Politecnico di Milano

Scuola di Ingegneria Industriale e dell'Informazione

Tesi di Laurea Magistrale in Ingegneria Matematica

Measuring reputational risk of a sovereign state: Italy as a case study.

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Anno Accademico 2013/2014

Abstract

In the current economic context reputation can influence financial dynamics in sovereign states. In fact sovereign states bonds interest rates are determined by the default risk and by the credibility perceived by other countries. The aim of the thesis is to evaluate how reputational events affect the Italian spread, considered as a proxy for Italian financial health, choosen as case study. In order to do that it is required to build a local linear regression model able to model spread dynamics not correlated to reputational events. The selected regressors are FTSE-MIB to capture economic Italian dynamics, an aggregate of eurozone countries spreads able to explain European trends and EURO/DOLLAR exchange rate to show the Europe-world behaviour.

213 events divided into 12 categories were selected over the period between 7th May 2008 and 31th December 2013. 69 of them resulted significantly impacting on Italian spread, 30 making it increase and 39 decrease.

Different categories have demonstrated to impact on spread in different ways. Considering the 5 most frequent categories "Judiciary events premier", "Consumers confidence", "Government defeated" and "Vote of confidence" resulted to influence Italian spread, while "PIL comunication" does not produce significative changes in its behaviour.

Italian Abstract

Nell'attuale contesto economico la reputazione pu influenzare le dinamiche finanziarie degli stati sovrani. Infatti i tassi d'interesse delle obbligazioni degli stati sovrani sono determinati dal rischio di default e dalla credibilità percepita dagli altri paesi.
Lo scopo della tesi è di valutare in che modo gli eventi reputazionali influenzano lo spread italiano, scelto come indicatore della salute finanziaria dell'Italia. A questo proposito è necessario costruire un modello di regressione lineare locale capace di predire le dinamiche dello spread non basate su eventi reputazionali. I regressori scelti sono il FTSE-MIB che cattura le dinamiche dell'economia italiana, un aggregato di spreads di altri paesi delll'eurozona capace di spiegare i trend europei e il tasso di cambio EURO/DOLLARO per identificare le dinamiche mondiali.
213 eventi divisi in 12 categorie sono stati selezionati nel periodo fra il 7 Maggio 2008 e il 31 Dicembre 2013. 69 sono risultati essere significativamente impattanti sullo spread italiano, 30 aumentandolo e 39 diminuendolo. Le differenti categorie di eventi hanno dimostrato di impattare sullo spread in diverso modo. Considerando le 5 categorie pi numerose "Eventi giudiziari premier", "Fiducia consumatori", "Governo battuto" e "Voto di fiducia" sono risultate influenzare lo spread italiano, mentre "Comunicazione PIL" non produce variazioni significative nel suo comportamento.

Contents

List of Figures

LIST OF FIGURES

List of Tables

1

Introduction

In the current economic context reputation is considered a strategic asset through which companies can create economic value. A good reputation, in fact, can bring about various benefits, such as the attraction of new investments, clients and partners. Accordingly to the idea that not only financial corporates are struggled by reputational risk, we moved the focus from firms to sovereign states. Considered on a country scale, reputation influences international confidence about the country where the event takes place, that is reflected on interest rates on bonds issued by that country. Zoli (2013) (1) shows that relevant political events influence the credibility of a certain country through the impact they produce on the 10-year-bond-yield spread. Fucusing on Italian dynamics, the purpose of the thesis is to evaluate the impact of reputational events on Italian spread. In this context the thesis objective is to develop, through a quantitative approach, a model able to determine which reputational events impacted on Italian spread and which categories of events mostly influence its dynamic.
In order to do that the work is divided into two main parts:

- Build a linear regression model able to evaluate Italian spread dynamics;
- Study the impact of reputational events on Italian spread, evaluating which categories of events mostly influence it.

In the first part, the aim is to select the optimal explanatory variables able to explain spread dynamics in a short time window with a daily temporal resolution. In literature auto-regressive models with higher time resolution are usually used(Favero 2012 (2)), but a great number of possible regressors is proposed (Zoli 2013 (1)). Moreover it is

necessary to select the time window typology (fixed, adaptive...) and amplitude.
In the second part of the thesis impacts of reputational events are evaluated. They are introduced into the model through dummy variables switching from 0 to 1 at the day the reputational event considered occurs. Amplitude of a certain event impact is estimated with the β coefficient corresponding to the associated dummy variable, while the evaluation reliability of the result is given by the respective p-value. Once obtained all these parameters we analyze which categories mostly impact through ANOVA one-way and qualitative approaches.

1.1 Italian introduction

Nell'attuale contesto economico la reputazione è considerata un bene strategico attraverso il quale le compagnie possono creare valore economico. Una buona reputazione, infatti, può portare vari benefici, come l'attrazione di nuovi investimenti, clienti e partner. In accordo con l'idea che non solo le società finanziarie sono minacciate dal rischio reputazionale, l'attenzione sarà spostata dalle aziende agli stati sovrani. Considerata su scala statale, la reputazione influenza la fiducia internazionale circa lo stato in cui un evento si svolge, che viene poi riflessa sui tassi d'interesse delle obbligazioni emesse dallo stato in esame. Zoli (2013) (1) mostra che eventi politici rilevanti influenzano la credibilità di un certo paese attraverso l'impatto che producono sullo spread calcolato sulle obbligazioni decennali. Concentrandosi sulle dinamiche italiane, lo scopo della tesi è di valutare l'impatto di eventi reputazionali sullo spread Italia-Germania. In questo contesto l'obiettivo della tesi è di sviluppare tramite un approccio quantitativo un modello capace di determinare quali eventi reputazionali hanno influito sullo spread italiano e quali categorie di eventi maggiormente ne influenzano le dinamiche.
Con questo fine il lavoro è stato diviso in due sezioni principali:

- Costruire un modello di regressione lineare capace di stimare le dinamiche dello spread italiano

- Studiare l'impatto di eventi reputazionali sullo spread italiano, valutando quali categorie di eventi maggiormente lo influenzano

Nella prima parte l'obiettivo è quello di individuare i migliori regressori capaci di spiegare le dinamiche dello spread in brevi finestre temporali con una risoluzione temporale giornaliera. In letteratura sono solitamente utilizzati modelli autoregressivi con maggiori risoluzioni temporali (Favero 2012 (2)), ma è proposto un grande numero di regressori (Zoli 2013 (1)). Inoltre è necessario selezionare la conformazione e dimensione della finestra temporale da considerare.
Nella seconda parte della tesi sono stimati gli impatti dei vari eventi reputazionali. Essi sono introdotti nel modello attraverso variabili dummy, che si accendono il giorno in cui si svolge la pubblicazione dell'evento reputazionale corrispondente. L'ampiezza dell'impatto di un certo evento è stimata con il coefficiente β corrispondente alla variabile dummy associata, mentre la significatività data dal rispettivo p-value. Una volta ottenuti tutti i parametri si analizza quali categorie sono maggiormente impattanti attraverso one-way ANOVA e approcci più qualitativi.

2

State of the art

Even if the focus of the thesis is on reputational risk quantitative analysis, our literature review started from the search for articles which treated reputation in a qualitative way, in order to put theoretical basis to our work. Protecting a firms reputation is the most important and difficult task facing senior risk managers, reputational risk emerges as the main concern for the majority of risk managers ahead of regulatory risk, human capital risk, IT network risk, market risk and credit risk. (3).
Reputational risk measurement is not new in literature, several studies were carried out with the objective to measure reputational losses. Most of these works examine the reputational effects from a qualitative point of view and almost all of them are focused on firm analysis, in fact a negative event can change the reputation of a company to the eyes of the stakeholders. There are different approaches about this topic. Murphy et al. (2004) (4) focused on the study of the impact of events connected to legal misconducts of different listed companies, Gillet et al. (2010) (5) and Fiordelisi et al. (2013) (6) focused on the effects of announcements of operational losses in banking and financial industry to see if, together with an operational loss, there would also be a reputational one. Cazzaniga and D'Ettole (2013) (7) and Belloni (2013) (8) proposed a model able to quantify a reputational loss due to a potentially impacting event in Oil&Gas companies.
Moving the focus on a country scale, reputation is still a relevant asset that strongly affect the financial and economic health of a sovereign state. In fact it influences the credibility of a country perceived by other countries, that is then reflected on bonds interest rates. The riskier an investment in a country is perceived, the higher are bonds

interest rates to encourage people to invest. It is then necessary to understand which drivers, in addition to purely economic factors, affect the credibility of a country.
In order to adopt a quantitative approach, bonds interest rates are a proper indicator of the financial health of a country. Nowadays spread is a unit of measure of the financial health and credibility of a State and it is calculated from 10-years-bond interest rate (Binda 2013 (9)), so it is an index that can be strongly influenced by reputational events. About how reputational events impact on Italian spread, Zoli (2013) (1) shows that both international and Italian-specific news are found to have a sizable impact on daily variations in Italian 10-year spread. It is also shown that bad and good news related to important international events on the global and european sovereign crisis (e.g. the start of the Irish or Greek program), as well as positive and negative news related to Italy specific events (e.g. approval of consolidation of reform measures), have a statistically significant and large impact on daily changes in spreads. Finally Binda (2013) (9) developed a new approach to evaluate the impact of a reputational event through the spread jump caused by it.
Because the fundamental aspect on which the thesis is based is the identification of reputational events impact on Italian BTP10y-BUND10y spread, the bibliographic research needs to look for factors influencing the spread or correlated with it, with the aim of using good predictors to build the linear regression model to be used to estimate the Italian spread.
Spread is commonly utilized as indicator of the financial uncertainty of a country (Italy in this case). The analysis of the relationship between emerging market sovereign spreads and country-specific fundamentals/global factors has been the subject of a large number of empirical studies. The literature has established several explanatory variables, both global and country-specific, which affect spreads.
The seminal paper of Edwards (1985)(10) finds that key drivers of spreads are country-specific fundamentals such as external debt, debt service, investment ratio, deficit/GDP ratio and GDP growth rate. These indexes were widely used in literature (examples are Favero(2012)(2), Bernoth et al(2012)(11), de Grauwe and Yuemei (2013)(12)).
Luengnaruemitchai and Schadler (2007)(13) and Hartelius et al. (2008)(14) further expand the list of global factors and county-specific fundamentals that have significant effect on spreads. As regards the global factors, in addition to the level of international interest rates they find that the uncertainty about the level of rates and global risk

aversion are also important determinants of spreads. Specifically, they find that an increase (decline) in either the level or the volatility of the U.S. Federal funds futures rate and a higher (lower) global risk aversion are associated with higher (lower) country risk premium. As regards the country specific factors, they find that country fundamentals, as captured by economic, financial and political indicators, as well as the sovereign credit rating outlook also significantly affect spreads.
Considering eurozone countries fiscal fundamentals are used to capture country-specific dynamics, but it is also relevant to capture global risk dynamics. An index that captures this type of uncertainty is *US corporate BaaAaa spread*. This variable is introduced to capture the influence of time-varying risk aversion, which is a world factor commonly believed to influence euro area credit spreads (Codogno et al. (2003)(15), Geyer et al.(2004)(16) and Bernoth et al. (2006)(11)).
Other proxies for the market global volatility are the VIX, that is Chicago Board Options Echange Volatilty Index (Mody (2009)(17), Di Cesare et al. (2012)(18), Zoli (2013)(1)) andl TED spread (Eichler 2014(19)).
As well as country specific variables and global variables, for Italy it is also necessary to capture eurozone country dynamics. Codogno et al. (2003)(15), Geyer et al. (2004)(16) e Bernoth et al. (2006)(11) show that euro area sovereign spread strongly comove. Zoli (2009)(1) shows that Spain's spread is a good explanatory variable for local linear regression models where the response variable is Italian spread.
Usually as explanatory variable that captures the european dynamics is adopted a weighted sum of other eurozone countries' spreads. Galesi and Sgherri (2009)(20) propose weights based on cross-country financial flows, Vansteenkiste (2007)(21) uses weights which are based on the geographical distances among regions, while Favero(2012)(2) adopts time-varying weights inversally proportional to the distance in terms of debt.
Zoli (2009) (1) also shows that both international and Italian-specific news are found to have a sizable impact on daily movements in Italian 10-year spreads. Dummy variables capturing bad and good news related to important international events on the global and European sovereign crisis, as well as positive and negative news related to Italy specific events have a statistically significant and large impact on daily changes in spreads.

3

Research methodology

3.1 Data collection

3.1.1 Italian spread explanatory variables

The time period considered is between 7th May 2008 and 31th December 2013. During this time lapse variables were collected to build the best local linear regression model to estimate and fit the Italian spread (difference between the 10-years Italian government bond yield and the corresponding German one). The variable selection will be operated in Section 4.1. Starting from the model selected, we will then estimate reputational events impacts as it is explained in Section 4.2 and Section 5.1. According with the literature we decided to use an explanatory variable to approximate the Italian dynamics, another one to estimate the eurozone countries dynamics and a third one to capture the European dynamics in relation to the world and the global uncertainty perceived by the financial markets.

Unfortunately the quantities mainly used in literature to explain the country-specific dynamics are the *fiscal fundamentals*, which usually change in value with a monthly temporal resolution, as it happens for debt to GDP ratio (the one that is used most frequently). Because of this reason , they cannot be considered in the explanatory variables selection. We choose the FTSE-MIB index, which changes every day and has the mathematical properties requested. The FTSE-MIB is the benchmark stock market index for the Borsa Italiana, the Italian national stock exchange. It is strongly correlated with the healthy of Italian economy and with the confidence that international markets have in the Italian one.

According to Codogno et al. (2003) (15), Geyer et al. (2004) (16) e Bernoth et al. (2006) (11) we used spreads of other countries to estimate the eurozone dynamics, which the Italian one is strongly correlated with. The choosen countries are the other four PIIGS (Portugal, Ireland, Greece and Spain) because their economies are similar to the Italian one in terms of weakness, and the countries that trade more with Italy in terms of financial flows, which are Austria, France, Belgium, Nederlands and Great Britain. We grouped the spreads of these countries in different ways with the aim to obtain an explanatory variable that properly explains the European dynamics.
Moreover we decided to test as local regressors the DAX index and the 10-year Germany government bond yield. The DAX (Deutscher Aktienindex (German stock index)) is a blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange. These two last regressors were decided to be tested because of their strict relation with German economic and financial health, that can be considered an indicator of the strength and health of all eurozone countries.
For the last category of explanatory variables, many attempts were made to find the best local regressor. We tested the BAA-AAA spread following Favero (2012)(2) and Codogno et al. (2003) (15), the VIX as suggested by Luengnaruemitchai and Schadler (2007) (13), Hartelius et al. (2008) (14), Mody (2009) (17), Di Cesare et al. (2012) (18) and Zoli (2013) (1), the TED spread as proposed by Eichler (2014) (19) and the EURO/DOLLAR exchange rate.

Italy	**Europe**	**World**
FTSE-MIB	Europe counties spread	BAA-AAA spread
	DAX	VIX
	10-yr german bond yield	TED spread
		EURO/DOLLAR exchange

Table 3.1: Candidate regressors - Overview of tested explanatory variables.

We considered only days from monday to friday, because during saturdays and sundays there are no variations in spreads and so it is useless to build a linear regression model considering these days.

3.1.2 Reputational events selection

One of the fundamental aims of the thesis is to find which categories of events are more impacting on the Italian spread. According to this purpose, 262 potentially relevant events selected in the period considered were divided into 12 different categories/tags:

- **New parliamentar groups/change in coalitions:** without falling of government the coalitions between parties change;
- **PIL comunication:** pubblication of news about PIL (Prodotto Interno Lordo - Gross Domestic Product);
- **Minister resignations**;
- **Premier resignations** ;
- **Judiciary events minister:** any news concerning legal affairs of a minister in charge at that moment;
- **Judiciary events premier:** any news concerning legal affairs of the prime minister in charge at that moment;
- **Consumers confidence:** events are ISTAT publications of the consumer confidence index, which measures the italians' "optimism" about the actual economic situation and in the early future;
- **Government defeated:** when a government doensn't get the majority in a parliamentar vote;
- **Government establishment:** when a new government is created;
- **Motion of no confidence:** when a government is no longer deemed fit to hold that position ;
- **Elections:** any relevant news concerning elections;
- **Vote of confidence:** when a new government is created or receives a motion of no confidence.

These 13 categories are regrouped on three different groups, depending on the source of the news. Data about "PIL comunications" and "Consumers confidence" are taken from ISTAT (the Italian National Institute for Statistics), the category "Vote of confidence" get the data from the website http://www.senato.it, while all the other categories found their events in the main newspapers using LexisNexis as search engine. For further informations about the event selection see Pozzi (2014) (23).
If an event happened on saturday or sunday the tag was put on the following monday, because the spread would be influenced in the first day after the break.

3.2 Event study methodology

After the event identification, collection and categorization, the collected data were analyzed with an event study methodology. The methodology consisted in two steps:

- the evaluation of the impact of the single events on the international confidence about Italian market;
- the identification of categories of events which are more impacting.

The first step was based on the estimate of the impact of each single event. This result was achieved through the local linear regression model developed in Chapter 4, where every event was inserted in the model as a dummy variable. β coefficients and p-values referred to each dummy variable gave the informations about impact amplitude and significance of the reputational events considered on the Italian spread.
The second step had the aim to identify which categories of event mostly impact in terms of market reactions. The levels of the factor that were analyzed are the 12 categories defined in Section 3.2. The analysis was carried out through both a qualitative and quantitative approach. The first one resulted in different graphical explorations able to identify patterns in the distributions of β coefficients and p-values obtained in the previous section. The quantitative analysis was performed through a one-way ANOVA on the same coefficients.
Since this methodological section represents the main part of the work, the details and results were divided into two Chapters:

- Chapter 4: selection of the best local linear regression model.

- Chapter 5: Evaluation of the impact of the single events and analysis of the most impacting categoriesevaluation of the impact of all the single events.

4

Model selection

This chapter describes the development of the model used to evaluate the impact of reputational events on the Italian spread value. We need so to select the explanatory variables able to estimate the Italian spread and the linear regression model characteristics.
We adopted a *Market model approach*, that models the variation of the response variable through a linear regression model in which the event is included as regressor through a dummy variable, which enables the analyst to distinguish the temporal window before the event and after the event, as in Arena et al. (2013) (24), Binda (2013) (9), Belloni (2013) (8) and Cazzaniga and D'Ettole (2013) (7).

4.1 Explanatory variables selection

The aim of this section is to select the regressors that best fit the model on small time windows, as the ones that will be used in further sections. In the next chapter we will introduce the dummy variables representing each reputational event. Following Favero (2012) (2) we decided to fit a three-variables regression model, one variable for each of the following dynamics that have to be captured in order to estimate correcly the Italian spread:

- strictly Italian economical dynamics;
- the European trend, whereby the Italian one is strongly correlated;
- the world trend and the global markets volatility.

4.1.1 Italian dynamics

The variable used to capture strictrly Italian dynamics is the FTSE-MIB, which is the benchmark stock market index for the Borsa Italiana, the Italian national stock exchange. The index consists of the 40 most-traded stock classes on the exchange. It captures the economic dynamics of the Italian market, explaining spread variations due to purely economic factors.

As it is possible to notice in fig. 4.1 MIB has a behaviour correspondant to the Italian spread, with different sign (i.e. when the MIB increases the spread decreases, accordingly to the financial and economic meaning). Moreover locally they have strongly linear dynamics (fig. 4.2).

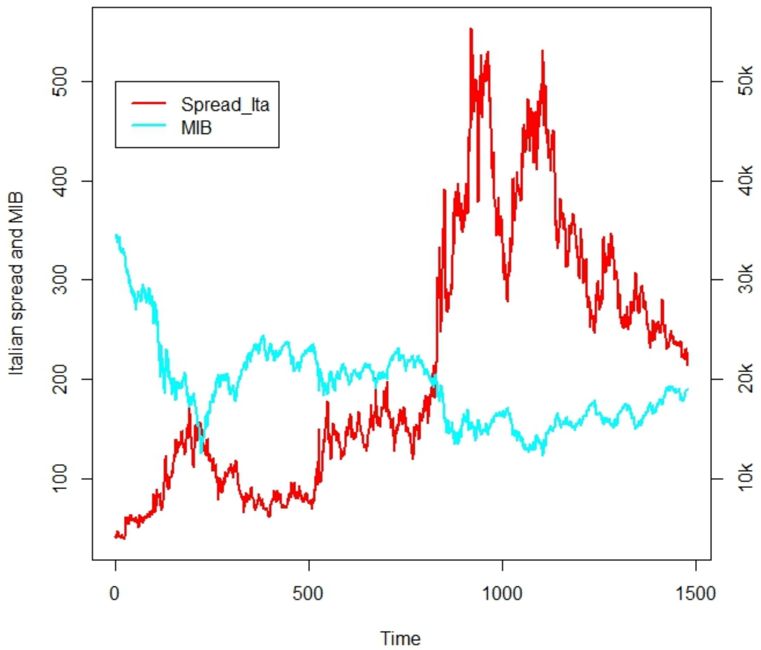


Figure 4.1: Time course of italian spread and MIB over the considered period.

