Effects Of Volatility Shocks On The Dynamic Linkages Between Exchange Rate, Interest Rate And The Stock Market: The Case Of Turkey

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Abstract

This study analyzes the dynamic relationship between exchange rate (against US dollar), interest rate and the stock market (both in local currency) of Turkey from January 2003 to September 2013. In particular, the paper tries to answer if the correlations between these important variables change abruptly in high volatile periods and if they do, is this change temporary or permanent? In that manner, we first estimate the dynamic correlations between these variables using VAR(\textit{p})-FIAPARCH(1,\textit{d},1)-cDCC(1,1) approach. Then, we endogenously detect the volatility shift dates by a novel method of penalized contrast function. The relation between the dynamic correlations and the high volatile periods is then investigated by two different approaches. Results reveal that volatility shocks create abrupt changes in the dynamic correlations, however this effect is only short term and do not sustain between consecutive high volatility regimes. Thus, policymakers and investors do not need to worry about long run contagion effects.

\textsuperscript{*}The views expressed in this work are those of the authors and do not necessarily reflect those of the Borsa Istanbul or their members.

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JEL: C51, C61, E44, E58, F31, G01
1. Introduction

For many investors and policymakers, it is crucial to understand the dependencies between the three major financial markets, namely; foreign exchange (fx), bond and stock markets. Considering investors, the correlation structure between these markets can be used to construct portfolio strategies. For the policymakers, it is important to analyze the transmission channel between these markets to adopt proper policies and forecast the full impact of their decisions. Moreover, the importance of this analysis is enhanced considering the fact that correlations are time-varying.

There has been a lot of studies on the dynamics of these markets in the literature and the theoretical background on the subject is solid. Regarding the relation between stock and bond markets, usually a negative correlation is observed (Shiller and Beltratti, 1992). The background behind this phenomena is explained by the discount factor in stock pricing i.e. an increase in the interest rates lowers the present values of the equities. However, recent literature presents counter evidence in special circumstances. For example, according to Andersen et al. (2007) and Baele (2010), such a negative relation holds only during the contraction periods in business cycle. The authors state that positive relation can occur due to the cash flow effect i.e. increases in the interest rates could be results of higher growth and hence, greater profits for companies during an expansion in the business cycle. Similar results come from Rigobon and Sack (2003). According to authors, the correlation may change signs depending on the direction of the information flow between these two markets.

The connection between the fx and bond markets can also be explained by theoretical background. For example, exchange rates and interest rates are connected by the uncovered interest rate parity (UIP): Risk-neutral investors will be indifferent among the available interest rates in two countries since the
exchange rate between these two countries is expected to adjust resulting with an elimination of a potential interest rate arbitrage. According to Lothian and Wu (2011), there are small deviations from UIP in the short run, however the theory holds much better on the long run.

The dependency between fx and stock markets is also well studied. Indeed, the theory is categorized into three main models to explain this dependency. According to flow-oriented approach, changes in the exchange rate lead to changes in stock prices: Exchange rate movements affect international economic activities, thereby influencing real economic variables, hence affecting costs of a company with considerable exports/imports resulting with an impact on the company’s stock price. Stock-oriented approach states that causation is from stock prices to exchange rate by inflows and outflows of foreign capital: Foreign investors are attracted by a persistent increase (decrease) in stock prices leading to capital inflows (outflows) resulting in an appreciation (depreciation) of the local currency. Finally, asset-market approach implies a weak/none relationship between stock prices and exchange rate. Accordingly, the exchange rate is treated like an asset; it’s value is determined by the expected future exchange rates and information that affects future value of exchange rate may differ from the ones that cause changes in stock prices.\(^1\) Besides these approaches, stock markets can also influence exchange rates through the wealth effect. Accordingly, increases in equity values will increase the impact on the money demand for a nation’s currency by an increase in the aggregate wealth of its citizens. Empirical studies (Roll, 1992; Chow et al., 1997) usually find a positive relation between dollar appreciation against local currencies and stock returns (of that local markets). However, as in the case of the relationship between bond and

\(^1\)See Phylaktis and Ravazzolo (2005) for further discussion.
stock market, some studies (Soenen and Henninger, 1988) argue that the sign of this relationship may be depend on time and be negative in special cases.

Considering the complex relationship explained above, the analysis of the dynamic interaction between these three markets is not easy but crucial, not only for investment and risk management issues, but also for the economic and financial stability.

