

# **Essays in Corporate Finance**

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## Abstract

This project includes three essays in Corporate Finance.

The first part of the thesis investigates the relationship between Financial Development and Economic Growth for a set of 77 countries over the period 1960-1995. Borrowing the methodology suggested by Beck, Levine and Loayza (2000), I study the previous relationship using a cross-country regression model and a panel technique. My results suggest that Private Credit, defined as credits by financial intermediaries to the private sector divided by GDP, has a positive impact over Economic Growth. My findings also point out that Economic Growth is positively affected by openness to trade and average years of schooling. The relationship between Financial Development and Economic Growth is independent of the degree of financial development as well as the initial level of income of a given country. Differently from other papers, I can study whether the finance-growth nexus is persistent over time: using a similar dataset for an extended period, 1960-2010, I show that the impact of Private Credit over Growth is significative also in the most recent past.

The second part of the thesis explores the stock-prices comovements for a set of 7 countries over the period 2000-2014. The study explores how the volatilities and correlations in one country, mainly Italy, are affected by the volatilities and correlations in another country. Differently from other papers, I focus on a larger set of countries and on a sample period that allows to distinguish between the Pre Great Recession period and the Post Great Recession period. The analysis is conducted by considering several GARCH models, for the volatility comovements, and MGARCH models, for the correlation comovements. The best GARCH model in my setting is the EGARCH model which provides information on the impact of positive innovations on volatility. Among the MGARCH models, I focus on the CCC model and the DCC model. My results point out that the strenght of the relationship among countries is amplified after a crisis event, which is consistent with most of the "contagion" literature.

The last part of the thesis analyzes the relationship between long-term debt and average investment during the 2007 crisis. Very few papers have analyzed the real effects of debt maturity. To analyze the impact of the debt structure on firms' performance I use a matching approach methodology (Abadie-Imbens estimator) which allows to distinguish between a treatment group and a control group: the first one refers to the group of firms whose long-term debt

is maturing at the time of the crisis, while, on the other hand, the control group refers to those firms that are out of the treatment but have similar firm characteristics like cash flow, size, Q, cash holdings and long-term leverage. My results show that firms with debt maturing during the period of the crisis experience a much more pronounced fall in investment. Results are tested using a Parallel Trend Test which allows to better define whether the results are driven by the maturity argument or not.

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*A Michele.*

*La tua forza di volontà e il tuo sorriso mi accompagneranno sempre.*

## **Part I**

# **Is Finance Development affecting Economic Growth?**



# Chapter 1

## The Finance-Economic Growth Nexus

### 1.1 Introduction

The fundamental question in economic growth that has preoccupied researchers is why do countries grow at different rates. The empirical growth literature has come up with numerous explanations of cross-country differences in growth, including factor accumulation, resource endowments, the degree of macroeconomic stability, international trade and ethnic and religious diversity. The list of factors that might affect the growth rate of a given country can be expanded with no limits.

One of the most interesting questions in this field is: *Is financial development an important factor affecting economic Growth?*

This question has been analyzed in different papers from different points of view. Although it seems fairly obvious, the link between financial depth and economic growth is challenging and requires specific techniques to deal with the endogeneity problem that this question creates. If it is true that financial development and the efficiency of the banking sector represent an impulse for economic growth, people may also argue that the degree of economic development influences how organized and complex financial markets can be.

Theoretical and empirical works supporting the central role of financial markets in economic development are very much in progress. This paper analyzes the relationship between financial and economic growth using a set of 77 countries starting from 1960 until 2010. Following the

methodologies suggested by Beck, Levine and Loayza (2000), I find that Private Credit, my proxy for financial development, has a significant effect on growth over all the sample period considered. The results are robust to a number of tests. Differently from other papers, I can analyze the relationship between the outcome and the independent variables up to the most recent time and verify that the level of initial income or the degree of the financial development do not have a meaningful role.

This chapter is organized in the following way. First, a brief description of the literature will be provided. Then the methodology will be described and the main results will be presented. A short summary of the results concludes the chapter.

## 1.2 Literature Overview

The study of the relationship between economic growth and financial development has known a peak in the last two decades.

The early studies of Gurley and Shaw (1955), Goldsmith (1969) and Hicks (1969) seem to suggest that financial development stimulates economic growth. Similar ideas are reported by Shaw (1973) who advocates that financial intermediaries promote investment and consequently contribute in boosting economic growth rates.

One of the most relevant papers studying the finance-growth nexus is King and Levine (1993). The authors study a sample of 70 countries introducing new measures of financial development and examining the impact of financial development on economic growth, capital accumulation and factors' productivity. Their results show a link between financial development indicators and growth. Accordingly, Levine and Zevros (1998) reach the conclusion that financial development is an accurate indicator of economic growth. They point out that levels of bank development and incoming liquidity are significantly and positively correlated with economic growth and productivity future rates. They further mention statistically significant relationships between savings rates and financial development variables.

Another significant paper of the area is Spiegel (2001). Here, the author examines the relationship between financial development indicators and economic growth using a panel data approach which allows for endogeneity of regressors and the optimum use of the lagged dependent variables. The results of the paper indicate that financial development indicators are

correlated with total factor productivity growth as well as with physical and human capital accumulation.

The link between financial development and growth can be analyzed considering different perspectives. An interesting aspect to consider is the causality relationship between financial development and growth.

Jayaratne and Strahan (1996) analyze the finance-growth nexus exploiting the relaxation of bank branch restrictions in United States for the sample period 1972-1992. The authors estimate a fixed-effects model where the dependent variable, per capita income, is regressed over an indicator variable that is equal to one for states permitting branching via merger and acquisitions. This specification is a generalization of the difference-in-differences approach and allows to control for the business cycle. The results suggest that per capita economic growth increases significantly following intrastate branch deregulation. The rationale behind this result is the following. Deregulation improves banks' screening and monitoring of borrowers causing a better financial intermediation. The improved efficiency of the financial system makes it easy to get funds in the economy leading to a faster economic growth. The paper shows a number of robustness checks to convince that the results are not driven by pro-growth policy changes occurred in the same sample period considered. In addition, the authors show that the growth effects of branching are not long lasting and tend to diminish within ten years.

Another important paper of the field is Rajan and Zingales (1998). The main argument of the authors is that industrial sectors that are in need of external finance grow faster in countries with more developed financial markets.

The model estimated throughout the paper is structured in the following way: the dependent variable is the growth in value added for each specific industry and the regressors include the industry's share in value added in manufacturing in 1980 and an interaction term between the industry dependence on external financing and a measure of financial market development.

The amount of external finance used by U.S firms in a specific industry is used as a proxy for the desired amount that foreign firms would have raised had their financial markets been developed. The U.S. represents, thus, the benchmark of the paper. The dependence on external finance is defined as capital expenditures minus cash flow from operations over capital expenditures.

Financial development is defined in two different ways. The first one is known as the "capitalization ratio" and is defined as the sum of the domestic credit and stock market capitaliza-

tion over GDP. The second proxy for financial development uses the accounting standards in a country. The rationale behind this proxy is the following: the better the standards of financial disclosure in a country, the easier it will be for firms to raise funds from outside investors.

The paper confines the analysis to manufacturing firms in 41 countries from 1980 to 1990.

The authors show that the interaction variable between external dependence and financial development is positive and highly significant for all measures of financial development. This result is robust to a sample of only mature firms, to a sample period that goes from 1970 to 1980 and to a sample of Canadian firms. The validity of the results is investigated also by decomposing the effect of financial development into its effect on growth in the number of establishments and growth in the size of existing establishments. Growth in the number of establishment requires more external financing and should be affected more by the degree of financial development. This is exactly the result found by the authors. Rajan and Zingales admit that there are potential concerns for endogeneity and, for this reason, they choose to instrument accounting standards with predetermined institutional variables like the origin of a country's legal system (La porta et al., 1996) and the integrity/efficiency of the legal system. The instrumental approach do not change the main results.

The effect of financial development over growth has been analyzed in different industrial sectors and countries. An interesting study is the one conducted by Barra, Destefanis and Lavadera (2013), who use Italian disaggregated data. The authors borrow two measures of finance quality and volume from Hasan et al.(2009) to test the nexus between financial development and growth. However, differently from Hasan et al. (2009), the paper considers only one country limiting the sources of unobserved heterogeneity. In addition, it explores the effects of the cooperative banks and banks' market power on growth in a larger sample period (2001-2010) that includes also the 2007-2008 financial crisis.

### **1.3 Methodology**

The methodology of this paper follows Beck, Levine and Loayza (2000).

In this paper the authors try to assess the impact of financial intermediary development on economic growth, total factor productivity growth, physical capital accumulation and private savings rates. In order to study this relationship, two different techniques are exploited. In

particular, a *cross-country regression model with instrumental variables* is considered together with a *panel technique* that is able to solve some problems that the first methodology has.

### 1.3.1 IV Estimator

The **first** technique is based on a cross-sectional IV estimator. Using data from 63 countries over the period 1960-1995, Beck, Levine and Loayza analyze the link between financial intermediary development and economic growth estimating the following model:

$$Y_i = \alpha + \beta Finance_i + \gamma' X_i + \varepsilon_i. \quad (1.1)$$

The dependent variable,  $Y_i$  is either *Growth*, *Capgrowth*, *Prod* or *Saving*. *Growth* is computed through an OLS regression of the logarithm of real per capita GDP on a constant and a time trend. The estimated coefficient on the time trend is a measure for the growth rate. *Capgrowth* is the growth rate of the per capita physical capital stock<sup>1</sup>. *Prod* represents the growth rate of productivity. Formally, it is defined as:  $Prod = Growth - \alpha Capgrowth$ , with  $\alpha$  that equals the capital share. Finally, the *Private Savings* rate is a ratio of gross private saving to gross private disposable income.

The variable **Finance**<sub>*i*</sub> provides information on the ability of financial intermediaries to research and identify profitable ventures, monitor and control managers, ease risk management and facilitate resource mobilization. Beck, Levine and Loayza suggest three different measures of financial development: *Private credit*, *Liquid Liabilities over GDP* and *Commercial-Central Bank*. To control for simultaneity bias, a particular instrumental variable for the financial intermediary development is used. A good instrument must satisfy two conditions: (1) it has to be exogenous to economic growth and (2) it has to be correlated with financial intermediary development.

As suggested by different studies, a good instrument for financial development is the *legal origin* for each country *i*. The explanation they provide is the following: the English, French and German legal systems are mainly the product of colonization and occupation, which can be interpreted as exogenous events. Moreover, legal origins are important for explaining the country's laws on creditor rights, shareholder rights and private property rights as well as

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<sup>1</sup>The capital stock is defined as  $K_{i,t+1} = K_{i,t} + I_{i,t} - \delta_i K_{i,t}$ .

the country's level of bank and stock market development which are all factors affecting the efficiency of the financial system.

The set  $\mathbf{X}_i$  includes controls that are associated with economic growth.

Finally,  $\varepsilon_i$  is the error term of the regression equation.

This first technique has some disadvantages:

1. It does not allow for an analysis of the time series dimension of the data;
2. Estimates might be biased by the omission of country-specific effects;
3. There is no opportunity to control for the endogeneity of all the regressors.

In order to solve these problems, a different estimator is used: *dynamic Generalized-Method-of-Moments (GMM) panel estimator*.

### 1.3.2 GMM Estimator

The **second** technique is based on a panel estimator. Using data from 77 countries over the period 1960-1995, Beck, Levine and Loayza analyze the link between financial intermediary development and economic growth over time within specific countries exploiting the following econometric model:

$$y_{i,t} = \alpha' X_{i,t-1}^1 + \beta' X_{i,t}^2 + \mu_i + \lambda_t + \varepsilon_{i,t}. \quad (1.2)$$

In equation 1.2  $y_{i,t}$  is the dependent variable,  $\mathbf{X}_{i,t-1}^1$  is the set of lagged explanatory variables,  $\mathbf{X}_{i,t}^2$  is the set of contemporaneous explanatory variables,  $\mu_i$  is the country-specific effect,  $\lambda_t$  is the time-specific effect and, finally,  $\varepsilon_{i,t}$  is the time-varying error term.

This methodology allows to solve many of the problems that we usually observe in the cross-country model. In detail, the panel model allows for time series variation in the data and for the inclusion of lagged dependent variables as regressors, accounts for unobserved country-specific effects and controls for endogeneity of all the explanatory variables.