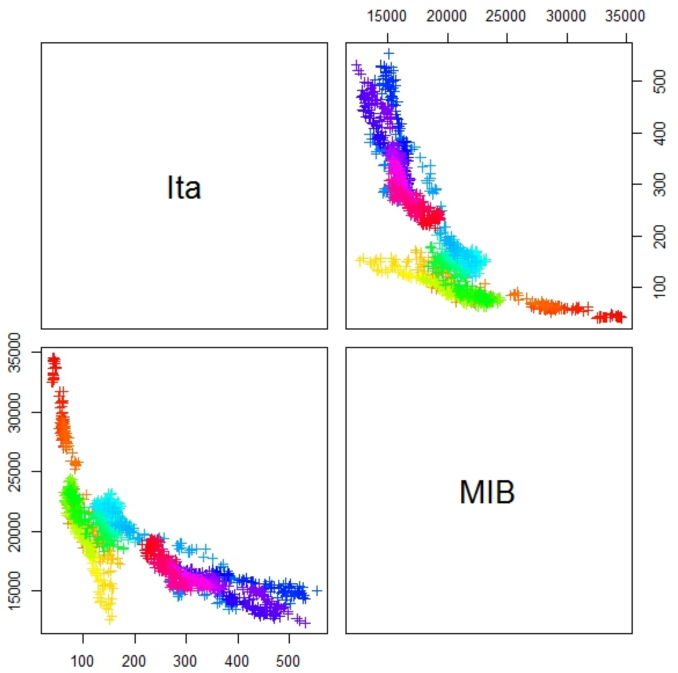


Figure 4.2: Coupled data of MIB and italian spread.

4.1.2 European dynamics

The second explanatory variable we needed to choose is the one relative to European financial dynamics, whereby the Italian spread is strongly correlated. The possible candidates were:

- **DAX index:** a blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange. It represents the economic health of Germany, that can be considered a good proxy for the european economic health;

- **BUND:** the Germany 10-year bond yield, an indicator for international credibility of Germany and then of Europe;

- **Aggregates of other country spreads:** as suggested by Codogno et al. (2003) (15), Geyer at al. (2004) (16) and Bernoth et al. (2006) European spreads seem

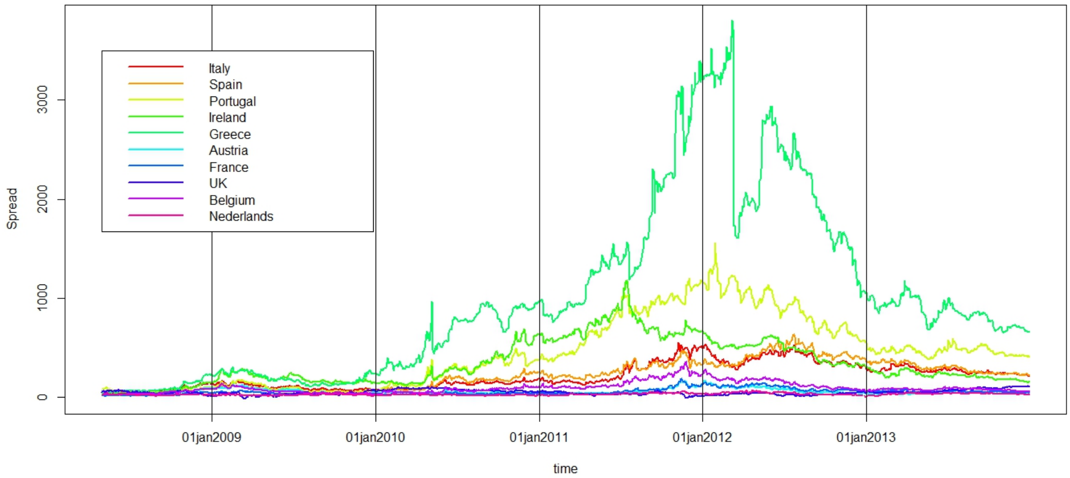


Figure 4.3: Time course of eurozone countries spreads: they have a common behaviour.

to strongly comove. Fig. 4.3 shows this behaviour. The aggregates considered differ for the weights assigned to each country:

1. Constant weights: the obtained regressor is the average of other countries spreads;
2. Weights inversely proportional to the distance in terms of debt/GDP ratio, as suggested by Favero (2012) (2);
3. Weights proportional to the cross-country financial flows (Galesi and Sgherri 2009 (20));

The three last candidates are aggregates of spreads of other countries, i.e. they are obtained as in eq.4.1

$$regressor = \sum_{i=1}^{n} \omega_i^* spread_i \tag{4.1a}$$

$$\omega_i^* = \frac{\omega_i}{\sum\limits_{i=1}^{n} \omega_i} \tag{4.1b}$$

where $spread_i$ are spreads of considered countries, and ω_i are the associated weights. For the first hypothesis (constant weights) we have

$$\omega_i^* = \frac{1}{n} \tag{4.2}$$

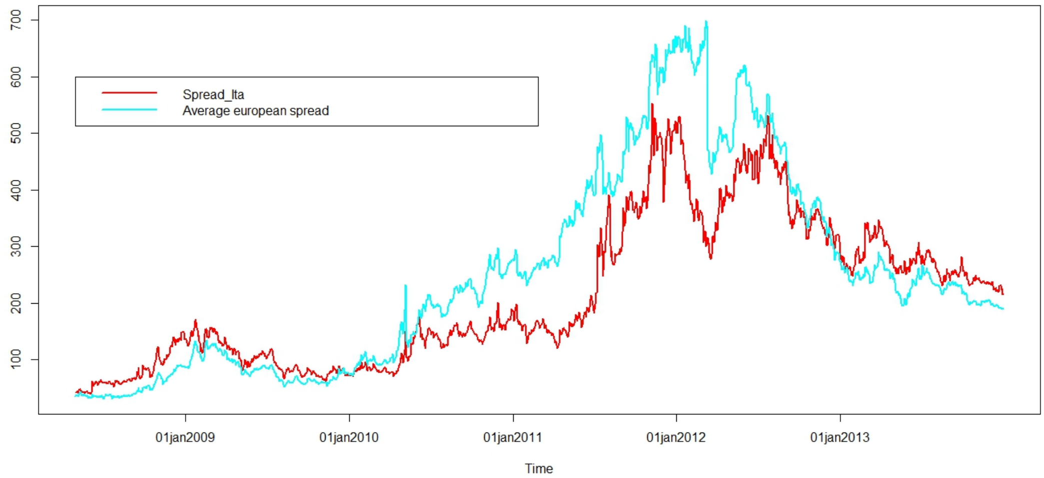


Figure 4.4: Average european spread compared with the Italian one: dynamics are similar, both locally and globally.

in fig. 4.4 we showed the really similar trend of Italian spread and the regressor obtained as spreads average of other European countries.

For the second (weights based on distance in terms of debt)

$$\omega_i^t = \frac{1}{\mid d_i^t - d_{ita}^t \mid} \tag{4.3}$$

where d_i^t is debt to GDP ratio for country i at year t. In this case fig. 4.5 shows that the obtained regressor and Italian spread have similar dynamic but not as good as the previous one. In fact Greece has a debt to GDP ratio similar to Italy, so its spread influences the regressor in a too strong way. Moreover Greece has a spread in the period considered much greater than other countries,so its influence in the regressor construction is even stronger.

Finally we considered weights proportional to the cross-country financial flows between each country and Italy. Since estimating values about cross-country financial flows and obtaining accurate data on them is difficult and usually not accurate, following Galesi and Sgherri (2009) (20) we decided to approximate these quantities with the bank lending exposures. The exposure of a national banking system towards other countries is the sum of bonds of other countries held, plus credits disbursed by other countries banks, plus minor factors.

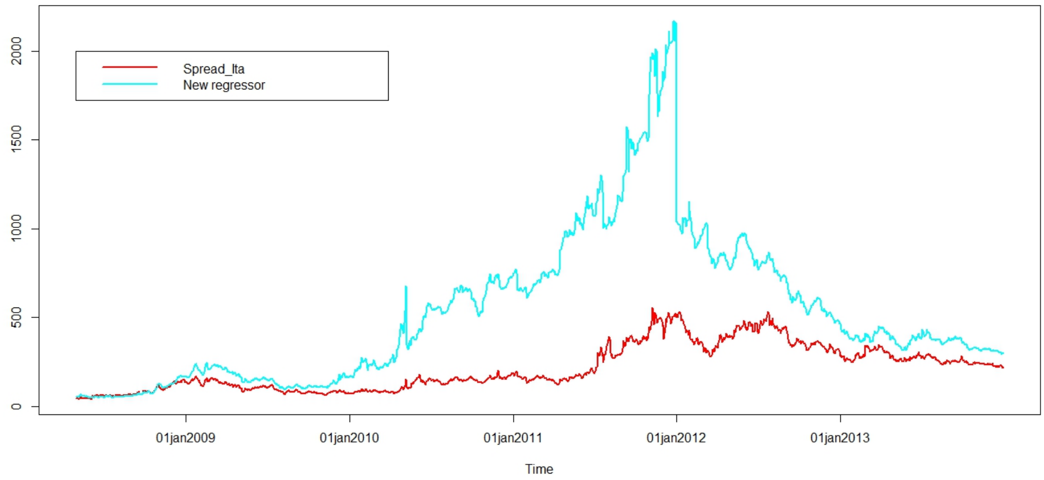


Figure 4.5: Regressor obtained through weights inversely proportional to distance in terms of debt to GDP ratio compared with the Italian spread.

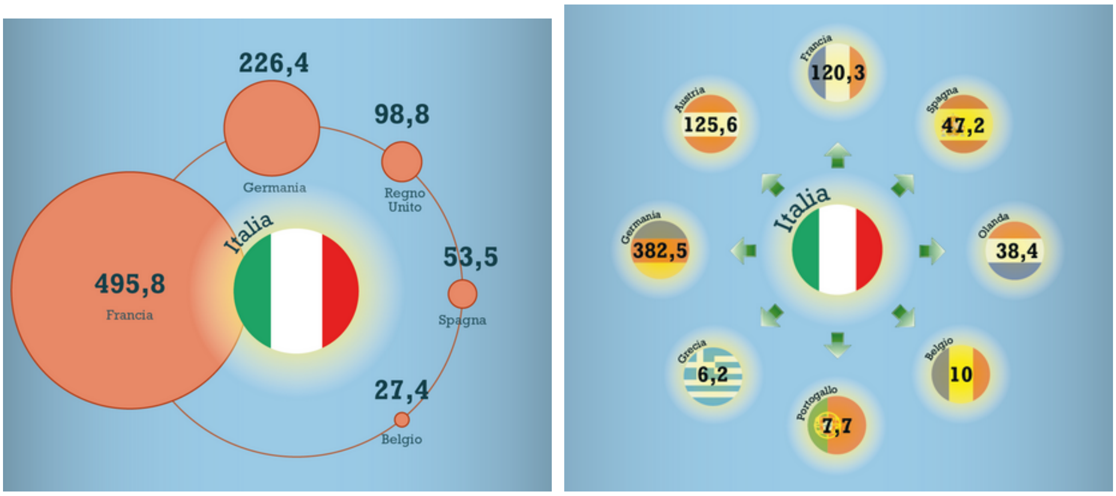
As it is possible to notice in fig. 4.6 Italy is exposed to Germany (obviously there is no spread associate with it), Austria, France, Spain, Netherlands, Belgium, Portugal and Greece (across European countries). The most exposed country toward Italy is France, an then Germany, United Kingdom, Spain and Belgium. Data were obtained by Bank of Intenational Settlements (**?**).

The regressor obtained in this way is strongly correlated with Italian spread, locally they have coupled dynamics (fig. 4.7).

The selection among the five proposed regressors (three aggregates with different weights, DAX and BUND)was operated testing each regressor on temporal windows of dimension 15 and 30, with the aim of understanding which explanatory variable best fits the local linear regression model (the response variable was the Italian spread). For each size of the time window, the dataset was divided into parts of the selected size, and for each of them was fitted a linear regression model:

$$Spread_{ita}^{t} = \beta_0 + \beta_i regressor_i^t + \epsilon_i^t \tag{4.4}$$

for each regressor in analysis. The quantities compared between different regressors were the average R^2 and an estimate of the significance of the regressor, that was the number of p-values lower than 0.05.



(a) Exposure of European countries banks to Italy.

(b) Exposure of Italian banks towards eurozone countries.

Figure 4.6: Bank lending exposure of Italy towards other countries and of other countries toward Italy (courtesy of http://www.linkiesta.it).

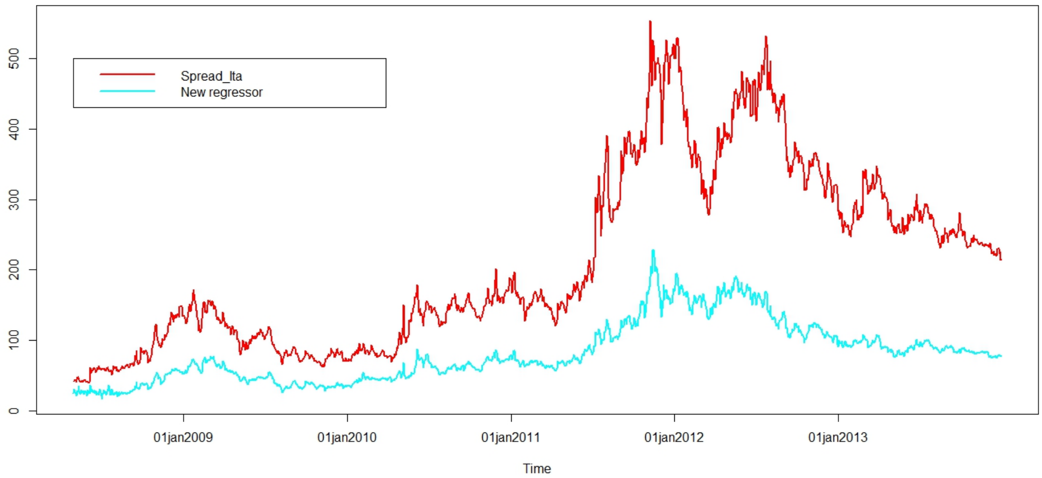


Figure 4.7: Regressor obtained through weights proportional to cross-country financial flows compared with the Italian one.

Regressor	Average R^2	P-values lower than 0.05
DAX	0.385	55
BUND	0.501	69
Constant w.	0.572	77
W. prop. to debt/GDP distance	0.517	72
W. prop. to fin. flows	0.603	80

Table 4.1: Results obtained through windows of size 15, 98 samples.

Regressor	Average R^2	P-values lower than 0.05
DAX	0.330	31
BUND	0.425	39
Constant w.	0.577	44
W. prop. to debt/GDP distance	0.499	40
W. prop. to fin. flows	0.587	43

Table 4.2: Results obtained through windows of size 30, 49 samples.

The obtained results are resumed in tab. 4.1 and in tab. 4.2. The best performer is the regressor obtained with weights proportional to the cross country financial flows, indeed it produces in both cases the best average R^2 and the highest number of p-values lower than 0.05 in the case of windows of size 15, and the second best in the case of windows of size 30.

In fig. 4.8 we showed all the components taking part in the composition of the choosen regressor, with weights builded considering both directions of exposure. Each line in the graph is the spread of a certain country multiplied for its respective weight. The principal components are the French spread, due to the huge exposure of French banks toward the Italian ones, and the Spanish spread, due both to the high mutual exposure and the higher value of its spread.

The selected regressor was obtained considering weights proportional both to the exposure of Italian banks towards foreign banks and to the exposures of foreign baks towards the Italian ones, that is we considered the total mutual exposure between each country and Italy. Subsequently we operated a more precise analysis, with the aim of understanding if both directions of exposure are significant. Hence two new aggregate regressors were builded, one using weights proportional to the exposure of only Italian

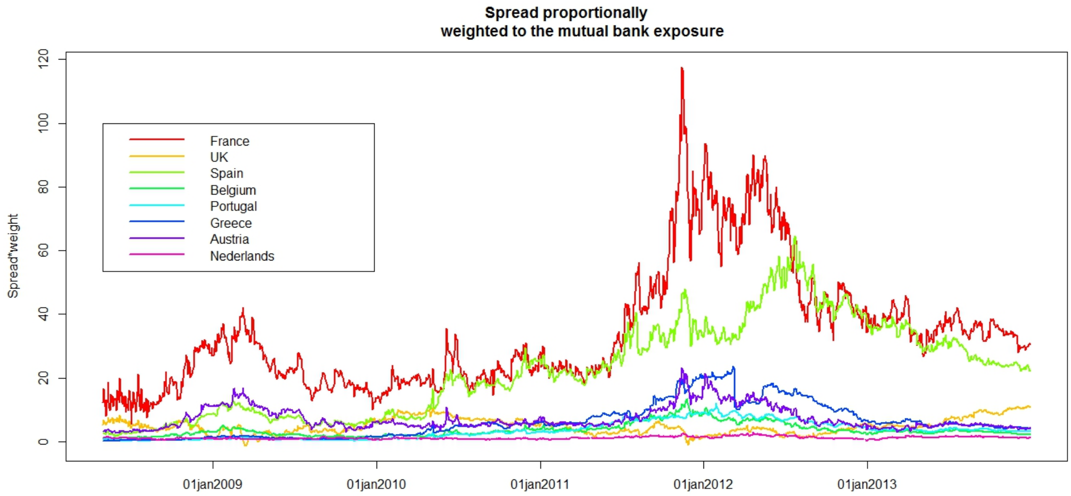


Figure 4.8: Components of the regressor obtained through weights proportional to the mutual banks exposure, used as a proxy for the cross country financial flows.

banks to foreign banks, one using weights proportional only to the exposure of foreign banks toward the Italian ones. In fig. 4.9 and 4.10 we reported the components (spreads of countries multiplied for their respective weights) of the first of the two new regressors, obtained considering only outgoing exposures, and the complete regressor obtained summing the partial components compared to the Italian spread. Here all the countries considered contribute significatively to the regressor, only Belgium has an impact lower than others.

Fig. 4.11 and fig. 4.12 show the same graphs referred to the regressor that considers exposures of foreigner banks to the Italian ones in order to compute the country-specific weights. Here the French impact is extremely high, due to the big part of Italian banks debt holded by French banks, so the French spread impacts on the regressor for more than 60%.

Subsequently the previous analysis was repeated with the purpose of understanding which of the three regressors obtained through cross-country financial flows weights best fits the model. Tab. 4.3 and 4.4 report the obtained results. The best regressor for Italian spread is the one that considers weights proportional to the Italian banks exposure towards other eurozone countries banks. This result is consistent: the economical and financial dynamics of a country that owes a certain amount of money to

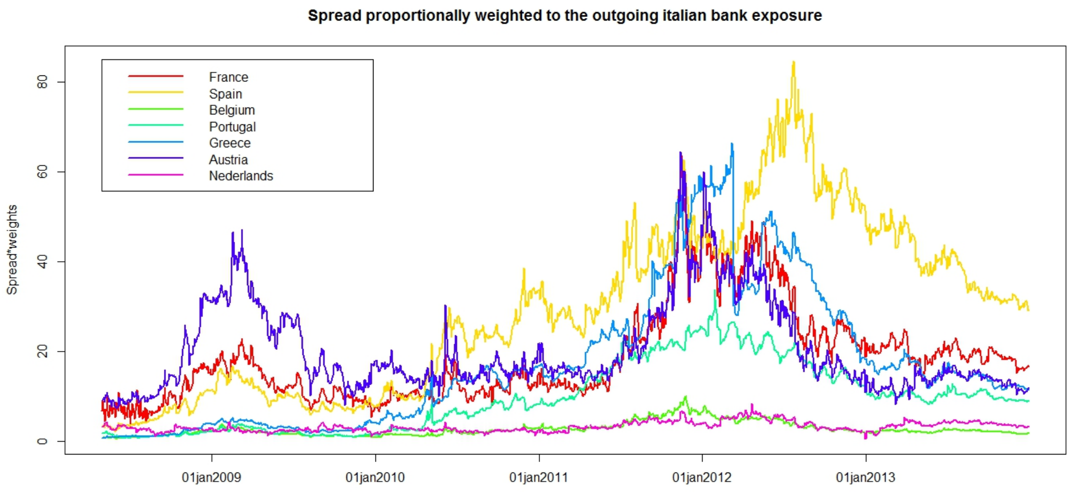


Figure 4.9: Components of the regressor obtained through weights proportional to the italian banks exposure to the foreign ones.

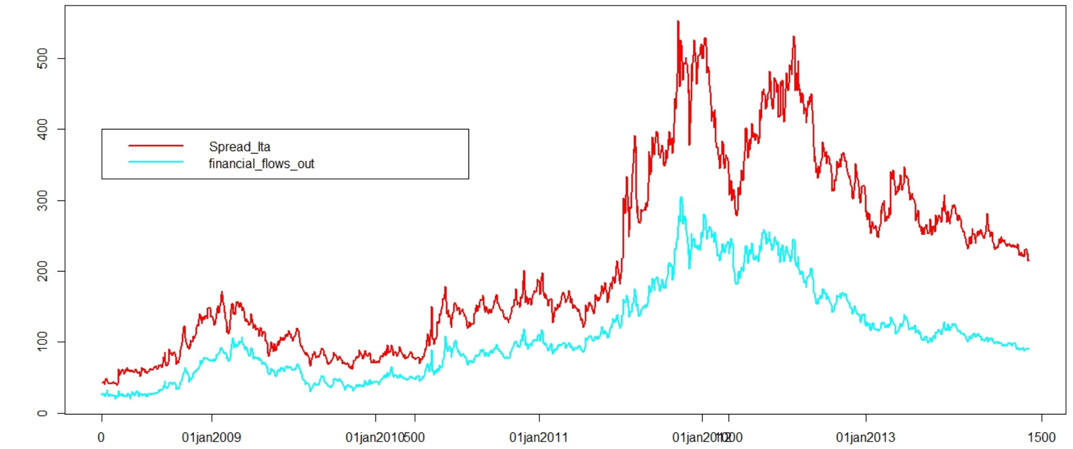


Figure 4.10: Regressor obtained considering only outgoing exposures.

