Dependence and financial contagion in the stock market during the great recession*

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Abstract

In this paper, we investigate whether financial contagion happened in stock markets of selected OECD industrialized countries during the last great recession. More precisely, we analyze whether the co-behavior of their financial markets was based on normal interdependence or, by the contrary, they suffered contagion, a situation that is found when there is structural breaks affecting the transmission mechanism of financial stocks. We use factors models to capture the financial markets co-behavior by examining which markets were the most internationally synchronized and exhibited the greater common factors. We distinguish between the common component – linked to global liquidity conditions and agent's risk aversion – and the idiosyncratic component – linked to the improvement of the economic fundamentals of a given country. Then, we test for contagion by identifying structural breaks in the common factors. Our sample covers 21 developed countries using daily data of domestic stock markets during the period 2004-2011. We find evidence of significant instabilities in cross-market linkages during the crisis.

Keywords: Contagion, financial crisis, factor model, principal components; stock market.

JEL classification: C12, C22

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1 Introduction

The financial crisis that was originated in the US in 2007 developed into a global financial turmoil and a long lasting recession in many economies in the globe. The origin of the crisis can be traced back to the increase of unpaid mortgage loans, mostly extended to less creditworthy borrowers (sub-prime loans), that affected the stability of financial institutions exposed to them as well as to the tenants of financial products tied to these mortgages. This all resulted in the collapse of large financial institutions, the bailout of affected banks and downturns in stock markets, which, in turn, required political intervention.

The crisis affected other countries due to standard practices of the financial institutions such as securitization and off balance sheet financing. By the end of 2007, equity markets started falling from their recent peaks due to repercussions of the sub-prime problem in the US and western countries such as the US, UK, Ireland or Greece suffered fast and sudden downturns in their financial markets. Even some of them required assistance from international institutions such as the International Monetary Found (IMF) or the European Central Bank (ECB) aimed at reestablishing financial stability and the confidence in their banking and financial systems.

Significant correlations among movements in industrialized financial markets are observed during these months. It is a piece of a draw evidence of contagion or financial shock spillover among financial markets across different regions. Contagion alters the correlations among financial markets, but not the interdependence that link these markets. Monitoring the changes of the correlations are important in international investment for international portfolio management and risk assessment. Furthermore, the cross-border contagion may have significant consequences for financial stability. The instability finance has led us to analyze the main causes of co-variation of the stock markets in the most industrialized countries during the financial crisis. This unsteadiness and the conjoint movement of several markets is known like financial contagion or interdependence.

Nevertheless, it is necessary to understand that the globalization and the different process of integration has caused a clear interrelationship among the financial variables. Consistently, any analysis that pursues to investigate the presence of contagion has to take into account this relation to guarantee that the conclusions of the study are not misleading.

In the present paper we analyze the presence of contagion in the financial crisis taking into account the strong dependence that exists among the economies. The main contributions of the article are twofold. First, we analyze the current crisis using up to date data, which allows us to give possible solutions to the present situation. Second, we carry out the study using the flexible framework that defines the specification of common factor models. Factor models aim to control for the strong dependence that exists among the financial variables. Further, factor models allow us take into account any channel of transmission that is acting to spread the crisis among the countries. This technique also identifies and quantifies the effects of the crisis transmission without resorting to ad hoc identification of the pertinent fundamentals. Besides, this procedure allows us to obtain conclusions that are robust to the omission of relevant variables and simultaneous equations bias problems.[1] From a policy point of view, it is essential to provide policy markers with timely and appropriate measures of correlation changes and contagion. This will certainly help design appropriate policy responses and prepare contingency plans.

This article proceeds as follows. Section 2 briefly discusses the main contagion empirical literature. Section 3 discusses data. Section 4 analyzes the empirical results focusing on, first, the order of integration of the time series and, second, on the analysis of parameter stability of the estimated common factors. Finally, Section 5 presents some concluding remarks.

2 Contagion literature: An overview

In this section, we give a short overview of the empirical approximations that have been followed in the literature to analyze the presence of contagion in periods of crisis. Although the focus of this section is based on the empirical approaches, it is worth to introduce a brief comment on the theoretical contributions that have tackled the issue of financial crises and contagion. An extensive literature exists in the strictly theoretical field, which has given rise to diverse models or generations of models that explain the transmission of financial crises among countries and financial markets.[2]

Due to evolution of the theoretical models, it is possible to find different definitions of contagion.[3] Basically, there is two ways to define the financial contagion. The first concept defines contagion depending on the channels of transmission that are used to spread the effects of the crisis. The second concept defines contagion depending on whether the transmission mechanisms are stable through time.[4] If the transmission among markets has been stable in different moments of time we could conclude that there is a relation of interdependence among markets, whereas if this transmission changes throughout the time, then, we will be facing a situation of contagion.[5]

The definition that we assume in this paper is the one that allows us to confirm the existence of contagion with regard to the situation of interdependence. This definition of contagion conveys the break or breaks in the channels of contagion owing to financial panics, herding or switching expectations across instantaneous equilibria.

