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Chouliaras, Andreas and Grammatikos, Theoharry

Luxembourg School of Finance

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Andreas Chouliaras*, Theoharry Grammatikos
Luxembourg School of Finance**

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Abstract

We examine the transmission of extreme stock market returns among three groups of countries: the Euro-periphery countries (Portugal, Ireland, Italy, Greece, Spain), the Euro-core countries (Germany, France, the Netherlands, Finland, Belgium), and the major European Union -but not euro- countries (Sweden, UK, Poland, Czech Republic, Denmark). Using extreme returns on daily stock market data from January 2004 till March 2013, we find that transmission effects are present for the tails of the returns distributions for the Pre-crisis, the US-crisis and the Euro-crisis periods from the Euro-periphery group to the Non-Euro and the Euro-core groups. Within group effects are stronger in the crisis periods. We find that the transmission channel does not seem to have intensified during the crisis periods, but it transmitted larger shocks (in some cases, extreme bottom returns doubled during the crisis periods). Thus, as extreme returns have become much more "extreme" during the financial crisis periods, the expected losses on extreme return days have increased significantly. Given the fact that stock market capitalisations in these country groups are trillions of Euros, a 1% or 2% increase in extreme bottom returns (in crisis periods) can lead to aggregate losses of tens of billions Euros in one single trading day.

JEL classification: G01, G15.

Keywords: Financial Crisis, Financial Contagion, Spillover, Euro-crisis, Stock Markets.

* Corresponding author. E-mail address: andreas.chouliaras@uni.lu
** Luxembourg School of Finance, 4, rue Albert Borschette, 1246 Luxembourg.

1. Introduction

The recent global financial crisis began as a crisis of the subprime mortgage loans in the United States of America in 2007 and continued with multiple waves of financial distress that hit the global financial markets. Since the beginning of 2010 the Euro area faces a severe financial crisis. What started off as a sovereign debt crisis from Greece soon transmitted to Portugal, Ireland, Cyprus and, at least partially, to Spain and Italy. Pretty soon it became clear for Europe that beneath the sovereign debt crisis surface there also existed a severe banking crisis. The evolution of this crisis and the propagation of financial distress from one country to another, with multiple asset classes being hurt (stock markets, bond yields, CDS spreads), make the case of studying the transmission of extreme returns more pertinent than ever[1].

A number of researchers investigate the recent eurozone financial crisis and its transmission effects, giving particular emphasis on the sovereign debt and the Credit Default Swaps (CDS) markets. Missio and Watzka (2011) report the existence of contagion effects using dynamic conditional correlation models (DCC). Metiu (2012) employs a simultaneous equations model and examines the tails of bond yield distributions, an approach derived from the Extreme Value Theory and Value-at-Risk theories, and finds structural shift contagion effects for the crisis periods. Other papers, however, do not find contagion effects for the sovereign bond and the credit default swaps markets. See, for example, Caporin, Pelizzon, Ravazzolo, and Rigobon (2013) and Bhanot, Burns, Hunter, and Williams (2012).

Although the Euro-crisis started off mostly as a sovereign debt crisis, the study of stock markets during financial crises has not been examined sufficiently in the previous literature despite them being the most liquid markets. In this paper we investigate the stock market financial transmission effects of the european financial crisis (and the US-crisis) for three groups of countries: two groups of eurozone countries, the Euro-core eurozone countries (Germany, France, Netherlands, Belgium, Finland) and the Euro-periphery eurozone countries (Portugal, Ireland, Italy, Greece, Spain), and finally a group for European Union (EU) but not euro countries (Sweden, UK, Poland, Czech Republic, Denmark).

The correlations framework has been widely used by previous authors in related studies but there is no consensus in the research literature as to how to best define contagion when using that framework. Forbes and Rigobon (2001) claim that heteroskedasticity biases correlation tests for contagion[2]. To avoid this problem we follow the extreme returns approach proposed mainly in two papers, Bae, Karolyi, and Stulz (2003) and Boyson, Stahel, and Stulz (2010). Bae et al. (2003) examine the coincidence of extreme return shocks across countries within a group and across groups, while Boyson et al. (2010) study hedge funds contagion. A number of other studies have also used this methodology[3]. Moving in line with multinomial logistic analysis, as proposed by Bae et al. (2003) and Boyson et al. (2010), we can use control variables (covariates) in order to justify the characteristics of extreme returns. Furthermore, this approach allows us to study the effects within groups, and the crisis transmission across groups. Since it is well accepted that the most vulnerable eurozone countries -the Euro-periphery group- were the most badly hit by the Euro-crisis, our main interest is to study the

[1]The shock transmission literature is extensive. See, for example Allen and Gale (2000), Rigobon (2002), Kaminsky, Reinhart, and Vegh (2003), Pericoli and Sbracia (2003), Bekaert, Harvey, and Ng (2005), Forbes and Rigobon (2001), Aït-Sahalia, Cacho-Diaz, and Laeven (2010), Dungey, Fry, González-Hermosillo, and Martin (2005), Corsetti, Pericoli, and Sbracia (2005).

[2]By applying a correction they find no contagion for the 1997 Asian crisis. On the other hand, Corsetti et al. (2005) claim that the variance restrictions imposed by Forbes and Rigobon (2001) are "arbitrary and unrealistic". They find evidence for at least five countries facing contagion effects during the Hong Kong stock market crisis of 1997.

[3]See, for example, Markwat, Kole, and van Dijk (2009), Lucey and Sevic (2010), Christiansen and Ranaldo (2009), Gropp, Duca, and Vesala (2009), Chouliaras and Grammatikos (2013)

crisis transmission from the Euro-periphery group to the other two groups (Euro-periphery vs. Euro-core, Euro-periphery vs. Non-euro)[4],[5]. We find that extreme returns in Euro-periphery countries are related to extreme returns in the Euro-core and the Non-euro country groups. In order to test if the crises result in a fundamental shift in the transmission mechanism the extreme returns methodology is applied not only on the entire period (as in previous studies), but also separately on each of the three subperiods (Pre-crisis, US-crisis, Euro-crisis). Interestingly, we find that the transmission channel did not intensify during the crises. Simply it transmitted larger shocks.

