45.8	-47.2	-52.6	-46.0	-41.6
JC	-42.8	-50.0	-33.8	-41.9	-44.2	-43.9
C	-18.9	-15.5	-21.1	-23.8	-17.2	-13.6

Note: The critical values for 5% and 1% significance levels are -3.43 and -2.86, respectively. I include an intercept but not time trend in the test equation; for the spectral estimation and bandwith selection I use Barlett kernel method and Newey−West method, respectively.

Figure 37: **RV Unit Root Test***



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* I apply Philips Perron test to check the stationarity of the all four valotility measures, RV, RNV, JC and C. I include an intercept but not time trend in the each test equation; for the spectral estimation and bandwith selection I use Barlett kernel method and Newey−West method, respectively.

Figure 38: **RNV Unit Root Test (Philips Perron Test)**

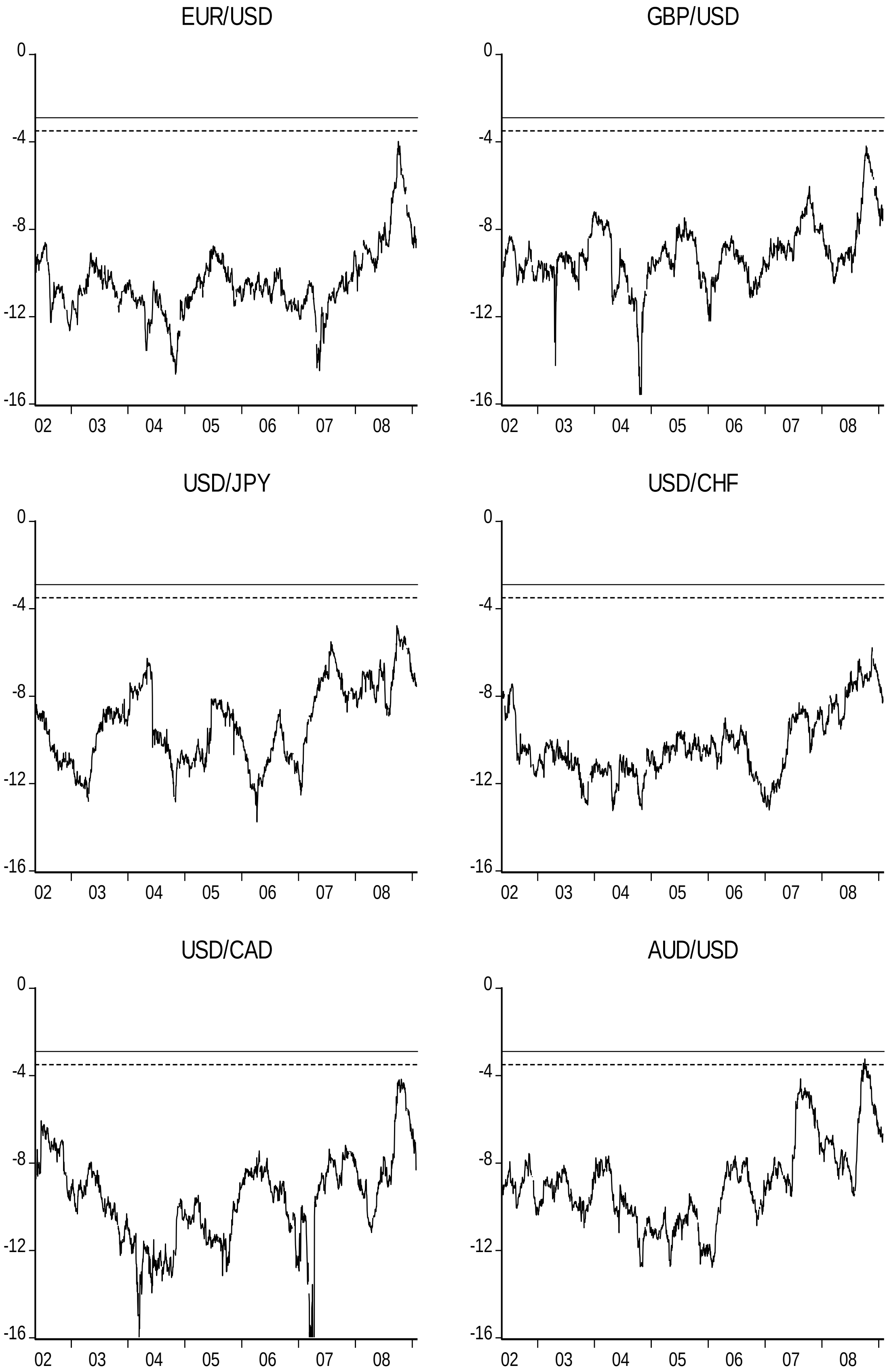

FIGURE 39: **JC Unit Root Test (Philips Perron Test)**

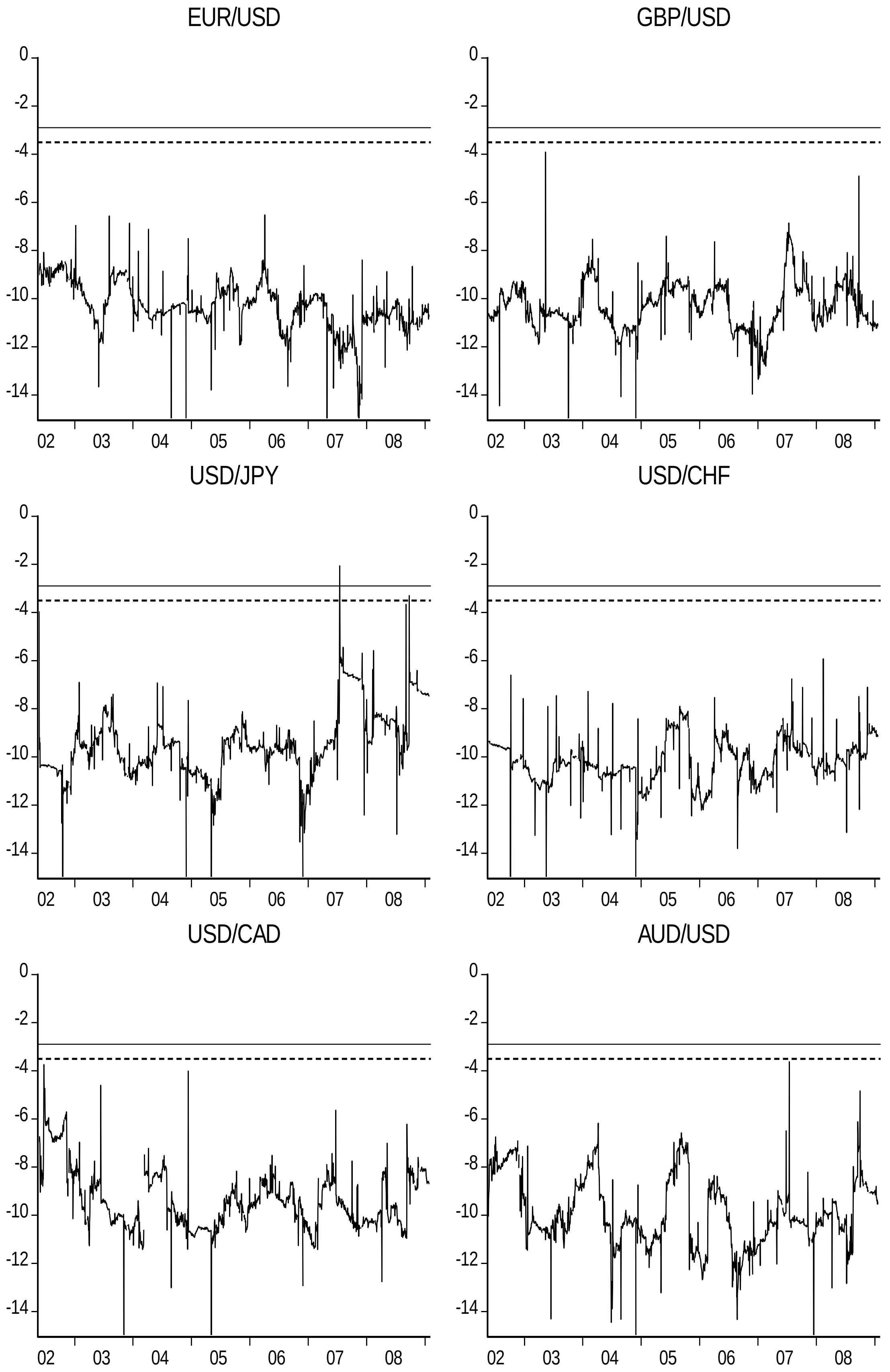

Figure 40: **C Unit Root Test**

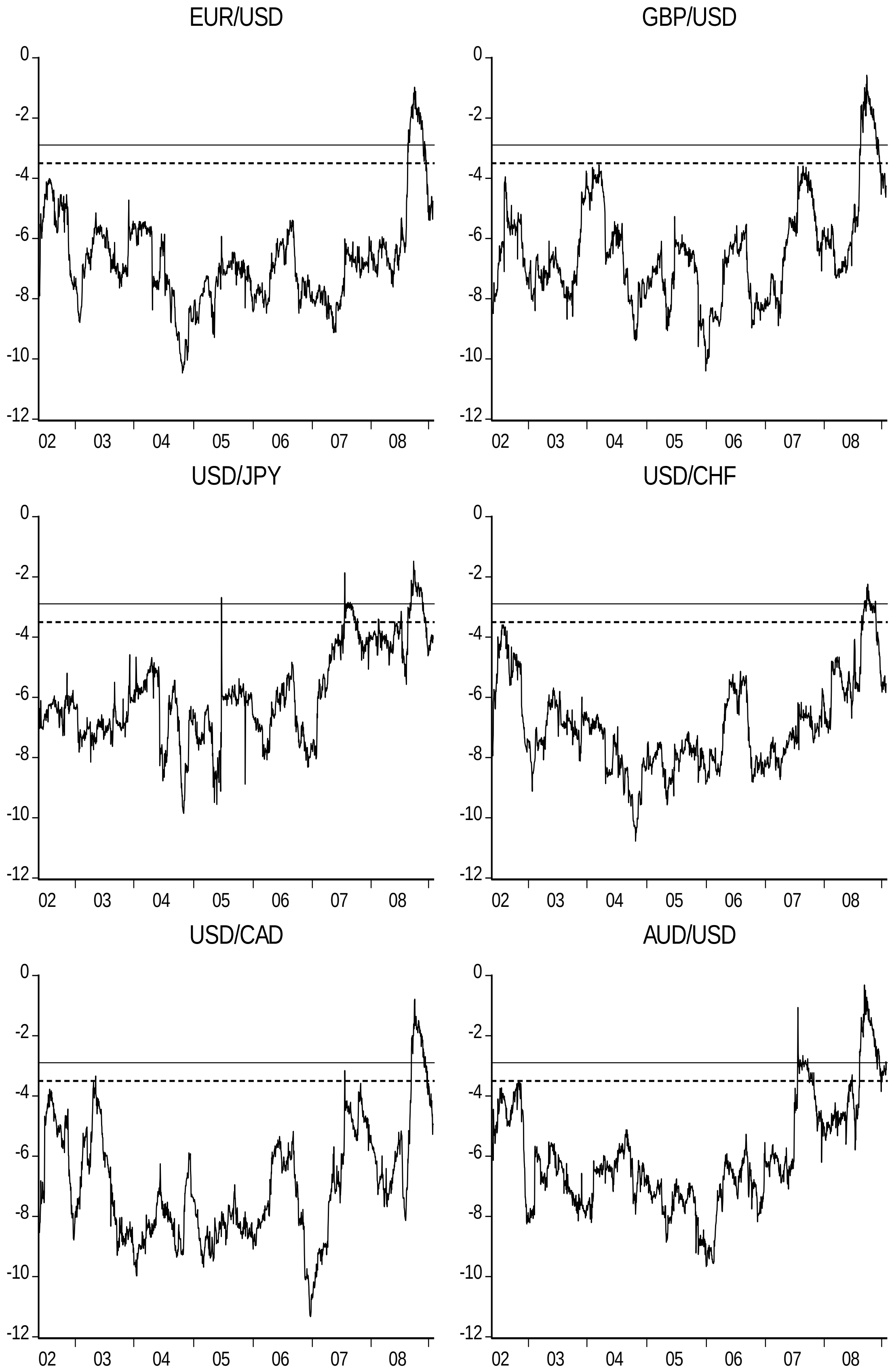

FIGURE 41: **RV Cointegration Test (Trace Test, For Non-stationary Rolling Windows)**