As it can be anticipated, in this study, we aim to understand the dynamic relationship between three main indicators of economic and financial performance of a country, namely exchange rate, interest rate and the benchmark stock market index. In particular, we will analyze the dynamics of the volatility shift contagion effect which is defined as a significant change in the co-movement of asset returns between consecutive volatility regimes (Forbes and Rigobon, 2002). In this case, detecting volatility shift contagion is of extreme importance. If such a contagion effect does not exist, then there is no need for pro-active portfolio adjustment in high volatile periods and the possibility of risk diversification among these assets may increase. Similarly, policymakers do not require to react actively to prevent the contagion. On the other hand, if there exists a contagion effect, knowing its existence is crucial for hedging purposes and financial stability as policymakers should understand how volatility is transmitted across these variables in order to formulate appropriate policies to avoid the likely contagion. As we have experienced in the last decade, such policies may be crucial in limiting the impact of global crises.

In this study, we will focus on a leading emerging market, Turkey. Since 1993 to 2001, political and economical instability went hand in hand in Turkey. High inflation and budget deficits were two main problems causing the severe recessions of 1994, 1999 and 2001. Recessions forced the government to make major policy reforms. In 2002, exchange rate was allowed to float and inflation
targeting was adopted. The result was a decade of high and broadly stable economic growth. Moreover, in recent years, Turkey has become one of the most important emerging economies in the world and plays a significant role in global trade and finance. Due to these progresses, we will focus on the last decade in our analysis.

The structure of our analysis will be as follows: We first estimate a VAR model for these variables and detect sudden and gradual changes in the volatility of the VAR return-residual series using a penalized contrast function method of Lavielle (2005) that previously applied on different financial time series by Lavielle and Teyssiere (2007). Since we endogenously detect the shift points, periods of relatively high and low volatility are defined regardless of whether a financial crisis is the true cause. In the next step, we estimate a consistent dynamic conditional correlation (cDCC) model of Aielli (2013) to evaluate co-movements between the return series. Finally, we will analyze if the volatility shifts create significant changes in the dynamic correlations using dummy regression analysis and alternatively, Markov switching regression analysis.

The study contributes to the literature in two ways. First, this is the first study that investigates the volatility shock effects on the dynamics of the fx, bond and stock markets in Turkey. Second, the results have important implications considering policymakers and investors. In particular, we show that volatility shift contagion exists between exchange rate, interest rate and the stock market, however the contagion effect is temporary and fades away in a short time interval. Thus, policymakers should not necessarily react to prevent the contagion effect during high volatile periods, if this is what desired. Similarly, investors that cross hedge using these assets need not to worry as the abruptly changed correlations during high volatile regimes are expected to achieve their regular levels shortly.
2. Data and methodology

The data used in our study covers a period from January 2, 2003 to September 5, 2013 and comes from two different sources. We obtain the daily exchange rates (against US dollar) and interest rates (in local currency) from the Central Bank of the Republic of Turkey and daily BIST100 index values (in local currency) are obtained from Borsa Istanbul database. The interest rates are the annualized compound yield of the highest liquid government bond on a given day.

We will analyze the dynamic relationship between the changes in these three variables. For the interest rate, the daily changes will be taken as the first differences i.e.

\[ r_{IR,t} = \Delta IR_t = IR_t - IR_{t-1} \]

For the exchange rate and stock market, instead of the log-returns we take the actual returns i.e.

\[ r_{USDTRY,t} = (USDTRY_t - USDTRY_{t-1})/USDTRY_{t-1}, \]
\[ r_{BIST100,t} = (BIST100_t - BIST100_{t-1})/BIST100_{t-1}, \]

To capture the joint dynamics, we first estimate an unrestricted VAR model

\[ r_t = \varphi_0 + \Phi_1 r_{t-1} + ... + \Phi_p r_{t-p} + \varepsilon_t \quad (1) \]

where \( r_t = [r_{1,t}, ..., r_{n,t}]' \) is the vector of \( n \) asset returns, \( p \) is the order of VAR, \( \varphi_0 \) is a vector of constants with length \( n \), \( \Phi \) are coefficient matrices and \( \varepsilon_t = [\varepsilon_{1,t}, ..., \varepsilon_{n,t}]' \) is the vector of VAR residuals.\(^2\)

In the next step, we obtain the conditional volatilities \( h_{i,t} \) from univariate

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\(^2\)We let \( p \) vary from 1 to 10. The optimal length is 6 according to Akaike Information Criterion.
FIAPARCH\((1,d,1)\) model of Tse (1998) for an extended flexibility. In particular, we estimate the following

\[
h_{i,t}^{\delta/2} = \omega + \{1 - [1 - \beta L]^{-1}(1 - \phi L)(1 - L)^d\}(|\varepsilon_{i,t}| - \gamma \varepsilon_{i,t})^\delta \tag{2}
\]

where \(\omega \in (0, \infty)\), \(|\beta|\) and \(|\phi| < 1\), \(0 \leq d \leq 1\), \(\gamma\) is the leverage coefficient and \(\delta\) is the parameter for the power term that takes finite positive values, while \((1 - L)^d\) is the financial differencing operator expressed in terms of a hypergeometric function (see Conrad et al. (2008) for the expression of this function).

