LONG TERM RELATIONSHIP BETWEEN CDS AND CURRENCY EXCHANGE RATES: THE TURKISH CASE[1]

CDS ile Döviz Kurları Arasındaki Uzun Dönemli İlişki: Türkiye Örneği

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ABSTRACT: The main objective of this study is to analyze the long-term relationship between exchange rate and credit default swaps (CDS) based on high frequency time series as representative of Turkey's risk premium. In general, the long-term relationship describes a long period of time in the literature. However, although the time periods used in the testing of financial and economic hypotheses have taken a long period of time, the use of new techniques is needed due to the high frequencies. In the analysis of long-term relationships with high-frequency time series, the transition and the continuity of the shocks should be considered together. Therefore, in this study, partial integration method considering these two features was used as an analysis tool. The most important feature of the analysis is that it gives information about the long term relationship based on these properties. This information is a random process based on the tendency to revert to the mean in the period covered and is the result of the applied test. Hence, the relationship between variables, namely exchange rates and Turkey's CDS, are analyzed by using non-linear causality tests. Thus, it is also analyzed whether the effects such as jump and break on these variables change over time. Policy recommendations are made for Turkey based on the empirical findings to contribute to the relevant literature.

Keywords: Risk Premium, Credit Default Swaps (CDS), Nonlinear Granger Causality Test, High Frequency Time Series.

ÖZ: Bu çalışmanın temel amacı, Türkiye'nin risk primlerini temsil eden "kredi temerrüt takası" (CDS- credit default swap) ve döviz kurları arasındaki uzun dönemli ilişkinin analizini yüksek frekanslı zaman verilerine dayalı olarak analiz etmektir. Genel olarak uzun dönemli ilişki literatürde uzun bir zaman dönemini tanımlamaktadır. Oysa günümüzde finansal ve iktisadi hipotezlerin testinde kullanılan zaman dönemleri uzun bir dönemi almış olsalar bile, frekansların yüksek olmasından dolayı, yeni tekniklerin kullanımına ihtiyaç duyulmaktadır.

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Uzun dönemli ilişkilerin yüksek frekanslı zaman serileri ile analizinde şokların geçişgenliği ile sürekliliği birlikte dikkate alınmalıdır. Bundan dolayı bu çalışmada bu iki özelliği dikkate alan kısmi tümleşme yöntemi analiz aracı olarak kullanılmıştır. Analizin en önemli özelliği belirtilen özelliğe dayalı uzun dönemli ilişki hakkında bilgi vermesidir. Bu bilgi ele alınan dönemde ortalamaya dönme eğilimine göre bir rastsal süreç olup uygulanan testin bir sonucu olmaktadır. Bu çalışmada kullanılan yaklaşım ile Türkiye'nin CDS ile döviz kurları arasındaki uzun dönemli ilişki yüksek frekanslı zaman serileriyle analizi yapılmıştır. Elde edilen ampirik bulgulara dayalı olarak Türkiye için politika önerileri sunulmuştur.

Anahtar Kelimeler: Risk Primi, Kredi Temerrüt Takası (CDS), Doğrusal Olmayan Granger Nedensellik Testi, Yüksek Frekanslı Zaman Serisi.

INTRODUCTION

Derivatives are designed as hedging instruments to eliminate various types of risks arising from counterparties' inability to fulfill their obligations. Specifically, credit derivatives are widely used to give protection and provide insurance against violations of contracts by borrowers. Among these credit derivatives, Credit Default Swaps (CDS) are the most widespread instruments traded frequently all over the world (Hull and White, 2001:12-15). Blythe Masters, a former executive at JP Morgan designed the very first CDS in 1994. CDS spreads provide timely information for investors and permit for a correct assessment of risk compared to credit ratings or bond yield spreads for an entity (Corte et al. 2015: 7-8).