The remainder of this paper is organized as follows. Section 2 presents the data. Section 3 presents the basic model and we explain how we study the crisis transmission within and across groups. Section 4 provides a set of robustness and alternative specifications. Section 5 is a conclusion.

2. The Data

The main area of study for this paper is the European Union area. Thus, we create three country groups: the Euro-periphery group contains the periphery eurozone countries (Portugal, Ireland, Italy, Greece, Spain), the second group, Euro-core, contains the core countries of the Eurozone (Germany, France, the Netherlands, Finland, Belgium), and the Non-euro group contains the major European Union (but not Euro) countries (Poland, Sweden, Czech Republic, UK, Denmark)[6]. We examine the period from 01/01/2004 till 13/03/2013 using daily financial data obtained from the Thomson Reuters Datastream. Our selection of countries for the Eurozone follows to a large extent the studies of Missio and Watzka (2011), Caporin et al. (2013), Bhanot et al. (2012), and Metiu (2012). Country group log returns (expressed in local currency) and standard deviations are calculated on the equally weighted mean portfolio of the country stock market daily returns (expressed in local currency) for each group. Table 1 shows the summary statistics and correlation matrices of the percentage returns of the major stock market indices (Panel A and Panel B)[7]. To be able to make comparisons between normal and abnormal times in the financial markets, we split our sample in three subperiods (Pre-crisis, US-crisis Euro-crisis):

- the Pre-crisis period (from 1 January 2004 till 26 February 2007)
- the US-crisis period (from 27 February 2007 till 7 December 2009).[8]
- the Euro-crisis period (from 8 December 2009 till the end of our sample period, 13 March 2013.

On 27 February 2007, the Federal Home Loan Mortgage Corporation (Freddie Mac) announced that it will no longer buy the most risky subprime mortgages and mortgage-related securities. On 8 December 2009, the Greek debt was downgraded by Fitch from A- to BBB+, with a negative outlook.

[4]Another study that uses this approach is Thomadakis (2012), but our main difference is that he considers the Eurozone countries as one group, thus not studying the within eurozone dynamics of the various subgroups, and he studies the interactions mainly with the USA, for the industrials sectors of the stock exchanges.

[5]One critique on Bae et al. (2003) and Boyson et al. (2010) is that they arbitrarily pick the top and the bottom 5% from the sample of returns to examine the joint occurrence of extreme returns. This critique has indeed some merit but a choice of cutoff points is a necessary decision in order to proceed with this methodology and to study the tails of the marginal return distributions in order to see what happens in the presence of extreme returns. The results of our study were found to be robust in the change of the percentiles.

[6]We take the biggest five stock markets from each group using the market capitalisation ranking (as of 2011) from `http://www.indexmundi.com/facts/indicators/CM.MKT.LCAP.CD/rankings`

[7]All stock indices used are the Thomson Reuters Datastream indices created for each country

[8]We use 27 February 2007 as the start of the financial crisis, as used by the Federal Reserve Bank of St. Louis in their Timeline of Events and Policy Actions. The timeline can be found at `http://timeline.stlouisfed.org/index.cfm?p=timeline`.

Insert Table 1 here

For the Pre-crisis period all groups of countries had positive mean returns, consistent with the overall optimism in the financial markets. The best performing markets were firstly the Non-euro countries (+0.101%) followed by the Euro-periphery countries (+0.089%). Regarding the standard deviation we see that we have rather low values for all country groups as this was a period of relative calmness for the financial markets. During the US-crisis period all country groups had a negative mean return. The Euro-periphery countries were the most badly hit with a mean (daily) return of -0.075%, followed by the Euro-core countries which had a mean (daily) return of -0.049%, then the Non-euro with a -0.024%. Compared to the Pre-crisis period, the standard deviations have increased significantly in the crisis periods for all three country groups. The descriptive statistics for the Euro-crisis period show that once more the Euro-periphery countries were the most severely affected from the financial crisis (mean daily return of -0.017%). The other two groups have positive mean returns for this period, indicating that they were able to better cope with the crisis. The standard deviations were lower than in the US-crisis period but still higher than the Pre-crisis period, especially for the Euro-periphery group. As far as the correlations are concerned the main remark is that they increased between the Pre-crisis and the crisis periods. The correlation between the Non-euro and the Euro-periphery group grew from the Pre-crisis value of 0.429 to 0.677 in the US-crisis period, then went down to 0.520 at the Euro-crisis period. The correlation between the Euro-periphery and the Euro-core followed a similar pattern, increasing from 0.579 Pre-crisis to 0.729 in the US-crisis, then declined to 0.646 in the Euro-crisis period, still much higher than the Pre-crisis period. The correlation between the Non-euro and the Euro-core group increased from 0.522 Pre-crisis to 0.727 in the US-crisis period, remaining at the elevated level of 0.734 in the Euro-crisis. To summarize, for both crisis periods (US and Euro-crisis) the correlations are higher than what they were in the Pre-crisis period, and the most hit group is found to be the Euro-periphery group having negative mean returns in both crisis periods.

3. Extreme Returns

3.1. The Base Model

According to Bae et al. (2003) and Boyson et al. (2010), an extreme return is one that lies below (or above) the lowest (or the highest) quantile of the marginal return distribution respectively. This methodology concerns the counts of joint occurrences of extreme returns within a group on a particular day. The original approach studies the extreme returns counts for the entire test period, taking as thresholds for extreme returns the 5th and the 95th percentiles. In our case, and in order to have a sufficient number of observations, we choose as thresholds the 10th and the 90th percentiles, as in Boyson et al. (2010) (our findings are robust to the 5th and 95th percentiles). Thus, for each country we consider returns below the 10th percentile as extreme bottom returns and those above the 90th percentile as extreme top returns for this country.