Among the econometric approaches that make possible the analysis of contagion, we have selected the methodology that is based on the use of common factor models. We have chosen this approach because it avoids to impose just an unique channel of contagion on the model, but it allows to fit the various possibilities of mechanisms of transmission among countries. In addition and as mentioned above, the consideration of common factors will allow us to eliminate problems associated with the omission of relevant variables and simultaneous equations estimation bias.[6]

[1] See Forbes and Rigobon (2002) for the econometrics problems about contagion testing.

[2] The development of the literature from first through fourth-generation models, or the so-called 'institutional' models, is reviewed by Breuer (2004).

[3] See Pericoli and Sbracia (2003) for the different definitions of contagion.

[4] This definition of contagion is related to the approach of Boyer et al. (2002) and Forbes and Rigobon (2001, 2002).

[5] Overviews of the issues are provided by Dornbusch et al. (2000), Pericoli and Sbracia (2003), Belke and Setzer (2004) and De Bandt and Hartmann (2001), among others.

[6] See Forbes and Rigobon (2002) for the econometrics problems about contagion testing.

One of the first approximations that used factor models in this empirical field was Kaminsky and Reinhart (2002), although the principal aim of their study was the analysis of the interdependence among markets. After this seminal work, a notable volume of literature has analyzed the presence of contagion using this methodology on different markets and financial crises. Our approach is then more related to the work of Corsetti, Pericoli and Sbracia (2005), who use a common factors model to analyze the financial contagion.[7] The main contribution of our article is the study of presence of contagion in the period of economic crisis taking into account the interdependence that exists among the financial markets of different developed economies. One measure to assess the degree of changes in co-movements among equity markets is to look at the common factors of the returns among financial markets over time. Previous studies show that common factors among asset returns is time varying – e.g. Longin and Solnik (1995) and Engle (2002).

3 Data and sample

We evaluate the international impact of the subprime crisis 2007 in stock markets. The data source is Thomson Financial Datastream, from which we have selected a sample including 21 OECD industrialized economies: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, and US. Specifically, the Datastream list is DSGLOBAL and the datatype is recalculated aggregate return index. The frequency of the data set is daily (Monday to Friday) and the period covers from 1 January 2004 through 4 March 2011. The daily returns are in national currencies.

4 Results

4.1 Univariate analysis

The use of the econometric techniques that are applied in this paper requires the assessment of the stochastic properties of the daily returns time series. In this section we compute the unit root tests in Ng and Perron (2001) to analyze the order of integration of the time series, since these statistics are shown to have good properties in terms of empirical size and power. Table 2 presents the results of the seven test statistics that have been computed for both the time series in first difference and in levels.

As can be seen, the results of the analysis of the variables in first difference depends on the statistic that is used. Whereas the null hypothesis of unit root is rejected for the Z_α and ADF statistics at the 5% level of significance for most of the countries, the null hypothesis is not rejected when using the other statistics. Results of the different test statistics are conclusive when we focus on the level of the variables, for which the null hypothesis of unit root is not rejected in any case.

[7] See also Dungey et al. (2005) and Bekaert, Harvey and Ng (2005).

Consequently, the overall conclusion that is obtained in this section is that all time series are, at least, I(1) non-stationary stochastic processes.

4.2 Panel data analysis

The econometric literature on non-stationary panel data has grown fast since the nineties. One reason for its popularity is to allow for the inference on the stochastic properties of time series allowing for a greater volume of information, a fact which is expected to result in an improvement in the power of univariate unit root test statistics such as the ones applied in the previous section. However, the validity of this presumption requires ensuring that the panel unit root test that are used are suitable for the data set that is analyzed, since some of the proposals in the literature assume that the time series of the panel are independent.

One the hypothesis of this paper has been that the performance of different assets traded on international markets is strongly correlated with each other given the high mobility of capital and globalization and integration processes have intensified in recent years. In order to test this hypothesis we have computed the CD test of Pesaran (2004), a test statistic that specifies the null hypothesis of no correlation against the alternative hypothesis of correlation. The test statistic is based on the average of pair-wise Pearson's correlation coefficients $\hat{p}_j$, $j = 1, 2, \ldots, n$, $n = N(N-1)/2$, of the residuals obtained from an autoregressive (AR) model:

$$\Delta y_{i,t} = f_i(t) + \delta_i y_{i,t-1} + \sum_{k=1}^{p_i-1} \gamma_{i,k} \Delta y_{i,t-k} + \varepsilon_{i,t},$$

where $y_{i,t}$ is the daily return of the i-th individual, $f_i(t)$ denotes the deterministic component – given either by a constant or a linear time trend – and $\varepsilon_{i,t}$ is the disturbance term that is assumed to be independently distributed across i and t, $i = 1, \ldots, N$, $t =, \ldots, T$. The CD statistic of Pesaran (2004) is given by:

$$CD = \sqrt{\frac{2T}{n}} \sum_{j=1}^{n} \hat{p}_j \to N(0,1).$$

Under the null hypothesis of cross-section independence the CD statistic of Pesaran (2004) converges to the standard normal distribution. Table 3 presents the results of calculating the CD for different orders of autoregressive model – we consider $p_i = p\ \forall i$. As can be seen, the null hypothesis of independence is clearly rejected at a significance level of 5% for all values of p considered. This result indicates that the analysis of stochastic properties of the panel data set using unit root tests must take into account the presence of cross-dependence.

