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Cointegration and Extreme Value Analyses of Bovespa and the Istanbul Stock Exchange*

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Abstract
This paper investigates the long-term financial integration and bivariate extreme dependence between Bovespa and the Istanbul Stock Exchange. While a static cointegration test presents no evidence of long-term cointegration, the introduction of a structural break into the model shows that Bovespa and the ISE were cointegrated following the local crisis in Turkey in 2000. Dynamic cointegration tests and DCC-GARCH analysis also reveal that Bovespa and the ISE reacted strongly not only to systemic crises as expected, but also unexpectedly to local crises in each other. This shows that equity prices in two emerging markets in distant regions of the world can co-move in the absence of significant trade and financial linkages. This suggests that there are underlying processes that affect equity prices other than trade, financial linkages, macroeconomic ties, and FDI as the prior literature suggests. While episodic cointegration is found for Bovespa and the ISE, the extremes of these markets still possess asymptotic independence, suggesting diversification opportunities.

1. Introduction

International diversification suggests that low correlations between international stock markets result in lower risk for a given level of return. Accordingly, low correlations between developed and emerging markets have attracted international investors' attention to emerging market assets. However, recent studies have proven that the correlations are time-varying and accordingly investors need a more accurate measure of international stock market interdependence/co-movement.

In a recent paper, Cuadro-Saez et al. (2009) show that emerging market economies are a systemic driver of global asset prices in crisis as well as in tranquil times. They find that country-specific shocks in emerging market economies result in financial spillovers to mature markets and other emerging markets not only in their own vicinity, but also faraway. This is new, as prior research suggests that contagion most probably occurs between financially related countries in the same region (Hernandez et al., 2001). Bilateral trade is the most significant determinant of stock market correlations, and the stock markets of countries that are in the same region are more correlated than those in different regions (Pretorius, 2002). Thus, bilateral trade linkages between countries affect returns and hence the possibility of a crisis (Forbes, 2000; Forbes and Chinn, 2003). However, Collins and Gavron (2005) show that con-

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tagion can also take place in the absence of strong trade linkages and the most influenced countries are those with weaker economies.

The objective of this paper is twofold: (i) to examine if two economies that have negligible trade linkages can in fact be cointegrated in the long run, (ii) to investigate if they respond not only to systemic crises as expected, but also to local shocks in each other in the absence of strong trade or financial linkages. In this respect, the co-movement of the stock markets of Brazil and Turkey, two important emerging markets with similar economic backgrounds, is examined.

Despite being in different and distant regions of the world, these markets have been showing similar patterns in response to the recent global crisis and their relations with the IMF have had a considerable effect on their macroeconomic fundamentals as well as on their stock markets. Both countries are classified as emerging markets and went through hyperinflationary periods and severe recessions in the early 1990s. These countries then turned to the IMF and were heavily indebted to it. Until very recently both countries were implementing IMF-backed stabilization programs. However, short-term real interest rates have been quite high from 2000 onwards in both countries.

These markets also have similar economic histories. Following the 1998 Russian crisis, first Brazil in January 1999 then Turkey in November 2000 and February 2001 experienced liquidity crises. These crises led to major devaluations, which resulted in the exchange rates being freely floated. Duman and Heise (2009) mention that the central banks of both economies then implemented inflation targeting as their policy regime and announced quantitative deficit targets under IMF-imposed fiscal austerity programs. Kaminsky et al. (2003) mention that the Brazilian and Turkish crises were not as systemic as expected despite influencing neighboring economies. However, Cabalerro and Panageas (2004) mention that Brazil and Turkey are the most susceptible to global factors due to the weaknesses of their economies. In a recent paper, Frank and Hesse (2009) show that Brazil and Turkey were affected similarly by the subprime crisis in the sense that the co-movements of these equity markets increased significantly during the crisis.

Accordingly, the Brazilian stock market has been closely followed by traders in the Istanbul Stock Exchange and is considered to contain information on the direction of global liquidity. In this respect, the Brazilian and Turkish stock markets are observed to be susceptible to developments and crises in each other. Cuadro-Saez et al. (2009) show that the Brazilian stock market reacts to shocks in the Emerging Europe region, including Turkey. Interestingly, however, bilateral trade between Turkey and Brazil is negligible. As of 2009 Brazil's exports to Turkey make up less than 0.7% of its total exports, while imports from Turkey account for less than 0.25% of its total imports. However, following the approach of Ulku (2011) we show that an exclusive linkage exists between Bovespa and ISE returns. Bovespa and the ISE contain approximately 3% incremental information for each other, which cannot be explained by common global factors.[1]

We examine the long-term nature of the relationship between the Bovespa and ISE stock markets using the cointegration approach of Johansen (1991) to investigate whether or not these markets possess a common stochastic trend in the long run.

[1] These results, not reported here for brevity, are available from the authors.

However, Forbes and Rigobon (2002) mention that cointegration tests do not test directly for contagion, and that the long-run relationships between countries may change due to higher trade linkages or capital mobility. Thus, cointegration tests fail to detect contagion that takes place in crisis periods. Accordingly, we also employ dynamic cointegration tests following Gilmore et al. (2008) and cointegration tests with a structural break following Lucey and Voronkova (2008) and Voronkova (2004). Considering short-run relationships, Forbes and Rigobon (2002) point out that conditional correlations may be higher during turmoil periods due to higher volatilities, while average unconditional correlations could be stable. Thus, we also investigate the short-run dynamics using Engle's (2002) DCC-GARCH approach. Finally, we investigate the extreme dependence between the markets throughout the sample period.

Our research contributes to the literature by applying static and dynamic cointegration tests together with extreme value tests to investigate equity co-movements in a time-varying fashion in the long run as well as in turmoil periods.[2] In the period 1996–2009 the static cointegration test does not reveal any evidence of a long-run relationship between the Bovespa and ISE stock exchanges. However, the dynamic cointegration tests reveal periods of cointegration, especially during Turkey's local twin liquidity crisis of 2000–2001. Cointegration tests with an unknown structural break date also confirm the 2001 Turkish crisis as a structural break date.[3]The short-run dynamic relationship between the markets is examined using Engle's (2002) DCC-GARCH approach, which also reveals increasing correlation during the Brazilian crisis of 1999 and the Turkish crisis of 2000 and 2001. The findings strongly confirm our expectations that two emerging markets' equity prices can comove in the absence of significant trade and financial linkages not only in systemic crisis periods, but also during periods of local crisis in each other. Furthermore, the joint occurrence of extreme returns and losses is investigated using bivariate extreme value analysis. The dependence of extreme returns in both the left and right tails have important roles in the decision-making processes of risk managers and international portfolio investors. A positive strong dependence between extreme returns of Bovespa and the ISE in the left tail would imply compounding risk in portfolios that invest in both markets. The findings of the bivariate extreme value analysis show asymptotic independence between these two markets.

The paper is organized as follows. Section 2 gives a literature review, Section 3 presents the econometric methodologies, Section 4 describes the data, Section 5 discusses the empirical results, Section 6 gives the robustness checks, and Section 7 concludes.

[2] Our objective is to show that bilateral trade or financial linkages are not a pre-condition for two economies to share a common stochastic trend in the long run. As we are not investigating the sources of asset co-movements, we do not decompose the correlations or co-movements by principal component analysis or a similar approach.

[3] Our results are robust to estimations made with both the Bovespa/S&P500 and ISE100/S&P500 series and the Bovespa/MSCI Emerging Markets Index (EMI) and ISE100/EMI series to control respectively for global returns and emerging markets performance.

2. Literature Review

2.1 Cointegration Literature

Modern portfolio theory builds upon the correlation between financial assets, where low correlation results in diversification. In the mean-variance framework, correlation is the measure of co-movement in returns. However, correlation is a short-term measure and gives no clue about the long-term behavior between financial markets. In fact, risk-return analyses in the standard mean-variance approach use return data, where long-term trends are lost while price data is differenced.