This procedure is followed for all countries in all groups. Top extreme returns are treated separately from bottom extreme returns. Extreme bottom and top counts are reported in Table 2. For each country we calculate the days for which it had an extreme (bottom or top) return separately. Then, the extreme returns count for each group and day is given as the sum of the extreme returns for all countries that belong to that group for that specific day.

Insert Table 2 here

The left side of Table 2 presents bottom return counts and the right side shows top return counts. A count of i units for bottom returns is the joint occurrence of i extreme bottom returns on a particular day for a specific group. By counting the total number of days with extreme returns of a given count and identifying which countries participate in those events and how often we have a good overview of the extreme returns for each country and group of countries.

We notice that out of the 10% lowest returns for all Euro-periphery countries the Greek stock market had the most days (106) on which it was the only country experiencing a bottom extreme return, followed by Ireland (56 days) and Portugal (37 days). A total of 54 days are reported for the Euro-periphery countries on which all of them experienced extreme bottom returns. For the Euro-core countries, 109 days are found that all five countries experienced an extreme bottom return shock. On 55 days all five Non-euro countries experienced bottom extreme returns, with the Czech Republic having the most days (84) as the only country experiencing an extreme bottom return. On the other hand, from the top 10% distribution, all Euro-periphery countries experienced an extreme top return on 40 days. There are a total of 91 days on which five Euro-core countries experienced extreme top returns. On a total of 28 days, all Non-euro countries had an extreme top return, with the Czech Republic once more having the most days (95) with extreme top returns.

The graphical illustrations of bottom extreme return counts for the three groups appear in the following Figure:

Insert Figure 1 here

It is obvious that extreme bottom returns have a much higher density in the crisis periods. What we observe is a "bottom extreme returns clustering", since as one would expect most of the extreme bottom returns fall within the crisis periods. This happens for all the three (3) groups of the fifteen (15) European countries we study, and provides a visual confirmation of the quantitative result we found as far as the intensification of extreme returns is concerned.

The methodology of Bae et al. (2003) can be applied to study two types of spill-over effects: within groups and across groups. In this paper we mainly focus on effects across groups.

3.2. Examining the presence of extreme returns transmission

In order to capture the effects within a group we consider a polychotomous variable, like Bae et al. (2003) and Boyson et al. (2010). In the theory of multinomial logistic regression models, if P_i is the probability of an event category i out of m possible categories, a multinomial distribution can be defined by

$$P_i = P(Y_t = i|x_j) = \frac{G(\beta_i' x_j)}{1 + \sum_{j=1}^{m-1} G(\beta_j' x_j)}, \tag{1}$$

where x is the vector of covariates and β_i the vector of coefficients associated with the covariates. The function $G(\beta_i' x)$ many times takes the form of an exponential function $exp(\beta_i' x)$, in which case Equation 1 represents a multinomial logistic (or multinomial logit) model. Such models are estimated using maximum likelihood, with the log-likelihood function for a sample of n observations given by

$$logL = \sum_{i=1}^{n}\sum_{j=1}^{m} I_{ij} logP_{ij}, \tag{2}$$

where I_{ij} is a binary variable that equals one if the ith observation falls in the jth category, and zero otherwise. Goodness-of-fit in these models is measured using the $pseudo - R^2$ approach of McFadden (1974) where the unrestricted (full model) likelihood, L_Ω, and restricted (constants only) likelihood, L_ω, functions are compared:

$$pseudoR^2 = 1 - [logL_\omega/logL_\Omega]. \tag{3}$$

To capture the range of possible outcomes, and yet have a concrete model, we have a total of six categories: 0, 1, 2, 3, 4, and 5 extreme return counts. For a model that has only constants, m-1, or five parameters, need to be estimated. But for every covariate added to the model, such as the daily average exchange rate changes, five additional parameters need to be estimated, one for each outcome. The top and the bottom extreme returns are estimated separately. Finally, we compute the probability of a count of a specific level, P_i, by evaluating the covariates at their unconditional values,

$$P^*_{ij} = \frac{exp(\beta'_i x^*_j)}{1 + \sum_{j=1}^{m-1} exp(\beta'_j x^*_j)}, \tag{4}$$

where x_j* is the unconditional mean value of x_j.
The coefficients that are given by a multinomial logistic regression compare the probability of a given outcome with the base outcome (in our case the outcome 0 is the base outcome - i.e. the outcome where no country has an extreme return). As mentioned in Greene (2003), the coefficients of such a model are not easy to interpret. This is why it is necessary to differentiate 1 in order to obtain the partial effects of the covariates on the probabilities

$$\delta_{ij} = \frac{\delta P_{ij}}{\delta \beta_i} = P_{ij}[x_j - \sum_{k=0}^{J} P_{ik}\beta_k] = P_{ij}[\beta_j - \bar{\beta}] \tag{5}$$

In multinomial logistic regressions the coefficients correspond to probabilities. Thus, these partial effects give us the marginal change in probability for a unit change in the independent covariate. In such models we are interested in seeing whether these marginal effects are statistically significant or not. These marginal effects may even have different signs than the corresponding coefficients, since the derivative $\frac{\delta P_{ij}}{\beta_{ik}}$ can have a different sign than the coefficient β_{jk}. [9]

In our case, we have a variable Y_t that counts the number of extreme returns and takes the value