In this paper, regarding the importance of CDS as an entity's risk indicator (Kalbaska and Galtkowski, 2012: 15-16), the asymmetric relationship between USD exchange rates and Turkey's CDS is analyzed by using partial co-integration approach. The organization of the work is as follows: Firstly, the trading logic behind CDS are discussed depending on the financial market structures. Also major facts and figures of both Turkey and global financial markets related to CDS are introduced. Secondly, the relevant literature is presented based on experiences from CDS figures of various countries. Thirdly, the data and methodology are explained. Specifically, descriptive statistics are presented and unit root test results of the data are summarized. Afterwards, the test hypothesis is established. The model and empirical results are given and also discussed in detail by comparing with findings in other countries. In conclusion, the policy recommendations are made for Turkey regarding the asymmetric relationship between USD and Turkey's CDS for the last five-year (2013-2018) period. The major contribution of this work is that, to our knowledge, partial co-integration approach is firstly applied for Turkey's CDS data by using R-codes from financial modeling studio (2018).

TRADING LOGIC AND THE ROLE OF CDS MARKETS

Credit derivatives markets operate as an essential signal for market participants and regulatory authorities. However, it is crucial to make a distinction between CDS as an instrument and the global credit derivatives market. Credit default swap is designed as a flexible financial instrument which can be bought and sold between individual and corporate investors to protect against default risk (Palladini and Portes, 2011: 8-9). The trading logic of CDS contracts is similar to the insurance contracts against triggering events for credit default. It should be noted that CDS is an over-the-counter (OTC) instrument, in other words, they are traded via a broker and dealer network. This trading process is different from centralized exchange mechanism such that the bid-ask spread is wider (Dutra, 2015:22-23).

CDS is considered more efficient hedging instrument compared to conventional credit risk management instruments such as loan sales, credit limits, portfolio diversification, securitization and for this reason, CDS usage have increased so fast especially subsequent to the Global Financial Crisis (GFC) in 2008. In relation to GFC, the SEC have taken some precautions to reduce some of the risks and potential harms associated with the OTC markets by approving designated entities such as Chicago Mercantile Exchange to play critical role as central counterparties (CCPs)[2] for credit derivatives (BIS, 2009:55-56). After GFC, CDS markets were restructured by joint work of industry groups, market participants and infrastructure providers and regulators such as the Federal Reserve Bank of New York, the European Central Bank, the U.K. Financial Services Authority (FSA), the U.S. Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC) in order to diminish systemic risk. In this way, CDS markets have become more attractive for lenders and investors to hedge their risks and also CDS markets are treated as a market-based price determination mechanism (ICE, 2010: 2-3). On the one hand, CDS markets facilitate low cost of capital for debt issuers globally, on the other hand, they reduce risks for contract holders.

THE RELEVANT LITERATURE REVIEW

There are various empirical works such as Norden and Weber, (2004); Baba and Inada, (2009); Meng et al. , (2009); Calani, (2013); Tamakoshi and Hamori, (2016); Sabkha et al., (2017) related to CDS risk premium and relationship with different macroeconomic indicators and financial instruments. In pioneering work of Merton (1974), the relationship between credit spreads and leverage,

[2] CCPs are demanded to extend market resilience by decreasing counterparty risk and operational risk and increasing transparency. In addition, the CCPs execute multiparty netting of exposures as well as payments.

volatility, and interest rates was explained. CDS are accepted as a good indicator of country risks starting from 2008 up to the present. Based on the empirical findings in Pan and Singleton, 2008; Longstaff et al., 2011; Palladini and Portes, 2011; Mano, 2013, this is due to the fact that sovereign CDS markets are more liquid compared to other markets[3]. In addition, CDS spreads provide information about how financial markets value the relationship between a country's default risk associated with currency devaluations which is called *Twin D*, i.e. default and devaluation[4] over various time horizons.