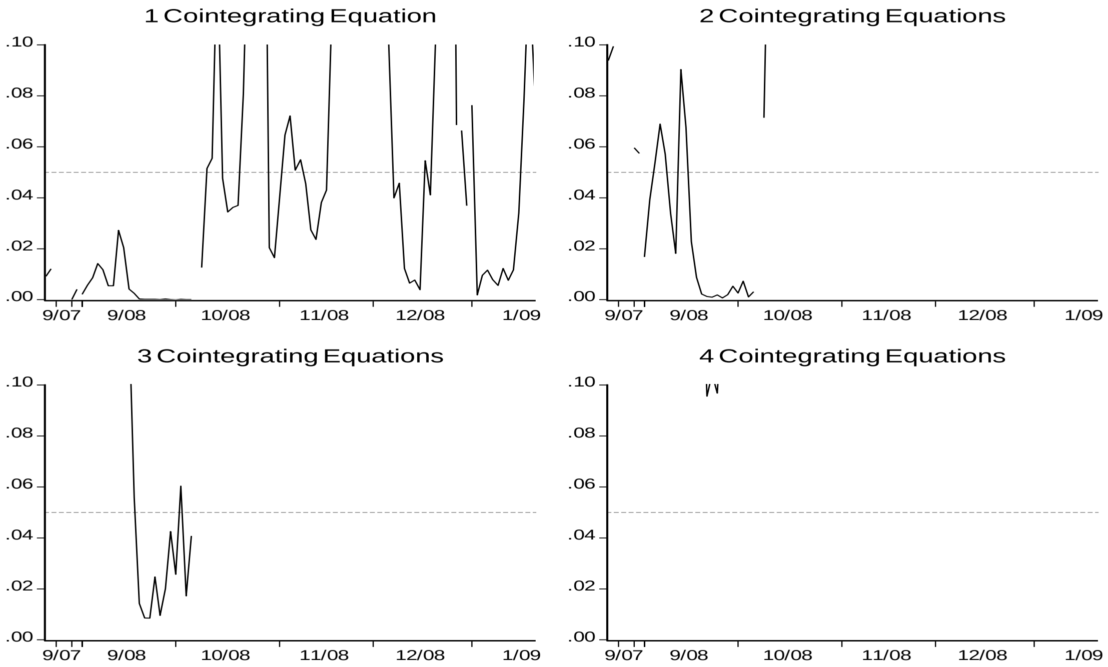

FIGURE 42: **RV Cointegration Test (Maximum Eigenvalue Test, For Non-stationary Rolling Windows)**

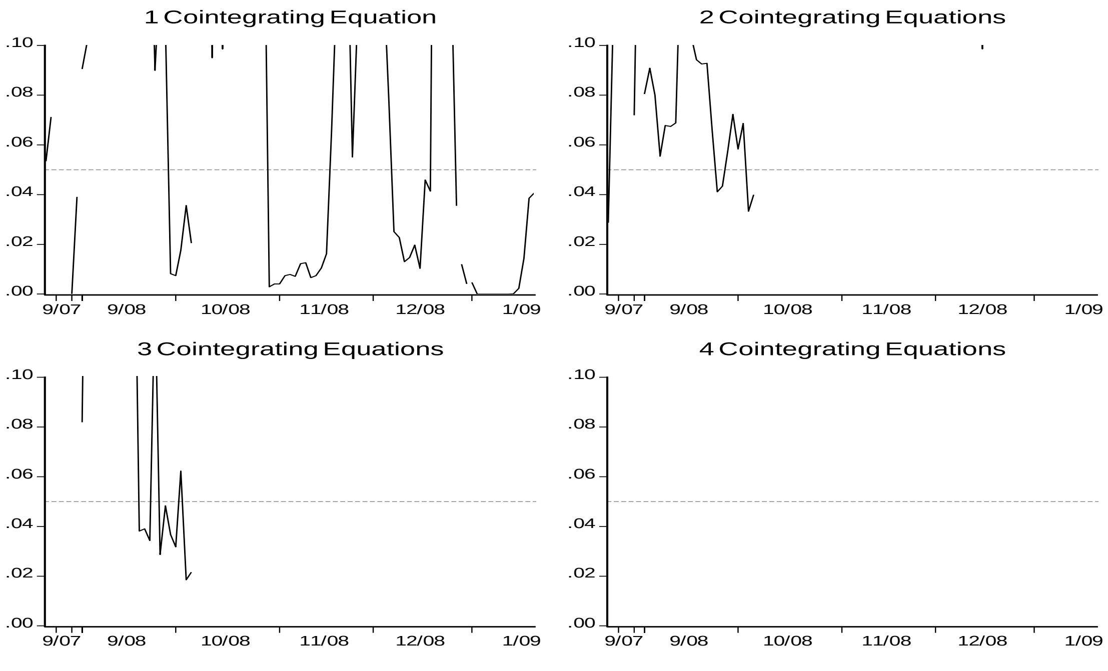

FIGURE 43: **C Cointegration Test (Trace Test, For Non-stationary Rolling Windows)**

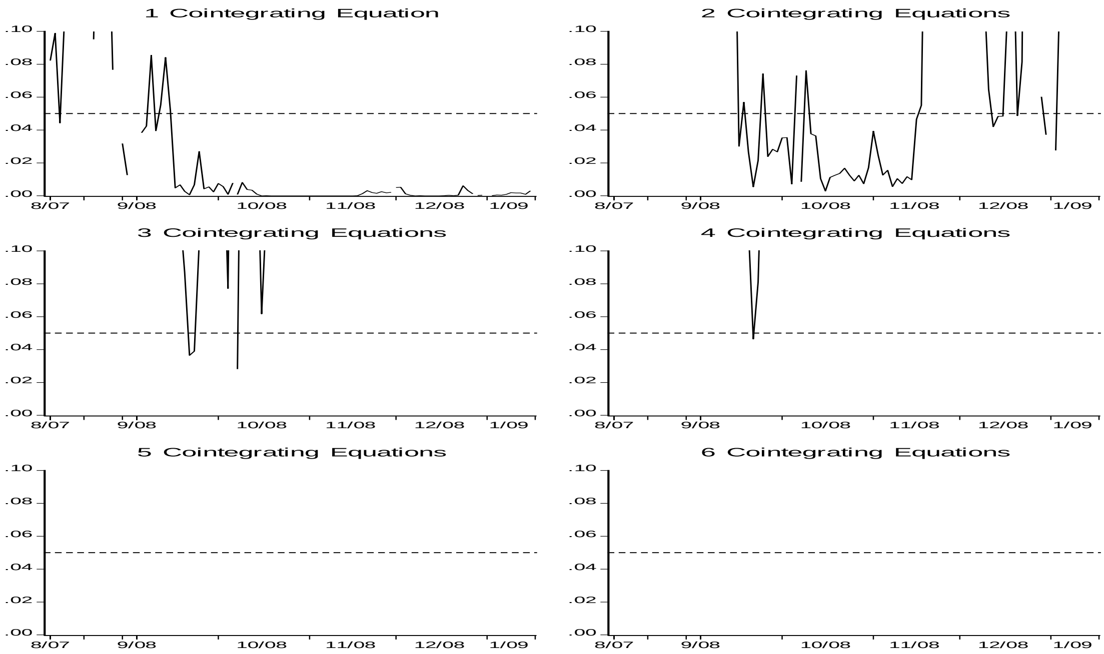

FIGURE 44: **C Cointegration Test (Maximum Eigenvalue Test, For Non-stationary Rolling Windows)**

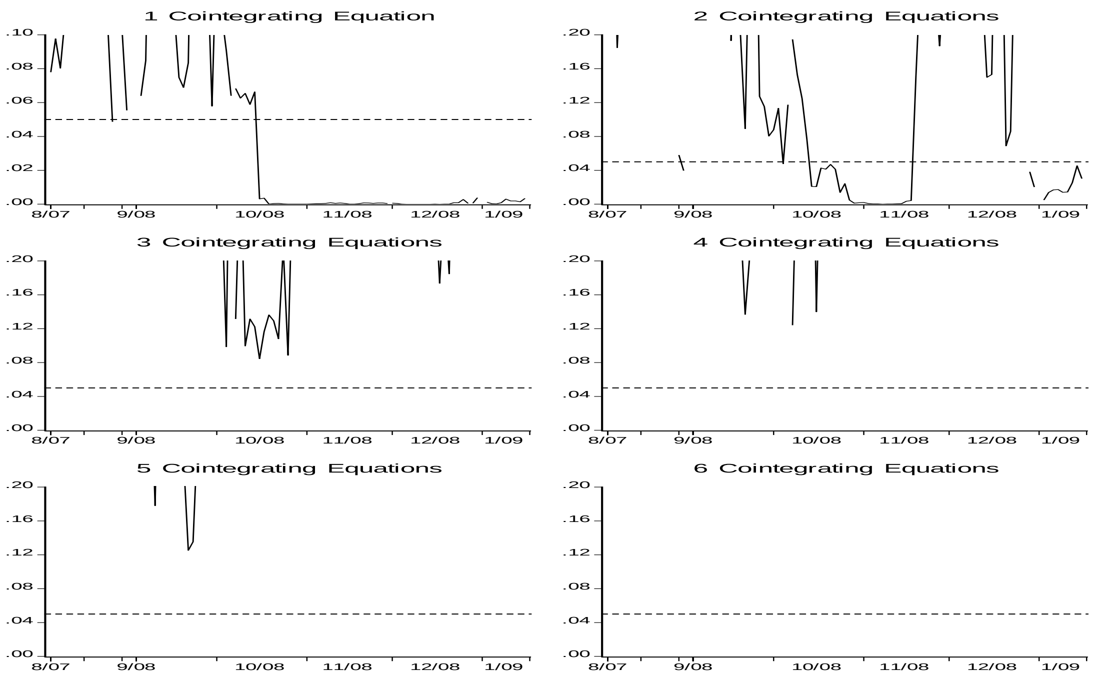

Figure 45: **RV VAR Based vs VEC Based Spillover Plots (For Non-stationary Rolling Windows)**