[9] To elaborate a little further on why it is crucial that marginal effects are calculated for such models, it is known that the coefficients of a multinomial logistic are obtained from comparing the probability of a given outcome with the base outcome. In our case, the outcome is 0, in other words, no extreme returns in the group. Thus, the estimated coefficient for covariate x_{13} for outcome 3, which is β_{13} and is the coefficient for the 1st covariate, calculated for the 3rd outcome, measures the probability of having an outcome equal to 3 (3 extreme returns in the group), instead of an outcome 0 (no extreme returns in the group), for a unit change in the covariate x_{13}. But in reality, there is also the possibility of having the outcome 2 instead of 0 for a unit change in covariate x_{13}. This is exactly why we need the marginal effects, to calculate the probabilities associated with a unitary covariate change in adjacent categories, and not taking as an alternative only the base outcome (0 in our study). This happens because the coefficients of a multinomial logistic regression model exhibit what is known as the "log odds ratio" property:

$$\ln \frac{P_{ij}}{P_{i0}} = \beta'_i x_j \tag{6}$$

i when extreme returns (top or bottom) occur for the same day in i stock market indices on day t. This variable is calculated separately for the Euro-core, the Euro-periphery, and the Non-euro groups. Then, in the multinomial logistic regression Equation 4 P_i is equal to $P(Y_t = i|x_t)$ where $Y_t = 0, 1, 2, ...k$ is the extreme return count variable that is created for the Non-euro, and for each of the country groups we defined (Euro-periphery vs. Euro-core etc.). So, we have k=5 for all three country groups, where x_t is a vector of explanatory variables (covariates), on day t. In Equation 4, the argument of the exponential part (representing the logistic function) is a function of the covariates (x_t) and the coefficients(the betas). This function is a linear expression of the arguments. Let's call it $g_i(t)$. We will use this function (which will take different forms) to study both the "within" and "across" groups extreme returns effects.

3.3. Effects within groups

In this section, we study the three country groups to determine whether there exist effects within them. Each of these groups has it's own set of covariates. In line with Bae et al. (2003) and Gropp et al. (2009), as independent variables incorporated in $g_i(t)$ we have the intercept, the conditional volatility of the group stock index at time t (h_t)[10], the average exchange rate change (per US dollars) in the group (e_t), the average short term (ST) interest rate level in the group (i_t) as a proxy for the interbank short term liquidity risk[11], and the average long term (LT) spread change (b_t) vis-*à*-vis Germany as a proxy for the sovereign risk change[12].

We include exchange rate changes following Bae et al. (2003) who find that when currencies fall on average (which means that e_{it} rises) extreme returns are more common. Thus, the logistic regression $G(\beta_i' x) = exp(g_i(x_t))$ of equation 1 has the following form for $g_i(x_t)$:

$$g_i(x_t) = b_{0i} + b_{1i}h_{it} + b_{2i}e_{it} + b_{3i}i_{it} + b_{4i}b_{it} \tag{7}$$

where i=0, 1, 2, 3, 4, 5 for each country group, the extreme return count for the group. Equation 7 represents the inter-group effects formula for the three groups examined. For each group we calculate the equally weighted average group values, on a daily basis, of the conditional volatility (h_{it}), the exchange rate change (e_{it}), the short term (ST) interest rates levels (i_{it}), and the Long Term (LT) spread change vis-*à*-vis Germany (b_{it}).

We estimate these models for each group, for the entire sample and for each of the three time periods. It is worth noting that, in the second case, the extreme return counts are calculated separately for each of the three periods. In other words, in each of the three periods the bottom and top extreme values correspond to the respective 10% and 90% threshold points of each period. We first present in Table 3 the detailed findings for the Euro-periphery group for bottom extreme returns and for the entire period.

Insert Table 3 here

The probability that no Euro-periphery country has a bottom tail return is equal to 77.49%. This

[10] The conditional volatility is estimated using an EGARCH(1,1) model to the equally-weighted group indexes.

[11] Short term interest rates are available in Datastream (3-month Interbank interest rates).

[12] Spreads are calculated as the difference between the yield of the 10 year government bond of country i's debt and the yield of the 10 year German government bond. Naturally, for the Euro-core group, one of the five countries is Germany, so, for Germany, the LT Spread Change will be zero, but the other four Euro-core countries will have their respective LT daily spread change.

is calculated as the fraction of the number of 0 extreme returns divided by the total days $\frac{1859}{2399} = 0.774$. The coefficient β_{01} corresponds to the event Y=1, in other words the event where only one Euro-periphery country has an extreme return (an exceedance) on that day, and the probability of this event is calculated as $P_1 = \frac{\exp(\beta_{01})}{1+\sum_{i=0}^{5}\exp(\beta_{0i})}$. This probability is found to be equal to 10.3%. If currencies in the group fall on average (in which case e_{it} rises), the probability of extreme returns increases, since the signs of the exchange rate marginal effects are positive, and statistically significant at the 5% level for the first exceedance, and at the 1% level for the coincidence of two, three, four and five bottom extreme returns. In their study Bae et al. (2003) measured returns in dollars and the fact that they came up with very similar results made them wonder whether the stock return contagion they measured was actually foreign exchange contagion. Thus, they also estimated their models in local currencies, but the results were similar to the dollar returns. But we estimate our models in local currencies from the beginning, so we do not face such an issue. The results for ST interest rates are mixed since two marginal effects are statistically significant, for the outcomes of one and five bottom counts in the group, but with contradictory signs. Regarding the LT spread change in the group vis-*à*-vis Germany, we find positive and statistically significant marginal effects. For all extreme bottom outcomes except for the second, the marginal effects are significant at the 1% level. The positive sign of the coefficient indicates that a 1% increase in the average Euro-periphery LT spread increases the probability of extreme bottom returns in the group. A change of 1% in the average LT spread of the Euro-periphery group, increases the probability of one bottom extreme return by 19.7%. To simplify the presentation in Table 4 we show a summary for the within groups results, for the entire sample, and the three periods separately. The number of "+" (or "-") indicates the number of statistically significant (in the 1% or 5% levels) and positive (or negative) marginal effects.

Insert Table 4 here

Pre-crisis the effect of covariates on the probability of extreme returns is rather weak, while the role of covariates increases significantly in the crisis periods in most of the cases. The results are even stronger when we take the extreme returns over the entire period which notably includes the US-crisis as well. The effect of volatility is somehow smaller in the Euro-crisis period compared to the Pre-crisis period, for the bottom tail. Exchange rate changes are not significant for the bottom count of the Non-euro group in the Pre-crisis period, with zero significant marginal effects, while they became significant in four of the five cases in the Euro-crisis period. Exchange rate changes have a positive coefficient for the bottom tail, and a negative coefficient for the top tail. This means that higher exchange rates (i.e. weaker currencies) lead to a higher probability of extreme bottom returns and a lower probability of extreme top returns. Average ST interest rates are not significant in most of the cases, while average LT spread changes become more significant in the Euro-crisis period, especially for the Euro-core and the Euro-periphery group as far as the bottom tails are concerned, and the Non-euro and Euro-core groups for the top tail returns. For the bottom tail, higher average group LT spread changes (i.e. an increase in the average group sovereign risk) lead to higher probabilities of extreme group bottom returns, while they decrease the probability of extreme top returns.