The panel data unit root tests that are applied in this paper are those of Bai and Ng (2004), Moon and Perron (2004) and Pesaran (2007), which that take into account the presence of cross-section dependence by specifying a model of common factors. Of the three approaches the most general one is the proposal in Bai and Ng (2004), provided that it allows to test the order of integration of the idiosyncratic and common components in a separate way. Therefore, it is possible to identify the source of non-stationarity that will be reflected in the observed time series. For this reason, in what follows we give a brief description of the procedure of Bai and Ng (2004).

The approach of Bai and Ng (2004) assumes that the observable variables can be decomposed as:

$$y_{i,t} = D_{i,t} + F_t' \pi_i + e_{i,t},$$

$t = 1, \ldots, T$, $i = 1, \ldots, N$, where $D_{i,t}$ denotes the deterministic part of the model – either a constant or a linear time trend – F_t is a $(r \times 1)$-vector that accounts for the common factors that are present in the panel, and $e_{i,t}$ is the idiosyncratic disturbance term, which is assumed to be cross-section independent. The vector of loading parameters π_i measures the effect that the common factors have on the i-th time series. The unobserved common factors and the idiosyncratic disturbance terms are estimated using principal components on the first difference model. The estimation of the number of common factors can be obtained using the panel BIC information criterion in Bai and Ng (2002).

Once both the idiosyncratic and common components have been estimated, we can proceed to assess their order of integration using unit root tests. On the one hand, it is possible to test whether there are stationary or non-stationary common factors using the MQ test statistic in Bai and Ng (2004) – either in its parametric and/or non-parametric version. Therefore, using these statistics we will be able to conclude how many of the r common factors (if any) that have been estimated are I(0) stationary factors (r_0) and how many are I(1) non-stationary factors (r_1), so that $r = r_0 + r_1$. On the other hand, we can test the panel unit root hypothesis focusing on the idiosyncratic shocks ($e_{i,t}$).

As can be seen, this technique can determine the source of possible non-stationarity. It is possible that the non-stationarity of the observed variables is the result of the presence of I(1) common factors – or a combination of I(0) and I(1) common factors – which implies that the panel data set is non-stationary and that the source of non-stationarity is a common cause for all the series that define the panel. In this case, we should conclude that there are global permanent shocks affecting the whole panel. It could also be the case that the source of non-stationarity of the panel is given by I(1) idiosyncratic disturbance terms, a fact that implies that shocks that affect only each time series (i.e., not the global shocks) have a permanent character.

We have mentioned above that the approach of Bai and Ng (2004) nests the ones in Moon and Perron (2004) and Pesaran (2007). Once the Bai and Ng (2004) procedure has been described, it is worth indicating the differences that exist among the three approaches. As noted in Bai and Ng (2010), the proposals in Moon and Perron (2004) and Pesaran (2007) control the presence of cross-section dependence allowing for common factors, although the common factors and the idiosyncratic shocks are restricted to have the same order of integration (and dynamics). Therefore, it is not possible to cover situations in which one component (e.g., the common factors) is I(0) and the other component (for example, the idiosyncratic shocks) is I(1), and vice versa. In practical terms, the test statistics in Moon and Perron (2004) and Pesaran (2007) focus on the idiosyncratic shocks, where the dynamics of both the idiosyncratic and the common components are restricted to be the same.

Table 4 provides the results of the unit root panel data statistics discussed above, both for the level and the first difference of the time series. First, we present the values of the two test statistics of Pesaran (2007) – denoted as CIPS and CIPS* statistics – for different values of the order of the autoregressive correction (p). As can be seen, the test statistics clearly reject the null hypothesis of unit root for the different series. On the other side and with the exception of the statistics that bases on the use of $p = 0$ and $p = 1$ lags, the test statistics of Pesaran (2007) do not reject the null hypothesis of panel unit root at the 5% level of significance for the series in levels. The test statistics of Moon and Perron (2004) – denoted as t_a and t_b – show a clear rejection of the null hypothesis of panel unit root for both for the level and the first difference of the time series.

