PhD THESIS DECLARATION

The undersigned

SURNAME *Sadeghzadeh*
FIRST NAME *Mehdi*
PhD Registration Number *1465699*

Thesis title: *Essays in Liquidity and Asset Pricing*

PhD in *Finance*
Cycle *25th*
Candidate's tutor *Carlo Favero*
Year of thesis defence *2015*

DECLARES

Under *his/her* responsibility:

1) that, according to Italian Republic Presidential Decree no. 445, 28th December 2000, mendacious declarations, falsifying records and the use of false records are punishable under the Italian penal code and related special laws. Should any of the above prove true, all benefits included in this declaration and those of the temporary embargo are automatically forfeited from the beginning;

2) that the University has the obligation, according to art. 6, par. 11, Ministerial Decree no. 224, 30th April 1999, to keep a copy of the thesis on deposit at the "Bilioteche Nazionali Centrali" (Italian National Libraries) in Rome and Florence, where consultation will be permitted, unless there is a temporary embargo protecting the rights of external bodies and the industrial/commercial exploitation of the thesis;

3) that the Bocconi Library will file the thesis in its "Archivio istituzionale ad accesso aperto" (institutional registry) which permits online consultation of the complete text (except in cases of a temporary embargo);

4) that, in order to file the thesis at the Bocconi Library, the University requires that the thesis be submitted online by the candidate in unalterable format to Società NORMADEC (acting on behalf of the University), and that NORMADEC will indicate in each footnote the following information:

   - thesis *Essays in Liquidity and Asset Pricing*;
   - by *Sadeghzadeh Mehdi*;
   - defended at Università Commerciale "Luigi Bocconi" – Milano in *2015*;
   - the thesis is protected by the regulations governing copyright (Italian law no. 633, 22th April 1941 and subsequent modifications). The exception is the right of Università Commerciale "Luigi Bocconi" to reproduce the same for research and teaching purposes, quoting the source;

5) that the copy of the thesis submitted online to NORMADEC is identical to the copies handed in/sent to the members of the Thesis Board and to any other paper or digital copy deposited at the University offices, and, as a consequence, the University is absolved from any responsibility regarding errors, inaccuracy or omissions in the contents of the thesis;

6) that the contents and organization of the thesis is an original work carried out by the undersigned and does not in any way compromise the rights of third parties (Italian law, no. 633, 22nd April 1941 and subsequent integrations and modifications), including those regarding security of personal details; therefore the University is in any case absolved from any responsibility whatsoever, civil, administrative or penal, and shall be exempt from any requests or claims from third parties;

7) that the PhD thesis is not the result of work included in the regulations governing industrial property, was not produced as part of projects financed by public or private bodies with restrictions on the diffusion of the results, and is not subject to patent or protection registrations, and therefore not subject to an embargo;

Date *31/01/2015*

SURNAME *Sadeghzadeh*
FIRST NAME *Mehdi*

Contents

List of Figures

List of Tables

Acknowledgements

I would like to thank my supervisor Professor Carlo Favero for his great support and help, Francesco Corielli for his continuous availability and advices, Paolo Colla for the time he devoted to read my research and his invaluable comments.

I also would like to thank my fellow students in Bocconi University with whom I spent more than five year of my life and who will be my friend for the rest of my life.

I would like to express my sincere gratitude to my wife, who inspired me and provided constant encouragement during the entire process and my parents for their endless support.

Abstract

The first chapter of my thesis is devoted to give a new look to the relation between the stock market return and liquidity in US stock markets. The notion of liquidity underlying this thesis is the ease of trading. While most of the empirical literature on liquidity-return relation concludes that illiquidity has a positive effect on stock returns, this paper documents strong empirical evidence on the asymmetry of the effect. More specifically, cross-sectional regression results show that the effect of illiquidity on individual stock returns is positive if the stock underperforms the market and negative if the stock outperforms the market. Empirical analysis also shows that the mentioned asymmetric effect is more pronounced in times of higher market illiquidity. A theoretical model is proposed to explain this new evidence by attributing the asymmetry of the effect to liquidity providing. Simply put, the model suggests that the effect of illiquidity is the change in expected return that is received by liquidity providers and paid by investors demanding it. In the model's framework, the change in expected returns is affected by how the stock is currently performing and how illiquid it is, i.e. how liquidity providing is worthy. Hence, illiquidity-return relation is expected to be more pronounced when market is less liquid, or when liquidity becomes more expensive.

