Modelling Long Memory and Default Risk Contagion in Sovereign Bond Markets.

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Abstract

The aim of this paper is to examine and measure default risk contagion in Latin American sovereign debt prices based on three salient characteristics of Emerging Bond Markets (EBM): a high degree of volatility persistency, the existence of risk premiums and a high fractional comovement of spread changes. To this end, a new bivariate $FIGARCH(1,d,1)-in-Mean$ model is proposed. We conjecture that the nature of this contagion is global, based on informationally inefficient and incomplete markets and resulting of the type of herding behaviour described by Calvo (1999), in which fundamentals turn insufficient to explain contagion. High persistency is explained as the result of market rigidities and the manner in which EBM market operates; fractional comovement, in turn, gives support to the view on the existence of a common global factor driving EBM in the same direction, and risk premiums (risk aversion and pure risk) are time varying and seem to significantly explain spread changes. In general, the findings call for the creation of global financial structures with the ability to supervise, to intervene in face of liquidity squeezes (as in Calvo (2002)) and to provide market participants with efficient and quality information to prevent contagion.

Keywords: Default Risk Contagion, Emerging Bond Markets, Long Memory, bivariate FIGARCH-in-Mean, Financial Stability.

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1 Introduction

The contagion episodes in Latin America (LA) during the nineties have been commonly attributed to direct trade links and weak fundamentals. However a full explanation of such events cannot be drawn without analyzing the conduct of international financial markets and in particular the deportment of debt prices in Emerging Bond Markets (EBM).

Fundamentals seem insufficient to explain contagion. Beattie (2000) suggests for instance that the contagion observed in LA from the Asian and Russian turmoils is more characteristic of a financial crisis in which investment flows are at least as important as economic fundamentals in prompting a given crisis[1]. Eichengreen and Mody (1998) believe, in addition, that spread changes in EBM over time are, to a good extent, explained by shifts in market sentiment rather than by shifts in fundamentals.

Furthermore, it is believed that during the contagious events in the nineties, developed markets may well have served as the conduit between regions of developing markets. There is in fact some early evidence suggesting that the actual base of crisis transmissions and contagion may have been the off-shore Brady markets -see Baig and Goldfajn (2000) and Kaminsky and Reinhart (2002).

The nature of this global financial contagion has been explained by Calvo (1999) as the result of *herding behavior*[2] generated in a liquidity-crunch setting. EBM are populated by two types of investors: informed and uniformed[3]. Uninformed investors have few incentives to obtain costly information about the countries held in their portfolios and hence follow the behavior of well informed investors. In order to meet unexpected margin calls during the Russian crisis for instance, institutional investors were forced to sell their Emerging Markets (EM) bond holdings, including those of LA, despite in many cases being still good viable options. The resulting massive sell-off of bonds could have been falsely interpreted by uniformed investors as a deterioration of LA credit -see also Beattie (2000).

Jostova (2002) considers that this kind of rush massive sell-offs are not automatic or immediate in EBM. They lack 'noise traders' and that prevents them from being completely informationaly efficient. Institutional investors have strict 'tracking error' and 'diversification' constraints that don't allow portfolio managers to freely cash out EM bonds to face sudden liquidity crunches. In addition, dedicated investors are reported to react more slowly to market signals since they pursue returns relative to a bench-

[1]In fact the volume of Russian trade with EM and specially with Latin America is not significant.

[2]Calvo (2002) has also offered a *global hazard* explanation for contagion.

[3]Herding behaviour has also been linked to market volatility -see Eichengreen and Mody (1998).

mark (EMBI+). Departures from the benchmark would lead to substantial investment and business risk. Jostova (2002) suggests that these facts may allow for the existence of various degrees of *persistency*, a potential stylized fact, we consider, of EBM. In fact, Calvo (2002) has pointed out that financial rigidities are a salient feature in these markets and are almost surely behind severe crisis.

Eichengreen and Mody (1998) have suggested under these circumstances that *risk premiums* may additionally fail to adjust to reflect deteriorating economic conditions, news and to capture the response to changes in the spreads of other countries.

A very stylized fact of EBM is the *strong comovement* between the spreads noticed among others by Mauro et al. (2000) and Fiess (2003). Some observers consider that this synchronization is perhaps an indication that investors regard shocks as common or that a single global factor is driving all EM spreads in the same direction -see Cunninham et al. (2001).

A widely preferred tool to examine the comovement of sovereign *spreads* is the cross-correlation coefficient. This is assumed to provide information on the speed, degree and direction of contagion. Even though this seems a very feasible measure for short term cross market dependencies, such indicator has at least two major criticisms: it does not take into account the apparent long-run relationship of these bonds and disregards the existence of risk premia.

Forbes and Rigobon (1999) argue, in fact, that such a measure often finds contagion where there is only interdependence. Contagion is not, in their view, the result of changing autocorrelations but it comes from changing volatilities. Baig and Goldfajn (2000) suggest in fact that excluding volatilities from the analysis may be wrong, since by definition contagion is the result of panic, margin calls, thin markets, etc., factors which are at the same time held responsible for changes in volatility.

In the view of all these EBM features, the aim of this paper is to examine and measure long term default risk contagion in Latin American sovereign markets. Default contagion is statistically defined as the existence of long run interdependence and, in particular, as the situation in which the perception of default risk in one sovereign country changes the perception of sovereign default risk of another.

We perform this task by proposing two new bivariate FIGARCH-in-Mean models to the literature that are motivated by the salient features of EBM. This new approach, in contrast with existing techniques to model contagion, allows to capture the observed persistency, the fractional comovement and risk premium of these markets simultaneously.

Although there have been results reporting the existence of comovement in these markets, there has not been an explicit modelling of the long term persistency and risk premia in Emerging Bond markets despite their potential influence on capital flows and fundamentals. The FIGARCH-in-Mean models here proposed overcome these weaknesses in the literature of contagion and provide to the applied econometric literature a new bivariate model.

Among the empirical findings we report a high degree of default risk contagion (interdependence) between Latin American bond markets. This finding is related to financial inflexibilities, microstructure effects and, in general, to herding behavior. We also find high degrees of persistency, i.e., long memory, strong evidence of fractional comovement and significant risk premiums.

The following section of the paper provides a descriptive analysis of the Emerging Market Bond Indexes (EMBI) of JP Morgan and renders the operative concepts of contagion used throughout.

The third section investigates the Long Memory properties in Latin American sovereign markets. The data shows evidence of short-term persistency and a battery of heuristic and semiparametric methods also suggest the existence of Long Memory. The first estimates of the Long Memory parameter as well as of the contagion parameter are provided.

Univariate Long Memory models and the econometric models of Teyssière (1997) and Brunetti and Christopher (2000) are described in detail in section four. Then, based on the salient features of Emerging Bond Markets, two new bivariate FIGARCH(1,d,1)-in-Mean specifications are proposed.

Quasi-Maximum Likelihood Estimation (QMLE) results are reported in section five. In addition to the discussion of the econometric performance of the new specifications, we argue about the existence of persistency, of common shocks driving the behavior of global markets, default risk contagion and risk premium.

Policy implications and the significance of our findings to the understanding of Sovereign Emerging Bond Markets are discussed in the conclusions.

2 Sovereign Emerging Bond Markets

Sovereign Emerging Bond Markets (EBM) have grown impressively since the first issuance of Brady bonds by Mexico in 1990, and have become one of the largest and most liquid international markets. Overall, the amount of outstanding debt, including Eurobonds up to the first quarter of 2002 summed to more than 300 US$ billion, 50 percent of which come from Latin American issues[4].

The usual suspects in every analysis of spillover and contagion, i.e., Argentina, Brazil, Mexico and more recently Venezuela, account for more than

[4] However, the composition of oustanding debt has changed very significantly in the past years. By the end of 2001 Merrill-Lynch reports that Brady bonds alone accounted for 39% of the original face, compared with more than 50% in the mid-nineties. They expect this trend to continue as a result of the retirement of Brady debt through exchanges, buybacks, calls, warrant exercises, defaults and subsequent restructuring and amortizations.

90% of market debt in Latin America and drive around 50 or 60% of most emerging market bond indices. The Brady debt alone issued by these countries to date sums more than 51 US$ billion.

Sovereign bond price dynamics is also of crucial importance given the direct and indirect influences on fundamentals. Default risks and their probabilities in emerging markets have been associated to capital flows, GDP, stock markets, good prices, exchange rates, interest rates and other policy variables (see Min (1998), Ferrucci (2003) and Fiess (2003) for instances).

In this section we analyze daily long term sovereign credit spreads as proxied by the Emerging Bond Market Indexes (EMBI) of JP Morgan for different Latin American countries and provide the working definition for contagion to be used throughout this paper.

2.1 Data Analysis

Figure 1 shows the spreads in logs for Brazil, Mexico and Venezuela from December 31^{st} 1990 to July 10^{th} 2002. The sample in Argentina begins on April 30, 1993 with the first issue of Brady Bonds. EMBI spreads provide a single measure of pure sovereign default risk of a given country and may be readily interpreted as excess returns over US treasuries. A relatively high spread may indicate a greater risk of default and also a lower return on risk-free investments.

Some authors have documented the high degree of cross correlation among EMBI spreads as well as a remarkable comovement, common trends and hence potential common shocks -see Mauro et al. (2000), Jostova (2002) and Fiess (2003). By considering the whole sample, individual time varying risk premiums are strongly suggested by the data and the relative premium between two given countries does not seem stable[5]. For this reason, the kinetics of these bonds should be analyzed together instead of country by country.

The first difference of the spreads in logs, i.e. s_t, is presented in Figure 2. By definition, changes in the spread can be interpreted as changes in *excess returns* over US treasuries. These changes reflect general emerging market prospects and hence the credit risk attached to emerging market assets -see Cunninham et al. (2001).

Periods of high volatility in these variables are mostly related to currency crisis in Latin America and other latitudes. For instance, the Tequila Crisis ignited immediately after the Peso devaluation in December 1994 affected, naturally the Mexican spread almost immediately. Bond prices of external debt in the rest of the countries responded to different degrees and duration

[5] This conjecture is in direct contrast with the analysis of Forbes and Rigobon (2000) who by analyzing a shorter sample and the difference between any two given spreads suggested a relatively constant risk premium as measured by the difference of two given spreads.

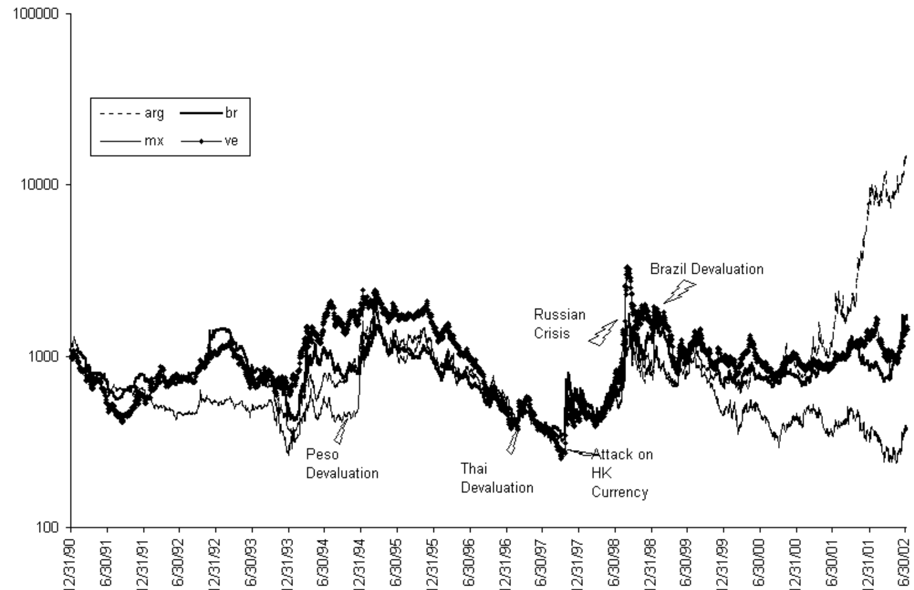

Figure 1: EMBI spreads in logs 31 Dec. 1990 - 30 Jun. 2002.

after the nominal devaluation as shown in the plots by the vertical lines. Even more interesting is to observe that there seems to be contagion following the crises in Hong Kong or Russia, countries with no significant direct trade links with Latin America[6].

Spread changes in these plots also show some of the common stylized facts of returns, namely, the presence of clusters and an apparent degree of short range dependence. There are potential high comovement and time varying volatility.

