School of Social Sciences
CITY UNIVERSITY LONDON

Department of Economics

The Cross-Section of Interbank Rates:A Nonparametric Empirical Investigation

Giulia Iori
City University London

Burcu Kapar
City University London

Jose Olmo[1]
Centro Universitario de la Defensa, Zaragoza

Department of Economics
Discussion Paper Series
No. 12/03

[1] Corresponding author: Centro Universitario de la Defensa de Zaragoza. Academia General Militar. Ctra. Huesca s/n. Zaragoza. 50090. Spain, Email: jolmo@unizar.es.

The Cross-Section of Interbank Rates: A Nonparametric Empirical Investigation

Giulia Iori, *City University London*
Burcu Kapar, *City University London*
Jose Olmo*, *Centro Universitario de la Defensa, Zaragoza*

August 2012

Abstract

This paper analyzes the distribution of lending and borrowing credit spreads in the European interbank market conditional on main features of banks such as their size, operating currency and nationality. This is done by means of nonparametric kernel estimation methods for the cross-sectional density of interbank funding rates over a large sample of European banks trading in the e-MID market. The analysis is repeated over consecutive non-overlapping periods in order to assess and compare the effect of the factors during crisis and non-crisis periods. We find evidence of important differences between the borrowing and lending segment of the interbank market that are augmented during crises periods. Our results strongly support the existence of a size effect in the borrowing market. Largest banks enjoy the highest lending rates and the lowest borrowing rates. The collapse of Lehman Brothers accentuates the differences in funding conditions. In both borrowing and lending segments, crises are corresponded by high volatilities in daily funding costs. Banks using the Euro currency and in countries not affected by sovereign debt crises are benefited by lower funding costs. Our nonparametric analysis of densities conditional on banks' nationality suggests that distress in the interbank market can serve as an early warning indicator of sovereign risk.

Keywords: e-MID Interbank Market, Financial Crisis, Nonparametric kernel estimation, Sovereign risk, Systemic Risk.

*Corresponding address: Centro Universitario de la Defensa de Zaragoza. Academia General Militar. Ctra. Huesca s/n. Zaragoza. 50090. Spain. E-mail: jolmo@unizar.es. T:+34 976739776. The research leading to these results has received funding from the European Union, Seventh Framework Programme FP7/2007-2013 under grant agreement FET Open Project FOC, Nr. 255987. Financial support from the Spanish Government through project MICINN ECO2011-22650 is also gratefully acknowledged.

1 Introduction

Interbank markets are the main instrument for the transmission of monetary policy targets from central banks to the overall economy. These markets are responsible for distributing liquidity across the financial system by allowing the transfer of funds from banks with a surplus to banks with a deficit. This is discussed for example in Ho and Saunders (1985), Bhattacharya and Gale (1987) and Freixas, Parigi and Rochet (2000), amongst others. These authors note the insurance role of interbank markets against idiosyncratic liquidity shocks.

The functioning of interbank money markets has been questioned during the recent financial crisis. The connectivity between banks offered by these markets increases their exposures to systemic risk and serves as a channel of contagion between distressed economies. This is illustrated for example in Iazetta and Manna (2009) and empirically noted by the dramatic changes recently observed in the interbank money markets worldwide. During the crisis, interbank interest rates underwent record levels and trading activity in these markets saw an unprecedented decline in most market segments. The collapse of major financial institutions such as Lehman Brothers contributed to the loss of confidence in the health of the overall financial system and the rise in risk aversion levels that led to the dry up of liquidity in interbank markets. This increase in funding rates between banks also produced the flight to quality from the interbank money market to the European Central Bank (ECB) deposit facilities. To overcome this malfunctioning of the interbank money market, central banks around the world considered nonconventional measures mainly centered on injecting liquidity into the system. The success of these measures has been mixed with interest rate spreads remaining at levels well above those observed before the financial crisis.

The aim of this study is to describe the characteristics of borrowing and lending in the European interbank market during the recent years. This is done by analyzing the cross-section of all interbank lending and borrowing operations in the e-MID money market from 2006 to 2009. The cross-sectional analysis of spreads over the average cross-sectional interest rate prevailing in the market sheds light on the lending and borrowing patterns across banks and the role of key variables such as bank size, nationality or their positioning in the money market (lending or borrowing side). The methodology to do this is empirical and consists on estimating the cross-sectional density function of lending and borrowing rates observed during the analyzed period. We propose the use of nonparametric kernel methods to let data speak by themselves. In contrast to most parametric alternatives, this approach can identify the existence of multimodal distributions and accommodate highly leptokurtic and asymmetric density functions. This methodology is novel in this field and contrasts to most of the related literature that explains the determinants of funding rates, see Gabrieli (2011a ,2011b), Cocco et al. (2009), Angelini et al. (2011) and Afonso et al. (2011), using parametric panel data regression models. This analysis is complemented with the study of the density of volatility of daily spreads over monthly periods. The rationale for doing this is to assess the distributional relationship between the magnitude of funding rates and their variation.

A distinctive contribution of this work is the database analyzed. We use data on overnight transactions from July 2006 to August 2009 on the e-MID money market trading system. The e-MID market represents the only readily available source of micro data on interbank transactions in the Euro area and offers the most comprehensive dataset reflecting actual transactions and not offered rates. The overnight segment is strongly influenced by the Eurosystem's operational framework implying that overnight rates are less exposed to market participant's speculative behavior.

The empirical results of this study provide interesting insights for understanding the role of borrowers and lenders characteristics in this transparent environment. Our findings suggest the existence of asymmetric behavior between the borrowing and lending market. Size is a relevant variable for explaining spreads in the borrowing market but not so important in the lending market. Largest banks enjoy the highest lending rates and the lowest borrowing rates. The collapse of Lehman Brothers accentuates the differences in funding conditions. The volatility of spreads also provides information on the health of the interbank market. Interestingly, we observe a positive distributional relationship between increases in volatility and subsequent increments in funding rates and distress in the interbank market. The empirical analysis also explores the role of the main currency used by banks in the dynamics of the density function of spreads and on the relationship between distress in the interbank market and sovereign risk. Our findings suggest that banks using the Euro currency and in countries not affected by sovereign debt crises obtain lower funding costs.

The remainder of this article is organized as follows. Section 2 explains the properties of the e-

MID interbank market and describes our dataset. Section 3 describes the econometric methodology based on density kernel estimation to assess the behavior of lenders and borrowers conditional on banks size, currency and banks' nationality. Section 4 discusses the empirical findings obtained from applying these methods to our large dataset. Lastly, Section 5 concludes. Tables and figures are collected in the appendix.

2 Data and the e-MID Market

This section introduces the characteristics of the e-MID interbank market and the dataset used for our empirical analysis.

2.1 The e-MID Market

The e-MID company, established in 1990, makes use of an electronic platform to manage the interbank unsecured deposit market in Europe. It is the only electronic trading platform for interbank deposits in the Euro area and in the US. Under the supervision of Bank of Italy, credit institutions and investment companies can participate in this market if their total net asset size is respectively at least 10 million US Dollars (or its equivalent in another currency) and 300 million euros (or its equivalent in another currency). Before the financial crisis, the platform had 246 members from 29 EU countries and the US, of which 30 were central banks acting as market observers. Interbank deposit maturities range from overnight to one year with overnight contracts representing nearly 90% of total volume. After the crisis, the number of countries with banks actively participating in the e-MID market is sixteen: Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain, Switzerland and United Kingdom.

One distinctive feature of the platform is that it is fully transparent. Buy and sell proposals appear on the platform with the identity of the bank posting them. In the overnight market segment, a buy transaction is an interbank loan proposed by the borrowing bank submitting a bid quote on the screen, hence revealing itself as liquidity-short to the market; a sell transaction is an interbank loan initiated by the lender submitting an ask quote on the screen, hence revealing itself as liquidity-long. The platform does not offset any counterparty risk; search costs are identical for all platform participants. In this market, each trader can choose any counterparty present in the book to start the trade. The two parties can negotiate the terms and conditions of the specific trade, change the quantity/price or refuse the transaction at all. During the financial crisis we observe a decrease in the volume of transactions and number of participants largely because of the transparency of e-MID market that induces banks to search for alternative, less transparent sources of funding. Thus, before the crisis, the amount of transactions executed on e-MID platform account for 17% of total turnover in unsecured money markets in the Euro Area, decreasing to around 10% of market share after the financial crisis.

Figure 1 presents monthly average of daily volume and number of transactions over the sample period. There is clear evidence that participation in this market decreases during the crisis. Some of this decline can be explained by a general decrease in the interbank transactions as banks prefer to deposit their money in ECB rather than lending it to each other at the prevailing interest rates. The other obvious reason is related to the transparent nature of the market. Banks, especially borrowers, may avoid to reveal their liquidity shortage appearing on the borrowing side. Hence they may prefer to trade in a less transparent environment during financial shocks in order to avoid being openly seen in the market.

Table 1 presents average transaction size of different sized Italian banks and foreign ones participating in the e-MID system. These statistics reveal a correlation between transaction and institution size for domestic banks. Transaction sizes are proportional to their asset size which is in line with the findings of Furfine (1999) for the FED funds market. Table 1 also reports the market share of foreign and different sized domestic banks with respect to the total number of transactions and amounts traded. Foreign banks have more than 50% total volume market share in both sides of the market. High participation of foreign banks in the e-MID market acknowledges its international character.

2.2 Data

The dataset used for this study consists of all the transactions recorded in the platform between 12 July 2006 to 8 September 2009. For each transaction, we have comprehensive information about the date, the time of trade, quantity exchanged, the interest rate, transaction side (buy or sell) and the code of the quoting and ordering banks. Our sample contains 125 Italian and 90 foreign banks acting as borrowers, lenders or both during the period of study. Although the identity of the banks is not available to us, we have information on capitalization for the Italian banks and the origin country for all banks. Italian banks are classified into 5 groups according to their weighted asset portfolio: major banks (higher than 60 billion euro), large banks (from 26 to 60 billion euro), medium banks (from 9 to 26 billion euro), small banks (from 1.3 to 9 billion euro) and minor banks (less than 1.3 billion euro). We only consider overnight (O/N) and the overnight long (ONL) contracts where ONL refers to contracts when more than one day is present between two consecutive business days. The interest rate is expressed as an annual rate and the amount of the transaction is quoted in millions of Euros.

The trading activity of borrowers/lenders is affected by the reserve maintenance period, announced by the ECB, rather than by calendar month effects. This is so because banks need to comply with regulatory requirements on the amount of capital held over such periods. Empirically, for the EONIA rates, Gaspar et al. (2008) report an increase in market activity towards the last days of the reserve maintenance period described by a remarkable increment in the number of transactions and in the underlying volatility of interest rates. To capture these effects, we focus on monthly periods determined by the reserve maintenance period that correspond in our data sample to 38 monthly periods.