It is a fact that the number of studies on CDS spreads have been increased dramatically after the global financial crisis in 2008 (Aldasoro and Ehlers (2018: 1-2). After its commencement in the 1990s, CDS markets have grown steadily until the Great Financial Crisis (GFC) of 2007–09 (BIS, 2018). Considering business environment in the GFC period, it was understood that credit rating agencies have provided misleading information to the public. For this reason, CDS have been used as a substitute for rating scores (Altman and Rijken, 2011:2-4). Altman and Rijken (2011:31) argue that the Asian Crisis period in 1997-1998 was not captured by CDS risk premiums since CDS markets were not liquid enough at that time. In pioneering work of Reinhart (2002), it is claimed that currency exchange rate crisis mostly goes after default risks and hence, credit rating agencies are systematically not succeeding in anticipating currency exchange crisis. According to the key figures of BIS (2018), the market share of CDS investment score has gone up to 64% at the end of 2017. Stulz (2009) argues that the increasing importance of CDS spreads is due to the fact that CDS markets become a good indicator of global financial activity and they tend to be concentrated and standardized. Particularly, the maturity of CDS contracts is concentrated around five years. Therefore it is a fact that CDS spreads produce consistent, timely and more accurate assessments of credit conditions than rating agencies. Compared to CDS, rating agencies are paid by an issuer and generally fieldworks for rating reviews can take weeks or months to prepare the end result while CDS are traded continuously.

The key determinants of CDS premiums are discussed in the current literature such as high volatility in global financial markets and frequent changes in risk appetite (Pan and Singleton, 2008, Longstaff et al., 2011; Fender et al., 2012; Fontana and Scheicher, 2016), uncertainties in a country's financial markets (Gündüz and Kaya, 2014; Belke and Gokus, 2014) and public sector debt burden (Zhang, 2003; Zoli, 2005; Corsetti et. al, 2013).

[3] Most characteristics of sovereign CDS are identical to corporate CDS contracts. Except it should be noted that "default" is not mentioned in the obligation lists of sovereign CDS, because bankruptcy court for sovereign issuers does not exist internationally (Pan and Singleton, 2005: 5-6).

[4] Even if these two types of events rarely take place in emerging countries and unlikely case in mature countries, default risk is usually connected with devaluations (Augustin et al, 2018: 1-2).

Akkuş et al (2018) analyze the relationship between Turkish bonds and CDS for Turkey and calculate the risk premium. In this work, the authors concluded that there is a strong positive correlation the volatility in CDS risk premiums is transferred to the Turkish bonds via volatility spillovers. Kechagioglou (2010) argues that CDS is volatility dependent, and for this reason it is required to use dynamic modeling methods. Neziri (2009) states that CDS prices can be used as an indicator for equity markets based on the supporting empirical findings of CDS as a "predictive power for equity markets". The author indicates that the lead time is commonly observed in one month period. In addition, Kunt and Taş (2009), Fender et al., (2012), Akdogan and Chadwick (2013), Ural and Demireli (2015), Kim, Salem and Wu (2015), Gunay and Shi (2016), Bouri et al. (2016) and Varlık and Varlık (2017) also had works on Turkey's CDS markets.

THE DATA, METHODOLOGY AND EMPIRICAL FINDINGS

Data

Turkey's CDS spreads (namely, LCDS) and USD currency exchange rates (namely, LKUR) are taken for the five-year period (January 02, 2013 – October 04, 2018). The data is transformed to the logarithmic return series before starting the analysis. The major reason for this logarithmic transformation process is to conform the normality assumption by dealing with skewness of the data by eliminating the effects of extreme changes on data. In addition, when the first difference of the logarithmic financial time series is taken, we obtain return series with a continuous form. The descriptive statistics and graphics of our return series are indicated in Table 1 and Figures 1 and 2 simultaneously.