Finally, the approach of Bai and Ng (2004) allows us to make the analysis of integration of the idiosyncratic and common components separately. With respect to the idiosyncratic component, we see that the panel ADF statistic rejects the null hypothesis of panel unit root both for the level and the first difference of the time series, a situation that agree with the conclusions drawn by Pesaran's (2007) statistics. If we focus on the common factors, the panel BIC Bai and Ng (2002) selected three common factors – the specified maximum is four. When these factors are extracted from the first difference time series, we see that three common factors are characterized as I(0) stochastic processes. On the other hand, when the analysis is carried out using the levels of the time series, at least one of the three common factors are characterized as an I(1) stochastic process – the MQ non-parametric test concludes that $r_1 = 1$, while the parametric version determines that $r_1 = 2$.

To sum up, the conclusion to be drawn from the analysis in this section is that the panel data set is I(1). The richer interpretation that allows the procedure of Bai and Ng (2004) indicates that the non-stationarity of the series of returns comes from both the idiosyncratic component and the presence of, at least, one common stochastic trend. These results lead us to have to work with the variables in first difference to analyze the presence of contagion in the great recession.

4.3 Analysis of the contagion effect during the great recession

After establishing the need to differentiate the variables to warrant that the panel data set is I(0), we proceed to compute two test statistics in order to assess whether the samples were fit for the principal components analysis. The results are shown in Table 5, which shows, on the one hand, that the Kayser-Meyer-Olkin measure of sampling adequacy indicate that the use of principal components is adequate, reaching almost 100%. On the other hand, the Bartlett's test of sphericity also provides adequate values. Therefore, principal components analysis can be applied to our data set.

Table 6 shows the explanatory power of the common factors in the variation of the sample of industrialized countries. Only those components with an explanatory power above 1 were selected – i.e., the components that explain more than would explain one of the original variables. The results therefore show that the common factors provide a high explanatory power since the three first principal components explain 76.3% of the variability of the stock markets of the analyzed countries.

Table 7 reports the rotated common factors. As can be seen, the common factors have a strong geographic component: the first one explains mostly the European zone, the second one the North American zone while the third one the Asian and Oceania zone. These results suggest that stock markets within each zone behave similarly.

Let us now focus on the analysis of financial contagion. First, in order to get an initial picture of the situation, we have split the sample in two subsamples (tranquil and turbulent periods) using as the exogenous break point the date in which the central banks – mainly the Federal Reserve and the European Central Bank – coordinated efforts to increase the liquidity of the markets. We define tranquil and turbulent periods as stretching from 1 January 2004 to 31 July 2007 and from 1 August 2007 to 4 March 2011, respectively. It should be beard in mind that this analysis is conditional to the exogenous selection of the break point, an assumption that would be addressed below when we apply test statistics that endogeneize the selection of the structural breaks.

The analysis of the principal components of each separate period revealed wide differences on the behavior of the common factors. These differences are in the number of common components – 3 during the quiet period and 2 during the turbulent period. Another feature was that the explanatory power of the common factors is also different. The two common factors during the crisis explain 73.9% of the variability of the returns, while the first three on the previous period only explain 69.8% of such variability. Therefore, this initial picture suggests that the behavior of the markets and the interrelations among the analyzed countries changed during the great recession.

Should interdependence happened in times of crisis, we would have found that common factors that stock markets interdependence in times of crisis would be the same, in probabilistic terms, as those present in quiet times. Further, if the factors that explain market interdependence in times of crisis differ from the ones that explain them in more quiet times, we could conclude that contagion happened in stock markets during the great recession.

In order to assess whether there has been changes in the interdependence of the markets and, in turn, whether there has been financial contagion, we have proceeded to carry out an analysis of structural stability of the common factors assuming that the break dates are unknown. Firstly, we have applied the tests statistics developed by Andrews and Ploberger (1994) to test for the presence of structural breaks on the common factors. The results in Table 8 indicate that the test statistics fail to reject the null hypothesis of absence of structural change affecting the level of the process, which could lead us to conclude that common factors were not affected by the presence of structural instabilities. However, there are two main shortcomings of the aforementioned test statistics that should be considered. First, these statistics only accommodate the presence of one structural change under the alternative hypothesis. Therefore, the test statistics may show lack of statistical power if there is more than one structural change affecting the time series. Second, these test statistics assume that the variance of the time series is constant throughout the analyzed period. This is an important limitation when financial data are analyzed. In our case, the common factors show higher variability in the turbulent time period that has been defined above. Therefore, to overcome these limitations we have considered to implement the test statistics in Bai and Perron (1998), provided that these statistics allow for both the presence of multiple structural breaks and heterogeneous variance across regimes.

The computation of the Bai and Perron (1998) test statistics has been done allowing for a maximum of three structural changes that affect the level of the common factors. We have estimated the break points using the sequential procedure of Bai and Perron (1998). The results reported in Table 9 indicates that the procedure detects, at most, one structural change for each common factor. For the first common factor, the estimated break point is 04/06/2007. It must be pointed out that the estimation of this break point is in accordance with the previous analysis, where the break point was selected exogenously considering the extended opinion on the beginning of the financial crisis. The significance of this factor in explaining the market behavior is very high since it explains 52.1% of the market variability. Hence, we can conclude that contagion happened in times of the great recession among the twenty-one industrialized countries that have been studied, and that such contagion was stronger in the European economies.