We first define the spread of each transaction as the deviation of the transaction interest rate from the daily average market rate. More formally,

$$s_{b,t} = r_{b,t} - \overline{r}_{d,t} \tag{2.1}$$

with $r_{b,t}$ an individual interest rate outstanding for bank b at time t, and $\overline{r}_{d,t}$ the average rate of all transactions in the market on day t. The interest in analyzing the spread rather than the crude interest rate is for cross-comparison purposes between the banks trading in the interbank market. In order to reduce the noise due to extreme movements in funding rates we consider aggregate daily spreads computed over the reserve maintenance periods. For a bank b executing $T_{b,m}$ transactions on a given month m, we calculate the monthly average credit spread as

$$\overline{s}_{b,m} = \frac{1}{T_{b,m}} \sum_{t=1}^{T_{b,m}} s_{b,t}.$$

This statistic is complemented with a measure of volatility that provides information on the distribution of the variability of daily funding costs for each bank over the monthly maintenance period. The monthly standard deviation of the daily spread of each bank is

$$sd_{b,m} = \sqrt{\frac{1}{T_{b,m}} \sum_{t=1}^{T_{b,m}} (s_{b,t} - \bar{s}_{b,m})^2} \tag{2.2}$$

The number of borrowers varies from month to month between 62 and 127 and the number of lenders between 78 and 156. The number of observations on a particular month may be smaller than the number of banks, simply because some banks may not be active during that period.

We implement our methodology on six subperiods to control for the impact of important market events. Table 2 presents information about the sub-periods considered in this study. We consider January 2007, August 2007, March 2008, September 2008 and March 2009 as the dates defining the different periods in the European interbank market. February 2007 corresponds to the crash of the Shanghai Stock Exchange considered as one of the first signals of the financial crisis. Therefore, we consider July 2006 to January 2007 as the 'Pre-crisis Period'; January 2007 to August 2007 as a ' Financial Markets Unease Period '. August 2007 is accepted as the date when sub-prime mortgage crisis spilled over into the interbank market, hence, we consider from August 07 to March 08 as the 'Interbank Crisis Period '. In March 2008, Bear Sterns collapsed and its collapse is the prelude to the increased tension in the investment banking sector. Right after, financial markets experienced the largest bankruptcy with the collapse of Lehman Brothers in September 2008 triggering heightened concerns on counterparty risk and the cease in lending activities between commercial banks. Considering these important dates, we classify March 08 to September 08 as 'Pre-Lehman Period' and September 08 to March 09 as 'Post-Lehman Period'. Lastly, we consider the period from March 09 to September 09 as the 'Post-Crisis Period' when the interbank market shows the first signals of recovery.

3 Econometric Methodology

This section discusses the methods necessary to perform our empirical analysis. We concentrate on modeling the cross-section of interest rates and underlying volatility outstanding in the interbank market over the recent years. To do this we present the main techniques for nonparametric kernel density estimation and the corresponding estimation of the quantile function.

Let $(x_1, x_2, ..., x_n)$ be an iid sample drawn from some distribution with an unknown density function $f(\cdot)$. Its nonparametric kernel density estimator is

$$\hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^{n} K(\frac{x - x_i}{h}) \tag{3.1}$$

where $K(\cdot)$ is a kernel function and h is a bandwidth parameter. The kernel function must be a density function, nonnegative and symmetric. The size of bandwidth chosen for kernel density estimation determines the degree of smoothing produced. The kernel function and bandwidth parameters accommodate a wide range of options that provide some flexibility in the estimation of the density. For a nice review on nonparametric kernel methods the interested reader is referred to Li and Racine (2007).

Conditional density estimation is the realization of regression where instead of estimating the expected value $E(Y|X)$ with Y the response variable and X the regressor vector, it models the full density $f(Y|X)$. By doing this, the method provides valuable information about skewness, kurtosis, multi modality, extreme values and any other statistics that require knowledge of the underlying distribution. The following paragraphs detail the kernel method for conditional density estimation with the appropriate kernel functions chosen for each variable, conditional quantile functions and bandwidth selection method for our model specifications.

Let $g(\cdot, \cdot)$ and $\mu(\cdot)$ denote the joint and marginal densities of (X, Y) and X, respectively. We refer to Y as the dependent variable which is the spread/volatility in our models below and X as the vector of explanatory variables which in our application corresponds to a vector of ordered discrete factors such as monthly time period or banks' asset size and (unordered) discrete factors such as Euro/Non-Euro and Crisis/Non-Crisis classifications. We use $\hat{f}$ and $\hat{\mu}$ to denote the corresponding kernel estimators and

$$\hat{f}(y|x) = \frac{\hat{g}(x, y)}{\hat{\mu}(x)} \tag{3.2}$$

for the kernel estimator of the corresponding conditional density function. It is immediate to observe that the conditional density estimation is the ratio of two kernel density estimators. As Y is a univariate continuous random variable, the kernel estimation of the joint density $g(\cdot, \cdot)$ and marginal density $\mu(\cdot)$ are given by

$$\hat{g}(x,y) = n^{-1}\sum_{i=1}^{n} K^d(x^d, X_i^d, \lambda) k_{h_0}(y, Y_i) \tag{3.3}$$

and

$$\hat{\mu}(x) = n^{-1}\sum_{i=1}^{n} K^d(x^d, X_i^d, \lambda). \tag{3.4}$$

The kernel function for the continuous dependent variable Y (spread/volatility) is

$$k_{h_0}(y, Y_i) = h_0^{-1} k((y - Y_i)/h_0) \tag{3.5}$$

where $k((y - Y_i)/h_0)$ is one of the multiple choices existing in the literature (e.g. Gaussian, Uniform, Epanechnikov) and h_0 is the smoothing bandwidth parameter corresponding to Y.

The kernel function for discrete random variables is more convoluted than for continuous random variables. We use Wang and van Ryzin (1981) type kernel function below for the ordered discrete factors, monthly time period and asset size classifications used in our posterior empirical analysis. This function takes the form:

$$K^d(x^d, X_i^d, \lambda) = \begin{cases} 1-\lambda, & \text{if } X_i^d = x^d, \\ \frac{(1-\lambda)}{2}\lambda^{|X_i^d - x^d|}, & \text{if } X_i^d \neq x^d \end{cases}$$

where λ is the smoothing vector for the ordered discrete factor X and can lie between 0 and 1.

For the analysis focused on dichotomic conditional variables, such as Euro against Non-Euro currencies and Crisis against Non-Crisis classifications, we use the following kernel function developed by Aitchison and Aitken (1976):

$$K^d(x^d, X_i^d, \lambda) = \begin{cases} 1-\lambda, & \text{if } X_i^d = x^d, \\ \frac{\lambda}{(c-1)}, & \text{if } X_i^d \neq x^d \end{cases}$$

where λ is the smoothing vector for the discrete factor X and c is the number of (discrete) outcomes assumed by the factor; λ in this case lies between 0 and $(c-1)/c$. As conditional variables have two outcomes (Euro, Non-Euro or Crisis, Non-Crisis) in this context, the bandwidth parameter λ lies between 0 and 0.5.

The estimation of conditional quantiles is also relevant in our analysis to determine the distribution of cross-sectional interest rates and volatility. A conditional quantile $q_\alpha(x)$ with $0 < \alpha < 1$, is defined as

$$q_\alpha(x) = \inf\{y \in Y : F(Y|X) \geq \alpha\}. \tag{3.6}$$

This is estimated by inverting the estimated conditional cumulative distribution function corresponding to the conditional density above. This distribution is denoted as $\hat{F}(Y|X)$ and obtained from integrating $\hat{f}(y|x)$ over the domain of the random variable Y. For a given value of α and x, the conditional quantile is obtained as follows;

$$\hat{q}_\alpha(x) = \inf\{y \in Y : \hat{F}(Y|X) \geq \alpha\} = \hat{F}^{-1}(\alpha|x), \tag{3.7}$$

with $\hat{F}^{-1}(\cdot|x)$ the inverse of the estimated cumulative distribution function $\hat{F}(\cdot|X)$.

In both theoretical and practical settings, nonparametric kernel estimation has been established as being relatively insensitive to the choice of the kernel function. The same cannot be said for bandwidth selection. A widely employed technique to determine the optimal vector of bandwidth parameters is least squares cross-validation methods. The advantage of this method over other alternatives, such as a rule of thumb or plug-in methods, is that cross-validation automatically discards irrelevant information from the vector X (see Hall et al. (2004) and Li and Racine (2007, p. 69)). The method automatically determines which components of X are relevant and irrelevant, through assigning large smoothing parameters to the latter and consequently shrinking them toward the uniform distribution on the respective marginal distributions. Least squares cross validation produces asymptotically optimal smoothing for relevant components, while eliminating irrelevant components by oversmoothing. This method is based on the principle of selecting a bandwidth that minimizes the integrated square error of the resulting conditional density estimation, defined as

$$ISE = \int \left[\hat{f}(y|x) - f(y|x)\right]^2 \mu(x) M(x^c)dxdy \tag{3.8}$$

where $M(\cdot)$ is a weight function giving different importance to different sections of the conditional distribution.

4 Empirical Findings

This section is divided into three related blocks. First, we analyze the conditional density of the cross-section of monthly average daily spreads in the interbank market conditional on banks size. Second, we explore the impact of the main currency used by banks and the effect of bank nationality, with a special emphasis on the spreads of banks on countries under sovereign debt distress. Finally, we consider the dynamic version of these densities in order to assess the monthly performance of the interbank market and the relationship between the density of spreads and volatilities in this market.

4.1 Size Matters

Asset size is an important variable to determine the characteristics of a commercial bank. In fact, Angelini et al. (2011) note that before the crisis, banks' asset size is the only relevant variable that determines borrowing spreads faced by banks. These authors also consider the rating or the capitalization ratio of banks as potential proxies for bank characteristics, however they find that these variables are not statistically significant. This empirical finding is supported for the US money market by early studies such as Stigum (1990), Allen and Saunders (1986) and Furfine (2001) that draw attention to the tiering structure in the federal funds market by which large institutions get favorable rates compared to smaller institutions regardless the side of the transaction they are on. A recent study by Gabrieli (2011) confirms this tiering structure of the European market during the different phases of the crisis.

By conditioning on the size of banks trading in the interbank market, our nonparametric estimates of the density of the cross-sectional spreads uncover significant differences. Our data sample only contains information on asset size for Italian banks. There are 125 banks in our sample. The conditioning information set is defined by a discrete categorical random variable taking five possible values where a value of 1 corresponds to the smallest group of banks and a value of 5 to the biggest banks. Figure 2 reports the nonparametric densities for the borrowing spreads over the different subperiods and Figure 3 the nonparametric estimates of the volatilities as defined in (2.2). Figures 4 and 5 report the analogous densities for the lending rates. Tables 3 and 4 report the bandwidth parameters corresponding to the different kernel density estimates.

These charts describe an interbank money market that abruptly moves from a stable market condition defined by similar funding rates across banks regardless the size to a heterogeneous market characterized by very different borrowing/lending conditions at the start of the crisis. On the borrowing side, we observe important differences between the density of the largest (Italian) banks and the rest of banks. This difference is accentuated after the tensions in debt markets that emerged in September 2008. During this period the differences in borrowing costs between banks of different sizes are substantial; the existence of three modes in the density of the spreads on the largest banks signals the clustering of banks in terms of their creditworthiness. Banks in the left tail of the distribution enjoy significantly smaller borrowing rates than the rest of banks. Nevertheless, there is another group of banks with rates not far from the average borrowing rate over this period. The existence of three modes also indicates that size is not the only relevant variable for explaining borrowing rates. A recent study by Gabbi et al. (2012) suggests for example that some larger banks have better exploited changing microstructure features of the interbank market during the crisis. After the crisis the differences between banks decrease but are still noticeable. The charts in Figure 3 reveal an increase in volatility as we move towards the Lehman Brothers collapse. This phenomenon is not observed simultaneously for all banks. The densities evolve from having one to two modes and the tails also become thicker revealing the existence of two types of banks: some banks exhibiting similar funding costs over this period and other banks exhibiting highly variable funding costs. This variability becomes systemic after the collapse of Lehman Brothers. Interestingly, after the second phase of the crisis, the group of largest banks also exhibits the largest variations in borrowing costs. This implies that for some days of the maintenance period these banks obtain very favorable rates compared to the average spread on that day, and other days the funding rates are close to the average daily spread. These measures of volatility give evidence of tension and uncertainty in interbank markets over the crisis periods. After 2009, the volatility in the borrowing segment considerably declines and returns to levels before 2007.