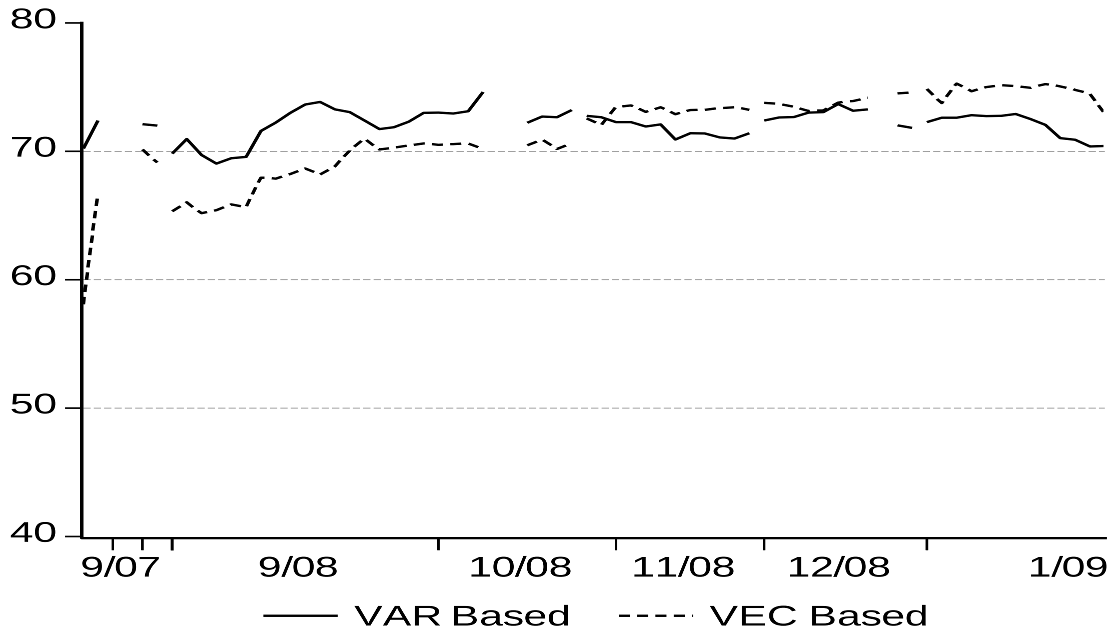

Figure 46: **RV VAR Based vs VEC Based Spillover Plots (For all Rolling Windows)**

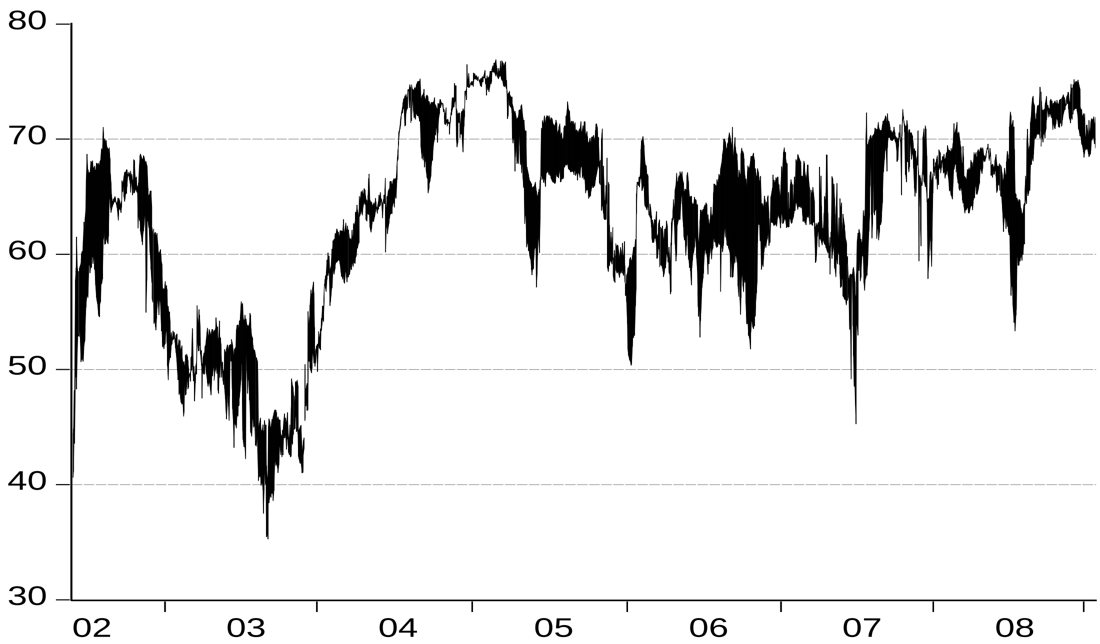

FIGURE 47: **C VAR Based vs VEC Based Spillover Plots (For Non-stationary Rolling Windows)**

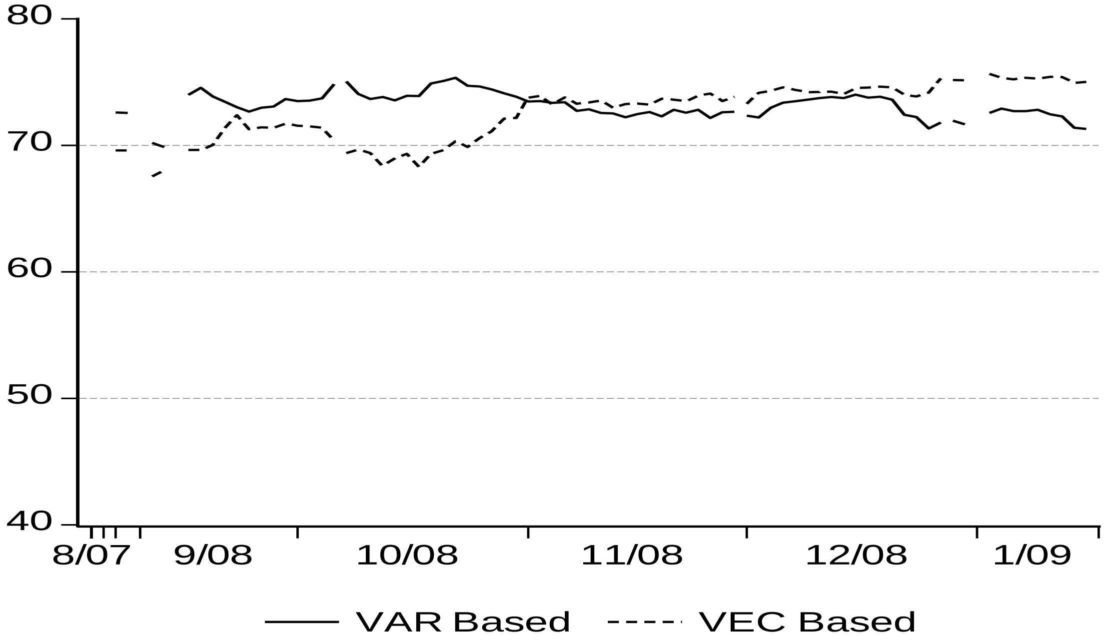

FIGURE 48: **C VAR Based vs VEC Based Spillover Plots (For all Rolling Windows)**