It is worth noticing that we have also detected another structural change estimated at the 10/03/2009 that would have affected the second common factor, although the evidence in favor of this structural break is weaker – we require to work at the 10% level of significance. We can observe from Table 7 that this effect had a bigger influence in the North American countries and that the contagion, considering the new structural change, was of higher magnitude. Furthermore, the variable determines 64.3% of the observed variability of the analyzed countries and such contagion had an important effect in the analyzed countries. As was the case for the structural break of the first component, the date coincides with two relevant economic events: first, the agreement between EU ministers to supply more funds to the IMF and, second, an appearance of Ben Bernanke in which he claimed for a reform to the financial architecture that should include "improvements" in the valuation models of bank assets. The date was signaled as the Bear Market Rally[8] mainly in the US, which allow us to validate our results.

5 Conclusions

The present article contributes to the analysis of the current situation of the financial markets by stating that the market behavior in such a turbulent period is marked by a strong transversal dependence that differs from the previous situation. We focus on a panel data set defined with the most industrialized OECD countries, which has led us to conclude that, under the current economic conditions, the dependence that links the financial markets of these countries has a unique character that can be associated to a financial contagion.

Our analysis bases on the specification of a common factor model that aims to control for the presence of cross-section dependence. The applied techniques allowed us to detect that just

[8] The beginning of an upward correction within a downward tendency.

three common factors explain most of the stock market variability during the crisis. Furthermore, these common factors behave differently in times of financial turmoil than in more tranquil times. Thus, the application of test statistics to assess the structural stability of the common factors has revealed the presence of two structural breaks, each of them affecting only one common factor. The estimated break points are in concordance with, first, the coordinated intervention of the central banks to increase the liquidity of the markets and, second, with the definition of strategies that will lead to regulate the financial markets.

Finally, it should be stressed that the economic literature associates contagion behavior with factors such as risk aversion by investors or overall liquidity conditions, among others. The framework that has been used in this paper with the specification of a common factor model accounts for all possible channels of transmission. In this regard, our approach mitigates the potential drawbacks caused by misspecification errors. However, we cannot ascertain which specific contagion channel is more prevalent in the present study, a question that we will address in further research.

References

[1] Andrews, D. W. K. and Ploberger, W. (1994). Optimal tests when a nuisance parameter is present only under the alternative, Econometrica, 62, 1383–1414

[2] Bai, J. (2003). Inference on factor models of large dimensión, Econometrica, 71, 135–171.

[3] Bai, J. (2004). Estimating cross-section common stochastic trends in nonstationary panel data, Journal of Econometrics, 122, 137-183.

[4] Bai, J. and Ng, S. (2002). Determining the number of factors in approximate factor models. Econometrica, 70, 91–221.

[5] Bai, J. and Ng, S. (2004). A PANIC attack on unit roots and cointegration, Econometrica, 72, 1127–1177.

[6] Bai, J. and Ng, S. (2008). Large Dimensional Factor Analysis, Foundations and Trends in Econometrics, 3, 2, 89-163.

[7] Bai, J. and Ng, S. (2010). Panel Unit Roots Tests with Cross-section Dependence: A Further Investigation, Econometric Theory, 26, 1088-1114.

[8] Bai, J. and Perron, P. (1998). Estimating and testing linear models with multiple structural changes, Econometrica, 66, 47-78.

[9] Bekaert, G., Harvey, C.R., Ng, A., (2005). Market Integration and Contagion. Journal of Business, 78(1). University of Chicago Press, 39–70.

[10] Belke, A. and R. Setzer (2004). Contagion, Herding and Exchange Rate Instability – A Survey, Working Paper, Universität Hohenheim.

[11] Boyer, B. H., Gibson, M. S. and Loretan. M. (1999). Pitfalls in tests for changes in correlations, International Finance Discussion Paper, 597R, Federal Reserve Board.

[12] Corsetti, G., Pericoli. M. and Sbracia. M. (2005). Some contagion. some interdependence. More pitfalls in tests of financial contagion, Journal of International Money and Finance, 24, 1177-1199.

[13] De Bandt, O. and Hartmann P. (2001). Systemic Risk: A Survey. In Financial Crisis, Contagion and the Lender of Last Resort: A Book of Readings, Ed. C. Goodhart e G. Illing, Oxford University Press.

[14] Dornbusch, R., Park, Y. C. and Claessens, S. (2000). Contagion understanding how it spreads, World Bank Research Observer, 15 (2), 177–197.

[15] Dungey, M., Fry, R., González-Hermosillo, B. and Martin, V. L. (2005). Empirical modelling of contagion a review of methodologies, Quantitative Finance, 5, 9–24.