The analysis of the lending segment in Figure 4 exhibits less contrast. Lending rates are similar across bank sizes. It is only after the collapse of Lehman Brothers that the group of largest banks has the highest lending rates. The corresponding densities are also bimodal giving support to the idea that not only size matters for explaining lending rates. The high spreads obtained by large banks could be the result of relationship lending, as suggested by Cocco et al. (2009), Affinito

(2011), and Brauning (2011). The analysis of volatility in Figure 5 shows similar patterns to those observed for the borrowing segment. The overall picture describes a market in which size is a key variable for determining bank profitability. Largest banks enjoy highest lending rates and lowest borrowing rates over the cross-section of banks acting in the e-MID market.

4.2 The Role of Operating Currency and Bank's Nationality

Our sample covers a non-crisis and a crisis periods. The number of active countries in the e-MID market over both periods is sixteen. Most of these countries have adhered the Euro currency. These countries are Austria, Belgium, France, Germany, Greece, Ireland, Luxembourg, Netherlands, Portugal and Spain. A few other participating countries such as Britain, Denmark, Norway, Poland and Switzerland do not use the common currency, though. Commercial banks in the second group of countries are not allowed to open a Euro account with the ECB, and hence they cannot use ECB deposit facilities. Figures 6 and 7 describe the densities of interbank spreads conditional on the main currency on which the bank operates. The graphs show no differences in funding rates until the second phase of the crisis (Lehman Brothers collapse). After it, the nonparametric densities indicate larger funding costs for banks in non-Euro countries than for banks in countries using the Euro as main currency. On the lending side, we find the same results. Non-Euro banks request higher spreads for lending funds to other banks than Euro banks. These higher lending rates are likely to be due to the need of counteracting higher borrowing costs.

Although our sample does not contain information on size for foreign banks, it is plausible to assume that foreign banks are of comparable size to the largest Italian banks. This assumption is supported by the statistics on average transaction size for foreign banks reported in Table 1 and by observational evidence that notes that large European banks trade in international markets but smaller ones are restricted to domestic markets. Figures 6 and 7 also present the comparison between the densities of the largest Italian banks and foreign banks. These figures reveal interesting insights on the extent of asymmetric information by borrowers and lenders on large banks of different nationalities. During the 'Interbank Crisis' period and afterwards, funding conditions become tougher for foreign banks compared to their domestic counterparties. This phenomenon marks a rupture in the integration of the interbank market. From this period, we observe a segmented market that favors domestic banks. These findings are in line with the theoretical framework developed in Freixas and Holthausen (2005) on the role of asymmetric information on interbank markets.

The study of banks' nationality on the cross-sectional distribution of spreads has recently gained importance given the unprecedented increase in spreads observed in some European sovereign debt markets. Although our sample ends in August 2009, we investigate whether there is early evidence of any discrepancy on funding conditions between banks based in countries experiencing a sovereign crisis in posterior periods and the rest of banks. Countries exposed to sovereign crisis are Greece, Ireland, Portugal and Spain. Figures 8 and 9 represent the densities of interbank spreads conditional on being in the latter group of countries or not. The differences reflected in borrowing conditions after the collapse of Lehman Brothers are very significant. Banks in countries under sovereign distress experience borrowing rates well above those of banks based in undistressed economies. The lending side, on the other hand, does not reflect significant differences in funding rates between banks from distressed economies and the rest of European banks. These findings show evidence of borrowing difficulties for banks in these countries well before the respective countries had trouble in funding themselves. Further, these results suggest that the rise in funding costs that these countries have experienced is largely due to the collapse of their banks and the need of financing mounting levels of private debt.

We must note that this is an aggregate result obtained from pooling information from banks in the four countries above mentioned. In order to extract meaningful information on which countries are mainly driving these results a more detailed analysis conditioning on specific countries and not on economic regions should be performed. With this purpose, we choose to focus on Greece and compare their banks' funding conditions with those of banks in Britain and Germany. The results in Figures 10 and 11 illustrate the remarkable differences in borrowing conditions between banks based in Germany and Greece. These graphs also reveal a more pronounced effect of the Lehman Brothers collapse on the borrowing rates of British banks than of German banks indicating the higher exposure of the British banking sector to the US economy. On the lending side, we do not observe substantial differences on spreads conditional on banks' nationality. It is interesting to observe that in the last period Greek banks exhibit a bimodal distribution indicating the existence of a small group of, possibly troubled, banks offering lending rates well below market rates.

4.3 Dynamics of Spreads: Mean and Volatility

The above densities discussed in previous sections provide very detailed information about the performance of the interbank market over six subperiods covering the period 2006 to 2009. The density functions obtained in previous subsections are computed by pooling information on interest rates for each bank obtained over the months comprised in each subperiod. This methodology is very useful for obtaining aggregate measures of cross-sectional spreads over periods of economic relevance, however, the pooling of information for constructing the above densities can average out variations in monthly interest rates and neglect the occurrence of more pronounced peaks and troughs in the monthly dynamics of the cross-sectional distributions.

In this subsection, we perform a more detailed analysis of the monthly time series of spreads. This study is complemented by the dynamic analysis of the density of rates' volatility as discussed in Section 2.2. For expositional purposes we concentrate on a discrete set of relevant quantiles of the distribution of these quantities rather than their complete density functions. The study focuses on the 10%, 25%, 50%, 75% and 90% percentiles. This can be easily done by exploiting the flexibility of the nonparametric kernel density estimation method that allow us to obtain quantiles of the relevant underlying distributions. Figure 12 presents this dynamic quantile analysis for the means and volatilities of the borrowing spreads; Figure 13 reports the analysis corresponding to the lending spreads.

The mean and volatility patterns are similar across borrowing and lending costs. At the beginning of the sample, interbank rates show very little dispersion indicating small differences in borrowing and lending conditions across banks participating in the e-MID market. The graph reports an increase in the dispersion of rates that becomes apparent from July 2007 until January 2008. This increase in the dispersion of bank rates signals a heterogeneous performance in both segments of the interbank market. During these months the risk premium on banks searching for liquidity varies substantially indicating important differences in borrowing and lending conditions across banks trading on the interbank market. The distribution of both borrowing and lending rates remains symmetric during this period, this is not so during the second phase of the crisis. In the borrowing segment, the median spread during this period is below zero indicating that more than 50% of the banks in the e-MID market obtain funding rates below the cross-sectional average. This implies the presence of a few problematic banks viewed as risky and receiving large borrowing rates. These findings suggest that whereas the crisis is widespread in the banking sector during the first phase of the crisis and affects all banks in the system in a similar way, during the second phase, it is of a more idiosyncratic nature and can be pinned down to the collapse of a few distressed banking institutions. The dispersion in funding rates and asymmetric cross-sectional distribution becomes more moderate during 2009 without managing to recover the levels prior to the crisis. The lending market exhibits similar findings; the asymmetric behavior of lending rates is less apparent than in the borrowing side and indicates that the increase in asked rates is of similar magnitude across the spectrum of banks in the supply side of the e-MID system.

The analysis of the quantile process of volatilities yields interesting findings. Volatility spikes characterized in this framework by increases in the upper quantiles of the distribution of volatilities are prior to the spikes observed in the distribution of spreads. This empirical finding provides support to the existence of what is called in the analysis of equity market returns as *leverage effect*. Roughly speaking, increases in the volatility of spreads are responded by increases in funding rates over the next periods. Thus, during the period January to May 2007 banks in the upper quantiles experience important differences in funding rates over the maintenance period. This phenomenon signals high levels of uncertainty in the interbank market over the health of these banks. At the start of the crisis, July 2007, uncertainty is resolved and troubled banks receive high and stable borrowing rates over the next periods. During the second phase of the crisis, spread and volatility increases go hand in hand. Borrowing and lending rates widen over this period due to the existence of a few troubled banks. In contrast to the first phase of the crisis, this period is characterized by huge levels of uncertainty in the whole banking sector that is reflected in highly variable daily spreads over the maintenance periods.

5 Conclusion

Interbank markets are the main instrument for the transmission of monetary policy targets from central banks to the overall economy. This market is responsible for supplying liquidity to the financial system through the buying and selling operations of participant commercial banks. The cross-section of interbank rates provides useful information on the performance of the banking sector.

This article explores the cross-sectional distribution of aggregate monthly rates obtained as the average of daily spreads. These spreads are defined as deviations of daily funding rates from the daily average interest rate outstanding in the market. The reference market that we use is the e-MID market. Our dataset contains 125 Italian banks and 90 foreign banks acting as borrowers, lenders or both between 12 July 2006 and 8 September 2009. Our empirical analysis is based on nonparametric kernel estimation methods for the density of the different quantities under study. The analysis is threefold: we explore the effect of banks size, the main currency used by banks and their nationality, on the spreads observed in the e-MID interbank market. We find evidence of important differences between the borrowing and lending markets. The results strongly support the existence of a size effect in the borrowing market. Size is a key variable for determining bank profitability; largest banks enjoy highest lending rates and lowest borrowing rates over the cross-section of banks acting in the e-MID market. The collapse of Lehman Brothers accentuates the differences in funding conditions between largest banks and the rest.

The dynamic analysis of the cross-section of spreads shows that the 2007 and 2008 crises have different implications. The first crisis has widespread effects on the entire banking sector, reflected in higher borrowing spreads across the sector. The second crisis caused by the collapse of some major financial institutions produces uncertainty in daily interest rates in both borrowing and lending segments. However, the quantile process of spreads shows an interbank market given by a small sample of troubled banks exhibiting high spreads with the rest of banks obtaining borrowing spreads below the cross-sectional average. In both borrowing and lending segments, we observe that crises are corresponded by a large variability in daily funding costs.

Our analysis of the role of the Euro currency on the spread faced by banks participating in the e-MID market suggests that banks in the Euro currency area obtain lower funding rates than banks based in non-Euro countries. This can be due to the existence of the European Central Bank acting as a potential liquidity provider in the Euro system or to the perception that Euro countries are less risky than their non-Euro counterparts. Interestingly, non-Euro countries also have higher lending rates. The analysis of the relationship between interbank rates and sovereign crisis reveals important differences in borrowing costs between banks in Greece, Ireland, Portugal and Spain compared to the rest of banks. These results suggest that distress in the banking sector of these countries is prior to the occurrence of their respective sovereign crises, and the interbank market provided early warning signals of the incoming sovereign crisis.

References

[1] Affinito, 2011. Do Interbank Customer Relationships Exist? And How did They Function over the Crisis? Learning from Italy. Bank of Italy Working Paper 826.

[2] Afonso, G., A. Kovner and A. Schoar, 2011. Stressed, Not Frozen: The Federal Funds Market in the Financial Crisis. Journal of Finance 66 (4), 1109-39.

[3] Aitchison,J. and C. G. G. Aitken, 1976. Multivariate Binary Discrimination by the Kernel Method. Biometrika 63, 413-420.

[4] Allen, L. and A. Saunders, 1986. The Large-Small Bank Dichotomy in the Federal Funds Market. Journal of Banking and Finance 10, 219-230.