Table 1: Descriptive Statistics

Variables	LKUR	LCDS
Mean	0.000836	-4.604399
Median	4.65E-05	-4.605497
Maximum	0.147066	-4.379438
Minimum	-0.064754	-4.745158
Std. Dev.	0.009238	0.027519
Skewness	**3.158720**	**0.818016**
Kurtosis	**57.66725**	**11.51075**
Jarque-Bera	185238.3	4594.191
Probability	0.000000	0.000000

Compared to the normal distribution where the skewness is expected to be zero, both of the series exhibit positive skewness and hence, they are not normally distributed. Skewness figures of these series (LKUR is 3.158 and LCDS is

0.818) give information about the lack of symmetry. The positive values for the skewness show that both of the series are skewed to the right. This could be interpreted that the right tails of LKUR and LCDS are longer relative to the left tails. Kurtosis is used as a measure of whether the data are heavy-tailed or light-tailed compared to normal. Thus, LKUR and LCDS exhibit heavy-tailed (outliers) characteristics which is parallel to the general structure observed in financial markets. There is an increase in the volatility during the period of 2017-2018. Jarque–Bera test rejects the normality for the DF distribution (Table 1).

Figure 1: USD Currency Exchange Rates Return Series (2013-2018)

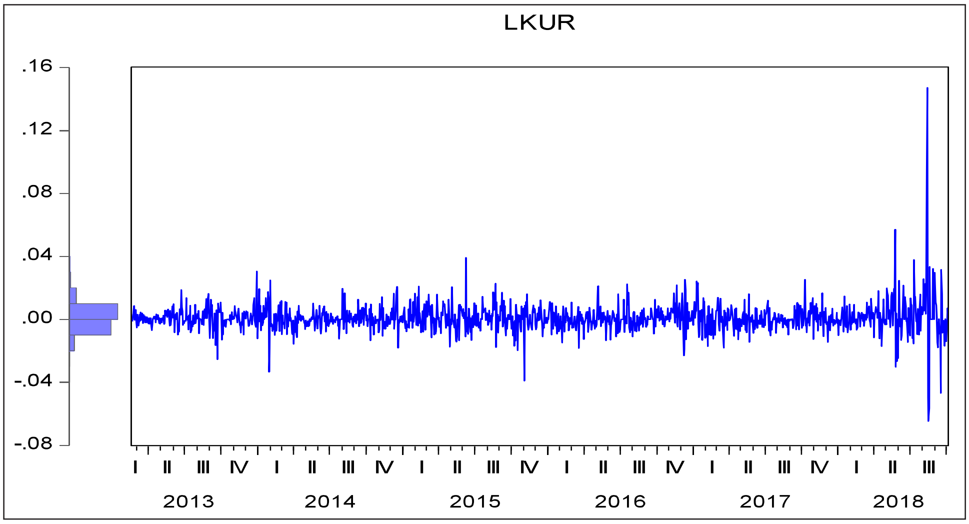
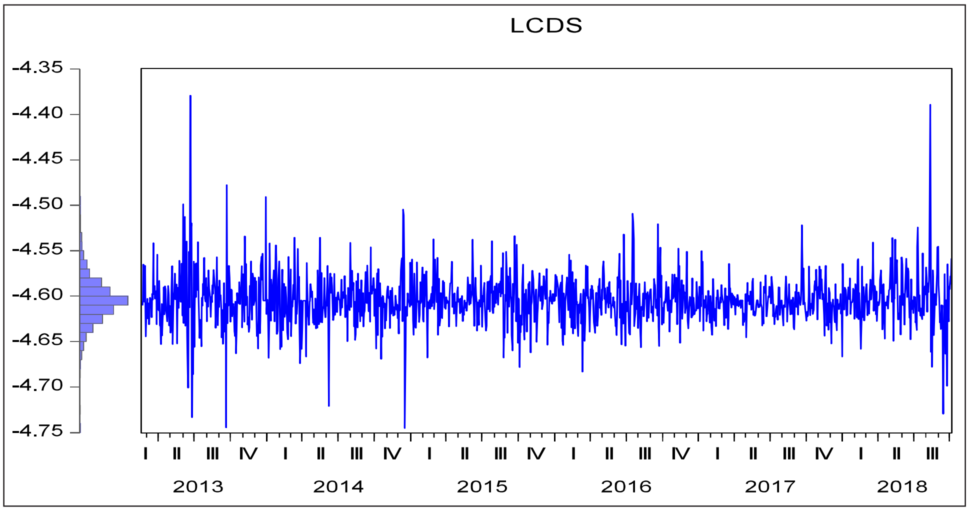