2.1. Dynamic conditional correlation

The dynamic correlations between the analyzed variables will be obtained by the cDCC model of Aielli (2013) using VAR residuals. To consider cDCC modeling, we start by reviewing the DCC model of Engle (2002). Assume that \(E_{t-1}[\varepsilon_t] = 0\) and \(E_{t-1}[\varepsilon_t \varepsilon_t'] = H_t\), where \(E_t[\cdot]\) is the conditional expectation on \(\varepsilon_t, \varepsilon_{t-1}, \ldots\). The asset conditional covariance matrix \(H_t\) can be written as

\[
H_t = D_t^{1/2} R_t D_t^{1/2} \tag{3}
\]

where \(R_t = [\rho_{ij,t}]\) is the asset conditional correlation matrix and the diagonal matrix of the asset conditional variances is given by \(D_t = diag(h_{1,t}, \ldots, h_{n,t})\). Engle (2002) models the right hand side of Eq.(3) rather than \(H_t\) directly and proposes the dynamic correlation structure

\[
R_t = \{Q_t^\ast\}^{-1/2} Q_t \{Q_t^\ast\}^{-1/2},
\]

\[
Q_t = (1 - a - b) S + au_{t-1} u_{t-1}' + b Q_{t-1}, \tag{4}
\]

where \(Q_t \equiv [q_{ij,t}], u_t = [u_{1,t}, \ldots, u_{n,t}]'\) and \(u_{i,t}\) is the transformed residuals i.e. \(u_{i,t} = \varepsilon_{i,t}/h_{i,t}\), \(S \equiv [s_{ij}] = E[u_t u_t']\) is the \(n \times n\) unconditional covariance matrix of \(u_t\), \(Q_t^\ast = diag\{Q_t\}\) and \(a, b\) are non-negative scalars satisfying \(a + b < 1\). The resulting model is called DCC.
However, Aielli (2013) shows that the estimation of $Q$ by this way is inconsistent since $E[R_t] \neq E[Q_t]$ and he proposes the following consistent model with the correlation driving process

$$Q_t = (1 - a - b)S + a\{Q_{t-1}^{*1/2}u_{t-1}u'_{t-1}Q_{t-1}^{*1/2}\} + bQ_{t-1}$$  \hspace{1cm} (5)

where $S$ is the unconditional covariance matrix of $Q_{t}^{*1/2}u_t$.

### 2.2. Detection of the volatility shifts

We will use the change point detection method of Lavielle (2005) to find the volatility shift points in the VAR return-residuals.\(^3\) The methodology can be summarized as follows: We consider a sequence of random variables $Y_1, ..., Y_n$ that take values in $\mathbb{R}^p$. Assume that $\theta \in \Theta$ is a parameter denoting the characteristics of the $Y_i$’s that changes abruptly and remains constant between two changes. The change occur at some instants $\tau_1^* < \tau_2^* < ... < \tau_{K^* - 1}$. Here $K^* - 1$ is the number of change points hence we have $K^*$ number of segments.\(^4\)

Now, let $K$ be some integer and let $\tau = (\tau_1, \tau_2, ..., \tau_{K-1})$ be a sequence of integers satisfying $0 < \tau_1 < \tau_2 < ... < \tau_{K-1} < n$. For any $1 \leq k \leq K$, let $U(Y_{\tau_{k-1}+1}, ..., Y_{\tau_k}; \theta)$ be a contrast function useful for estimating the unknown true value of the parameter in the segment $k$; i.e. the minimum contrast estimate $\hat{\theta}(Y_{\tau_{k-1}+1}, ..., Y_{\tau_k})$, computed on segment $k$ of $\tau$, is defined as a solution of the following minimization problem:

$$U(Y_{\tau_{k-1}+1}, ..., Y_{\tau_k}; \hat{\theta}(Y_{\tau_{k-1}+1}, ..., Y_{\tau_k})) \leq U(Y_{\tau_{k-1}+1}, ..., Y_{\tau_k}; \theta), \ \forall \theta \in \Theta, \ \ (6)$$

---

\(^3\)To prevent misunderstandings, the reader is asked to consider the mathematical notations in Section 2.2 and 2.2.1 independent from the other parts of this manuscript.