[5] Angelini, P., A. Nobili and C. Picillo, 2011. The Interbank Market after August 2007: What has changed and why? Journal of Money,Credit and Banking 43 (5), 923-958.

[6] Bhattacharya, S. and D. Gale, 1987. Preference Shocks, Liquidity and Central Bank Policy, in W. Barnett, and K. Singleton (eds.), New Approaches to Monetary Economics, 69-88, New York: Cambridge University Press.

[7] Brauning F. and F. Fecht, 2011. Relationship Lending and Peer Monitoring: Evidence from Interbank Payment Data. Working Paper.

[8] Cocco J. F., F. J. Gomes and N. C. Martins, 2009. Lending Relationships in the Interbank Market, Journal of Financial Intermediation, 18.

[9] Freixas, X., B. M. Parigi and J. Rochet, 2000. Systemic Risk, Interbank Relations and Liquidity Provision by the Central Bank. Journal of Money, Credit and Banking 32 (3), 611-638.

[10] Freixas, X. and C. Holthausen, 2005. Interbank Market Integration under Asymmetric Information. Review of Financial Studies 18 (2), 459-490.

[11] Furfine, C. H., 1999. The Microstructure of the Federal Funds Market. Financial Markets, Institutions and Instruments 8 (5), 24-44.

[12] Furfine, C. H., 2001. Banks as Monitors of Other Banks: Evidence from the Overnight Federal Funds Market. The Journal of Business 74, 33-57.

[13] Gabbi G., G. Germano, V. Hatzopoulos, G. Iori and M. Politi, 2012. The Microstructure of European Interbank Market and Its Role in the Determination of Cross-Sectional Credit Spreads. Working Paper.

[14] Gabrieli, S., 2011a. The Functioning of the European Interbank Market During the 2007-08 Financial Crisis. CEIS Working Paper 158.

[15] Gabrieli S., 2011b. Too-interconnected versus Too-Big-to-Fail: Banks' Network Centrality and Overnight Interest Rates. Tor Vergata University Working Paper.

[16] Gaspar, V., G. P. Quiros and H. R. Mendizabal, 2008. Interest Rate Dispersion and Volatility in the Market for Daily Funds. European Economic Review 52, 413-440.

[17] Hall, P., J. Racine and Q. Li, 2004. Cross-Validation and the Estimation of Conditional Probability Densities. Journal of the American Statistical Association 99, 1015-1026.

[18] Ho, T. and A. Saunders, 1985. A Micro-Model of the Federal Funds Market, Journal of Finance 40, 977-990.

[19] Iazzetta, C. and M. Manna, 2009. The Topology of the Interbank Market: Developments in Italy Since 1990. Bank of Italy Working Paper 711.

[20] Li, Q. and J. S. Racine, 2007. Nonparametric Econometrics. Princeton University Press.

[21] Stigum, M., 1990. The Money Market. Third Edition. Homewood, Ill.: Dow Jones-Irwin.

[22] Wang, M. C. and J. van Ryzin, 1981. A Class of Smooth Estimators for Discrete Distributions. Biometrika 68, 301-309.

Tables

Table 1. Participation of Different Groups to the e-MID Market

	Market Share (Transaction Number)		Market Share (Total Volume)		Average Transaction Size	
	Borrower	**Lender**	**Borrower**	**Lender**	**Borrower**	**Lender**
Minor-Domestic (31 Banks)	5%	10.4%	2%	3%	17	16
Small-Domestic (63 Banks)	47%	50%	16%	19%	17	19
Medium-Domestic (16 Banks)	15%	11%	10%	11%	32	31
Large-Domestic (9 Banks)	14%	9%	12%	8%	42	45
Major-Domestic (6 Banks)	7%	7%	10%	11%	67	80
Foreign Banks (90 Banks)	11%	11%	50%	51%	220	212

Table 2. Information about Sub-Periods

Dates	Explanation	Number of Months	Periods
July 06-Jan 07	2006-2 Before Crisis	6	Period 1
Jan 07-Aug 07	2007-Financial Markets Unease	6	Period 2
Aug 07-Mar 08	Interbank Crisis	8	Period 3
Mar 08-Sep 08	Before Lehman Brothers Collapse	6	Period 4
Sep 08-Mar 09	After Lehman Brothers Collapse	6	Period 5
Mar 09-Sep 09	2009-Post Crisis	6	Period 6

Table 3. Optimal Bandwidth Parameters of Conditional Density Estimation of Spread & Volatility on Asset Size

	Period	Asset Size	Spread	Observation Number	Asset Size	Volatility of Spread	Observation Number
Borrower	**Period 1**	0.09(1.00)	0.002	462	0.77(1.00)	0.040	431
	Period 2	0.23(1.00)	0.003	441	0.89(1.00)	0.010	407
	Period 3	0.17(1.00)	0.007	582	0.29(1.00)	0.029	532
	Period 4	0.27(1.00)	0.012	411	0.32(1.00)	0.014	389
	Period 5	0.07(1.00)	0.036	374	1.00(1.00)	0.024	334
	Period 6	0.07(1.00)	0.018	365	0.38(1.00)	0.012	324
Lender	**Period 1**	0.26(1.00)	0.002	605	0.28(1.00)	0.002	581
	Period 2	0.26(1.00)	0.003	571	0.51(1.00)	0.003	553
	Period 3	0.66(1.00)	0.004	741	0.54(1.00)	0.004	715
	Period 4	0.19(1.00)	0.008	553	0.73(1.00)	0.003	527
	Period 5	0.31(1.00)	0.023	510	1.00(1.00)	0.16	479
	Period 6	0.13(1.00)	0.014	499	1.00(1.00)	0.008	466

Note: Bandwidth Parameters of Conditional Densities are estimated with Least Squares Cross-Validation Method for each sub-periods covering from July 2006 to August 2009. Kernel Function for Spread and Volatility is Gaussian and Kernel Function for Asset Size is Wang and van Ryzin (1981).

Table 4. Optimal Bandwidth Parameters of Conditional Density Estimation of Spread on Nationality Classifications

	Period	Euro-NonEuro	Spread	Observation Number	Crisis-NonCrisis	Spread	Observation Number
Borrower	**Period 1**	0.50(0.5)	0.001	266	0.25(0.5)	0.003	266
	Period 2	0.40(0.5)	0.003	276	0.10(0.5)	0.003	276
	Period 3	0.50(0.5)	0.007	307	0.25(0.5)	0.006	307
	Period 4	0.25(0.5)	0.014	227	0.01(0.5)	0.004	227
	Period 5	0.37(0.5)	0.036	135	0.01(0.5)	0.036	135
	Period 6	0.50(0.5)	0.018	116	0.02(0.5)	0.014	116
Lender	**Period 1**	0.14(0.5)	0.002	303	0.05(0.5)	0.002	303
	Period 2	0.25(0.5)	0.002	344	0.10(0.5)	0.002	344
	Period 3	0.25(0.5)	0.006	434	0.09(0.5)	0.007	434
	Period 4	0.02(0.5)	0.011	297	0.25(0.5)	0.011	297
	Period 5	0.50(0.5)	0.038	176	0.50(0.5)	0.038	176
	Period 6	0.50(0.5)	0.026	117	0.50(0.5)	0.026	117

Note: Bandwidth Parameters of Conditional Densities are estimated with Least Squares Cross-Validation Method for each sub-periods covering from July 2006 to August 2009. Kernel Function for Spread and Volatility is Gaussian and Kernel Functions for Euro/Non-Euro and Crisis/Non-Crisis classifications are Aitchison and Aitken(1976).

Figures

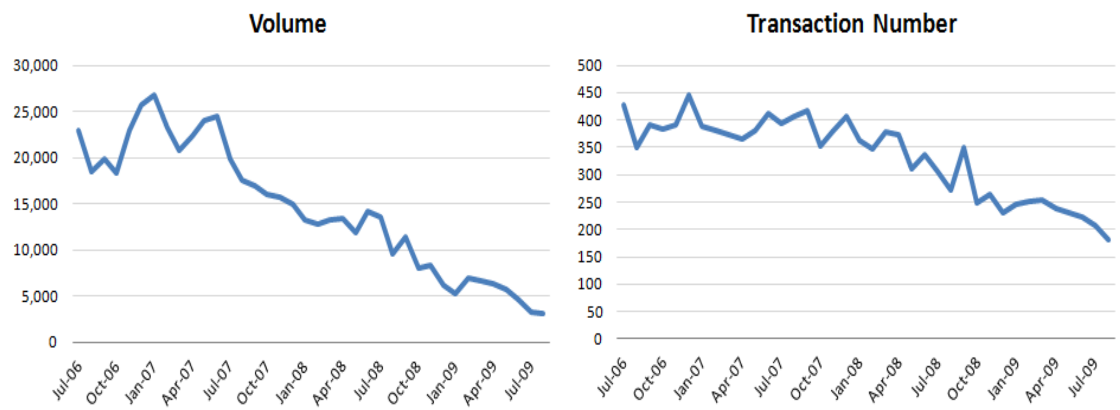

Figure 1: Monthly Average of Daily Volume and Number of Transactions

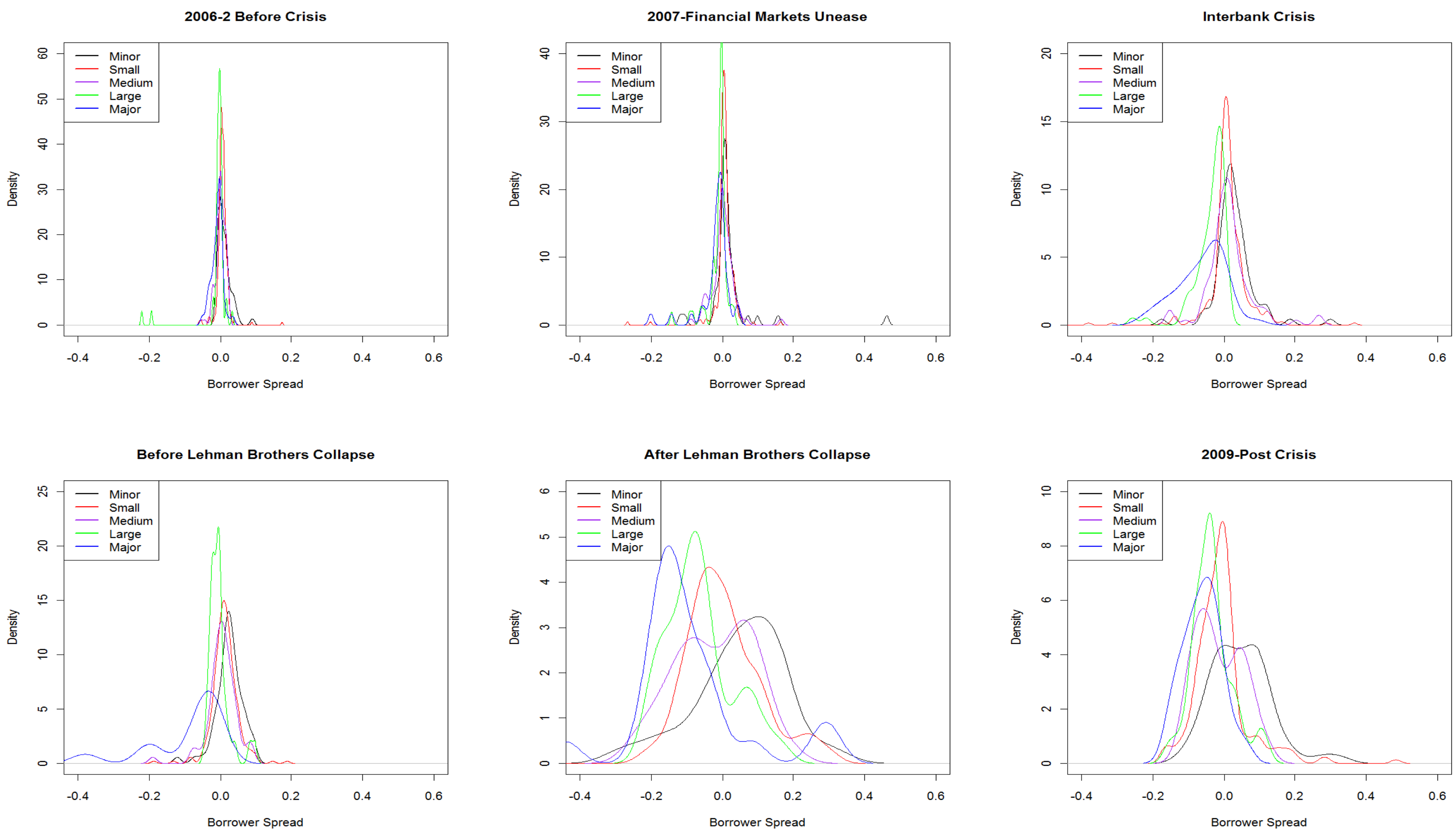

Figure 2: Estimated Conditional Densities of Spreads for Minor, Small, Medium, Large and Major Domestic Borrowers. Sample Period: 2006:07-2009:09. Kernel Function for Spread: Gaussian