Figure 2: Turkey's CDS Spreads Return Series (2013-2018)



It is a fact that financial time series have a more complicated dynamic structure than a simple AR(1) model. For this reason, unit root testing in financial time series is the essential step in the construction of econometric modeling. In order to test the stationarity of our return series, firstly the Augmented Dickey Fuller Test (ADF) (Dickey and Fuller, 1979, 1981) is used and ADF unit root test results are shown in Table 2-a. Although ADF test is the most widely accepted unit root test in the literature due to its simple construction and feasibility, Phillips-Perron (PP) test (Phillips and Perron, 1988) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test (Kwiatkowski et.al 1992) are additionally applied to determine the integration order of data more confidently[5]. PP and KPSS test results are summarized in Table 2-b and Table 2-c simultaneously. It should be noted that the return series are equivalent to the first difference of the data and hence, the first differences are stationary according to the three unit root tests, i.e. ADF, PP and KPSS tests. The unit root test results in Table 2-a-b and c support that LKUR and LCDS are stationary. Based on the ADF and PP test results, both of the series with their first difference have no unit root and they are stationary and hence, the null hypothesis is rejected. Compared to the other two tests, the null hypothesis of KPSS test check the stationary condition for the series and this time, the null hypothesis is accepted. The unit root test results of ADF, PP and KPSS tests are all consistent with our expectations and therefore we proceed on the next step.

Table 2-a: ADF -Unit Root Test Results of LKUR and LCDS

Variables	Level			First Difference	
	Constant	Constant + Intercept	Constant + Trend + Intercept	Constant	Constant + Intercept
LKUR	-1.84	-2.3	0.36	-6.53*	-6.22*
LCDS	-1.84	-2.3	0.36	-21.52*	-21.51*

*: significant at 1% confidence level.

Table 2-b: PP-Unit Root Test Results of LKUR and LCDS

Variables	Level			First Difference	
	Constant	Constant + Trend	Without Constant + Trend	Constant	Constant + Trend
LKUR	0.95	-1.24	3.49	-32.61*	-32.81*
LCDS	-1.95	-2.29	0.38	-32.31*	-32.30*

*: significant at 1% confidence level.

[5] In addition to ADF test, PP and KPSS tests are recommended based on the length of time series, number of observations and the value of parameters to increase the power and confidentiality of test results (Arltová Markéta and Darina Fedorová, 2016: 51-52). On the other hand, Pesaran (2015) demonstrates that PP and ADF tests are asymptotically equivalent.

Table 2-c: KPSS-Unit Root Test Results of LKUR and LCDS

Variables	Level			First Difference	
	Constant	Constant + Trend	Without Constant + Trend	Constant	Constant + Trend
LKUR	4.40*	0.18**	-	0.21	0.08
LCDS	1.00*	0.27*	-	0.08	0.08