On the other hand, cointegration, first introduced by Engle and Granger (1987), is a long-term measure of diversification based on price data. If there exists a linear combination of two nonstationary series integrated of order one that is stationary, these series are called cointegrated series. It follows that these two series will not drift apart too much, meaning that even if they deviate from each other in the short term, they will revert to the long-run equilibrium.[4] This fact makes cointegration a very powerful approach for portfolio diversification purposes, especially for the long term. Meanwhile, cointegration does not imply high correlation; two series can be cointegrated and yet have very low correlations. Yet again, two series could be correlated but not cointegrated (Morley and Pentecost, 2000).

Kasa (1992) has pointed out that for investors with long-term investment horizons, low correlations could suggest overestimated gains if equity markets share a common stochastic trend in the long term. The majority of papers analyze the long-term diversification opportunities between and among the developed markets (Bessler and Yang, 2003) and emerging equity markets (Metin and Muradoglu, 2001) as well as the integration and convergence across regions (Phylaktis and Ravazzolo, 2005 for the Pacific Basin region, and Serletis and King, 1997; Masih and Masih, 2004; Verchenko, 2000; Gilmore and McManus, 2002; and Yuce and Simga-Mungan, 2000 for the EU region and the CEE markets). Morana and Beltratti (2008) show that market integration results in higher return correlations and co-movement in volatilities for the developed economies of the US, the UK, Japan, and Germany. They decompose the co-movements in prices, returns, and volatilities into common and idiosyncratic factors by principal component analysis to investigate the sources of changes in co-movements. While they find a positive and robust linkage between correlation and volatilities and evidence of common factors in co-movements, they report that idiosyncratic factors, explained by weak economic fundamentals, may still dominate the co-movements.

Metin and Muradoglu (2001) investigate the degree of market integration of emerging markets with the major world stock exchanges and with their regional counterparts. They find that all national markets in the study, including Brazil and Turkey, are cointegrated with world leaders as well as with their regional counterparts in the period from 1988 through 1998. The results also indicate that emerging equity markets are affected from shocks to world leaders and to their emerging regional counterparts in the long run. However, Metin and Muradoglu (2001) do not investigate cointegration between countries from different regions of the world, ex-

[4] Richards (1995) mentions that cointegration suggests predictability in asset prices and presents a discussion of weak-form market efficiency. He suggests that the interpretation of cointegration results should be based on an economic model.

cept for controlling for the cointegration of emerging markets within a region with world leaders. We contribute to their work by showing that integration may occur between emerging countries from different regions of the world in the absence of strong trade and financial linkages.

Tabak and Lima (2002) study the cointegration of Latin American markets with the US between 1995:01 and 2001:03 and present evidence of non-cointegration among them, while short-term causality is observed. The causality flows from the Brazilian stock market to other Latin American stock markets. Fernandez-Serrano and Sosvilla-Rivero (2003) in the 1988–1998 period find bivariate cointegration between the Brazilian market and the S&P500 and DJ indexes. However, the introduction of structural breaks into the model reveals cointegration between Brazil and the S&P500 index during Asian crisis. While Tuluca and Zwick (2001) find unidirectional causality from the US to Brazil in the pre-Asian crisis period, in the post-crisis period it disappears. On the other hand, Soydemir (2000), employing a four-variable VAR model, find that the US and Brazil have weaker linkages compared to other Latin American markets according to the results of impulse response functions.

Darrat and Benkato (2003) examine the integration of the Turkish stock market with the US, UK, Japanese, and German stock markets in the period 1986:01–2000:04. The results indicate one cointegrating vector in the multivariate case. Further examination of the pre-liberalization and post-liberalization subperiods reveals that the Turkish stock market became integrated after it was liberalized. The post-liberalization period includes the Asian-Russian crises, and volatility clustering behavior examined with GARCH processes indicates that the ISE became more volatile in this period. Finally, Granger causality tests identify the US and the UK as the main sources of volatility spillovers to the ISE. In a recent paper, Erbaykal et al. (2008) finds a cointegrating vector between the Brazilian, Argentine, and Turkish stock markets and show that Bovespa has a strong influence on the ISE. However, they investigate cointegration in a multivariate setting using a static cointegration approach and control for neither global common factors nor overall emerging markets performance, which could explain the asset price co-movements. In a dynamic framework we show that the cointegration relationship between Bovespa and the ISE is time-varying and we find the structural break date to be March 2001, which coincides exactly with the aftermath of the Turkish liquidity crisis. This finding confirms our expectation that the two economies respond to local crises in each other and are cointegrated in the absence of financial or trade linkages. Cointegration between the two stock markets persists even more strongly after controlling for global shocks. We also show that the ISE holds more information for Bovespa. Contrary to their findings, we find that extreme information flows from the ISE to Bovespa.

2.2 Extreme Value Theory

Extreme Value Theory (EVT) differs from traditional statistical models, which concentrate on estimating the tendencies of central observations, by having a methodology that focuses on extreme events and ignores central behaviors. EVT was first employed in the engineering field. It was Longin (1996) that first used EVT on financial data. In the last decade, studies on EVT in finance have been drawing attention. The assumption of a normal distribution of financial returns used in risk management calculations has been widely criticized because of the heavy-tailed property of financial returns. EVT can analyze extreme returns without any underlying distribution assumption.

Univariate extreme value theory was initially used in risk analysis, such as VaR computations and expected shortfall estimations, then bivariate EVT also began to be used in financial studies. Bivariate studies in particular analyze the dependence between two data series of interest. Mendes-Moretti (2002) studied bivariate extreme value models of several pairs of indexes representing the North American, Latin American, and emerging markets. They analyzed the role of asymmetric models, finding which market drives the dependence, and express the degrees of dependence using measures of linear and nonlinear dependence. Ledford and Tawn (2003) present tools that can be implemented by using existing estimation methods for extremes and they illustrate their study with theoretical examples and simulation studies and by application to rainfall and exchange rate data. Poon et al. (2004) show that the multivariate approach to studying extreme events such as systemic risk and crisis is the most efficient and effective by using five major stock index returns.

3. Methodology

3.1 Cointegration and Causality

The precondition for applying cointegration tests is that the series should be integrated of the same order. Accordingly, the unit root tests of Augmented Dickey-Fuller (1981) and Phillips-Perron (1988) are employed to test the stochastic properties of time series. Unit root tests are first applied to the levels and then to the first differences of the series.

Two basic methodologies are evident for testing cointegration: the Engle-Granger (1987) and Johansen (1991) methodologies. Alexander (2001) suggests that it is only valid to regress log asset prices on log prices when these prices are cointegrated, then the regression will define the long-run equilibrium. However, the Engle-Granger (1987) methodology, based on OLS regression, is most suitable for bivariate settings, where the choice of the dependent variable is not in question. This methodology can identify only one cointegration vector, while there can be more in multivariate analyses. The Johansen (1991) methodology is a maximum likelihood approach for testing cointegration in multivariate autoregressive models. Its objective is to find the linear combination that is most stationary, relying on the relationship between the rank of a matrix and its eigenvalues. In an unrestricted VAR (k) model letting $\mathbf{x}_t$ be a vector of $I(1)$ variables, $\mathbf{x}_t$ can be modeled by

$$\mathbf{x}_t = \mathbf{A}_1\mathbf{x}_{t-1} + \ldots + \mathbf{A}_k\mathbf{x}_{t-k} + \boldsymbol{\varepsilon}_t \tag{2}$$

Rewriting in VECM form

$$\Delta\mathbf{x}_t = \mathbf{\Pi}\mathbf{x}_{t-1} + \sum_{i=1}^{k-1}\mathbf{\Gamma}_i\Delta\mathbf{x}_{t-i} + \mathbf{u}_t \tag{3}$$

where:

$$\mathbf{\Pi} = \sum_{i=1}^{k}\mathbf{A}_i - \mathbf{I} \qquad \mathbf{\Gamma}_i = -\sum_{j=i+1}^{k}\mathbf{A}_j$$