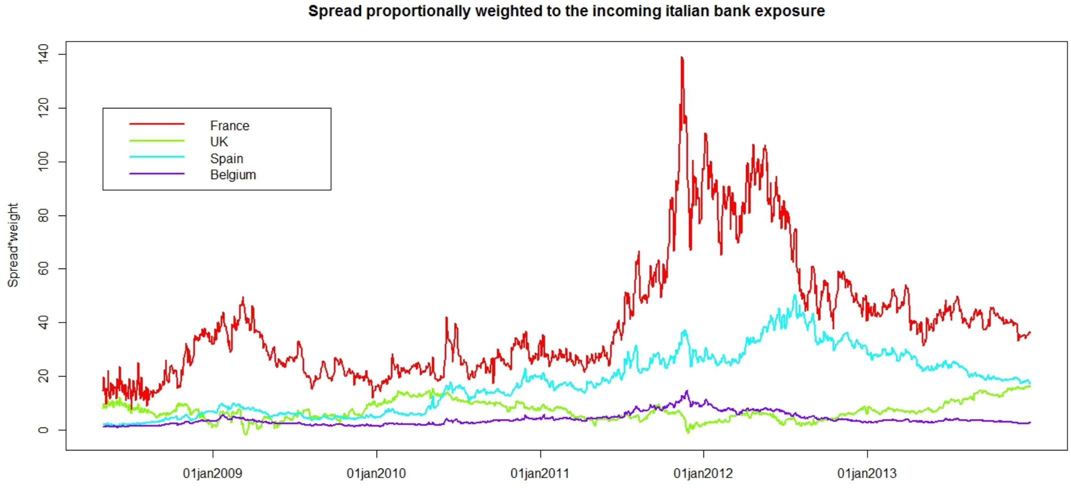


Figure 4.11: Components of the regressor obtained through weights proportional to the foreign banks exposure to the italian ones.

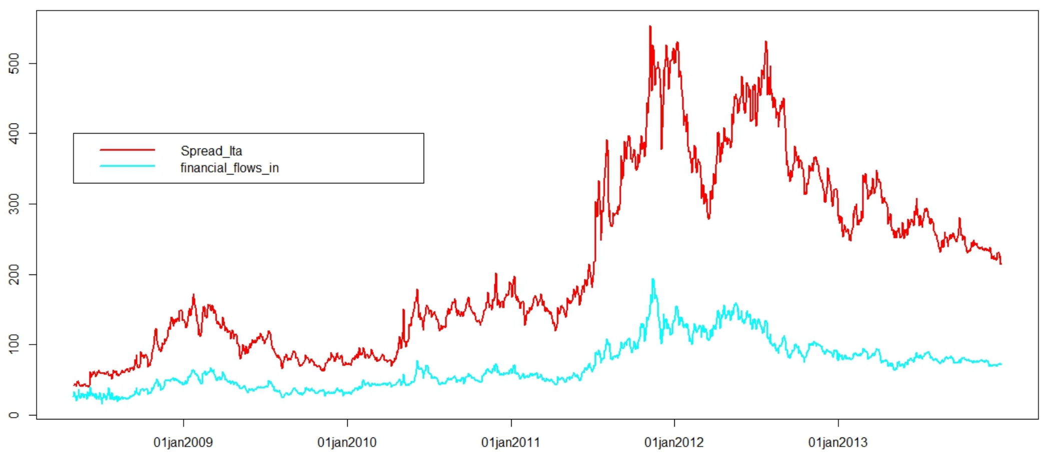


Figure 4.12: Regressor obtained considering only incoming exposures.

Italian banks influence the risk that the debt could not be extinguished. Therefore the dynamics of countries the Italian banks are exposed towards which affect the Italian spread more than countries that are exposed towards Italian banks.

Regressor	**Average R^2**	**P-values lower than 0.05**
W. prop. to mutual exposure	0.603	80
W. prop. to italian banks exposure	0.639	82
W. prop. to foreign banks exposure	0.552	77

Table 4.3: Results obtained through windows of size 15, 98 samples.

Regressor	**Average R^2**	**P-values lower than 0.05**
W. prop. to mutual exposure	0.587	43
W. prop. to italian banks exposure	0.636	45
W. prop. to foreign banks exposure	0.534	41

Table 4.4: Results obtained through windows of size 30, 49 samples.

4.1.3 Europe-world dynamics and global volatility

The last part of variable selection provides a regressor able to capture how the European economy relates with the global one and/or the global market volatility, that influences spreads in a strong way. Literature proposes many possibilities, but unfortuntely most of them does not fit our scope, because of their temporal resolution. In fact they are calculated every month or week, and our scope needs something with a daily time resolution.
The proposed regressors, as specified in section 3.1.1, are:

- **VIX:** the Chicago Board Options Exchange Market Volatility Index, a popular measure of the implied volatility of S&P 500 index options. It represents one measure of the market's expectation of stock market volatility over the next 30 day period, used by Luengnaruemitchai and Schadler (2007) (13), Hartelius et al. (2008) (14), Mody (2009) (17), Di Cesare (2012) (18).

- **TED spread:** proposed by Eichler (2014) (19), it is the price difference between three-month futures contracts for U.S. Treasuries and three-month contracts for

Eurodollars having identical expiration months. The Ted spread can be used as an indicator of credit risk. This is because U.S. T-bills are considered risk free while the rate associated with the Eurodollar futures is thought to reflect the credit ratings of corporate borrowers.

- **BAA-AAA spread:** The credit ratings of AAA and BAA are the two ends of the ratings spectrum for investment-grade corporate bonds as provided by the Moody's rating agency. The yield difference between bonds with these ratings has historically indicated whether the economy was in a period of recession or expansion. This variable can capture the inuence of time-varying risk aversion, which is a world factor commonly believed to inuence euro area credit spreads (Codogno et al. (2003) (15), Geyer et al.(2004) (16), Bernoth et al. (2006) (11) and Favero (2012) (2)).

- **EURO/DOLLAR exchange rate:** it can capture the relationship between the European economy and the American one. A high EURO/DOLLAR exchange rate disadvantages the European export, so this regressor is expected to be negatively correlated with the Italian spread.

In fig. 4.13, 4.14, 4.15 and 4.16 we reported the trends of these four candidates over the period considered, dimentionally re-scaled to be compared to the Italian spread. The EU/DOL exchange rate graph was also inverted, because of its negative correlation with it. A first qualitative analysis shows that VIX, BAA-AAA spread and EU/DOL exchange rate have a local behaviour correlated with the Italian spread, while in TED spread this correlation seems to be more elusive.
Also for this group of regressors we operated the analysis developed previously, results are reported in tab. 4.5 and 4.6. The best results, both considering average R^2 and p-values lower than 0.05, are obtained regressing on EU/DOL exchange rate. The final model is then:

$$Spread^t_{Ita} = \beta_0 + \beta_{MIB} MIB^t + \beta_{sp}(\sum_{i=1}^{n} \omega_i Spread^t_i) + \beta_{ED} ED^t + \epsilon^t \qquad (4.5)$$

where ED is the EU/DOL exchange rate, ω_i are the weights proportional to cross country financal flows estimated through the exposure of Italian banks towards other eurozone countries banks, β are coefficients of respective regressors, n is the number of countries used to build the aggregate regressor.

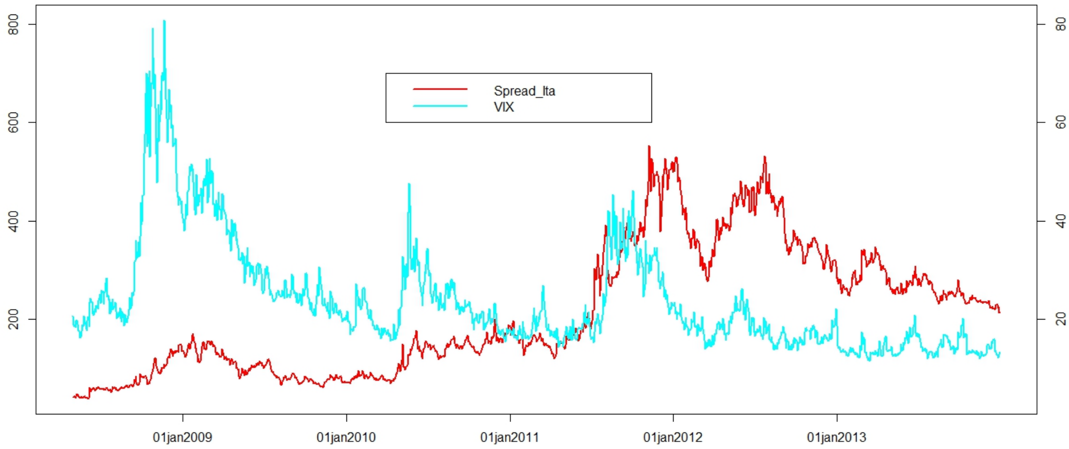


Figure 4.13: VIX rescaled compared with italian spread.

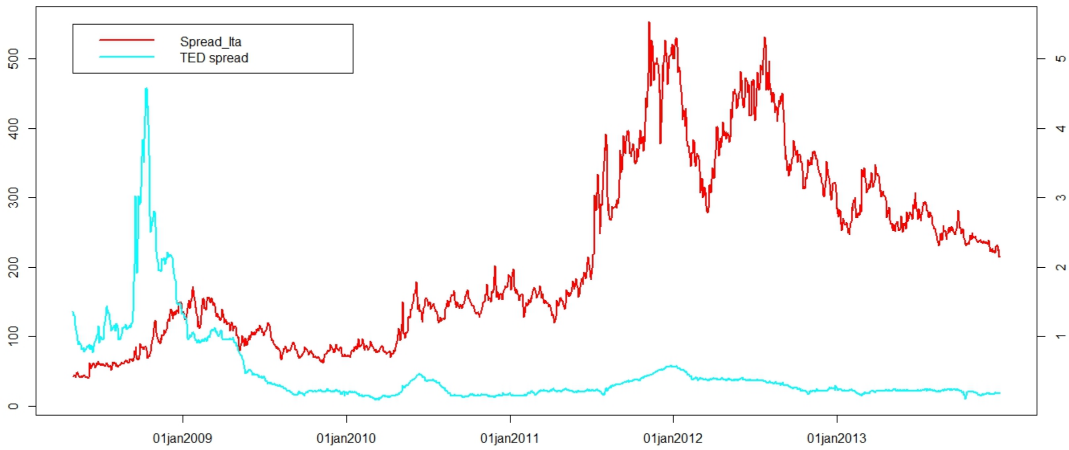


Figure 4.14: TED spread rescaled compared with italian spread.

Regressor	Average R^2	P-values lower than 0.05
VIX	0.262	40
BAA-AAA spread	0.271	37
TED spread	0.227	34
EU/DOL exchange rate	0.312	48

Table 4.5: Results obtained through windows of size 15, 98 samples.

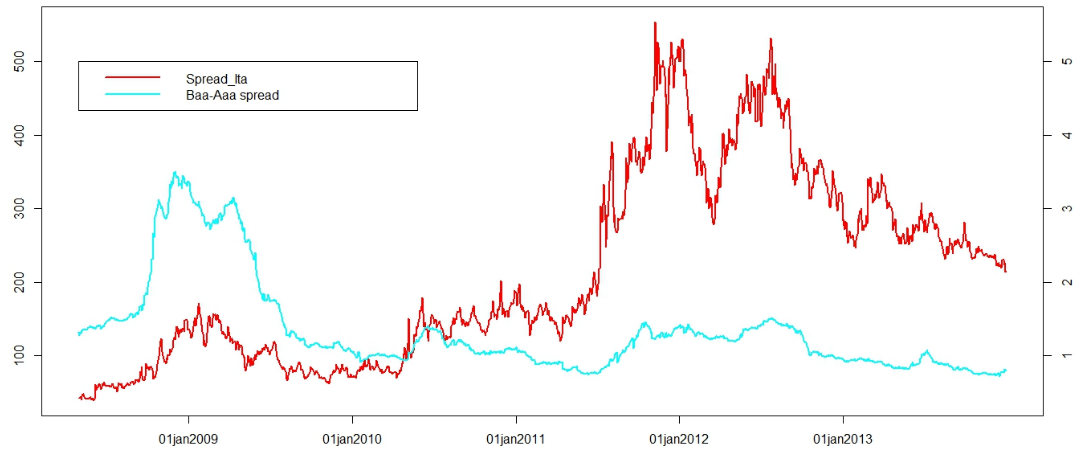


Figure 4.15: BAA-AAA spread rescaled compared with italian spread.

Figure 4.16: EURO/DOLLAR exchange rate rescaled compared with italian spread.

Regressor	Average R^2	P-values lower than 0.05
VIX	0.243	29
BAA-AAA spread	0.298	34
TED spread	0.211	27
EU/DOL exchange rate	0.307	34

Table 4.6: Results obtained through windows of size 30, 49 samples.

4.2 Rolling window linear regression

According with the previous literature, we adopted a local linear regression model, considering only a certain number of days before and after the event. In fact the focus is on evaluating the impact of reputational events on spread, so we need to point out spread dynamics in a temporal neighbourhood of every event.
The previous literature used fixed dimension window (Binda 2013 (9)) or adaptive dimension window (Belloni 2013 (8), Cazzaniga and D'Ettole 2013 (7) and Arena et al. 2013 (24)). They used to analyze each event considering the jump between the linear regressions estimated before and after the event realization.
We decided to adopt a rolling time window. This approach consists in evaluating the spread in every day of the dataset using a mobile window of fixed dimension centered in the day being estimated. We choose this approach because of the high events frequency. In fact each reputational event is represented through a dummy variable, that switches from 0 to 1 at the day when the news relative to the event is published. The high number of events over the period considered engenders 213 dummy variables out of 1479 days forming the dataset. The high frequency of events, and so of dummy variables, generates problems due to overfitting in the estimates using ordinary approaches. Moreover effects due to a certain event could be hidden by other effects caused by reputational events realized a few days before or after the day being estimated.
The impact of every event is obtained through the value of β coefficient associated with the relative dummy variable and its standard deviation, when the day being estimated is the day the news concerning the event is published.
For every day t the spread estimate through the linear regression model realized on the time window centered in the day being estimate is the following:

$$Spread^t = \beta_0 + \sum_{i=1}^{n} \beta_i^t X_i^t + \sum_{j=i}^{m} \beta_{D_j}^t I_{t \geq t_j}^t + \epsilon^t \tag{4.6}$$

Where:

- $Spread^t$ is the value of Italian spread at day t;
- n is the number of fixed regressors (3 in the case in analysis);
- β_i^t are the linear model coefficients of fixed regressors;

- X_i^t are the values of fixed regressors at day t;
- $\beta_{D_j}^t$ are the linear model coefficients of dummy variables relative to events happening during the time window considered;
- $I_{t \geq t_j}^t$ are the dummy variables of the events realizing in the time window considered, they are constant equal to 0 until the correspondant event realizes, then they switch to constant equal to 1 after the event occurs;
- ϵ^t is the residual of the model, $\epsilon \sim N(0, \sigma^2)$.

Moreover we assigned to the data in the selected time windows weights decreasing with their distance from the central point of the window (i.e. the day that is being estimated).
A fixed rolling window and the use of weights make our model belonging to *Kernel smoothing methods* .For further informations about this class of methods see Hastie et al. (2011) (25). The important difference from the classical approach to this methods is that we considered temporal distances between data instead of geometric statistical distances. This allowed us to assign more relevance to the days near to the day being estimated in terms of time, pointing out possible strange behaviours due to reputational events.
Selections of time window amplitude and weights pattern will be developed in section 4.3.
Here are described inferential procedures based on the local model with the additional assumption that the errors ϵ have normal distribution.
In the case of weighted linear regression the quadratic form that has to be minimized to obtain the *least squares estimation* for β is:

$$S(\beta) = \sum_{i=1}^{n} w_i (y_i - \mathbf{x_i^T} \beta)^2 = (\mathbf{y} - Z\beta)^T W (\mathbf{y} - Z\beta) \tag{4.7}$$

where Z is the design matrix and W is a diagonal matrix with the weights corersponding to the i-th element of the window on the i-th place of the diagonal.
Derivating the quadratic form 4.7 in $\beta^{\mathbf{T}}$ and setting it equal to 0 is obtained:

$$\hat{\beta} = (Z^T W Z)^{-1} Z^T W \mathbf{y} \tag{4.8}$$

The obtained estimator for β is unbiased:

$$\begin{aligned}
E[\hat{\beta}] &= E[(Z^T WZ)^{-1} ZW\mathbf{y}] = \\
&= E[(Z^T WZ)^{-1} ZW(Z\beta + \epsilon)] = \\
&= \beta + E[(Z^T WZ)^{-1} Z^T W\epsilon] = \\
&= \beta + E[E[(Z^T WZ)^{-1} Z^T W\epsilon \mid Z]] = \\
&= \beta + (Z^T WZ)^{-1} Z^T W E[\epsilon \mid Z] = \\
&= \beta
\end{aligned}$$

because $E[\epsilon \mid Z] = 0$.
Moreover

$$\begin{aligned}
cov(\hat{\beta}) &= E[(\hat{\beta} - \beta)(\hat{\beta} - \beta)^T] = \\
&= E[((Z^T WZ)^{-1} Z^T W\epsilon)((Z^T WZ)^{-1} Z^T W\epsilon)^T] = \\
&= \sigma^2 (Z^T WZ)^{-1}
\end{aligned}$$

where σ^2 is the residuals estimated variance:

$$\sigma^2 = \frac{\hat{\epsilon}^T \hat{\epsilon}}{n - r} \tag{4.9}$$

where n is the dimension of the window, r the number of regressors and $\hat{\epsilon}$ is the vector of residuals.
A confidence ellipsoid for β is easily constructed. It is expressed in terms of the estimate covariance matrix $s^2(Z^T Z)^{-1}$, where $s^2 = \hat{\epsilon}^{\mathbf{T}} \hat{\epsilon}/(n - r - 1)$.
A $100(1 - \alpha)$ percent confidence region for β is given by

$$(\beta - \hat{\beta})^T Z^T Z(\beta - \hat{\beta}) \leq (r + 1)s^2 F_{r+1,n-r-1}(\alpha) \tag{4.10}$$

where $F_{r+1,n-r-1}(\alpha)$ is the upper $100(1-\alpha)$th percentile of an F-distribution with $r+1$ and $n - r - 1$ degrees of freedom.
Also, *simultaneous* $100(1 - \alpha)$ percent confidence intervals for the β_i are given by

$$\hat{\beta}_i \pm \sqrt{\widehat{Var(\hat{\beta}_i)}} \sqrt{(r + 1)F_{r+1,n-r-1}(\alpha)}, \quad i = 0, 1...r \tag{4.11}$$

where $\widehat{Var(\hat{\beta}_i)}$ is the diagona element of $s^2(Z^T Z)^{-1}$ corresponding to $\hat{\beta}_i$.

4.3 Kernel and bandwidth selection

As anticipated in the previous section, we need to determine the pattern and the amplitude of the rolling time window, that is the shape of weights assigned to data in the local linear regression and its bandwidth.

Local linear regression achieves flexibility in estimating the regression function over the domain $\Re^p$, where p is the number of regressors, by fitting a different but simple model separately at each query point x_0. This is done by using only those observations close to the target point x_0 to fit the simple model.

We considered the temporal distance instead of the geometric distance between data. In this way the temporal distance of a datum to the day being estimated is the only factor influencing the weight assigned to that datum during the linear regression estimate. This procedure results in assigning more relevance to days near to the day being estimated. The way the relevance of a datum decreases while its temporal distance from the day being estimated increases is determined via a weighting function or *kernel* $K_\lambda(t_0, t_i)$, which assigns a weight to t_i based on its distance from t_0. λ is the *kernel* bandwidth and t_0 is the day in which the spread is being estimated.