Regression (2) can be estimated using the techniques proposed by Chamberlain (1984), Holtz-Eakin et al. (1990), Arellano and Bond (1991) and Arellano and Bover (1995), who

propose the *General Method of Moments estimator*. Arellano and Bond (1991) suggest to *first difference* regression (1.2) in the following way:

$$y_{i,t} - y_{i,t-1} = \alpha'(X_{i,t-1}^1 - X_{i,t-2}^1) + \beta'(X_{i,t}^2 - X_{i,t-1}^2) + (\varepsilon_{i,t} - \varepsilon_{i,t-1}). \quad (1.3)$$

This procedure introduces a new problem: a correlation between the new error term  $(\varepsilon_{i,t} - \varepsilon_{i,t-1})$  and the lagged dependent variable may arise when it is included in  $(X_{i,t-1}^1 - X_{i,t-2}^1)$ . In order to face and solve this problem, Beck, Levine and Loayza, exploit the moment conditions  $E[X_{i,t-s}(\varepsilon_{i,t} - \varepsilon_{i,t-1})] = 0$  for  $s \geq 2$  and  $t = 3, \dots, T$ , proposing a *2-step GMM estimator*. This estimator is easy to implement following a 2-step procedure: in the first step, the error terms are assumed to be both independent and homoskedastic, across countries and over time. Then, in the second step, the residuals obtained in the first step are used in such a way to have a consistent estimate of the variance-covariance matrix, relaxing the previous assumptions of independence and homoskedasticity. This estimator is usually referred to as the *difference estimator*.

The difference estimator shows some conceptual and econometric problems. By taking the first difference, there is the risk to loose the cross-country dimension of the data and to increase the measurement error biases. Furthermore, studies show that the difference estimator is characterized by a large finite-sample bias and poor precision. To address these problems, Beck, Levine and Loayza use an alternative method that estimates the regression in differences jointly with the regression in levels, as suggested by Arellano and Bover (1995). The method is known as the *system estimator*. The implementation of this method requires an additional assumption according to which the correlation between the country-specific effect and the levels of the explanatory variables is constant over time. Under this assumption, there is no correlation between the differences of the explanatory variables and the country-specific effect and, thus, lagged differences can be used as instruments for the regression in levels.

## 1.4 Implementation and Results

The first thing I do is to estimate the relationship between financial development and growth using the **cross-sectional** data set. This means that I have to estimate equation (1.1). In order

to get these estimates, I consider two sets of control variables ( $\mathbf{X}_i$ ): the "simple" conditioning set includes private credit, initial income per capita and average years of schooling, whereas the "policy" conditioning set includes private credit, initial income per capita, average years of schooling, openness to trade, inflation, government size and black market premium. Equation (1.1) is estimated using a *2-step feasible GMM*. The results are provided in *table (1.1)* of the appendix. The first observation I can do is that Private Credit is positively correlated with long-run growth. This result is true in both the simple and policy conditioning sets. The variables average years of schooling, openness to trade and inflation are positively correlated with growth. Naturally, the Black Market Premium is negatively correlated with growth. Table 1.1 provides also the results for the *Hansen test of overidentifying restrictions*. The results indicate that the orthogonality conditions cannot be rejected at any level of significance, which, in turn, implies that it is not possible to reject the null hypothesis that the instruments are appropriate.

As anticipated above, in the cross-sectional model, estimates might be biased by the omission of country-specific effects. This means that the coefficient for financial development is not able to represent the causal effect of financial development over growth.

After the cross-sectional analysis, I study the issue of causality between financial and real development using **panel data**. In *table 1.2* of the appendix, I present the results when the **first difference model** is estimated. The results refer to the *1-step GMM* estimator and the *2-step GMM* estimator, with and without the *Windmeijer correction*. The coefficients are reported for *both* the simple and the conditioning sets. The results I get move all in the same direction: financial intermediary development (Private Credit) has a positive impact on economic growth. However, the level of significance changes a little bit. What I get with the panel data estimation is that the Private Credit is positively correlated with economic growth, but the level of significance is very low above all if we move from the 2-step GMM estimator *without* the Windmeijer correction to the 2-step GMM estimator *with* the Windmeijer correction. The reason relies on the fact that standard errors increase when we introduce the correction. As in the cross-sectional analysis, I observe that the coefficient associated to the black market premium is negative. On the contrary, I get different signs, with respect to the ones I have for the simple cross-section model, when I consider the inflation variable or the average years of schooling variable. Also for the panel model I report the *Hansen test of overidentifying restrictions*. Once again, it is not possible to reject the null hypothesis.

*Table 1.3* of the appendix provides the results when the **system estimator** is applied. As



for the first difference model, the results refer to the *1-step GMM* estimator and the *2-step GMM* estimator, with and without the *Windmeijer correction*. The coefficients are reported for both the simple and the conditioning sets. The signs, the magnitude and the level of significance of the coefficients are very close to the ones I get for the first difference model. As before, Private Credit is positively correlated with financial development, but the level of significance is weak, above all when considering the extended set.

It is possible to get additional information about the relationship between economic growth and financial development by dividing countries into three groups according to the **degree of financial development**. The partition of the countries is such that the first group corresponds to the first quartile, the second group corresponds to the second and third quartile and the third group corresponds to the last quartile. The estimator that is used is the GMM system estimator *with* the Windmeijer corrected standard errors and the extended information set (*policy* conditioning set). From a methodological point of view, I construct two dummy variables: *lowpr* and *highpr*. *Lowpr* is a dummy variable that takes value 1 if the level of financial development is below the 25% quartile, while *highpr* is a dummy variable that takes value 1 if the level of financial development is above the 75% quartile. Once defined the two dummy variables, I construct two interaction variables, *Private* $\times$ *lowpr* and *Private* $\times$ *highpr*. The inclusion of these two variables among the regressors allows us the study the impact over economic growth of the different levels of financial development. The estimates for this part are presented in *table 1.4* of the appendix.

The first thing I observe is that it is very hard to find a coefficient that is statistically significant. As it is possible to notice from the table, the coefficients associated to Private Credit, Average years schooling and Openness are positive, but not statistically significant. Also the coefficients related to the two interaction variables are positive, but not significant. The impact of Initial Income over growth is negative, but not significant. The same is true for Government Size and Inflation. The only coefficient that is statistically significant is the one for the variable Black Market Premium, that is negative, as expected.

Countries can be partitioned not only considering the level of financial development, but also considering the **level of initial income**. The methodology to use in order to conduct this analysis is symmetric to the one I used previously. I define two dummy variables, *lowinc* and *highinc*. *Lowinc* is a dummy variable that takes the value of 1 if the level of financial income is below the 25% quartile, while *highinc* is a dummy variable that takes the value of 1 if the

level of financial income is above the 75% quartile. Then, I define two interaction variables,  $Private \times lowinc$  and  $Private \times highinc$ . The introduction of these variables is useful to assess the relationship between initial income, financial development and growth. As above, the estimator is the GMM system estimator *with* the Windmeijer corrected standard errors and the extended information set (*policy* conditioning set). The results are presented in *table 1.5*.

The results I get are very similar to the results I get in table 1.4. Only the coefficient for the variable Black Market Premium is statistically significant. The coefficient for Private credit is positive, but not statistically significant. From the table, I also observe that the coefficients for the two interaction variables have different signs: the coefficient for  $Private \times lowinc$  is negative, meaning that countries with a very low level of initial income are less affected by financial intermediary development in terms of growth rates. The coefficients for the two interaction variables are not significant.

The last thing I consider is to study the **evolution of the relationship between financial development and growth over time**. As before, the relationship can be described by an equation where on the right hand side we have the growth rate of GDP while on the left hand side we have the initial level of GDP, Private Credit, Public Consumption and Openness.

The procedure I adopted is the following: I considered the 77 countries that Beck, Levine and Loayza considered in the original paper. Then, using the Penn World Tables, I looked for real GDP, openness and public consumption. I downloaded data for each country in such a way to cover the period 1960-2010. In order to simplify the dataset, I modified the year variable to have only 5-non overlapping years. Using this approach, I got only 10 values for the year variable (1 corresponds to the first 5-year period, 1961-1965; 2 corresponds to the second 5-year period, 1966-1970, and so on). Then, I redefined all the variables in average terms.

The data set 1960-2010 can be easily divided to get two different data sets: the first one covers the period 1960-1990, whereas the second covers the period 1991-2010. The results for the first data set are presented in *table 1.6* of the appendix. The estimates are reported only for the system GMM estimator with Windmeijer corrected standard errors.

From the table, I notice that the coefficients associated to Private Credit, Openness and Initial GDP are very close to zero, but negative. No one of the coefficients reported is statistically significant.

Repeating the exercise with the data set 1991-2010 allows us to have different results. The estimates are reported in *table 1.7* of the appendix. Now, the coefficient for the variable Private

credit is positive and highly significant, meaning that high financial development is responsible for high GDP growth. This is the only coefficient that is statistically significant. As in the previous analysis, all the other coefficients are not statistically significant.

A comparison among the tables *1.6* and *1.7* can be useful to see how the relationship between financial development and GDP growth moves across time. The relationship between growth and financial development is strong and positive above all in the most recent past (1991-2010), which is intuitively understandable given the development of the banking and financial sector.

## **1.5 Final Remarks**

This paper has analyzed the link between financial development and growth for a sample period of about 40 years. The main results suggest that the efficiency of the financial sector, proxied by Private Credit, affects economic growth: the relationship is positive, significant and stable over time. The results are consistent across different methodologies and are robust to the inclusion of different controls. Finally, I showed that the level of initial income of a given country does not play any role as well as the degree of the financial development.

## 1.6 Appendix

Table 1.1: Cross-section, 1960-1995

	(1)	(2)
	Simple	Policy
Private Credit	2.515*** (3.10)	2.977*** (2.82)
Initial Income per capita	-1.689*** (-3.94)	-1.954*** (-4.88)
Average years of schooling	1.046 (1.34)	1.339 (1.58)
Openness to Trade		0.607 (1.61)
Inflation		4.220* (1.69)
Gov. size		0.0414 (0.19)
Black Mkt Premium		-0.238 (-0.18)
Constant	4.849* (1.95)	1.642 (0.41)
$N$	71	63
Hansen statistic	0.147	0.286
p-value of Hansen statistic	0.929	0.867

$t$  statistics in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.2: First Difference Model

	(1)	(2)	(3)	(4)	(5)	(6)
	D1GMM-s	D2GMM-s	DWind-s	D1GMM-p	D2GMM-p	DWind-p
Private Credit	1.697* (1.68)	1.314* (1.70)	1.314 (0.82)	0.224 (0.23)	0.0872 (0.41)	0.0872 (0.10)
Initial Income	-7.927*** (-3.68)	-6.779*** (-6.28)	-6.779*** (-2.72)	-8.371*** (-3.25)	-9.215*** (-15.51)	-9.215*** (-3.37)
Av.yrs schooling	-7.867*** (-3.44)	-6.084*** (-3.88)	-6.084** (-2.09)	-6.865** (-2.32)	-4.621*** (-2.82)	-4.621 (-1.13)
Openness				0.817 (0.63)	2.065*** (3.14)	2.065 (0.94)
Gov. size				-0.875 (-0.59)	0.0428 (0.07)	0.0428 (0.03)
Inflation				-3.126 (-1.21)	-4.593*** (-5.43)	-4.593* (-1.95)
Black Mkt Premium				-1.113 (-1.58)	-1.183*** (-4.05)	-1.183 (-1.46)
<i>N</i>	402	402	402	374	374	374
Sargan statistic	24.44	24.44	24.44	56.25	47.06	47.06
p-value of Sargan	0.437	0.437	0.437	0.167	0.470	0.470
AR(2) test statistic	-0.0356	-0.109	-0.108	0.495	0.459	0.441
p-value of AR(2)	0.972	0.913	0.914	0.621	0.646	0.659
Countries	78	78	78	78	78	78

*t* statistics in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.3: System Estimator

	(1)	(2)	(3)	(4)	(5)	(6)
	S1GMMs	S2GMMs	SWinds	S1GMMp	S2GMMp	SWindp
Private Credit	1.688*** (3.13)	1.968*** (7.98)	1.968*** (4.10)	0.0473 (0.09)	0.185 (1.42)	0.185 (0.33)
Initial Income	-0.953 (-1.10)	-0.932** (-2.36)	-0.932 (-1.28)	-0.364 (-0.55)	-0.278** (-2.14)	-0.278 (-0.47)
Av.yrs schooling	1.875 (0.92)	1.505 (1.52)	1.505 (0.81)	2.039 (1.29)	1.582*** (4.88)	1.582 (0.99)
Openness				1.292 (1.29)	1.130*** (7.97)	1.130 (1.12)
Gov. size				0.242 (0.25)	0.280* (1.69)	0.280 (0.31)
Inflation				-0.424 (-0.27)	-0.332 (-1.09)	-0.332 (-0.20)
Black Mkt Premium				-1.473*** (-2.82)	-1.440*** (-16.90)	-1.440*** (-3.30)
<i>N</i>	481	481	481	452	452	452
Sargan statistic	45.08	45.08	45.08	62.58	62.58	62.58
p-value of Hansen statistic	0.232	0.232	0.232	0.883	0.883	0.883
AR(2) test statistic	-0.367	-0.413	-0.412	0.0539	0.0726	0.0721
p-value of AR(2) test statistic	0.714	0.680	0.681	0.957	0.942	0.943
Countries	78	78	78	78	78	78

*t* statistics in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.4: Financial Dev.