Granger's representation theorem states that if the coefficient matrix $\mathbf{\Pi}$ has reduced rank $r < m$, there exist $(m \times r)$ matrices $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ each with rank r such that $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$ and $\boldsymbol{\beta}'\mathbf{x}_t$ is stationary. Then r gives the number of cointegrating relations, $\boldsymbol{\beta}$ gives the cointegrating vectors, and $\boldsymbol{\alpha}$ gives the parameters in the model. The rank of $\mathbf{\Pi}$ will be full rank if all the variables in $\mathbf{x}_t$ are stationary, will equal zero if there are no linear combinations of I(1) variables that is stationary, and will equal r if the series are cointegrated. The Johansen (1991) methodology provides two statistics to determine the number of cointegrating vectors. Johansen and Juselius (1990) advise a "trace" statistic, which tests the null hypothesis of r cointegrating relations against the alternative of n cointegrating relations, where n is the number of variables in the system for $r = 0,1,2\ldots n-1$.

$$\lambda_{tr}(r) = -T \sum_{i=r+1}^{n} \ln(1-\lambda_i) \tag{4}$$

where T is the sample size and λ are the estimates of the eigenvalues of $\mathbf{\Pi}$. The second statistic provided by the Johansen methodology is called the "maximum eigenvalue," which tests the null hypothesis of r cointegrating relations against the alternative of $r+1$ cointegrating relations.

$$\lambda_{\max}(r, r+1) = -T \log(1-\lambda_{r+1}) \tag{5}$$

for $r = 0,1,2\ldots n-1$.

It follows that when the eigenvalues are all zero, the rank of the matrix will be zero, implying non-cointegration. In some cases the trace and maximum eigenvalue statistics may yield different results and Alexander (2001) indicates that the results of the trace test should be preferred. The critical values are presented by Johansen and Julieus (1990) and Osterwald-Lenum (1992).

3.2 Cointegration with a Structural Break of Unknown Time and Dynamic Cointegration Tests

As suggested by Gregory and Hansen (1996) the instability in the cointegration vector parameter may result in biased cointegration results. Thus, standard tests may reject the null of a zero cointegrating vector when there is a structural break in the data. Following Voronkova (2004) and Lucey and Voronkova (2008) we employ a cointegration analysis with an unknown date. We use the approach of Lutkepohl et al. (2004) to investigate the cointegration with a structural shift at an unknown time. This procedure estimates first the break date and then the deterministic trends. Finally, the Johansen (1991) procedure is used to estimate the cointegrating vector with the series adjusted for deterministic trends.[5]

Following Gilmore et al. (2008) we also employ dynamic cointegration analysis. We use a rolling window approach to investigate the dynamic cointegration relationship between the Bovespa and ISE stock exchanges.[6] We select a fixed window

[5] For brevity we do not provide the econometric methodology here. Please refer to Lütkepohl et al. (2004) for the econometric methodology of the cointegration test with a structural break of unknown time. We use the URCA package in R (Pfaff, 2008).

[6] Pascual (2003) shows that the rolling-window test is statistically more powerful than the recursive approach of Hansen and Johansen (1992).

length of 2 years and roll it forward a month at a time.[7] The trace statistic is calculated and rescaled to a 90% critical value. The plot shows the periods of cointegration, where a rescaled value of the trace statistic greater than 1 means cointegration. Due to the window length of 2 years, the cointegration that appears in a given year in the plot is the result of previous 2 years' data.

3.3 DCC-GARCH Approach

In order to analyze the evolution of correlation over the sample period, dynamic conditional correlation (DCC) models are used. Tsay (2010) mentions parsimonious models for ρ_t in describing time-varying correlations. In the study, the DCC-GARCH model proposed by Engle (2002) is applied. In this two-step method, first a GARCH model is estimated for each univariate data series and next the residuals of the estimated GARCH model are used in estimating the conditional correlations. The model defines the conditional covariance matrix of returns as $\mathbf{H}_t$

$$\mathbf{H}_t \equiv \mathbf{E}_{t-1}\left(r_t r_t'\right) = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t$$

where r_t denote asset returns, which follow the assumption of a normal distribution $N(0, \mathbf{D}_t\ \mathbf{R}_t\ \mathbf{D}_t)$, $\mathbf{D}_t$ is a diagonal $k \times k$ matrix of time-varying conditional standard deviations from univariate GARCH models, and $\mathbf{R}_t$ is a time-varying correlation matrix containing the conditional correlations. The proposed model rewrites the equation as

$$\mathbf{R}_t \equiv \mathbf{E}_{t-1}\left(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'\right) = \mathbf{D}_t^{-1}\mathbf{H}_t\mathbf{D}_t^{-1} \text{ since } \boldsymbol{\varepsilon}_t = \mathbf{D}_t^{-1}\mathbf{r}_t$$

The dynamic conditional correlations are estimated using the following set of equations.

$$\mathbf{D}_t^2 = diag\{w_i\} + diag\{\kappa_i\} \circ r_{t-1}r_{t-1}' + diag\{\lambda_i\} \circ \mathbf{D}_{t-1}^2$$

$$\boldsymbol{\varepsilon}_t = \mathbf{D}_t^{-1}\mathbf{r}_t$$

$$\mathbf{S} = \mathbf{E}\left[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'\right]$$

$$\mathbf{Q}_t = \mathbf{S} \circ \left(u' - \theta_1 - \theta_2\right) + \theta_1 \circ \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}' + \theta_2 \circ \mathbf{Q}_{t-1}$$

$$\mathbf{R}_t = diag\{\mathbf{Q}_t\}^{-1}\mathbf{Q}_t\ diag\{\mathbf{Q}_t\}^{-1}$$

where $\boldsymbol{\varepsilon}_t$ is the standardized innovation vector and $\mathbf{S}$ is defined as the unconditional correlation matrix of the residuals $\boldsymbol{\varepsilon}_t$ of the asset returns $\boldsymbol{I}_t$. In matrix $\boldsymbol{I}_t^{I}$, λ_i is a declining weight parameter giving more weight to more recent volatilities $\boldsymbol{I}_{t-1}^{2}$, and κ_i is the parameter for squared lagged asset returns. In matrix $\mathbf{Q}_t$, $\mathbf{i}$ is a vector of ones, θ_1 and θ_2 are nonnegative scalar parameters satisfying $0<\theta_1+\theta_2<1$, and ° is the Hadamard product. $\mathbf{R}_t$, a time-varying correlation matrix, is a function of covariance matrix $\mathbf{Q}_t$.

[7] Richards (1995) suggests that there may be a small-sample bias in Johansen tests in a multivariate setting with a long lag structure. Hence, asymptotic critical values may result in rejection of the null of no cointegration when it should be accepted. Accordingly, in dynamic cointegration test we estimate pairwise cointegration with 2 lags instead of a multivariate setting. Our lag structure is decided according to AIC criterion and Richards (1995) suggest that asymptotic values are relatively close to empirically determined critical values for small samples for a lag structure of 2.

With this methodology, we are able to examine the short-run behavior of the time-varying correlations and trace the effects of numerous important crisis events observed within the sample period.

3.4 Extreme Value Theory

Extreme value analysis is applied to either block extrema or exceedances of a predetermined threshold. In this study, we use exceedance data and apply Peaks Over a Threshold (POT) models. Threshold choice in extreme analysis is crucial, as picking a low threshold would imply selecting events from the central part of the distribution and computing biased estimates, whereas a high threshold would end up with too few data and unstable estimates.

3.4.1 Threshold Selection

The threshold for determining extreme events is determined as the 5th and 95th percentile for the lowest and highest returns, respectively, for the data series of both Bovespa and the ISE. These threshold choices are visualized by threshold choice plots and mean residual life plots.[8]

3.4.2 Bivariate GPD Models

The strength of the dependence between the extreme returns of Bovespa and the ISE is estimated by the fitting joint exceedances to a bivariate extreme value distribution using the censored maximum likelihood procedure. This methodology is exclusively described in Ledford and Tawn (1996).