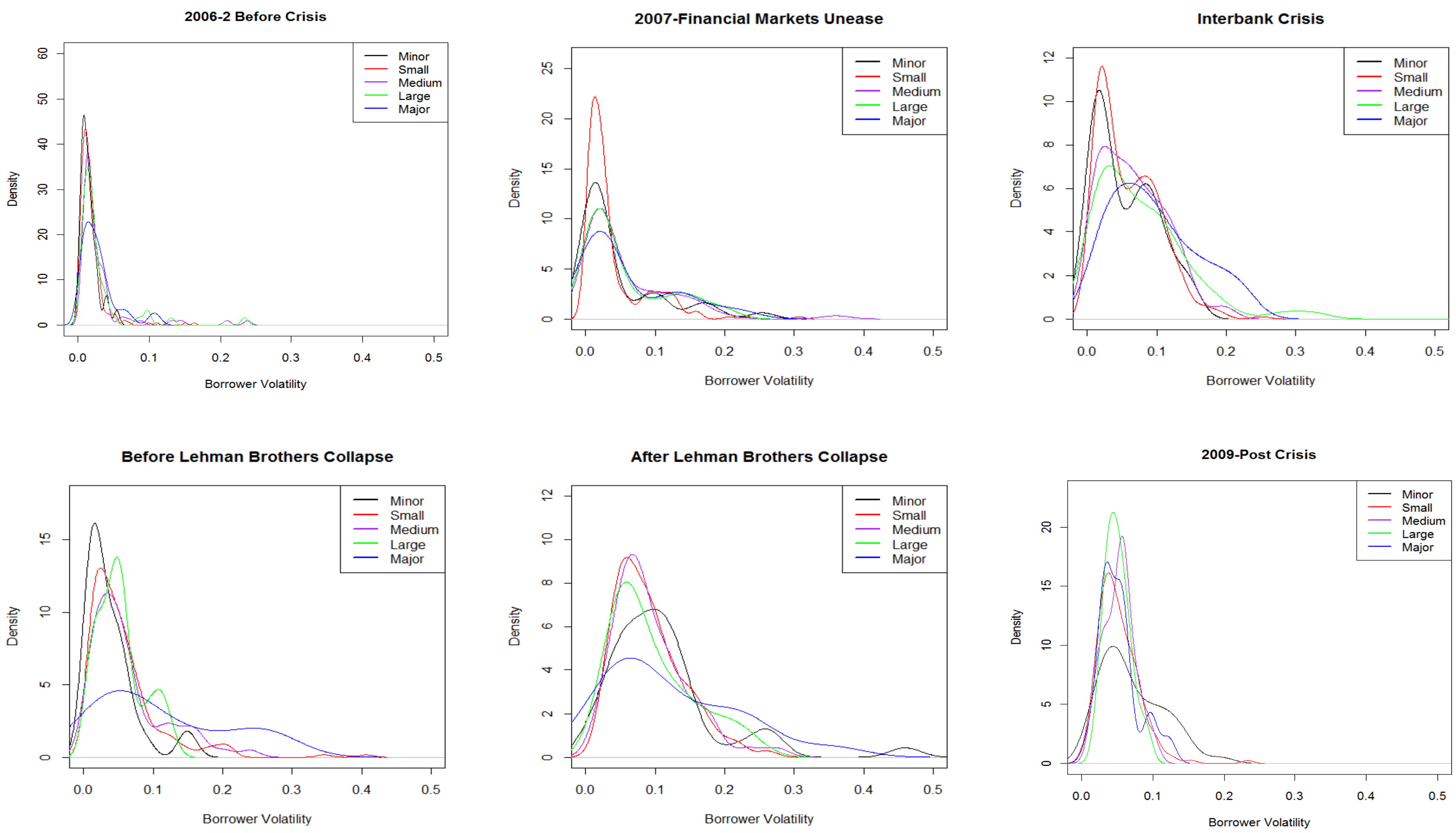

Figure 3: Estimated Conditional Densities of Volatility of Spreads for Minor, Small, Medium, Large and Major Domestic Borrowers. Sample Period: 2006:07-2009:09. Kernel Function for Spread: Gaussian

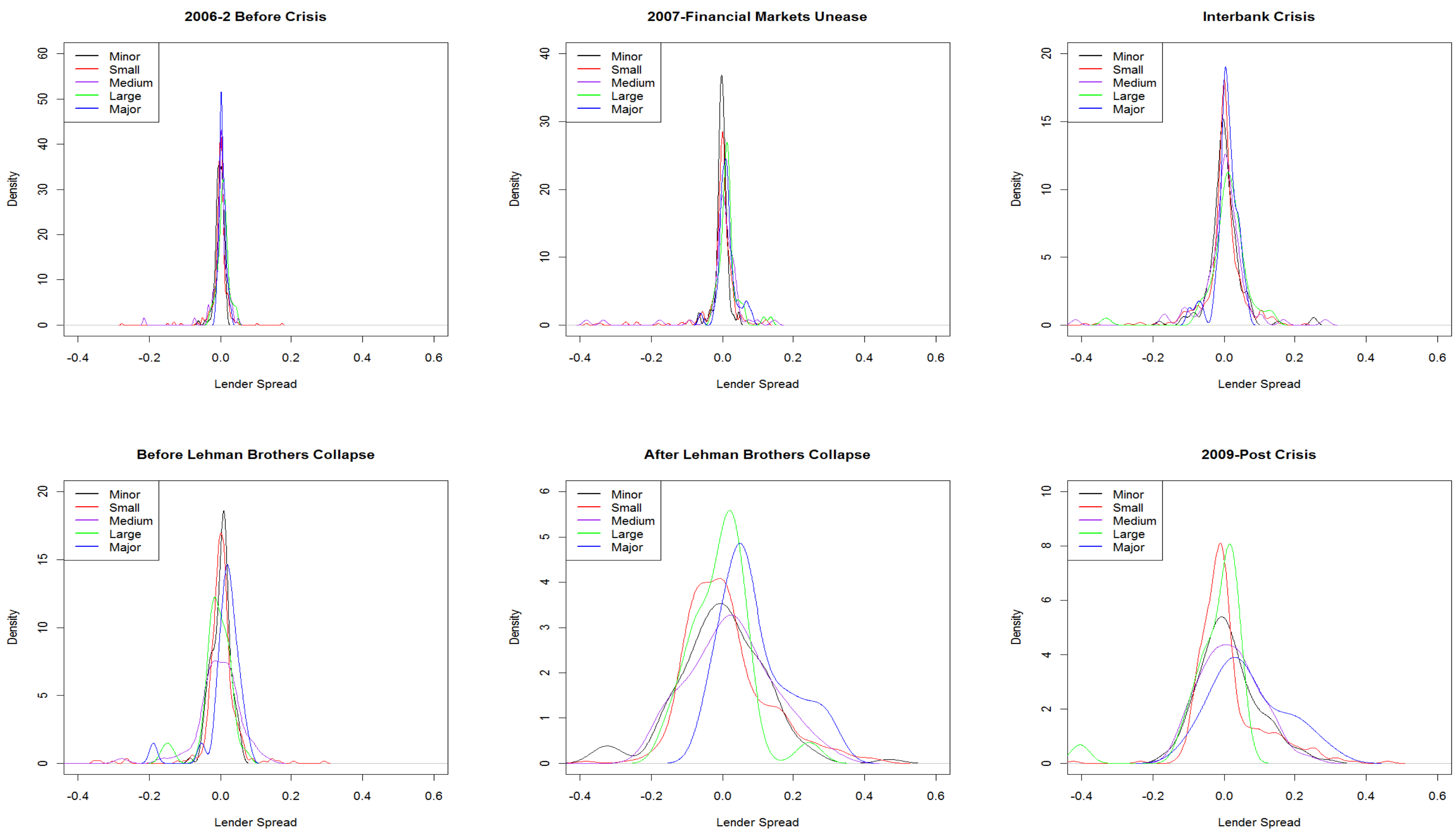

Figure 4: Estimated Conditional Densities of Spreads for Minor, Small, Medium, Large and Major Domestic Lenders. Sample Period: 2006:07-2009:09. Kernel Function for Spread: Gaussian