EMBI are foreign currency denominated instruments and hence the large spread changes in crisis periods may also reflect currency depreciations. Microstructure effects such as the result of transaction costs, asymmetric information and liquidity may also be important factors behind this behavior. Summary descriptive statistics of this data are presented in Table 1.

2.2 Defining Contagion

This paper adopts one the broadest definition of *contagion* in the literature that identifies it as any channel linking countries and causing markets to commove -see Forbes and Rigobon (2000). Although the possibility of

[6]By analyzing the cases of Brazil and Argentina, Beattie (2000) argues that the extent of contagion is a function of fiscal and monetary positions and financial integration in world capital markets.

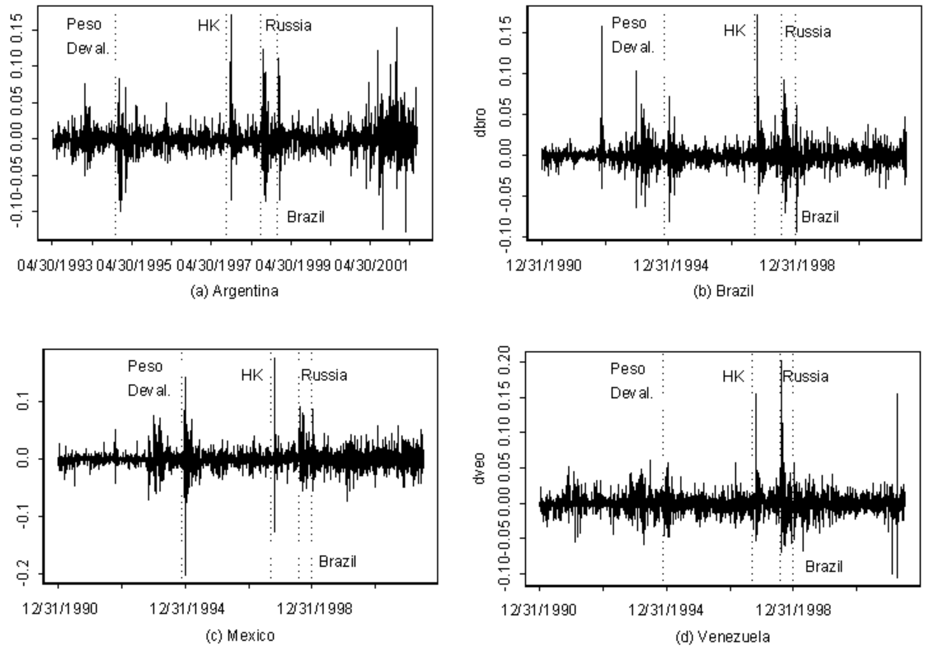

Figure 2: EMBI spread changes to July 10^{th} 2002.

trade links is admitted, the nature we assign to this type of contagion is mostly financial and rests on incomplete information, liquidity constraints and herding behavior.

There are of course alternative conventions and they have been well summarized by Edwards (2000) and Forbes and Rigobon (2000) among others. S*hift contagion*[7] for instance arises when there is a significant increase in cross market linkages after a shock to an individual country in the region; while *interdependence* arises if the transmission of a shock is a continuation of cross market linkages that exist during more tranquil periods that could, in addition, be explained by fundamentals.

Edwards (2000) has summarized as well the theoretical sources of contagion, namely multiple equilibria, incomplete information models and liquidity squeezes. The third of these sources suggest that in front of a difficult situation dedicated investors may decide to sell-off other securities in the same asset class, resulting in drastic declines in prices of countries originally unaffected by the crisis, even with strong fundamentals. This is because the assessment of risks is global; in periods of heightened risk aversion, investors

[7] This definition appears consistent with the one of Edwards (2000) who defines *residual contagion* as those situations where the extent and magnitude to which a shock is transmitted internationally exceeds what was expected *ex ante*.

would choose to retrench from emerging markets as a whole independently of particular fundamentals in local markets -see Hausler (2003).

Table 1: EMBI, descriptive statistics, daily spread changes $(s_t)^a$ in logs.

	$\overline{x}$	σ	S^b	K^c	JB^d	$Min.$	$Max.$	n	LB(20)^e
Argentina	0.0005	0.0188	0.8775	11.61	13,780	-0.1274	0.1709	2,398	67.61*
Brazil	0.0001	0.0130	1.9415	24.60	77,712	-0.0934	0.1725	3,007	96.25*
Mexico	-0.0002	0.0164	0.3330	18.95	45,041	-0.2031	0.1764	3,007	82.05*
Venezuela	0.0001	0.0147	1.7089	24.60	77,299	-0.1045	0.2020	3,007	101.69*

*Significant at the 1% level. ^{a} s_t=log(S_t)-log(S_{t-1}) where S_t is the EMBI spread; ^{b}Skewness; ^{c}Kurtosis; ^{d}Jarque-Bera statistic; ^{e}Ljung-Box Statistic, order in brackets.

Incomplete information and liquidity crunches are behind the type of contagion described by Eichengreen and Mody (1998), Calvo (1999) and Beattie (2000). Costly information generates the existence of informed and uninformed investors. Dedicated institutional investors are usually followed by uninformed investors who in addition may react more to news and market sentiment. During a local financial turmoil, margin calls may arise in which EM informed investors would have to resort most probably to big sell-offs of bonds of the same class in order to meet liquidity requirements[8]. The sell-off of bonds, say LA issues, would be carried out independently of how good and viable are the fundamentals. Beattie (2000) notices for instance that in the event of the Russian crisis, Brazilian government bonds (with a large EM share) were the obvious victims since they were one of the most viable options to meet liquidity needs. The massive sell-off may have falsely been interpreted as a deterioration of Brazilian credit by unsophisticated (uninformed) investors.

3 Detection of Long Memory in EM

Jostova (2002) has recently reported the presence of short term persistency in Emerging Bond Markets arising from financial rigidities, market operation procedures and the markets being not completely informationaly efficient. We conjecture that the sluggishness in the operation of EM may also result in long term persistency or Long Memory.

The study of the long memory in high frequency data can be traced to the study of Mandelbrot (1971) who considered the possibility of long range dependency in asset returns and more recently to Lo (1991), Ding and Granger (1996) and Baillie et al. (1996) who have studied long memory in levels and volatility for different assets. The presence of Long Memory

[8]Massive sell-offs of bonds are quite possible in Emerging Bond Markets. The minimun contract size of Brady bonds for instance is of the order of US$ 2 million.

in the volatility of sovereign EBM however has not as yet been examined in the literature[9].

The aim of this section is to fill this gap by examining the individual and joint long memory properties of Emerging Bond Market indexes in LA. We employ some heuristic procedures and then move to more formal parametric and semiparametric methods to test for long range dependency. The first estimations of the memory parameter in levels and volatility are also provided.

3.1 Auto & Cross Correlations (spillover)

Ding and Granger (1996) suggest that a time series shows long memory if the rate of decay of the estimated conditional variances seems hyperbolical rather than exponential. In their study they look for long memory in exchange rates and stock returns and find that this property is strongest when the power (d) -associated to the absolute value of such returns- is d=1/4 and d=3/4 respectively.

In Figure 3 we graphically analyze this property for the data described in section 2.1. We present the autocorrelation functions of the simple daily log differences (s_t) and of the absolute transformation ($|s_t|$) bounded by a 95% confidence interval[10]. We observe that in all cases s_t present an exponential decay rate (see lighter lines), they only have significant autocorrelations for the very first lags while the rate of convergence of the absolute transform is much lower (dark lines). Most of the countries present significant absolute value autocorrelations for more than one hundred lags and Brazil (panel b), has the first negative autocorrelation not before lag 350.

Despite the apparently different decay rates just reported, it is interesting to notice that all the EMBI pairs considered show a local minimum (significant or not) around lag 100. This would suggest that all four countries sustain a 'common degree' of long memory. This conjecture will be formally tested in the next sections.

As with ACF, cross correlograms suggest as well that simple return cross correlations decay exponentially while absolute values exhibit a hypergeometric decay rate.

The graphical examination suggests strong and significant long run volatility cross dependencies in the absolute value of spread changes see dark lines panels (a) and (b).

For ease of exposition, we examine in Figure 4 the linear cross correlation between the Brazilian and Mexican simple returns *i.e.* $\rho_{mx,br}$, -see light lines- and also between absolute returns, i.e. $\rho_{|brt,mxt-i|}$, -dark lines-[11]. Panels (a)

[9]The Long Memory properties of foreing exchange markets with Two Component GARCH models have been studied in another paper.

[10]Confidence intervals are depicted by the dotted lines and are calculated as $\frac{2}{\sqrt{T}}$.

[11]Given that the aim is to examine the joint long memory properties, we do not analyze

and (b) show the ACF up to lag 400, while panels (c) and (d) show a 60-day zoom of the cross correlations.

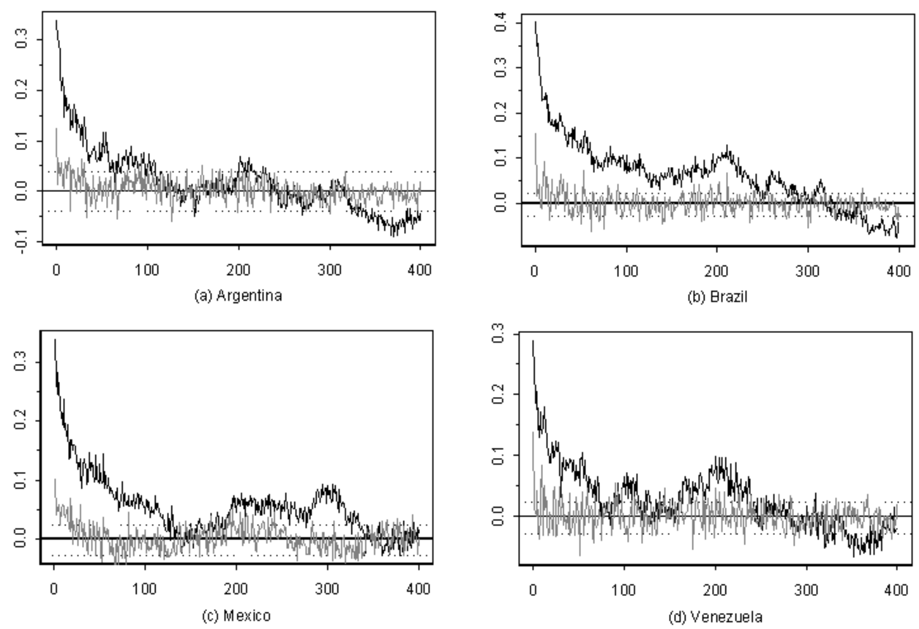

Figure 3: EMBI, Autocorrelation of $|s_t|$ and s_t from high to low, daily log differences 31 Dec. 1990 10 Jul. 2002.

With respect to the short run it is also observed that *contemporaneous* spread differences in Mexico are related to *past spread* lag differences in Brazil -see panel (c). There are significant positive cross correlations every 10 lags suggesting that past spread changes in Brazil would positively affect contemporaneous Mexican default risks -see panel (c). In the case where Brazil leads Mexico -see panel (d)-, the positive cross correlation is stronger and more regular. Daily past default risk increases (decreases) in Mexico would lead to contemporaneous increases (decreases) in the Brazilian spread changes. This pattern is valid at least for the first forty days before the cross autocorrelation function starts oscillating and loosing significance.

In Table 2 we present a summary of the cross long range dependence properties for the series under analysis. The first column shows the lead/lag relationships between the six pairs of countries as represented by the cross correlation coefficients $\rho_{1t,2t-i}$ and $\rho_{2t,1t-i}$. There is an equal contemporaneous response between countries only for the first lags and apparent asymmet-

other combinations further to save space. Results and details may be obtained from the author.