The second chapter studies the the effect of liquidity of corporate bond market inspired by finding in the first chapter. The empirical evidence provided by this paper supports those of chapter one. In other words, The results of testing for nonlinearity in illiquidity-yield spread in corporate bond market on the other hand suggest that illiquidity asymmetrically affects bond yields spreads.

The third chapter studies the effect of liquidity in sovereign bond market. This paper analyzes the Eurozone sovereign bond markets over 2003 to 2012 to investigate how variations in bond yields are affected by credit, liquidity and redomination risk, specially before and during Euro-zone crisis period. The key contribution of this paper is to show the so-called flight to liquidity effect is not supported by empirical analysis after taking in to account all the playing factors affecting bond yields. The results suggest that the default risk is the most relevant driver for the yields specially for high yield countries.

Chapter 1

Asymmetric effect of Illiquidity on Stock Returns
The role of current performance

Chapter One:

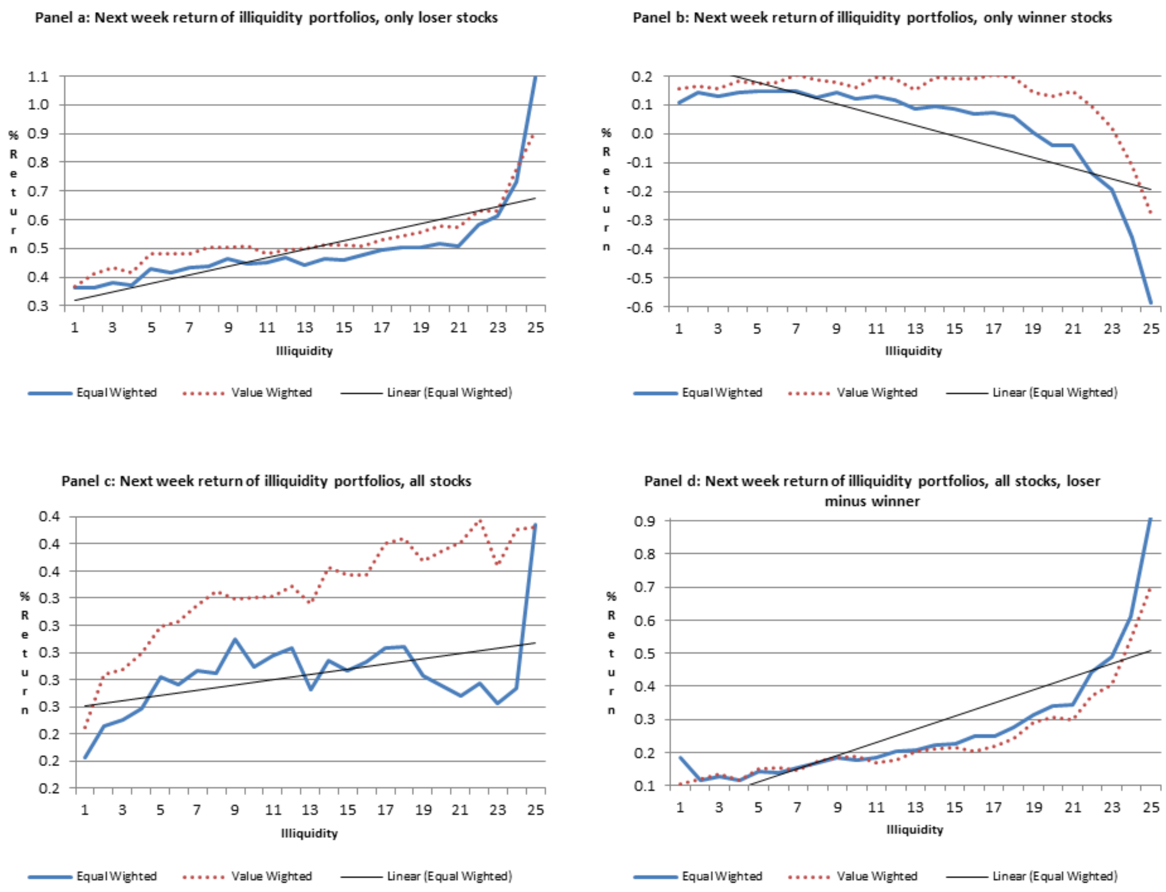
Asymmetric effect of Illiquidity on Stock Returns
The role of current performance