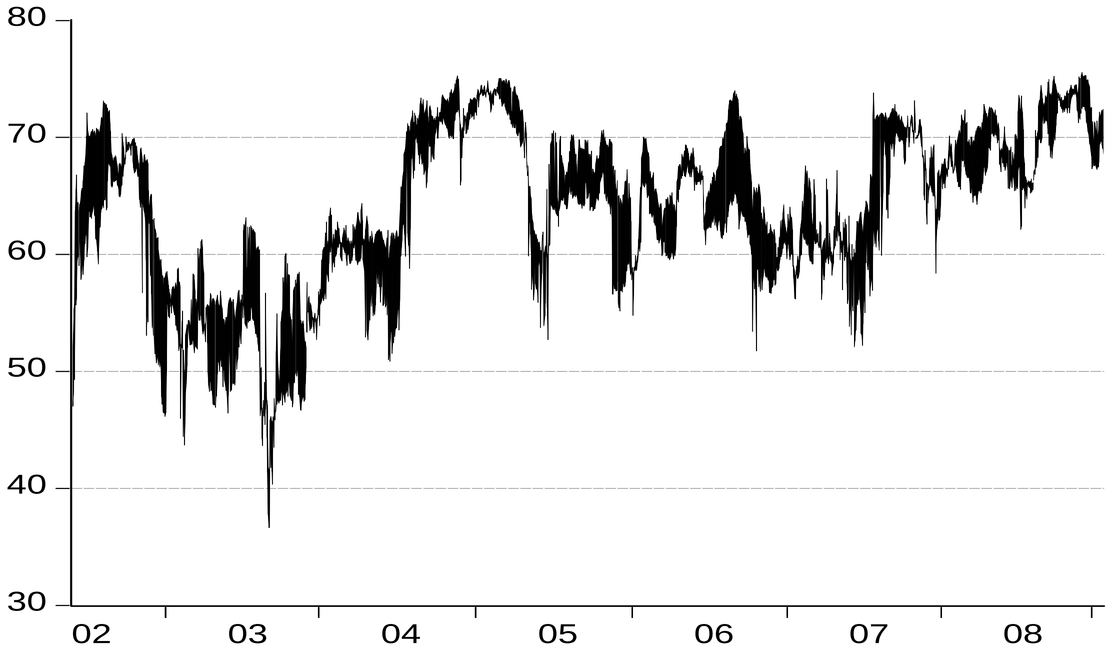

FIGURE 49: **RV Spillovers 1-to-6 Lag Lengths (Max-Min Error Band and Median)**

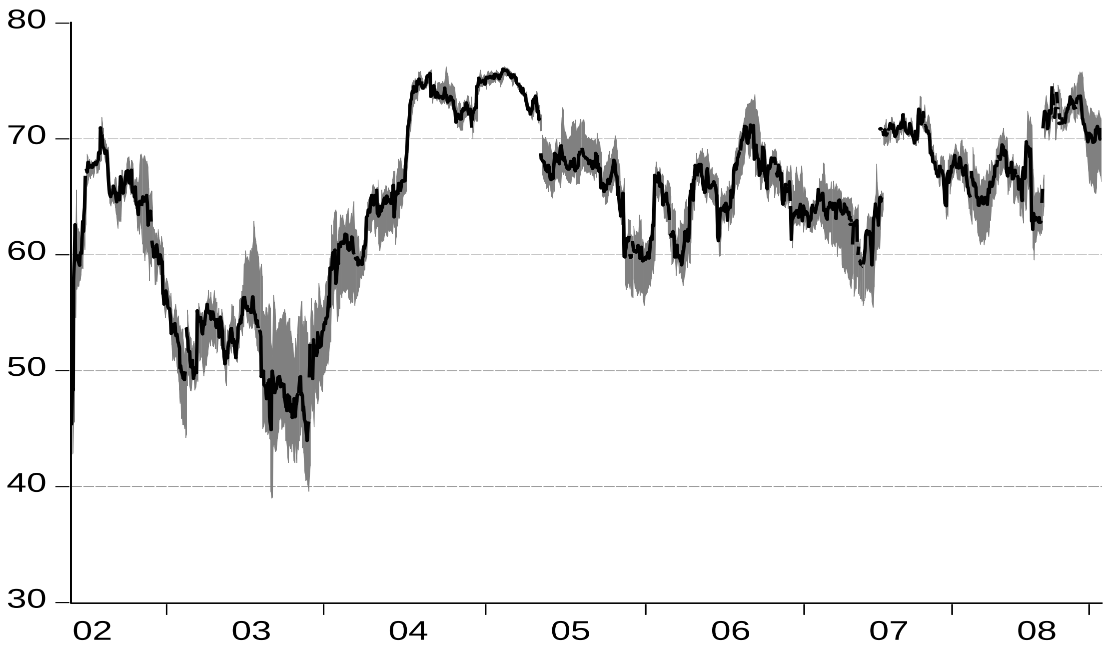

FIGURE 50: **RNV Spillovers 1-to-6 Lag Lengths (Max-Min Error Band and Median)**

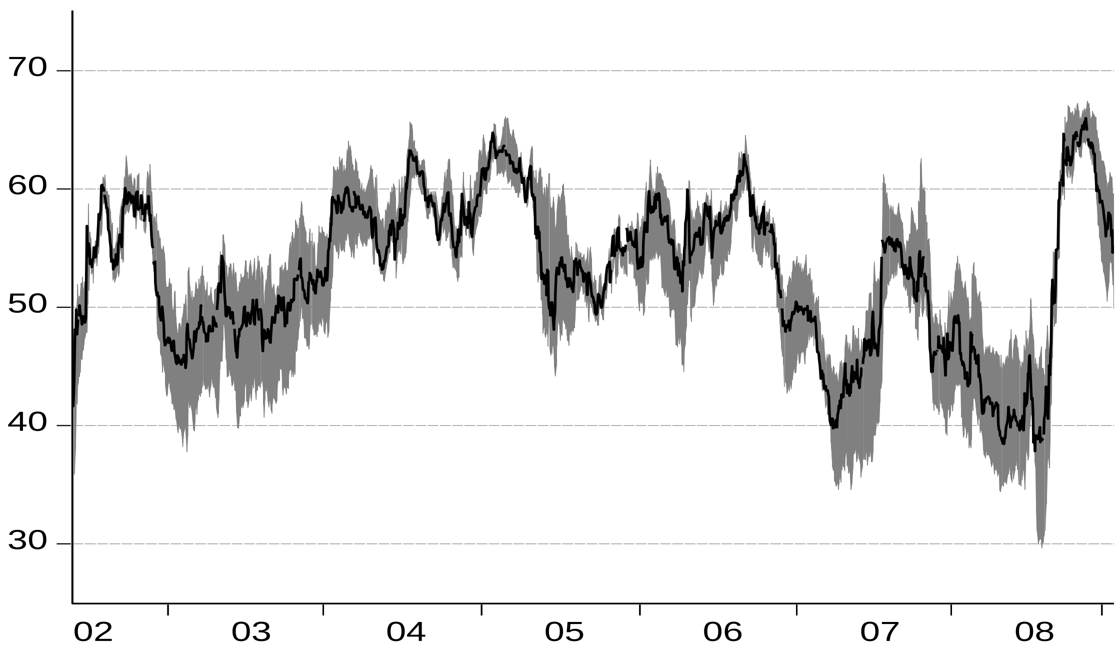

FIGURE 51: **JC Spillovers 1-to-6 Lag Lengths (Max-Min Error Band and Median)**

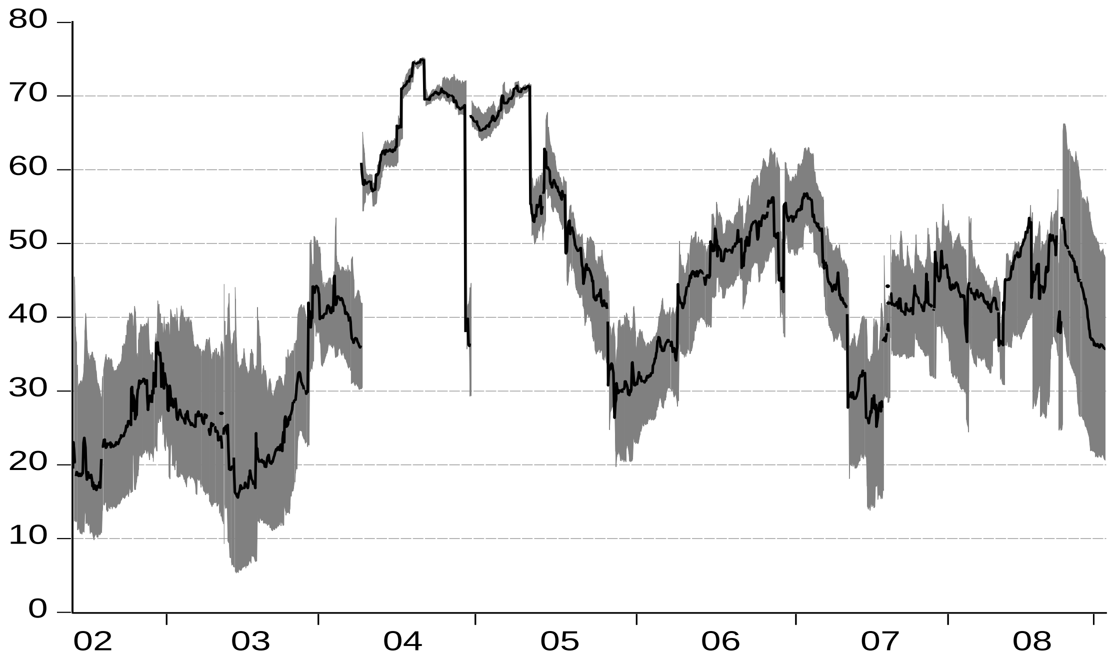

FIGURE 52: **C Spillovers 1-to-6 Lag Lengths (Max-Min Error Band and Median)**

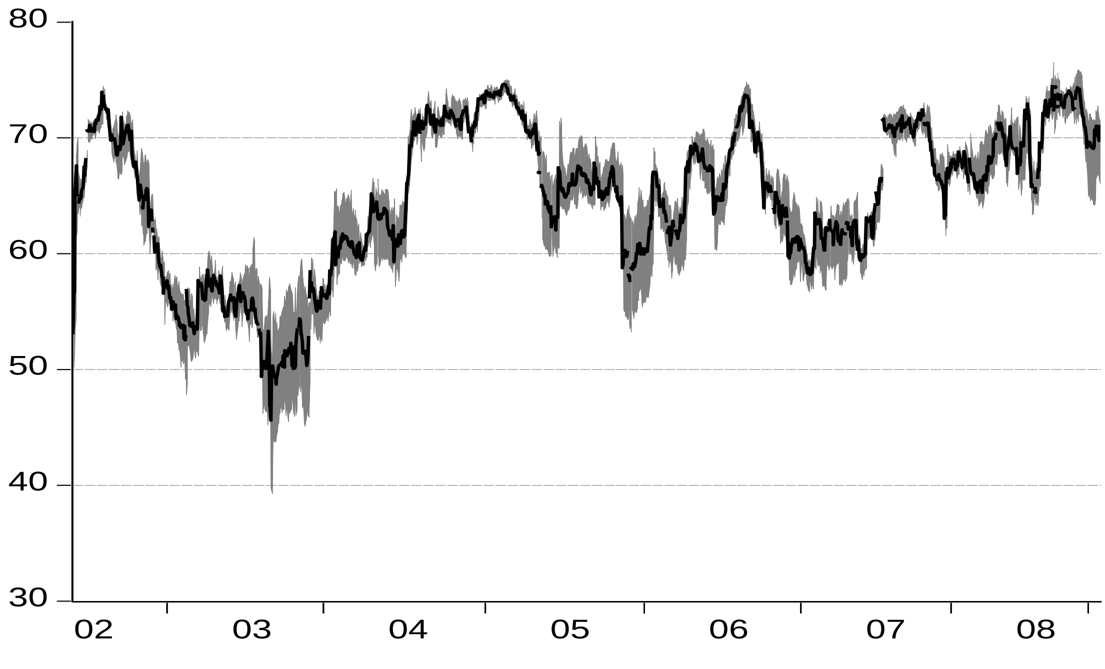

Figure 53: **RV Spillovers 5-to-10 Forecast Horizons (Max-Min Error Band and Median)**

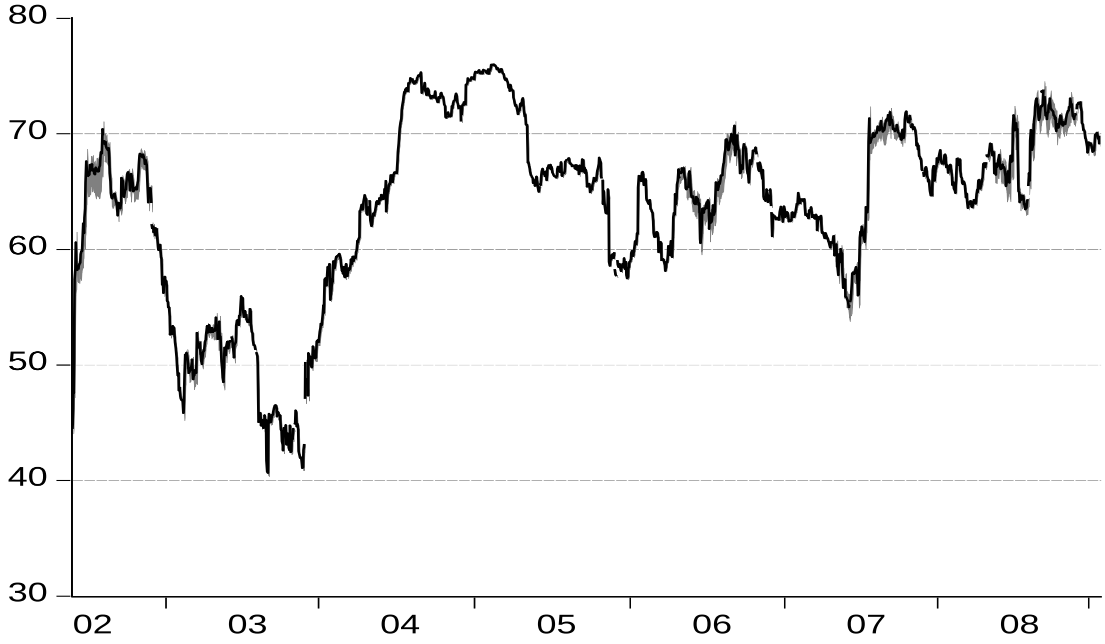

Figure 54: **RNV Spillovers 5-to-10 Forecast Horizons (Max-Min Error Band and Median)**

Figure 55: **JC Spillovers 5-to-10 Forecast Horizons (Max-Min Error Band and Median)**

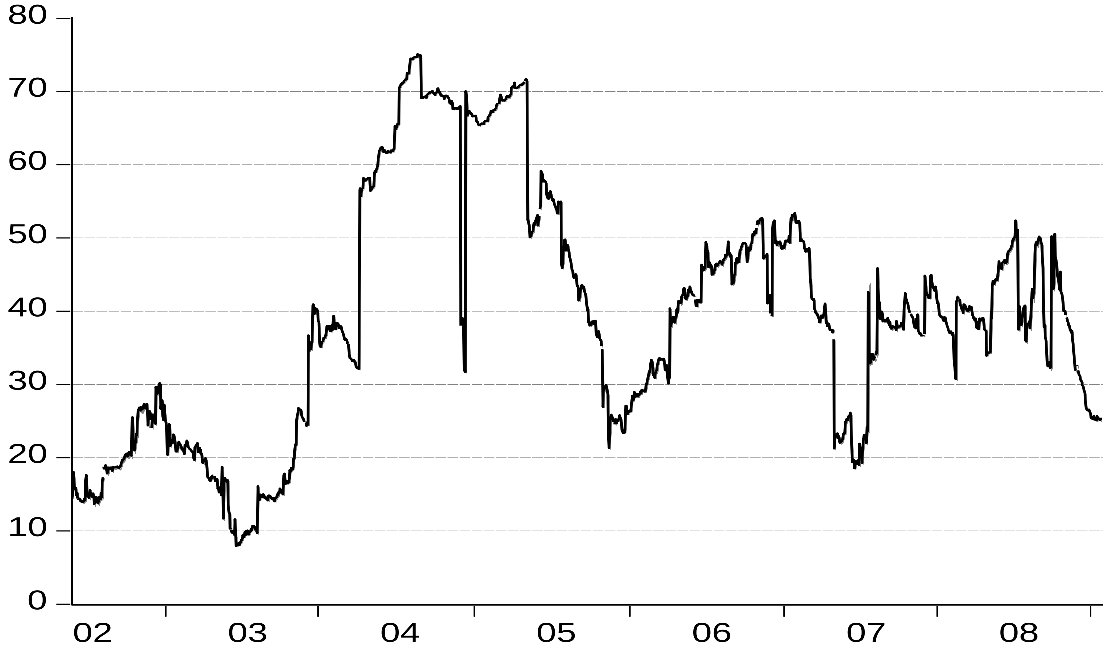

Figure 56: **C Spillovers 5-to-10 Forecast Horizons (Max-Min Error Band and Median)**