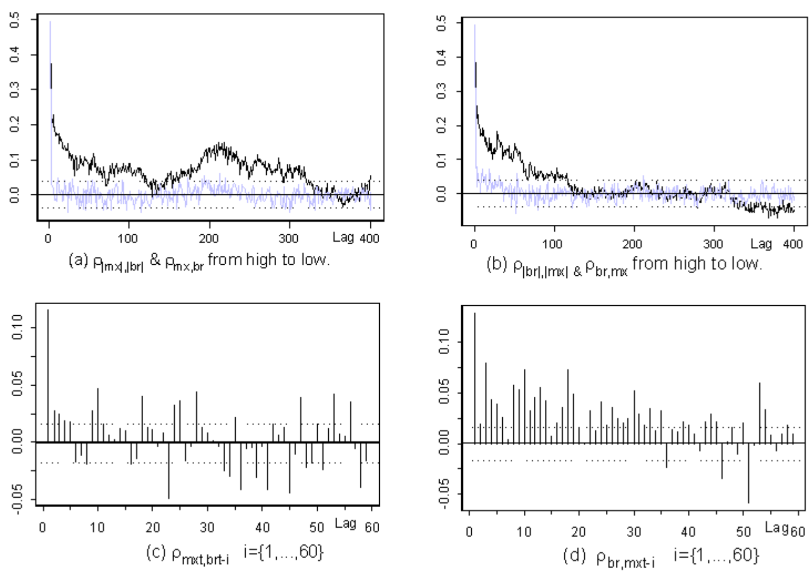

Figure 4: EMBI, Cross Correlogram Mexico vs. Brazil for $|s_t|$ and s_t.

ric impacts afterwards -see panels (a) and (b). Except for the pair Argentina Mexico, all countries show significant cross correlations at least until lag fifty.

We broadly define spillover as the impact of past volatility shocks to the current behavior of spread yields. A statistically significant cross correlation at time i will indicate spillover effects to the leading country. In the last column of Table 2 we show the point at which the last significant positive correlation before the first crossing of the axis takes place and label it as spillover. This measure will give interesting features of long range dependencies and also will reveal whether lead/lag relationships are really symmetric.

Volatility shocks originated three months before in Mexico or Brazil - see first two rows-, have significantly affected Argentina's contemporaneous default risk. Current default risks in Brazil or Mexico were accordingly affected by volatility shocks originated in Argentina approximately three months in the past.

There is a surprising symmetric lead-lag response in these countries: volatility shocks spread at similar rates from one country to another[12].

[12]Notice that this symmetric behavior cannot be confirmed for the pairs Mexico-Venezuela and Brazil-Venezuela.

Table 2: EMBI, cross correlation pairs at different lag values.

$lag(i)$	1	10	50	100	150	200	300	Neg.[a]	Spill[b]
Panel (a): $\boldsymbol{\rho}_{1t,2t-i}$									
$\rho_{art,brt-i}$	0.5864	0.1087	0.0232	0.0074	-0.0145	0.0526	-0.0077	65	55
$\rho_{art,mxt-i}$	0.5041	0.1341	0.0544	0.0000	-0.0441	-0.0013	0.0198	67	59
$\rho_{art,vet-i}$	0.4340	0.0688	0.0165	-0.0064	-0.0648	-0.0119	-0.0065	47	40
$\rho_{brt,mxt-i}$	0.4917	0.1702	0.1411	0.0559	0.02139	0.0265	0.0015	124	116
$\rho_{brt,vet-i}$	0.4862	0.1416	0.1218	0.0652	0.0516	0.0442	0.0118	158	151
$\rho_{mxt,vet-i}$	0.4204	0.1233	0.0669	0.0596	0.0242	0.0565	0.0638	139	130
Panel (b): $\boldsymbol{\rho}_{2t,1t-i}$									
$\rho_{brt,art-i}$	0.5864	0.0958	0.0412	0.0068	-0.0062	0.0015	0.0030	63	57
$\rho_{mxt,art-i}$	0.5041	0.1254	0.0469	0.0243	-0.0077	0.0125	0.0259	66	58
$\rho_{vet,art-i}$	0.4340	0.0579	0.0158	0.0193	-0.0009	0.0613	-0.0180	36	30
$\rho_{mxt,brt-i}$	0.4917	0.1734	0.0580	0.0679	0.0590	0.1319	0.0696	128	120
$\rho_{vet,brt-i}$	0.4862	0.1395	0.0840	0.0823	0.0613	0.1378	-0.0009	290	286
$\rho_{vet,mxt-i}$	0.4204	0.1157	0.0632	0.0424	0.0027	0.0549	-0.0105	80	70

[a] Lag at which the first negative value is observed. [b] Lag at which the autocorrelation function first crosses the horizontal axis. Note: Standard errors (x2) for pairs with Argentina 0.0417; all others 0.0365.

3.2 Semiparametric Estimates of Long Memory

So far we have graphically explored long memory in sovereign spread markets by fixing the power transform d to unity. In this section we present more formal methods for the detection of long range dependence and provide the first estimations of the memory parameter for EMBI. We analyze first the individual bond indexes and second a nonlinear combination of spreads to explore contagion (joint degrees of fractional integration).

3.2.1 Individual bond indexes[13]

In Table 3 we show for each country the first difference of default risks s_t, the absolute transform $|s_t|$ and squared differences s_t^2. These last two transforms have been widely used in the literature as proxies for the variance -see Ding and Granger (1996), Teyssière (1997) and Giraitis et al. (2003).

The first three rows show some of the latest tests for the detection of Long Memory[14]. The Modified Rescaled Range of Lo (1991) is presented in

[13] The following sections presume some knowledge of parametric and semiparametric methods in Long Memory analysis by the reader. The reader is reffered to the authors cited here and references therein.

[14] Lobato, the Rescaled Variance statistic and Rescaled Variance tests of long memory were programmed in S-PLUS. Lo's test as well as the Periodogram, Whitle and Local Whittle estimations were computed in the same software using Taqu's programs available on line. ARFIMA(0,1,0) estimations were performed in Ox 3.10 using the G@RCH module.

the first row (V_{LO}). In contrast with the traditional R/S test, Lo (1991) test takes into account potential short range dependencies and is more robust to many forms of weak dependence.

The statistic was calculated for a bandwidth $q = 9$[15]. In the case of simple log differences s_t, the null of no-long range dependence cannot be rejected for Brazil and Venezuela while it is rejected for Argentina and Mexico only at the 5 and 10% respectively. If we move to analyze our proxies of volatility $|s_t|$ and s_t^2, we confirm the existence of long memory in the volatility of default risks in emerging markets at the 1% level[16].

Lobato and Robinson (1998) have proposed a semiparametric test for $I(0)$ of a time series against fractional alternatives. As with the Whittle estimator below, semiparametric in this context refers to the lack of a parametric form of the spectrum in the neighborhood of the zero frequency. Under the null $I(0)$ this statistic has normal limit distribution.

We report Lobato and Robinson (1998), i.e., t_n, test statistic in the second row of the Table for a bandwidth of $m = n^{4/5}$ where n is the sample size[17]. In all s_t, $|s_t|$ and s_t^2 we are able to reject the null of $I(0)$ in favor of long memory[18]. The stronger rejection is again observed in the volatility proxies, it is convenient to notice that according to this test there is long memory (stationarity) in the simple first difference of sovereign spreads.

Our final test for long memory is based on the rescaled variance test (V/S) for stationarity recently proposed by Giraitis et al. (2002). The motivation of this test resides in the interesting debate about the existence of long memory in market data. The common findings of long range dependence in the absolute transformations and squared returns, including those of Ding and Granger (1996), and the claims of stationary ARCH models thus derived, appear spurious according to recent research. In fact, Giraitis et al. (2002) suggest that the finding of long memory in volatility may not indicate strong dependence but is more the result of some forms of nonstationarity like trends or changing parameters.

This statistic has been refined in Giraitis et al. (2002) to test for stationarity against deterministic trends and unit roots. Strikingly, using this new $T_q(\widehat{d})$ test they found that the absolute powers of the SP&500 -taken

[15]Note that this is the case for both $n = 3007$ and $n = 2398$, derived from $q = 4(n/100)^{0.25}$.

[16]Lo (1991) states that as q becomes large relative to the sample size n, the finite-sample distribution of the estimator can be radically different from its asymptotic limit, while if a small q is choosen it would not potentially take into account substantial autocovariances. We checked the sensitivity of this finding by exploring also $q = 5, 20$ and 40; in all cases the qualitative conclusions remain unaltered.

[17]We tried different values of m including $m = \{n^{3/5}, n^{2/5}\}$ and the results remain qualitatevely unchanged.

[18]When the hypothesis is rejected on the lower side of the distribution, evidence for *antipersistency* would be suggested. This phenoma may arise if a given series has been overdifferenced for instance.

as a prime example of a long memory time series- do not follow in reality a stationary model. This evidence adds up to the claims of "spurious long memory" reported by Lobato and Savin (1998) or Mikosch and Starica (2000) among others.

We present the $T_q(\widehat{d})$ test for *stationarity* with d unknown in the forth row of Table 3, where $\widehat{d}$ denotes the Whittle long memory estimator. Given that $T_q(\widehat{d})$ takes smaller values than the quantil $c_{5\%}(\widehat{d})$ and $c_{10\%}(\widehat{d})$ for all the cases considered[19], the results confirm the empirical finding of stationarity for spread changes (s_t) -see first column of each sovereign bond.

Interestingly, in contrast with the findings of Giraitis et al. (2002) for the SP&500, we do not find evidence to reject the hypothesis of stationarity with unknown d for the absolute and squared spread change values.

Overrall, the tests here considered find significant evidence for the existence of long range individual volatility dependencies in Latin American EBM.

We turn now to an a priori set of parametric and semiparametric estimations of the memory parameter.

The first long memory estimate (d_p) using the periodogram method[20] is presented in the second panel of Table 3. The fractional differencing parameter d' derived from an $ARFIMA(0, d\prime, 0)$ model is presented in the following row. The last two rows present the Whittle and Local Whittle estimators respectively.

It is hardly surprising to observe that the estimations for each bond index are very similar both in levels and in volatility. For instance, the memory parameter associated with s_t lies around $d \approx 1/5$, while it seems to be around $d \approx 1/2$ for the measures of volatility, i.e., $|s_t|$ and s_t^2 respectively. Volatility proxies show a longer memory than the simple log differences[21].

The striking similarity of the memory parameter between the countries, in line with the graphical analysis before, suggest that two given yield spreads may share common orders of long range dependence[22].

3.2.2 Interdependent Long Memory

It is as well possible that EBM not only share the same degree of long range dependence but also that there exists a long run nonlinear interdependent association that exhibits co-persistency. To explore such possibility, in the first three rows of Table 4 we present the tests for long memory using the

[19] Giraitis et al. (2002) provides the formulas to calculate the critical values at the 5 and 10% levels respectively:

$\mathrm{CV}_{5\%}{=}-1.98d^5 + .73d^4 - .05d^3 + .63d^2 - .66d + .19$

$\mathrm{CV}_{10\%}{=}-.27d^5 + .48d^4 - .55d^3 + .66d^2 - .53d + .14$

[20] For details of this and the following estimations the reader is refered to the Appendix.

[21] The reader may note that such finding seems independent of the sample size.

[22] The statistical theory and properties to perform such tests on semiparametric statistics has not been still developed.

Table 3: EMBI, tests for Long Memory and semiparametric estimates of d.

	Argentina			Brazil			Mexico			Venezuela		
	s_t	$\lvert s_t \rvert$	s_t^2	s_t	$\lvert s_t \rvert$	s_t^2	s_t	$\lvert s_t \rvert$	s_t^2	s_t	$\lvert s_t \rvert$	s_t^2
Tests For Long Memory												
V_{LO}^a	1.88*	2.32*	2.17*	1.15	3.07*	2.65*	1.82***	3.53*	2.47*	1.51	3.18*	2.79*
t_n^b	3.39*	41.52*	28.23*	2.32**	46.38*	30.55*	3.54*	46.65*	30.56*	1.66**	47.18*	32.04*
$T_q(0)^c$	0.14	0.14***	0.13	0.04	0.26**	0.18***	0.08	0.24**	0.13	0.07	0.31*	0.23**
${T_q}^d$	0.07	0.02	0.02	0.02	0.03	0.02	0.04	0.04	0.02	0.03	0.06	0.04
${c_{0.05}}^e$	0.13	0.07	0.06	0.13	0.06	0.06	0.13	0.07	0.06	0.14	0.08	0.08
${c_{0.010}}^e$	0.10	0.04	0.04	0.09	0.04	0.03	0.10	0.04	0.04	0.10	0.05	0.05
Long memory estimates												
$\widehat{d}_p^f$	0.21	0.39	0.39	0.18	0.48	0.43	0.26	0.41	0.37	0.16	0.38	0.38
$\widehat{d}_{arf}^g$	0.10	0.26	0.26	0.11	0.28	0.30	0.10	0.24	0.26	0.10	0.23	0.23
$\widehat{d}_W^h$	0.10	0.26	0.26	0.11	0.28	0.30	0.10	0.25	0.26	0.10	0.23	0.23
$\widehat{d}_{LW}^i$	0.10	0.24	0.26	0.11	0.26	0.28	0.10	0.24	0.25	0.09	0.22	0.22

$^{*}, ^{**}, ^{***}$ Denote significance at the 1, 5 and 10% levels respectively. ^{a} V_{LO} is de Modified Rescaled Range of Lo with confidence interval [0.8090,1.8620]; $^b t_n = -\frac{\sqrt{m}\widehat{C}_1}{\widehat{C}_0}$ is Lobato's test with C_1 and C_0 defined in Lobato and Robinson (1998). ^{c} The rescaled variance test $T(\widehat{d})$ reduces to V_{LO} when d=0. Ho:stationarity against long memory with critical values 0.2685, 0.1869, 0.1518 at the 1,5 and 10 % levels respectively. ^{d}The bandwidth parameter used for the estimations is $q=n^{0.5}$; ^{e}Critical va lues; ^{f} d_p periodogram estimation of d; ^{g}ARFIMA(0,1,0) estimation of the fractional differencing parameter; ^{h} d_W Whitle estimate; ^{i} d_{LW} Local Whittle estimate with bandwidth m=n/4.

absolute product transforms[23] $|s_{1t}s_{2t}|$. Preliminary estimates of the joint long memory parameter are given using Whittle and Local Whittle methods assuming that the true model is an $ARFIMA(0, d', 0)$ process.