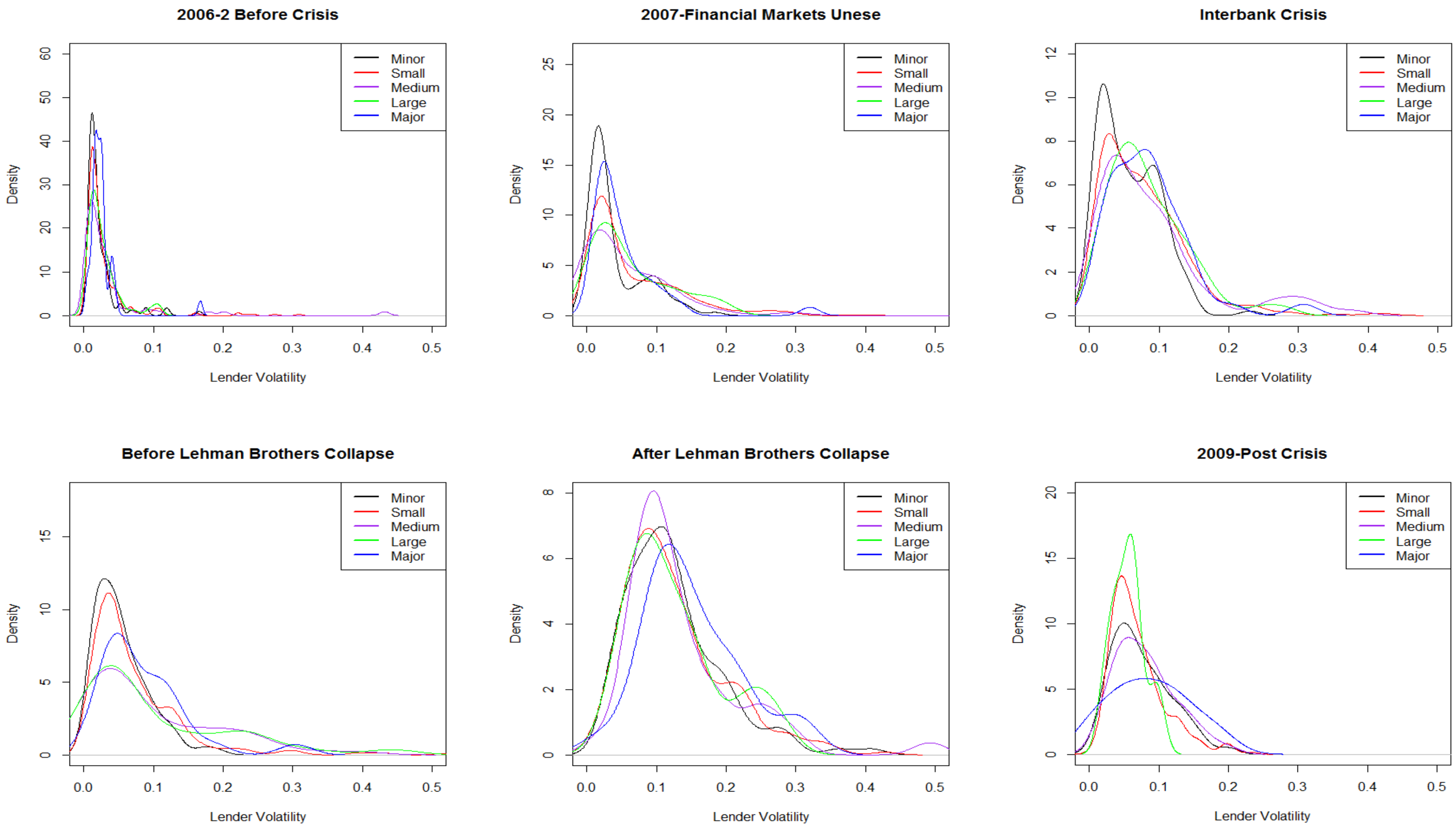

Figure 5: Estimated Conditional Densities of Volatility of Spreads for Minor, Small, Medium, Large and Major Domestic Lenders. Sample Period: 2006:07-2009:09. Kernel Function for Spread: Gaussian

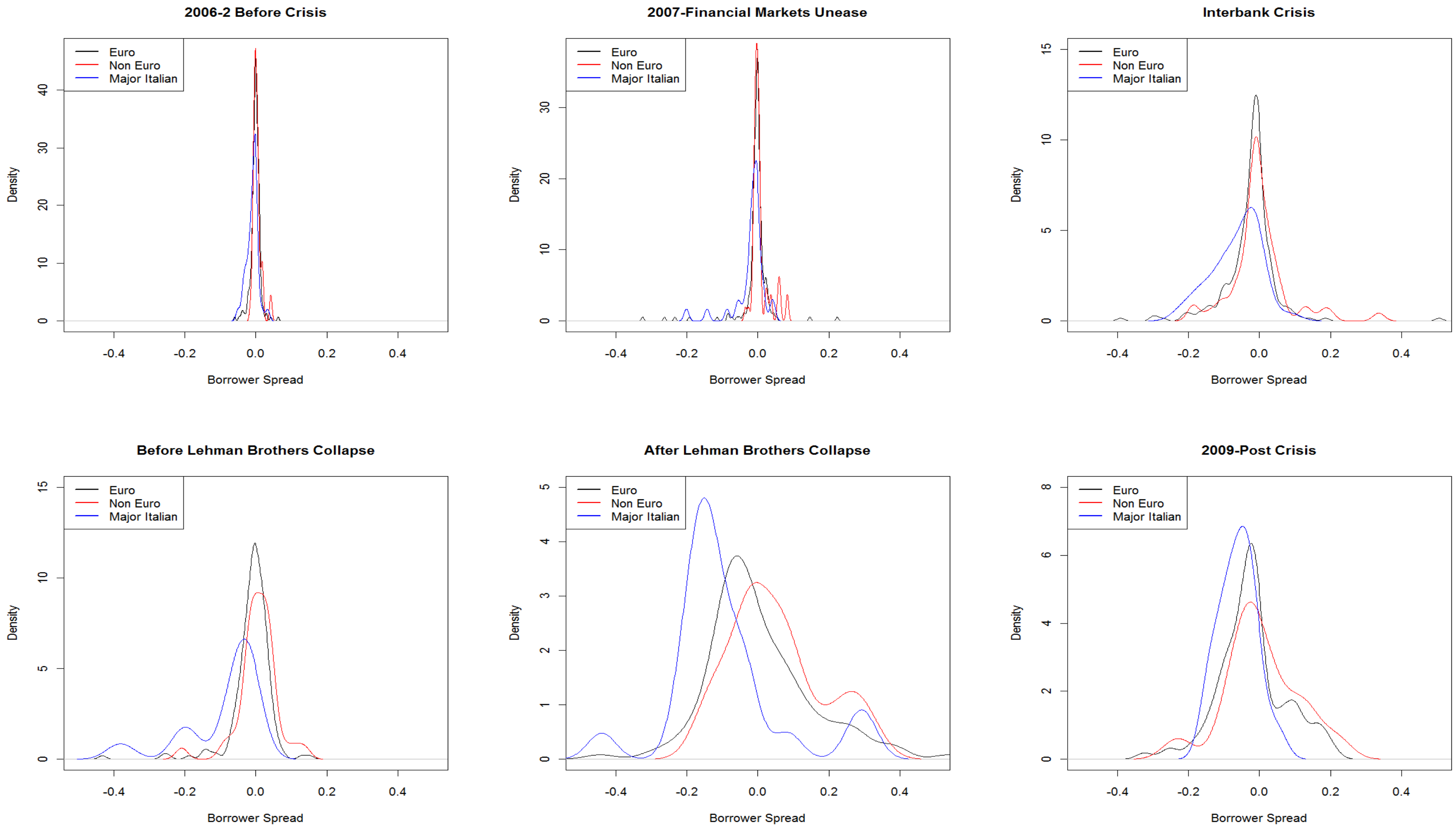

Figure 6: Comparison of Estimated Conditional Densities of Spreads for Foreign Borrowers using Euro or other currency with Major Domestic Borrowers. Sample Period: 2006:07-2009:09. Kernel Function for Spread: Gaussian

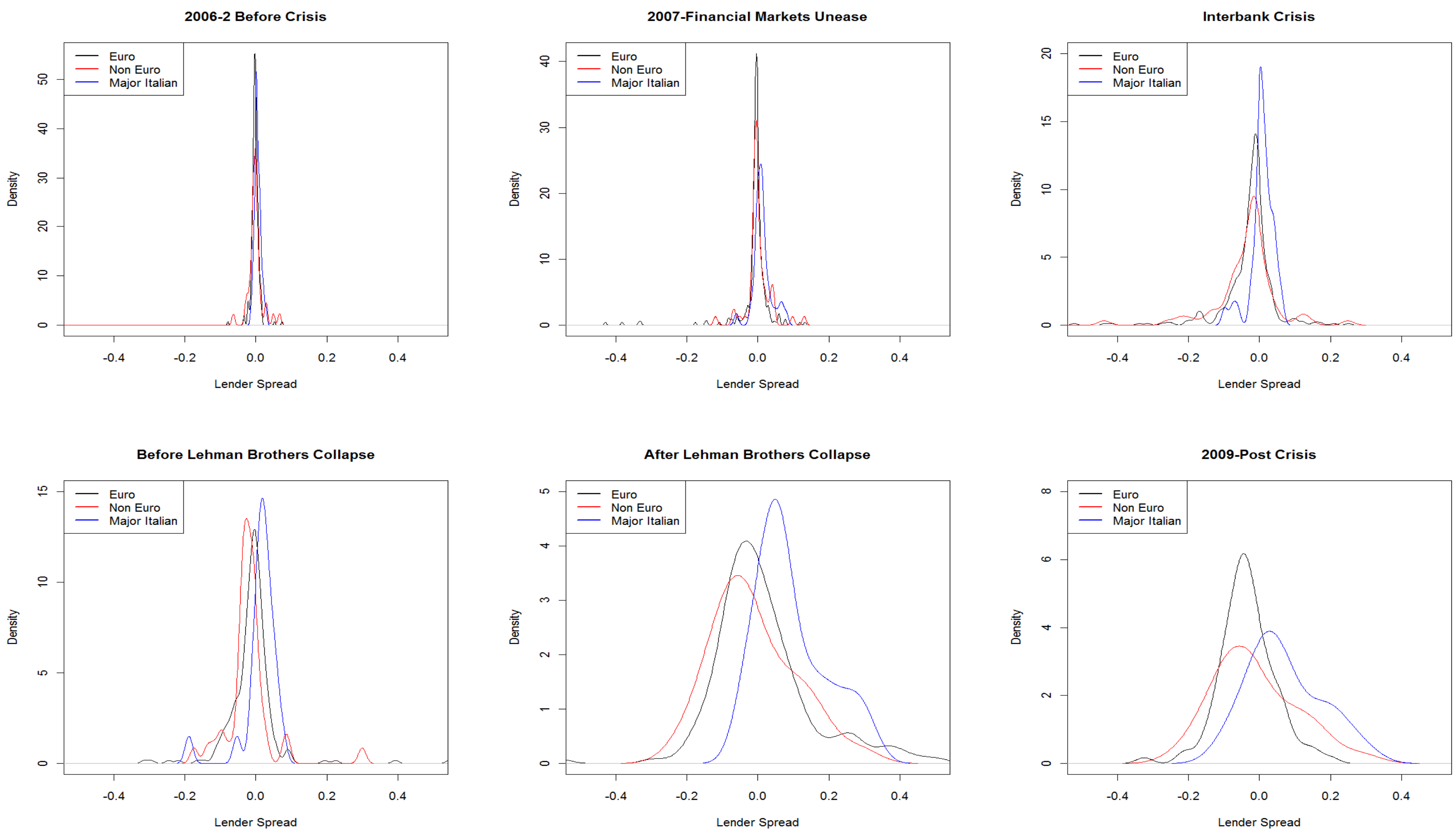

Figure 7: Comparison of Estimated Conditional Densities of Spreads for Foreign Lenders using Euro or other currency with Major Domestic Lenders. Sample Period: 2006:07-2009:09. Kernel Function for Spread: Gaussian