1.1 Introduction

The effect of illiquidity on stock returns has been studied by numerous numbers of papers. Almost all of the researchers who studied this effect conclude that stock returns increase with illiquidity or illiquidity risk. There are number of reasons to expect such effect. A wise investor would ask for a premium for taking the risk of difficult trading in the future. Since this risk is higher for less liquid securities, the return should be higher for more illiquid assets to compensate investors for this risk. Another way of explaining the effect is using "transaction cost". Due to the fact that the transaction cost of trading a more illiquid security is higher, ceteris paribus, its demand and consequently its price are lower, which in turn means that its current return is lower and next period return is higher. As a matter of fact, these two arguments are the basis for two very popular frameworks for analyzing the illiquidity-return relation, which will be described later.

However, none of the mentioned explanations are compatible with the new empirical evidence that this study documents. Figure (1.1) gives a very basic idea of how returns are asymmetrically affected by illiquidity. There are four panels in this figure showing the weekly returns of twenty five illiquidity portfolios using the data on the universe of NYSE-AMEX stocks over the sample period 1962 through 2011 and Amihud [2002]'s illiquidity measure. In each week, all stocks in the sample for that week are ranked by their illiquidity measure and divided into twenty five illiquidity portfolios. In each portfolio, individual stock's net return, which is stock's weekly return minus market return, is computed. Then, portfolios are further grouped into loser stocks group (stocks with negative net return) and winner stocks group (stocks with positive net return). Finally, returns in the next week for all portfolios are computed. In all the panels, both the value-weighted and equal-weighted return of illiquidity portfolios are graphed and the straight black lines present the trend lines for equal-weighted returns. Panel a graphs the return of loser illiquidity portfolios. There is a clear upward trend in both equal-weighted and value-weighted returns. This is what we expect based on current literature. However, what we don't expect to observe is what panel b graphs. There is a negative trend in both value-weighted and equal-weighted returns for winner illiquidity portfolios. Similar to panel a, the trend for value-weighted return is less strong. One possible explanation for this would be that illiquidity and size are highly negatively correlated. Generally, larger firms are more liquid. As a result, within each illiquidity portfolio, less illiquid stocks are larger ones and this in turn mitigates the effect of illiquidity on portfolios' value-weighted return. Panel c graphs the return for the merged illiquidity portfolios. No obvious pattern could be observed for equal-weighted return, but an upward trend exists for value-weighted return. This is what we get when we don't take into account the asymmetry of the effect of illiquidity. Although in this case the positive effect still prevails, obviously, this is not all we can get from the effect of illiquidity on returns, having in mind panel a and *b*. Panel *d* graphs the return of the merged illiquidity portfolios where the sign of the return of winner illiquidity portfolios is altered. In fact, panel *d* has the same spirit as a trading strategy that goes long on loser illiquidity stocks and shorts on winner illiquidity stocks. In this case, the effect of illiquidity is definitely positive for both value-weighted and equal weighted returns. For monthly frequency the same pattern is observable, which is not reported for the sake of brevity.