As expected, the three methods provide strong statistical evidence for joint long range persistency. In particular, the *"acid"* $T_q(\widehat{d})$ test cannot reject the null of stationarity with unknown mean in favor of deterministic trends or unit roots.

If we rely in the estimation provided by the local Whittle estimator, the highest common long memory is reported by the combination Brazil-Mexico, while the lowest memory is reported by the pair Argentina-Brazil.

In addition to the extensive empirical findings suggesting that the variation in sovereign bond markets are substantially explained by a long run equilibrium relationship with themselves and with fundamentals -see Jostova (2002) and Ferrucci (2003)-, in this section we have identified an additional source from which shocks to EBM may be propagated. The long range own and cross dependencies are no doubt a highly stylized characteristic of

[23] A similar analysis was carried out for the absolut transform $|s_{1t}s_{2t}|^{0.5}$ and the squared product $s_{1t}^2 s_{2t}^2$ with the same basic qualitative conclusions.

sovereign bond markets.

Table 4: EMBI, tests for Long Memory and semiparametric estimates of the joint memory parameter for $|s_{1t}s_{2t}|$.

	$\|s_{art}s_{brt}\|^a$	$\|s_{art}s_{mxt}\|$	$\|s_{art}s_{vet}\|$	$\|s_{brt}s_{mxt}\|$	$\|s_{brt}s_{vet}\|$	$\|s_{mxt}s_{vet}\|$
V_{LO}^b	3.2017*	3.1252*	3.4714*	2.5614*	2.8749*	2.5001*
t_n	37.0855*	35.7835*	36.3970*	29.5235*	30.1306*	29.7365*
$T(0)$	0.3074*	0.2719*	0.3843*	0.2093**	0.2626**	0.2062**
$T(\widehat{d})$	0.0949	0.0633	0.1049	0.0222	0.0299	0.0276
$c_{0.05}(\widehat{d})$	0.1087	0.0930	0.1017	0.0547	0.0573	0.0642
$c_{0.10}(\widehat{d})$	0.0763	0.0642	0.0709	0.0339	0.0359	0.0415
d_W	0.1528	0.1818	0.1688	0.3022	0.2870	0.2682
d_{LW}	0.1427	0.1770	0.1576	0.2796	0.2715	0.2509

[a] $s_{art}s_{brt}$ stands for the combination Argentina-Brazil, $s_{art}s_{vet}$ stand for the pair Argentina-Venezuela. [b] For a definition of these tests see notes in Table 3.

4 Parametric long memory in volatility

The aim of this section is to develop an econometric model that is able to capture the salient characteristics of EBM: high persistency, fractional comovement and risk premiums.

To this end we first introduce the basic concepts of long memory in univariate time series analysis and then move to multivariate Generalized Autorregressive Conditional Heteroskedastik (ARCH) processes to propose, based on Teyssière (1997) and Brunetti and Christopher (2000) approaches, two new bivariate FIGARCH-in-Mean models.

4.1 Univariate FIGARCH

In this section, similar to the Autocorrelation analysis of the previous section, we will not restrict ourselves to the extreme Time Series case in which a shock remains significant for infinite time horizons, i.e., unit root case, or even to the case of a stationary process, where shocks die out exponentially. Instead we will explore the possibility of fractional orders of integration, that is, the situation in which shocks remain important for long time periods and the autocorrelation function decays hypergeometrically.

A Generalized Autorregressive Conditional Heteroskedastik (GARCH) behavior of the residuals ε_t may be expressed as

$$\varepsilon_t|\Omega_{t-1} = \eta_t\sqrt{h_t} \tag{1}$$

where η_t is an independent identically distributed (*i.i.d.*) random process with mean equal to zero and variance equal to unity. Notice that $E(\varepsilon_t|\Omega_{t-1}) = 0$ and $Var(\varepsilon_t|\Omega_{t-1}) = h_t$.

The most parsimonious construction for the conditional variance is given by the GARCH(1,1) model proposed by Bollerslev (1986):

$$h_t = w + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{2}$$

In this case, α is the volatility clustering parameter while β measures the impact of past conditional variances. Positivity, stability and stationarity conditions require that α, $\beta > 0$ and $\alpha + \beta < 1$. This sum is usually referred in the literature as the mean reverting parameter and is a measure of shock persistency.

Rearranging equation (2) we get the ARMA(1,1) representation for the squared residuals (ε^2):

$$\varepsilon_t^2(1-\phi) = w + (1-\beta L)v_t \tag{3}$$

where $\phi = (\alpha + \beta)$ and $v_t = \varepsilon^2 - h_t$.

In practice it is commonly found that ϕ is indistinguishable from unity. To take into account this regularity Engle and Bollerslev (1986) put forward the Integrated GARCH model (IGARCH):

$$\varepsilon_t^2(1-\phi)(1-L) = w + (1-\beta L)v_t \tag{4}$$

where L is the lag operator. In this formulation, a shock to the conditional variance remains significant for future horizons, it would not die out with time. The stationarity properties of this model are further examined by Nelson (1990) who points out that even though the IGARCH model is not covariance stationary, i.e., the volatility does not decay at a geometric rate, it is still strictly stationary and ergodic.

As Bollerslev and Mikkelsen (1996) remark, even though empirical estimates cannot often reject the null of integrated processes, intuition suggests that the volatility is in fact mean reverting. In fact, Baillie et al. (1996) notice that the knife-edge distinction between $I(0)$ and $I(d)$ processes can be far too restrictive. Moreover, the widespread finding of IGARCH may well be spurious and only due to misspecification. To overcome such possibility, Baillie et al. (1996) proposed the Fractionally Integrated Generalized Autorregressive Conditionally Heteroskedastik or FIGARCH class of processes for ε_t which is obtained from (4) by simply replacing the first differencing operator $(1-L)$ with the fractional differencing operator $(1-L)^d$, i.e.,

$$\varepsilon_t^2(1-\phi)(1-L)^d = w + (1-\beta L)v_t \tag{5}$$

This model reduces to a simple GARCH(1,1) process when $d = 0$ and to an IGARCH(1,1) process when $d = 1$. In the first case, shocks to the conditional variance decay at an exponential rate while in the second they remain important for forecasts of all horizons. In a FIGARCH process, shocks to the variance decay at a hyperbolic rate.

The fractional differencing operator has a binomial expansion more conveniently expressed in terms of the hypergeometric function:

$$\begin{aligned} (1-L)^d &= F(-d,1,1;L) \\ &= \sum_{k=0}^{\infty} \Gamma(k-d)\Gamma(k+1)^{-1}\Gamma(-d)^{-1}L^k \\ &= \sum_{k=0}^{\infty} \pi_k L^k \end{aligned} \tag{6}$$

An alternative $FIGARCH(1,d,1)$ expression in terms of the conditional variance, or infinite ARCH representation, is obtained by rearranging equation (5):

$$\begin{aligned} h_t &= \frac{w}{1-\beta(1)} + \left[1 - \frac{(1-\phi L)(1-L)^d)}{1-\beta L}\right]\varepsilon_t^2 \\ h_t &= \frac{w}{1-\beta(1)} + \lambda(L)\varepsilon_t^2 \end{aligned} \tag{7}$$

where $\lambda(L)$=$\lambda_1 L + \lambda_1 L + ...$ To ensure positiveness of the conditional variance all the coefficients in the infinite ARCH representation must be nonnegative. In particular, for the case of the $FIGARCH(1,d,1)$ process in equation (7) the conditions for the process to be well defined and positive are given by Baillie et al. (1996) and Bollerslev and Mikkelsen (1996). These can be observed if we re express the lag polynomial $\lambda(L)$ in (7) as

$$\begin{aligned} \lambda_1 &= \phi - \beta + d \\ \lambda_k &= \beta\lambda_{k-1} + \Big[(k-1-d)k^{-1} - \phi\Big]\,\delta_{k-1} \text{ for } k \geq 2 \\ \delta_k &\equiv \delta_{k-1}(k-1-d)k^{-1},\ k=2,3,... \end{aligned} \tag{8}$$

where δ_k are the coefficients in the Maclaurin's series expansion. From here Bollerslev and Mikkelsen (1996) show the following conditions which are sufficient to ensure that all corresponding ARCH parameters are all nonnegative:

$$\begin{aligned} \beta - d &\leq \phi \leq (2-d)/3 \\ d\,[\phi - (1-d)/2] &\leq \beta(\phi - \beta + d) \end{aligned} \tag{9}$$

Baillie et al. (1996) explain that for $0 < d \leq 1$ the hypergeometric function evaluated at $L = 1$ equals 0 so that $\lambda(1) = 1$, and for this reason the second moment of the unconditional distribution of ε_t is infinite, and the FIGARCH process is clearly not weakly stationary. However, by extending the properties of IGARCH processes Nelson (1990) and Bougerol and Picard (1992) show the FIGARCH process is still strictly stationary an ergodic.

4.2 Bivariate Fractional GARCH

By using the Bollerslev (1990) Constant Correlation model (CCC) the individual analysis of long memory can be fairly easy extended to a multivariate setting. Such parametrization assumes that the correlation matrix of the vector of residuals is constant while the conditional *variance-covariance* matrix (H_t) still varies:

$$H_t = diag(\sqrt{h_{11,t}}, ..., \sqrt{h_{NN,t}})\mathbf{R}diag(\sqrt{h_{11,t}}, ..., \sqrt{h_{NN,t}}) \tag{10}$$

$\mathbf{R}$ is the time invariant, positive definite, correlation matrix:

$$\mathbf{R} = \begin{bmatrix} 1 & ... & \rho_{1N} \\ ... & ... & ... \\ \rho_{N1} & ... & 1 \end{bmatrix} = \begin{bmatrix} 1 & ... & \frac{h_{1N,t}}{\sqrt{h_{11,t}}\sqrt{h_{NN,t}}} \\ ... & ... & ... \\ \frac{h_{N1,t}}{\sqrt{h_{NN,t}}\sqrt{h_{11,t}}} & ... & 1 \end{bmatrix} \tag{11}$$

In the bivariate case the CCC model reduces to

$$\begin{aligned} H_t &= \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} \\ \rho_{21} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} = \\ &= \begin{bmatrix} h_{11,t} & \rho\sqrt{h_{11,t}}\sqrt{h_{22,t}} \\ \rho\sqrt{h_{11,t}}\sqrt{h_{22,t}} & h_{22,t} \end{bmatrix} \end{aligned} \tag{12}$$

where $|\rho_{12}| < 1$ is the correlation coefficient. The individual conditional variances $h_{1,t}$, $h_{2,t}$ may be assumed to be simple univariate GARCH(1,1) processes as follows

$$\epsilon_t|_{t-1} \sim N(0, H_t), \qquad \{H_t\}_{ij} = h_{ij,t} \tag{13}$$

$$\begin{aligned} h_{ii,t} &= \omega_i + \alpha_{ii}\varepsilon^2_{i,t-1} + \beta_i h_{ii,t-1}; \text{ for } i = 1,2 \\ h_{12,t} &= \rho_{12}\sqrt{h_{11,t}}\sqrt{h_{22,t}}, \end{aligned} \tag{14}$$

To simultaneously model long range auto and cross dependencies Brunetti and Christopher (2000) assumed that the individual conditional variances follow a $FIGARCH(1,d,1)$ so that

$$\begin{aligned} h_{ii,t} &= \frac{\omega_i}{1-\beta_{ii}(1)} + \lambda_{ii}(L)\varepsilon_{i,t}^2;\ \text{for } i=1,2 \\ h_{12,t} &= \rho_{12}\sqrt{h_{11,t}}\sqrt{h_{22,t}}, \end{aligned} \tag{15}$$

where $\lambda_{ii}(L) = \left[1 - \frac{(1-\phi_{ii}L)(1-L)^{d_i}}{1-\beta_{ii}L}\right]$ and $i = 1, 2$.