In summary, the findings so far indicate a much tighter relationship of the fundamental factors (covariates) affecting the extreme stock market movements within each group during the Euro-crisis and US-crisis periods compared to the Pre-crisis period.

3.4. *Effects across groups*

Next we test for across groups effects. This deals with the question of whether the number of extreme return counts in one group (e.g. the Euro-periphery group) can help predict the number of extreme returns in other groups (the Euro-core and the Non-euro groups). According to Bae et al. (2003) and Boyson et al. (2010), if a fraction of extreme returns in one group is unexplained by its own covariates, but can be explained by extreme returns in another area, this can be interpreted as evidence of transmission of the crisis across groups[13].

Our primary interest is to study for across-groups effects from the Euro-periphery group to the Non-euro and the Euro-core groups. To examine this question, we reestimate the models of Table 4 for the Euro-core and Non-euro groups respectively, adding a covariate related to the extreme return count (Y^*_{jt}) from the Euro-periphery. In this case the equations for the across groups examination take the following shape:

$$g_i(x_t) = b_0 + b_1 h_{it} + b_2 e_{it} + b_3 i_{it} + b_4 b_{it} + b_5 Y^*_{jt} \tag{8}$$

For example, to examine if the Euro-periphery group provokes transmission effects in the Euro-core group the dependent variable is the number of extreme returns in the Euro-core group and the first three covariates of the right hand side concern the Euro-core group, while the last covariate is related to the count of extreme returns of the Euro-periphery group on that day. The null hypothesis of no transmission effects can be rejected in case the coefficient of Y^*_{jt} is found to be statistically significant.

In Table 5 we present the detailed across groups effects from the Euro-periphery extreme bottom returns to the Euro-core group for the entire period:

Insert Table 5 here

The main variable of interest is the "Bottom Count Euro-periphery" variable, which is the Y^*_{jt} in equation 8. We see that this variable is positive and significant for all five Euro-core bottom outcomes. In other words a higher value of bottom Euro-periphery extreme returns increases the probability of bottom extreme returns for the Euro-core group as well. For one more Euro-periphery country having extreme bottom returns, there is an increase of 8.8% in the probability of one Euro-core country having extreme bottom returns. Given the fact that the baseline predicted probability of one Euro-core country having an extreme bottom return is 6.4%, this marginal effect is very significant both economically and statistically.

Table 6 provides the summary results for the across groups effects, for the entire period and the three time periods we examine (the Pre-crisis, the US-crisis and the Euro-crisis periods) separately.

Insert Table 6 here

The evidence supports the hypothesis that there exist important (positive) effects from the Euro-periphery to the other two groups. Extreme bottom (or top) return counts in the Euro-periphery

[13] In general, the definition of contagion is far from being simple and commonly accepted. Pericoli and Sbracia (2003) provide five of the most widely accepted definitions of financial contagion. According to one of their definitions "Contagion is a significant increase in the probability of a crisis in one country, conditional on a crisis occurring in another country.". According to another of their definitions, "Contagion occurs when cross-country comovements of asset prices cannot be explained by fundamentals". Hence, these definitions are consistent with Bae et al. (2003) and Boyson et al. (2010).

group have a significant (and positive) impact on the extreme return counts of the Euro-core and Non-Euro groups in most of the cases. The results are stronger for the entire sample period (which also includes the US-crisis) but the number of statistically significant coefficients does not change between the Pre-crisis and the crisis periods.

The findings indicate that extreme returns in the Euro-periphery group are indeed associated with extreme returns in the other two European groups but this relationship, interestingly and perhaps contrary to popular belief, does not seem to have intensified during the Euro-crisis period. Of course, the absolute size of the effects is stronger since the same 10% cutoff values are higher during the crisis periods, as Table 7 shows:

Insert Table 7 here

In other words, the coefficients may be smaller during the crisis period, but the shocks became deeper in terms of the expected losses for the different groups, indicating an intensification of the effects. This is also verified by the average returns on the days with extreme bottom outcomes which appear on Table 8:

Insert Table 8 here

Indeed, one can easily compare the Pre-crisis with the crisis periods and see the evident intensification of extreme bottom returns. For example, the average return on days where four (4) Non-euro country had an extreme bottom return (column 4) is -1.694% in the Pre-crisis period, while it increases to -2.565% in the Euro-crisis period. For the outcome where all five (5) Euro-core countries had an extreme bottom return on the same day (column 5) the average return decreased from -1.776% in the Pre-crisis to -2.802% in the Euro-crisis period. Thus, an "extreme bottom return" in the Euro-crisis period, is much more intense than an "extreme bottom return" in the Pre-crisis period. Although the cutoff does not change (10% of the marginal distribution in both periods), the actual returns themselves are much more negative. This results in higher expected losses for investors in the occurrence of an "extreme event" (which by definition happens in 10% of the days for all countries). We perceive this as indication that although the transmission channels do not seem to intensify during the crises, the transmitted shocks are larger. Given the fact that stock market capitalisations in these country groups are trillions of Euros, a 1% or 2% increase in extreme bottom returns (in crisis periods) can lead to aggregate losses of tens of billions Euros in one single trading day.