[16] Eichengreen, B.. Rose, A.K. and Wyplosz, C. (1996). Contagious currency crises First tests, Scandinavian Journal of Economics, 98. 463–484.

[17] Forbes. K. J. and Rigobon, R. (2001). Measuring contagion conceptual and empirical issues. In Claessens, S. and Forbes, K.J. (Eds.). International Financial Contagion. Kluwer Academic Press. Boston. MA.

[18] Forbes, K. and Rigobon, R. (2002). No Contagion. Only Interdependence Measuring Stock Market Co-movements, Journal of Finance, 57, 2223–2261.

[19] Kaminsky, G. L. and Reinhart, C. M. (2002). Financial Markets in Times of Stress, Journal of Development Economics, 69, 451-470.

[20] Moon, H. R. and Perron, B. (2004). Testing for Unit Root in Panels with Dynamic Factors, Journal of Econometrics, 122, 81-126.

[21] Ng, S. and Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power, Econometrica, 69, 1519–1554.

[22] Pericoli, M. and Sbracia, M. (2003). A Primer on Financial Contagion, Journal of Economic Surveys, 17, 571-608.

[23] Pesaran, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels, Cambridge Working Papers in Economics, No. 435, University of Cambridge, and CESifo Working Paper Series No. 1229.

[24] Pesaran, M. H. (2007). A Simple Panel Unit Root Test in the Presence of Cross Section Dependence, Journal of Applied Econometrics, 22, 265-312.

[25] Stock, J.H. and Watson, M.W. (1988). Testing for Common Trends, Journal of the American Statistical Association, 83, 1097-1107.

[26] Stock. J.H. and Watson, M.W. (2006). Forecasting with Many Predictors. Handbook of Economic Forecasting. ed. by Graham Elliott, Clive W. J. Granger and Allan Timmermann. Elsevier, Capítulo 6, 515-554.

[27] Stock. J.H. and Watson, M.W. (2011). Dynamic Factor Models, Oxford Handbook of Forecasting. Michael P. Clements and David F. Hendry (eds). Oxford University Press.

Table 1: Descriptive statistics

	Min	Max	Mean	Variance	Asymmetry	Kurtosis
AUSTRALIA	-675.05	488.83	2.99	97.09	9425.56	-0.44
AUSTRIA	-44.67	52.55	0.15	7.65	58.52	-0.49
BELGIUM	-368	396.8	1.04	60.94	3714.11	-0.36
CANADA	-441.14	442.29	2.43	66.99	4487.91	-0.64
DENMARK	-783.99	570.27	2.95	95.46	9111.87	-0.43
FINLAND	-85.97	129.72	0.23	16.14	260.36	-0.01
FRANCE	-562.71	585.59	1.40	88.17	7773.23	-0.13
GERMANY	-193.33	330.87	0.64	27.71	767.95	0.44
GREECE	-216.28	252.12	-0.12	38.62	1491.73	-0.30
IRELAND	-1149.05	892.09	-1.03	205.93	42407.11	-0.56
ITALY	-417.75	444.47	0.54	64.60	4173.35	-0.22
JAPAN	-49.7	62.16	0.02	8.94	80.00	-0.41
NETHERLAND	-267.03	227.45	0.64	37.96	1440.80	-0.46
NEW ZEALAND	-56.26	66.81	0.24	9.60	92.08	-0.32
NORWAY	-297.75	313.1	1.68	60.34	3640.56	-0.49
PORTUGAL	-35.26	32.24	0.08	4.25	18.05	-0.45
SPAIN	-102.33	129.11	0.27	15.54	241.55	-0.07
SWEDEN	-326.11	395.45	2.31	74.63	5570.04	-0.09
SWITZERLAND	-120.92	166.76	0.38	20.68	427.81	-0.25
UK	-2307.16	2533.82	9.88	373.70	139652.35	-0.20
US	-392.65	403.8	1.04	54.48	2968.57	-0.42

Table 2: Unit root tests of Ng and Perron (2001)