In order for H_t to be positive definite it is required that $h_{11,t}$ and $h_{22,t}$ are positive and the conditional correlation matrix is positive definite. Bollerslev (1990) noticed that under the assumption of time invariant correlations, the Maximum Likelihood Estimate (MLE) of the correlation matrix is equal to the sample correlation matrix of the standardized residuals. Hence this is a parsimonious specification where positive definiteness of the variance covariance matrix is ensured if $|\rho|<1$, $\beta_{ii} - d_i \leq (1/3)(2-d_i)$ and $d_i[\phi_{ii} - 1/2(1-d_i)] \leq \beta_{ii}(\phi_{ii} - \beta_i + d_i)$. The conditional variance of the system is stationariy for all $0 \leq d_i \leq 1$ -see Brunetti and Christopher (2000).

Analogous to the individual representation in (5), Brunetti and Christopher (2000) present the CCC-FARIMA representation in terms of the squared residuals as

$$\Phi(L)\begin{pmatrix} (1-L)^{d_1} & 0 \\ 0 & (1-L)^{d_2} \end{pmatrix}\begin{pmatrix} \varepsilon_{1t}^2 \\ \varepsilon_{2t}^2 \end{pmatrix} = w + B(L)v_t \tag{16}$$

where $\Phi_0 = B_0 = I$. From this form, direct testing for common orders of long memory, i.e., $d_1 = d_2$, is possible.

In the context of contagion, a Constant Correlation assumption may be as well be too restrictive given the episodes of crises and seemingly structural changes in Emerging Markets during all the nineties. more importantly perhaps is that none of the parameters in (16) could be readily used to measure contagion[24].

In order to explore the possibility of time varying correlation Teyssière (1997) relaxed the constancy assumption by allowing the conditional covariance to be time varying and hence:

$$\begin{aligned} s_{1t} &= c_1 + \varepsilon_{1t} \\ s_{2t} &= c_2 + +\varepsilon_{2t} \end{aligned} \tag{17}$$

$$h_{ij} = w_{ij} + \left(1 - \frac{(1-\phi_{ij}L)(1-L)^{d_{ij}}}{1-\beta_{ij}L}\right)\varepsilon_{it-k}\varepsilon_{jt-k} \qquad i,j = 1,...,n$$

[24] Of course this could be generally circumvented by empolying a conventional impulse response analysis.

This extension will be useful to capture and test the presence of long range cross dependencies. In particular the parameter d_{12} in two given countries becomes our measure of contagion and degree of fractional comovement. As pointed out by Teyssière (1997) there is no analytical set of conditions for insuring positive definiteness of the conditional variance covariance so this has to be implemented numerically in the estimation procedure.

4.3 Bivariate Fractional GARCH-in-Mean process

To complete the analysis of emerging markets yield spreads it is necessary to examine whether a time varying risk premia drives the behavior of EMBI in Latin America. Our proxy for risk premium is given by the conditional second moments of these bond prices and our proposal for the parsimonious random walk case is presented below:

$$
\begin{aligned}
s_{1t} &= c_1 + \gamma_{11} h_{1t} + \gamma_{12} h_{2t} + \varepsilon_{1t} \\
s_{2t} &= c_2 + \gamma_{21} h_{1t} + \gamma_{22} h_{2t} + \varepsilon_{2t} \\
\begin{matrix} h_{1t} \\ h_{2t} \end{matrix} & \begin{matrix} = \\ = \end{matrix} \begin{matrix} \frac{w_1}{1-\beta_{11}L} \\ \frac{w_2}{1-\beta_{22}L} \end{matrix} + \begin{matrix} \left(1 - \frac{(1-\phi_{11}L)(1-L)^{d_1}}{1-\beta_{11}L}\right) \varepsilon_{1,t}^2 \\ \left(1 - \frac{(1-\phi_{22}L)(1-L)^{d_2}}{1-\beta_{22}L}\right) \varepsilon_{2,t}^2 \end{matrix} \\
h_{12,t} &= \rho_{12} \sqrt{h_{11,t}} \sqrt{h_{22,t}}
\end{aligned}
\tag{18}
$$

The key difference with other existing bivariate GARCH-M models is the inclusion of long memory in the conditional variances[25]. As an additional feature, in the empirical section we will not only employ the cross conditional variances (h_{1t} or h_{2t}) as regressors but also the conditional covariances, i.e., h_{12t}, in order to approximate the likely connection between yield spreads and other factors as in Baillie and Bollerslev (1990)[26].

Notice also that similar to Teyssière (1997) this model can easily be extended by relaxing the assumption of time invariant correlation in which case we would have an extra equation describing the behavior of the time varying conditional covariances and an estimate of d_{12} as follows:

$$
s_{1t} = c_1 + \gamma_{11} h_{1t} + \gamma_{12} h_{2t} + \varepsilon_{1t}
$$

[25] Kim (2000) for instance has used a multivariate CCC-GARCH(1,1)-M process similar to this specification to analyze monetary regimes and output volatility.

[26] Smith and Wickens (2002) have suggested that a proper measure of the risk premium in stochastic discount factor models should include the covariance of yield spreads with consumption and prices. Given the high frequency nature of the data, information on consumption and prices cannot be obtained for these countries. However if we assume that the paths of consumption and prices are relativelely smooth as in Baillie and Bollerslev (1990) it would be reasonable to expect that the influence of these variables is very small. These issues will be discussed further in the next section.

$$
\begin{aligned}
s_{2t} &= c_2 + \gamma_{21} h_{1t} + \gamma_{22} h_{2t} + \varepsilon_{2t} \\
h_{1t} &= \frac{w_1}{1-\beta_{11}L} + \left(1 - \frac{(1-\phi_{11}L)(1-L)^{d_1}}{1-\beta_{11}L}\right)\varepsilon_{1,t}^2 \\
h_{2t} &= \frac{w_2}{1-\beta_{22}L} + \left(1 - \frac{(1-\phi_{22}L)(1-L)^{d_2}}{1-\beta_{22}L}\right)\varepsilon_{2,t}^2 \\
h_{12t} &= \frac{w_{12}}{1-\beta_{12}L} + \left(1 - \frac{(1-\phi_{12}L)(1-L)^{d_{12}}}{1-\beta_{12}L}\right)\varepsilon_{1,t}\varepsilon_{2,t}
\end{aligned} \qquad (19)
$$

Hence, model (19) can also include cross conditional covariances in-Mean replacing individual variances. In this cases as well as in Teyssière (1997) model however, the positivity conditions have not been derived analytically and so they have to be numerically imposed during estimation.

Empirical findings for high frequency financial returns suggest in general that resulting innovations are usually non-normal and exhibit some degree of serial autocorrelation. To overcome such possibility in the estimation of these models we use the Quasi-Maximum Likelihood Estimation (QMLE) approach of Bollerslev and Wooldridge (1992)[27].

5 Estimation Results

Section three documented evidence for long range individual and cross dependencies in Sovereign Bond Markets in Latin America. Semiparametric estimation of the memory parameter however has been criticized -see Baillie (1996) for instance- due to the poor performance in terms of bias and mean squared error. To overcome this we now present the bivariate Fractional Integrated GARCH estimations of the memory parameter with the methods described in the previous section.

The proposed models will be able to capture the individual and cross long range dependencies found in EM and will allow direct tests of common orders of fractional integration, a very likely characteristic of these markets. In this context and by relaxing the Constant Correlation assumption we will be able to estimate the long range default risk contagion parameter, i.e., d_{12}.

By definition, EMBI indexes can be thought as excess returns over US treasuries. Spreads are usually regarded as the premium for holding defaultable sovereign instruments which in turn depend on the intrinsic credit risk of the economic conditions in a given emerging market[28]. Albeit the limi-

[27] For details on robusteness, consistency, ergodicity and asymptotic normality properties of the estimated parameters see Baillie et al. (1996).

[28] Apart from default risks, spreads should also reflect various other risks: exchange rate risk, interest rate risk and liquidity risk. Benczur (2001) notices that the first of these should be almost nil while liquidity risk is the result of market conditions, volatility components or assymetries. We implicitly include some of these factors in the individual conditional variances and left the interesting question of asymmetries for another study.

tations imposed by the high frequency nature of the data to capture more robust sources of risks, the model is finally extended to take into account an in-Mean time varying risk premium which is assumed to be a proportional function of the conditional variances and covariances of default risk changes.

5.1 Common long memory

Model selection tests[29] prefer random walk models for the mean equation and $FIGARCH(1, d, 1)$ process for the variance equation. To capture the seemingly long run comovement between sovereign markets, Table 5 reports the QML estimations of (15)[30], the bivariate Constant Correlation long memory model.

Credit risks as proxied by spreads are the reflection of the potential default of any country on its obligations. The individual conditional variances (h_{11} and h_{22}) in our model are in turn interpreted as individual *credit risk perceptions* of investors on a given country and their behavior is traced by all ϕ, β and d.

Even though it is common to use time varying cross correlations to assess the extent of comovement in EMBI, by fixing the measure of contagion over the whole sample period we assume, according to what has been reported in the literature[31], that long run linkages are time invariant and all source of volatility contagion would be due to the behavior of the individual conditional variances. The correlation coefficient is intended to capture the long run common responses to shocks and the potential for contagion or broadly speaking for comovement.

Not surprisingly perhaps, the highest degree of long term comovement in

[29] We tried different $FARIMA(p, d, q) - FIGARCH(1, d, 1)$ specifications and used the Log-likelihood value, Schwartz Information Criterion (SIC) and Akaike Information Criterion (AIC) to discriminate between models. As Teyssière (1997) points out, the statistical properties of the AIC and BIC have not been stablished for the class of long memory ARCH process, however we consider that they provide good reasonable guidance. They are calculated herein as:

$$AIC = -2ln(L(\widehat{\theta})) + 2 * n_\theta$$
$$SIC = -2ln(L(\widehat{\theta})) + n_\theta * \ln(n)$$

where $L(\widehat{\theta})$ is the maximized likelihood value, n_θ is the number of estimated parameters and n is the sample size.

[30] The initial estimation procedure was kindly provided by Celso Brunetti, University of Pennsylvania. The estimation strategy consisted in using starting values from univariate $FIGARCH(1, d, 1)$ models. Optimization problems were encountered in most of the estimations due to the presence of outliers, we decided to constrain atipical observations to be no greater than three standard deviations. The original samples of Argentina-Brazil and Argentina-Mexico converged satisfactorily without removing outliers. In all the estimations we used BFGS optimization algorithm although estimations via BHHH were very similar and usually less computer intensive.

[31] See Fiess (2003) and Mauro et al. (2000) for instance.