Figure 1.1: This figure plots the time series average of weekly returns of twenty five illiquidity portfolios using the data on the universe of NYSE-AMEX stocks over the sample period 1962-2011 and Amihud [2002]'s illiquidity measure. In each week, all stocks in the sample for that week are ranked by their illiquidity measure and divided into twenty five illiquidity portfolios. In each portfolio, individual stock's weekly returns minus market return (net-return) are computed. Then, portfolios are further grouped into loser stocks group (negative net-return) and winner stocks group (positive net-return). Finally, returns in the next week for all portfolios are computed. In all the panels, both the value-weighted (red dotted line) and equal-weighted (blue line) returns are ploted and the straight black lines present the trend lines for equal-weighted returns. Panel *a* and *b* plot the return of loser and winner illiquidity portfolios, respectively. Panel *c* graphs the return for the merged illiquidity portfolios and finally panel *d* graphs the return of the merged illiquidity portfolios where the sign of the return of winner stocks is altered.



To explain the above surprising pattern in returns with respect to illiquidity, this paper proposes a theoretical model that attributes the asymmetry to costly liquidity providing. The fundamental assumption of the model is that there are impatient investors in the market that would trade a security as a response to its current performance. The model's basic intuition is that liquidity providers change their required return for the liquidity they provide to impatient investors. Liquidity providing may increase or decrease the expected return of liquidity providers depending on whether liquidity is provided to impatient traders who want to sell a security that has faced a negative price change, or traders willing to buy a security that has a recent price appreciation. In the former case where a security currently has a negative return but is liquid enough, there is no reason to expect a change in the expected return. But in case the security is illiquid, liquidity providers that accommodate the selling pressure caused by traders trying to get rid of that security, will ask for higher return. Hence, we would expect an increase in return as a reward to liquidity providers. This reward is increasing in how much worthy the provided liquidity is, i.e. trader's selling pressure. Two factors may affect selling pressure. First, securities that have a recent poor performance are subject to be sold more aggressively by impatient traders and those with poorer performance face stronger selling pressure. Second, for higher illiquidity levels selling pressure is higher because it makes it more difficult to sell the unwanted security.

In the latter case where a stock has a recent good performance, the story is almost the same. Demand pressure would be caused by impatient traders willing to buy the security which is increasing in security's illiquidity and its level of good performance. Likewise, liquidity providers who fulfill such demand would ask for higher return, which in this case translates in a negative change in security's return. As seen in figure (1.1), the distinction between the cases where illiquidity affects loser or winner securities would add a lot of explanatory power to the illiquidity measure. As will be shown, it also considerably increases the goodness of feet of a model that studies the cross-sectional differences of stock returns.

The proposed theoretical model suggests that underlying process that generates such pattern in data is the premium asked by liquidity providers to impatient investors. This explanation treats current return as a way to introduce attractiveness and would work with other sources of attractiveness as well. Simply put, if there is an illiquid security which is very attractive for some investor to buy, or unattractive enough to sell, we would observe the same pattern. In the section for the theoretical model, I will show how traders' misperception of a stock's value accompanied by supply shocks generates conditional negative autocorrelation. Here the term "misperception" is a general term to describe all the motivations that make some traders (but not all of them) impatient in trading a stock. I don't study the nature of these motivations but only assume the existence of some of them that initiate the selling or buying pressure. This impatience should be accompanied by illiquidity to generate the negative autocorrelation in returns. Otherwise, liquidity providing is worthless and there is no reward on that.

Given the existence of the relation between illiquidity and returns described above, it is normal to expect a more pronounced effect when the whole market is more illiquid.

This is because when the market is more illiquid, liquidity providing becomes worthier and more expensive for investors asking for it. I also test this hypothesis in the empirical part of the paper and show how data supports it.

The rest of the paper is organized as follows. In section II, I briefly review the literature on the effect of illiquidity on stock returns. In section III, using the US stock market data, I present empirical evidence on the asymmetry of the effect of illiquidity on stock returns. In this section, I also present the implications of the new empirical evidence on Acharya and Pedersen [2005] results. In section IV, I present a simple theoretical model to explain the mechanism thorough which illiquidity affects stock returns. And finally in section V, I conclude.