\(^4\)\(\ast\) is used to denote the true value.
For any $1 \leq k \leq K$, let $G$ be

$$G(Y_{\tau_k-1+1}, ..., Y_{\tau_k}) = U(Y_{\tau_k-1+1}, ..., Y_{\tau_k}; \hat{\theta}(Y_{\tau_k-1+1}, ..., Y_{\tau_k}))$$  \hspace{1cm} (7)$$

Then define the contrast function $J(\tau, y)$ as

$$J(\tau, y) = \frac{1}{n} \sum_{k=1}^{K} G(Y_{\tau_k-1+1}, ..., Y_{\tau_k})$$  \hspace{1cm} (8)$$

where $\tau_0 = 0$ and $\tau_k = n$. When true number $K^*$ segments is known, for any $1 \leq k \leq K^*$, the sequence $\hat{\tau}_n$ of change point instants that minimizes this kind of contrast has the property that

$$\Pr(|\hat{\tau}_{n,k} - \tau_k^*| > \delta) \to 0, \text{ when } \delta \to \infty \text{ and } n \to \infty$$  \hspace{1cm} (9)$$

In particular, this result holds for weak or strong dependent processes.

We consider the following model

$$Y_i = \mu_i + \sigma_i \varepsilon_i, \hspace{0.5cm} 1 \leq i \leq n$$  \hspace{1cm} (10)$$

where $(\varepsilon_i)$ is a sequence zero-mean random variables with unit variance.

To detect the changes in the volatility, we take $(\mu_i)$ is a constant sequence and $(\sigma_i)$ is a piecewise constant sequence. Even if $(\varepsilon_i)$ is not normally distributed, a Gaussian log-likelihood can be used to define the contrast function. Let $\mu = \mu_1 = ... = \mu_{\tau_k}$, and

$$U(Y_{\tau_k-1+1}, ..., Y_{\tau_k}; \sigma^2) = (\tau_k - \tau_{k-1}) \log(\hat{\sigma}^2) + \frac{1}{\hat{\sigma}^2} \sum_{i=\tau_k-1+1}^{\tau_k} (Y_i - \mu)^2$$  \hspace{1cm} (11)$$

Then,

$$G(Y_{\tau_k-1+1}, ..., Y_{\tau_k}) = (\tau_k - \tau_{k-1}) \log(\hat{\sigma}^2_{\tau_k-1+1: \tau_k})$$  \hspace{1cm} (12)$$
where

$$\sigma^2_{\tau_{k-1}+1:\tau_k} = \frac{1}{\tau_k - \tau_{k-1}} \sum_{i=\tau_{k-1}+1}^{\tau_k} (Y_i - \bar{Y})^2$$

(13)

is the empirical variance of \((Y_{\tau_{k-1}+1}, ..., Y_{\tau_k})\) and \(\bar{Y}\) is the empirical mean of \(Y_1, ..., Y_n\).

### 2.2.1. Finding the Number of Shift Points

When the number of shift points is unknown, it is estimated by minimizing a penalized version of \(J(\tau, y)\). For any sequence of change point instants \(\tau\), let \(pen(\tau)\) be a function of \(\tau\) that increases with the number \(K(\tau)\) of segments of \(\tau\). Then, let \(\hat{\tau}_n\) be the sequence of change point instants that minimizes

$$F(\tau) = J(\tau, y) + \varphi pen(\tau)$$

(14)

where \(\varphi\) is a function of \(n\) that goes to zero at an appropriate rate as \(n\) goes to infinity. The estimated number of segments \(K(\hat{\tau}_n)\) converges in probability to \(K^*\). The proper \(pen(\tau)\) and the penalization parameter \(\varphi\) are chosen according to Lavielle (2005).

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5For further details, refer to Lavielle (2005) and Lavielle and Teyssiere (2007).
3. Empirical results

Table 1 presents the statistical properties of the returns as well as the unit root test results. We can see that stock market has the highest daily average return over the study period, followed by the exchange rate. However, the average daily return of the stock market is much more higher compared to the exchange rate's return. On the other hand, The changes in the interest rate exhibit negative returns (-0.02%) on a daily basis, thus confirming the successful reforms by the monetary and fiscal policy of Turkey in the last decade to decrease the interest rates.

The unconditional volatility of stock market, measured by standard deviations, is larger than twice the volatility of the exchange rate and four times that of the interest rate. Return distributions are skewed to the left for the interest rate and the stock market and skewed to the right for the exchange rate. Also, all market returns exhibit excess kurtosis (fat tails). Skewness and kurtosis coefficients indicate that return series are far from normally distributed. This departure from normality is formally confirmed by the Jarque-Bera test statistics that rejects normality at the 1% level for all series.6

The Table 1 also presents the results of the conventional stationarity test for our return series (unit root tests contain a constant). Augmented Dickey-Fuller (ADF) test rejects the null hypothesis of unit root for all the return series at the 1% significance level. All the return series are therefore stationary.