Table 5: EMBI, CCC-FIGARCH(1,d,1) QML estimations.

	s_{art}, s^{a}_{brt}	s_{art}, s_{mxt}	s_{art}, s_{vet}	s_{brt}, s_{mxt}	s_{brt}, s_{vet}	s_{mxt}, s_{vet}
Conditional Mean						
μ_1	-0.0427	-0.0479	-0.0418	-0.0174	-0.0267	-0.0402
.	(0.0227)	(0.0240)	(0.0247)	(0.0128)	(0.0132)	(0.0176)
μ_2	-0.0657	-0.0577	-0.0644	-0.0270	-0.0317	-0.0332
.	(0.0158)	(0.0224)	(0.0224)	(0.0169)	(0.0201)	(0.0202)
Conditional Variances						
ω_1	0.1428	0.1433	0.1318	0.0327	0.0374	0.0424
.	(0.0133)[b]	(0.0143)	(0.0245)	(0.0058)	(0.0059)	(0.0069)
β_1	0.4446	0.4878	0.2817	0.5004	0.5029	0.5451
.	(0.0229)	(0.0288)	(0.1019)	(0.0222)	(0.0212)	(0.0204)
ϕ_1	0.3162	02686	0.0897	0.2820	0.2886	0.3041
.	(0.0178)	(0.0201)	(0.0914)	(0.0149)	(0.0147)	(0.0160)
d_1	0.3675	0.4628	0.3371	0.4361	0.4229	0.3918
.	(0.0355)	(0.0402)	(0.0351)	(0.0298)	(0.0295)	(0.0319)
ω_2	0.0941	0.1363	0.1067	0.0506	0.1569	0.1433
.	(0.0173)	(0.0173)	(0.0231)	(0.0076)	(0.0204)	(0.0198)
β_2	0.2234	0.6218	0.4449	0.5469	0.3995	0.3915
.	(0.1196)	(0.0592)	(0.0318)	(0.0226)	(0.0243)	(0.0264)
ϕ_2	0.0615	0.1437	0.3509	0.2964	0.3826	0.3789
.	(0.1031)	(0.0381)	(0.0200)	(0.0172)	(0.0127)	(0.0133)
d_2	0.4296	0.6693	0.2981	0.4073	0.2348	0.2422
.	(0.0353)	(0.0716)	(0.0400)	(0.0343)	(0.0255)	(0.0267)
ρ_{12}	0.7155	0.6078	0.5998	0.5189	0.5624	0.4944
.	(0.0052)	(0.0074)	(0.0109)	(0.0099)	(0.0109)	(0.0108)

[a]For the definition of these pairs see footnotes at Table 4. [b]Robust standard errors in parathesis.

the samples is observed in Argentina-Brazil with 71.6 percent. The association of Argentina with Mexico and Venezuela follows with 60.8 and 59.9% respectively. The extent of comovement in the rest of the pairs is no less than 49 percent. Such high degree of integration suggests that investors may regard shocks as common or that there may be a common global financial factor driving default risks in the same direction.

We like to believe that this could also be the result of similar degrees of long memory. As we can observe in Table 5 and in line with the graphical inspection and semiparametric estimations shown in section three, the memory parameters -see d_1 and d_2 in each of column- do not seem to depart too much from each other.

We now formally test whether two given default risks share the same degree of long range dependence by re-estimating the bivariate $FIGARCH(1, d, 1)$

specifications imposing $d_1 = d_2$[32]. The last row of Panel (a) in Table 7 shows the optimized mean log-likelihood of these constrained models. Except for the cases Brazil-Venezuela and Mexico-Venezuela[33], a simple likelihood ratio cannot reject the hypothesis of common orders of fractional integration.

Despite both markets reporting independent volatility process, credit risk perceptions seem to be driven by a common information arrival process. This finding gives support to the view of Forbes and Rigobon (2000) for Latin American markets in the sense that volatility is not driven by any individual country or subset of countries, but it is instead shared by all countries in the region. These conclusions add to the propositions of Kaminsky and Reinhart (2002) suggesting that developed markets act as conduits between regions of developing countries. Price formation is market linked, default spreads are to a significant extent formed in the off-shore market independently of fundamentals.

5.2 Default risk contagion

In agreement with the graphical observation on previous sections, the results found above indicate that the duration of volatility shocks to LA Emerging Markets is very similar. We now resort to our broad definition of contagion to find out whether a shock originated in one given country shows long term spillover effects on a second market. We perform this by extending the above framework to consider the possibility of long range cross interdependencies.

The long term time invariant comovement assumption may seem far too restrictive given the number of crisis and financial turmoils observed in Latin America during the nineties. In fact, time varying cross correlations (contagion) have been found in stock and bond markets and have been reported in many studies of financial stability -see Hausler (2003) and Cunninham et al. (2001)-.

Thus, to take this fact into account, in Table 6 we relax such assumption and present the estimation results of the unrestricted bivariate $FIGARCH(1, d, 1)$ model introduced in equation (17) of section four.

As shown in the first two panels -(a) and (b)- of Table 7, in agreement with the findings of Teyssière (1997) and Teyssière (1998), in the six cases considered the value of the log-likelihood function increases strongly and selection criteria (AIC and SIC) overwhelmingly favor the unrestricted $FIGARCH(1, d, 1)$ model.

The conditional covariance (h_{12}) measures the *shared credit risk perception* associated to any two given markets. That is, the risk perceived by the investor for holding two bond instruments in the same class of quality and

[32]This can be directly done using Brunetti and Christopher (2000)'s framework. To save space we only show the maximized mean likelihood value, the estimation results of the restricted specifications are available upon request.

[33]This exceptions were graphically suggested in section three.

reputation. The joint long memory parameter, i.e., d_{12}, in this equation is of special interest. It indicates the extent of long term *default risk contagion* and, as shown, turns out highly significant in all cases[34].

We formally define *default risk contagion* as the situation in which the risk perception of default in one sovereign government or market affects the risk perception of default in another market with similar credit quality[35]. Notice that this definition allows for the possibility of contagion even in bonds issued by countries with different fundamentals but perhaps with the same investment ranking (credit risk), class or reputation.

The orders of individual fractional integration as well as their statistical significance do not seem to be affected by the relaxation of the time invariant correlation assumption. The hypothesis of common long range dependencies in Brady markets is examined once more. The optimized likelihood functions resulting from the imposition of $d_1 = d_2$ are presented in the forth of Panel (b) in Table 7 and are labeled $L(\theta)_{d_1=d_2}$. With the exception of the last two columns, once again we find that a common global financial factor seems to drive sovereign spreads in the same direction.

In section three, it was suggested that the decay rate of individual volatilities was different to that of the joint volatility measures. To test this hypothesis we re-estimate the model in equation (17) by imposing the restriction of common orders of fractional integration not only in the conditional variances but also in the conditional covariances, i.e., $d_1 = d_2 = d_{12}$. The row labeled $L(\theta)_{d_1=d_2=d_{12}}$ at the bottom Panel (b) in Table 7 shows the minimized mean log-likelihood of these estimations. The results show a strong rejection of the null indicating that even though countries may individually share the same type of long range dependencies, contagious shocks are propagated differently.

We believe that the extent of contagion measured here by d_{12} depends on the degree of global integration and financial openness of the country in question more than on a priori direct trade links or fundamentals. The highest parameter estimate observed in Mexico and Brazil for instance could hardly be the result of trade since these countries are far from being major trading partners. Market participants may perceive instead both bond spreads as derived from bonds with the same reputation in which case a volatility shock to one may affect the perception of default risk of the other.

In contrast with the literature suggesting that contagion may be explained by fundamentals, default risk contagion in sovereign markets seems to be importantly explained by global financial factors and market conditions. Crisis turmoils or shocks to volatility may spillover to other countries depending on microstructure effects, financial rigidities, weak and inade-

[34] Notice that d_{12} implicitly assumes that contagion is symmetric, fact which is in line with the graphical findings in section three.

[35] Definitions for credit contagion can be found in Avellaneda and Wu (2001) or Giesecke and Weber (2003).

quately supervised financial markets and herding behavior.

5.3 The risk premium

As we have mentioned before, another stylized fact of emerging bond markets is the existence of risk premia. Spreads reflect the compensation required by investors for holding defaultable bonds. The size and direction of the yield curve may give information not only on investors attitude to risks but also about expectations on potential defaults. A positive slope would indicate that default in the near term, as perceived by investors, is unlikely and viceversa. -see Cunninham et al. (2001)[36].

Forbes and Rigobon (2000) noticed that despite the individual high volatility associated with each spread, the differences in risk premium between any two given countries seem remarkably stable. Employing a rather standard and simplified asset pricing theory, we now examine first whether there is a time varying risk premium, as proxied by the conditional variances, and second whether it drives default risk changes in EM. To this aim, we extend the basic Constant Correlation and unrestricted FIGARCH(1,d,1) approaches proposed by Brunetti and Christopher (2000) and Teyssière (1997) respectively, to include in-Mean terms as described in equations (18) and (19)[37]. The results are presented in Tables 8 and 9.

As with the basic cases, i.e., the no in-Mean specifications reported in the last two sections, the optimized likelihood value increases strongly when the Constant Correlation assumption is relaxed. The unrestricted model, now with in-Mean terms, is strongly preferred over the time invariant correlation model -see likelihood value $L(\widehat{\theta})$ and SBC in Panels (c) and (d) of Table 7.

We now compare the results of both the CCC and the unrestricted in-Mean estimations. By looking at the decision criteria in Table 7 it is quite evident that the Likelihood value has improved, Schwartz criteria that penalizes for the inclusion of additional parameters strongly prefers the new specification with in-Mean process. The memory as well as the rest of the parameter estimates remain highly significant and the magnitudes do not seem to be affected importantly. As a matter of fact most of the estimates as well as their precision remain practically unchanged.

The results for the individual effect and significance of the in-Mean conditional variances in Table 9 is generally mixed among the different pairs

[36] We do not study in detail different maturities and hence a formal investigation of the yield curve is not performed.

[37] In addition to this specifications, we also considered the inclusion of two additional in mean functions: $g = \sqrt{H_t}$ and $g = \log(H_t\ )$. Preliminary results suggest that the conclussions that follow apply also to such specifications and the squared root transformations seem to perform better than simple in-mean effects.

considered. The statistical superiority[38] of this specification lead us to conclude that time varying risk premia in emerging bond markets jointly drives the behavior of excess returns in Emerging Bond Markets.

The estimations presented here show that increased perceptions of risk must be compensated by a higher risk premium. In good extent, the perception of risk by investors relates to the relative sentiment of improvement (or deterioration) in the bond market. The higher (reduced) willingness to bear certain risk would reflect the degree of investors risk aversion. Hence a given risk premium parameter reflects both risk and risk aversion and the greater the in-Mean coefficients the greater the risk perception and risk aversion for that particular market.

For instance, by looking at column three of Table 9 we note that Argentinean excess returns changes over US treasuries are significantly affected by the investors perception of risk in Venezuela (γ_{12}) as well as by investor's risk perceptions in Argentina (γ_{11}); Venezuelan spread returns in contrast are affected only by their own conditional volatility.

Interestingly, in the case of Brazil and Mexico -see forth column of Table 8-, spread changes are affected by the investors perception of risk in the second country (γ_{12} and γ_{12}) as well as by its own. Investors may require compensation for investing in Brazil equivalent to the parameter associated with the perception of risk in Mexico and viceversa. This finding would reinforce the claim that reputation and credit quality of these two countries have been regarded by investors as equivalent during the nineties.

The negative coefficients that appear in some cases would indicate not only that investors in EBM are risk loving but that credit risks, a reflection of debt repayment capacity, would be negative. These estimates are not statitisticaly significant in general[39].

The risk premia here obtained could also be interpreted as a broad (raw) estimation of the probability of default associated with a given spread. The lower the compensation required for holding a defaultable bond, the lower the implicit perception of credit risk for a given country and probability of default.

5.4 In-Mean shared default risk perceptions

The low significance of the in-Mean parameter estimates may reflect however, as pointed out by Eichengreen and Mody (1998), that risk premiums are incapable of adjusting to reflect changing economic conditions, news and to changes in other countries.

[38]The statistical performance of these new FIGARCH-in-Mean specifications with different functional forms are being investigated in continuing work. The models are also extended to consider the effect of assymetries in a bivariate FIEGARCH context.

[39]The only exception will be presented below in the combination Brazil-Venezuela where covariance in-mean terms are included.

Smith and Wickens (2002) suggest that conditional covariances with relevant macroeconomic factors would explain better the dynamics of risk premia. However, the high frequency nature of our measurements bounds our simplified asset pricing model to very few choices.

Consequently, we now proxy the risk premium by the conditional covariance. The estimations of equation (19) with the conditional covariance and variance in-Mean terms are shown in Table 10 -see coefficients γ_{11}, γ_{12}, γ_{21} and γ_{22}.

An interesting implication of these estimates is that increased default risks affect the shared risk perception in the first place and secondly, via in-Mean impacts, the actual expected changes in excess returns of a second country.

The shared perception of risk between Argentina and Brazil for instance significantly predicts Brazilian excess returns over US treasuries, while the individual risk perception of this country (γ_{22}) does not[40].

Interestingly, some of the negative in-Mean coefficients reported in the previous subsection are now statistically significant such as the in-Mean effect (γ_{11}) in the penultimate column, indicating that emerging market investors overall had a higher willingness to bear the risk of investing in Brazil. The risk premium in this case would reflect the effect of risk perception as well as a risk loving behavior.