Mendes and Moretti (2002) study the dependence of extreme returns using four bivariate GPD models: the logistic, asymmetric logistic, mixed, and asymmetric mixed models. These models are also described in Klüppelberg and May (2006). A brief summary of each is given below.

3.4.2.1 Logistic Model

The logistic model has the following dependence function:

$$A:[0,1]\to[0,1],\quad w\mapsto\left\{(1-w)^{1/\alpha}+w^{1/\alpha}\right\}^{\alpha} \tag{6}$$

where $0<\alpha\leq 1$. This gives the joint distribution function:

$$G(x,y)=e^{-V(x,y)}=e^{-\left(x^{-1/\alpha}+y^{-1/\alpha}\right)^{\alpha}} \tag{7}$$

for x, $y>0$. Complete dependence is obtained when $\alpha\to 0$, and total independence is when $\alpha=1$.

3.4.2.2 Asymmetric Logistic Model

The asymmetric logistic model has the dependence function:

$$A:[0,1]\to[0,1],\quad w\mapsto(1-\theta_1)(1-w)+(1-\theta_2)w+\left[(1-w)^{1/\alpha}\theta_1^{1/\alpha}+w^{1/\alpha}\theta_2^{1/\alpha}\right]^{\alpha} \tag{8}$$

[8] These visual tools are provided in Ribatet (2006)'s POT package. For brevity these plots are excluded and are available on request.

where $0 < \alpha \leq 1$, $0 \leq \theta_1 \leq 1$, $0 \leq \theta_2 \leq 1$. The corresponding exponent measure for the joint distribution function is

$$V(x,y) = \frac{1-\theta_1}{x} + \frac{1-\theta_2}{y} + \left\{ \left(\frac{x}{\theta_1} \right)^{-1/\alpha} + \left(\frac{y}{\theta_2} \right)^{-1/\alpha} \right\}^{\alpha} \tag{9}$$

for $x, y > 0$. Complete dependence corresponds to $\theta_1 = \theta_2 = 1$ and $\alpha \to 0$. Independence is obtained when either $\alpha = 1$, $\theta_1 = 0$ or $\theta_2 = 0$.

3.4.2.3 Mixed Model

The dependence function for the mixed model is

$$A:[0,1] \to [0,1], \quad w \mapsto \alpha w^2 - \alpha w + 1 \tag{10}$$

where $0 \leq \alpha \leq 1$. The mixed model is defined by the joint distribution function

$$G(x,y) = e^{-\left(\frac{1}{x}+\frac{1}{y}\right)+\frac{\alpha}{x+y}} \tag{11}$$

for x, $y > 0$. Independence is obtained when $\alpha = 0$. Total dependence, however, cannot be modeled.

3.4.2.4 Asymmetric Mixed Model

The dependence function for the asymmetric mixed model is

$$A:[0,1] \to [0,1], \quad w \mapsto \theta w^3 + \alpha w^2 - (\alpha + \theta) w + 1 \tag{12}$$

where $\alpha \geq 0$, $\alpha + 2\theta \leq 1$, $\alpha + 3\theta \geq 0$. The asymmetric mixed model is defined by the joint distribution function

$$G(x,y) = e^{-\left[\left(\frac{1}{x}+\frac{1}{y}\right)-\frac{(\alpha+\theta)x+(\alpha+2\theta)y}{(x+y)^2}\right]} \tag{13}$$

for x, $y > 0$. Independence is obtained when $\alpha = \theta = 0$. Total dependence, however, cannot be modeled.

3.4.3 Extremal Dependence

The extremal dependence structure is the relationship between two data series when observations in each series are extreme. In risk management analysis, it is important for decision makers to estimate the chance of loss on an investment given that the other investment is generating extreme losses. The dependence structure can be classified under four main groups: perfect dependence, independence, asymptotic dependence, and asymptotic independence. Asymptotic dependence implies that joint exceedances are more common compared to the case where the data series are independent. Asymptotic independence, on the other hand, implies fewer joint exceedances compared to the case of perfect dependence.

Coles et al. (1999) discusses in detail how dependence can be analyzed by the χ and $\overline{\chi}$ measures. These dependence measure estimates depend on the quantile level taken as the threshold. A positive (negative) χ implies that the data are positively (negatively) associated. A χ estimate approaching zero as higher quantiles are taken implies asymptotic independence. For independent (perfectly dependent) variables, the χ estimate will be equal to zero (one) for all quantile levels. Poon and Tawn (2004) discuss why the χ statistic is better than the Pearson correlation ρ, in identifying the type of extremal dependence structure.

Coles et al. (1999) determines the dependence of extreme observations as $\lim_{z\to z^*} \Pr\left(Y > z \middle| X > z\right)$, the probability of one variable being extreme given that the other is extreme. Accordingly, Coles et al. (1999) defines the χ-statistic as $\chi = \lim_{u\to 1} \Pr\left(V > u \middle| U > u\right)$, where U and V are transformed Uniform[0,1] variables of the marginal distributions of random variables X and Y.

Defining

$$\chi\left(u\right) = 2 - \frac{\log \Pr\left(U < u, V < u\right)}{\log \Pr\left(U < u\right)}$$

for $0 \le u \le 1$, it follows that $\chi = \lim_{u\to 1} \chi\left(u\right)$.

Coles et al. (1999) states that except for the special case of independence, all bivariate extreme value distributions are asymptotically dependent, and that

$$\chi = 2 - V(1,1) = 2\left(1 - A(0.5)\right) \tag{14}$$

Recent studies have observed asymptotic independence commonly in their multivariate extreme value analyses. In such cases, as the χ statistic approaches 0, this measure is limited in giving the relative strength of the dependence. A second dependence measure $\overline{\chi}$ is thus defined to measure the relative strength of the dependence.

Defining

$$\overline{\chi}\left(u\right) = \frac{2\log \Pr\left(U > u\right)}{\log \Pr\left(U > u, V > u\right)} - 1$$

for $0 \le u \le 1$, where $-1 \le \overline{\chi}\left(u\right) \le 1$ for $0 \le u \le 1$,

it follows that $\overline{\chi} = \lim_{u\to 1} \overline{\chi}\left(u\right)$ for which $-1 < \overline{\chi} \le 1$.

For asymptotic dependence, we have to have $\overline{\chi}$ approach 1 with higher quantiles. The degree of asymptotic dependence will be implied by the χ estimate. In the case of asymptotically independent variables, $\overline{\chi}$ is used as a measure of dependence strength. For independent variables $\overline{\chi} = 0$ for all quantile levels.

4. Data

The data of the study comprise the monthly and daily closing stock price series of the Bovespa and ISE100 indexes of, respectively, the Brazilian and Istanbul stock exchanges and the S&P500 index, and the MSCI Emerging Markets Index (EMI). We compiled the data from the official websites of the Brazilian and Istanbul stock exchanges, the Yahoo Finance website, and the MSCI website. The investigation period starts on January 1, 1996 and extends to May 7, 2009. Monthly data is

Table 1 Full Period Descriptive (monthly returns)

	BOVESPA	ISE100	S&P500
Mean	0.004	0.001	-0.002
Median	0.013	-0.002	0.001
Maximum	0.126	0.176	0.044
Minimum	-0.202	-0.202	-0.279
Std. Dev.	0.044	0.062	0.031
Skewness	-1.015	-0.189	-4.790
Kurtosis	6.032	4.326	43.142
Jarque-Bera	88.736	12.686	11354.22
Probability	0	0.002	0
Observations	160	160	160

used for the cointegration analysis to control for non-synchronous trading and time-zone differences (Baumöhl and Vyrost, 2010). The stock price indexes are denominated in local currencies following Voronkova (2003), adjusted for inflation and converted to natural logarithms. The objective in using local currencies is to obtain cointegration results based solely on movements in asset prices by eliminating the effect of exchange rate changes, especially if the exchange rate is highly volatile. The countries under examination have been through various devaluations, which could have distorted the findings. Furthermore, Alexander (2001) stresses the importance of doing cointegration analyses in local currencies for detecting asset price co-movements. Similar to Frank and Hesse (2009) and Muradoglu et al. (2000) we use the S&P500 closing price series to control for global returns and common shocks in the cointegration analysis. To control for global shocks, we conduct the cointegration analysis with the Bovespa/S&P500 and ISE100/S&P500 series. We present our main findings using the S&P500 series, as the US market is a price leader (Masih and Masih, 1999) and provide the estimations made with the EMI series to control for performance similarities in emerging markets in the robustness checks section. The descriptive statistics provided in *Table 1* are calculated with first-differenced series, which give continuous rates of return.