6In the tables throughout this paper, *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.
Table 1: Descriptive statistics of the raw returns from 02/01/2003 to 05/09/2013

<table>
<thead>
<tr>
<th></th>
<th>USDTRY</th>
<th>IR</th>
<th>BIST100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>-0.0553</td>
<td>-0.0761</td>
<td>-0.1249</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0001</td>
<td>-0.0002</td>
<td>0.0009</td>
</tr>
<tr>
<td>Max</td>
<td>0.0674</td>
<td>0.0594</td>
<td>0.1289</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.0090</td>
<td>0.0047</td>
<td>0.0188</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.8296</td>
<td>-0.1435</td>
<td>-0.1482</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>7.4293</td>
<td>71.072</td>
<td>4.4507</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>6494.9***</td>
<td>566170***</td>
<td>2230.1***</td>
</tr>
<tr>
<td>ADF</td>
<td>-30.30***</td>
<td>-31.02***</td>
<td>-29.46***</td>
</tr>
<tr>
<td>Observations</td>
<td>2690</td>
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</tbody>
</table>

Fig. 1 displays daily exchange rate, interest rate and the stock market, while Fig. 2 plots the return residuals of the VAR model fitted to the daily changes in these time series and also displays the volatility shifts in them. Volatility clustering is apparent for all the time series, i.e., large (small) changes tend to be followed by large (small) changes over consecutive days. This characteristic reveals the presence of conditional heteroskedasticity in the variance process of the return series, and thus justifies the use of GARCH specifications to adequately model the return volatility of the financial time series.
Figure 1: Daily values of the USDTRY, interest rate and BIST100 index from January 2003 to September 2013.
Table 2: Parameter estimates for VAR(6), FIAPARCH(1,d,1) and cDCC(1,1) process

<table>
<thead>
<tr>
<th></th>
<th>USDTRY&lt;sub&gt;t&lt;/sub&gt;</th>
<th>IR&lt;sub&gt;t&lt;/sub&gt;</th>
<th>BIST100&lt;sub&gt;t&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coefficient</td>
<td>p-value</td>
<td>coefficient</td>
</tr>
<tr>
<td>USDTRY&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.0020</td>
<td>0.964</td>
<td>0.0983***</td>
</tr>
<tr>
<td>USDTRY&lt;sub&gt;t-2&lt;/sub&gt;</td>
<td>0.0859**</td>
<td>0.017</td>
<td>0.0107</td>
</tr>
<tr>
<td>USDTRY&lt;sub&gt;t-3&lt;/sub&gt;</td>
<td>-0.0490</td>
<td>0.201</td>
<td>-0.0026</td>
</tr>
<tr>
<td>USDTRY&lt;sub&gt;t-4&lt;/sub&gt;</td>
<td>0.0723*</td>
<td>0.086</td>
<td>0.0268*</td>
</tr>
<tr>
<td>USDTRY&lt;sub&gt;t-5&lt;/sub&gt;</td>
<td>-0.0159</td>
<td>0.685</td>
<td>-0.0012</td>
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<tr>
<td>USDTRY&lt;sub&gt;t-6&lt;/sub&gt;</td>
<td>-0.0120</td>
<td>0.737</td>
<td>0.0065</td>
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<tr>
<td>IR&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>-0.0894</td>
<td>0.242</td>
<td>-0.0863</td>
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<tr>
<td>IR&lt;sub&gt;t-2&lt;/sub&gt;</td>
<td>-0.0759</td>
<td>0.230</td>
<td>-0.0980</td>
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<tr>
<td>IR&lt;sub&gt;t-3&lt;/sub&gt;</td>
<td>0.0240</td>
<td>0.646</td>
<td>0.0027</td>
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<td>IR&lt;sub&gt;t-4&lt;/sub&gt;</td>
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<td>0.288</td>
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<tr>
<td>IR&lt;sub&gt;t-5&lt;/sub&gt;</td>
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<td>0.483</td>
<td>-0.0422</td>
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<tr>
<td>IR&lt;sub&gt;t-6&lt;/sub&gt;</td>
<td>0.0530</td>
<td>0.345</td>
<td>0.0801</td>
</tr>
<tr>
<td>BIST100&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.0133</td>
<td>0.350</td>
<td>-0.0176***</td>
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<tr>
<td>BIST100&lt;sub&gt;t-2&lt;/sub&gt;</td>
<td>0.0024</td>
<td>0.878</td>
<td>-0.0105</td>
</tr>
<tr>
<td>BIST100&lt;sub&gt;t-3&lt;/sub&gt;</td>
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<td>0.625</td>
<td>-0.0073</td>
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<tr>
<td>BIST100&lt;sub&gt;t-4&lt;/sub&gt;</td>
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<td>0.422</td>
<td>0.0059</td>
</tr>
<tr>
<td>BIST100&lt;sub&gt;t-5&lt;/sub&gt;</td>
<td>0.0102</td>
<td>0.493</td>
<td>-0.0107</td>
</tr>
<tr>
<td>BIST100&lt;sub&gt;t-6&lt;/sub&gt;</td>
<td>0.0265**</td>
<td>0.045</td>
<td>-0.0045</td>
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<tr>
<td>constant</td>
<td>0.0000</td>
<td>0.817</td>
<td>-0.0002*</td>
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<table>
<thead>
<tr>
<th></th>
<th>USDTRY</th>
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</thead>
<tbody>
<tr>
<td>coefficient</td>
<td>0.0134***</td>
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</tr>
<tr>
<td>p-value</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