6 Conclusions and discussion

The aim of this paper has been to examine and measure default risk contagion in Latin American sovereign markets based on three salient features of Emerging Markets: a high degree of volatility persistency, the existence of risk premiums and a high comovement between spread changes. In contrast with the current literature measuring contagion[41] the here-proposed bivariate $FIGARCH(1, d, 1)$ models are able to capture these hallmarks simultaneously while allowing direct testing on the contagion parameter.

Default risk contagion is defined as the situation in which the risk perception of default in one sovereign government affects the risk perception of default in another market with similar credit risk. We presume that the nature of this contagion is global, based on informationaly inefficient and incomplete markets, and resulting from the herding type of behavior described by Calvo (1999), where fundamentals turn to be insufficient to explain contagion.

[40] We have to be cautious about the conclusion drawn from this last estimation since the optimized likelihod value is at best the same as the those from Table 9. The only case in which there is a clear preference for covariance in-mean terms is in Argentina-Brazil.

[41] See Forbes and Rigobon (1999) who have proposed an adjusted correlation coefficient and Edwards and Susmel (2001) that employ a Switching GARCH model to measure volatility dependence for instance.

We conjecture that the extent and severity of long term contagion is an increasing function, not only of the soundness of local economic policies and investment exposures, but also of the degree of global financial integration and openness of a given country. It is not surprising to note in the view of this argument, abstracting from the risk premia, that the highest degree of interdependence (d_{12}) is shown by Brazil and Mexico, countries that have pursued economic policies consistent with a greater global integration. In contrast, the lowest degree of interdependence is shown by Argentina and Venezuela.

The finding of long term persistency in Emerging Markets is explained, in agreement with Jostova (2002), as the result of financial market rigidities and informational deficiencies. Portfolio re-allocation after a sudden liquidity crunch is not automatic or immediate due to the way institutional investors operate in Emerging Bond Markets and the lack of 'noise traders' among other factors. Dedicated investors react more slowly to market signals since they pursue returns relative to a benchmark. We report empirical evidence indicating that the degrees of persistency are high and not statistically different from country to country.

A potential implication of this result is that local policies oriented at constraining the effect of crises -capital controls, etc.- may only be of temporary use given the existence of more long term linkages in Emerging Bond Markets. Short-run isolation strategies would be costly and only delay a country's adjustment to equilibrium. This conclusion is in line with the arguments of Forbes and Rigobon (2000).

The results also suggest a high degree of fractional comovement in these markets. This outcome reinforces the claims of Mauro et al. (2000), Fiess (2003) and Cunninham et al. (2001) who report strong comovement between spreads themselves and with fundamentals. We interpret this result, along with the one on common persistence, as additional evidence supporting the claim that a single factor seems to be driving EM spreads in the same direction. Episodes of contagion have had a common base of transmission being either Brady markets (Baig and Goldfajn (2000)) or any other developed financial market acting as the conduit between regions of developing markets (Kaminsky and Reinhart (2002)). The rate of decay of the fractional comovement parameter (d_{12}) is nonetheless lower than the individual parameters of volatility persistency, i.e., d_i with $i = [1, 2]$ respectively. The long term sovereign default contagion reported here means that a sudden liquidity crunch, derived perhaps from margin calls, would affect the spread in third countries not only contemporaneously but also in the foreseeable future.

In addition, there has been evidence for instance suggesting that precarious derivative positions from Asian and Russian investments forced investors to sell viable Latin American bonds to service margin calls[42]. Hence in line with this view, our results also support the promotion and a better use of OTC derivative markets[43] which, we expect, will hedge and ultlimately extenuate the effects of liquidity squeezes to third countries. Accordingly, given the high degree of global integration and the existence of long term market linkages (that may in addition be possibly magnified during crisis turmoils), our results advocate for a more integrated and comprehensive supervision of Emerging Bond Markets[44].

We also report the existence of a time varying risk premium. This may be the result of changing risks attached to a given emerging bond or changing degrees of investors risk aversion, or both. Moreover, risk premiums seem to significantly explain default risk changes in Emerging Markets. For instance, Argentinian sovereign returns over US treasuries have been affected during the nineties by investors' perceptions of risk in Brazil, Mexico and Venezuela. Brazilian sovereign returns, in turn, have been affected by the risk aversion that investors attached to Mexico and Venezuela, while in contrast, Mexican and Venezuelan sovereign returns seem to have been somehow isolated from the perceptions of risk developed in other Latin American markets.

The high volatility and turmoils experienced in Latin American markets during the nineties suggest obviously that default risks and risk premium may have changed to different levels in response to the Russian, Brazilian or more recently the Argentinean crisis. This is being dealt in continuing research adopting a shift contagion definition. The aim of this paper has been to document the existence of long range time dependencies, fractional comovement and a time varying risk premium in Emerging Bond Markets using the broadest definition of contagion available in the literature.

On the other side, given the lack of systemic instruments and strong legal frameworks for dealing with global crises, a comprehensive structural reform of the international financial system has been recently promoted by Calvo (2002) and the International Monetary Fund (IMF). The first of these views considers that contagion is the result of imperfect information and one way of stopping it would be to make a credible announcement that some global institution will stand ready to buy bonds from the other emerging markets in order to prevent a collapse in prices and, in the end, stabilize an Emerging Market Index like the EMBI+. Calvo (2002) proposes the creation of an Emerging Market Fund (EMF) endowed with G3 debt instruments to

[42] See Beattie (2000).

[43] It may be of interest for dedicated investors to observe that due to the presence of long memory traditional hedging may become unreliable. Derivative pricing techniques rely on martingale methods which are inconsistent with long range dependencies. Hence new pricing methods or adjustments are needed to take into account this finding.

[44] The Emerging Bond Market, as it has been working since 1990, is not fromally regulated. There is however a self policing structure with a non-binding code of conduct issued by the Emerging Markets Trading Association. There is no participation of regulators of the issuing countries whatsoever.

prevent contagion, to back potential meltdowns and to pump liquidity into the market to prevent liquidity crises that may affect fundamentals[45].

The IMF Sovereign Debt Restructuring Mechanism (SDRM)[46] aims on the other side at providing an orderly restructuring of sovereign debt. It works, according to the factsheet, on the prevention and on the crisis management efforts undertaken in response to the global market turmoil in the late 1990's. The focus are the actual creditors and debtor countries.

Overall, in the light of our findings, we believe in one side that regulation is indeed required to help in the restructuring of Sovereign Emerging Market debt, but firm steps are also needed to consolidate supervision and preventive measures such as hedging or the creation of a fund to back liquidity squeezes. A critical issue would be, if we believe in the herding behavior hypothesis, the institutionalized provision of quality information for market participants about Emerging Market countries, not because it is costly to gather by individual dedicated investors, but to prevent uninformed investors join the massive sell-offs of bonds by falsely interpreting them as indication of poor credit in Emerging Markets.

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[45] The aim of this EMF is preventive while the Contigent Credit Line of the IMF and the Lerrick-Meltzer proposal, that the IMF should stand ready to buy a country's debt at a large discount, aim at the epicenter of a crisis. For more details the reader is referred to Calvo (2002) and references therein.

[46] See factsheet at http://www.imf.org/external/np/exr/facts/sdrm.htm

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Table 6: EMBI, unrestricted FIGARCH(1,d,1) QML estimations.

	s_{art}, s_{brt}^{a}	s_{art}, s_{mxt}	s_{art}, s_{vet}	s_{brt}, s_{mxt}	s_{brt}, s_{vet}	s_{mxt}, s_{vet}
Conditional Mean						
μ_1	-0.0475	-0.0552	-0.0348	-0.0223	-0.0183	-0.0415
.	(0.0250)	(0.0250)	(0.0251)	(0.0134)	(0.0133)	(0.0176)
μ_2	-0.0572	-0.0481	-0.0569	-0.0309	-0.0316	-0.0372
.	(0.0189)	(0.0250)	(0.0231)	(0.0170)	(0.0191)	(0.0202)
Conditional Variances						
ω_1	0.1133	0.1769	0.1549	0.0228	0.0223	0.0404
.	(0.0112)	(0.0272)	(0.0269)	(0.0134)	(0.0050)	(0.0068)
β_1	0.4784	0.3588	0.2684	0.5063	0.5204	0.5483
.	(0.0138)	(0.0807)	(0.0894)	(0.0603)	(0.0189)	(0.0176)
ϕ_1	0.3230	0.1809	0.0928	0.2946	0.3071	0.3121
.	(0.0122)	(0.0703)	(0.0835)	(0.0581)	(0.0125)	(0.0136)
d_1	0.3539	0.3900	0.3019	0.3788	0.3858	0.3759
.	(0.0245)	(0.0310)	(0.0268)	(0.0262)	(0.0251)	(0.0272)
ω_2	0.0748	0.1947	0.0972	0.0431	0.1007	0.1234
.	(0.0131)	(0.0286)	(0.0188)	(0.0073)	(0.0149)	(0.0182)
β_2	0.1886	0.3424	0.4818	0.5456	0.4624	0.4395
.	(0.0539)	(0.0733)	(0.0253)	(0.0202)	(0.0215)	(0.0224)
ϕ_2	0.0011	0.1454	0.3483	0.3018	0.3635	0.3768
.	(0.0446)	(0.0601)	(0.0169)	(0.0152)	(0.0129)	(0.0123)
d_2	0.3441	0.4020	0.3034	0.3965	0.2729	0.2463
.	(0.0232)	(0.0330)	(0.0338)	(0.0304)	(0.0258)	(0.0245)
Conditional Covariance						
ω_{12}	0.0573	0.1282	0.0837	0.0149	0.0201	0.0369
.	(0.0093)	(0.0181)	(0.0191)	(0.0052)	(0.0061)	(0.0096)
β_{12}	0.3599	0.3842	0.4348	0.2976	0.5134	0.5215
.	(0.0299)	(0.0677)	(0.0650)	(0.0199)	(0.0168)	(0.0169)
ϕ_{12}	0.1971	0.2311	0.2819	0.3055	0.3576	0.3780
.	(0.0310)	(0.0666)	(0.0626)	(0.0408)	(0.0110)	(0.0116)
d_{12}	0.3599	0.3391	0.2582	0.4989	0.2848	0.2439
.	(0.0299)	(0.0260)	(0.0249)	(0.0448)	(0.0220)	(0.0233)

[a] See notes in Table 5.

Table 7: EMBI, Decision Criteria FIGARCH(1,d,1) estimations.

	s_{art}, s_{brt}^a	s_{art}, s_{mxt}	s_{art}, s_{vet}	s_{brt}, s_{mxt}	s_{brt}, s_{vet}	s_{mxt}, s_{vet}
Panel (a): $CCC-FIGARCH(1,d,1)$						
$L(\theta)^b$	-4,911.3	-5,989.1	-5,361.4	-5,624.1	-5,391.9	-6,389.3
AIC[c]	9,844.6	12,000.3	10,744.7	11,270.3	10,805.9	12,800.7
SBC[d]	9,908.2	12,063.8	10,808.4	11,336.3	10,871.9	12,866.7
$L(\theta)^e_{d_1=d_2}$	-4,911.9	-5,991.3	-5,361.6	-5,624.3	-5,397.9	-6393.9
Panel (b): *Unrestricted FIGARCH(1,d,1)*						
$L(\theta)$	-4,737.7	-5,794.5	-5,268.4	-5,524.4	-5,300.8	-6,342.7
AIC	9,503.5	11,617.0	10,564.8	11,076.8	10,629.6	12,713.4
SBC	9,584.4	11,697.9	10,645.8	11,160.9	10,713.7	12,797.5
$L(\theta)_{d_1=d_2}$	-4,737.9	-5,794.5	-5,268.4	-5,524.5	-5,304.5	-6,347.8
$L(\theta)_{d_1=d_2=d_{12}}$	-4,610.3	-5,840.3	-5,275.3	-5,540.1	-5,309.4	-6,357.1
Panel (c): *CCC-FIGARCH(1,d,1) Variance in-Mean*						
$L(\theta)$	-4,906.0	-5,982.5	-5,564.7	-5,619.9	-5,386.4	-6,648.6
AIC	9,842.0	11,995.0	11,159.4	11,269.9	10,802.7	13,327.2
SBC	9,928.7	12,081.7	11,246.1	11,359.9	10,892.9	13,417.3
Panel (d): *Unrestricted-FIGARCH(1,d,1) Variance in-Mean*						
$L(\theta)$	-4,731.0	-5,786.4	-5,260.2	-5,519.1	-5,297.6	-6,339.5
AIC	9,498.1	11,608.8	10,556.5	11,074.2	10,631.2	12,715.0
SBC	9,602.1	11,712.9	10,660.5	11,182.4	10,739.4	12,823.2
Panel (e): *Unrestricted-FIGARCH(1,d,1) Covariance in-Mean*						
$L((\theta)$	-4,729.3	-5,787.4	-5,261.9	-5,522.4	-5,297.5	-6,339.9
AIC	9,495.2	11,610.8	10,559.9	11,080.9	10,630.5	12,715.7
SBC	9,598.7	11,714.9	10,663.9	11,188.9	10,739.2	12,823.9

[a]See Table 4 for these definitions. [b]Maximized Log likelihood. [c]Akaike Information Criteria. [d]Schwartz Bayesian Criteria. [e]L(.) is the maximized likelyhood function of the restricted model. The sub-index indicates the type of restriction.