An examination of the descriptive table reveals that both indexes had positive yet volatile returns during the investigation period. Interestingly, the S&P500 index had a negative mean return. However, this is due to the subprime mortgage crisis. *Figure 1* shows the time series plot of the indexes at level values. Bovespa and the ISE100 show a similar pattern, especially during the systemic crisis periods of the 1997 Asian crisis, the 1998 Russian crisis, the 2000 dot-com crisis, and the 2008 subprime crisis, as well as during the local crisis periods of the 1999 Brazilian and 2000–2001 Turkish crises. The excess kurtosis indicates the influence of extremes on the stock market return distributions in all series. In all cases Jarque-Bera tests reject normality.

Table 2 presents the results of the unit root analyses. The pre-condition of the series being integrated of the same order is verified with the ADF (1981) and PP (1988) tests. The tests are applied to levels and first differences where the model includes a constant and a trend. The appropriate lag lengths are chosen according to the AIC-Akaike Information Criterion and the critical values are obtained from MacKinnon (1996). For all series the presence of a unit root cannot be rejected in

Figure 1 Time Series Plot of Index Values at Log Levels Indices of ISE, Bovespa and SP500

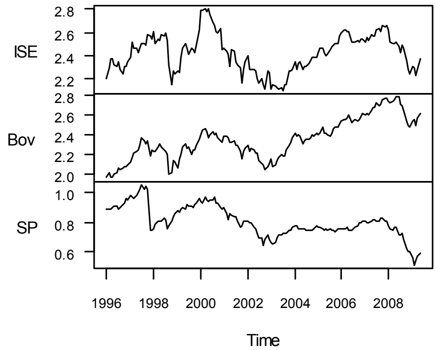


Table 2 Unit Root Tests

	ADF		PP	
	levels	**first differences**	**levels**	**first differences**
BOVESPA	-2.404	-11.903	-2.534	-11.908
ISE100	-2.574	-12.034	-2.733	-12.022
BOVESPA/S&P500	-1.111	-11.726	-0.911	-14.345
ISE100/S&P500	-3.067	-12.803	-3.073	-12.837

Note: *MacKinnon (1996) one-sided *p*-values.

levels, while no unit root is found in the first differenced series at the 5% level, indicating that all the series are integrated of order one.

Daily return data is used for the extreme value analysis, as high frequency data is preferred. The use of extreme value theory requires high frequency and independent and identically distributed data. The Box-Pierce[9] and Ljung-Box[10] tests of the daily log return time series do not reject the null hypothesis of independence at the 10% level. Hence, GARCH residuals are not employed in the analysis.

5. Empirical Findings

5.1 Cointegration Tests

Having proven that all series are integrated of order one, we proceed with the cointegration analysis of Johansen (1991). In the remainder of the paper we provide both bivariate Bovespa and ISE100 estimations and bivariate Bovespa/S&P500 and ISE100/S&P500 estimations to control for global returns. The analyses are made under the model with a constant and linear trend in the cointegration vector and the optimal lags are chosen to minimize the AIC and set at 2 in first differences, while it is also found that the results are robust to alternative lags. *Table 3* panel A presents the bivariate Bovespa and ISE100 estimations of the Johansen (1991) cointegration analysis. The trace test result of 20.57 is found to be less than the 5% critical value of 25.87 and accordingly the null hypothesis that the Bovespa and

[9] The *p*-values of the Box-Pierce test are 10.06% and 33.29% for the ISE100 and Bovespa log returns, respectively.

[10] The *p*-values of the Ljung-Box test are 10.04% and 33.27% for the ISE100 and Bovespa log returns, respectively.

Table 3 Static Cointegration Test Results

Panel A: Bivariate Cointegration of BOVESPA and ISE100				
Hypothesis				
H_0	H_A	Trace test	5 % critical values	Prob.**
$r = 0$	$r \geq 1$	20.578	25.872	0.198
$r \leq 1$	$r \geq 2$	5.322	12.518	0.551
		Maximum Eigenvalue	5 % critical values	Prob.**
$r = 0$	$r = 1$	15.256	19.387	0.18
$r \leq 1$	$r = 2$	5.322	12.518	0.551

Panel B: Bivariate Cointegration of BOVESPA/S&P500 and ISE100/S&P500				
Hypothesis				
H_0	H_A	Trace test	5 % critical values	Prob.**
$r = 0$	$r \geq 1$	10.283	15.495	0.259
$r \leq 1$	$r \geq 2$	0.468	3.8415	0.494
		Maximum Eigenvalue	5 % critical values	Prob.**
$r = 0$	$r = 1$	9.815	14.264	0.224
$r \leq 1$	$r = 2$	0.468	3.841	0.494

Note: **MacKinnon-Haug-Michelis (1999) *p*-values.

Table 4 Cointegration Test with a Structural Break of Unknown Time Results

Panel A: Bivariate Cointegration of BOVESPA and ISE100			
Hypothesis			
H_0	H_A	Trace test	5 % critical values
$r = 0$	$r \geq 1$	24.34***	15.830
$r \leq 1$	$r \geq 2$	9.28**	6.790

Panel B: Bivariate Cointegration of BOVESPA/S&P500 and ISE100/S&P500			
Hypothesis			
H_0	H_A	Trace test	5 % critical values
$r = 0$	$r \geq 1$	31.01***	15.83
$r \leq 1$	$r \geq 2$	14.13***	6.79

Notes: *** denotes significance at 1 % level
** denotes significance at 5 % level
* denotes significance at 10 % level

ISE100 indexes are not pairwise cointegrated ($r = 0$) is accepted. This finding is supported by the Maximum Eigenvalue test result of 15.25, which is also smaller than the respective 5% critical value of 19.38. Both test results suggest that these stock markets do not have a long-run equilibrium. This means that they do not share a common stochastic trend. Panel B of *Table 3* presents the results for the bivariate cointegration of the Bovespa/S&P500 and ISE100/S&P500 series. The trace and maximum eigenvalue test statistics are below their 5% critical values, hence we again confirm that Bovespa and ISE100 are not cointegrated in the period 1996:01 to 2009:05.

We continue our analysis with the methodology of Lutkepohl et al. (2004) and estimate the cointegration relationship with an unknown structural break date. We use a lag structure of 2, chosen according to the AIC, and estimate in both bivariate settings as before. *Table 4* presents the test results. The trace statistics in both

Figure 2a Bivariate Results; Bovespa and ISE
24-Month Rolling-Window Lambda Trace Statistic for ISE and Bovespa

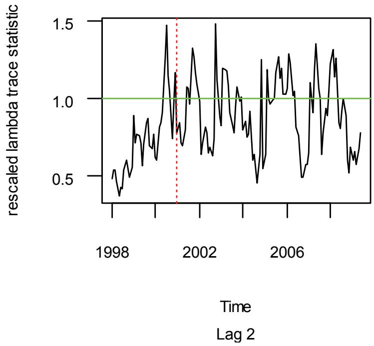
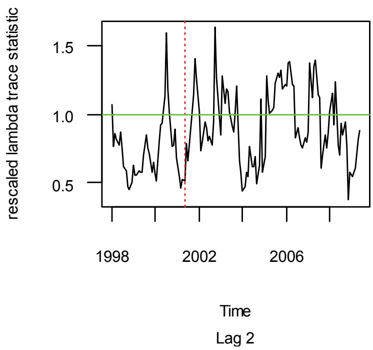


Figure 2b Multivariate Results; Bovespa, ISE, S&P500
24-Month Rolling-Window Lambda Trace Statistic for ISE/SP500 and Bovespa/SP500



Notes: The lambda trace statistic is calculated over a rolling window of 24 months. The window is moved a month at a time. The statistics are plotted against the end of each time interval. Plots above 1.0 indicate one cointegration relation according to a critical value of 90%. The vertical dotted line represents the structural break dates according to Lutkepohl et al. (2004) methodology.

bivariate settings exceed the 5% critical values and confirm bivariate cointegration with a structural break. The date of the bivariate Bovespa and ISE100 break is estimated as 12:2000, which coincides with the Turkish liquidity crisis of November 2000. The date of the bivariate Bovespa/S&P500 and ISE100/S&P500 break is estimated as 04:2001, which is in the aftermath of the Turkish twin liquidity crisis of November 2000–February 2001.