1.2 Review of the literature

The existing literature on illiquidity-return relation is vast and contains a lot of evidence regarding positive premium for illiquidity, not only in stock markets, but also in other security markets like options and bond markets. Beside the importance of the reported findings about the illiquidity effect, one of the major concerns in the literature is how to measure illiquidity. In the existing literature, illiquidity is (mostly) defined as the ease of trading a security. But there are many ways to interpret the word "ease". The disagreement on how to measure illiquidity is reflected in the fairly big number of measures that are proposed to proxy it. Each of the measures captures one aspect of illiquidity (or meaning of the word "ease"). Discussing about details of these measures or the advantages or disadvantages of each of them is not the aim of this paper. A good reference on illiquidity sources and its aspects is Amihud et al. [2005].

Amihud and Mendelson [1986] is one of the very first papers studding the illiquidity effect on returns in the US equity market. Using the effective spread as the measure for illiquidity, the authors present evidence of the positive effect of illiquidity on stock returns. However as they conclude, the effect is decreasing in illiquidity as in equilibrium more illiquid stocks are held by investors with longer investment horizons and it decreases the compensation they ask for holding more illiquid shares. Ever since, researchers attempted to study the relation and making contribution by, such as, using various measures for illiquidity (e.g. Swan and Westerholm [2002]), testing the effect in other markets like option market (e.g. Christoffersen et al. [2012]) and bond market (e.g. Amihud and Mendelson [1991]), testing the anticipated relation using data from other countries (e.g. Koch [2010] and Bekaert et al. [2005]), testing the time-series effect as well as the cross-sectional effect (e.g. Amihud [2002]), measuring illiquidity risk premium (e.g. Pastor and Stambaugh [2003] and Acharya and Pedersen [2005]) and so on and so forth.

There are two main approaches in the literature to study the effect of illiquidity on returns. The first approach takes illiquidity as one of the deterministic characteristics that affects the security's price. In this approach there is no illiquidity risk involved and in most cases, it is used to examine the explanatory power of illiquidity level toward cross-sectional differences in returns. Among others, Amihud and Mendelson [1986], Swan and Westerholm [2002] and Amihud [2002]follow this approach. As mentioned above, the authors using this approach generally report that less liquid securities have higher returns.

The second approach on the other hand, takes illiquidity as systematic risk. In this approach, securities with higher exposure to illiquidity related-risks are expected to have higher returns. Hence, unlike the previous approach, expected return of securities would be higher depending on how much they are subject to illiquidity risk, even though their illiquidity level is not high. For example Pastor and Stambaugh [2003] argue that stocks with greater sensitivity to market-wide liquidity, exhibit higher expected returns. Acharya and Pedersen [2005]'s study adjusts the capital asset pricing model to take into account illiquidity risk. Their simple model introduces three new betas and add them to the one conventional beta in CAPM model. They also present empirical evidence supporting their model implied predictions. I discuss this paper in more detail in the next section.

In this paper the first approach is taken. I use individual stock's illiquidity to explain cross-sectional differences in returns. But unlike the previous studies, I take into account the asymmetry of the effect and show how it improves the explanatory power of the model (see section III). To my knowledge, this is the first time that the asymmetric effect of illiquidity is taken into account. However, there are two papers that are in close relation to my work and worth reviewing.

Campbell et al. [1993] study the relation between trading volume and return autocorrelation. Although the paper is not directly related to illiquidity, its underlying logic is very useful in understanding the mechanism of changing the expected returns. In their model, price fluctuations could be attributable to new follow of public information that causes all traders to adjust their valuation of the stock, or it could be due to selling pressure caused by random jumps in risk aversion of a part of investors. In the former case there is no reason to believe that expected returns on the stock market would change. While in the latter case, voluntary liquidity providers require higher expected return to compensate for their inventory risk bearing (immediacy providing). This is brought about by a decrease in current price and return. Hence, while it changes the price, new flow of public information is unlikely to cause high volume of trade. On the other hand, risk aversion jumps are followed by risk reallocations that are reflected in high trading volume. As a result, return reversals are more likely to be accompanied by larger negative autocorrelation in stock returns.