Therefore the aim of this section is to evaluate which *kernel* best fits the model and the optimal bandwidth. Hastie et al. (2011) (25) suggest four different *kernel* shapes:

- Nearest neighbour: simply considered the 2λ data around x_0;
- Epanechnikov quadratic kernel:

$$K_\lambda(x_0, x_i) = D\left(\frac{\mid x_i - x_0 \mid}{\lambda}\right) \tag{4.12}$$

where

$$D(t) = \begin{cases} \frac{3}{4}(1 - t^2) & \text{if } \mid t \mid \leq 1, \\ 0 & \textit{otherwise}; \end{cases} \tag{4.13}$$

- Tri-cubic kernel:

$$K_\lambda(x_0, x_i) = D\left(\frac{\mid x_i - x_0 \mid}{\lambda}\right) \tag{4.14}$$

where

$$D(t) = \begin{cases} (1- \mid t \mid^3)^3 & \text{if } \mid t \mid \leq 1, \\ 0 & \textit{otherwise}; \end{cases} \tag{4.15}$$

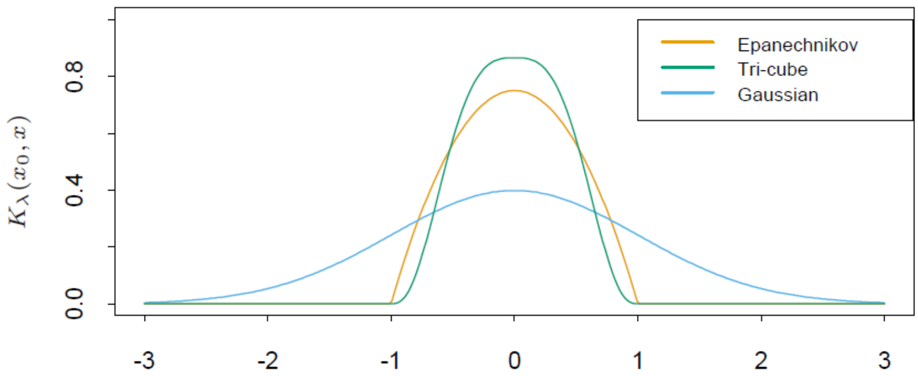


Figure 4.17: A comparison of three popular kernels for local smoothing. Each has been calibrated to integrate to 1. The tri-cube kernel is compact and has two continuous derivatives at the boundary of its support, while the Epanechnikov kernel has none. The Gaussian kernel is continuously differentiable, but has infinite support.

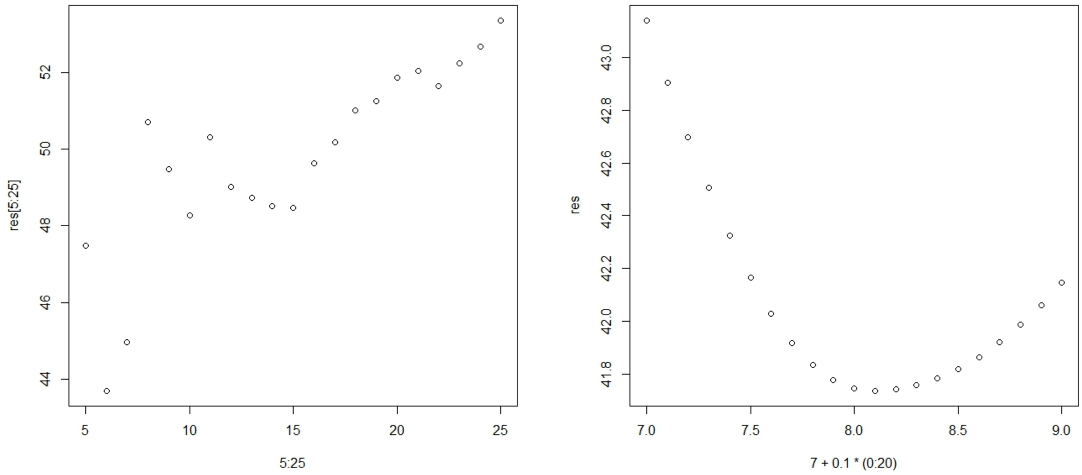
- Gaussian kernel: is the only one with infinite support, therefore it accounts every data in every estimate. In this case λ does not represent the half of the window width, it is instead the standard deviation.

$$K_\lambda(x_0, x_i) = \frac{1}{\sqrt{2\pi\lambda^2}} e^{-\frac{1}{2\lambda}(x_i - x_0)^2} \tag{4.16}$$

The optimal bandwidth for each *kernel* was choosen through cross-validation, i.e. all the data were estimated using their realtive windows but not themselves in fitting the model, then the sum of residuals was calculated:

$$res_\lambda = \sum_{t=1}^{n} (Spread_{Ita}^t - \widehat{Spread_{ita}^t})^2 \tag{4.17}$$

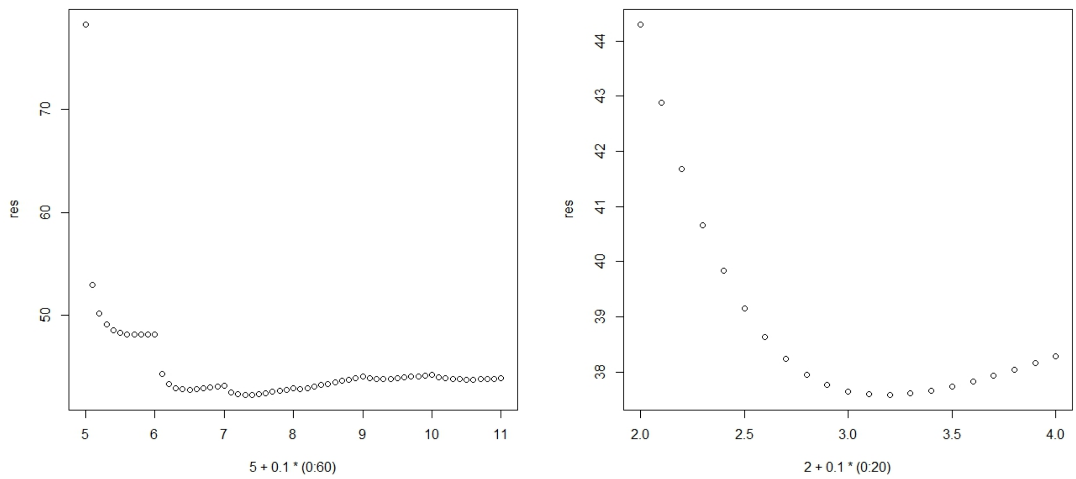
where n is the number of data available.
The choosen λ is the one that minimizes this quantity. Large λ implies lower variance (more observations) but higher bias. For the four *kernels* considered, the graph obtained calculating res_λ for multiple values are reported. Fig. 4.18 and 4.19 show that rectangular (nearest neighbour) and Epanechnikov kernels have irregular trends, while tri-cubic and gaussian ones display a more regular pattern. Moreover the two smoother *kernels* provide a lower minimum sum of residuals, showing they better fulfill model requirements.



(a) Nearest neighbour

(b) Tri-cubic kernel

Figure 4.18: Residuals of rectangular and tri-cubic kernels, computed varying the bandwith in the optimal range.



(a) Epanechnikov kernel

(b) Gaussian kernel

Figure 4.19: Residuals of epanechnikov and gaussian, computed varying the bandwith in the optimal range.

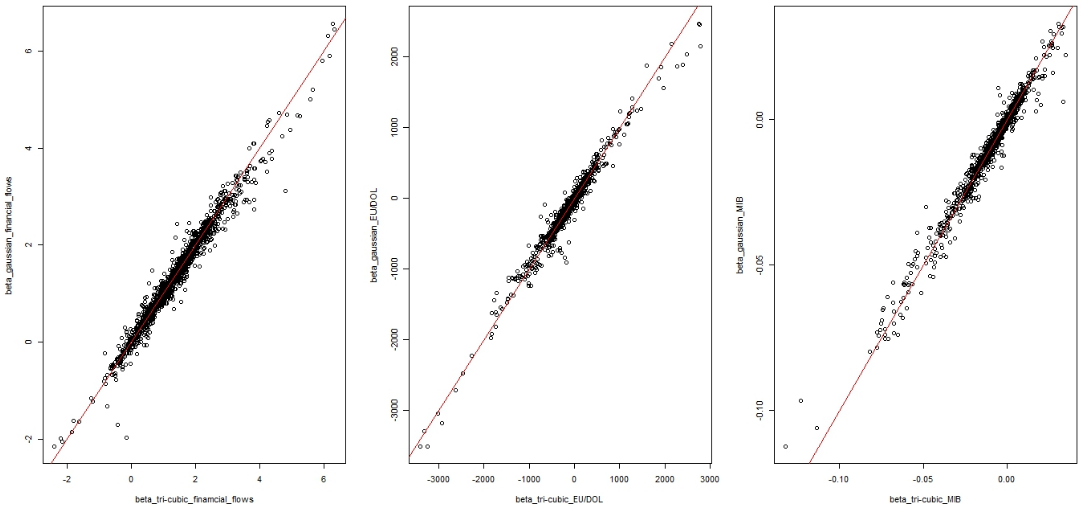


Figure 4.20: Scatterplot of β obtained through tri-cubic and gaussian *kernel*. They are strongly correlated, an indication for the results similarity in these two approaches.

Gaussian *kernel* produces a lower minimum, but the number of data where the R^2 is higher than 0.8 is 76%, against 79% adopting a tri-cubic *kernel* (results obtained using the optimal bandwith for each *kernel*). Moreover we wanted to consider more the data near to the datum being estimated and the tri-cubic *kernel* has a support much smaller than the gaussian one (that theoretically includes the whole dataset). The larger support would also have implied a much bigger computational charge. Anyway the two different approaches produce strongly similar results, as shown in fig. 4.20. The scatterplots of the three fixed regressors coefficients obtained through the tri-cubic and gaussian *kernel* present strongly linear patterns. This shows a robustness of the model respect to the two best performing *kernels*.
Therefore we decided to adopt the tri-cubic *kernel*. The minimum in tri-cubic *kernel* is reached with a bandwidth of 8.1, so with a window width of 17 considering also the estimated datum.

In order to complete the analysis about the optimal kernel, we reported the real Italian spread compared with the fitted results obtained through the tri-cubic *kernel* with optimal bandwith (fig. 4.21 - 4.27). In this fitting the dummy variables correspondant to the potentially reputational events in analysis were also used as regressors. For further discussions about the impacts of dummy variables see Chapter 5. These graphs show that the final model properly fits the data.

In order to have a more quantitative information about the fitting, 1172 out of

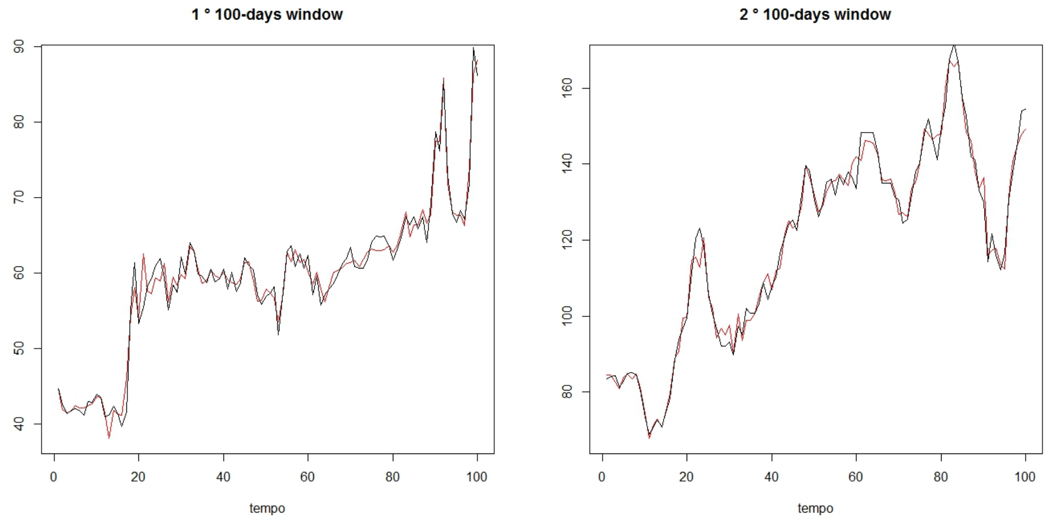


Figure 4.21: Days 1-100 and 101-200

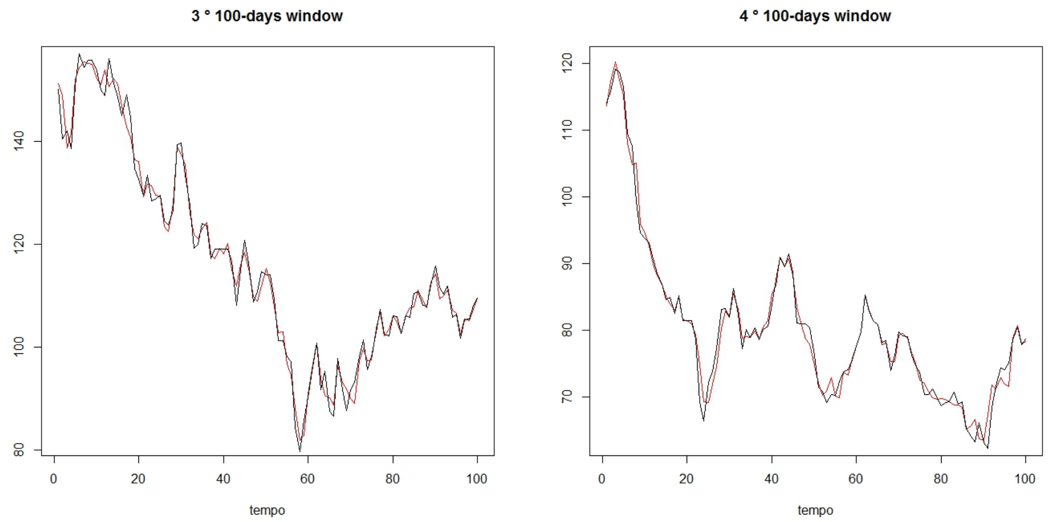


Figure 4.22: Days 201-300 and 301-400

1479 local linear regressions (80.3%) produce a R^2 greater than 0.8, so in all these days the spread value is well estimated through the model. Fig. 4.28 shows that data where R^2 is lower than 0.8 are usually grouped in windows. Within them the R^2 falls until it

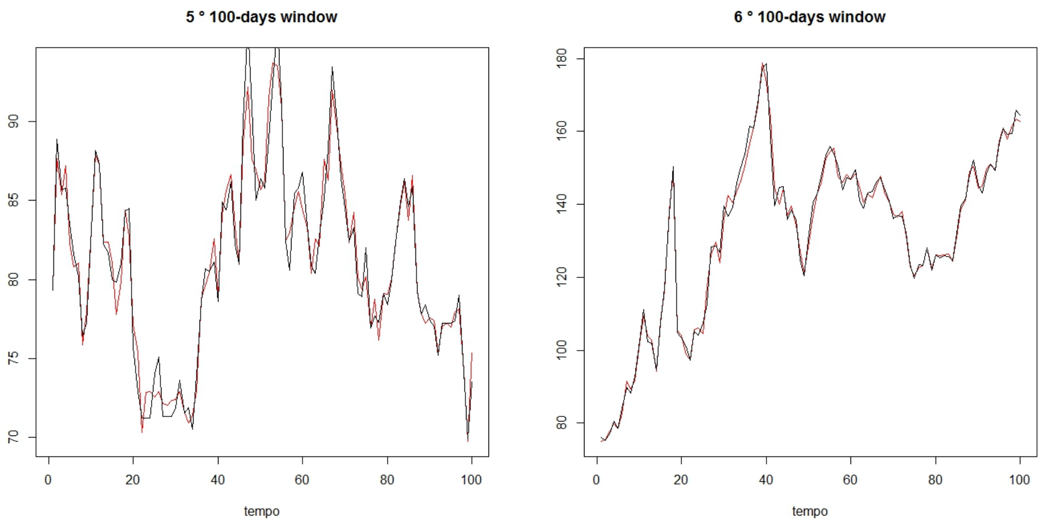


Figure 4.23: Days 401-500 and 501-600

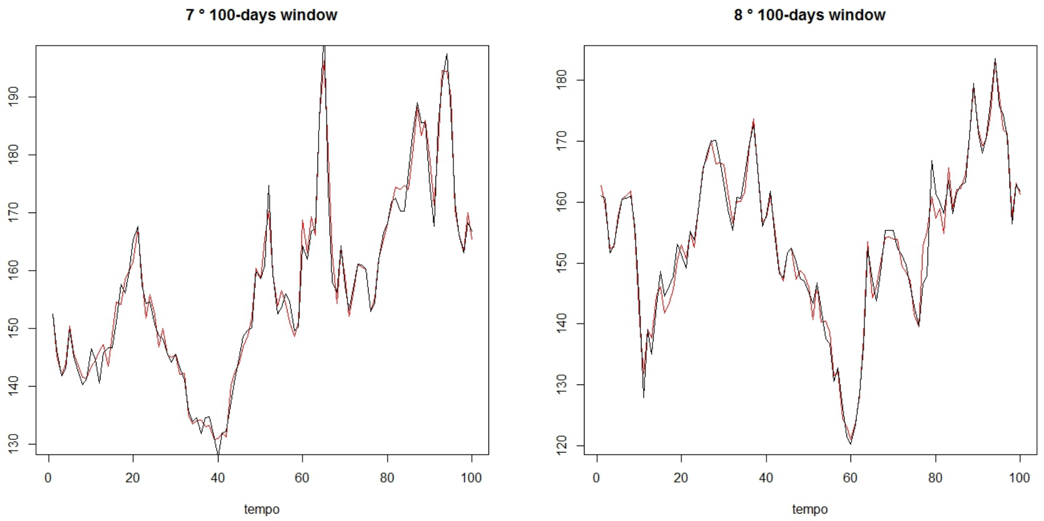


Figure 4.24: Days 601-700 and 701-800

reaches a minimum (or two) and then returns to its normal behaviour over 0.8. Future developements can try to explain these falls, possible explanations include points or short periods in which the three fixed regressors and the reputational dummy variables are not sufficient to explain the Italian spread behaviour and possible influence points.