Table 8: EMBI CCC-FIGARCH(1,d,1) Variance-in-Mean QML estimations[a].

	s_{art}, s_{brt}	s_{art}, s_{mxt}	s_{art}, s_{vet}	s_{brt}, s_{mxt}	s_{brt}, s_{vet}	s_{mxt}, s_{vet}
Conditional Mean						
μ_1	-0.0963	-0.1320	-0.1336	-0.0429	-0.0849	-0.0655
.	(0.0277)	(0.0305)	(0.0283)	(0.0173)	(0.0179)	(0.0211)
μ_2	-0.1057	-0.0917	-0.1162	-0.0473	-0.1131	-0.0698
.	(0.0184)	(0.0299)	(0.0273)	(0.0233)	(0.0328)	(0.0252)
γ_{11}	0.0283	0.0289	0.0294	-0.0234	-0.0137	0.0082
.	(0.0143)	(0.0165)	(0.0139)	(0.0288)	(0.0252)	(0.00147)
γ_{12}	0.0176	0.0205	0.0321	0.0293	0.0547	0.0139
.	(0.0115)	(0.0127)	(0.0071)	(0.0142)	(0.0140)	(0.0071)
γ_{21}	0.0010	0.0025	-0.0004	0.0349	0.0009	0.0037
.	(0.0049)	(0.0068)	(0.0051)	(0.0278)	(0.0258)	(0.0097)
γ_{22}	0.0519	0.0203	0.0487	-0.0106	0.0644	0.0289
.	(0.0189)	(0.0164)	(0.0167)	(0.0227)	(0.0315)	(0.0186)
Conditional Variances						
ω_1	0.1426	-0.0917	0.1236	0.0327	0.0363	0.0591
.	(0.0134)	(0.0299)	(0.0124)	(0.0058)	(0.0058)	(0.0081)
β_1	0.4420	0.4741	0.4415	0.5002	0.4972	0.5041
.	(0.0233)	(0.0755)	(0.0245)	(0.0220)	(0.0213)	(0.0528)
ϕ_1	0.3183	0.2586	0.3132	0.2858	0.2981	0.2749
.	(0.0183)	(0.0589)	(0.0187)	(0.0147)	(0.0143)	(0.0464)
d_1	0.3634	0.4599	0.3736	0.4284	0.4037	0.4429
.	(0.0366)	(0.0458)	(0.0373)	(0.0294)	(0.0286)	(0.0346)
ω_2	0.0929	0.1379	0.1653	0.0513	0.1567	0.1813
.	(0.0179)	(0.0177)	(0.0218)	(0.0076)	(0.0207)	(0.0177)
β_2	0.2093	0.6167	0.3278	0.5442	0.3976	0.2958
.	(0.1279)	(0.0597)	(0.0287)	(0.0229)	(0.0239)	(0.0242)
ϕ_2	0.0593	0.1399	0.3338	0.2968	0.3854	0.3561
.	(0.1115)	(0.0377)	(0.0168)	(0.0176)	(0.0125)	(0.0131)
d_2	0.4169	0.6631	0.3324	0.4064	0.2293	0.2879
.	(0.0349)	(0.0715)	(0.0337)	(0.0351)	(0.0249)	(0.0262)
ρ_{12}	0.7154	0.6088	0.5943	0.5198	0.5627	0.4982
.	(0.0053)	(0.0080)	(0.0089)	(0.0099)	(0.0108)	(0.0101)

[a] See notes in Table 5.

Table 9: EMBI unrestricted FIGARCH(1,d,1) Variance-in-Mean QML estimations[a].

	s_{art}, s_{brt}	s_{art}, s_{mxt}	s_{art}, s_{vet}	s_{brt}, s_{mxt}	s_{brt}, s_{vet}	s_{mxt}, s_{vet}
Conditional Mean						
μ_1	-0.1063	-0.1556	-0.1712	-0.0598	-0.0652	-0.0759
.	(0.0307)	(0.0317)	(0.0400)	(0.0213)	(0.0196)	(0.0267)
μ_2	-0.1169	-0.1115	-0.1832	-0.0605	-0.0920	-0.1165
.	(0.0234)	(0.0329)	(0.0387)	(0.0268)	(0.0303)	(0.0339)
γ_{11}	0.0249	0.0294	0.0479	-0.0139	-0.0084	0.0163
.	(0.0153)	(0.0154)	(0.0218)	(0.0298)	(0.0254)	(0.0211)
γ_{12}	0.0262	0.0273	0.0472	0.0338	0.0429	0.0136
.	(0.0197)	(0.0121)	(0.0286)	(0.0149)	(0.0170)	(0.0231)
γ_{21}	0.0013	-0.0001	0.0149	0.0439	0.0102	0.0139
.	(0.0062)	(0.0083)	(0.0127)	(0.0308)	(0.0274)	(0.0168)
γ_{22}	0.0656	0.0479	0.0779	-0.0087	0.0405	0.0502
.	(0.0184)	(0.0366)	(0.0271)	(0.0230)	(0.0304)	(0.0292)
Conditional variances						
ω_1	0.1116	0.1709	0.1490	0.0243	0.0227	0.0408
.	(0.0111)	(0.0262)	(0.0269)	(0.0089)	(0.0050)	(0.0068)
β_1	0.4788	0.3639	0.2550	0.4872	0.5186	0.5479
.	(0.0140)	(0.0839)	(0.0947)	(0.0809)	(0.0189)	(0.0178)
ϕ_1	0.3237	0.1883	0.0847	0.2812	0.3114	0.3127
.	(0.0125)	(0.0728)	(0.0878)	(0.0740)	(0.0125)	(0.0140)
d_1	0.3526	0.3884	0.2939	0.3685	0.3772	0.3746
.	(0.0250)	(0.0323)	(0.0269)	(0.0354)	(0.0249)	(0.0281)
ω_2	0.0703	0.1832	0.0908	0.0436	0.0991	0.1191
.	(0.0127)	(0.0276)	(0.0192)	(0.0114)	(0.0150)	(0.0183)
β_2	0.1984	0.3638	0.4811	0.5433	0.4632	0.4436
.	(0.0538)	(0.0693)	(0.0243)	(0.0242)	(0.0211)	(0.0222)
ϕ_2	0.0146	0.1649	0.3535	0.3016	0.3644	0.3774
.	(0.0453)	(0.0571)	(0.0163)	(0.0173)	(0.0128)	(0.0122)
d_2	0.3393	0.3992	0.2930	0.3965	0.2713	0.2451
.	(0.0237)	(0.0339)	(0.0326)	(0.0346)	(0.0256)	(0.0244)
Conditional Covariance						
ω_{12}	0.0555	0.1152	0.0785	0.0162	0.0205	0.0370
.	(0.0086)	(0.0165)	(0.0191)	(0.0081)	(0.0061)	(0.0096)
β_{12}	0.3618	0.4258	0.4308	0.4850	0.5123	0.5215
.	(0.0301)	(0.0614)	(0.0692)	(0.0596)	(0.0168)	(0.0168)
ϕ_{12}	0.1998	0.2687	0.2855	0.2921	0.3597	0.3789
.	(0.0319)	(0.0628)	(0.0668)	(0.0536)	(0.0110)	(0.0117)
d_{12}	0.3072	0.3419	0.2502	0.2952	0.2807	0.2422
.	(0.0194)	(0.0268)	(0.0245)	(0.0260)	(0.0219)	(0.0234)

[a]See notes in Table 5.

Table 10: EMBI, unrestricted bivariate FIGARCH(1,d,1) covariance-in-Mean QML estimations[a].

	s_{art}, s_{brt}	s_{art}, s_{mxt}	s_{art}, s_{vet}	s_{brt}, s_{mxt}	s_{brt}, s_{vet}	s_{mxt}, s_{vet}
Conditional Mean						
μ_1	-0.1188	-0.1424	-0.1381	-0.0390	-0.0368	-0.0638
.	(0.0306)	(0.0312)	(0.0378)	(0.0197)	(0.0173)	(0.0244)
μ_2	-0.1222	-0.0939	-0.1549	-0.0382	-0.0863	-0.1095
.	(0.0231)	(0.0322)	(0.0368)	(0.0253)	(0.0305)	(0.0329)
γ_{11}	0.0450	0.0457	0.0409	-0.0303	-0.0777	0.0010
.	(0.0219)	(0.0187)	(0.0255)	(0.0398)	(0.0429)	(0.0288)
γ_{12}	0.0080	0.0137	0.0543	0.0775	0.1499	0.0425
.	(0.0355)	(0.0258)	(0.0501)	(0.0512)	(0.0592)	(0.0611)
γ_{21}	0.0700	0.0517	0.0396	0.0663	-0.0038	-0.0046
.	(0.0317)	(0.0344)	(0.0485)	(0.0566)	(0.0556)	(0.0546)
γ_{22}	0.0031	-0.0058	0.0544	-0.0210	0.0508	0.0662
.	(0.0346)	(0.0261)	(0.0395)	(0.0280)	(0.0382)	(0.0374)
Conditional Variances						
ω_1	0.1127	0.1716	0.1553	0.0243	0.0242	0.0407
.	(0.0112)	(0.0260)	(0.0275)	(0.0089)	(0.0057)	(0.0068)
β_1	0.4765	0.3657	0.2538	0.4904	0.5044	0.5482
.	(0.0143)	(0.0821)	(0.0948)	(0.2812)	(0.0474)	(0.0178)
ϕ_1	0.3236	0.1899	0.0841	0.2812	0.2969	0.3121
.	(0.0127)	(0.0715)	(0.0880)	(0.0739)	(0.0431)	(0.0139)
d_1	0.3528	0.3858	0.2946	0.3734	0.3776	0.3758
.	(0.0253)	(0.0319)	(0.0271)	(0.0359)	(0.0266)	(0.0278)
ω_2	0.0712	0.1830	0.0947	0.0436	0.1004	0.1213
.	(0.0128)	(0.0276)	(0.0193)	(0.0113)	(0.0150)	(0.0185)
β_2	0.1928	0.3727	0.4790	0.5451	0.4627	0.4414
.	(0.0538)	(0.0697)	(0.0247)	(0.0243)	(0.0211)	(0.0222)
ϕ_2	0.0074	0.1731	0.3529	0.3011	0.3648	0.3784
.	(0.0449)	(0.0580)	(0.0164)	(0.0174)	(0.0127)	(0.0122)
d_2	0.3412	0.4036	0.2942	0.3987	0.2704	0.2431
.	(0.0237)	(0.0343)	(0.0329)	(0.0348)	(0.0254)	(0.0243)
Conditional covariance						
ω_{12}	0.0562	0.1168	0.0825	0.0162	0.0213	0.0372
.	(0.0087)	(0.0165)	(0.0194)	(0.0082)	(0.0062)	(0.0096)
β_{12}	0.3581	0.4276	0.4312	0.4867	0.5121	0.5219
.	(0.0302)	(0.0609)	(0.0692)	(0.0599)	(0.0166)	(0.0168)
ϕ_{12}	0.1974	0.2703	0.2867	0.2928	0.3587	0.3789
.	(0.0319)	(0.0625)	(0.0668)	(0.0536)	(0.0110)	(0.0116)
d_{12}	0.3082	0.3428	0.2508	0.2971	0.2825	0.2420
.	(0.0195)	(0.0269)	(0.0246)	(0.0263)	(0.0219)	(0.0233)

[a]See notes in Table 5.