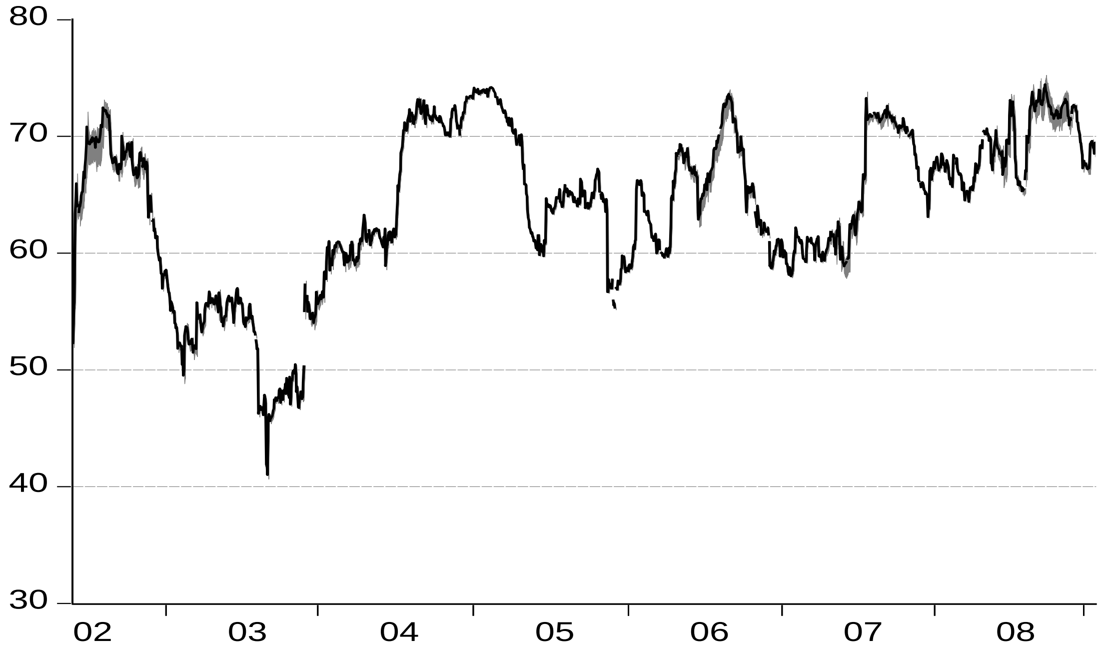

FIGURE 57: **Residuals Joint Normality Test**

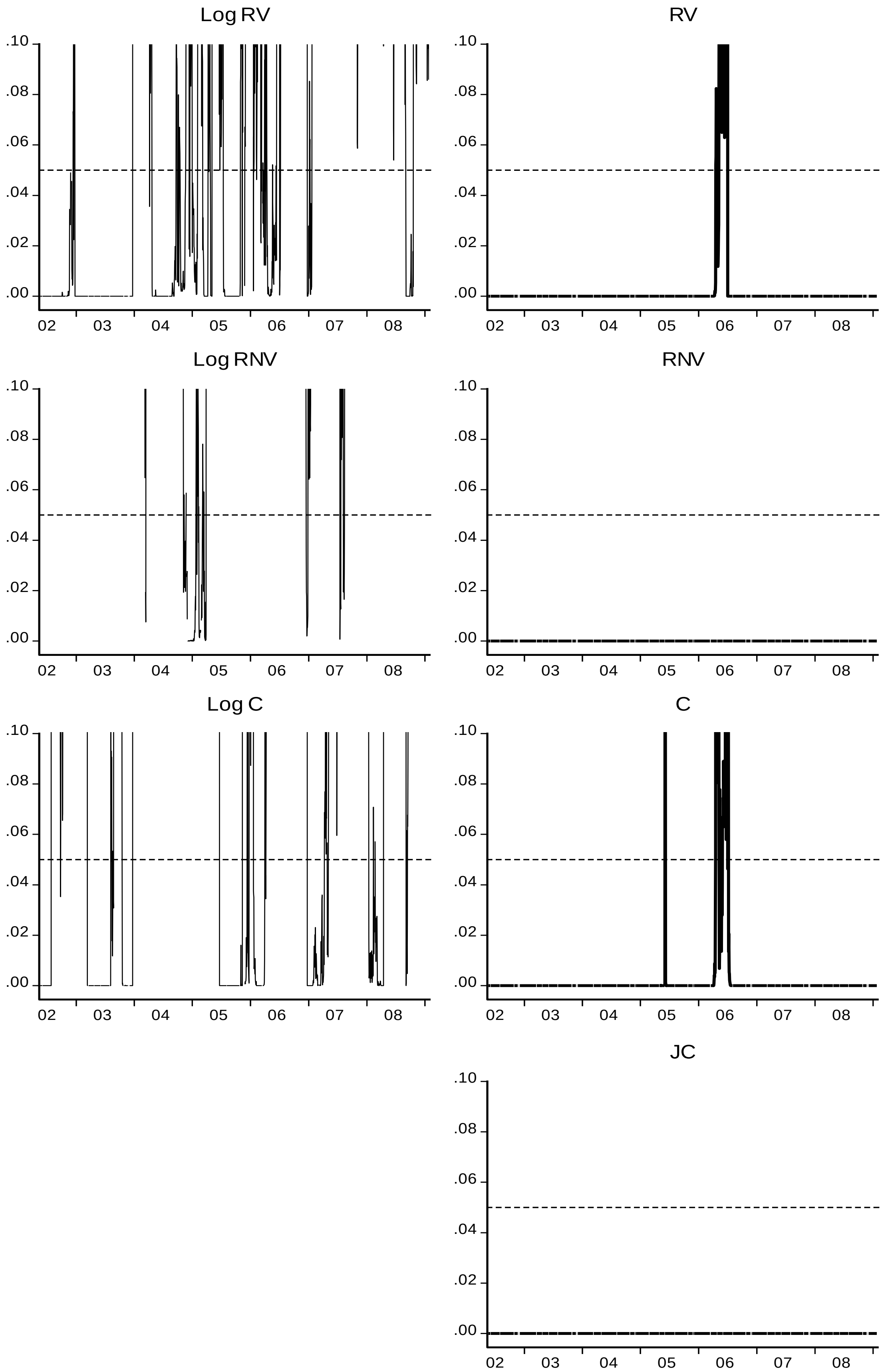

Figure 58: **Residuals Normality Test (Log RV Based VAR)**

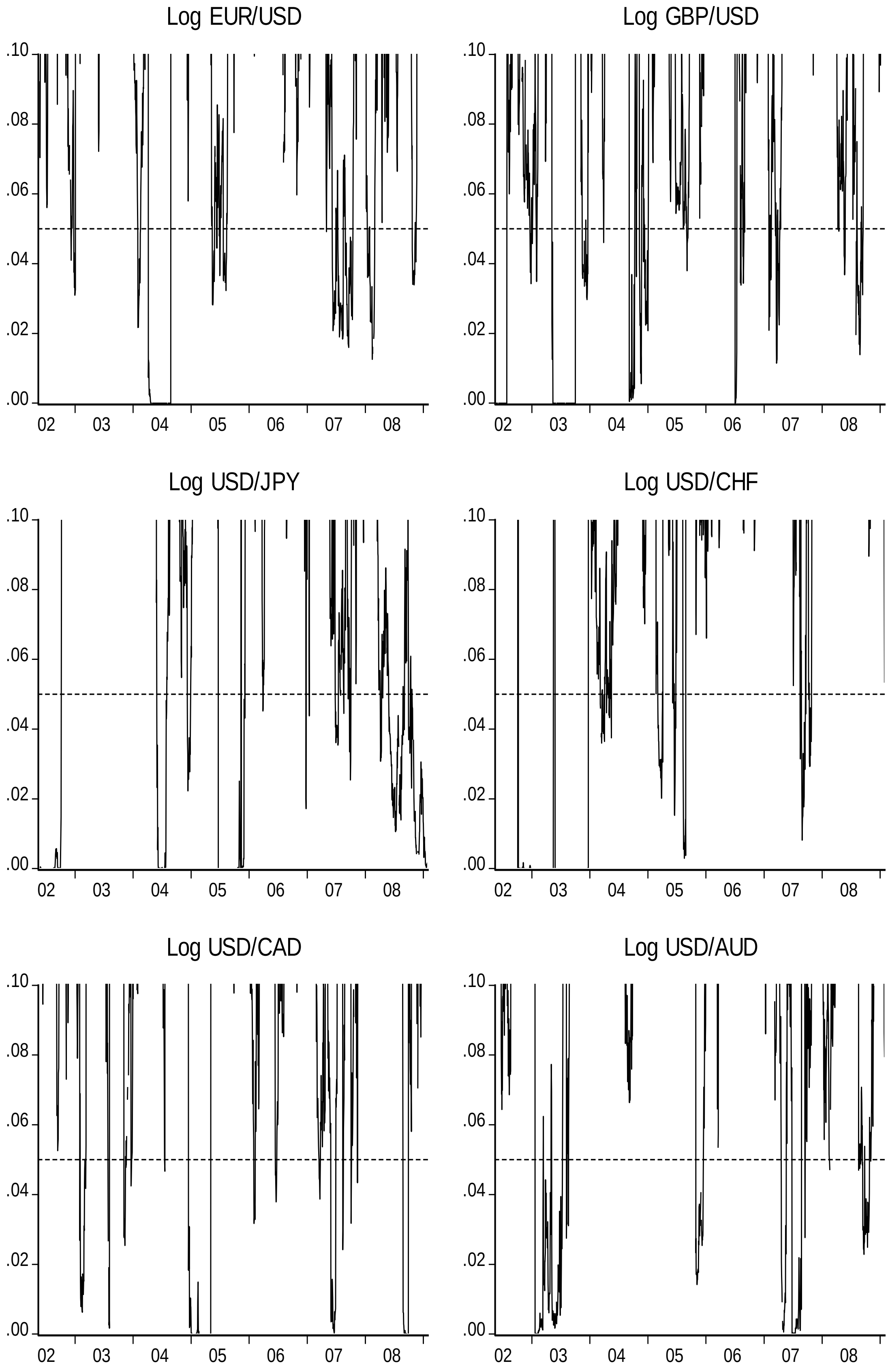

Figure 59: **Residuals Normality Test (Log RNV Based VAR)**