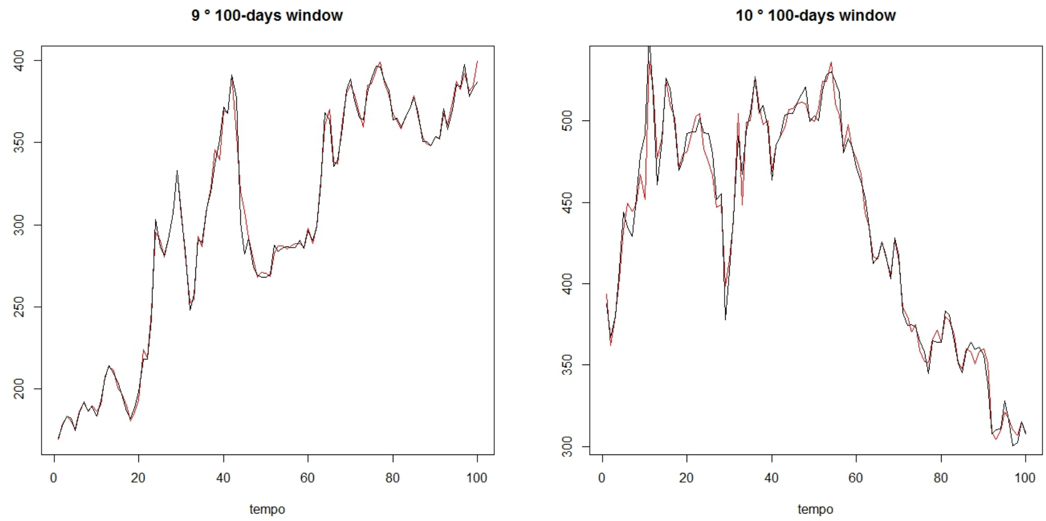


Figure 4.25: Days 801-900 and 901-1000

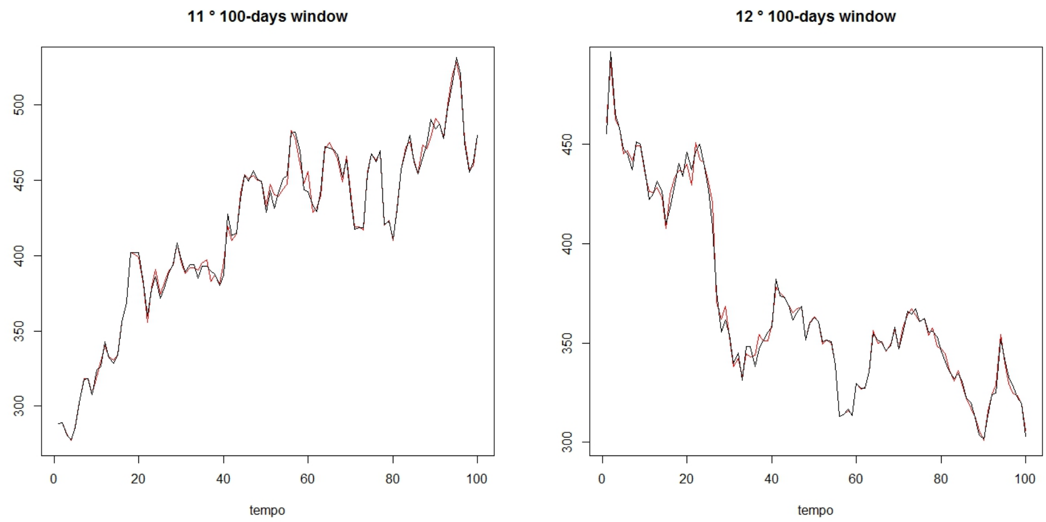


Figure 4.26: Days 1001-1100 and 1101-1200

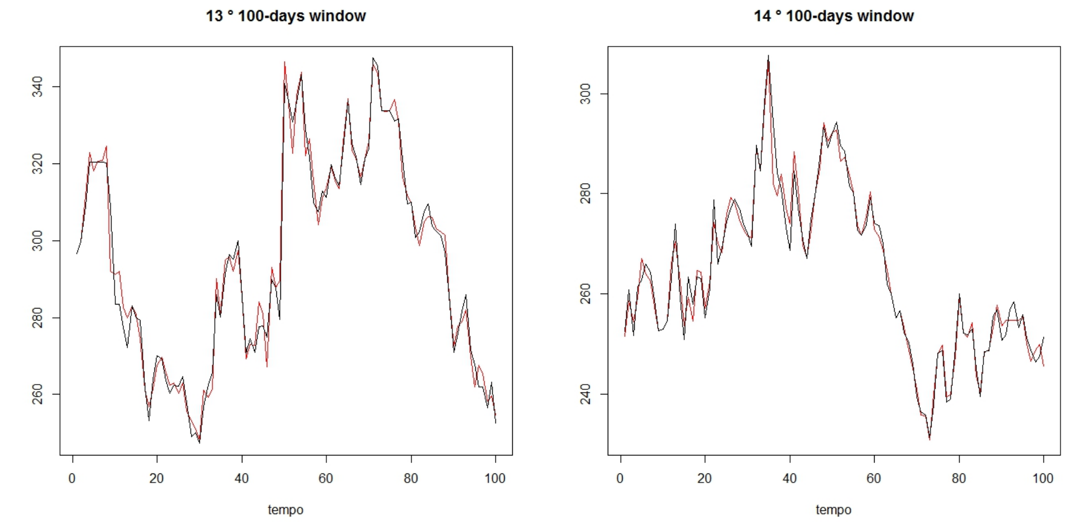


Figure 4.27: Days 1201-1300 and 1301-1400

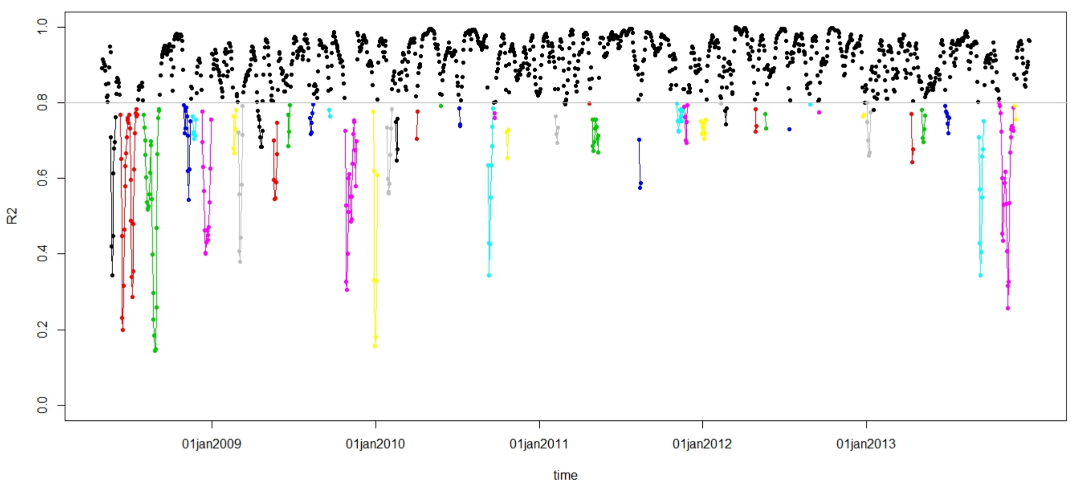


Figure 4.28: R^2 behaviour during the time interval considered. Falls under 0.8 are grouped in windows. Adjoining days with R^2 lower than 0.8 are reported with the same colour and linked.

5

Analysis of event impact categories

The purpose of this chapter is to evaluate the impact of every single event in the dataset and to identify which categories of potentially reputational events are more impacting on Italian spread. Specifically the aim is to achieve a methodological framework able to recognize if a single event is impacting or not (Section 5.1) and which categories more frequently impact (positively or negatively) on the financial indicator in analysis (Section 5.2).

5.1 Estimate of the impact of a single event

In this section the aim is to develop the requisite tools for estimate the impact of a certain event on Italian spread. Using the local linear regression model with fixed regressors, *kernel* and bandwidth selected in the previous chapter, all the events were represented through a dummy variable that switches from 0 to 1 at the day when the news relative to the correspondant reputational event was published. If the news was published on Saturday, Sunday or on a holiday, the dummy would switch to 1 on the first day available (the most frequent case is an event occurring in the week-end and the correspective dummy switching on the following monday). Because the selected bandwidth is 8.1 and it represents half of the window width, the time window considered in every linear regression is 17 days long, so in every linear regression would be used as regressors the three fixed regressors (MIB, eurozone spread aggregate and EU/DOL

exchange rate) plus all the dummy variables switching from 0 to 1 during the 17-days time window centered in the day being fitted, i.e. all the dummies relative to an event taking time less than 9 days before or after the day considered.
The events dataset consists of 262 events, but dummy variables considered are only 231. It happens because some events occur at the same day, and some events occur on Saturday or Sunday, so the impact on spread can be evaluated only at the following monday and the event could be overlaped to another one.
The impact of a certain event was estimated through two statistical parameters (β coefficient and p-value) associated with the dummy variable referred to the event being considered. Obviously these parameters were considered only when the day being estimated through the model is the day the event was published, i.e. the day the correspondant dummy variable switches from 0 to 1.
Specifically, the relevance of an event was estimated through the p-value associated with the correspondant dummy variable and through the confidence interval referred to the respective β coefficient, while the event impact amplitude was approximated with the β value. Fig. 5.1 reports all the dummy variables through these two relevant values, both considering absolute and relative impact. High p-values are usually associated with low values of β, and vice-versa.
Contour lines of the estimated frequency distribution of the coupled data are shown in fig. 5.2. The estimates were obtained through *kernel density estimation*, with the function `kde2d` in R (library MASS). It is possible to recognize three mass concentrations: one for non-significative events (high p-values and β coefficients near to zero), two for positively and negatively significative events (low p-values and β concentrated in a region respectively greater or lower than zero).
Fig. 5.3 shows all the β coefficients confidence intervals, reporting in red the ones that do not include zero (i.e. the ones that can be considered statistically significant). We overlaped the Italian spread trend: it shows that the β confidence interval amplitude is related to the spread absolute value, so in fig. 5.4 we reported the same graph re-scaled considering the relative impact, that is coefficients and variances divided for the spread value. In the two graphs are reported 95% confidence intervals for β coefficients. 69 out of 213 events (32%) produce a confidence interval that does not include zero (and a p-value lower than 0.05), so they can be considered statistically impacting on Italian spread. The p-value frequencies over all the 213 events are reported in the right side

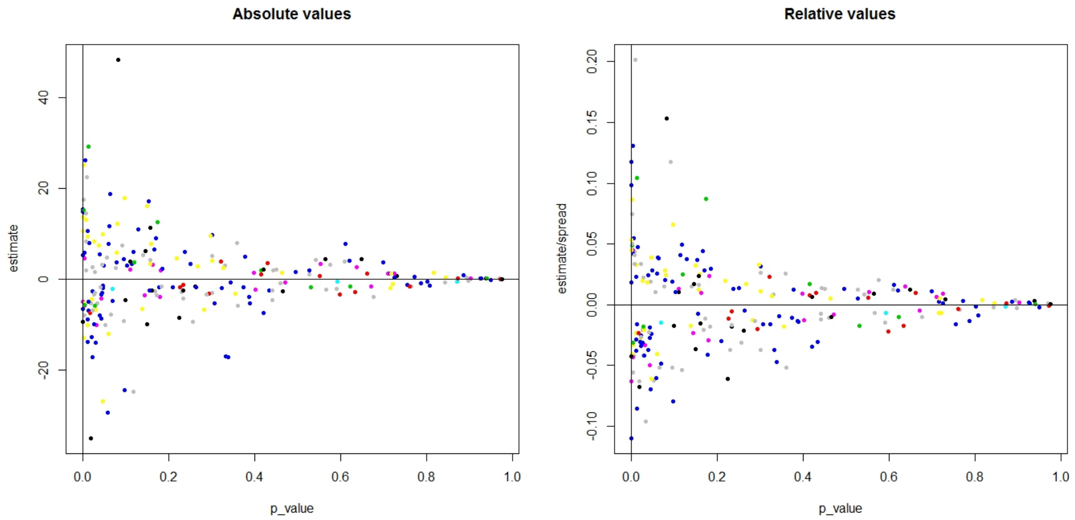


Figure 5.1: Each point represents a dummy variable through its β coefficient and its p-value. Different colours correspond to different events categories.

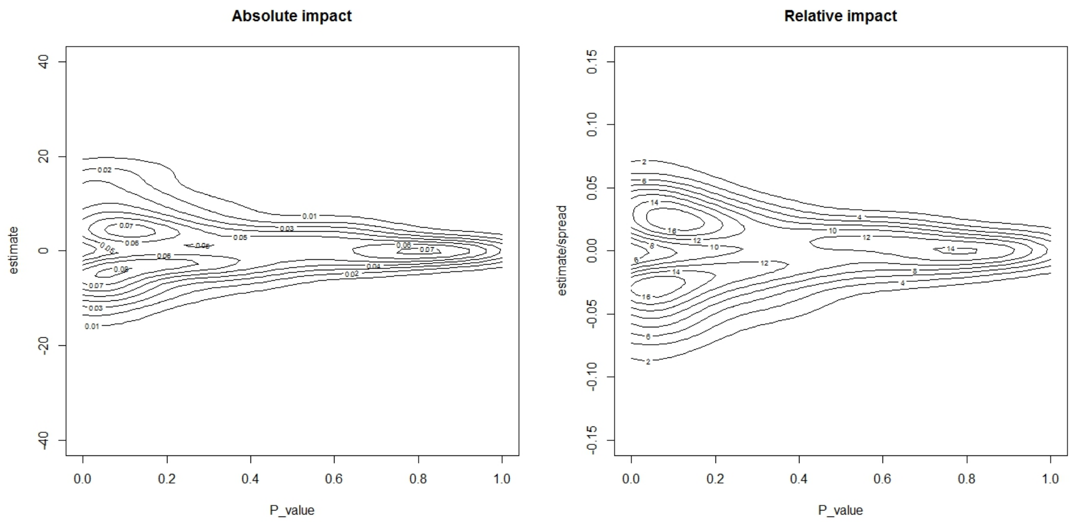


Figure 5.2: Contour lines of the p-value - β coefficient frequency distribution.

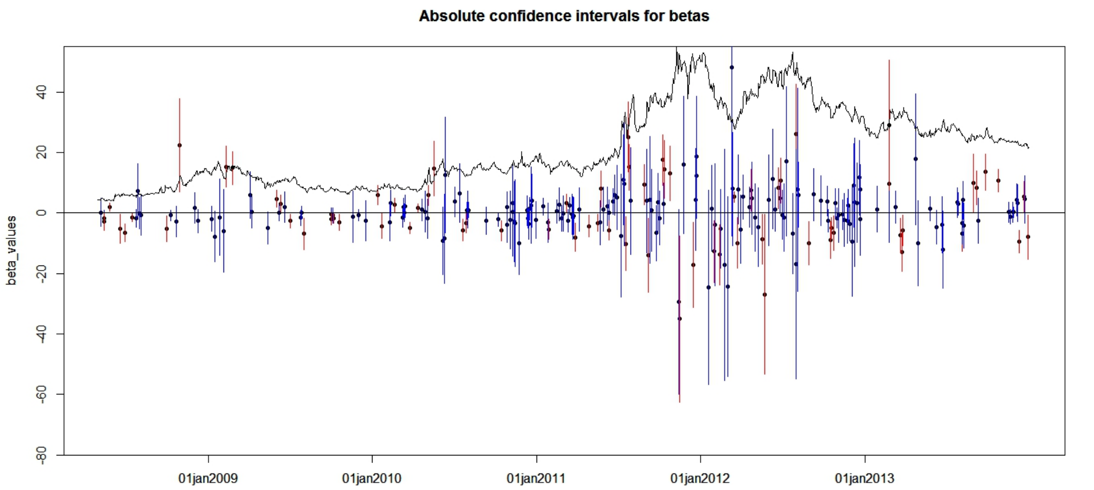


Figure 5.3: Estimate of absolute β coefficients relative to events and their 95% confidence interval: in red are reported confidence intervals not including zero. The Italian spread line shows that amplitudes are proportional to spread value.

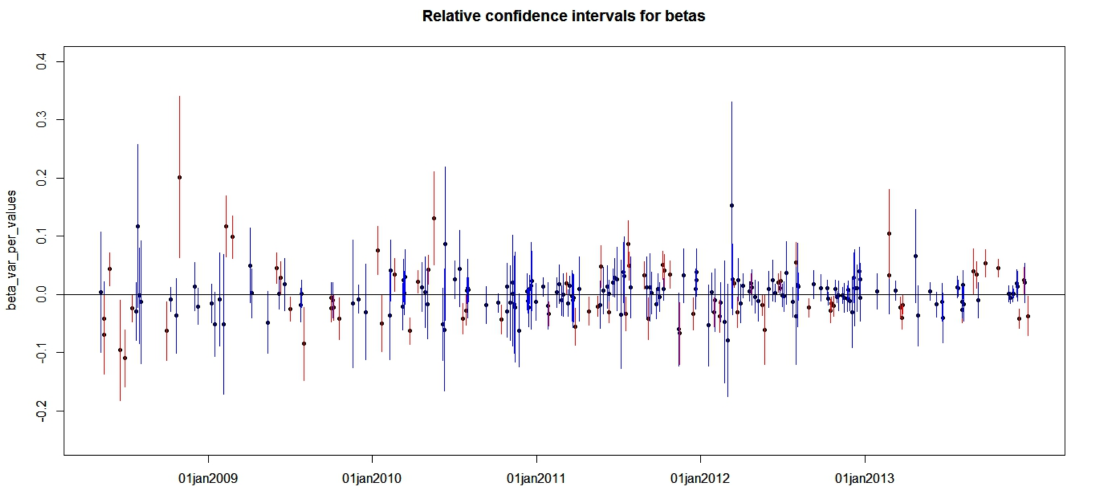


Figure 5.4: Estimate of relative β coefficients and 95% confidence intervals.

of fig. 5.5: the concentration of values under 0.05 is evident and provides a strong clue to the importance of considering reputational events in spread estimate.
The first graph in fig. 5.5 shows that β coefficients are both greater and lower than 0, so reputational events can affect spread both in a positive and negative way. Precisely 39 out of 69 statistically significant events have a negative associated coefficient, so these events produce the effect of decreasing spread, while 30 increase it. As said previously, 69 out of 231 events were recognized to be statistically significant: the p-values produced by their dummy variables are lower than 0.05. At this step of the analysis we showed the relevance of considering reputational events in spread evaluation, 32% of the events considered proved to have a significative impact on spread and so to influence the financial market confidence.
Unfortunately ordinary two-sided p-value cannot provide informations about if the event considered caused a spread growth or drop, but only if it affected the spread trend in some way. For this reason we calculated one-sided p-values for all the events in analysis (histogram in fig. 5.6b shows the expected distribution: low p-values for significative events with negative impacts, high p-values for the positive ones). Considering both p-values lower than 0.025 and greater than 0.975 we mantained the total significance level equal to 95%. In fact the same 69 events are identified, 39 with negative coefficient and 30 with a positive one. Through one-sided p-values we achieved the result of obtaining a single indicator able to show both the relevance of an event and an indication of which type of movement (growth or drop) it produced on Italian spread. We can already notice that events prodice growths and drops almost with the same-frequency, indicating that reputational events potentially affect the spread dynamic in both directions.

5.2 Analysis of impact of different categories

The final step of the analysis is to understand whether different categories impact or not on the Italian spread in different ways, and which categories mostly impact. In past literature, authors mostly used ANOVA and regression analysis. For example, in order to investigate how bank risk, profitability, intangible assets, capitalization, size and business area influence reputational damage, Fiordelisi (2013) (6) used additive

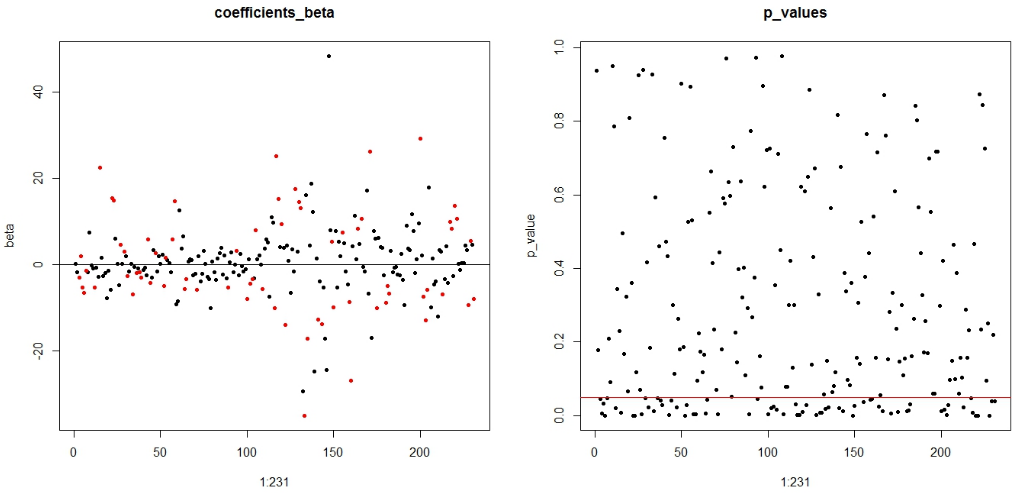
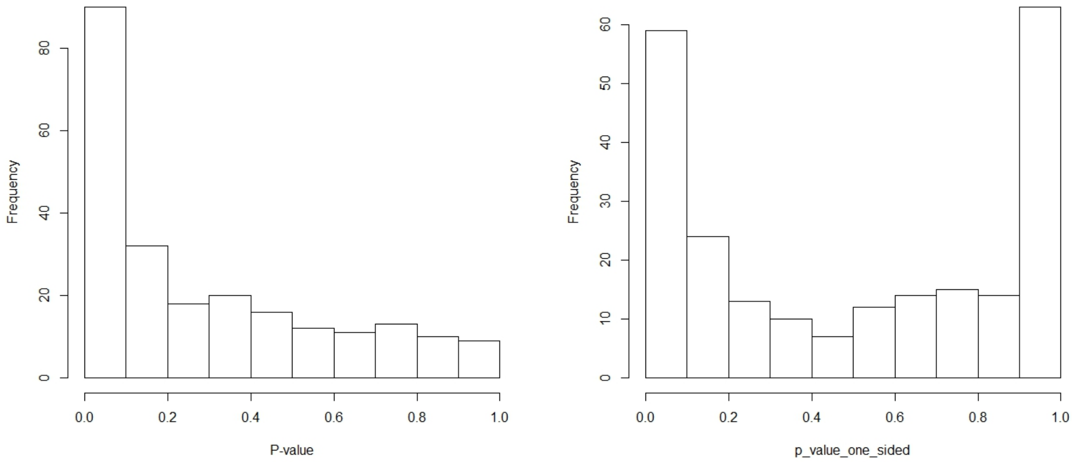


Figure 5.5: Betas and p-value of all the 213 events considered, 69 p-values are lower than 0.05,reported in the left graph with red dots).



(a) Two sided p-values **(b)** One sided p-values

Figure 5.6: Histograms of p-values associated with significance of the β coefficient referred to events dummies variables.

ANOVA and OLS regression. Belloni (2013) (8) and Binda (2013) (9) adopted one way and additive multi-way ANOVA using the geographic area, the category of the event, and other characteristics as factors.
In the case in analysis there is only one factor (i.e. tag of the event) with 12 levels. The important difference between past literature and our approach is that events considered affect Italian spread both in a positive and negative directions, that is an event belonging to a certain category can produce either a growth or a drop. This difference removes us from the standard framewok. Therefore we adopted both a qualitatitative and quantitative approach, using graphical rapresentations of regression results and one-way ANOVA.

5.2.1 Qualitative approach: graphical exploration

As discussed previously, the parameter used to evaluate whether an event impact is statistically significant or not is the p-value associated with the correspondant dummy variable, while β coefficient indicates the impact amplitude. In this section we aim to identify patterns in these values among different categories through graphical explorations. Unfortunately for several categories a low number of observations prevents from recognizing characteristics in parameters realizations: 6 out of 12 categories have a cardinalty lower than 10 and only 4 out of 12 have a cardinality greater than 20, so for 6 categories is almost impossible to achieve strong conclusions, while for 4 of them is easier to infer.
Firstly we analyzed p-values realizations, with the aim of understanding in which categories they produce a mass concentrated near to 0 (or two masses in 0 and 1 when one-sided-p-values are considered). When two or more events are overlapped and represented with the same dummy variable, p-value and β coefficient of that variable are reported in all these categories. Fig. 5.7-5.8 report p-values frequencies histograms for all the categories considered. In all the categories with high observations number the histograms show a mass concentrated in zero, which indicates the significance of events belonging to that categories. Considering categories with cardinality greater than 10, "Consumers confidence", "Government defeated" and "Vote of confidence" show a mass concentrated in 0, suggesting their frequencier are not uniform over the $[0, 1]$ interval, while it is more difficult to assess influence of "PIL comunication", "New parliamentar groups" and "Judiciary events premier". In order to be more accurate about the

p-values frequency patterns, we operated Pearson's chi squared tests. It tests a null hypothesis stating that the frequency distribution of certain events observed in a sample is consistent with a particular theoretical distribution. In our case the null hypothesis states that p-values are uniformely distributed (which would suggest the non-influence of the category considered). Because the minumum dataset size requested by the test is 5 samples for each interval and the categories considered can not provide so many samples, we operated a Pearson's chi squared test where p-values were computed via Monte Carlo. In every iteration the number of data of the category in analysis was sampled by a uniform distribution, and Pearson's chi squared test was operated between the original data (p-values of a certai category) and the new sample. We considered the same intervals reported in histograms in fig. 5.7-5.8, that is 10 intervals of amplitude 0.1. The final p-value is given by the average of all the p-values obtained in all the iterations (10^5 iterations for each category). Results reported in tab. 5.1 show that for 4 out of 12 p-values frequency distributions it is provided statistical evidence of non-uniformity. Only "PIL comunication" among the categories with cardinality greater than 10 seems to accept the null hypothesis of p-values uniform frequency distribution.