Avarmov et al. [2006] argue that given the implication of Campbell et al. [1993] model, the return reversals should be more pronounced for stocks with low liquidity. This reasoning is the basis of my theoretical model. They test this hypothesis using data from

CRSP for the universe of NYSE-AMEX stocks over the sample period 1962 through 2002. Their proxy for illiquidity is the Amihud [2002] measure (see section IV for more detail). What they found, however, is that return reversals are observed only for negative return stocks and for relatively short time horizons e.g. weekly data.

The theoretical model that I present in section IV is similar to Campbell et al. [1993] model in terms of the solution techniques and is based on Avarmov et al. [2006] idea. This is a simple model to show how illiquidity affects returns in an asymmetric way.

1.3 Empirical evidence

In this section, I present empirical evidence on the asymmetry of the effect of illiquidity on stock returns. The empirical analysis starts with analysis of the effect of illiquidity on individual stocks and portfolio returns over weekly as well as monthly frequency data. Then it continues with studding the effect of market illiquidity on return-illiquidity relation. Finally, I present the implications of this new findings for the results reported by Acharya and Pedersen (2005).

1.3.1 Methodology

The analysis is performed for both weekly and monthly frequency data using Fama-MacBeth cross-sectional regression method. In each period, individual stocks' return will be regressed on a bunch of explanatory variables all from previous period. Three empirical approached are employed to account for asymmetry in the effect of illiquidity on returns. The first approach would be using the interaction term between illiquidity and return to explain the return in the next period:

$$R_{t+1} = \alpha_0 + \alpha_1 R_t + \alpha_2 I_t + \alpha_3 I_t * R_t + \theta X_t$$

Where R_t and I_t are individual stock's return and illiquidity, respectively and X_t is consisting of all control variables in period t. A negative and significant coefficient is expected for the variable $R_t * I_t$ because I expect the illiquidity to increase the negative autocorrelation.

Another approach to examine the effect is changing the sign of illiquidity measure if the current return is positive (or negative). The reason is that the sign of the effect of illiquidity is conditional on the current return:

$$\frac{\partial R_{t+1}}{\partial I_t} < 0 \quad if \quad R_t \geq 0$$

$$\frac{\partial R_{t+1}}{\partial I_t} > 0 \quad if \quad R_t < 0$$

However, we can make it unconditional by changing the sign of it conditional on current return:

$$\frac{\partial R_{t+1}}{\partial(-I_t)} > 0 \quad if \quad R_t \geq 0$$

$$\frac{\partial R_{t+1}}{\partial I_t} > 0 \quad if \quad R_t < 0$$

This way, a (bigger in absolute term) positive effect would be expected no matter the current return is positive or negative. Empirically, the following model is tested:

$$R_{t+1} = \alpha_0 + \alpha_1 R_t + \alpha_2 I_t^* + \theta X_t$$

$$I_t^* \cong I_t * (-1) * 1_{R_t \geq 0} + I_t * 1_{R_t < 0}$$

Where 1 is the indicator function.

The third approach would be running the estimation using dummies for two groups of observations, observations corresponding to positive current return and observations corresponding to negative current return:

$$R_{t+1} = \alpha_0 + \alpha_1 R_t + \alpha_2 Dump_t * I_t + \alpha_3 Dumn_t * I_t + \theta X_t$$

$$Dump_t \cong 1_{R_t \geq 0} \quad , \quad Dumn_t \cong 1_{R_t < 0}$$

In this case, a negative sign is expected for α_2 and a positive sign is expected for α_3. The results corresponding to all the three approaches are reported in the following sections and would be compared to estimation of the specifications which does not consider the asymmetry of the effect.