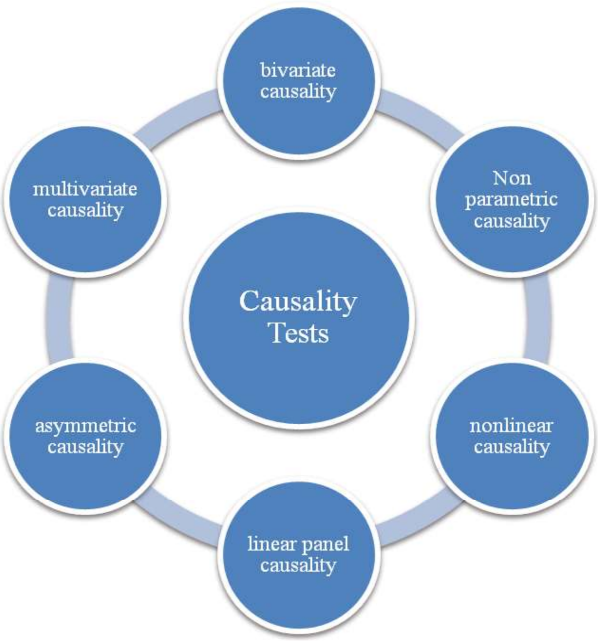
*: significant at 1% confidence level. **: significant at 5% confidence level.

METHODOLOGY

With innovative contributions of Granger (1981, 1983) and Engle and Granger (1987), co-integration is defined as multiple series moving together over time with a stochastic trend and this modeling approach is used widely in the literature. However, the major drawback of this classical co-integration approach is that it is mostly used for analyzing the linear relationships. Afterwards, the theoretical basis of co-integration is extended to deal with non linear relationships and also it is diversified from classical to partial co-integration and fractional co-integration to establish more robust models with realistic macro economic assumptions (Clegg et al., 2017: 2). In this respect, there are various causality tests used in the literature such as bivariate causality, multivariate causality, asymmetric causality, linear panel causality, nonlinear causality and non-parametric causality (Apergis, 2018: 280-281) (Figure 3). In our case, asymmetric causality is taken into consideration and explained the reason behind it as follows.

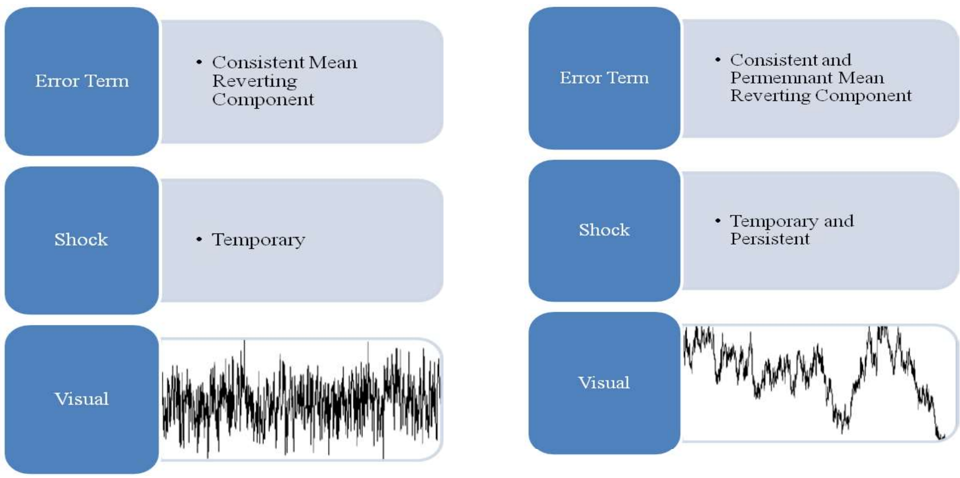
In this paper, partial co-integration (PCI) methodology is used. According to Alexander (2011), PCI can be used to detect partially co-integrated pairs of data in financial markets and business cycle models, for instance stock prices, portfolios, term structures, exchange rates and/or spot and futures prices. The comparison of classical co-integration with partial co-integration has been shown in Figure 4. The error term in a classical co-integration model is assumed to have a stationary mean reverting component whereas the error term in a partial co-integration model consists of sum of stationary mean reverting and permanent components. Shocks in the classical co-integration model are considered to be short-lived and temporary while in the partial co-integration model, shocks can be either temporary or persistent. The visualization of these two models is different and it is shown in Figure 4 simultaneously.