First difference of the time series

	Z_α	MZ_α	MSB	ADF	P_T	MP_T	MZ_t
AUSTRALIA	-1084.47^a	-79.47^a	0.08^a	-8.07^a	0.37^a	0.37^a	-6.27^a
AUSTRIA	-725.92^a	-7.36	0.25	-3.98^a	3.51	3.49	-1.87
BELGIUM	-442.09^a	-4.16	0.35	-2.32^a	5.93	5.89	-1.44
CANADA	-846.62^a	-7.28	0.26	-4.21^a	3.37	3.36	-1.91
DENMARK	-92.10^a	-1.20	0.54	-1.05	16.59	16.25	-0.64
FINLAND	-575.70^a	-3.22	0.36	-2.43^a	7.56	7.50	-1.15
FRANCE	-523.89^a	-7.17	0.25	-3.14^a	3.76	3.72	-1.81
GERMANY	-592.12^a	-14.44^a	0.18^a	-4.41^a	2.11^a	2.09^a	-2.59^a
GREECE	-224.44^a	-3.18	0.39	-1.71	7.77	7.66	-1.23
IRELAND	-506.01^a	-3.43	0.37	-2.40^a	7.19	7.14	-1.28
ITALY	-217.68^a	-4.33	0.33	-1.92	5.85	5.76	-1.42
JAPAN	-1067.39^a	-143.33^a	0.06^a	-8.75^a	0.18^a	0.18^a	-8.46^a
NETHERLAND	-379.90^a	-7.54	0.25	-2.81^a	3.37	3.34	-1.92
NEW ZEALAND	-901.60^a	-99.42^a	0.07^a	-7.96^a	0.26^a	0.26^a	-7.05^a
NORWAY	-803.52^a	-7.95	0.25	-4.30^a	3.11^a	3.11^a	-1.99^a
PORTUGAL	-293.86^a	-6.53	0.27	-2.55^a	4.03	3.98	-1.74
SPAIN	-372.38^a	-5.75	0.29	-2.49^a	4.48	4.43	-1.64
SWEDEN	-1624.49^a	-918.88^a	0.02^a	-37.89^a	0.03^a	0.03^a	-21.43^a
SWITZERLAND	-1842.87^a	-934.80^a	0.02^a	-42.62^a	0.03^a	0.03^a	-21.62^a
UK	-1710.55^a	-928.20^a	0.02^a	-39.70^a	0.03^a	0.03^a	-21.54^a
US	-1109.22^a	-25.98^a	0.14^a	-7.51^a	0.98^a	0.98^a	-3.50^a

Level of the time series

	Z_α	MZ_α	MSB	ADF	P_T	MP_T	MZ_t
AUSTRALIA	-3.52	-3.52	0.37	-1.31	25.81	25.72	-1.32
AUSTRIA	-1.17	-1.17	0.62	-0.73	72.55	71.90	-0.73
BELGIUM	-1.29	-1.28	0.61	-0.78	68.56	67.99	-0.78
CANADA	-5.26	-5.25	0.31	-1.55	17.34	17.30	-1.60
DENMARK	-2.67	-2.67	0.43	-1.15	34.23	34.08	-1.15
FINLAND	-2.83	-2.83	0.42	-1.18	31.88	31.77	-1.18
FRANCE	-2.55	-2.55	0.44	-1.12	35.77	35.58	-1.12
GERMANY	-3.10	-3.10	0.40	-1.23	29.45	29.40	-1.24
GREECE	-0.82	-0.82	0.61	-0.50	73.92	73.29	-0.50
IRELAND	-1.14	-1.14	0.62	-0.71	71.93	71.28	-0.71
ITALY	-1.48	-1.48	0.56	-0.82	58.47	57.96	-0.82
JAPAN	-1.87	-1.86	0.50	-0.93	47.15	46.76	-0.93
NETHERLAND	-2.64	-2.64	0.43	-1.15	34.63	34.52	-1.15
NEW ZEALAND	-2.58	-2.58	0.43	-1.10	35.01	34.72	-1.12
NORWAY	-2.94	-2.93	0.41	-1.21	31.14	30.97	-1.21
PORTUGAL	-2.26	-2.26	0.45	-1.02	38.76	38.58	-1.03
SPAIN	-2.49	-2.49	0.43	-1.07	35.05	34.85	-1.07
SWEDEN	-3.50	-3.50	0.38	-1.32	26.06	26.00	-1.32
SWITZERLAND	-2.03	-2.02	0.48	-0.97	43.53	43.31	-0.98
UK	-4.92	-4.91	0.32	-1.55	18.49	18.47	-1.55
US	-4.72	-4.71	0.32	-1.47	19.14	19.13	-1.50

Note: superscript a indicates rejection of the corresponding null hypothesis at 5% level of significance

Table 3: Pesaran's CD test of cross-section independence

	First difference of the time series			Level of the time series		
p	CD test	Mean	Median	CD test	Mean	Median
0	365.79	0.58	0.63	362.33	0.58	0.63
1	365.91	0.58	0.63	365.98	0.58	0.63
2	365.87	0.58	0.63	366.09	0.58	0.63
3	365.22	0.58	0.63	366.05	0.58	0.63
4	365.37	0.58	0.63	365.39	0.58	0.63
5	365.06	0.58	0.63	365.53	0.58	0.63
6	365.09	0.58	0.63	365.22	0.58	0.63
7	365	0.58	0.63	365.25	0.58	0.63
8	364.9	0.58	0.63	365.15	0.58	0.63
9	364.73	0.58	0.63	365.05	0.58	0.63
10	364.69	0.58	0.63	364.87	0.58	0.63
11	364.48	0.58	0.63	364.83	0.58	0.63
12	363.96	0.58	0.63	364.62	0.58	0.63
13	363.9	0.58	0.63	364.1	0.58	0.63
14	363.93	0.58	0.63	364.04	0.58	0.63
15	363.36	0.58	0.62	364.07	0.58	0.63