1.3.2 Data

Data is obtained for individual stocks from CRSP daily stock file for the universe of NYSE-AMEX stocks over the sample period 1962 through 2011. Dividend yield and book equity is obtained from COMPUSTAT. I only use the observations for ordinary common shares (share codes 11 and 12). Shares with price less than one dollar are dropped from the sample. For the weekly analysis, I require a share to trade every day of a week before it is included in the sample for that week. Following Avarmov et al. [2006], I define a week such that it starts on Wednesday and ends on Tuesday. For monthly analysis, a share should have at least fifteen observations in a month before including in the sample for that month. Monthly returns are directly obtained from CRSP monthly stock file. In case of missing data for a specific month, the return is computed using daily returns. Weekly returns as well as missing monthly returns are compound returns for the period of time they belong to. Returns are being adjusted for stock delistings to avoid survivorship bias, following Shumway [1997].

The illiquidity measure that is used in this paper is Amihud [2002]'s measure defined by:

$$ILLIQ^i_{t+1} = \frac{1}{Days^t_i} \sum_{d=1}^{Days^t_i} \frac{|R_t|}{V_d}$$

Where $Days^t_i$ is the number of observations available for stock i in period t, R_t is return in day d and V_d is dollar volume trading in the same day. This measure is computed for both weekly and monthly analysis. $ILLIQ$ is widely used in empirical studies including Acharya and Pedersen [2005] and Avarmov et al. [2006]. Table 1.1 gives some descriptive statistics of the data used in the analysis. Returns are net of market return at the same period they belong to. The interesting point of table 1 is that, on average, and for both weekly and monthly frequencies, individual stocks face a decrease in their net of market return.

1.3.3 Other control variables

Following Amihud [2002], I include *beta* in all specifications which is computed for each year and individual stock using Scholes and Williams [1977] method. In each cross-sectional regression in year t, the values for beta in year $t-1$ are used. Another way of incorporating beta in the specifications would be, for example, computing it exactly for one year ending at the week (or month) the cross-sectional regression is estimated. However, this procedure ends up with a completely insignificant coefficient for *beta*. To control for the possible effect of idiosyncratic risk on returns, standard deviation SD of each individual stock return is also computed in the same year and is used in the regression. In portfolio analysis, *beta* and standard deviation are computed as the simple mean of the *beta* and standard deviation of all stocks in each portfolio. Amihud [2002] also includes dividend yield in the cross-sectional regressions. Following Amihud, I use this variable *devyld* in the specifications to control for its explanatory power. $devyld_t$ is calculated as the sum of the dividends during the year prior to the year associated to week (month) t divided by the end-of-year price in the same year. Finally, I include book equity to market equity BE/ME in the regressions, which is reported by many papers to have explanatory power toward returns. Like other variables, in performing the portfolio analysis, I will use simple averages of these variables using all stocks in a portfolio as BE/ME and *devyld* of that portfolio.

To check the sensitivity of the results to using Amihud's illiquidity measure, the regressions are re-estimated using turnover as a measure for liquidity. Turnover is defined as the summation of the number of traded shares of a stock over its outstanding shares. This measure is used in a number of empirical studies as a proxy for liquidity. For example, Datar et al. [1998] conclude that NYSE stock returns are negatively related to turnover. To make turnover a measure for illiquidity, I use its product with minus one. Using inverted turnover would be a alternative way but since this measure would be highly nonlinear in turnover, I avoid it.

Table 1.1: Sample descriptive statistics

Weekly data	Mean	Var	SD	Min	Max
$R_{t+1}^{i} - R_{t+1}^{M}$	-0.00017	0.004	0.06	-0.994	1.00
$R_{t}^{i} - R_{t}^{M}$	0.00002	0.005	0.07	-0.876	26.98
$illiq_{t}^{i}$ (x10^6)	5.7	10,057.6	100.2	0	44,731.2
$trnvr_{t}^{i}$	15.5	1,169.7	34.2	0	9,992.8
$size_{t}^{i}$ (/10^6)	1,927.9	1.090e+08	10441.1	0.067	588,525.1
N	5,223,435				