Figure 3: Major Types of the Causality Tests



Source: Apergis, 2018.

Figure 4: The Comparison of Classical Co-integration with Partial Co-integration



Source: Clegg and Krauss, 2016.

In this work, weak form of co-integration, i.e. partial co-integration (PCI) is used as a methodology to analyze the asymmetric relationship between USD currency exchange rates and Turkey's CDS spreads for the five-year period. The major characteristic of partial co-integration (PCI) is that this approach allows residuals to involve two different components at the same time. These two components are defined as mean-reverting and random walk (Clegg et al., 2017: 1-2). This leads to two major advantages of PCI compared to other forms of co-integration types. First advantage is that it is possible to separate the transient and permanent components of data. Clegg and Krauss (2016) argue that PCI allows to investigate the dynamics associated with the transient components within the observations separately. Second advantage is that within mean reverting, proportion of a PCI framework can be calculated to classify the structure of variance and also to assess the degree of noise in the time series.

PCI Model

Clegg and Krauss (2016:4) present the PCI Model definition as follows: Let X_t and Y_t stand for target and factor time series simultaneously. They are partially co-integrated if there exists a parameter vector as equation 1, which satisfies the below conditions in equations 2, 3 and 4 respectively.

$$\boldsymbol{Y_t = \beta_1 X_{1,t} + \beta_2 X_{2,t} + \cdots .. + \beta_k X_{k,t} + W_t} \tag{1}$$

$$\boldsymbol{W_t = M_t + R_t} \tag{2}$$

$$\boldsymbol{M_t = \rho M_{t-1} + \varepsilon_{M,t}} \tag{3}$$

$$\boldsymbol{R_t = R_{t-1} + \varepsilon_{R,t}} \tag{4}$$

$$\boldsymbol{\varepsilon_{R,t} \sim N(0, \sigma_R^2)}$$

$$\boldsymbol{\beta_j \in R;\ \rho \in (-1, 1); \sigma_M^2, \sigma_R^2 \in R_0^+}$$

W_t in Equation (2) denotes partial autoregressive process; M_t in Equation (3) denotes transient (mean reverting) component and also, R_t in Equation (4) denotes permanent (random walk) component of PCI Model. These two equations, i.e. 3 and 4, are called hidden state variables (Clegg et al., 2017:5-6). As a consequence, X_t has both components namely observations and state equations with mean reverting and random walk components. In addition, (β=β_1, β_2,...β_k) is the partially co-integrating vector. Parameters are estimated based on the maximum likelihood approach.

The Hypothesis

A group of time series is defined to be partially co-integrated if they contain a linear combination which is partially autoregressive, e.g., that can be represented as a sum of an autoregressive series and a random walk. Depending on this assumption, the null hypothesis of a PCI Model consists of two main conditions.

- The first condition is that residual series is a pure random walk ($\boldsymbol{H_0^R}$)
- The second condition is that residual series is a pure AR(1) process ($\boldsymbol{H_0^M}$)
- It should be noted that these two conditions are tested separately. If and only if these two conditions are rejected independently, then the null hypothesis of "no partial co-integration" is rejected.
- The theorem of Wilks method is used to calculate p-values associated with the likelihood ratio test. If R code is run by setting to "wilk", p-values are determined under the assumption that holds the theorem of Wilks (Wilks, 1932).