	(1)
	SWind-p
Private Credit	0.184 (0.28)
Initial Income	-0.322 (-0.59)
Av.yrs schooling	1.708 (1.27)
Openness	1.804 (1.03)
Gov. size	-0.401 (-0.35)
Inflation	-0.950 (-0.58)
Black Mkt Pr.	-1.187** (-2.06)
Private $\times$ lowpr	0.148 (0.41)
Private $\times$ highpr	0.148 (0.72)
$N$	452
Sargan statistic	65.18
p-value of Hansen	1.000
AR(2) test statistic	0.219
p-value of AR(2)	0.827
Countries	78

*t* statistics in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.5: Initial Lev. Income

	(1)
	SWind-p
Private Credit	0.733 (1.24)
Initial Income	-0.748 (-0.84)
Av.yrs schooling	1.723 (1.23)
Openness	1.461 (0.87)
Gov. size	-0.677 (-0.57)
Inflation	-0.670 (-0.40)
Black Mkt Premium	-1.280** (-2.10)
Private $\times$ lowinc	-0.206 (-0.74)
Private $\times$ highinc	0.00817 (0.06)
$N$	452
Sargan statistic	70.89
p-value of Hansen	1.000
AR(2) test statistic	0.0451
p-value of AR(2)	0.964
Countries	78

$t$  statistics in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



Table 1.6: Panel, 1960-1990

	(1)
	SWind
Public Consumption	0.201 (1.07)
Openess	-0.00391 (-0.04)
Private Credit	-0.0757 (-0.51)
Initial GDP	-0.0656 (-0.49)
$N$	461
Sargan statistic	48.89
p-value of Hansen	0.158
AR(2) test statistic	-1.218
p-value of AR(2)	0.223
Countries	77

*t* statistics in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.7: Panel, 1991-2010

	(1)
	SWind
Public Consumption	-0.000847 (-0.17)
Openess	0.000744 (0.70)
Private Credit	0.000557*** (3.62)
Initial GDP	7.16e-08 (0.04)
$N$	308
Sargan statistic	25.86
p-value of Hansen	0.0561
AR(2) test statistic	-1.345
p-value of AR(2)	0.179
Countries	77

*t* statistics in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## **Part II**

# **Comovements across Countries**

## Chapter 2

# Comovements and Spillover

## Effects across Countries: A

## GARCH Approach

### 2.1 Introduction

It has been documented that volatility is an important feature to consider when dealing with financial markets. Higher volatility implies higher riskiness which, according to the Capital Asset Pricing Theory, implies higher average returns. An interesting aspect to consider regarding volatility is how the volatility in one country is affected by the volatility in another country. The relationship between international volatilities becomes fundamental when studying how international stock markets behave when they interact. Studies on the time-variation and nature of international stock market comovements have gained ground in finance in the last two decades. This increase of interest can be explained by two principal reasons: the international portfolio diversification issues and the recurrence of financial crises that occurred in both developed and emerging countries during the 1990's decade.

Investors may decide to reduce the riskiness of their portfolios by allocating their investment decisions in various classes of financial instruments, industries and other categories of assets that would move in different ways in response to the same event. This happens because the

portfolio's performance depends not only on the risk characteristics and the returns of the assets included in the portfolio but also on the correlation between them: higher correlation implies lower diversification benefits. Applying the same reasoning to the internationally held portfolios, investors will benefit the most from their portfolio if markets do not comove. The question is particularly interesting when emerging markets are taken into account. As a consequence of the market globalization process, emerging markets are more accessible and open to foreign investors. Since they are more integrated into the world stock market, many recent papers investigate whether the diversification benefits have been significantly reduced for these specific countries.

The second reason that has stimulated researchers to investigate the comovement of international stock markets is the willingness to study the "contagion" phenomenon. According to this phenomenon, if a crisis event occurs, it affects not only the neighboring countries, but also distant markets if these are related enough.

The aim of this paper is to analyze the comovement between some European and U.S. stock markets. More in detail, I am considering stock indices of Italy, Germany, France, Belgium, Austria, Sweden, Greece and United States before and after the Great Recession (2007-2009) to study whether the relationship among countries becomes stronger after a crisis event. Compared to other papers, I focus my attention mainly on Italy for a larger period of time.

The chapter is organized as follows. After a brief description of the main characteristics of the stock market series, such as the leverage effect, the volatility clustering phenomenon and the leptokurtosis, some theoretical ARCH/GARCH models will be tested to analyze how the volatility of each stock market series responds to past volatilities and innovations. Then, some MGARCH models will be presented to analyze the behavior of correlations through time and across countries. I will mainly focus on the Constant Conditional Correlation model, the Dynamic Conditional Correlation model and the Varying Conditional Correlation model.

## 2.2 Literature Review

The term "spillover effect" refers to the fact that an event in one country can produce reactions in another countries. One of the earlier works to analyze the spillovers of prices is Hamao and *al.* (1990). Hamao *et al.* (1990) explore the relationship between three marketplaces, New

York, London and Tokyo, using an ARCH type model revealing that significant spillovers exist between these three countries.

The same set of countries is analyzed by Koutmos and Booth (1995). In this paper the authors show that the transmission of volatility is asymmetric and is more pronounced when the news is bad and coming from either the US or the UK market.

The distinction between short-term and long-term comovements is investigated in Gilmore and al. (2007). Gilmore and *al.* use dynamic cointegration and principal components methods to examine the nature of the comovements between European developed markets and those of three Central European countries. The main results show that: *(i)* significant comovements are observed among different stock markets; *(ii)* there is evidence of a positive relationship between correlation and volatility, that is, correlations between international stock markets tend to be important in periods of high volatility or in time of financial troubles.

A number of papers has focused the attention on the distinction between emerging equity markets and developed markets. The two markets are clearly different for size and liquidity with the emerging markets being smaller and less liquid. Generally speaking, mean returns in emerging markets tend to be higher and correlations with global markets lower. Developed market returns, instead, are more predictable and their volatility is higher. A leading question is why volatility is so different in emerging countries. Higher volatility implies higher capital costs and, as a consequence, this feature can increase the value of delaying an investment, the so-called *option-to wait*. Bekaert et al. (2002) find that equity market liberalization is associated with higher average returns and lower volatility in emerging markets although not in all. Whereas the correlation between returns in emerging markets and global markets tends to increase after liberalization, the correlation remains fairly low suggesting that potential diversification benefits still exist in emerging market equities.

Many of the papers that are comparing emerging to developed markets focus their attention on the Latin American markets. The main reason for such an interest is that they rank among the most mature markets within the universe of emerging countries and they actually attract a particular attention from global investors thanks to their great market openness. Two papers deserve to be mentioned in this area. The first one is Choudry (1997). Choudry employs unit root tests, cointegration tests and error correction models to examine the long-run relationship between six Latin American markets and the US market and finds evidence of cointegration relationship and significant causality among these markets. The Latin American market is

investigated also in Arouri, Bellalah and Nguyen (2008). Instead of using a VAR model, this paper captures the cross-market linkages from the stock data using a multivariate Dynamic Conditional Correlation GARCH model. In addition, the paper studies the structural breaks in the time-paths of the conditional correlation indices to highlight whether the cross-market comovement encompasses significant changes in nature or not.

## 2.3 Data and Stylized Facts

The data used in this study are monthly stock-prices indices from January 1, 2000 through August 1, 2014. The data set consists of the stock indices of Italy (FITSEMIB), Germany (DAX), France (CAC40), Belgium (BEL 20), Austria (ATX), Sweden (OMXS30), Greece (FTSE/ATHEX) and United States (S&P 500 Composite Index). All the data are obtained from Yahoo finance.

Monthly stock returns are defined as:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}},$$

where  $R_t$  is the stock return at time  $t$  and  $P_t$  is the stock price at time  $t$ .

The evolution of stock returns over time is described in Figure 1<sup>1</sup>.

All the series show a higher volatility during the early 2000s Recession and during the Great Recession period (2007-2009).

The Early 2000s Recession is a decline in economic activity which mainly occurred in developed countries. The Recession affected the European Union during 2000 and 2001 and the United States in 2002 and 2003. France and Germany both entered recession towards the end of 2001, but in May 2002 both countries declared that their recession had ended after a mere six months each. The 2002-2003 Recession hit United States mainly in terms of high unemployment. Unemployment rose from 4.2% in February 2001 to 5.5% in November 2001, but did not peak until June 2003 at 6.3% after which it declined by mid-2005.

All the series are strongly affected by the 2007-2009 crisis. This crisis had origin in October 2007 in the U.S. stock market, when the Dow Jones Industrial Average index exceeded 14,000 points. It then entered a pronounced decline, which accelerated markedly in October 2008. By March 2009, the Dow Jones average had reached a trough of around 6,600. The crisis rapidly

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<sup>1</sup>All the figures are presented in the Appendix.

developed and spread into a global economic shock, resulting in a number of European bank failures, declines in various stock indexes and large reductions in the market value of equities and commodities.

Descriptive statistics are presented in Table 2.1. Table 2.1 reveals some interesting facts. The mean returns for Italy, France and Greece are negative. Austria has the highest average stock return followed by Germany and United States. All return series display negative skewness. In addition, all the series have a significant leptokurtic behavior. More in detail, the kurtosis and the skewness for Germany, Belgium, Austria and United States are significantly different from the kurtosis and the skewness of a normal distribution<sup>2</sup>. Furthermore, the kurtosis for Sweden is significantly different from the kurtosis of a normal distribution.

It is possible to get additional insights into the distribution of each series by looking at the comparison between the density function of each of these series and the Gaussian distribution. This comparison is provided in Figure 2.

Financial time series are usually characterized by two features: (1) *Leverage effect*; (2) *Volatility Clustering*.

The leverage effect shows the relationship between shocks and volatility. The main intuition is that bad news tend to have a larger impact on volatility than good news meaning that volatility tends to be higher in a falling market than in a rising market. This effect can be explained looking more closely at the stock market: as observed by Black (1976), bad news tend to drive down the stock price, thus increasing the leverage (debt-equity ratio) of the stock and causing the stock to be more volatile. Based on this conjecture, the asymmetric news impact on volatility is commonly referred to as the leverage effect. Theoretical studies suggest that a negative value of the correlation between  $R_t^2$  and  $R_{t-1}$  provides some evidence for potential leverage effect. All the series analyzed in this paper are characterized by such leverage effect.

The volatility clustering phenomenon refers to the observation, as noted by Mandelbrot (1963), that large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes. This phenomenon is analyzed mainly in an asset pricing setting. The general consensus in this field is that changes in the speed of flow of relevant information to the market - concerning either the exposure to risk or their prices - causes changes in price volatility which create clusters of high and low volatility. A quantitative

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<sup>2</sup>The Skewness and Kurtosis test are not shown in Table 1. Results are available upon request.

way to view the volatility clustering property is to consider the autocorrelations of the return series: while returns themselves are uncorrelated, absolute returns,  $|R_t|$ , or their squares,  $R_t^2$ , display a positive, significant and slowly decaying autocorrelation function.

All the series show the volatility clustering property<sup>3</sup>.

## 2.4 Methodologies

### 2.4.1 The ARCH model

In order to have an idea about how the comovement across stock markets work, it is important to take into consideration the basic ARCH model.

The ARCH model is developed starting from the AR(1) model.

The AR(1) is defined in the following way:

$$y_t = \rho y_{t-1} + u_t.$$

where  $u_t$  is distributed as a *white noise*,  $u_t \sim WN(0, \sigma^2)$ .