4. Robustness and alternative specifications

To verify the robustness of our results, as a first robustness check, instead of 10% and 90% extreme returns cutoffs, we used the 5% and 95% percentages. The results are robust in this change. Furthermore as a second robustness check, instead of the raw returns, we calculated extreme returns on the standardized residuals of a GARCH(1,1) model, accounting for the time-varying volatility effects, since in periods of high volatility, extreme returns are more probable. In order to calculate the volatility, we move in line with Christiansen and Ranaldo (2009), estimating a AR(1)-GARCH(1,1) model for each group's average returns:

$$Ret_t^{group} = c_0 + c_1 Ret_{t-1}^{group} + \epsilon_t \tag{9}$$

where ϵ_t $N(0, \sigma_t^2)$ and the variance follows a GARCH(1,1) process:

$$\sigma_t^2 = c_2 + c_3\sigma_{t-1}^2 + c_4\epsilon_{t-1}^2 \tag{10}$$

The volatilities are then obtained as the estimated $\hat{\sigma_t}$ from the AR(1)-GARCH(1,1) model. We notice that for the extreme returns counts filtered by a GARCH the effect of volatility is not significant (for the raw returns all volatility coefficients were found to be positive and statistically significant - in other words an increase in volatility increases the probability of extreme bottom returns).

5. Conclusion

We examine the existence of stock market shocks among three groups of countries: the Euro-periphery countries (Portugal, Ireland, Italy, Greece, Spain), the Euro-core countries (Germany, France, the Netherlands, Finland, Belgium), and the major European Union -but not euro- countries (Sweden, UK, Poland, Czech Republic, Denmark), using daily stock market data from January 2004 till March 2013. Our analysis is split in two parts: the first part concerns extreme stock index returns, controlling for various fundamentals derived from financial market data (volatility, exchange rate change, short interest rates, long term spread change). We find effects within the Euro-periphery group and from the Euro-periphery group to the Non-euro and the Euro-core groups for both the Pre-crisis and the Euro-crisis periods. The transmission channels do not appear to have changed as a result of the crisis, but they transmitted larger shocks. Thus, expected losses from extreme returns have increased in the crises periods, being evidence of an intensification of the effects during the recent financial crises.

The implications of the overall findings are quite significant for investors who may want to diversify their portfolios and should be aware of the stock indices movement dynamics and of how extreme shocks propagate from one group of countries to the others, affecting their portfolios' overall risk. Furthermore, it would be useful for policy makers in order to assess policy decision making in times of extreme shocks (such as crisis periods). The fact that the European financial markets are affecting one another provides evidence that in case that crisis episodes are not properly confronted, extreme returns may propagate and cluster, leading to significant losses for investors and institutions. Future research could also take into effect different models or move in the direction of higher frequency (intraday) financial markets dynamics. Given the fact that stock market capitalisations in these country groups are trillions of Euros, a 1% or 2% increase in extreme bottom returns (in crisis periods) can lead to aggregate losses of tens of billions Euros in one single trading day.

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Table 1: Descriptive Statistics and Correlations for Stock Indices

Panel A: Descriptive Statistics

	Pre-crisis 1/1/2004 - 26/2/2007			US-crisis 27/2/2007 - 7/12/2009			Euro-crisis 8/12/2009 - 13/3/2013		
	Non-euro	Euro-periphery	Euro-core	Non-euro	Euro-periphery	Euro-core	Non-euro	Euro-periphery	Euro-core
Mean (%)	0.101	0.089	0.081	−0.024	−0.074	−0.049	0.030	−0.017	0.029
Median (%)	0.113	0.104	0.115	0.012	0.012	0.017	0.034	0.017	0.047
Std. Dev. (%)	0.949	0.740	0.797	1.876	1.791	1.779	1.141	1.602	1.262
Minimum (%)	−6.020	−6.230	−9.926	−14.185	−13.341	−9.199	−6.805	−7.132	−7.787
Maximum (%)	8.505	4.816	6.203	15.236	10.509	16.062	6.406	12.474	8.240

Panel B: Correlations

	Pre-crisis 1/1/2004 - 26/2/2007			US-crisis 27/2/2007 - 7/12/2009			Euro-crisis 8/12/2009 - 13/3/2013		
	Non-euro	Euro-periphery	Euro-core	Non-euro	Euro-periphery	Euro-core	Non-euro	Euro-periphery	Euro-core
Non-euro	1.000			1.000			1.000		
Euro-periphery	0.429	1.000		0.677	1.000		0.520	1.000	
Euro-core	0.522	0.579	1.000	0.727	0.729	1.000	0.734	0.646	1.000

Note: European countries are split in three groups: the Euro-periphery countries (Portugal, Ireland, Italy, Greece, Spain), the Euro-core countries (Germany, France, Finland, the Netherlands, Belgium) and the European Union -non Euro- countries (Poland, Czech Republic, Sweden, UK, Denmark). Country group log returns (expressed in local currency) and standard deviations are calculated on the equally weighted mean portfolio of the country stock market daily returns (expressed in local currency) for each group.

Table 2: Counts of extreme bottom (and top) log returns for daily country group stock indices, January 1st 2004 to March 13th 2013.

	Mean return (%) when $i = 5$	Number of bottom counts						Number of top counts						Mean return (%) when $i = 5$
		5	4	3	2	1	0	0	1	2	3	4	5	
Non-euro														
POL	−3.446	55	41	38	49	57	1847	1783	82	47	40	43	28	3.653
SWE	−3.727	55	45	54	54	32	1847	1783	42	56	61	53	28	4.025
CZE	−3.828	55	27	28	46	84	1847	1783	95	57	31	29	28	4.022
UK	−3.241	55	52	60	43	30	1847	1783	37	56	62	57	28	3.572
DEN	−3.370	55	47	48	42	48	1847	1783	61	42	55	54	28	3.382
Subtotal		55	53	76	117	251	1847	1783	317	129	83	59	28	
Euro-periphery														
POR	−3.253	54	66	44	39	37	1859	1817	61	45	34	60	40	3.008
IRE	−3.944	54	54	26	50	56	1859	1817	69	47	31	53	40	3.522
ITA	−3.636	54	69	45	52	20	1859	1817	20	62	56	62	40	3.678
GRE	−4.160	54	35	22	23	106	1859	1817	108	32	20	40	40	4.200
SPA	−3.503	54	64	49	44	29	1859	1817	29	56	54	61	40	3.652
Subtotal		54	72	62	104	248	1859	1817	287	121	65	69	40	
Euro-core														
GER	−2.855	109	44	32	19	36	1970	1938	46	25	31	47	91	2.530
FRA	−3.137	109	56	46	19	10	1970	1938	13	35	41	60	91	2.842
NL	−3.169	109	51	37	22	21	1970	1938	20	27	50	52	91	2.782
FIN	−3.303	109	38	24	19	50	1970	1938	48	26	26	49	91	3.240
BEL	−2.809	109	35	32	27	37	1970	1938	51	29	29	40	91	2.534
Subtotal		109	56	57	53	154	1970	1938	178	71	59	62	91	