Next, we estimate the dynamic cointegration with a rolling window approach similar to Gilmore et al. (2008).[11] *Figure 2* shows the rolling window trace statistic for both bivariate settings, with a lag structure of 2 chosen according to the AIC. The *panel A* presents the pairwise results for Bovespa and ISE100. We observe episodic cointegration between the Bovespa and ISE100 indexes. Initial evidence of cointegration appears in the 2000–2001 period. Due to the 2 years lagged structure of dynamic cointegration analysis, this period coincides with the Russian 1998 and

[11] We repeat the same set of estimations with weekly data with a fixed window length of 104 weeks, exactly 2 years, and rolling a week forward at a time. Our findings remain the same.

Brazilian 1999 crises. After the structural break date of 12:2000, cointegration re-emerges in the 2001–2002 period, this time coinciding with the twin liquidity crisis of Turkey.[12] We also observe periods of cointegration in the aftermath of the Turkish crisis for the 2003–2004 period. Cointegration then disappears and reappears in the 2005–2006 period and in the 2007–2008 period, which is the subprime crisis period, confirming the findings of Frank and Hesse (2009).

Cointegration appears with a similar pattern in the bivariate Bovespa/S&P500 and ISE100/S&P500 analysis presented in *Figure 2 panel B*. The cointegration starts with the 1997 Asian crisis and then re-emerges in mid-2000, matching the Russian and Brazilian crises as before. It appears strongly in 2002 and 2003 after the structural break date of March 2001, matching the Turkish twin liquidity crisis. This confirms our previous dynamic cointegration results after controlling for global returns, proxied by the S&P 500 index. The Brazilian and Turkish stock markets share a long-run equilibrium and respond to local crises in each other despite being in distant regions and having insignificant trade and financial linkages. We also observe cointegration for 2003–2004 and in the post-2005 period, including the subprime crisis during 2007–2008.

5.2 Short-term Dynamics

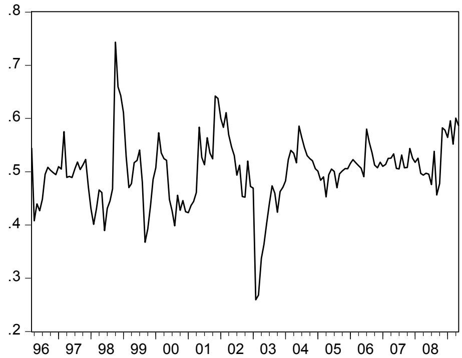
Alexander (2001) points out that cointegration is not a pre-condition for a lead-lag relationship to exist and that other common features between time series could result in causality. In this respect, the Engle-Granger (1987) causality test is generally applied to the first differences of the series to verify if there has been a causality running from one market to another in the short run. However, the causality test is in the bivariate setting only and thus does not incorporate any other common process that could affect the short-term relationship. Accordingly, the Granger causality test could be misleading about the true relationship between the Bovespa and ISE100 markets. Hence, following Lucey and Voronkova (2008) and Frank and Hesse (2009), the short-term interdependencies between the Bovespa and ISE100 indexes are investigated using the DCC-GARCH methodology of Engle (2002). The DCC-GARCH model of Engle (2002) permits a time-varying correlation structure and thereby enables us to make a better analysis of conditional correlations, especially during crisis periods. For this analysis, we use the residuals of the monthly ISE100 and Bovespa returns from a regression on S&P500 returns in the DCC-GARCH model. Thereby, we also control for common processes not included in the bivariate DCC-GARCH approach.

The Bovespa and ISE100 residual returns are estimated as an ARMA(1,1) model, where the correlation structure in between is estimated as a DCC-GARCH(1,1) specification. The model is estimated over the full sample period. *Figure 3* displays the estimated monthly conditional correlations between the Bovespa and ISE100 indexes' residual returns, which range between 0.25 and 0.75. Examining the graph,

[12] The 2000 dot-com bubble occurred in this period. However, the DCC-GARCH analysis between the ISE100-S&P500 and Bovespa-S&P500 pairs shows no significant change in correlations during this crisis. The ISE100-S&P500 correlation remains low at 0.12, while the Bovespa-S&P500 correlation was 0.30, close to its average values. Nonetheless, some of the cointegration relationship observed in 2001 could be attributed to the dot-com bubble, during which the dynamic conditional correlation between the ISE-Bovespa residual returns becomes 0.58.

Figure 3 Dynamic Conditional Correlation Coefficients between Bovespa and ISE Indices

DCC-GARCH



we detect seven main regimes; the 1997 Asian crisis, the 1999 Brazilian crisis, the 2000 dot-com crisis, the Turkish crisis in 2001–2002, 2003, 2004, and the 2008 subprime crisis. In the systemic Asian crisis, the correlations increase to 0.58. During the 1999 Brazilian crisis the correlations peak at 0.7, while we observe a correlation of 0.58 during the dot-com crisis. During the twin liquidity crisis in Turkey the correlations increase from 0.40 to 0.62. The rise in the conditional correlations follows the structural break dates of 12:2000 and 04:2001 indicated by the Luktepohl et al. (2004) test. At the beginning of 2003 we observe a plunge in the correlations to 0.25. In 2002, both Brazil and Turkey had general elections, during which these two markets' asset prices may have been dominated more by local factors than by global factors.[13] This may be the reason for the temporary fall in the correlations between these two stock market indexes. This relatively weaker correlation also matches the non-cointegration period of 2004–2005 in the dynamic cointegration tests. In the post-2004 period the conditional correlations increase and peak again during the subprime crisis, confirming the findings of Frank and Hesse (2009).

5.3 Bivariate Extreme Value

The 5th and 95th quantile thresholds for the ISE100 returns are -4.11% and 4.28% for the left and right tail, respectively. For Bovespa these quantiles as thresholds correspond to -3.44% and 3.19%. Given that there are 3,484 daily returns in the dataset, the 175 highest and 175 lowest extreme events exceeding selected thresholds in the studied time interval are used in the model estimations.

Because of the time zone difference when the returns are analyzed on the same calendar day, Bovespa opens after the ISE100 closes, i.e., Bovespa follows the ISE100. Same returns on the same calendar day imply that the Bovespa returns already incorporate ISE100 return information. Because of this information asymmetry, the same analysis is followed using one day lagged ISE100 returns and Bovespa returns so that the ISE100 opens after Bovespa closes, i.e., the ISE100 follows Bovespa.

[13] This is the only period when the general elections of two countries overlap in our sample period.