In the AR(1) process, the unconditional mean and the conditional mean (conditional on the information available at time  $t$ ) are given by:

$$\begin{aligned} E(y_t) &= 0; \\ E(y_t | \Omega_{t-1}) &= \rho y_{t-1}. \end{aligned}$$

Exploiting this information, it is possible to get that:

$$E(y_t)^2 = E(\rho y_{t-1} + u_t - E(y_t))^2.$$

Conditioning on the information available at time  $t$ , it is possible to observe that **the conditional variance of  $y_t$  is equal to the conditional variance of  $u_t$** . This result is extremely important if we want to have information about future volatility. In particular, *predicting future volatility is possible by exploiting a prediction for  $u_t$* .

If we assume that the conditional variance of  $u_t$  is described as:

$$Var(u_t | \Omega_{t-1}) = \alpha_0 + \alpha_1 u_{t-1}^2,$$

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<sup>3</sup>All the autocorrelations graphs are shown in the Appendix.



then, the conditional variance of  $y_t$  will be described by the same process.

To sum up, modelling the conditional variance requires two different kinds of information. We need a description of the evolution of  $y_t$  (the so-called *mean model*) and an equation providing some insights about the future behavior of volatility, that is, the conditional variance of  $y_t$  (equal to the conditional variance of  $u_t$ ), denoted, for simplicity, by  $h_t$ .

The expression for  $h_t$  :

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 \tag{2.1}$$

defines the famous ARCH(1) model.

The ARCH model can be generalized in the following way:

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i u_{t-i}^2. \tag{2.2}$$

Some restrictions on the parameters are needed. Whereas returns can be positive as well as negative, only positive values make sense for variances. This restricts the sum of the parameters ( $\alpha_0 + \alpha_1 + \dots + \alpha_q$ ) to be positive. In addition, the stationarity of the process requires that  $0 \leq \sum_{i=1}^q \alpha_i \leq 1$ .

Although the model is able to provide good information about the future behavior of volatility, it presents some important *disadvantages*.

First of all, the ARCH model is a descriptive model that might provide no information about the behavior of the data. As suggested by Nwoguru (2006), the ARCH class models are *naïve* as they assume that volatility can be explained solely through mechanical descriptive analysis, ignoring other sources of volatility such as liquidity, psychology or legal issues.

Furthermore, the ARCH model assumes symmetry in reaction to positive and negative shocks (the predicted future variance is a function of the squared residuals). This symmetry is not significative at all since we should be able to make a distinction between the two different kinds of shocks.

Finally, the ARCH models have a short memory specification. To characterize the model correctly we have to consider a larger number of lagged squared residuals.

A possible solution is offered by the GARCH family models.

## 2.4.2 The GARCH models

The GARCH model is presented as an extension of the previous ARCH model.

In general, it can be expressed in the following way:

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i u_{t-i}^2 + \sum_{i=1}^p \beta_i h_{t-i}. \quad (2.3)$$

The conditional variance, in the GARCH model, depends on the lagged squared residuals as well as on the lagged estimates of the variance. In other words, the generalized ARCH is revised to encompass a moving average term.

The Generalized model contains  $(q + p + 1)$  parameters and, as for the standard ARCH model, needs some specific conditions for the existence and the stability of the variance. In particular, it requires that  $0 \leq \alpha_i + \beta_i < 1$ , where all the coefficients are assumed to be non-negative. It is important to note that the summation  $\alpha_i + \beta_i$  must be smaller than one. If this is not the case, in fact, the variance is covariance non-stationary and the GARCH model may fail to correctly assess future period's data. In general,  $\alpha_i + \beta_i$  expresses the persistence of the model, or, saying in other terms, how long a shock to conditional variance remains in the data. In the standard GARCH (1,1) model<sup>4</sup>, larger values of  $\alpha_i$  lead to greater volatility in the forecasted errors, while high values of  $\beta_i$  indicate higher persistence.

The GARCH models present a lot of advantages. The Generalized model is a very parsimonious model. It can be shown that a simple GARCH(1,1) model mimics the behavior of the more complex ARCH( $\infty$ ). In addition, it seems that this kind of model accommodates quite well the stylized facts. In particular, the GARCH model provides good explanations for the volatility clustering phenomenon frequently observed in the data as well as for the leptokurtic distribution of returns (this happens mainly when the parameters  $\beta_i$  are strictly positive).

However, the GARCH models are also often criticized for some aspects. Many statisticians have argued that the GARCH models are "weak" because they impose restrictions to the parameters that subsequently are violated during estimations. Especially the restrictions that

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<sup>4</sup>With the terminology GARCH(1,1) model we refer to a model that has one ARCH component and one GARCH component. The ARCH component refers to the lagged squared residuals while the GARCH component refers to the lagged values of the variance.

$\alpha_i \geq 0$  and  $\beta_i \geq 0$  are often violated in practice leading to disqualification of the specification (Nelson, 1991).

Furthermore, as the ARCH model, also the GARCH model is a descriptive model that does not provide any kind of information about the source of the variance.

Many researchers have proposed modifications of the standard GARCH model in order to capture the asymmetric effect that is very often present in the data.

The first model in this direction is the so-called T-GARCH model.

The **T-GARCH** model is the one proposed by Glosten, Jagannathan and Runkle (1993). The model takes the form:

$$h_t = \alpha_0 + \sum_{i=1}^q (\alpha_i u_{t-i}^2 + \lambda d_{t-i} u_{t-i}^2) + \sum_{i=1}^p \beta_i h_{t-i}. \quad (2.4)$$

In its simplest version, the T-GARCH (1,1) model is given by:

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \lambda d_{t-1} u_{t-1}^2,$$

where  $d$  is a dummy variable that takes the value of 1 if  $u_{t-1}$  is smaller than 1 (bad news) and zero otherwise (good news).

As previously said, the model solves the problem of asymmetry that seems not to be well considered by the standard GARCH model. As in the basic model, some non-negativity conditions are required, such as  $\alpha_i + \lambda \geq 0$ ,  $\alpha_i \geq 0$  and  $\beta_i \geq 0$ . For stability reasons, we also need that the sum of all coefficients must be lower than 1.

An alternative specification of this model is provided by Zakoian (1994). In this case, the conditional future variance is given by:

$$h_t = \alpha_0 + \sum_{i=1}^q (\alpha_i |u_{t-i}| + \lambda d_{t-1} |u_{t-i}|) + \sum_{i=1}^p \beta |h_{t-i}| \quad (2.5)$$

where  $|u_{t-i}|$  and  $|h_{t-i}|$  are, respectively, the absolute values of innovations and past predicted variances.

Another model that can help explaining the famous asymmetric effect is the Exponential GARCH model (E-GARCH).

The **E-GARCH** model by Nelson (1991) solves several of the problems identified with the GARCH models. In order to exploit the empirical observation that volatility is negatively correlated to returns, the conditional variance of the E-GARCH is allowed being a function of the size and sign of the lagged residuals.

The model is defined as:

$$\ln(h_t) = \alpha_0 + \sum_{i=1}^q (\gamma z_{t-i} + \delta(|z_{t-i}| - E|z_{t-i}|)) + \sum_{i=1}^p \beta_i \ln h_{t-i} \quad (2.6)$$

where  $E(z_t) = \sqrt{2/\pi}$  and  $z_t = \frac{u_{t-i}}{\sqrt{h_{t-i}}}$ .

In the E-GARCH model, the most important parameters are  $\gamma$  and  $\delta$ . The parameter  $\gamma$  provides information about the asymmetry in the model. In particular, if  $\gamma = 0$ , then no asymmetry is identified. The parameter  $\delta$ , instead, gives an idea about the size effect of the shock. If  $\delta = 1$ , the shock is totally absorbed by the conditional variance.

Naturally, the impact of the shock on the future variance depends on the sign of  $z_t$ . If it is positive, the effect of the shock is given by  $(\gamma + \delta)$ , while if it is negative, then the effect of the shock will be given by  $(-\gamma + \delta)$ .

The log specification used by this model implies less conditions on the parameters: as it can be easily understood, the variance will be positive regardless of the sign of the coefficients. As a consequence, the only conditions needed are the ones for the stability. What we need is that  $|\beta| < 1$ .

A more general model that tries to capture the asymmetric effect is the P-GARCH model.

The **general asymmetric power GARCH** model was introduced by Ding, Granger and Engle (1993). According to this model, the variance  $h_t$  can be specified in the following way:

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i (|u_{t-i}| + \gamma_i u_{t-i})^d + \sum_{i=1}^p \beta_i h_{t-i}^d \quad (2.7)$$

The P-GARCH model is interesting because a large number of formulations can be tested. For instance, if we work under the assumption of free  $\alpha_i$ ,  $\beta = \gamma = 0$  and  $d = 2$ , then we will end up with the ARCH model. Furthermore, the GARCH model can be easily re-constructed from the P-GARCH model by assuming that  $\alpha_i$  and  $\beta_i$  are free and considering  $d = 2$  and  $\gamma = 0$ .

In the following sections, the GARCH models will be analyzed more closely. The basic model will be introduced and the main results will be pointed out as well.

## 2.5 Basic Model

As anticipated in the previous section, the use of the GARCH model requires the definition of two fundamental equations: the *mean equation* and the *variance equation*. These equations can be described in the following way:

$$\begin{aligned}
 ITA\_SR_t = & \alpha + \beta_1 AUS\_SR_t + \beta_2 FRE\_SR_t + \beta_3 DEU\_SR_t + \\
 & + \beta_4 BEL\_SR_t + \beta_5 SVE\_SR_t + \beta_6 GRE\_SR_t + \beta_7 USA\_SR_t. + \epsilon \quad (2.8)
 \end{aligned}$$

$$ITA\_h_t = \gamma_1 + \gamma_2 h_{t-1} + u_{t-1}^2 \quad (2.9)$$

Equation (2.8) describes the *mean equation*. Formally, to describe the evolution of stock returns, different specifications can be used. A possibility is to consider a random walk model. However, although this model is easy to implement, it does not match the evidence properly. MacKinlay and al. (1988) finds that stock returns do not resemble a random walk process when weekly returns are considered and proposes some alternative specifications including a lag for the returns.

The approach used in this paper is different. The dependent variable is the stock return for Italy. The regressors include the stock returns for U.S., France, Austria, Germany, Belgium, Sweden and Greece. The relationship between the independent variable and the regressors as indicated in equation (2.8) is shown in Table 2.2. Table 2.2 shows that the stock return for

Italy is positively correlated with the stock returns for France and Greece. The relationship is positive and highly significant.

Equation (2.9) describes the *variance equation*. More in detail, it provides information on the evolution of the conditional variance for the Italian stock return as a function of past variances and past residuals. Generally speaking, equations (2.8) and (2.9) describe the link between the European stock market and the US stock market and provide some useful insights about the countries affecting the volatility of the Italian stock return.

The approach used above somehow resembles the methodology used by Xiao and Dhesi (2010). In Xiao and Dhesi (2010), the authors study the existence of volatility spillover effects between the European and US stock markets using a multivariate GARCH model. They find that the US stock market is the main transmitter within the European stock market and that correlations are significantly time-varying over the sample period considered, January 2004-October 2009. However, Xiao and Dhesi do not investigate the contagion effect due to periods of crisis and, in particular, they do not compare the Pre-Great Recession Period with the Post-Great Recession Post.

## 2.6 GARCH Results

Table 2.3 reports the main results for the GARCH estimation.

The first column provides results for the basic GARCH model. The second column provides results for the EGARCH model. The last column shows the results for the TGARCH model.

According to the GARCH model, the conditional volatility for Italy can be described by:

$$h_t = \alpha_0 + (0.173)u_{t-1}^2 + (0.704)h_{t-1}.$$

As it is possible to observe from the table, the GARCH effect is highly significant. The ARCH effect is significant at the 10% level. The conditional variance for the Italian stock return is thus strongly influenced by past volatilities.

The EGARCH model provides more information and allows to make a comparison between the leverage effect and the symmetric effect<sup>5</sup>. The leverage effect is given by the EARCH coefficient. The symmetric effect is represented by the "*symmetry*" coefficient. The EARCH coefficient is positive, highly significant and equal to 0.215 meaning that positive innovations

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<sup>5</sup>The symmetric effect studies the relationship between the sign of the innovations (shocks) and the conditional volatility. The effect is symmetric if, independently of the sign, the effect on the volatility is the same.