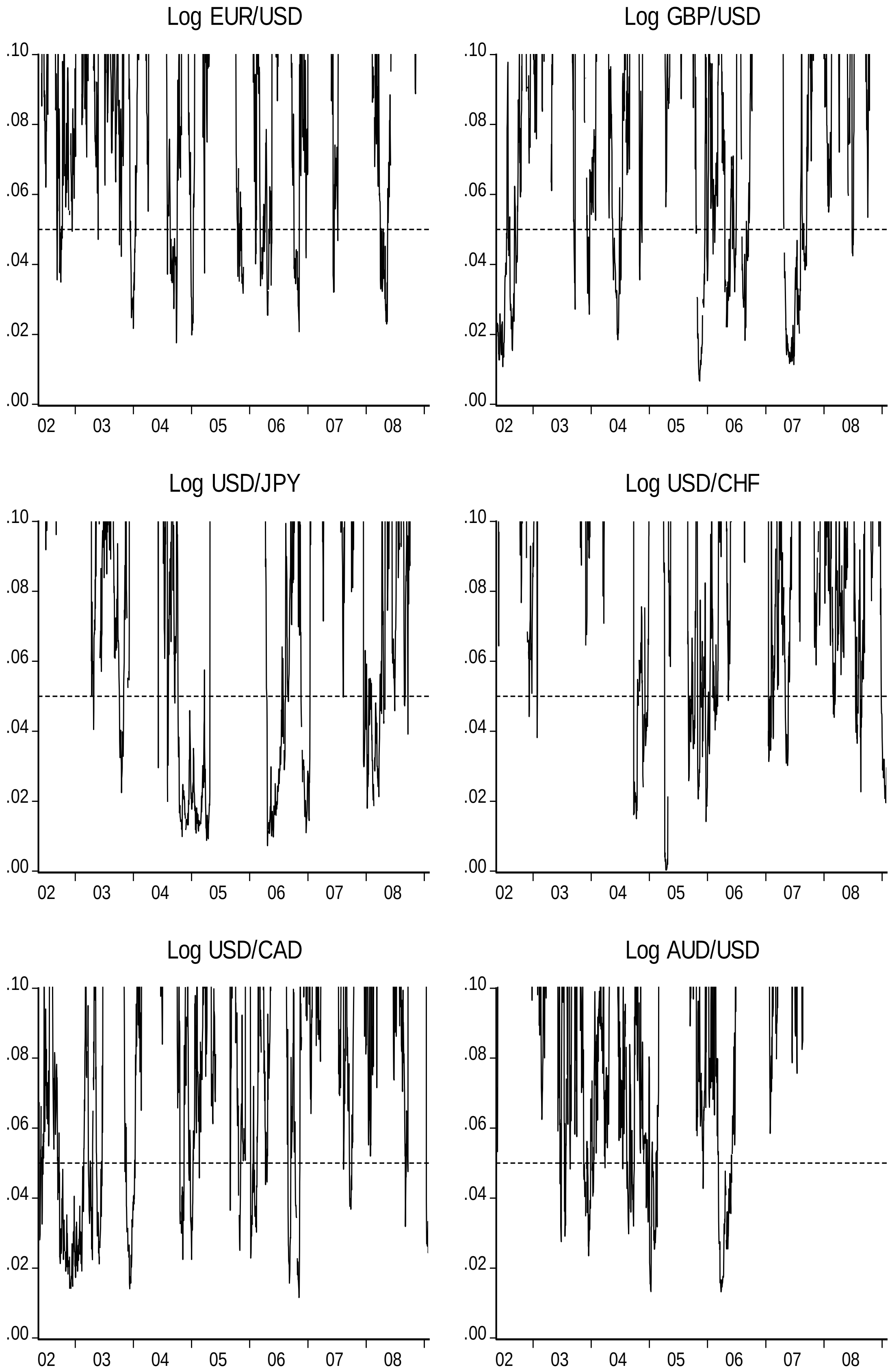

Figure 60: **Residuals Normality Test (Log C Based VAR)**

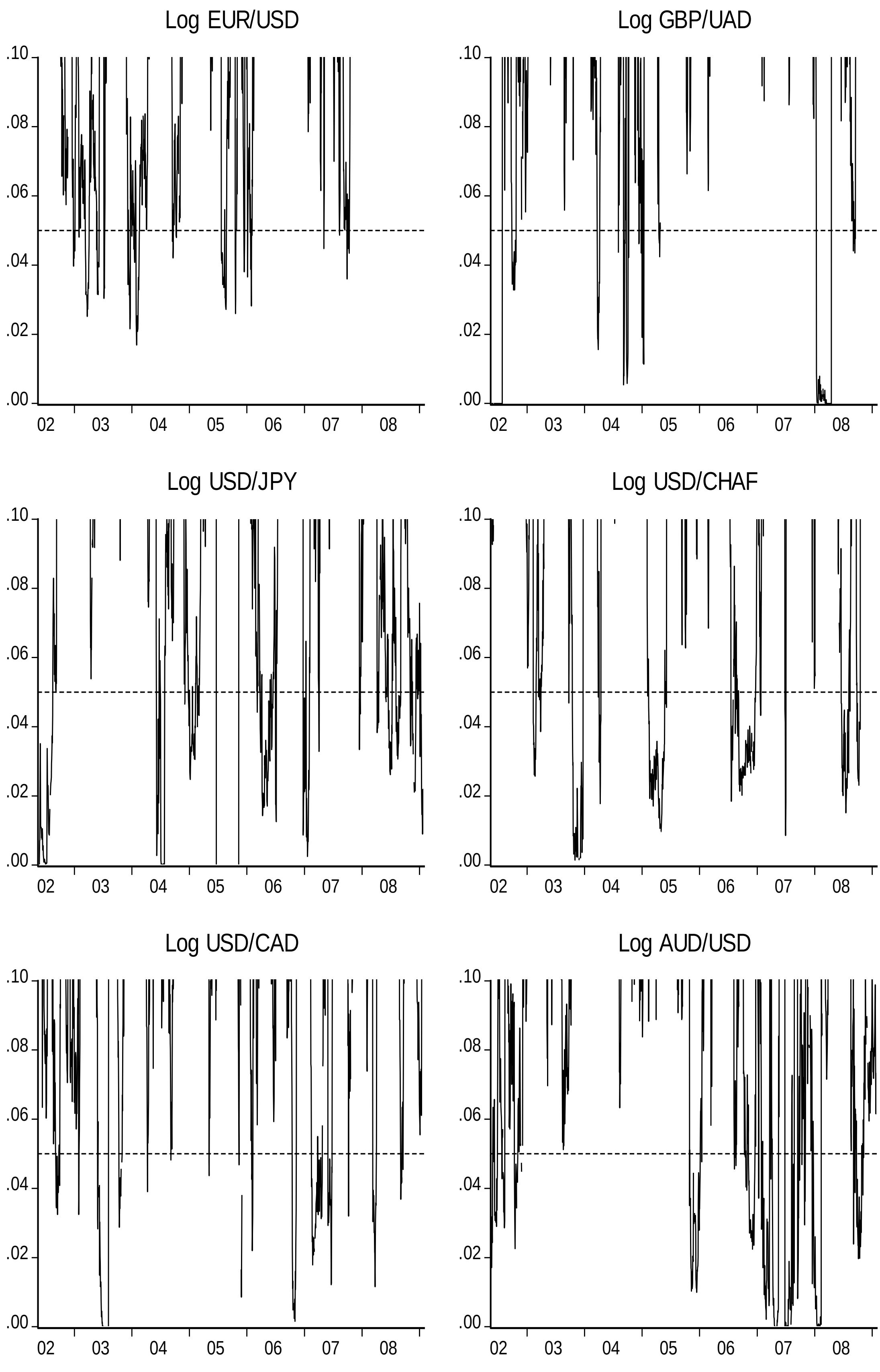

FIGURE 61: **Residuals Normality Test (RV Based VAR)**

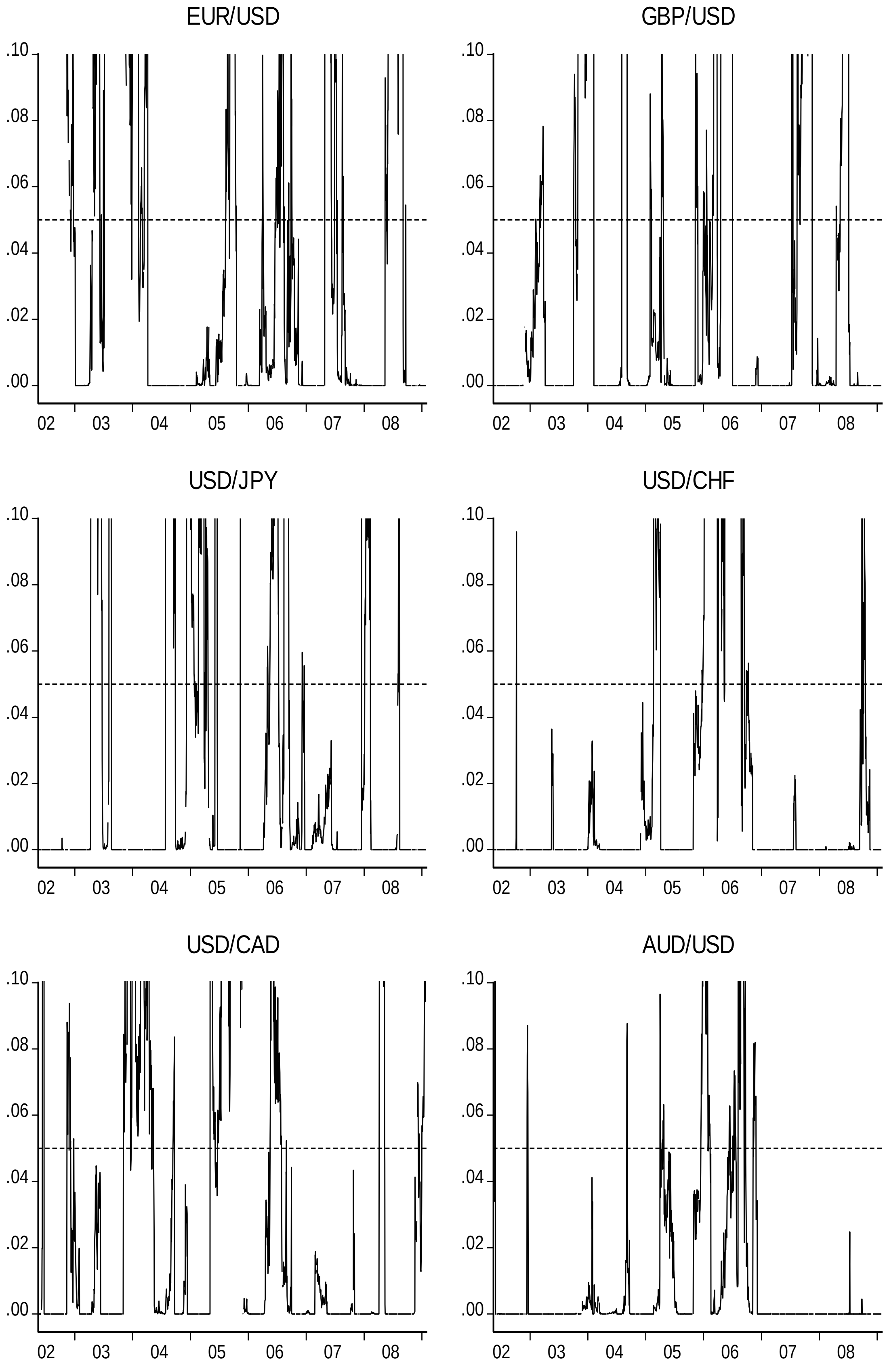

Figure 62: **Residuals Normality Test (RNV Based VAR)**

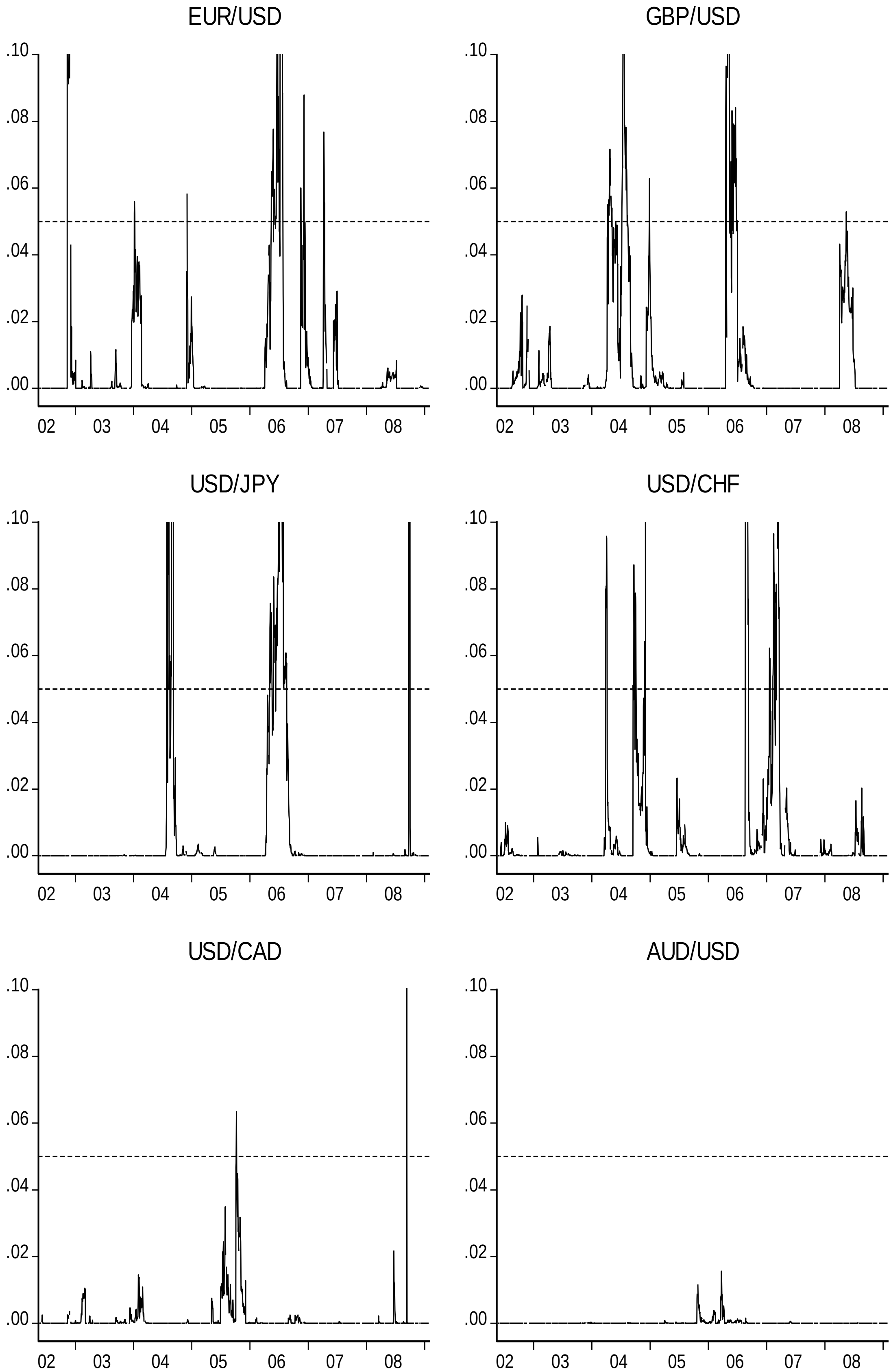