1. FIAPARCH: \( h_{i,t}^{1/2} = \omega + \{ 1 - [1 - \beta L]^{-1}(1 - \phi L)(1 - L) \}^d (|\varepsilon_{i,t}^e| - \gamma \varepsilon_{i,t}^e)^\delta. \)
2. The values in the parenthesis are p-values obtained from robust standard errors.

\[ \begin{align*}
\omega \times 10^6 & = 21.2*** (0.000) \\
\phi & = 0.441*** (0.000) \\
\beta & = 0.318*** (0.000) \\
\gamma & = 0.591*** (0.000) \\
\delta & = -0.366*** (0.000)
\end{align*} \]

\[ \begin{align*}
IR & = 68.2*** (0.000) \\
\rho & = 0.731*** (0.000) \\

BIST100 & = 0.018 (0.389) \\
\phi & = 0.424*** (0.000) \\
\beta & = 0.140* (0.094) \\
\gamma & = 0.459*** (0.000) \\
\delta & = 0.368*** (0.001)
\end{align*} \]

1. The values in the parenthesis are p-values obtained from robust standard errors.

The VAR coefficients in Table 2 show the strong explanatory power of the...
The estimation results for FIAPARCH model, presented in Table 2, show that the estimates of long memory parameters differ significantly from zero and unity. The tail parameter of the FIAPARCH model is also statistically significant, which confirms the existence of the leptokurtic behavior of return series. It is interesting to note that all the return series display strong evidence of volatility asymmetry as the parameter (γ) is statistically significant at least at the 5% level. The coefficient of asymmetric reaction of volatility to unexpected news (γ) is positive for the stock market and negative for the fx and bond market. Accordingly, conditional volatility is more affected by negative shocks than positive shocks for the stock market and vice versa for the fx and bond market.\(^7\)

Estimated values of the fractional differencing parameter \(d\) for the exchange rate, interest rate and stock market are 0.441, 0.731 and 0.424 respectively and are highly significant, indicating a high degree of persistence behavior. The differencing parameter is relatively higher for the interest rate compared to other two time series, indicating that persistence is even more amplified for the bond market. In overall, these findings suggest that shocks to FIAPARCH conditional volatility decays at a slow hyperbolic rate rather than an exponential rate.

\(^7\)Reader has to keep in mind that positive shocks for fx and bond market refer to negative sentiment in these markets.
Figure 2: Volatility shifts in the VAR residuals. Red and blue solid lines indicate an upwards and downwards shift respectively.
It is easy to interpret the endogenously detected upwards volatility shift dates given in Table 3. For example, the end of February 2003 is associated with the Iraq crisis, and in one month after this date the invasion of Iraq occurs. September 2008 and August 2011 refer to the important dates of the global financial crisis (collapse of the Lehman Brothers) and the eurozone sovereign debt crisis (heightened concerns about Greece’s default). Similarly, May 2013 is associated with the Fed’s tapering signals about the quantitative easing operations. This picture shows the vulnerability of the Turkish money and capital markets to the global shocks which is a common property among many emerging markets.

Table 3: Volatility level shift dates

<table>
<thead>
<tr>
<th>Date</th>
<th>Volatility</th>
<th>Date</th>
<th>Volatility</th>
<th>Date</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>27/02/2003</td>
<td>Up</td>
<td>27/02/2003</td>
<td>Up</td>
<td>27/02/2003</td>
<td>Up</td>
</tr>
<tr>
<td>25/03/2003</td>
<td>Down</td>
<td>28/03/2003</td>
<td>Down</td>
<td>15/04/2003</td>
<td>Down</td>
</tr>
<tr>
<td>02/09/2005</td>
<td>Down</td>
<td>10/10/2003</td>
<td>Down</td>
<td>05/09/2008</td>
<td>Up</td>
</tr>
<tr>
<td>04/05/2006</td>
<td>Up</td>
<td>04/05/2004</td>
<td>Up</td>
<td>14/01/2009</td>
<td>Down</td>
</tr>
<tr>
<td>07/07/2006</td>
<td>Down</td>
<td>26/05/2004</td>
<td>Down</td>
<td>03/02/2012</td>
<td>Down</td>
</tr>
<tr>
<td>19/07/2007</td>
<td>Up</td>
<td>06/06/2005</td>
<td>Down</td>
<td>27/05/2013</td>
<td>Up</td>
</tr>
<tr>
<td>22/08/2007</td>
<td>Down</td>
<td>12/05/2006</td>
<td>Up</td>
<td></td>
<td></td>
</tr>
<tr>
<td>26/09/2008</td>
<td>Up</td>
<td>31/10/2006</td>
<td>Down</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15/12/2008</td>
<td>Down</td>
<td>05/09/2008</td>
<td>Up</td>
<td></td>
<td></td>
</tr>
<tr>
<td>23/06/2009</td>
<td>Down</td>
<td>27/01/2009</td>
<td>Down</td>
<td></td>
<td></td>
</tr>
<tr>
<td>06/08/2012</td>
<td>Down</td>
<td>11/01/2010</td>
<td>Down</td>
<td></td>
<td></td>
</tr>
<tr>
<td>27/05/2013</td>
<td>Up</td>
<td>03/08/2011</td>
<td>Up</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>26/01/2012</td>
<td>Down</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>14/05/2013</td>
<td>Up</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Before commenting on the dynamic correlations and their relation to volatility shifts, we have to point out the major limitations and drawbacks of existing empirical literature on financial contagion which we will overcome in our study by the cDCC approach (Chiang et al., 2007):