Table 4: Panel data unit root tests

Pesaran's (2007) test statistics

p	First difference CIPS	First difference CIPS*	Levels CIPS	Levels CIPS*
0	-47.82	-6.19	-3.42^a	-3.42^a
1	-33.07	-6.19	-2.80^a	-2.80^a
2	-26.95	-6.19	-2.61	-2.61
3	-23.11	-6.19	-2.5	-2.5
4	-20.83	-6.19	-2.46	-2.46
5	-18.78	-6.19	-2.39	-2.39
6	-17.36	-6.19	-2.38	-2.38
7	-16.19	-6.19	-2.35	-2.35
8	-15.39	-6.19	-2.31	-2.31
9	-14.51	-6.19	-2.26	-2.26
10	-13.64	-6.19	-2.23	-2.23
11	-13.09	-6.19	-2.23	-2.23
12	-12.56	-6.19	-2.2	-2.2
13	-12	-6.19	-2.18	-2.18
14	-11.73	-6.19	-2.17	-2.17
15	-11.2	-6.19	-2.14	-2.14

Moon and Perron (2004) statistics

	First difference Test	First difference p-val	Levels Test	Levels p-val
t_a	-2850.62	0.000	-1.368^b	0.086
t_b	-96.02	0.000	-2.011^a	0.022

Bai and Ng (2004) statistics

	First difference Test	First difference p-val	Levels Test	Levels p-val
Idiosycratic (ADF)	-18.75	0.000	-0.05	0.480
	MQ_f	MQ_c	MQ_f	MQ_c
Non-stationary factors	$r_1 = 0$	$r_1 = 0$	$r_1 = 1$	$r_1 = 2$

Note: superscripts a and b indicate rejection of the corresponding null hypothesis at 5 and 10% level of significance, respectively

Table 5: KMO and Bartlett's Tests

		Test
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.973
Bartlett's Test of Sphericity	Approx. Chi-Squared	43637.133
	d.f.	210
	p-value	0.000

Table 6: Total variance explained

	Initial Eigenvalues		
Component	Total	% of Variance	Cumulative %
1	13.223	62.966	62.966
2	1.795	8.547	71.513
3	1.008	4.798	76.311
	Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %
1	13.223	62.966	62.966
2	1.795	8.547	71.513
3	1.008	4.798	76.311
	Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %
1	10.961	52.195	52.195
2	2.545	12.121	64.317
3	2.519	11.994	76.311

Note: The extraction method that is used is principal component analysis

Table 7: Rotated component matrix

	Component			Communalities
	1	2	3	Extraction
FRANCE	0.904	0.297	0.155	0.930
NETHERLAND	0.88	0.299	0.189	0.900
ITALY	0.879	0.28	0.148	0.872
SPAIN	0.868	0.261	0.125	0.837
UK	0.866	0.321	0.168	0.881
SWEDEN	0.849	0.261	0.109	0.801
BELGIUM	0.849	0.203	0.172	0.791
SWITZ	0.841	0.265	0.221	0.826
AUSTRIA	0.809	0.165	0.273	0.756
FINLAND	0.804	0.221	0.171	0.725
IRELAND	0.772	0.107	0.153	0.631
DENMARK	0.768	0.231	0.291	0.729
PORTUGAL	0.767	0.174	0.211	0.663
GERMANY	0.76	0.45	0.018	0.780
GREECE	0.688	0.027	0.257	0.540
NORWAY	0.681	0.309	0.263	0.628
US	0.373	0.846	-0.057	0.859
CANADA	0.313	0.859	0.135	0.855
AUSTRALIA	0.241	0.071	0.833	0.757
JAPAN	0.221	0.085	0.786	0.674
NEW ZEALAND	0.11	-0.032	0.759	0.590

Note: The extraction method that is used is principal component analysis. Rotation method: Varimax with Kaiser Normalization; rotation converged in 5 iterations

Table 8: Andrews and Ploberger (1994) test statistics

	1st common factor		2nd common factor		3rd common factor	
	Test	p-val	Test	p-val	Test	p-val
Sup LR F-statistic	6.08	0.16	3.70	0.42	3.35	0.48
Sup Wald F-statistic	6.08	0.16	3.70	0.42	3.35	0.48
Exp LR F-statistic	1.30	0.13	0.72	0.30	0.42	0.51
Exp Wald F-statistic	1.30	0.13	0.72	0.30	0.42	0.51
Ave LR F-statistic	1.86	0.13	1.16	0.28	0.71	0.49
Ave Wald F-statistic	1.86	0.13	1.16	0.28	0.71	0.49

Note: The test statistics test for the presence of one structural break in the level of the time series

Table 9: Structural breaks on the common factors. Bai and Perron (1998) procedure

	Significance level for the sequential testing procedure	
Common factor	10%	5%
1	-	-
2	26/7/2007	-
3	-	-