Figure 63: **Residuals Normality Test (JC Based VAR)**

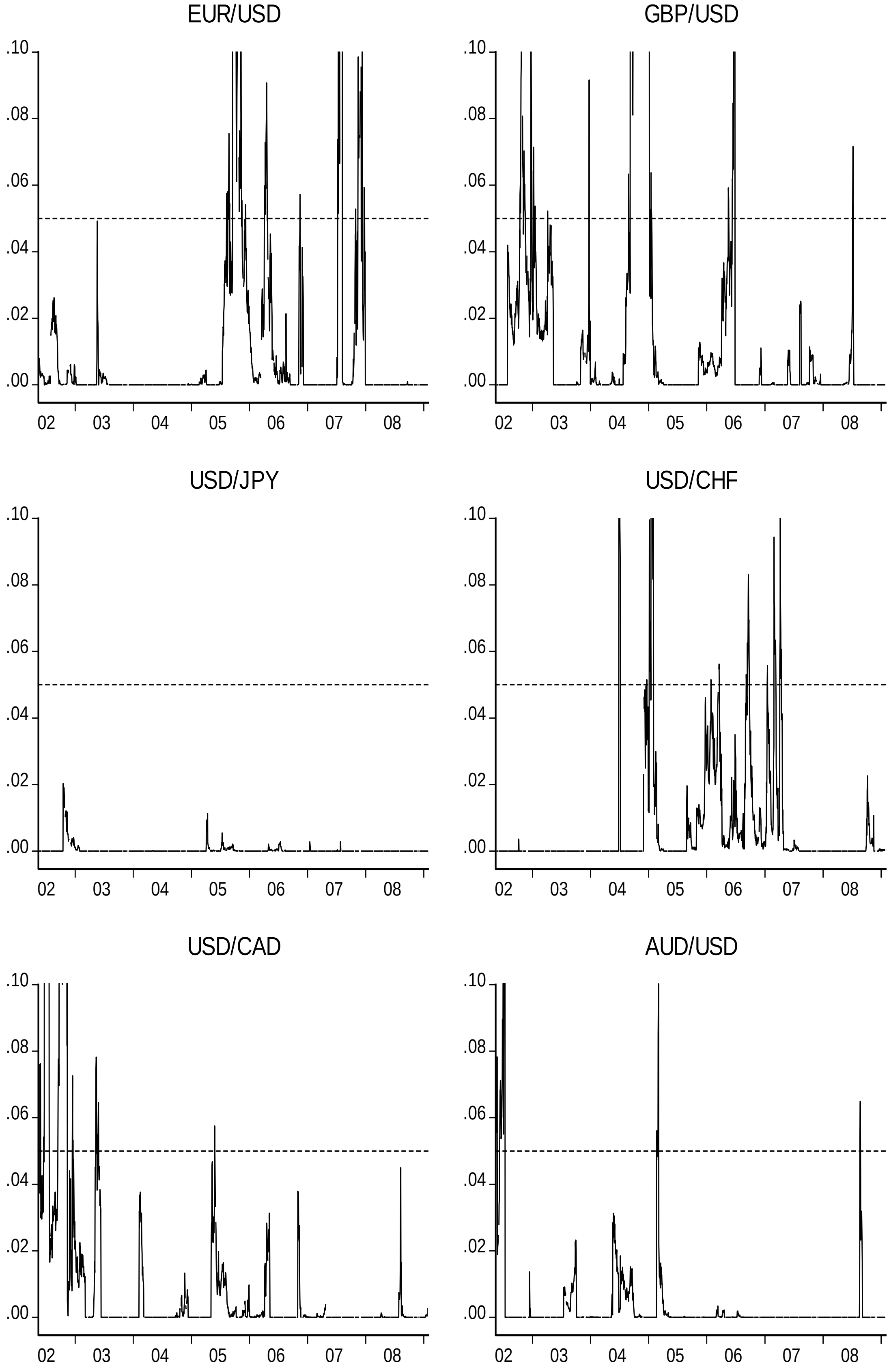

Figure 64: **Residuals Normality Test (C Based VAR)**

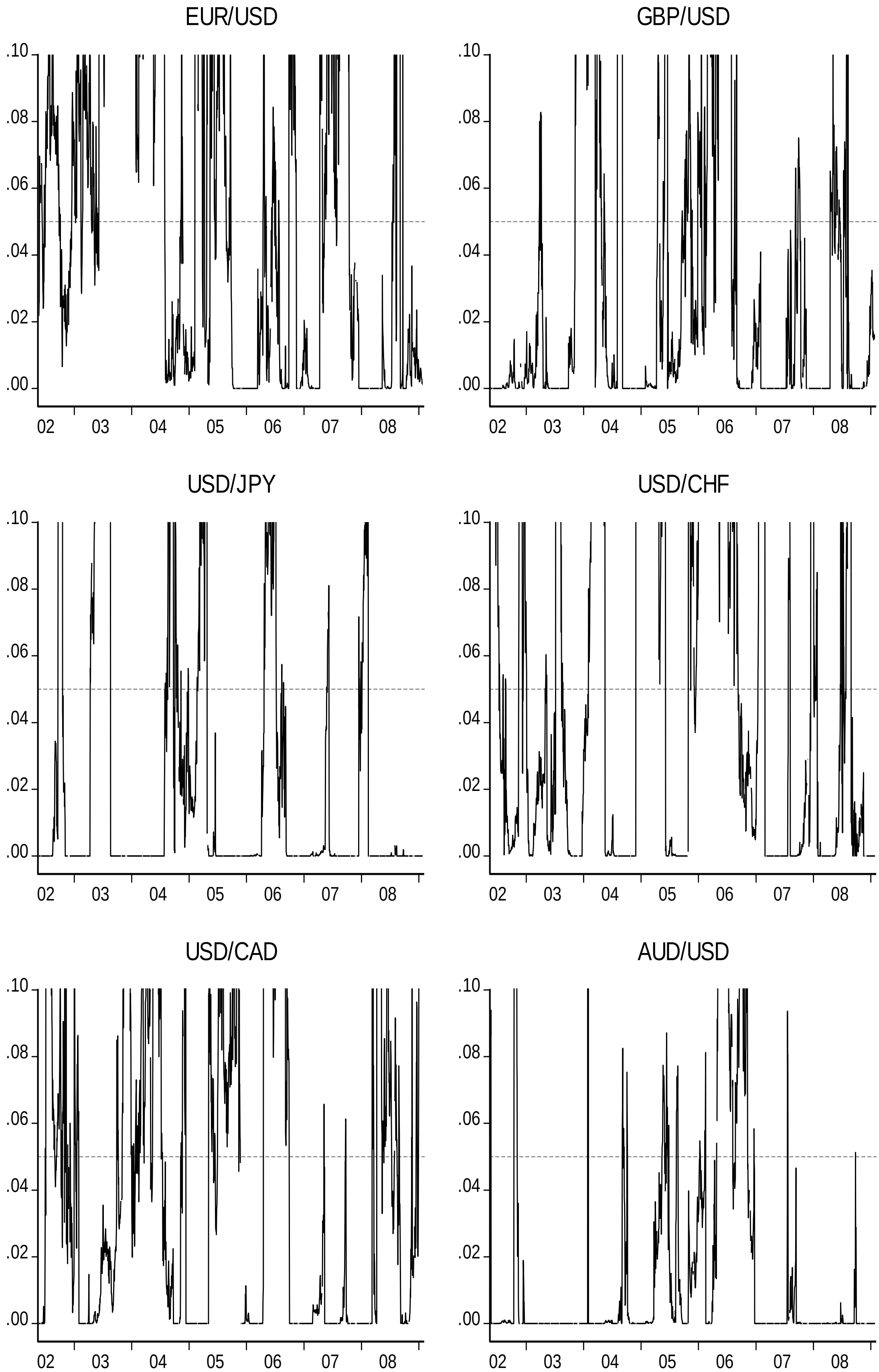

Figure 65: **RV Spillovers Different Rolling Windows Size (Max-Min Error Band and Median)**