The PCI Model Estimation and Empirical Findings

PCI Model is estimated by using the below variables via R program.

$$X_t = \begin{vmatrix} 1\,0 \cdots 0\ 0\ 0 \\ 0\,1 \cdots 0\ 0\ 0 \\ \vdots\ \vdots\ \ddots\ \vdots\ \vdots\ \vdots \\ 0\,0 \cdots 1\ 0\ 0 \\ 0\,0 \cdots 0\ \rho\ 0 \\ 0\,0 \cdots 0\ 0\ 1 \end{vmatrix} \begin{vmatrix} X_{1,t-1} \\ X_{2,t-1} \\ \vdots \\ X_{k,t-1} \\ M_t \\ R_t \end{vmatrix} + \begin{vmatrix} \varepsilon_{X_{1,t-1}} \\ \varepsilon_{X_{2,t-2}} \\ \vdots \\ \varepsilon_{k,t-1} \\ \varepsilon_{M,t} \\ \varepsilon_{R,t} \end{vmatrix} \quad (5)$$

Fitted values for PCI model by applying R codes:

Y[t] = X[t] (6)

M[t] = rho * M[t-1] + eps_M [t], eps_M[t] ~ N(0, sigma_M^2) (7)

R[t] = R[t-1] + eps_R [t], eps_R[t] ~ N(0, sigma_R^2) (8)

Y is the variable being modeled; $\boldsymbol{X_1, X_2, ..., X_N}$ indicates the independent variables; ***Z*** is the residual series of ***Y- beta***; ***M*** is the estimated state of mean reverting component; ***R*** is the estimated state of random walk component; ***eps_M*** is the innovation of the mean reverting component and ***eps_R*** is the innovation of the random walk component. In addition, **Rho** corresponds to a half-life of mean reversion.

Table 3: The Hypothesis Test Results

Hypothesis	Statistic	p-value
Random Walk	-2.82	0.060
AR(1)	-7.18	0.000

The two p-values of 0.060 and 0.000 indicate that LKUR and LCDS are partially cointegrated as shown in Table 3.

Table 4: PCI Model Parameter Estimation Results

Parameters	Estimate	Std. Err
beta_	18.6804	6.0202
rho	0.9963	0.0032
sigma_M	4.3915	0.1996
sigma_R	0.6460	1.1559

The PCI Model: LL = 4663.55, R^2[MR] = **0.979**

The positive and significant beta (18.68) means that there is a strong positive relationship between USD exchange rates (LKUR) and Turkey's CDS (LCDS). 97,9% of the variance in return series is explained by the mean reverting component of residual series within this strong relationship. In other words, random walk component of return series is very weak, i.e. 2,1%. Hence, LKUR has a dependency on LCDS and this relationship is said to be a partial co-integration characteristics for the last five years (2013-2018) in Turkey. This means that the shocks in the Turkish financial markets represented by the two variables emerge from the same source.

CONCLUDING REMARKS

It is noted that OTC markets and more specifically, CDS contracts within the OTC markets have been a locomotive of financial innovation and maintain as cost cutting and customized hedging instruments all over the world. Since GFC, the CDS contracts have been widely traded and CDS spreads are considered a proxy for riskiness and default likelihood of an entity. CDS markets also reflect risk perceptions about the financial health of countries by providing signals for financial stability. In addition, they are treated as the most liquid instruments in financial markets since they represent around the half of the credit derivatives.

Taking into consideration the high frequency nature of the data in financial markets, it is necessary to use partial integration methods instead of traditional co-integration techniques as the frequency of the studied time series increases. This is due to the fact that PCI modeling approach provides useful information for creating an efficient hedge portfolio.

Based on the empirical findings of PCI Model for Turkey, the USD exchange rate volatility in Turkey can be considered an important risk indicator of economy. When there is an increase in the USD exchange rate volatility, the borrowing costs will also increase in Turkey. Hence the USD exchange rates could be particularly effective on the demand for Turkey's foreign debt instruments. In this respect, it will provide information about the maturities of the positions taken for the estimated exchange rates of a yield curve based on CDS. It will be useful to conduct new research on this topic to analyze the current situation of yield curves. In addition, considering the relationship between CDS spreads and interest rates, it can be said that interest rates will be the most effective tool in terms of international financial transmission mechanism against exchange rate volatility.

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