(unanticipated price increases) are more destabilizing than negative innovations. This effect appears strong and larger than the symmetric effect (0.162). The EGARCH coefficient is positive and highly significant which tells us that independently of the specification used for the conditional variance, the actual variance of the Italian stock return is a function of past variances.

In the estimation of the TARCH model only two coefficients are significant: the TARCH coefficient and the GARCH coefficient. The significance of the GARCH coefficient confirms the predictions of the previous two models. The TARCH coefficient is positive and highly significant. The main intuition that it is possible to get from this result is that a leverage effect exists and the effect of bad news over the conditional variance is positive and equal to  $TARCH + ARCH = 0.483 - 0.0589 = 0.4241$ .

The estimation of the PGARCH model does not provide any information about the factors affecting the conditional variance.

## 2.7 MGARCH Models

In the previous sections, an analysis of the GARCH models has been proposed.

Exploiting GARCH models can be useful not only if we want to forecast future volatility, but also if we want to have an idea about future correlation. In this last case, we consider an extension of the univariate GARCH model.

The Multi-variate GARCH models allow to parametrize the conditional covariance matrix  $H_t$  as a function of  $q$  values of the squares and cross-products of the innovations, denoted in this case by  $\epsilon_t$ , as well as of  $p$  lagged values of the elements of  $H_t$ . In order to describe in detail the structure of a multi-variate GARCH model, let *vech* denote the vector-half operator, which stacks the lower triangular elements of an  $N \times N$  matrix as an  $[N(N + 1)/2] \times 1$  vector.

The multivariate extension of the univariate  $GARCH(p, q)$  model is:

$$vech(H_t) = W + \sum_{i=1}^q A_i^* vech(\epsilon_{t-i} \epsilon_{t-i}') + \sum_{j=1}^p B_j^* vech(H_{t-j}), \quad (2.10)$$

where

$W = \frac{N(N+1)}{2} \times 1$  vector of parameters;

$A_i^*, B_j^* = [N^* \times N^*]$  matrices of parameters with  $N^* = \frac{N(N+1)}{2}$ ;

$\epsilon_t = H_t^{1/2} v_t$ , where  $\epsilon_t$  defines the error for the model  $y_t = Cx_t + \epsilon_t$ , with:

$v_t = n \times 1$  vector of i.i.d. innovations;

$y_t = n \times 1$  vector of dependent variables;

$C = n \times k$  matrix of parameters;

$H_t^{1/2} =$  Cholesky factor of the time varying conditional covariance matrix  $H_t$ ;

$x_t = k \times 1$  vector of independent variables.

This model is usually called **VECH** model<sup>6</sup>.

To understand better how the model is defined, we can assume that  $N = 2$  and  $p = q = 1$ .

The VEC-GARCH (1, 1) model can be written in the following way:

$$\begin{bmatrix} h_{11,t} \\ h_{21,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} w_1^* \\ w_2^* \\ w_3^* \end{bmatrix} + \begin{bmatrix} a_{11}^* & a_{12}^* & a_{13}^* \\ a_{21}^* & a_{22}^* & a_{23}^* \\ a_{31}^* & a_{32}^* & a_{33}^* \end{bmatrix} \times \begin{bmatrix} \epsilon_{1,t-1}^2 \\ \epsilon_{1,t-1}\epsilon_{2,t-1} \\ \epsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11}^* & b_{12}^* & b_{13}^* \\ b_{21}^* & b_{22}^* & b_{23}^* \\ b_{31}^* & b_{32}^* & b_{33}^* \end{bmatrix} \times \begin{bmatrix} h_{11,t-1} \\ h_{21,t-1} \\ h_{31,t-1} \end{bmatrix}.$$

The problem of this model is the large number of parameters<sup>7</sup>. This problem is still present for low dimensions of  $N$  and small values of  $p$  and  $q$ . A natural restriction to this model is the *diagonal representation*.

For  $N = 2$  and  $p = q = 1$ , the diagonal representation provides the following model:

$$\begin{bmatrix} h_{11,t} \\ h_{21,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} w_1^* \\ w_2^* \\ w_3^* \end{bmatrix} + \begin{bmatrix} a_{11}^* & 0 & 0 \\ 0 & a_{22}^* & 0 \\ 0 & 0 & a_{33}^* \end{bmatrix} \times \begin{bmatrix} \epsilon_{1,t-1}^2 \\ \epsilon_{1,t-1}\epsilon_{2,t-1} \\ \epsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11}^* & 0 & 0 \\ 0 & b_{22}^* & 0 \\ 0 & 0 & b_{33}^* \end{bmatrix} \times \begin{bmatrix} h_{11,t-1} \\ h_{21,t-1} \\ h_{31,t-1} \end{bmatrix}.$$

<sup>6</sup>The VEC representation is due to Engle and Kroner (1995).

<sup>7</sup>The number of parameters is equal to  $[1 + (p + q)[N(N + 1)/2]^2]$ .



In a more compact way, taking in consideration the  $(i, j)$ th element in  $H$ , we have:

$$h_{ij,t} = w_i^* + a_{ii}^* \epsilon_{i,t-1} \epsilon_{j,t-1} + b_{ii}^* h_{ij,t-1}.$$

The  $(i, j)$ th element in  $H$  depends on the corresponding  $(i, j)$ th element in  $\epsilon_{t-i} \epsilon_{t-i}'$  and  $H_{t-1}$ . The *Diagonal* restriction reduces the number of parameters to  $[N(N+1)/2](1+p+q)$  and allows for a easier interpretation of the results.

Another model that belongs to the MGARCH family is the **CCC** model, that is, the Constant Conditional Correlation model.

In the Conditional Correlation family of MGARCH models, the diagonal elements of  $H_t$  are modeled as univariate GARCH models, whereas the off-diagonal elements are modeled as nonlinear functions of the diagonal terms. In particular, we have:

$$h_{ij,t} = \rho_{ij} \sqrt{h_{ii,t} h_{jj,t}},$$

where the diagonal elements  $h_{ii,t}$  and  $h_{jj,t}$  follow univariate GARCH processes and  $\rho_{ij}$  is a time-invariant weight interpreted as a conditional correlation.

Formally, the CCC model<sup>8</sup> can be written as:

$$\begin{aligned} y_t &= Cx_t + \epsilon_t \\ \epsilon_t &= H_t^{1/2} v_t \\ H_t &= D_t^{1/2} R D_t^{1/2} \end{aligned}$$

where

$y_t = m \times 1$  vector of dependent variables;

$C = m \times k$  matrix of parameters;

$x_t = k \times 1$  vector of independent variables which may contain lag of  $y_t$ ;

$H_t^{1/2} =$  Cholesky factor of the time varying conditional covariance matrix  $H_t$ ;

$v_t = m \times 1$  vector of normal, independent and identically distributed innovations;

$D_t$  is a diagonal matrix of conditional covariances,

---

<sup>8</sup>The CCC model was derived by Bollerslev in 1990.

$$D_t = \begin{pmatrix} \sigma_{1,t}^2 & 0 & \dots & 0 \\ 0 & \sigma_{2,t}^2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \sigma_{m,t}^2 \end{pmatrix}$$

in which each  $\sigma_{i,t}^2$  evolves accordingly to a univariate GARCH model of the form

$$\sigma_{i,t}^2 = \exp(\gamma_i z_{i,t}) + \sum_{j=1}^{p_i} \alpha_j \epsilon_{i,t-j}^2 + \sum_{j=1}^{q_i} \beta_j \sigma_{i,t-j}^2$$

where  $\gamma_i$  is a  $1 \times p$  vector of parameters,  $z_i$  is a  $p \times 1$  vector of independent variables including a constant term, the  $\alpha_j$ 's are *ARCH* parameters and the  $\beta_j$ 's are *GARCH* parameters; and

$R_t$  is a matrix of time-invariant unconditional correlations of the standardized residuals  $D_t^{-1/2} \epsilon_t$ ,

$$R = \begin{pmatrix} 1 & \rho_{12} & \dots & \rho_{1m} \\ \rho_{12} & 1 & \dots & \rho_{2m} \\ \dots & \dots & \dots & \dots \\ \rho_{1m} & \rho_{2m} & \dots & 1 \end{pmatrix}.$$

Note that the  $R$  matrix is *not* changing over time. This is the reason for which this model is usually called Constant Conditional Correlation model.

Similar to the Constant Conditional Correlation model is the Varying Condition Correlation model.

The **VCC** GARCH model<sup>9</sup> can be written as:

$$\begin{aligned} y_t &= Cx_t + \epsilon_t \\ \epsilon_t &= H_t^{1/2} v_t \\ H_t &= D_t^{1/2} R_t D_t^{1/2} \\ R_t &= (1 - \lambda_1 - \lambda_2) R_t + \lambda_1 \Psi_{t-1} + \lambda_2 R_{t-1} \end{aligned}$$

where

$y_t = m \times 1$  vector of dependent variables;

$C = m \times k$  matrix of parameters;

$x_t = k \times 1$  vector of independent variables which may contain lag of  $y_t$ ;

---

<sup>9</sup>The VCC model was proposed by Tse and Tsui (2002).

$H_t^{1/2}$  = Cholesky factor of the time varying conditional covariance matrix  $H_t$ ;

$v_t = m \times 1$  vector of normal, independent and identically distributed innovations;

$D_t$  is a diagonal matrix of conditional covariances,

$$D_t = \begin{pmatrix} \sigma_{1,t}^2 & 0 & \dots & 0 \\ 0 & \sigma_{2,t}^2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \sigma_{m,t}^2 \end{pmatrix}$$

in which each  $\sigma_{i,t}^2$  evolves accordingly to a univariate GARCH model of the form

$$\sigma_{i,t}^2 = \exp(\gamma_i z_{i,t}) + \sum_{j=1}^{p_i} \alpha_j \epsilon_{i,t-j}^2 + \sum_{j=1}^{q_i} \beta_j \sigma_{i,t-j}^2$$

where  $\gamma_i$  is a  $1 \times p$  vector of parameters,  $z_i$  is a  $p \times 1$  vector of independent variables including a constant term, the  $\alpha_j$ 's are ARCH parameters and the  $\beta_j$ 's are GARCH parameters;

$R_t$  is a matrix of conditional correlations,

$$R = \begin{pmatrix} 1 & \rho_{12,t} & \dots & \rho_{1m,t} \\ \rho_{12,t} & 1 & \dots & \rho_{2m,t} \\ \dots & \dots & \dots & \dots \\ \rho_{1m,t} & \rho_{2m,t} & \dots & 1 \end{pmatrix};$$

$\Psi_t$  is the rolling estimator<sup>10</sup> of the correlation matrix of  $\tilde{\epsilon}_t$ , which uses the previous  $m + 1$  observations; and

$\lambda_1$  and  $\lambda_2$  are parameters that govern the dynamics of conditional correlations ( $\lambda_1$  and  $\lambda_2$  are nonnegative and satisfy  $0 \leq \lambda_1 + \lambda_2 \leq 1$ ).

The DCC GARCH model resembles the VCC model. The main difference relies on the structure for the matrix of conditional correlations.

The DCC GARCH model<sup>11</sup> can be written as:

<sup>10</sup>A rolling estimator of a time series model is often used to assess the model's stability over time. When analyzing financial time series data using a statistical model, a key assumption is that the parameters of the model are constant over time. However, the economic environment often changes considerably and it may not be reasonable to assume that a model's parameters are constant. A common technique to assess the constancy of a model's parameters is to compute parameter estimates over a rolling window of a fixed size through the sample. If the parameters are truly constant over the entire sample, then the estimates over the rolling windows should not be too different. If the parameters change at some point during the sample, then the rolling estimates should capture this instability.

<sup>11</sup>The DCC model was proposed by Engle (2002).

$$\begin{aligned}
y_t &= Cx_t + \epsilon_t \\
\epsilon_t &= H_t^{1/2}v_t \\
H_t &= D_t^{1/2}RD_t^{1/2} \\
R_t &= \text{diag}(Q_t)^{-1/2}Q_t\text{diag}(Q_t)^{-1/2} \\
Q_t &= (1 - \lambda_1 - \lambda_2)R_t + \lambda_1\tilde{\epsilon}_{t-1}\tilde{\epsilon}'_{t-1} + \lambda_2Q_{t-1}.
\end{aligned}$$

All the parameters of the DCC model can be interpreted as for VCC model.

In the next section, these models will be analyzed more closely.

## 2.8 MGARCH Results

Table 2.4 reports the results for the MGARCH estimation.