Table 5 Positive Extreme Returns of Bovespa and ISE100 (Bovespa follows ISE100)

	χ	Deviance	σ_1	ξ_1	σ_2	ξ_2	α	θ_1	θ_2
log	0.048	698	0.018	0.162	0.011	0.396	0.965		
			(0.002)	(0.095)	(0.000)	(0.082)	(0.013)		
alog	0.094	692	0.019	0.164	0.012	0.344	0.659	0.215	0.235
			(0.002)	(0.103)	(0.002)	(0.108)	(0.307)	(0.231)	(0.169)
mix	0.094	692	0.019	0.170	0.012	0.342	0.187		
			(0.002)	(0.106)	(0.002)	(0.107)	(0.052)		
amix	0.093	692	0.019	0.164	0.012	0.341	0.147	0.026	
			(0.002)	(0.107)	(0.002)	(0.107)	(0.156)	(0.097)	

Note: Terms in parentheses are standard errors of parameter estimates.

Table 6 Negative Extreme Returns of Bovespa and ISE100 (Bovespa follows ISE100)

	χ	Deviance	σ_1	ξ_1	σ_2	ξ_2	α	θ_1	θ_2
log	0.174	645	0.019	0.160	0.014	0.243	0.868		
			(0.002)	(0.094)	(0.002)	(0.098)	(0.023)		
alog	0.175	645	0.019	0.152	0.014	0.247	0.839	0.710	0.982
			(0.002)	(0.096)	(0.002)	(0.098)	(0.121)	(0.498)	(0.805)
mix	0.175	648	0.019	0.138	0.014	0.269	0.350		
			(0.002)	(0.094)	(0.002)	(0.099)	(0.061)		
amix	0.175	648	0.019	0.138	0.014	0.270	0.332	0.012	
			(0.002)	(0.094)	(0.002)	(0.099)	(0.161)	(0.102)	

Note: Terms in parentheses are standard errors of parameter estimates.

Tables 5 and *6* provide the results of the models that estimate the dependence of the highest and lowest returns between these two stock markets, respectively. 26 of the highest 175 returns and 39 of the lowest 175 returns of both indexes coincide on the same calendar dates. Under the independence assumption, only 8.7[14] events would happen on the same day on average.

Table 5 presents the results of the models that estimate the dependence of the highest returns between these two stock markets. Among these models the logistic model has the lowest χ-statistic, implying the lowest degree of dependence. However, this model has higher deviance. All four models[15] have similar estimates for the shape (σ) and scale (ξ) parameters. The logistic model's α estimate close to one points to a low asymptotic independence. The asymmetric logistic, mixed, and asymmetric mixed models all imply asymptotic independence, with χ statistics close to zero.

Table 6 provides the results of the bivariate analysis of the lowest returns of Bovespa and the ISE100. All four models have close deviances and χ statistics. Compared to positive returns, negative returns have higher extreme dependence. Higher dependence can also be observed in Pickands' (1981) plots in *Figure 4*. The curves are further away from the horizontal line where total independence is observed.

[14] A 0.0025 probability times 3,484 days.

[15] As all bivariate extreme value distributions are asymptotically dependent, the $\bar{\chi}$ statistic is always equal to 1.

Figure 4 Pickands' Dependence Plots

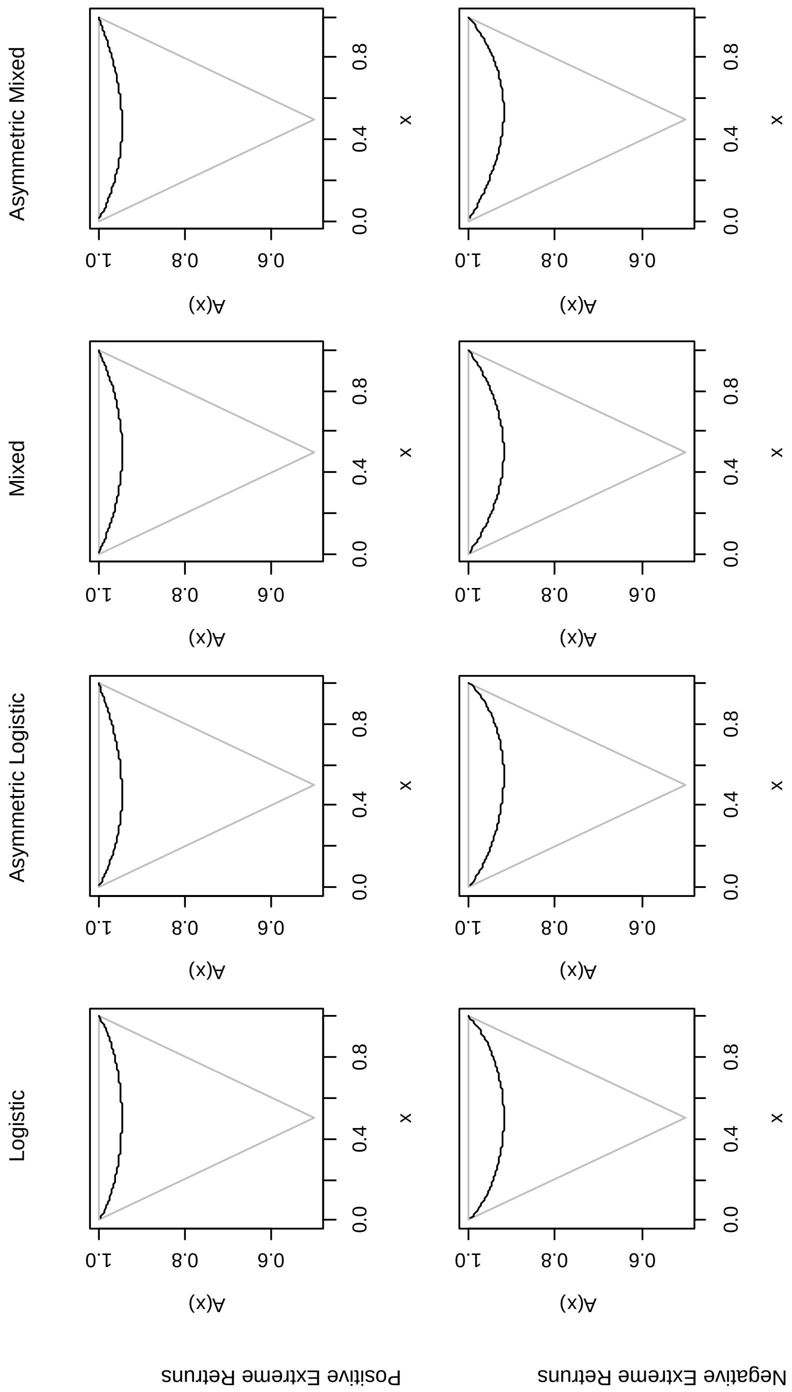


Table 7 Positive Extreme Returns of Bovespa and ISE100 (ISE100 follows Bovespa)

	χ	Deviance	σ_1	ξ_1	σ_2	ξ_2	α	θ_1	θ_2
log	0.076	694	0.020 (0.002)	0.114 (0.094)	0.011 (0.002)	0.444 (0.098)	0.944 (0.023)		
alog	0.031	702	0.016 (0.002)	0.167 (0.084)	0.011 (0.000)	0.379 (0.081)	0.945 (0.024)	0.414 (0.226)	0.430 (0.254)
mix	0.083	696	0.019 (0.002)	0.177 (0.105)	0.012 (0.000)	0.368 (0.083)	0.166 (0.050)		
amix	0.184	713	0.019 (0.002)	0.189 (0.109)	0.010 (0.000)	0.677 (0.141)	0.114 (0.157)	0.170 (0.110)	

Note: Terms in parentheses are standard errors of parameter estimates.

Table 8 Negative Extreme Returns of Bovespa and ISE100 (ISE100 follows Bovespa)

	χ	Deviance	σ_1	ξ_1	σ_2	ξ_2	α	θ_1	θ_2
log	0.128	690	0.019 (0.002)	0.189 (0.105)	0.011 (0.000)	0.517 (0.113)	0.905 (0.022)		
alog	0.099	680	0.019 (0.002)	0.134 (0.085)	0.014 (0.002)	0.213 (0.094)	0.314 (0.064)	0.999 (0)	0.805 (0.64)
mix	0.100	692	0.019 (0.002)	0.174 (0.099)	0.014 (0.002)	0.301 (0.102)	0.200 (0.054)		
amix	0.101	692	0.018 (0.002)	0.177 (0.099)	0.014 (0.002)	0.300 (0.104)	0.282 (0.129)	-0.054 (0.072)	

Note: Terms in parentheses are standard errors of parameter estimates.