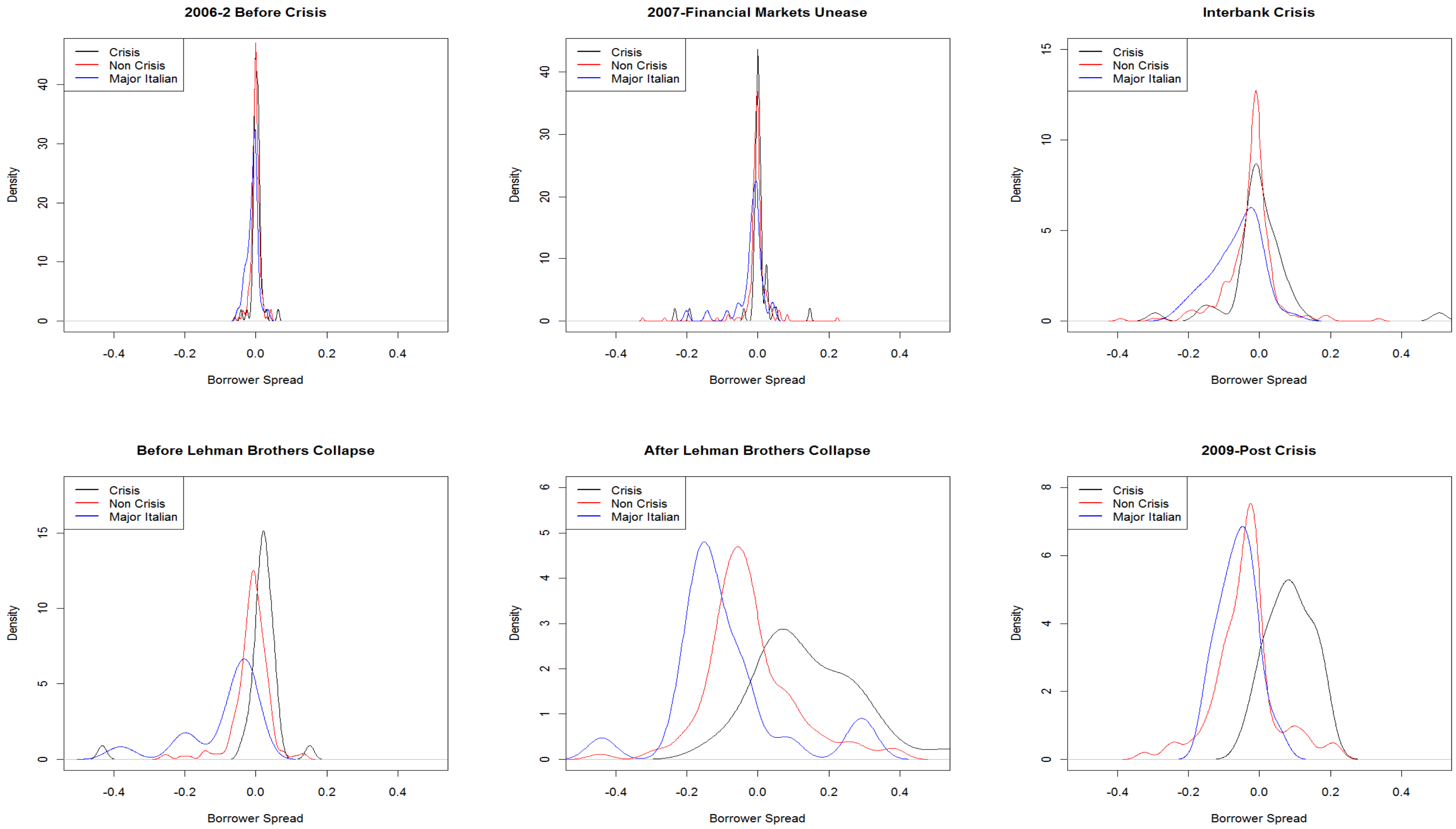

Figure 8: Comparison of Estimated Conditional Densities of Spreads for Foreign Borrowers experiencing Sovereign Crisis or not with Major Domestic Borrowers. Sample Period: 2006:07-2009:09. Kernel Function for Spread: Gaussian

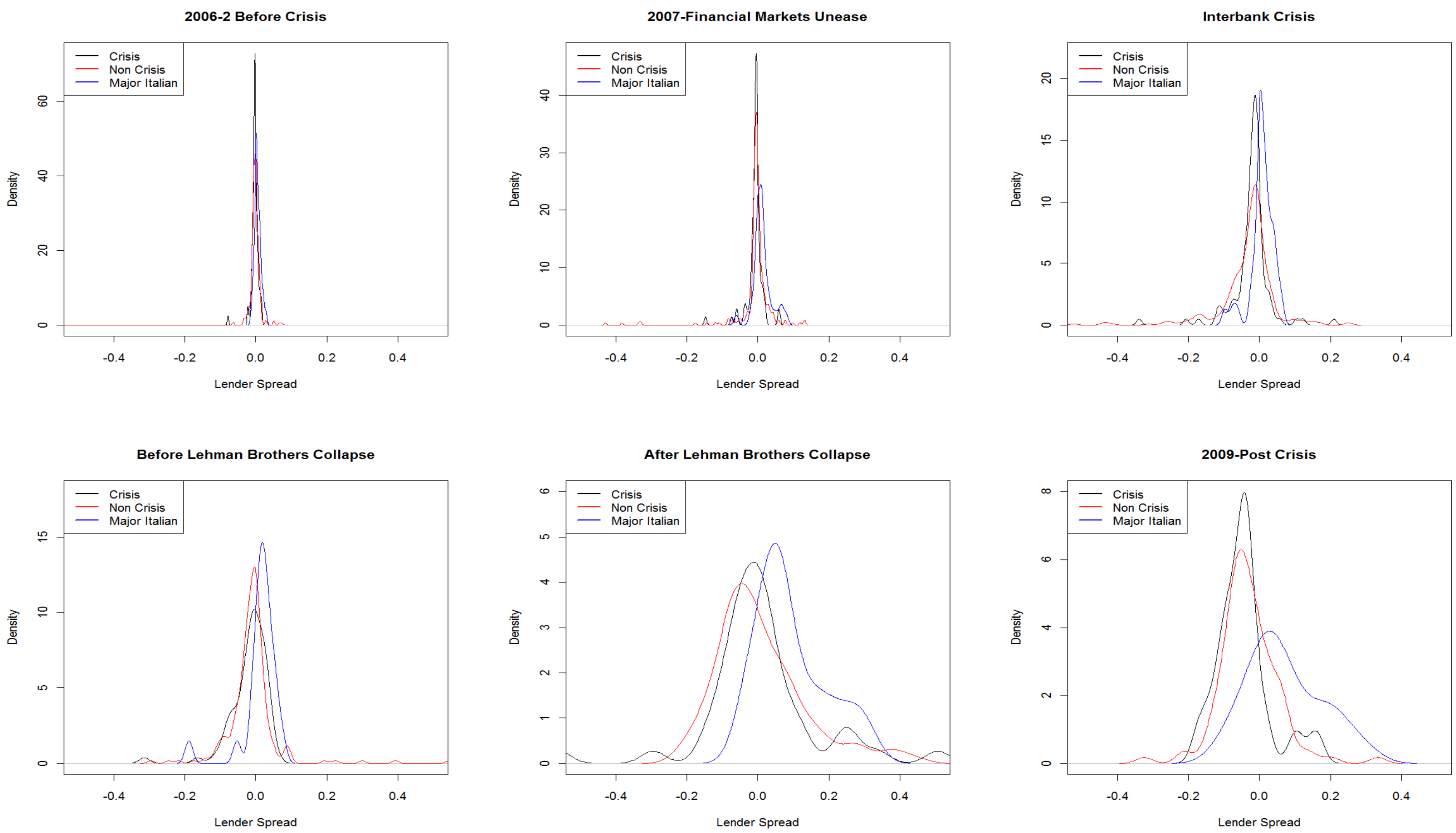

Figure 9: Comparison of Estimated Conditional Densities of Spreads for Foreign Borrowers experiencing Sovereign Crisis or not with Major Domestic Lenders. Sample Period: 2006:07-2009:09. Kernel Function for Spread: Gaussian

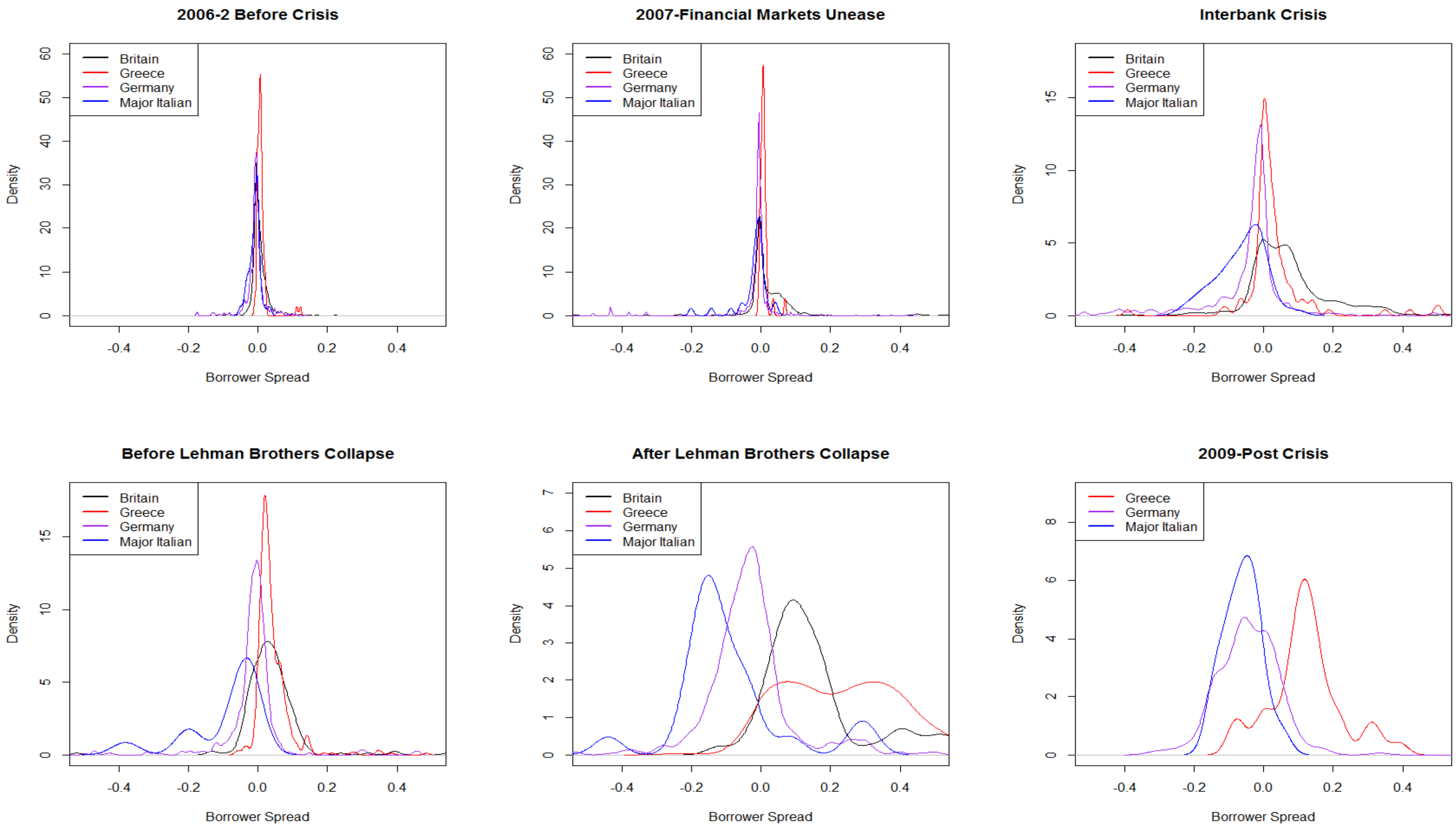

Figure 10: Comparison of Estimated Conditional Densities of Spreads for Britain, Germany, Greece with Major Domestic Borrowers. Sample Period: 2006:07-2009:09. Kernel Function for Spread: Gaussian