The first column provides results for the CCC model, the second column provides results for the DCC model<sup>12</sup>. All the correlations estimated using the CCC MGARCH model are statistically significant. The highest correlations occur between Italy and France, between France and Germany and between France and United States. The results are confirmed by the DCC MGARCH model. The correlations I get with this model are somehow larger than the estimated correlations of the CCC model. However, consistently with the previous model, the highest correlations occur between Italy and France, between France and Germany and between France and United States. The results for the VCC model, not reported, are consistent with the results got for the CCC and DCC MGARCH models.

The correlations in the Post-Great Recession period are shown in Table 2.5.

The first column provides the results for the CCC model, the second column for the DCC model. The results from the CCC model suggests that the correlations among some countries have increased after the crisis period. The correlation between Italy and France, Italy and United States, Germany and United States and between France and United States is much stronger after the crisis. All the estimated correlations are highly significant.

Less stronger are the results provided by the alternative model, the DCC MGARCH model. However, as shown in the table, the correlations between Italy and France and between France and United States have increased. The correlation between Germany and United States is stable over time.

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<sup>12</sup>For the MGARCH estimation, I am focusing on 4 countries: Italy, France, Germany and United States. The estimation for only four countries is easier and no convergence problems are involved.

## 2.9 Final Remarks

This paper has analyzed how market interacts in terms of volatilities and correlations. To this aim, several GARCH models are estimated. The most informative GARCH model seems to be the EARCH model which suggest that the estimated model is strongly influenced by the leverage effect, meaning that positive innovations (price increases) are more destabilizing than negative innovations. The correlation path over time is investigated using MGARCH models. Although the magnitude of the correlation coefficients depends on the estimated model, the models seem to suggest that in period of crisis and, more specifically after the Great Recession period, comovements across countries are stronger.

## 2.10 Appendix

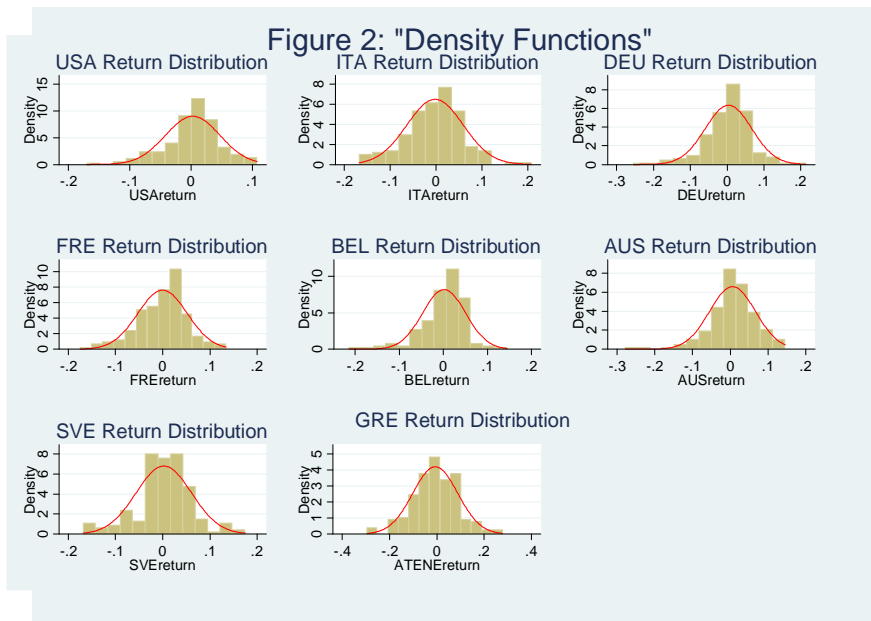
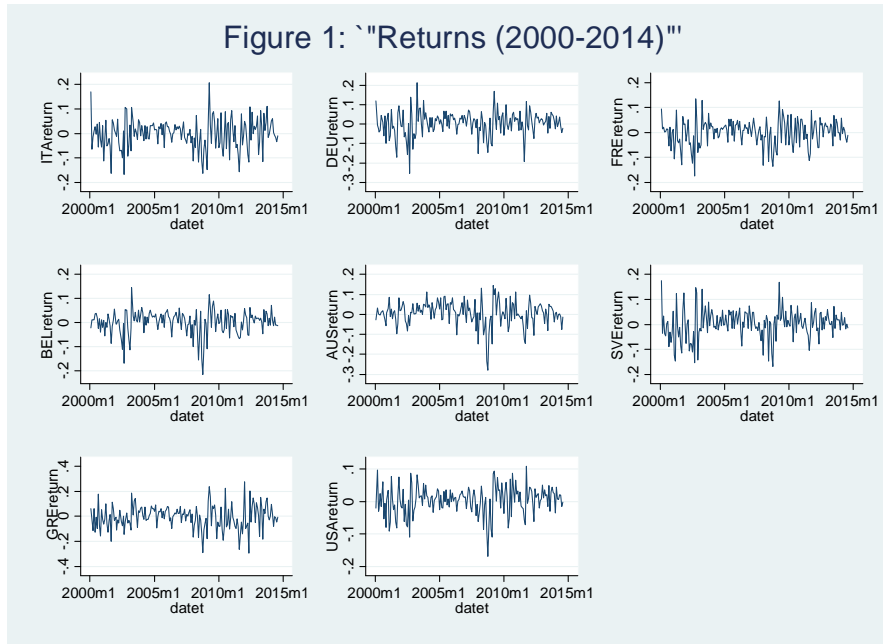
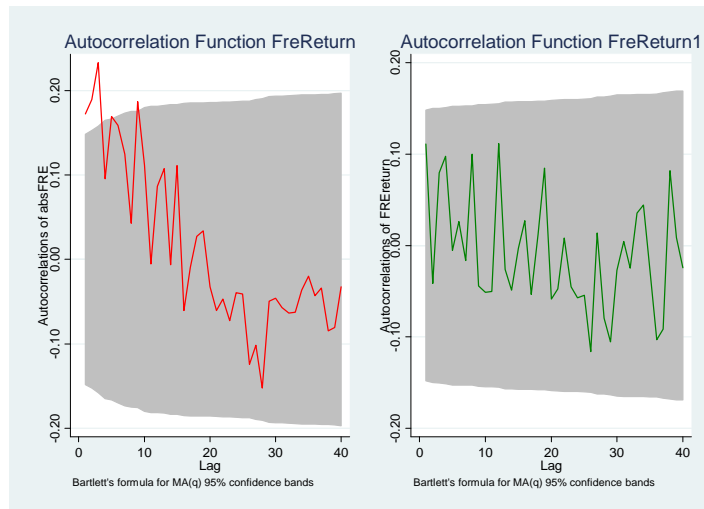
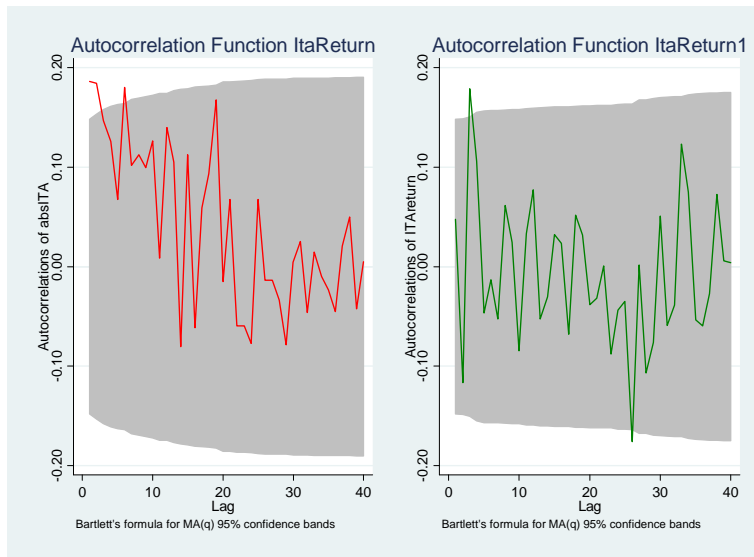
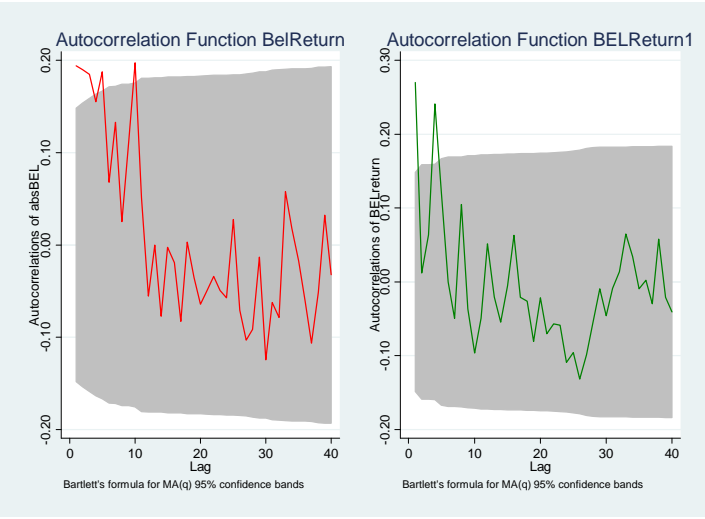
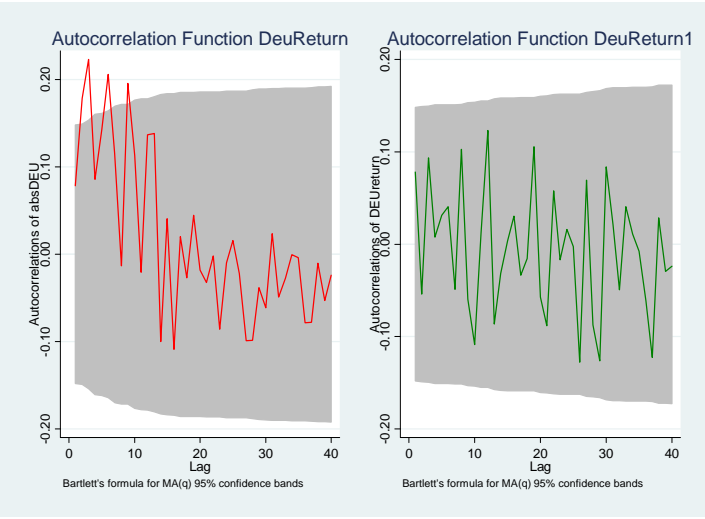


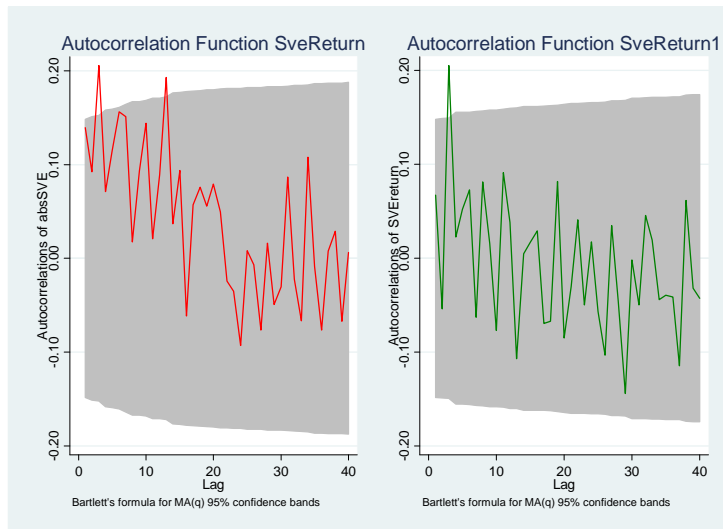
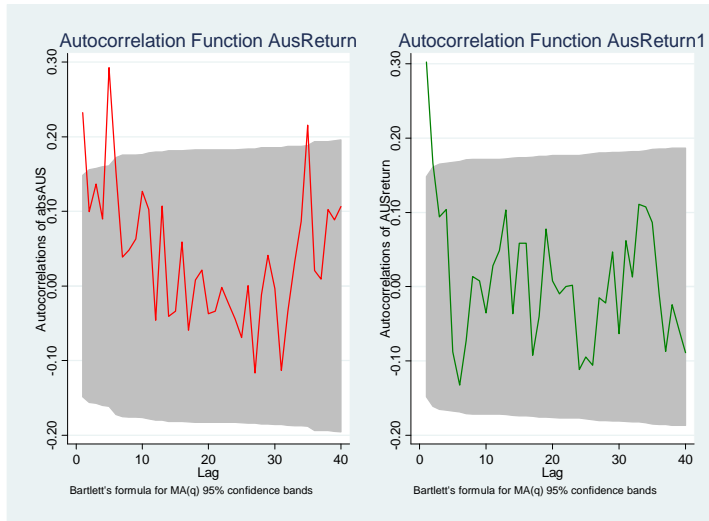
Table 2.1: Summary Statistics