First, since contagion is defined as significant increase in cross correlations (Forbes and Rigobon, 2002), it requires a time-varying observable correlation
level so that we can reveal if there is a dynamic increment or not. This problem is directly solved by cDCC modeling as it allows us to detect dynamic responses in correlations to news and innovations.

Second, there is a heteroskedasticity problem when measuring correlations, caused by volatility increases during the crisis. This is not a problem in our study since cDCC model estimates correlation coefficients of the standardized residuals and thus accounts for heteroskedasticity directly.
Figure 3: Dynamic conditional correlations between exchange rates, interest rates and stock market return-residuals obtained from VAR estimation. Red dashed lines correspond to the dates of the upwards volatility shifts in the relevant VAR residuals.
Table 4: Descriptive statistics of the dynamic conditional correlations

<table>
<thead>
<tr>
<th></th>
<th>USDTRY – IR</th>
<th>USDTRY – BIST100</th>
<th>IR – BIST100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>0.0169</td>
<td>-0.7003</td>
<td>-0.5774</td>
</tr>
<tr>
<td>Mean</td>
<td>0.2499</td>
<td>-0.5005</td>
<td>-0.2886</td>
</tr>
<tr>
<td>Max</td>
<td>0.5519</td>
<td>-0.3319</td>
<td>-0.0014</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.0719</td>
<td>0.0590</td>
<td>0.0767</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.5218</td>
<td>-0.3764</td>
<td>-0.2162</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>1.0838</td>
<td>0.4744</td>
<td>0.8489</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>252.5***</td>
<td>88.3***</td>
<td>101.2***</td>
</tr>
<tr>
<td>ADF</td>
<td>-4.94***</td>
<td>-4.69***</td>
<td>-4.59***</td>
</tr>
</tbody>
</table>

According to the Fig. 3, the dynamic correlations between bond and stock markets are always negative which validates the approach of discounting the expected dividends in calculating stock prices. Looking at Table 4, we see that the strongest dependency is between exchange rate and the stock market as the mean level of the dynamic correlation between these two markets is almost twice of the others. An interesting observation is the positive correlations between interest rates and the exchange rates and it points out a common phenomena that is observed in many emerging markets: In contrast to the theory where it states that an increase in the interest rates would attract capital to the country thus lowers the exchange rates, we see that exchange rates and interest rates tend to increase at the same time. The reason lies behind the fact that in many emerging markets with infamous history of budget deficits, the expectations channel play an important role in investment. If the interest rates increase for any reason, it is generally perceived as an upcoming problem in the country thus the hot money tend to leave in a very short time interval. Moreover, this reasoning works in both directions and eventually creates a feedback.

In Fig. 3, the red dashed lines are a combination of the upwards volatility shift dates of the relevant variables (for example in Fig. 3, the red dashed lines in the first sub-figure stand for the union of the upwards volatility shifts of USDTRY and interest rate return-residuals).
A careful reader looking at Fig. 3 can easily observe that on the days (or just within a few days) when volatility shifts upwards, the bivariate correlations experience abrupt changes. However, even for the same couple of variables, upwards volatility shifts may be related to different directions in the change of correlations (for example, consider the first two red dashed lines in the first sub-figure of Fig. 3. While the first volatility shock is associated with an upwards jump in the correlation, the second shock is associated with a severe decrease).