Category	**Pearson's test p-value**
PIL Comunication	0.373
New parliamentar groups/change in coalitions	0.418
Minister resignations	0.168
Premier resignations	1
Judiciary events minister	1
Judiciary events premier	0.048 *
Consumers confidence	1e-05 ***
Government defeated	1e-05***
Government establishent	1
Motion of no confidence	0.146
Elections	0.699
Vote of confidence	1e-05 ***

Table 5.1: Pearson's test p-value obtained via Monte Carlo. Two-sided p-values considered under the null hypothesis stating they come from a uniform distribution.

Then in fig. 5.9-5.10 we reported histograms of one-sided p-values referred to the 12 different categories in analysis. Also in this case strong conclusions can be achieved

only for groups with high cardinality. The five categories with highest cardinality seem to show a "U" behaviour in one-sided p-values frequency distributions. This pattern suggests that in these categories many events can be considered statistically impacting on spread, some of them with a positive coefficient, indicating that the spread increased after the news about them was published, while some others with a negative coeffcient. The two effects are quite balanced, that is all the categories considered showing this behaviour produce almost the same number of positive and negative responses. The only exception is provided by "Consumers confidence", where significant events that increase spread are almost double than the ones that decrease it.
Also with one-sided p-values we applied Pearson's chi squared test under the null hypothesis of p-valus uniform frequency distribution. Intervals considered were the same, that is 10 intervals of 0.1 amplitude each. Results are reported in tab. 5.2. The test provided the same results obtained when two-sided p-values were considered. "Judiciary eventspremier", "Consumers confidence", "Government defeated" and "Vote of confidence" prduced statistical evidence in refusing the ull hypothesis of one-sided p-values uniformity. This fact, along with the histograms patterns, is a strong clue of influence of events belonging to these categories on the Italian spread.

Category	**Pearson's test p-value**
PIL Comunication	0.277
New parliamentar groups/change in coalitions	0.961
Minister resignations	0.396
Premier resignations	1
Judiciary events minister	1
Judiciary events premier	0.044 *
Consumers confidence	1e-05 ***
Government defeated	1e-05***
Government establishent	0.281
Motion of no confidence	0.146
Elections	0.697
Vote of confidence	1e-05 ***

Table 5.2: Pearson's test p-values obtained via Monte Carlo. One-sided p-values considered under the null hypothesis stating they come from a uniform distribution.

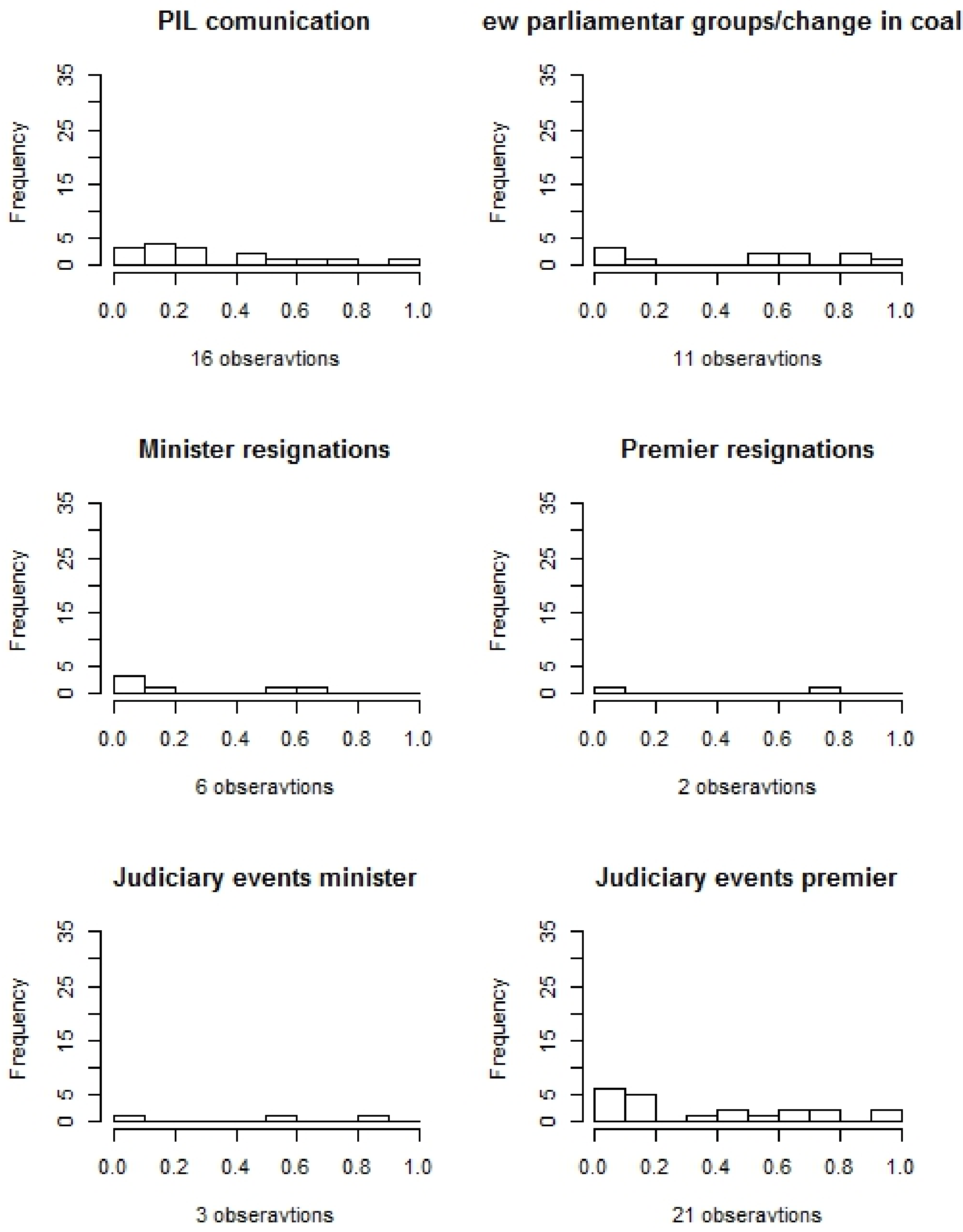


Figure 5.7: Histograms of two-sided p-values referred to the first six categories.

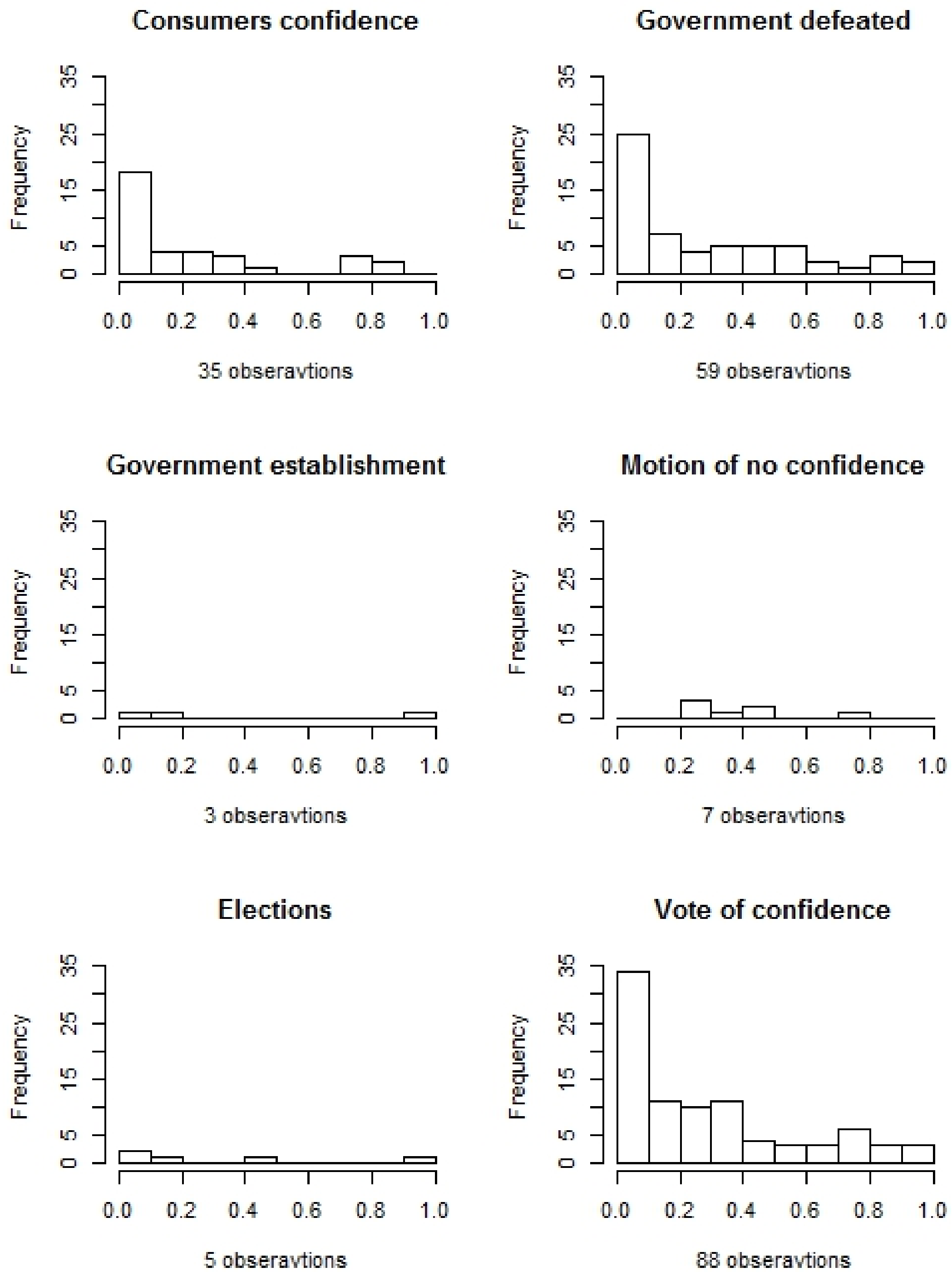


Figure 5.8: Histograms of two-sided p-values referred to the second six categories.

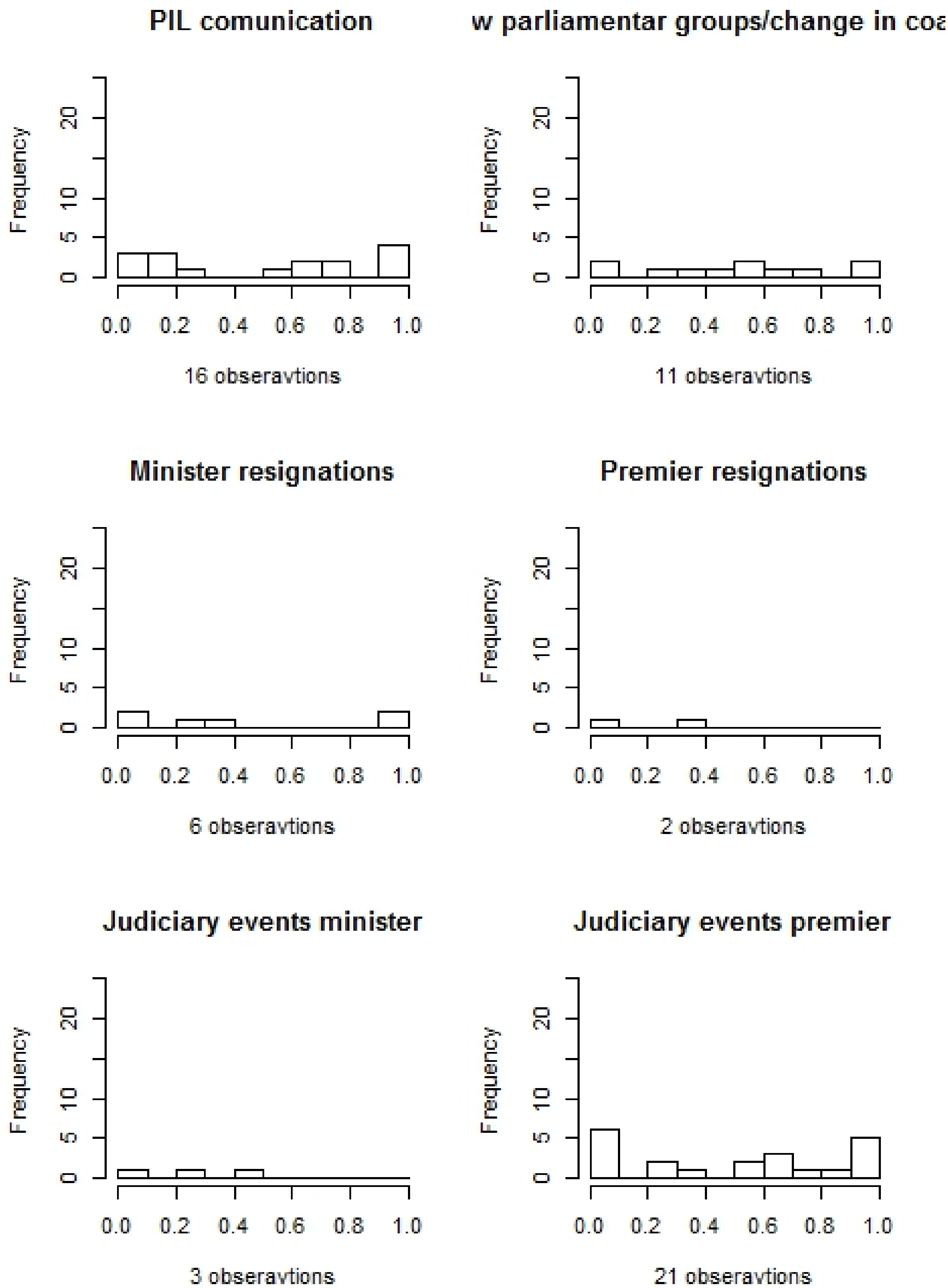


Figure 5.9: Histograms of one-sided p-values referred to the second six categories.

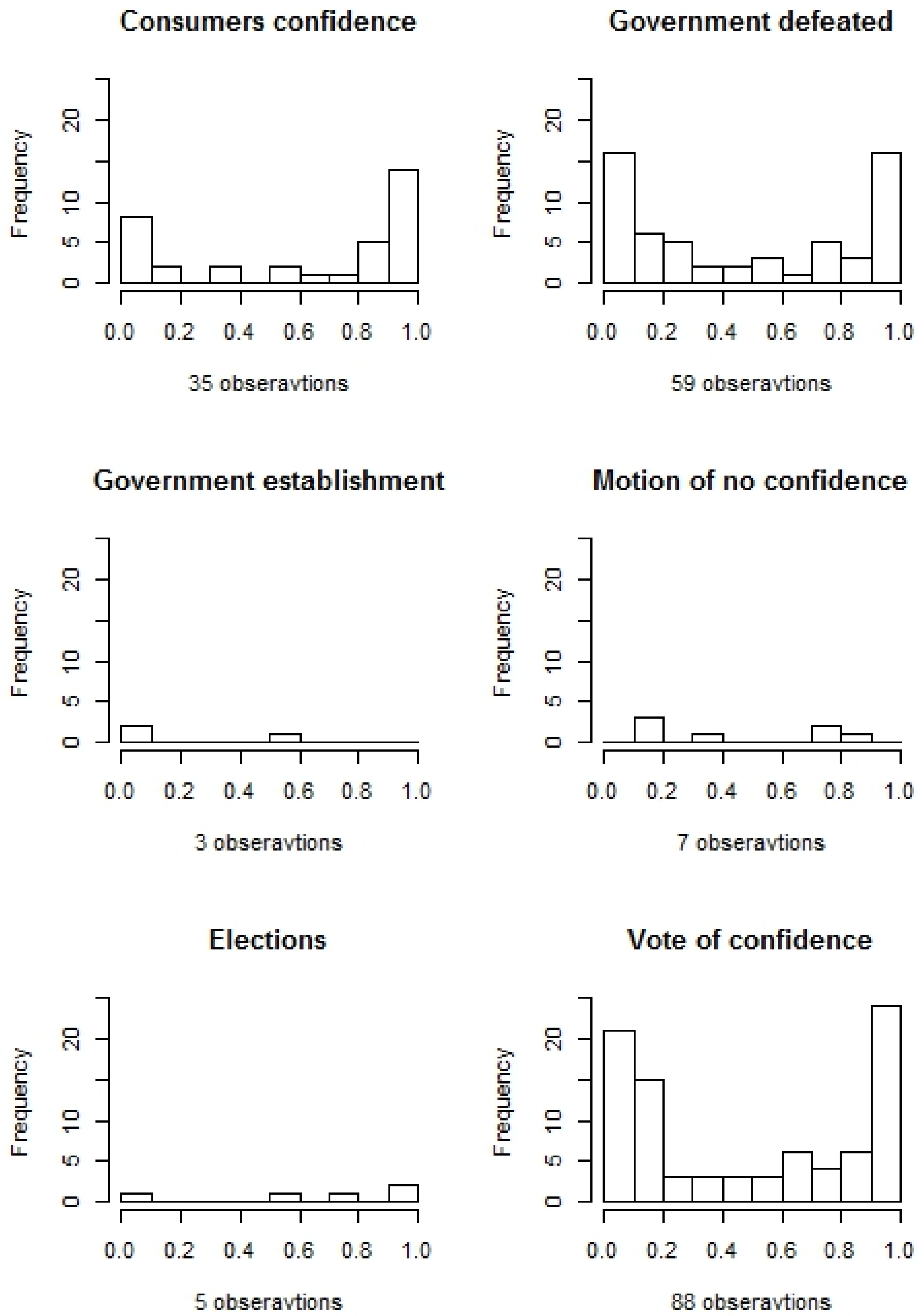


Figure 5.10: Histograms of one-sided p-values referred to the second six categories.

After the first analysis on different categories relevance in estimating the spread (through p-values analysis), we started to explore β coefficients and their distributions and patterns. The aim of this analysis is to show, for each category, whether coefficients aggregate in a neighbourhood of zero or not. As discussed before we are not in the standard framework, because not all the events belonging to a certain category produce an impact on spread in the same direction, that is some of them could increase it, while some others decrease it. In order to analyze these characteristics we computed kernel density estimations, through the R function `density`. This procedure computes the estimated distribution of β coefficients summing pointwise kernels centered on β values of each category. In the empirical kernel selection we choose a Gaussian kernel with a bandwidth of 1.5 for absolute coefficients and 0.01 for relative ones. Because we decided to use a Gaussian kernel, the bandwidth repersents the kernel standard deviation. We looked for distributions showing peaks where β coefficients are more concentrated. We adopted a system of weights inversely proportional to the variance of the coefficient associated. Results are reported in fig. 5.11 - 5.12 for absolute β coefficients and fig. 5.13 - 5.14 for the relative ones. In both of two cases we set weights inversely proportional to the coefficients standard deviation, with the purpose of assigning more relevance to the more satistically significant events. This approach caused small differences between absolute and relative results. In fact when absolute impacts are considered the β coefficients amplitude (and so their variance) increase when Italian spread value increase. This fact assigns more relevance to facts occurred in periods with low spread values.
Even in this case relevant conclusions cannot be obtained for categories with extremely low numerosity, consequently results accuracy is directly proportional to the group cardinality.
As previously we limited our descriptions to categories with at least 10 events. "PIL comunication", "New parliamentar groups/change in coalitions" and "Judiciary events premier" show two separate peaks, one centered in zero and with a negative value. This suggests that some events belonging to these categories does not influenced spread dynamics, while some others caused a spread drop. "Consumers confidence" estimation produced a tri-modal behaviour, with a peak lower than zero and two peaks greater. "Government defeated" usually yield to a spread increase, while sometimes β coefficients are negative. Finally "Vote of confidence" is the category with a higher number of observations and its β distribution shows a high peak lower than zero and a smaller

one greater than zero.
When relative coefficients are considered "PIL comunication", "New parliamentar group/change in coalitions" and "Judiciary events premier" produce the same β distribution estimation. The tri-modal behaviour of "Consumers confidence" appears mutated to a bi-modality, with a peak lower than zero and a bigger one greater than zero. "Government defeated" shows two symmetrical peaks, the positive one greater than the negative one, indicating that even if usually events belonging to this category produce a spread increase, sometimes they have a positive effect on spread, making it decrease. About "Vote of confidence" the peak greater than zero became more elusive than in the relative estimation, while the negative one is still clear. We can then assert that events belonging to this category usually caused a spread drop.