Statistics	ITA	GER	FRE	BEL	AUS	SVE	GRE	USA
Mean	-.0022	.0037	-.0003	.0017	.0060	.0023	-.0064	.0028
SD	.0614	.0631	.0523	.0488	.0607	.0587	.0950	.04430
Kurtosis	3.714	5.214	3.584	6.099	6.377	4.074	3.722	3.958
Skewness	-.1560	-.6033	-.4691	-1.149	-1.083	-.2139	-.1192	-.5720
N	175	175	175	175	175	175	175	175









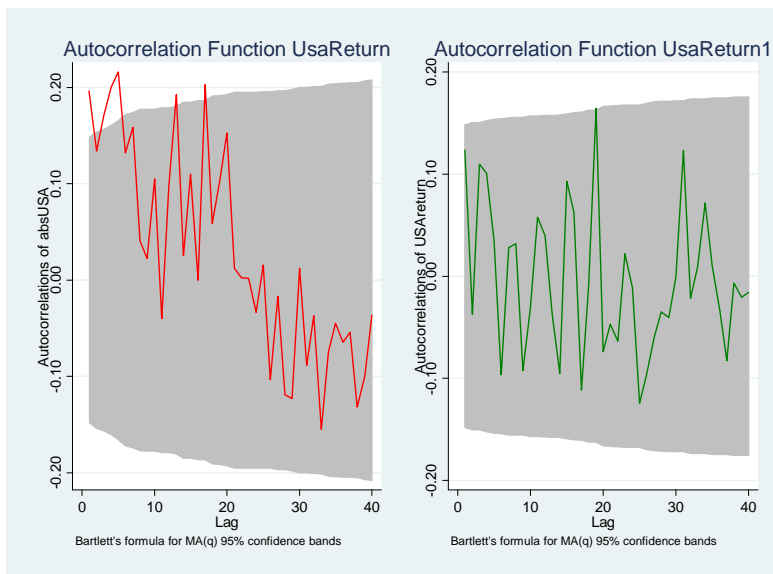
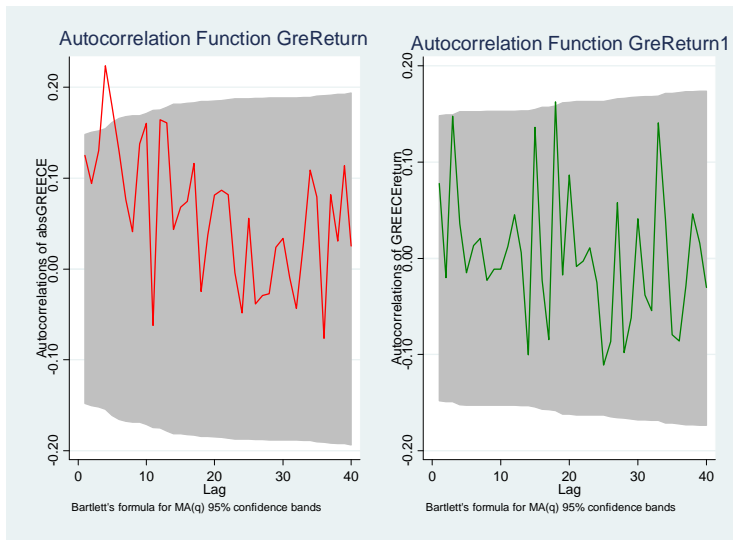


Table 2.2: Mean Equation Estimation

	(1) ITALY Return
GERMANY Return	-0.0946 (0.0886)
FRANCE Return	1.013*** (0.125)
BELGIUM Return	0.0141 (0.0855)
AUSTRIA Return	-0.00529 (0.0573)
SWEDEN Return	0.0212 (0.0650)
GREECE Return	0.139*** (0.0308)
USA Return	-0.0756 (0.0906)
Constant	-0.000415 (0.00209)
$N$	175
$R^2$	0.820

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 2.3: GARCH Model

	(GARCH) ITAreturn	(EARCH) ITAreturn	(TARCH) ITAreturn
Arch	0.173* (0.100)		-0.0589 (0.0589)
Garch	0.704*** (0.163)		0.659*** (0.144)
Earch		0.215** (0.108)	
Symmetry		0.162 (0.103)	
Egarch		0.868*** (0.0820)	
Tarch			0.483** (0.229)
$N$	175	175	175

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ 

Table 2.4: MGARCH Pre

	(CCC) ITAreturn	(DCC) ITAreturn
corr(ITAreturn,DEUreturn)	0.813*** (0.0249)	0.846*** (0.0299)
corr(ITAreturn,FREReturn)	0.894*** (0.0146)	0.912*** (0.0178)
corr(ITAreturn,USAreturn)	0.750*** (0.0321)	0.780*** (0.0428)
corr(DEUreturn,FREReturn)	0.909*** (0.0128)	0.928*** (0.0148)
corr(DEUreturn,USAreturn)	0.828*** (0.0236)	0.855*** (0.0301)
corr(FREreturn,USAreturn)	0.843*** (0.0219)	0.855*** (0.0300)
$N$	174	174

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 2.5: MGARCH Post

	(CCC)	(DCC)
	ITAret_crisis	ITAret_crisis
corr(ITAret_crisis,DEUret_crisis)	0.803*** (0.0270)	0.804*** (0.0384)
corr(ITAret_crisis,FREret_crisis)	0.916*** (0.0122)	0.917*** (0.0174)
corr(ITAret_crisis,USAret_crisis)	0.753*** (0.0328)	0.751*** (0.0451)
corr(DEUret_crisis,FREret_crisis)	0.888*** (0.0161)	0.888*** (0.0233)
corr(DEUret_crisis,USAret_crisis)	0.854*** (0.0206)	0.854*** (0.0303)
corr(FREret_crisis,USAret_crisis)	0.859*** (0.0198)	0.857*** (0.0277)
<i>N</i>	174	174

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Part III

# Long-Term Leverage and the Financial Crisis

## Chapter 3

# Relationship between Maturing Debts and Financial Crisis

### 3.1 Introduction

A financial crisis is defined as a major disruption in financial markets that is characterized by a sharp decline in asset prices and the failure of many financial and nonfinancial firms. When a crisis happens, the consequences might be amplified by four main factors: (1) the increase in interest rates; (2) the increase in lender uncertainty; (3) the asset market effect on balance sheets and (4) problems in the banking sector.

The existence of very high interest rates may create adverse selection problems. At high interest rates, those that are willing to pay more are also those that are more willing to undertake highly risky projects that promise the possibility of a high return rate (though not with a high probability). Investors wishing to pursue modestly risky investment projects with modest expectations of gain may be discouraged from borrowing and might well exit the market for loanable funds. Lenders, anticipating this adverse selection effect, may become discouraged from lending making borrowing, also for those people that have an average risk, much harder. The result could be a substantial decline in investment with a slower economic growth.

The increase in lender uncertainty is another important factor that might worsen a pre-existing financial crisis. Let's suppose that a negative financial shock occurs, like, for instance, an expected failure of a major financial firm previously thought to have been in good financial

conditions. This unexpected negative shock may increase the market uncertainty about the attributes and the credibility of potential borrowers. The greater uncertainty limits once again the lending activity.

As many economists have pointed out, the state of corporate balance sheets has important implications for the severity of financial crisis. More in detail, a reduction in the level of net worth, defined as the difference between what a firm owns (assets) and what it owes (liabilities), may have important consequences on the perceived level of riskiness on a given company on the capital markets. If a default occurs, creditors are entitled to take ownership of the assets of the firm with the implication that if a reduction in net worth occurs then also the collateral will diminish and lenders become reluctant to invest in an entity that may face solvency problems in the future.

An additional aspect to consider is the complexity of the banking sector. If banks suffer a deterioration in their balance sheets for whatever reason, they will have fewer resources to lend and bank lending will decline. This decline, in turn, will lead to a contraction in investment spending and a slow-down in economic activity. In particular, if the decline in bank lending is sufficiently severe, it can lead to a "*bank panic*." A bank panic (or bank run) is said to occur when large numbers of depositors lose faith in banks and seek to withdraw their funds all at the same time, leading to many bank failures.

The aim of this chapter is to investigate another potential factor that may amplify the crisis effect: the impact of long-term debts on the average corporate investment during the 2007 crisis. The main idea is that firms with debts maturing at the time of the crisis are more financially constrained and, as a consequence, experience a larger drop in investment. The purpose is to fill a gap in the literature: several papers analyze how firms choose their debt maturity structure, but very few studies focus on its impact on the firm performance.

The chapter is organized in the following way: after a brief literature review, the data will be discussed. A particular attention will be devoted to the data collection and the variable construction. In this section the matching approach will be further explained in order to better understand why the two groups (treated and controls), that share similar firm characteristics, are different. Finally, the main results will be presented together with some tests.



## 3.2 Literature Overview

Little has been done to study how debt maturity affects corporate investment in period of crisis.

Several papers, such as Barclay and Smith (1995), Stohs and Mauer (1996) and Guedes and Opler (1996) look at determinants of debt maturity. Barclay and Smith, for example, report that firms that have few growth options and are large have more long-term debt in their capital structures. Stohs and Mauer report that asset maturity is positively related to debt maturity. Finally, Guedes and Opler show that large firms with investment-grade credit ratings typically borrow on the short end and on the long end of the maturity spectrum, while firms with speculative-grade credit ratings borrow in the middle of the spectrum.

The determinants of debt maturity are investigated also from a theoretical point of view. The theoretical literature suggests that both high and low credit quality firms are likely to borrow short term, although for different reasons. High quality firms are willing to borrow short term to signal that they are not concerned about future liquidity shocks that might trigger refinancing. Low quality firms, instead, use short-term debt because they are capital constrained and, consequently, short-term debt is the only alternative they have.

The effect of credit supply shocks on corporate decisions is investigated in Chava and Purnanandam (2008) as well as in Lemmon and Roberts (2008). Chava and Purnanandam analyze the main effects of the Brazil-Russia-LTCM crisis and show that these effects become larger for bank-dependent firms that were more exposed to Russia. Lemmon and Roberts examine the effects of a contraction in the supply of risky credit (junk bonds) caused by changes in regulation and the collapse of Drexel Burnham Lambert. Their evidence suggests that risky firms' leverage remained constant while their investment declined as a result of changes in the junk-bond market landscape.

No one of the previous papers studies the real effects of long-term maturity. As previously anticipated, this will be the main purpose of the following sections.

## 3.3 Data Collection and Variable Construction

The data come from Compustat's North America Fundamental Annual, Fundamentals Quarterly and Ratings File. I work with a dataset that is the result of the merge of three different

files: a quarterly file that contains firms' characteristics, an annual file that contains debt maturity information and a file that categorize firms according to their credit ratings.

### 3.3.1 Quarterly File -

The quarterly data come from Compustat.

I drop observations for the financial institutions, not-for-profit organizations and governmental enterprises as well as ADRs. In other words, I disregard observations with SICs between 6000 and 6999 and with SICs bigger than 8000. I keep observations if I have missing values for the ADR ratio.

I drop observations if there are missing values for the variables total assets, property plant and equipment and sales. In addition, I drop values for cash holdings, property plant and equipment and capital expenditures if they are greater than the quarterly total assets.

I disregard observations if I have negative values for sales. I replace the negative values of quarterly total asset, cash holdings, property plant and equipment and capital expenditures with zero in order not to lose a large number of observations. I discard raw data from observations for which the value of total assets is less than \$10 million.

I construct two lagged variables: one for the total assets variable and another one for the total sales variable. These two lagged variables are then used to construct the asset growth variable and the sales growth variable. More precisely, I construct the two growth variables in the following way:

$$\begin{aligned} \text{Asset Growth}_t &= \frac{\text{Assets}_t - \text{Assets}_{t-1}}{\text{Assets}_t}; \\ \text{Sales}_t &= \frac{\text{Sales}_t - \text{Sales}_{t-1}}{\text{Sales}_t}. \end{aligned}$$

I drop all the observations displaying asset growth and sales growth greater than 100%.