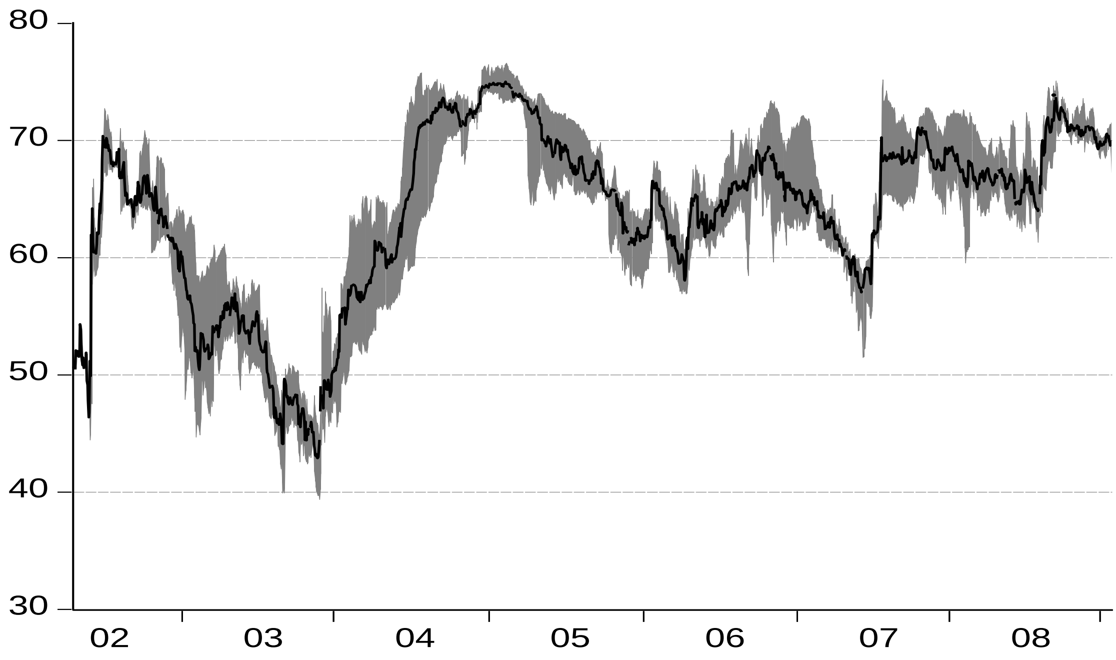

Figure 66: **RNV Spillovers Different Rolling Windows Size (Max-Min Error Band and Median)**

Figure 67: **JC Spillovers Different Rolling Windows Size (Max-Min Error Band and Median)**

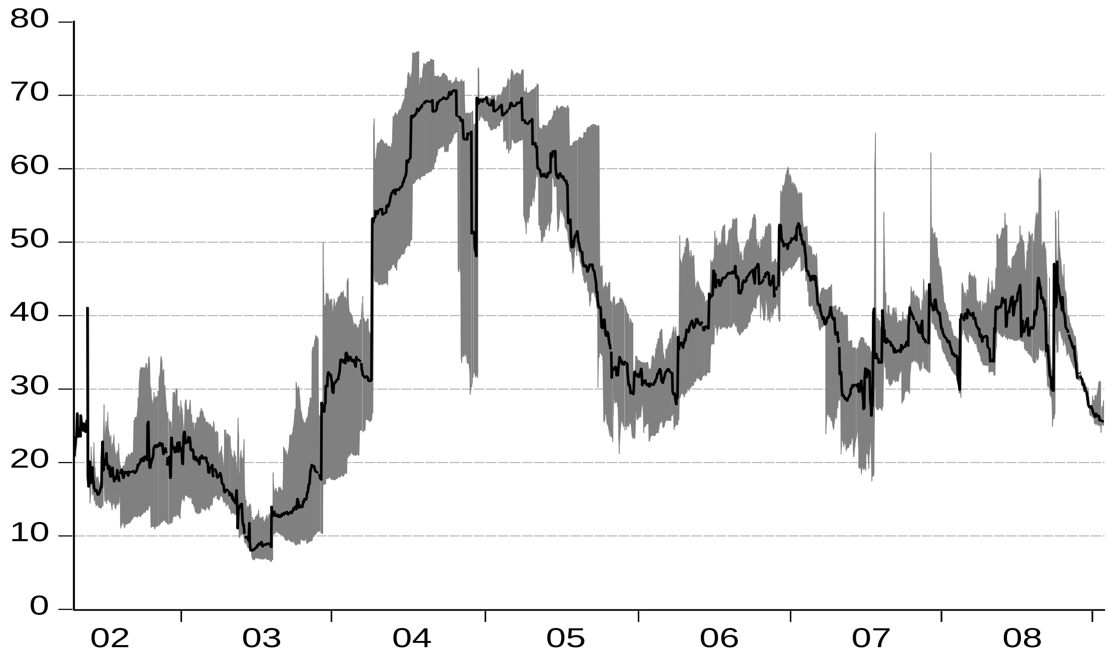

Figure 68: **C Spillovers Different Rolling Windows Size (Max-Min Error Band and Median)**

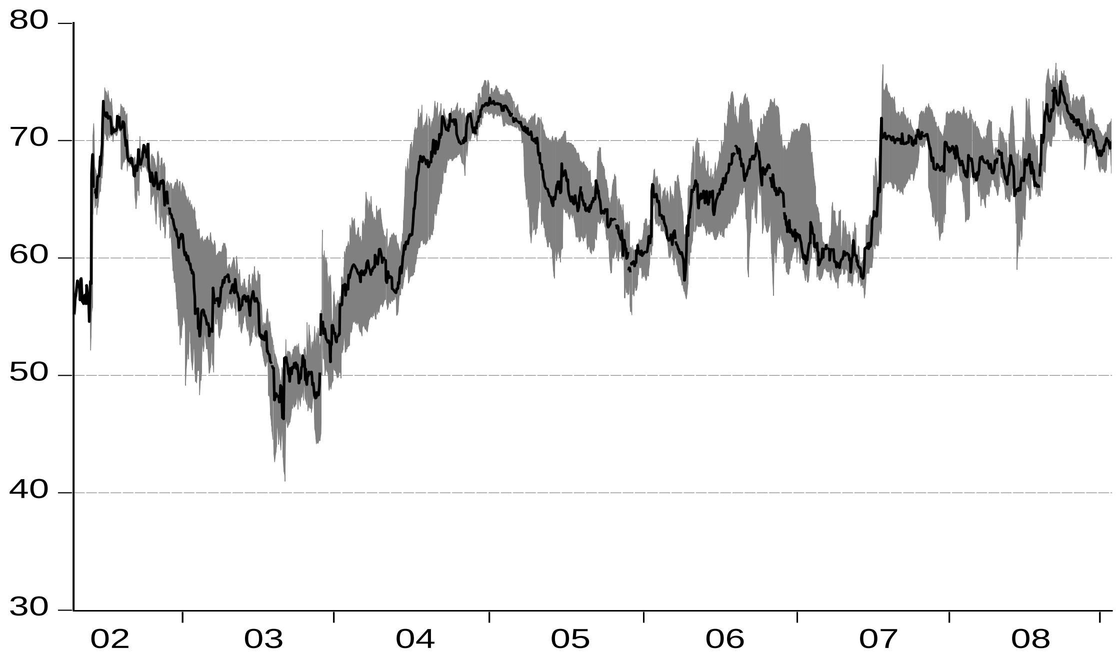

Figure 69: **RV Log vs Level Spillovers**

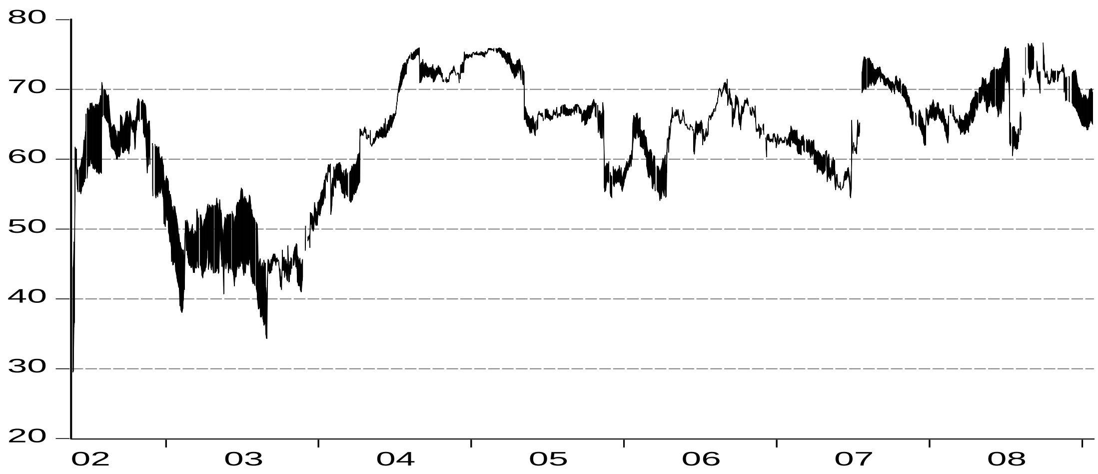

Figure 70: **RNV Log vs Level Spillovers**

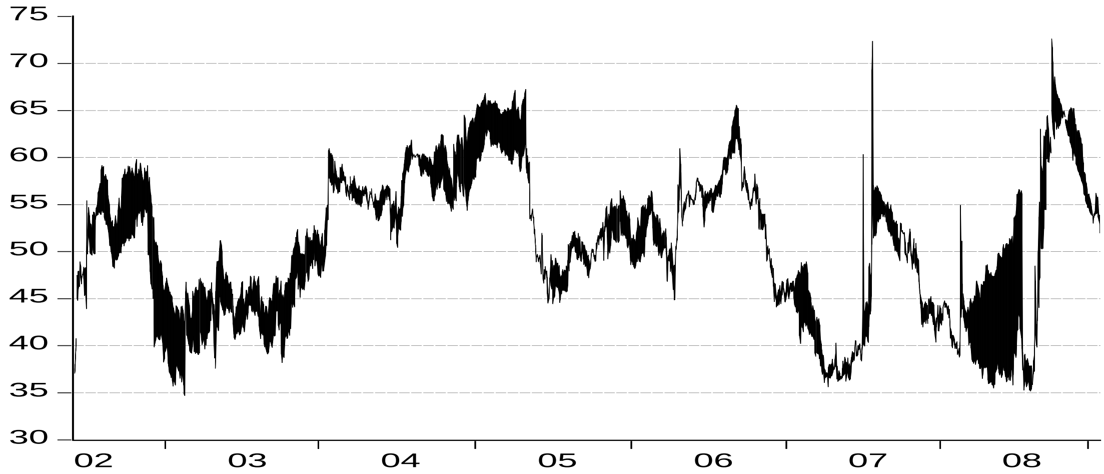

Figure 71: **C Log vs Level Spillovers**