Tables 7 and *8* use the ISE100 returns together with the Bovespa returns of the previous day such that the ISE100 opens after Bovespa closes. Using this lagged dataset, given that there are 175 days that exceed these threshold returns in both the ISE100 and Bovespa data series, it is noteworthy that again 23 of these highest returns and 26 of the lowest returns coincide on the same days. Under the independence assumption again only 8.7[16] events would happen on the same day on average.

In the analysis of the data series where the ISE100 returns follow after Bovespa closes, in *Tables 7* and *8*, again higher dependence can be observed on the negative tail relative to the positive tail. However, the dependence in both the right and left tails falls, with lower χ statistics compared to the models in *Tables 5* and *6*. So, one can conclude that the dependence between extreme returns between Bovespa and the ISE100 is higher when Bovespa opens after ISE100 closes. The dependences on the left tails are more evident, i.e., when one of these markets has extreme low returns, then the other market also tends to have a low return. The dependence of the extremes increases when Bovespa follows the ISE100 market.

Plotting Pickands' (1981) dependence functions in (6), (8), (10), and (12) helps us to detect the strength of the dependence. These plots are presented in *Figure 4*. The upper horizontal line is where there is total independence and the lowest broken line is where there is perfect dependence. In interpreting Pickands' (1981) depend-

[16] 0.0025 probability times 3,483 days

Figure 5 χ and $\bar{\chi}$ Plots of Daily log Returns of ISE and Bovespa on Same Calendar Days

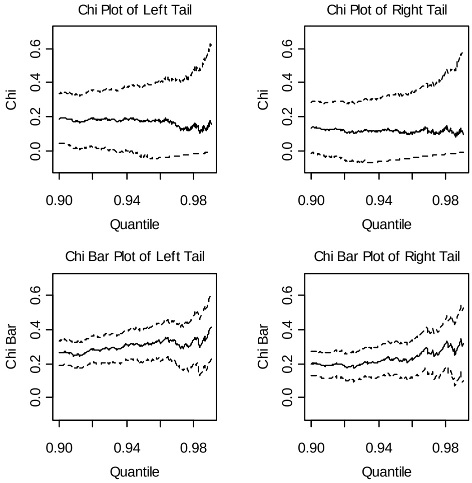
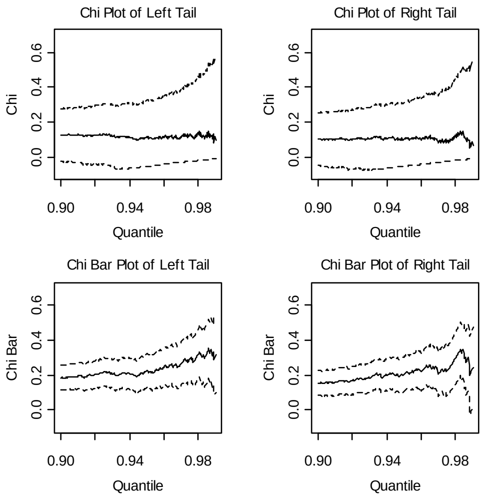


Figure 6 χ and $\bar{\chi}$ Plots of Daily log Returns of ISE lagged and Bovespa so that Bovespa Closes First and ISE Opens After



ence plots, one must take into account that the mixed and asymmetric mixed models cannot model perfect dependence.

The χ statistics estimated in the models above all imply asymptotic independence. Hence, the assumption of "$\bar{\chi}=1$" in the parametric estimation is questioned. Using the empirical approach of Coles et al. (1999), the $\bar{\chi}$ and χ measures are re-estimated for different quantile levels to understand the structure of the dependence.

Figure 5 displays the $\bar{\chi}$ and χ measures for the daily log returns of the ISE100 and Bovespa on the same calendar day, where the information flows from ISE100 to Bovespa. The charts for the left tail and right tail show the χ measures away from being equal to one. The same observation can be drawn from *Figure 6*, where the ISE100 returns are matched with the prior day Bovespa returns so that the information flow is in this case reversed. So we conclude that the Bovespa and ISE100 returns show asymptotic independence in both directions of information flow. In this case we have to consider the $\bar{\chi}$ measures in analyzing the level of dependence.

The plots show that the dependence in the left tail increases when the information flow is from the ISE100 to Bovespa. The dependence on the left tail is higher compared to the dependence on the right tail when the information flow is from Bovespa to the ISE100.

6. Robustness Checks

To investigate if the documented cointegration between Bovespa and the ISE100 could be due to performance similarities in emerging markets, we use the MSCI Emerging Markets Index (EMI) in our estimations, similarly to Ülkü (2011). We re-estimate the cointegration relationship with the Bovespa/EMI and ISE100/EMI series to control for the impact of performance similarities of emerging markets in both static and dynamic tests. While we find no cointegration relationship in the static tests, we report a dynamic cointegration relationship between the given series. The cointegration relationship appears episodic as before and is found for the Russian 1998 crisis, the Brazilian 1999 crisis, the 2000 dot-com crisis, the Turkish 2000–2001 liquidity crisis, and the post-2005 period. It disappears and re-emerges again in the subprime crisis period. The only difference from the ISE100/S&P500 and Bovespa//S&P500 series is that the structural break date is found as 05:1996.

The bivariate extreme value analysis of the daily log returns showed that the dependence in the left tail increases when the information flow is from the ISE100 to Bovespa. To investigate further whether this is due to global information picked up by the ISE before Bovespa, the bivariate analysis findings are also analyzed using the residuals of the Bovespa and ISE logreturns regressed against the S&P500 logreturns. The analysis is also repeated using lagged ISE returns. The findings of these studies show again that the two indexes show asymptotic independence and a higher degree of dependence on the left tail even when the global information effect is controlled for.

7. Conclusion

This study focuses on the financial integration of the Bovespa and Istanbul stock exchanges. These economies have been sharing similar fundamental economic problems, such as high inflation and high interest rates, for the past decade. Analyzing the recent global crises, it is also noteworthy that they displayed similar responses especially to the Russian 1998 crisis. After it, both markets went through serious devaluations accompanied by stock market crashes. Since then, Brazil and Turkey have been implementing IMF-backed stabilization programs, and it is observed in time-varying conditional correlations that during the Brazilian crisis of 1999 and the Turkish crisis of 2000–2001, Bovespa and the ISE100 had interestingly higher correlations. This similarity in economic histories and the high correlations between such distant emerging economies with negligible trade and financial linkages has to date remained unexplored.

We apply static and dynamic cointegration tests and reveal that Bovespa and the ISE100 were cointegrated during episodes of local crisis in Brazil in 1999 and Turkey in 2000–2001. What we know from the crisis and contagion literature is that global equity prices respond to common shocks and bilateral trade and financial linkages significantly affect asset price correlations and co-movements. But interestingly, these markets were not only cointegrated during local crisis periods, but also in the absence of strong bilateral trade and financial linkages. The cointegration tests with a structural break of unknown time also date the Turkish 2000 crisis as a structural break date after which these markets shared a long-run equilibrium. While we show that these markets still remain independent in extremes and hence offer diversification opportunities to international investors during times of turmoil, we find strong evidence of cointegration in the long run. Our findings remain robust in analyses where we include the S&P500 and EMI indexes as a proxy for global returns and emerging market performance.

These findings challenge our understanding of what drives co-movement of equity prices, as these economies neither had strong trade linkages nor are in the same region. This fact could be a result of convergence of the economies in response to IMF programs and policies that are quite parallel in each market. However, this issue requires more a in-depth examination of the sources of change in asset price co-movements and we leave it for further research.

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