### 3.3.2 Annual File

This file contains information related to the debt structure of the firm. I have information on the dollar amount of long-term debt maturing during the first year after the annual report (dd1), during the second year (dd2) and so on. In total, I have information for the first five years after the annual report. In addition, I have also an item from Compustat that describes the dollar amount of long-term debt that matures in more than one year (dltt).

I define the firm's total long-term debt as the sum of the long-term debt maturing during the first year after the annual report and the dollar amount of long-term debt that matures in more than one year (dltt+dd1).

I drop all the missing values for dd1 and dltt. The authors don't describe how they deal with dd2, dd3, dd4 and dd5. I replace the missing values of these variables with zero in order not to lose observations that might be meaningful. I require firms to satisfy the following conditions:

1. Firm's total long-term debt  $\leq$  Annual Assets
2. Long-term debt maturing in more than one year (dltt)  $\geq 0.05$ \*(Annual Assets)
3. Long-term debt maturing in more than one year (dltt)  $\geq$  dd2+dd3+dd4+dd5.
4. Notes payable  $\leq 0.1$ \* (assets annual) .

I replace missing notes payable with zero. I drop the missing values for total assets. I focus on firms that have 2007 fiscal year-end months in September, October, November, December and January. The rationale behind this restriction is to focus the attention on the exact period of the credit shock, which happened in the fall of 2007.

### 3.3.3 Rating File

Firms are categorized according to their credit rating. I create credit rating categories following the index system used by S&P. In particular, I generate a variable which takes the value 1 if the firm has an investment grade rating, the value 2 if the firm has a speculative grade rating and the value 3 if it is unrated<sup>1</sup>. The zero value is attached to all those firms that receive the evaluation NM meaning that the rating is not meaningful.

### 3.3.4 Final Dataset: treatment and control groups

I constructed the final dataset using the following procedure.

I start with the quarterly file. The initial number of firms in the quarterly file for the 2007 fiscal year is 11,170. I clean the data following the instructions described in the previous section.

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<sup>1</sup>Firms that receive an investment grade rating have one of the following ratings: AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-. Firms that receive a speculative grade rating have one of the following ratings: BB+, BB, BB-, B+, B, B-, CCC+, CCC, CC-, CC, CC, D.

After cleaning the data, the number of firms in the quarterly file is equal to 5,528 (2007 fiscal year).

Then, I work with the annual file containing all the information related to the debt structure of the firms. I apply all the filters previously described. After that, I merge the annual dataset with the quarterly one.

The result of the merge provides a dataset where the total number of firms for the 2007 fiscal year is 820.

To have the complete dataset I need to merge the rating file .

After merging the three datasets, I define the outcome variable. The outcome variable is defined as the change in a firm's investment, where the investment is defined as the ratio of quarterly capital expenditures to the lag of property plant and equipment . The change is measured around the fourth quarter of 2007. To be more explicit, the change in the firm's investment is given by the difference between the average investment for the first three quarters in 2008 and the first three quarters in 2007.

The final dataset allows me to define the treatment variable. This variable is equal to the ratio between the long-term debt maturing within one year and the total long-term debt. If the ratio is bigger than 20%, then the firms will be assigned to the treatment group. If the ratio is smaller than 20%, then the firms will be assigned to the non-treated group.

Among the non-treated firms, I am able to select a set of control firms. These firms are a match for each firm in the treatment group. The match is based on the Abadie-Imbens estimator. This estimator identifies similar firms in the treatment and control group using some firm characteristics like Q, cash flow, size, cash holdings and long-term leverage.

Q is defined as the ratio of total assets plus market capitalization minus common equity minus deferred taxes and investment tax credit to total assets. Cash Flow is defined as the ratio of net income plus depreciation and amortization to the lag of property plant and equipment. Size is defined as the log of total assets. Cash holdings is the ratio of cash and short term investments to total assets. Long-term leverage is the ratio of total long-term debt to total assets.

The matching technique exploits the averages of the firm characteristics for the first three quarters of 2007 as covariates. The procedure applies a bias-correction component to the estimates of interest and produces heteroskedastic-robust standard errors .

After adopting all the filters, the final number of firms is 544 (2007 fiscal year). The number

of firms in the treatment group is equal to 80. The number of firm in the control group is 42.

### 3.4 Summary Statistics

Panel A of the Table 3.1 compares the 80 firms that are in the treatment group with the 42 firms that are in the control group. I use the Pearson chi-squared statistic to test for differences in the medians of the variables of interest (Q, cash flow, size, cash, long-term leverage and investment) across the different groups.

My results suggest that treated firms have higher Q, cash flow and investment levels than firms that are assigned in the non-treated group. The treated firms are also smaller and have a lower leverage ratio. However, I find no statistical differences in the median values of the covariates I consider across treated and non-treated. The only difference that is statistically significant is the one related to the long-term leverage.

	Q	Cash Flow	Size	Cash	LT Leverage	Investment
<i>Panel A: Medians for Treated and Non-Treated Firms in 2007</i>						
Treated	1.765	0.109	5.571	0.068	0.213	0.174
Non-Treated	1.623	0.051	5.76	0.089	0.289	0.115
Difference	0.142	0.058	-0.189	-0.021	-0.076	0.059
Median Test	0.345	0.218	0.468	0.333	0.001	0.146
p-value						
<i>Panel B: Medians for Treated and Control Firms in 2007</i>						
Treated	1.765	0.109	5.571	0.068	0.213	0.174
Control	1.60	0.097	6.225	0.0506	0.28	0.167
Difference	0.165	0.012	-0.654	0.0174	-0.067	0.007
Median Test	0.527	0.948	0.173	0.560	0.080	0.846
p-value						

- Table 3.1: Pre-crisis characteristics of treated, non-treated and control firms at the end of 2007 -

Panel B compares the median values for treated and matched control firms. As anticipated in the previous section, the Abadie-Imbens estimator identifies a match for each firm in the treated group. As shown by the Median Test p-value, differences are not statistically significant.

It is possible to get additional insights looking at the entire distribution of the covariates.

		25 <sup>th</sup> %	Median	75%	Kolmogorov-Smirnov Test p-value
<i>Panel A: Characteristics for Treated vs Non-Treated Firms in 2007</i>					
Q	Treated	1.20	1.77	2.43	0.801
	Non-Treated	1.25	1.63	2.43	
Cash Flow	Treated	0.01	0.11	1.28	0.6
	Non-Treated	0.01	0.05	1.39	
Size	Treated	4.00	5.57	7.12	0.873
	Non-Treated	4.10	5.76	7.40	
Cash	Treated	0.03	0.07	0.20	0.727
	Non-Treated	0.02	0.09	0.28	
LT Leverage	Treated	0.14	0.21	0.32	<u>0.001</u>
	Non-Treated	0.18	0.29	0.43	
Investment	Treated	0.02	0.17	1.98	0.288
	Non-Treated	0.01	0.12	1.65	
<i>Panel B: Characteristics for Treated vs Control Firms in 2007</i>					
Q	Treated	1.20	1.77	2.43	0.685
	Control	1.29	1.60	2.33	
Cash Flow	Treated	0.01	0.11	1.28	0.912
	Control	0.01	0.10	0.76	
Size	Treated	4.00	5.57	7.12	0.285
	Control	4.97	6.23	7.21	
Cash	Treated	0.03	0.07	0.20	0.460
	Control	0.02	0.05	0.12	
LT Leverage	Treated	0.14	0.21	0.32	0.125
	Control	0.17	0.28	0.39	
Investment	Treated	0.02	0.17	1.98	0.460
	Control	0.01	0.17	1.23	

The previous table compares the entire distributions, rather than just the medians, for the different covariates across the three groups of interest: treated firms, non-treated firms and control firms. The test for differences in the distribution of a firm characteristic across two groups is conducted by using the corrected Kolmogorov –Smirnov’s D statistic.

The results are consistent with Table 3.1.

### 3.5 The Real Effects of the 2007 Panic

Panel A: Panel A shows the average quarterly investment for treated and non-treated firms in the first three quarters of 2007 and 2008. Heteroskedasticity-consistent standard errors are in parentheses.

Average Quarterly Investment/ Capital Stock (in Percentage points)

*Panel A: Investment Before and After the Fall 2007 Credit Crisis*

Investment in 2008 (Q1 to Q3) vs. Investment in 2007 (Q1 to Q3)

	2007	2008	2008-2007
<b>Treated Firms</b>	5.967*** (1.333)	4.313*** (1.772)	-1.654 (3.088)
<b>Non-Treated Firms</b>	7.420*** (2.529)	9.079*** (2.199)	1.658 (2.574)
<b>Difference</b>	-1.454 (3.421)	-4.765 (5.409)	

Treated and Non-Treated firms have different investment rates prior to the crisis. The average investment-to-capital ratio in the first three quarters of 2007 for treated firms is equal to 5.9% and for non-treated firms is equal to 7.42%. However, I do find a drop from 2007 to 2008 in the level of investment of treated firms. The level of investment drops to 4.313, a fall of 1.65 percentage points. Surprisingly, the level of investment for non-treated firms rises to 9.079. It is hard to explain why the non-treated firms behave in this way. A possible explanation comes from the summary statistics presented in Table 3.1. This table suggests that firms in the non-treatment group are usually bigger and have more cash. Given that they do not need to refinance a significant amount of debt following the crisis, they can use this debt to support more investments.

**Panel B:** Panel B shows the average quarterly investment for treated and control firms in the first three quarters of 2007 and 2008. Heteroskedasticity-consistent standard errors are in parentheses. The result I get suggests that the treatment group experiences a stronger decline in investment compared to the control group. The average investment for the control group is surprisingly high which might be explained through the inclusion/exclusion of specific firms.

*Panel B: Investment Before and After the Fall 2007 Credit Crisis*

Investment in 2008 (Q1 to Q3) vs. Investment in 2007 (Q1 to Q3)

	2007	2008	2008-2007
<b>Treated Firms</b>	5.967*** (1.333)	4.313*** (1.772)	-1.654 (3.088)
<b>Control Firms</b>	14.168 (7.373)	38.978 (20.471)	26.574 (21.758)

The experiment proposed in this Panel is repeated for the fiscal years 2006-2007. The aim of this exercise is to run a Placebo test to see what happens right before the crisis period. The results (not shown in the table below) suggest that both the two groups of firms experience

a drop in investment from 2006 to 2007. The change in investment from 2006 to 2007 is not significant in my results.

### **3.6 Parallel Trends**

In order to make sure that differences in the post-treatment period are associated to the treatment, an important test is to verify whether the treatment and control outcomes followed the same trend prior to the treatment.

In order to check the behavior of the two groups before the 2007 crisis, I use the following approach.

In the quarterly file I have a sample period from January 1998 to December 2012. I define a lag value for investment which allows me to have a measure for the quarterly change in investment. Then, I compute the average of the quarterly change across firms sorting the firms into treated and control. The result I get is that from 1998 up to the beginning of 2007 the average quarterly change in investment is negative for both groups. I don't find any significant difference among the two groups in the pre-crisis years in terms of the outcome variable.

### **3.7 Final Remarks: Different Methodology and Further Tests**

In the previous sections the impact of debt maturity over investment has been analyzed by exploiting a matching approach that allows to compare similar firms that differ only for the debts maturing at the time of the crisis. No other methodology is applied.

In order to check if the results are consistent across different methodologies, I estimate a simple regression model where the dependent variable is the investment change from 2007 to 2008 and the independent variables are the dummy variable for the treated plus all the covariates that I use for the matching estimation.

The results I get show me that the methodology plays an important role. The coefficient associated to the treatment variable is negative meaning that people in the treatment group with a higher proportion of debt maturing in one year will experience a higher drop in investment.



Although the sign is correct, I don't have any level of significance. The same results hold when I assume that the standard errors are robust.

The simplicity of the OLS approach gives me the possibility to consider some further extensions. For instance, it would be interesting to see how firms will behave if they have a higher proportion of long-term debt maturing in one year but they are classified as investment firms (higher credit ratings). If this is the case, I don't expect a huge decrease in investment. Investment firms have the possibility to use their credit rating to signal their quality and, thus, to get financing when needed without sacrificing future investments.

To check the validity of this statement, I run the same OLS regression considering only the investment rating category. The results show a coefficient for the treatment variable that is positive, although not statistically significant. Despite the level of significance, I strongly believe that working with firms that have an easier access to credit and have, thus, less financial constraints should potentially reduce the impact of debt maturity over investment.

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