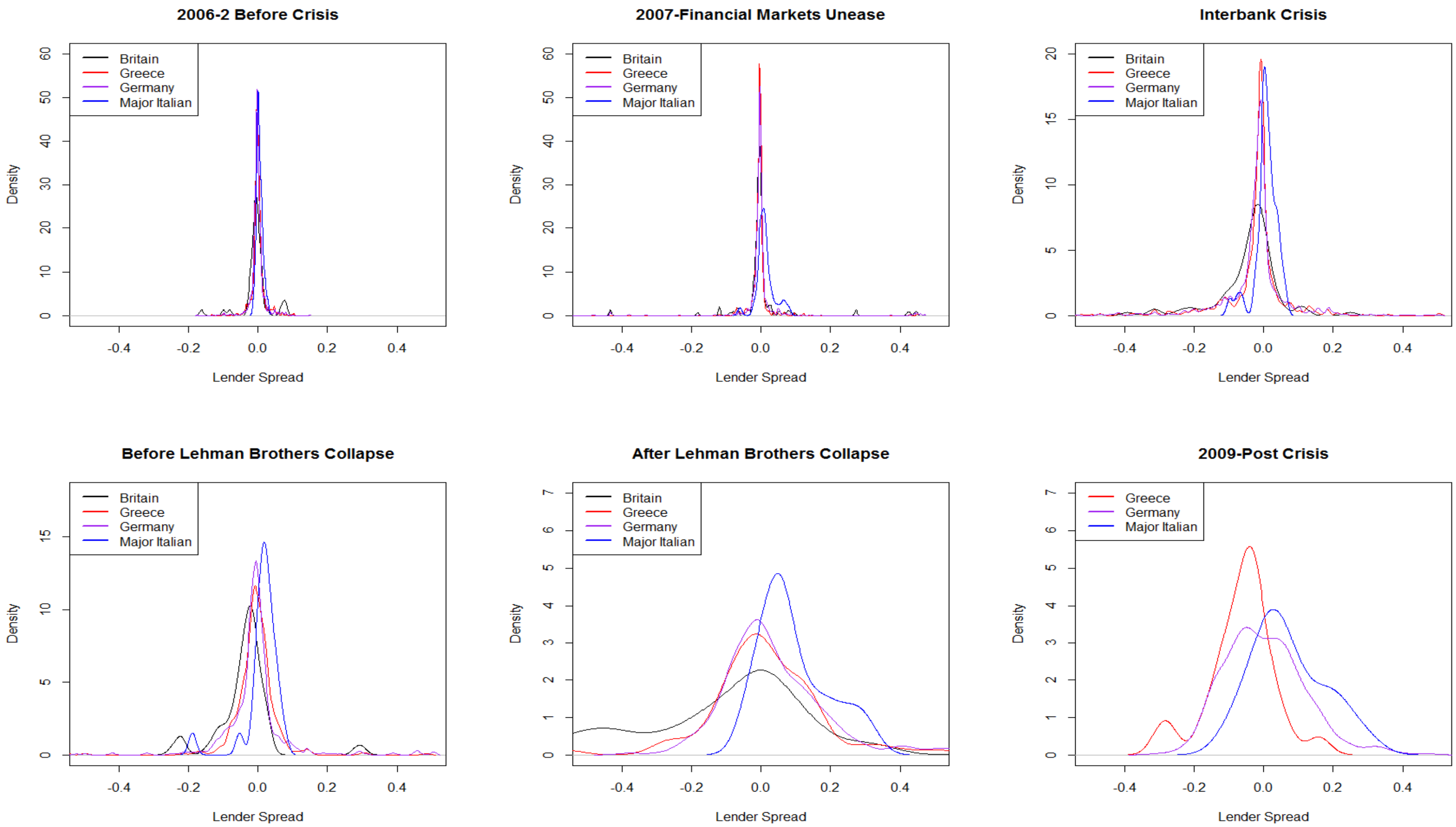

Figure 11: Comparison of Estimated Conditional Densities of Spreads for Britain, Greece and Germany with Major Domestic Lenders. Sample Period: 2006:07-2009:09. Kernel Function for Spread: Gaussian

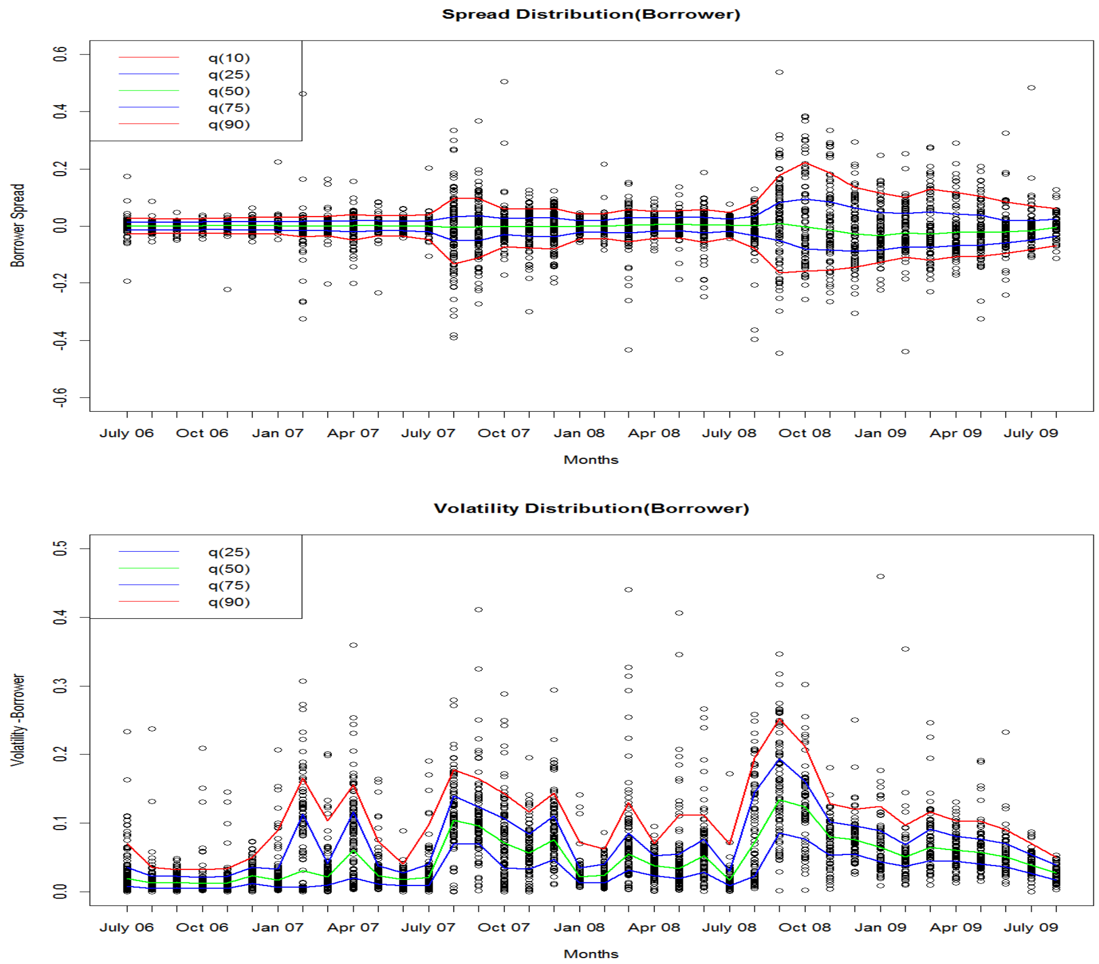

Figure 12: Conditional Density of Estimation of Borrower Spread-Volatility of Spread on Monthly Time Period with Conditional Quantile Functions for 10%, 25%, 50%, 75% and 90% Percentiles. Sample Period: 2006:07-2009-09. Bandwidth Selection Method: Least Squares Cross-Validation.

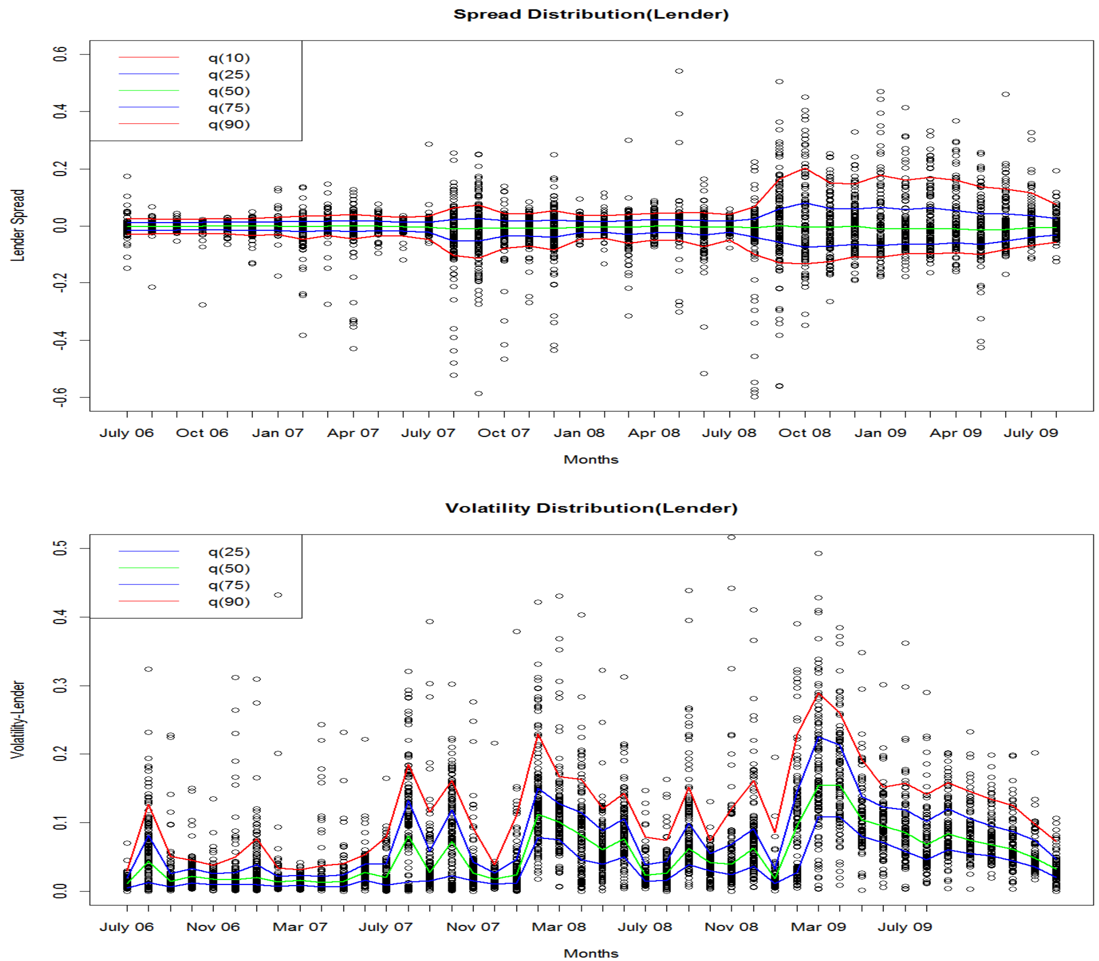

Figure 13: Conditional Density of Estimation of Lender Spread-Volatility of Spread on Monthly Time Period with Conditional Quantile Functions for 10%, 25%, 50%, 75% and 90% Percentiles. Sample Period: 2006:07-2009-09. Bandwidth Selection Method: Least Squares Cross-Validation.