In the third and last part of the qualitative analysis we considered simultaneously p-values and β coefficients referred to a certain category. As we computed for all the events together in the previous section, now for each category we realized a bi-dimensional kernel density estimation (through the R function `kde2d` of MASS package) over the bi-dimensional dataset, where each datum is constituted by the p-value and the β coefficient referred to a certain event. Contour lines of the computed configuration help in observing which type of reactions events of a certain categry produce. Results obtained through this analysis recall the ones given by the two previous techniques.
"PIL comunication" shows a mass concentrated in low p-values and estimations lower than zero, "New parliamentar group/change in coalitions" produces a tri-modal pattern with masses concentrated in low p-values with positive or negative coefficients and in high p-values and values of β coefficients near to zero. "Judiciary events premier" apparently confirms not to influence the spread in the absolute approach, while in the relative one seems to divide the effect in a neutral part and in a positive part (spread decreasing). The behaviours of "Consumers confidence", "Government defeated" and "Vote of confidence" are similar: a mass concentrated in high p-values with small β coefficients, grouping the events with no impact,and a mass given by events with low p-values and a higher amplitude of β coefficients, representing impacting events in a positive or negative way.

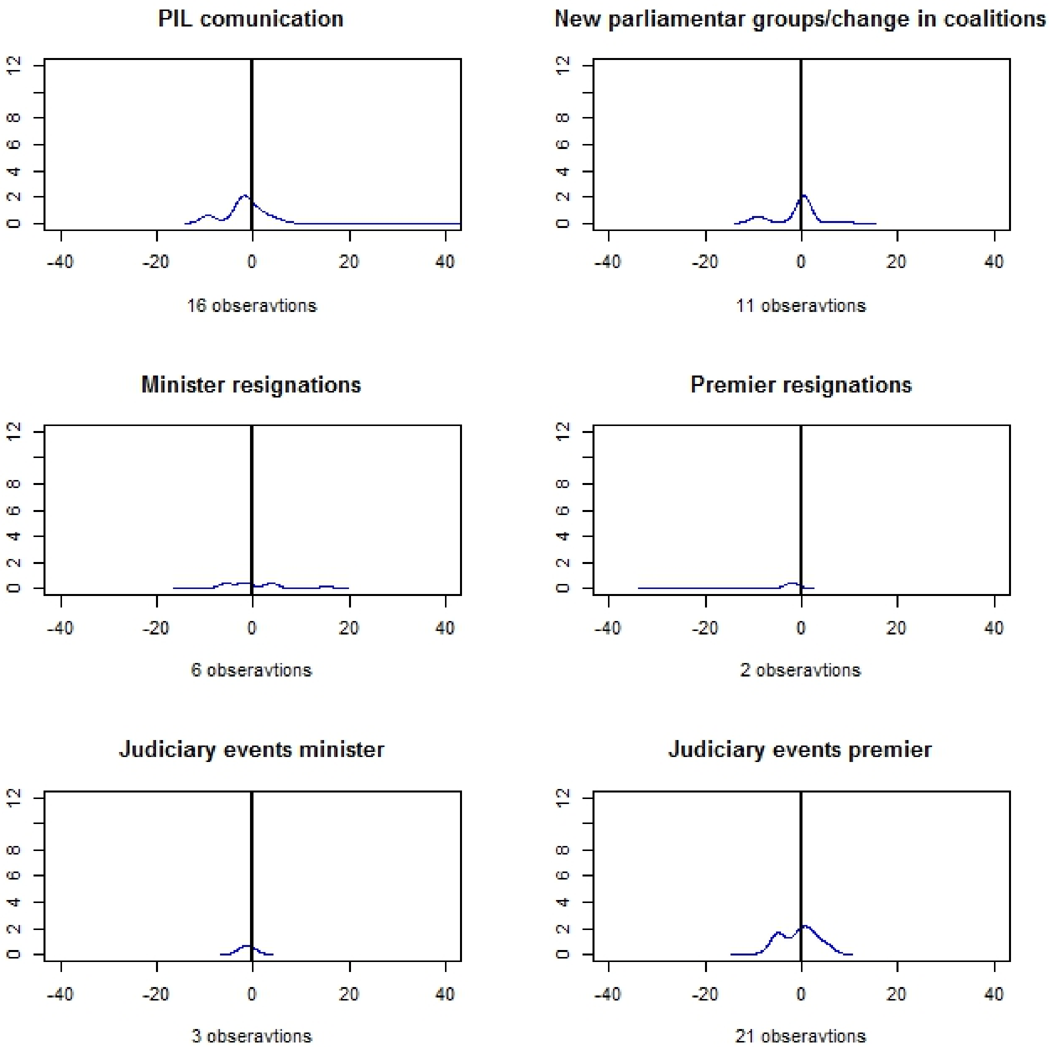


Figure 5.11: Kernel density estimations for absolute coefficients distributions in the first six categories: Gaussian kernel with standard deviation equal to 1.5.

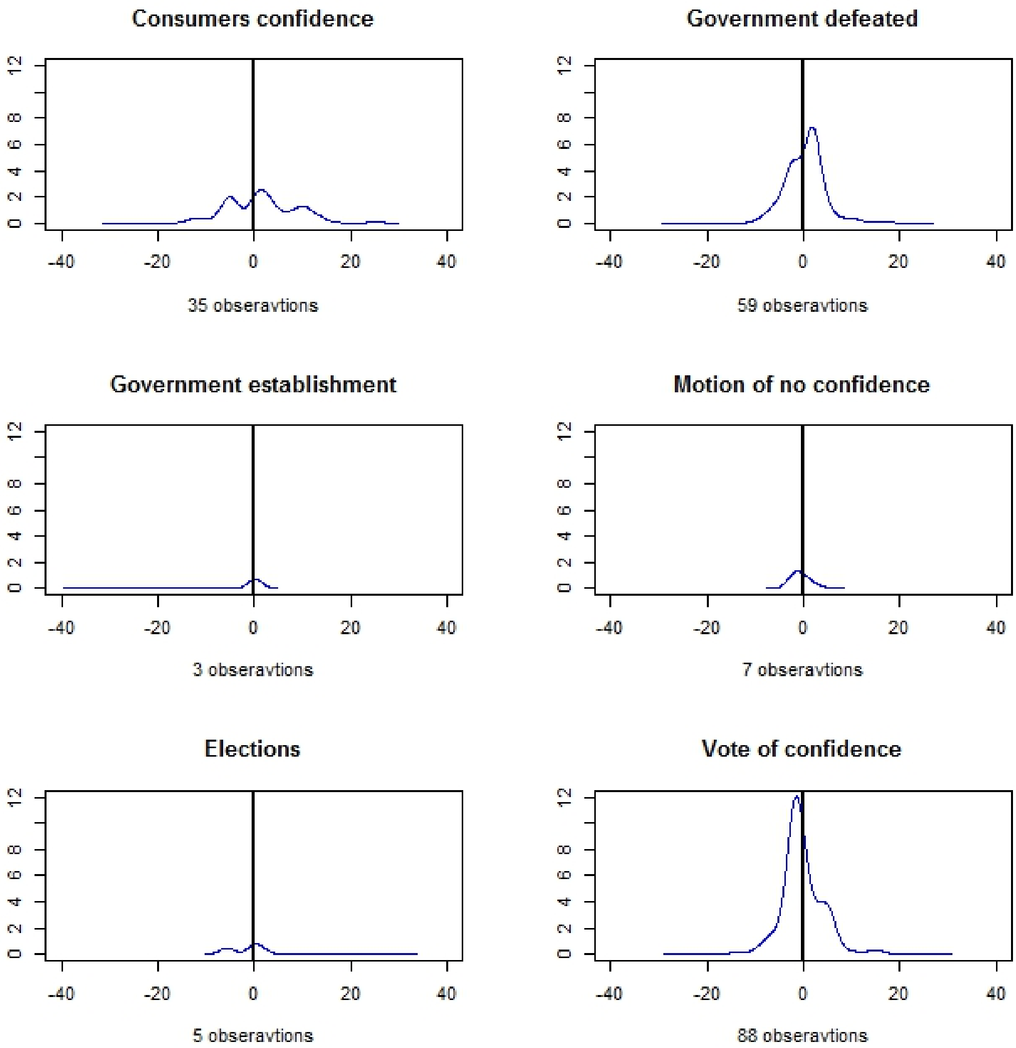


Figure 5.12: Kernel density estimations for the absolute coefficients distributions in the last six categories: Gaussian kernel with standard deviation equal to 1.5.

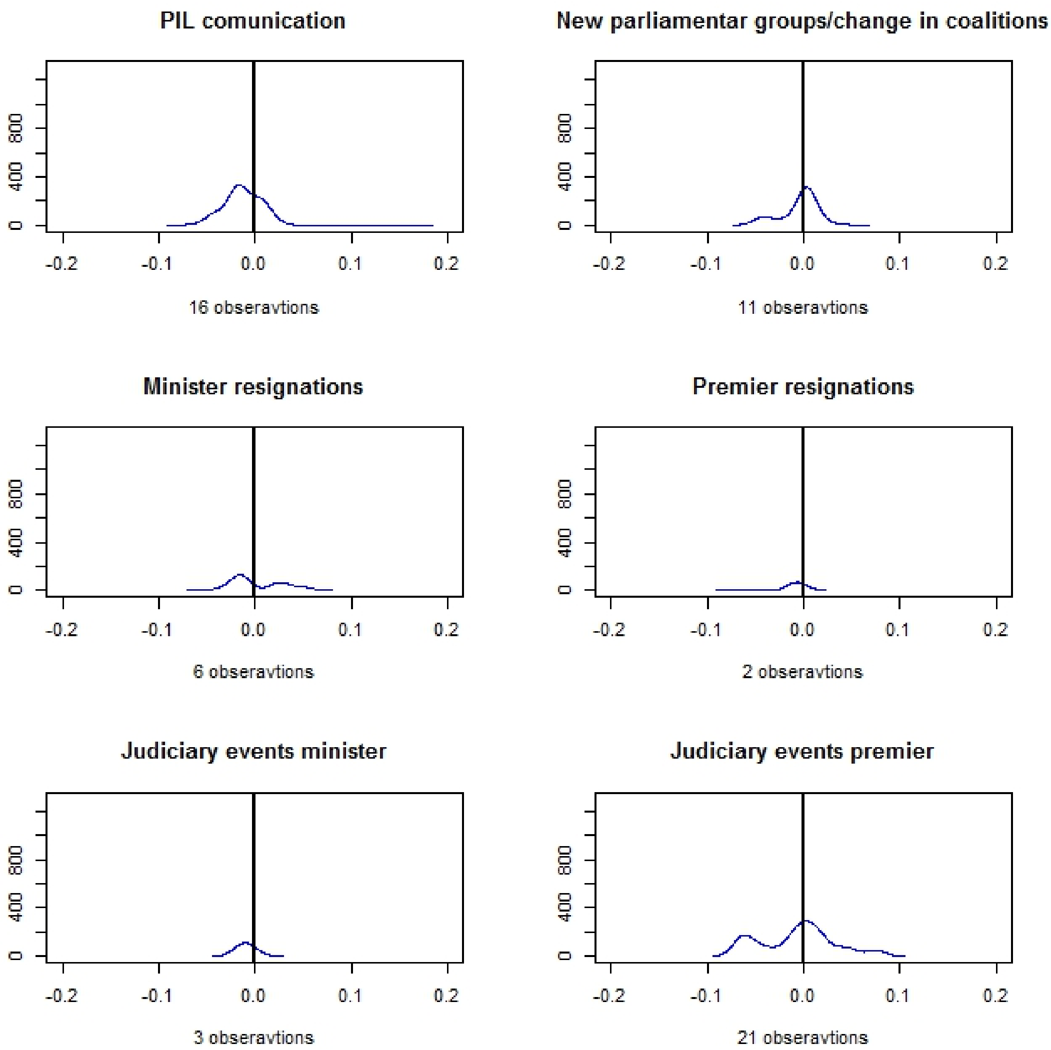


Figure 5.13: Kernel density estimations for the relative coefficients distributions in the first six categories: Gaussian kernel with standard deviation equal to 0.01.

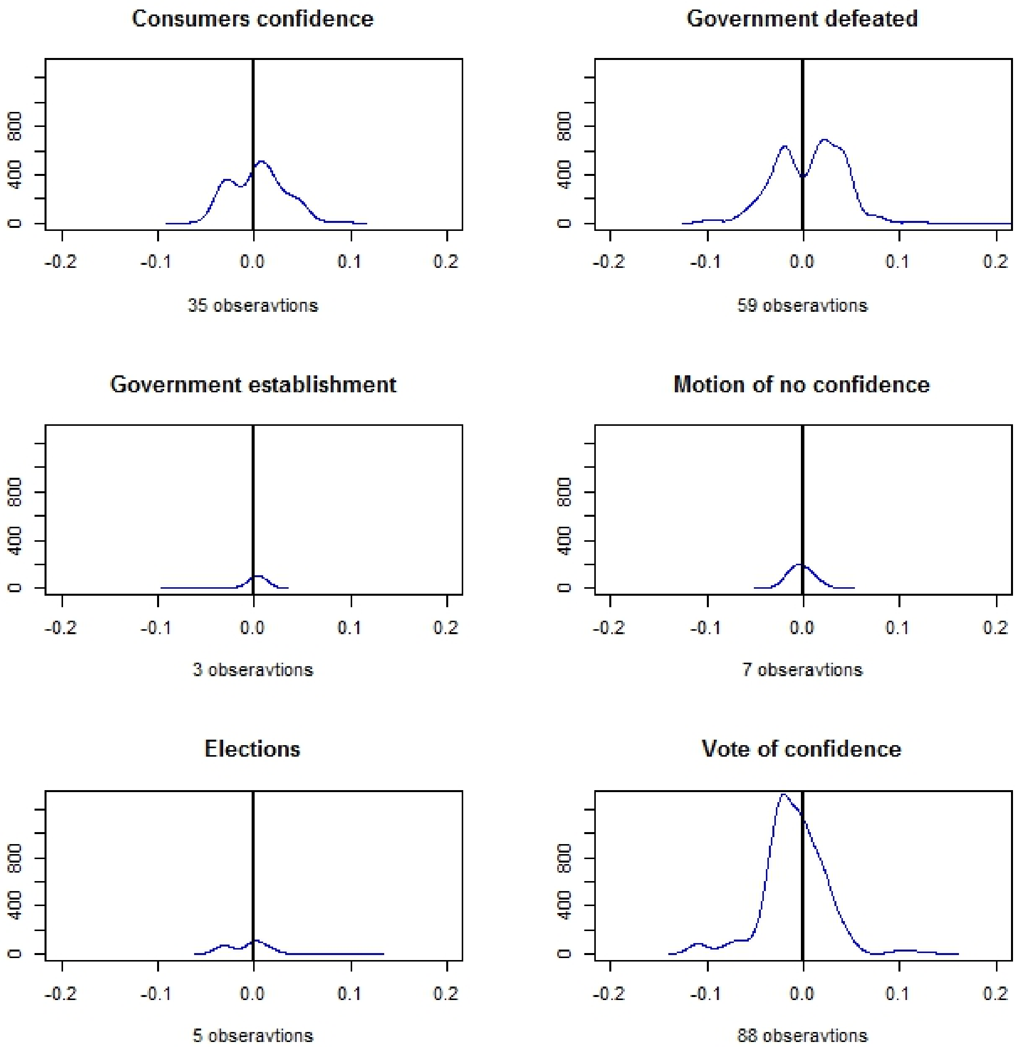


Figure 5.14: Kernel density estimates for the relative coefficients distributions in the first six categories: Gaussian kernel with standard deviation equal to 0.01.

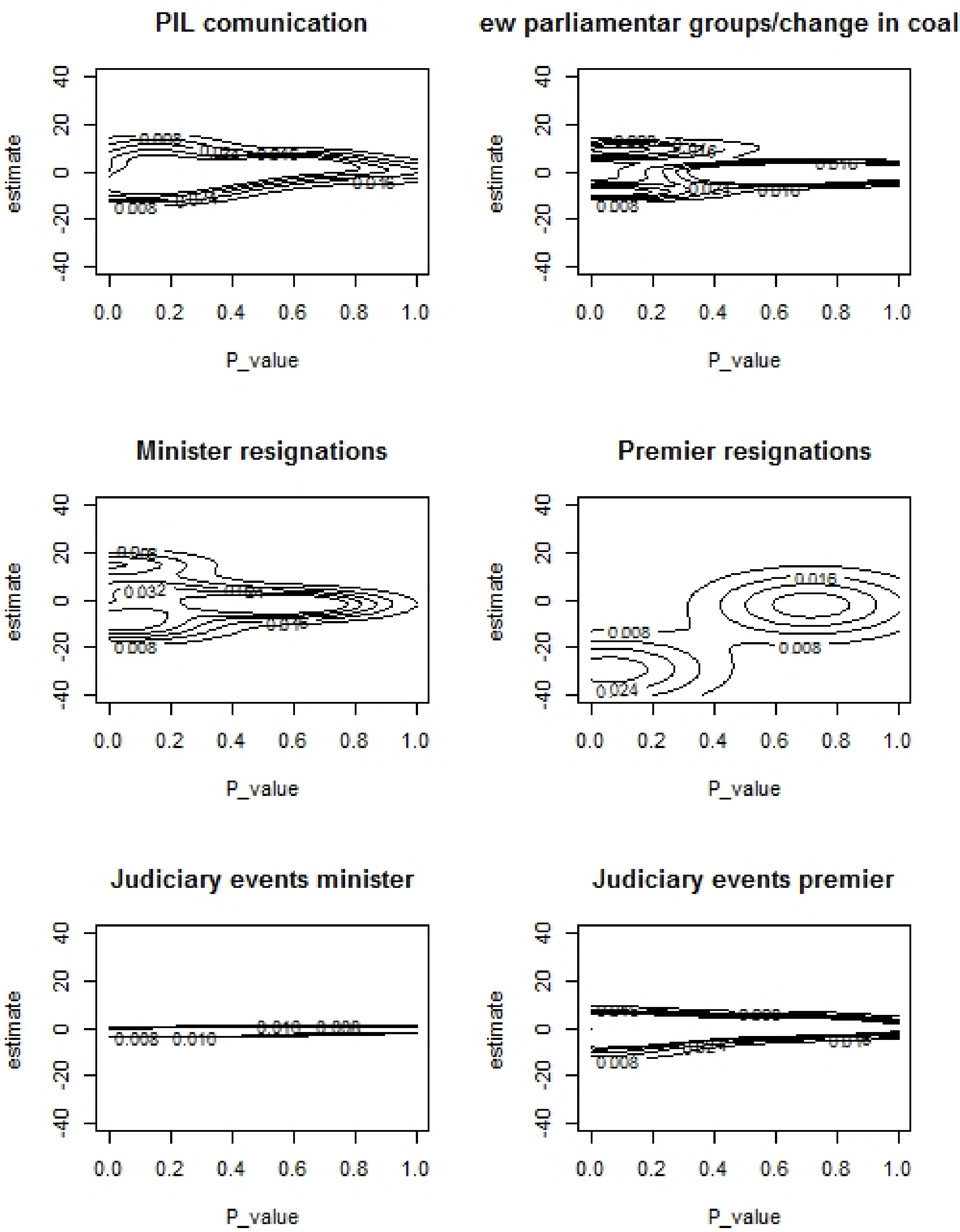


Figure 5.15: Contour plot for bi-dimensional kernel density estimates for the first six categories: absolute values considered.