Note: Extreme returns for daily stock index top (bottom) log returns are the ones belonging to the highest (lowest) 10% of all daily returns. The extreme counts are defined as the joint occurrence of extreme returns across different country indexes on the same day. For example, out of a total sample of 2399 trading days, there are 104 days where exactly two Euro-periphery countries had extreme bottom returns on the same day, and in 23 of those days Greece is the one of the two countries having extreme bottom returns.

Table 3: Within the Euro-periphery group bottom extreme counts of log returns for the entire period.

	(1)	(2)	(3)	(4)	(5)
	Margin / SE	Margin / SE	Margin / SE	Margin / SE	Margin / SE
Constant	-0.224***	-0.145***	-0.082***	-0.071***	-0.059***
	(0.015)	(0.011)	(0.010)	(0.010)	(0.009)
Volatility	0.085***	0.042***	0.018***	0.021***	0.014***
	(0.011)	(0.006)	(0.004)	(0.004)	(0.003)
Exchange Rate Change	0.024**	0.027***	0.015***	0.018***	0.010***
	(0.010)	(0.006)	(0.004)	(0.003)	(0.002)
ST Interest Rate	-0.012***	0.001	-0.000	-0.002	0.003***
	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
LT Spread Change	0.197***	0.017	0.113***	0.087***	0.065***
	(0.065)	(0.037)	(0.022)	(0.018)	(0.014)
Observations	2399	2399	2399	2399	2399
Baseline predicted probability	0.103	0.043	0.026	0.030	0.023
$Pseudo-R^2$	0.118				

Note: Columns (1) to (5) correspond to bottom extreme counts 1 to 5. In other words, column (1) presents the marginal effects in the case of one bottom count for the Euro-periphery group, and columns (2),(3),(4),(5) correspond to two, three, four and five bottom counts for this group. The value of 0.197 for the Euro-periphery LT spread changes (column 1) means that an increase of 1 percent in the average Euro-periphery long term spread (vis-à-vis Germany) increases the probability of one Euro-periphery having extreme bottom stock returns (i.e. one bottom Euro-periphery exceedance) by 19.7%, while the value of 0.024 for the average exchange rate change (column 1) means that a one percent increase in the average Euro-periphery exchange rate increases the probability of one bottom Euro-periphery exceedance by 2.4%.
(***) : significance at 1% level
(**) : significance at 5% level
(*) : significance at 10% level

Table 4: Within groups summary results for bottom and top extreme return counts.

	Bottom tail			Top tail		
Entire Period						
	Non-euro	Euro-periphery	Euro-core	Non-euro	Euro-periphery	Euro-core
Volatility	+ + + + +	+ + + + +	+ + + + +	+ + ++	+ + + + +	+ + + + +
Exchange Rate Ch.	+ + + + +	+ + + + +	+ + ++	− − − − −	− − − − −	− − −−
ST Interest Rate	++		+		− − −−	−
LT Spread Change	+ + + + +	+ + ++	+ + ++	− − − − −	− − − − −	− − −
$Pseudo-R^2$	0.120	0.118	0.093	0.111	0.096	0.091
Pre-crisis Period						
	Non-euro	Euro-periphery	Euro-core	Non-euro	Euro-periphery	Euro-core
Volatility	+ + +	+ + +	++	+ + +	+	++
Exchange Rate Ch.		−	−		+	+
ST Interest Rate	−−			−	+	
LT Spread Change	+	+		−		
$Pseudo-R^2$	0.040	0.039	0.036	0.044	0.016	0.038
US-crisis Period						
	Non-euro	Euro-periphery	Euro-core	Non-euro	Euro-periphery	Euro-core
Volatility	+ + +	+ + ++	+ + ++	+ + ++	+ + ++	+ + + + +
Exchange Rate Ch.	+ + + + +	++	+	− − −−	−	−−
ST Interest Rate				−−	−	−−
LT Spread Change	+	++		−	−−	
$Pseudo-R^2$	0.122	0.085	0.084	0.137	0.084	0.079
Euro-crisis Period						
	Non-euro	Euro-periphery	Euro-core	Non-euro	Euro-periphery	Euro-core
Volatility	+	++	++	+ + ++	−	+ + ++
Exchange Rate Ch.	+ + ++	+ + ++	+ + +	− − −−	− − −−	−−
ST Interest Rate	+					
LT Spread Change	+	+ + +	+ + ++	− − −−	−	− − −−
$Pseudo-R^2$	0.194	0.176	0.181	0.172	0.119	0.167

Note: The number of "+" (or "-") indicate the number of statistically significant (in the 1% or 5% levels) and positive (or negative) marginal effects. For example, for the bottom tail returns and the entire period sample, all five volatility marginal effects are significant and positive for the Non-euro group (this is why we have five plus symbols at the Non-Euro column), indicating that an increase in volatility increases the probability of extreme bottom returns in all five bottom extreme outcomes. For the top tail returns, the number of statistically significant marginal effects are five for the average exchange rate change in the Non-euro group, meaning that an increase in the average group's exchange rates (i.e. weaker group currencies on average) leads to lower probabilities of top Non-euro counts (for all five possible outcomes).

Table 5: Across groups effects: Euro-periphery to Euro-core bottom extreme returns for the entire period.