Although the abrupt changes in these correlations may first be anticipated as a contagion effect, a rough look at Fig. 3 shows that these changes quickly disappears after they occur. To formally see if this is the case here, we estimate the following equation

$$
\rho_{ij,t} = \nu_0 + \nu_1 \rho_{ij,t-1} + \sum_{k \in \text{upwards volatility shifts of } i \text{ or } j} \nu_k D_k + \eta_{ij,t}
$$

(15)

In Eq.(15), the first lag of the dynamic correlation is put in the model to get rid of the serial correlation effect. The dummy $D_k$ is a variable taking the value 1 between two consecutive upward volatility shifts (i.e. between consecutive red dashed lines in Fig. 3) of the relevant variables and zero elsewhere.\(^8\) In some of the cases, the upwards volatility shift dates of the two variables are too close such as the second upwards volatility shift date of USDTRY i.e. 04/05/2006 and the third upwards volatility shift date of the interest rate i.e. 12/05/2006. In such close cases, we take only the earlier shift date to construct the dummy variable $D_k$ to be used in the estimation of Eq.(15).

The estimation results are given in the Table 5 and they justify our intuition

\(^8\)Due to stationarity of all bivariate dynamic correlations (see ADF results in Table 4), we do not include a trend component in Eq.(15).
that the abrupt changes in the correlations are temporary. Specifically, for each
dynamic correlation series, statistically insignificant dummy coefficients in the
Eq.(15) indicate that the correlation during a specific period after a volatility
shock is not statistically different from that of the previous phase.

Table 5: Impacts of the upwards volatility shifts on bivariate correlations

<table>
<thead>
<tr>
<th>Date</th>
<th>Coefficient (p-value)</th>
<th>Date</th>
<th>Coefficient (p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>27/02/2003</td>
<td>0.0022 (0.1432)</td>
<td>27/02/2003</td>
<td>0.0003 (0.7203)</td>
</tr>
<tr>
<td>04/05/2004</td>
<td>-0.0004 (0.7362)</td>
<td>04/05/2006</td>
<td>-0.0010 (0.2464)</td>
</tr>
<tr>
<td>04/05/2006</td>
<td>0.0007 (0.5294)</td>
<td>19/07/2007</td>
<td>-0.0012 (0.2116)</td>
</tr>
<tr>
<td>19/07/2007</td>
<td>0.0017 (0.1423)</td>
<td>05/09/2008</td>
<td>-0.0005 (0.4506)</td>
</tr>
<tr>
<td>05/09/2008</td>
<td>-0.00005 (0.9624)</td>
<td>14/05/2013</td>
<td>-0.0018 (0.2750)</td>
</tr>
<tr>
<td>03/08/2011</td>
<td>-0.0005 (0.6586)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>14/05/2013</td>
<td>-0.0020 (0.2415)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Alternatively, we can observe similar results using a 3-state Markov switching regression, where dynamic correlations are regressed onto only constants that are allowed to switch to 3 different states. These states correspond to low, medium and high level regimes. Although we do not list the estimated parameters here, the visual results are presented in Figure 4 and show that majority of the volatility shifts are associated with a regime switch in the dynamic correlations. However, as concluded before, correlations switch to mid levels in a reasonable time interval.
Figure 4: Dynamic conditional correlations between exchange rates, interest rates and stock market returns presented within a 3-state Markov switching regression scheme.
4. Conclusion

In this study, we analyzed the dynamic linkages between fx, bond and the stock market of a leading emerging market; Turkey; by the help of two novel methodologies. Firstly, we calculated the dynamic conditional correlations between these markets by cDCC modelling of Aielli (2013). The time varying and significantly fluctuating correlations show the appropriateness of the cDCC methodology.

We witnessed a consistent negative correlation between bond and the stock markets which supports the theory of discounting dividends in stock price calculations. However, in contrast to the developed countries, we observed a consistent positive correlation between bond and fx markets. This is an evidence of the negative anticipation of the investors when interest rates increase in emerging markets with history of high budget deficits. Accordingly, an increase in the interest rates is perceived as a possible upcoming problem in the country. This event results with a severe capital outflow thus, creating a pressure favoring local currency depreciation against US dollar. Such a situation shows the importance of the expectations channel on capital in/out-flows to/from emerging countries.

Secondly, we obtained the volatility shifts in these market returns by a penalized contrast function. The nice thing about this methodology is that the shifts are detected endogenously, thus periods of relatively high and low volatility are defined regardless of whether a financial crisis is the true cause.

We revealed that in many cases, the source of the upwards volatility shifts are external, not caused by Turkey’s domestic problems. Such a situation shows that like many emerging countries, Turkey’s money and capital markets are not immune to global politic-economic-financial conditions.

We observed that the volatility shocks create severe changes in the dynamic
correlations between these markets, however an interesting observation is that the direction of these severe changes may be different for the same couple of markets. Thus, the response of the dynamic correlation against a volatility shock may be time dependent. However, the severe changes in the dynamic correlations (caused by volatility shocks) are valid only in the short run. Hence policymakers do not need to react to volatility shocks to prevent a long run contagion between these markets. Similarly, investors with cross hedge positions in these markets can preserve their allocations as the abruptly changed correlations are expected to return their regular levels in the medium-long run.
References