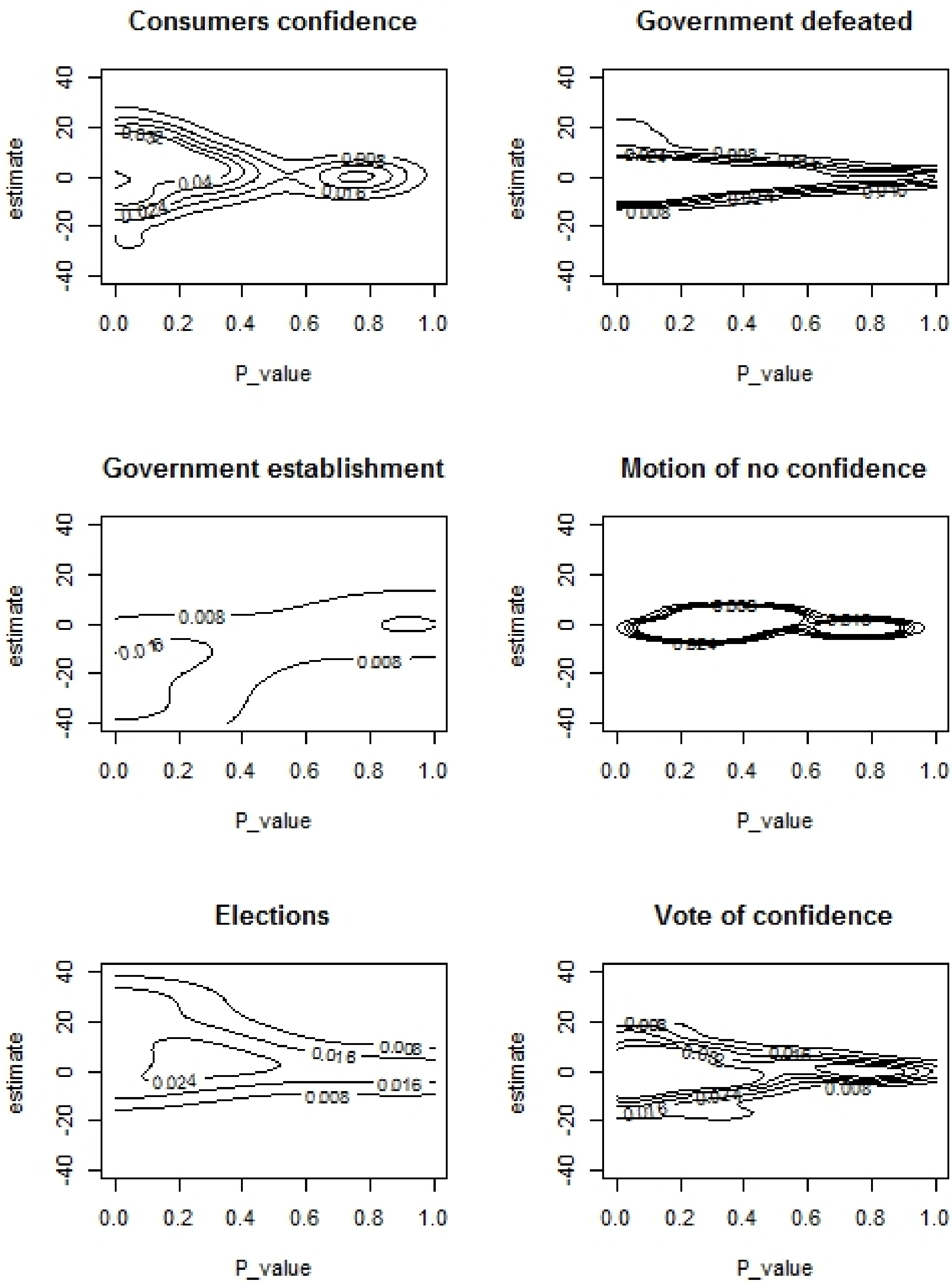


Figure 5.16: Contour plot for bi-dimensional kernel density estimates for the last six categories: absolute values considered.

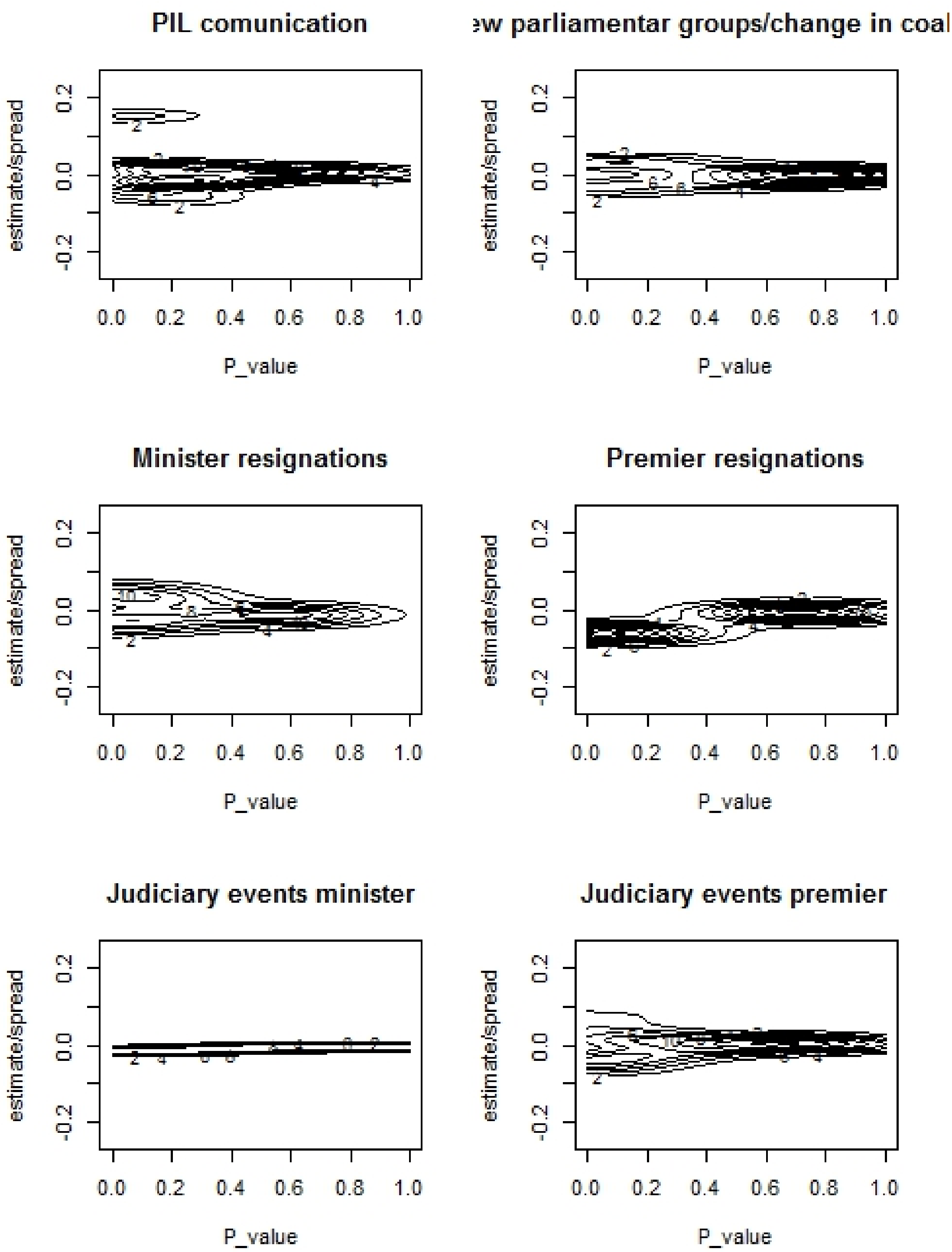


Figure 5.17: Contour plot for bi-dimensional kernel density estimates for the first six categories: relative values considered.

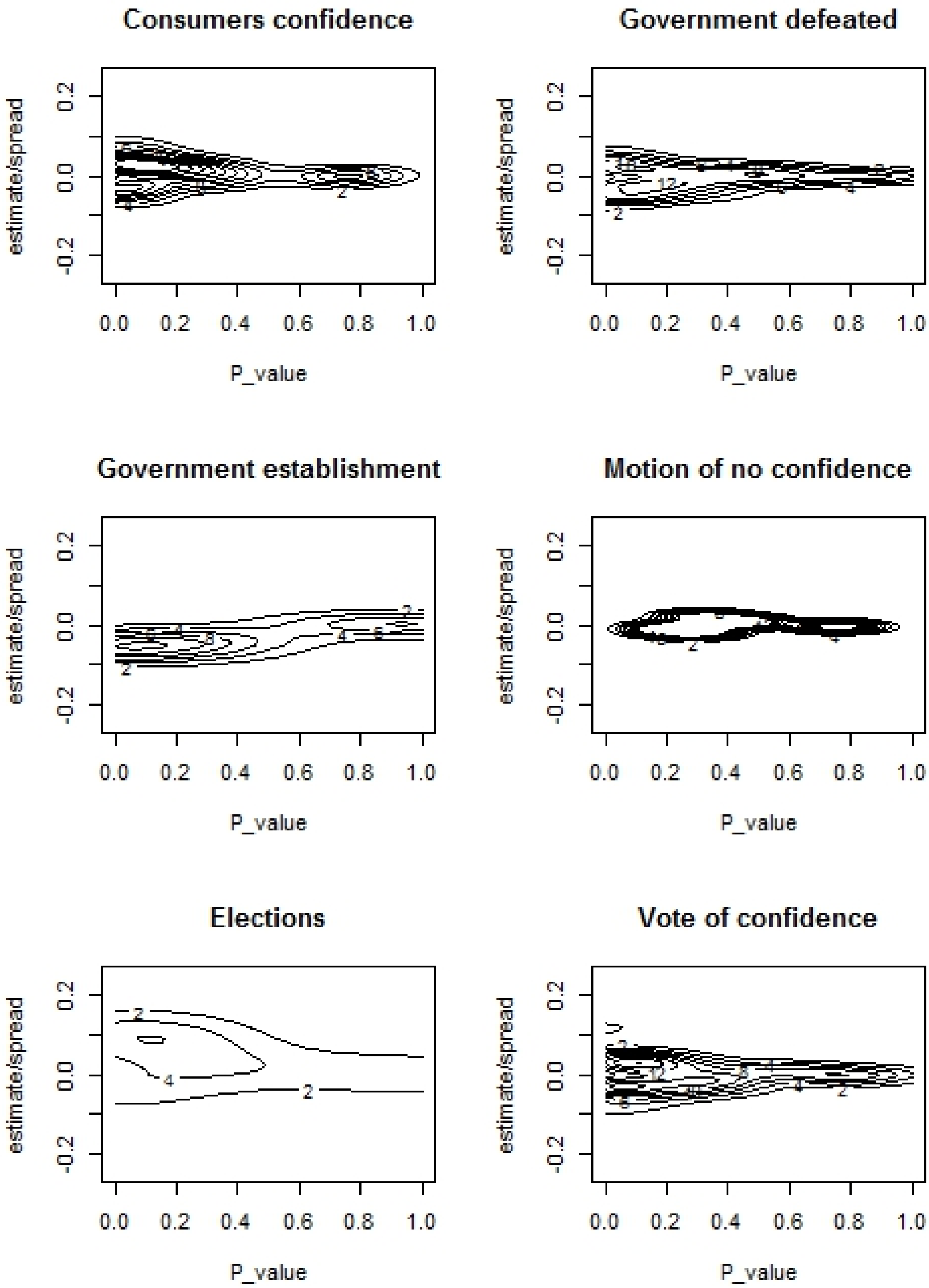


Figure 5.18: Contour plot for bi-dimensional kernel density estimates for the last six categories: relative values considered.

5.2.2 Quantitative approach: ANOVA one-way

Following the literature the best way to recognize if different categories of events produce a different impact is a one-way ANOVA, where the factor "category" is constituded by the 12 levels reported in subsection 3.1.2.
As discussed in the previous section, the β coefficient correspondant to a dummy variable was used as a proxy for the impact of a certain reputational event on the Italian spread. In order to avoid problems relative to mutual hiding caused by opposite sign of coefficients, we decided to develop the ANOVA model using the absolute values of the coefficients as variables considered.
In tab. 5.3 and 5.4 we showed the results for the analysis of variance carried out considering absolute or relative impact. In order to assign more relevance to the more statistically impacting events, we assigned to every datum a weightsinversely proportional to the variance of its relative β coefficient. Results provided by ANOVA show that factor "category" significantly influence variability in dummy variables coefficients when absolute impacts are considered (p-value 1.28%), while influence seems to be lower when the analysis is applied to relative values (p-value 8.44%).

	Df	**SumSq**	**P-value (F-test)**
category	11	53.9	0.0128 *
Residuals	219	475.7	

Table 5.3: Results for the weighted ANOVA, considering absolute impacts.

	Df	**SumSq**	**P-value (F-test)**
category	11	36.7	0.0844 .
Residuals	219	440.7	

Table 5.4: Results for the weighted ANOVA, considering relative impacts.

This difference in the two results could be due to a non-uniform distribution of events. As an example the category "Consumers confidence", which provides 35 events to the dataset, is gathered only in the second part of the period in analysis. This asymmetry was caused by the sources used to build the dataset. In fact "PIL comunication" and "Consumers confidence" start their series from a certain moment, for

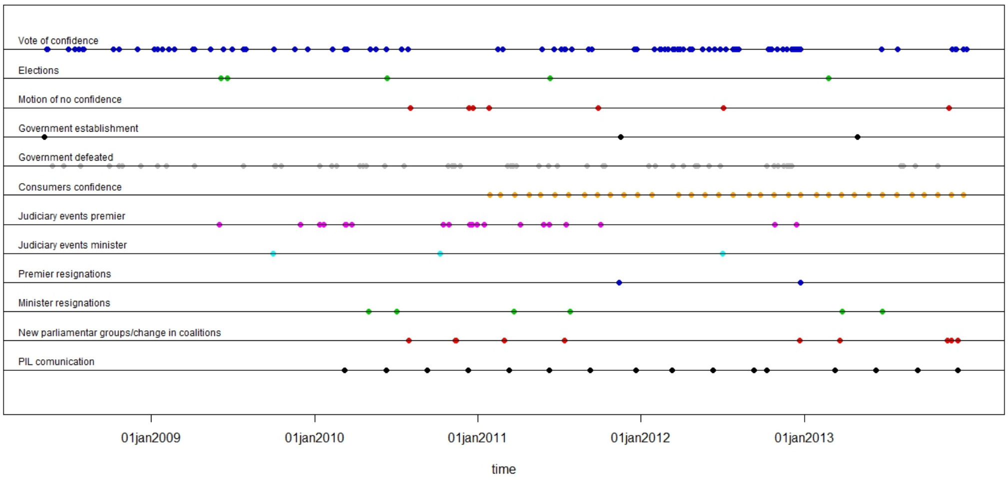


Figure 5.19: Temporal distribution of categories on the period considered.

further informations see Pozzi (2015) (23)
The non-uniformity in events distribution is shown in fig.5.19, that explains the difference between absolute and relative ANOVA results.

6

Conclusions and future developements

The first objective of the thesis was to build a linear regression model able to estimate with accurancy the Italian spread and it was achieved through a local linear regression model. Differently by the previous literature we adopted a rolling time window, assigning weights decreasing with the distance from the datum being estimated. The model developed belongs to *Kernel smoothin methods*. The main difference is that the distance considered in assigning weights is the temporal distance, instead of the geometric statistical distance. This model allowed the analysis to avoid problems given by high number of dummy variables, used as regressors representing reputational events, considered in each time window. Three fixed explanatory variables were adopted to explain Italian spread dynamics besides the dummy variables relative to reputational events:

- FTSE-MIB in order to explain strictly Italian dynamics;
- an aggregate of other eurozone countries spreads weighted proportionally to their cross-country financial flows with Italy (approximated with mutual banking exposure) that captures the European financial dynamics and in which measure Italy is connected to them;
- the EURO/DOLLAR exchange rate, with the aim of considering world dynamics and their influence on Italian spread.

Every reputational event was inserted in the model through a dummy variable switching from 0 to 1 at the day the news about that event was published and it was evaluated through two parameters associated to that variable: the p-value representing the significance of the event in estimating spread movements and the β coefficient that estimates the amplitude of its impact on Italian spread. Because a local linear regression model with rolling window was adopted, we considered parameters referred to each reputational event only when the window was centered in the day the event occurs.
Secondly the thesis aimed to evaluate the impact of each reputational event and to understand which categories mostly influence Italian spread dynamics. We showed that 69 out of 213 events considered produced a p-value correspondant to the respective dummy variable lower than 0.05, that is a 95% confidence interval on β not including zero. The 69 events resulted impacting produce both positive (30 events) and negative (39) coefficients, displaying that events can make the spread both increase and decrease. The analysis about the most impacting categories was costrained by the numerosity of each category. In fact the factor "category" is composed by 12 levels, but only 6 of them contain more than 10 events. The quantitative approach developed through one-way ANOVA showed that exists a difference between the different levels of the factor. In order to understand whether a specific category is impacting or not a qualitative exploration of p-values and β coefficient was operated. Kernel density estimations of β coefficients seem to show that all the 6 categories with a substantial number of events produce a distribution with average different to zero. When significances (that are estimation reliabilities) are considered, through p-values distributions, "Judiciary events premier", "Consumers confidence", "Government defeated" and "Vote of confidence" produce strong statistical significance through a Pearson's chi squared test refusing the null hypothesis they come from a uniform distribution. Only "PIL comunication" accepts the null hypothesis, so can be asserted that events belonging to this category do not influence Italian spread. "New parliamentar groups/change in coalitions" was not considered in this analysis because its numerosity is too low to operate the Pearson's test.
The greatest impediment in the last part of the thesis was the lack of a consistent number of events for 6 out of 12 categories. Future developements should include a longer period, with a much greater number of events considered, in order to obtain stronger statistical conclusions about all the categories in analysis. Moreover a subtler

caegorization of events could result in a deeper analysis, considering multi-level factors and groups of categories.
The R^2 falls over several contiguous days were not deepened. Probably in the windows with low R^2 is present a spread dynamic not captured by the three selected fixed explanatory variables and the dummy variables inserted to represent reputational events. Possible explanations include a missing fixed regressor or reputational events not contained in the dataset, that is some categories could have been neglected. Possible relevant class of news could have been ignored and this would have been affected both the fitting correctness and the analysis completeness.
In the analysis was used as financial health indicator the 10yrs bond spread, but were not considered neither tested other indexes.
The natural continuation of the thesis is the extension to other countries, both belonging to eurozone and not. Considering other European countries it will needed less effort, because the local linear regression model can be easily adapted, while the extension to a worldwide scale requires a change in the variables considered in the model.

Bibliography

[1] E. Zoli, "Italian sovereign spreads: their determinants and pass-through to bank funding costs and lending conditions," *IMF working paper*, vol. WP/13/84, 2013. 1, 2, 3, 6, 7, 10

[2] C. Favero, "Modelling and forecasting yield differentials in the euro area, a non-linear global var model," *Working Paper*, no. 431, 2012. 1, 3, 6, 7, 10, 15, 18, 27

[3] A. Ross, "Reputation: risk of risks," *Economist Intelligence Unit white paper*, 2005. 5

[4] R. S. Deborah Murphy and S. Tibbs, "Determinants of the stock price reaction to allegations of corporate misconduct: earnings, risk and firm size effects," *Unpublished working paper*, 2004. 5

[5] G. H. Roland Gillet and S. Plunus, "Operational risk and reputation in the financial industry," *Journal of Banking & Finance*, vol. 34, no. 1, pp. 224–235, 2010. 5

[6] M.-G. S. Franco Fiordelisi and P. Schwizer, "The determinants of reputational risk in the banking sector," *Journal of Banking & Finance*, vol. 37, no. 5, pp. 1359–1371, 2013. 5, 45

[7] N. Cazzaniga and S. D'Ettole, "Measuring reputational risk in electric utilities: a quantitative analysis of the stock market and web reactions to negative events," 2013. 5, 15, 30

[8] C. Belloni, "Sviluppo di modelli di stima e analisi del rischio reputazionale nel settore oil&gas," 2013. 5, 15, 30, 47

[9] R. Binda, "Market reactions to reputational events for oil&gas companies and states," 2013. 6, 15, 30, 47

[10] S. Edwards, "The pricing of bonds and bank loans in international markets: an empirical analysis of developing countries' foreign borrowing," *NBER working paper*, vol. 1689, 1985. 6

[11] J. v. H. Kerstin Bernoth and L. Schuknecht, "Sovereign risk premium in the european bond market," *Journal of international money and finance*, vol. 31, pp. 975–995, 2012. 6, 7, 10, 27

[12] P. de Grauwe and J. Yuemei, "Self fulfilling crisis in the eurozone: an empirical test," *Journal of international money and finance*, vol. 34, pp. 15–36, 2013. 6

[13] P. Luengnaruemitchai and S. Schadler, "Do economist and financial markets perspectives on the new members of the eu differ?," *IMF Working Paper*, no. WP/07/65, 2007. 6, 10, 26

[14] K. H. Kenichiro Kashiwase and L. E. Kodres, "Emerging market spread compression: is it real or is it liquidity?," *IMF Working Paper*, no. WP/08/10, 2008. 6, 10, 26

[15] L. Codogno, Favero and Missale, "Yield spreads on emu government bonds.," *Economic Policy*, vol. 18, no. 37, pp. 503–532, 2003. 7, 10, 17, 27

[16] A. Kossmeier, Geyer and Pichler, "Measuring systematic risk in emu government yield spreads," *Review of finance*, vol. 8, no. 2, pp. 171–197, 2004. 7, 10, 17, 27

[17] A. Mody, "From bear sterns to anglo irish: how eurozone sovereign spreads related to financial sector vulnerability," *IMF working paper*, vol. WP/09/108, 2009. 7, 10, 26

[18] M. T. e. G. G. Antonio di Cesare, Michele Manna, "Recent estimates of sovereign risk premia for euro-area countries," *Bancad'Italia - Occasional Papers*, vol. 128, 2012. 7, 10, 26

[19] S. Eichler, "The political determinants of sovereign bond yiels spreads," *Journal of international money and finance*, vol. 46, pp. 82–103, 2014. 7, 10, 26

[20] A. Galesi and S. Sgherri, "Regional fiancial spillovers across europe: a global var analysis," *IMF working paper*, vol. WP/09/23, 2009. 7, 18, 19

[21] I. Vansteenkiste and P. Hiebert, "International trade, technological shocks and spillovers in the labour market; a gvar analysis of the us manufacturing sector," *Working Paper series - European Central Bank*, vol. 731, 2007. 7

[22]

[23] D. Pozzi, 2015. 12, 65

[24] A. C. P. S. Marika Arena, Giovanni Azzone and S. Vantini, "Measuring down-size reputational risk in the oil&gas companies and states," *Paper presented at SCo2013*, 2013. 15, 30

[25] R. T. Trevor Hastie and J. Friedman, *The elements of statistical learning*. Springer, 2011. 31, 33

Ringraziamenti

A chi lo sa.