	(1)	(2)	(3)	(4)	(5)
	Margin / SE	Margin / SE	Margin / SE	Margin / SE	Margin / SE
Constant	-0.273***	-0.104***	-0.082***	-0.036***	-0.010**
	(0.017)	(0.013)	(0.013)	(0.009)	(0.004)
Volatility	0.041***	0.010*	0.007**	-0.001	0.001*
	(0.010)	(0.005)	(0.003)	(0.002)	(0.000)
Exchange Rate Change	-0.018*	0.002	-0.000	-0.002	-0.000
	(0.009)	(0.005)	(0.003)	(0.002)	(0.000)
ST Interest Rate	0.012***	0.003	0.005***	0.002**	0.000*
	(0.004)	(0.002)	(0.001)	(0.001)	(0.000)
LT Spread Change	0.335	0.122	0.009	0.034	0.004
	(0.255)	(0.117)	(0.072)	(0.037)	(0.006)
Bottom Count Euro-periphery	0.088***	0.031***	0.025***	0.014***	0.003**
	(0.010)	(0.005)	(0.005)	(0.004)	(0.001)
Observations	2399	2399	2399	2399	2399
Baseline predicted probability	0.064	0.022	0.024	0.023	0.045
$Pseudo-R^2$	0.373				

Note: Columns (1) to (5) correspond to bottom counts 1 to 5. In other words, column (1) presents the marginal effects in the case of one bottom count for the Euro-periphery group, and columns (2),(3),(4),(5) correspond to two, three, four and five bottom counts for this group. The value of 0.088 for the Euro-peripheryc bottom count (column 1) means that an increase of 1 Euro-periphery countries having extreme bottom returns increases the probability of one Euro-core country having extreme bottom stock returns (i.e. one bottom Euro-core count) by 8.8%.
(***) : significance at 1% level
(**) : significance at 5% level
(*) : significance at 10% level

Table 6: Across groups summary results for bottom and top extreme counts.

	Bottom tail		Top tail	
Entire Period				
	Non-Euro	Euro-core	Non-Euro	Euro-core
(from Euro-periphery)				
Volatility	+ + +	++	+ + +	+ + ++
Exchange Rate Change	+ + +		− − −−	
ST Interest Rate	+ + +	+ + +	+ + ++	+
LT Spread Change			−−	
Euro-periphery Bottom Extreme Count	+ + ++	+ + + + +	+ + ++	+ + + + +
$Pseudo-R^2$	0.299	0.373	0.228	0.321
Pre-crisis Period				
	Non-Euro	Euro-core	Non-Euro	Euro-core
(from Euro-periphery)				
Volatility			++	++
Exchange Rate Change		−		+
ST Interest Rate			−	
LT Spread Change			−	
Euro-periphery Bottom Extreme Count	+ + +	+ + ++	+ + +	+ + ++
$Pseudo-R^2$	0.223	0.281	0.159	0.245
US-crisis Period				
	Non-Euro	Euro-core	Non-Euro	Euro-core
(from Euro-periphery)				
Volatility	++	++	+ + +	+ + ++
Exchange Rate Change	+ + +		− − −	−
ST Interest Rate			−	−
LT Spread Change	+			
Euro-periphery Bottom Extreme Count	+ + ++	+ + ++	+ + ++	+ + ++
$Pseudo-R^2$	0.341	0.384		0.345
Euro-crisis Period				
	Non-Euro	Euro-core	Non-Euro	Euro-core
(from Euro-periphery)				
Volatility			+ + +	+ + +
Exchange Rate Change	+ + +		− − −	
ST Interest Rate		+		
LT Spread Change		+	−	−−
Euro-periphery Bottom Extreme Count	+ + +	+ + ++	+ + +	+ + ++
$Pseudo-R^2$	0.290	0.373	0.262	0.342

Note: The number of "+" (or "-") indicate the number of statistically significant (in the 1% or 5% levels) and positive (or negative) marginal effects. For example, for the bottom tail returns and the entire period sample, three out of five volatility marginal effects are significant and positive for the Non-euro group, indicating that an increase in volatility increases the probability of bottom Non-euro extreme counts in three out of five outcomes. For the top tail returns, the number of statistically significant marginal effects are four for the average exchange rate change, and have a negative sign in all four cases, meaning that an increase in the average group's exchange rates (i.e. weaker group currencies on average) lead to lower probabilities of extreme top returns in four out of five top Non-euro outcomes.

Table 7: 10% percentiles for the extreme bottom returns (%) of the three country-groups for all subperiods.

	Non-euro	Euro-periphery	Euro-core
Entire Period	-1.397	-1.555	-1.407
Pre-crisis	-0.957	-0.742	-0.831
US-crisis	-2.037	-2.060	-2.011
Euro-crisis	-1.262	-1.903	-1.450

Table 8: Average returns (%) on days with extreme bottom outcomes, for all subperiods.

	(1)	(2)	(3)	(4)	(5)
Entire period					
Non-euro	-1.876	-2.101	-2.195	-2.665	-3.523
Euro-periphery	-2.459	-2.295	-2.226	-2.724	-3.699
Euro-core	-2.047	-1.806	-1.949	-2.111	-3.055
Pre-crisis					
Non-euro	-1.341	-1.514	-1.501	-1.694	-2.624
Euro-periphery	-1.076	-1.108	-1.128	-1.512	-1.843
Euro-core	-1.154	-1.179	-1.141	-1.214	-1.776
US-crisis					
Non-euro	-2.570	-2.829	-3.222	-3.346	-5.156
Euro-periphery	-2.691	-2.978	-2.912	-3.484	-4.238
Euro-core	-2.732	-2.709	-2.734	-2.819	-4.236
Euro-crisis					
Non-euro	-1.606	-1.793	-1.894	-2.565	-2.852
Euro-periphery	-2.759	-2.574	-2.718	-2.888	-3.749
Euro-core	-1.848	-1.689	-1.759	-2.162	-2.802

Note: Columns one (1) to five (5) correspond to the count of extreme bottom returns. For example, column one (1) corresponds to one country in the group having an extreme bottom return on this day, while column five (5) corresponds to all five (5) countries in the group having extreme bottom returns on the same day.

Fig. 1. Extreme bottom return counts for all three country groups, for the entire period.