Monthly data	Mean	Var	SD	Min	Max
$R_{t+1}^{i} - R_{t+1}^{M}$	-0.00001	0.016	0.13	-1.047	3.99
$R_{t}^{i} - R_{t}^{M}$	0.00010	0.017	0.13	-1.046	12.5
$illiq_{t}^{i}$ (x10^6)	5.64	4,233.8	65.1	0	16,813.9
$trnvr_{t}^{i}$	64.07	14,478.2	120.3	0.001	27,691.0
$size_{t}^{i}$ (/10^6)	1,916.9	1.097e+08	10,473.2	0.083	579,242.3
N	1,206,374				

1.3.4 Fama-MacBeth regression analysis

In this section I present the results of Fama-MacBeth regressions for both weekly and monthly frequency data and for individual stocks as well as portfolio analysis.

Individual stock analysis

Table 1.2 presents the results of Fama-MacBeth regression analysis for weekly frequency data. In each week, returns of individual stocks at week $t+1$ are regressed on their current return, illiquidity meaure and other control variables. In all specifications, Ret_t^i has a negative and significant coefficient of order -0.08, which confirms our expectation that current return negatively affects future return. Surprisingly, beta appears with negative and insignificant coefficient, and standard deviation of return is positive and significant in all the specifications. The positive and significant coefficients on book to market equity suggest that there is a return premium for stocks with greater relative book value. Column (1) shows the regression using illiquidity as an independent variable without taking into account the asymmetry. This variable has a positive coefficient of magnitude 0.1 with high statistical significance, which means that on average, illiquidity has a positive impact on future returns as we observed in figure 1.1 panel c. In column (2), two other control variables, size and turnover, are added to the specification. Both variables appear with statistical significant coefficient. After this change, the coefficient on illiquidity increases to 0.17 with a relatively higher statistical significant. In column (3), the first empirical approach is tested by including the illiquidity-return interaction term. The coefficient on this variable is negative as expected and compared to the coefficient on illiquidity in column (2) has a considerably larger t-static. The goodness of fit of the model also slightly increases to 4.25 percent from 4.20 in column (2). Specification in column (4) is very interesting since it shows that illiquidity loses its significance in a regression where the illiquidity-return interaction term is included. In column (5), the variable of interest is defined as:

$$Illiq_t^* \cong Illiq_t * (-1) * 1_{R_t \geq 0} + Illiq_t * 1_{R_t < 0}$$

Comparing the coefficient on this variable and on illiquidity in Column (2) shows that the magnitude is more than doubled and the statistical significant is increased by a factor of three. However, the goodness of fit decreases to 4.12 percent in this specification. Column (6) and (7) explicitly show that the effect of illiquidity is asymmetric. Using *Dump* and *Dumn* which are dummy variables equal to one when current net return is positive and negative respectively, I apply the third empirical methodology.

[Table 1.2 here]

The results in these columns show that the effect of illiquidity is negative for positive net-return stocks and positive for negative net-return stocks. In column (6), the absolute value of the coefficients on illiquidity dummies has almost the same magnitude.

In a number of empirical studies e.g. Liu [2006] and Koch [2010], turnover is used as a measure of liquidity. Both studies find a strong negative relation between turnover and equity returns. However, the results of replicating tests using (minus) turnover as another measure for illiquidity with the same empirical methods are surprising.

[Table 1.3 here]

Table 1.3 presents the results using minus turnover (henceforth mturnover) as a measure for illiquidity. As this table shows, in the first two specifications containing mturnover, this variable comes with a negative and significant coefficient which is not what we expect. However, if we disentangle the effect of turnover on positive and negative net return stocks, the results become less surprising. Column (3) shows the result of applying the first empirical approach. The coefficient on mturnover-return interaction term becomes more significant both statistically and economically compared to the coefficient on mturnover in column (1). In column (5), the variable of interest if defined by:

$$mTrnvr_t^* \cong mTrnvr_t * (-1) * 1_{R_t \geq 0} + mTrnvr_t * 1_{R_t < 0}$$

The coefficient on this variable has the predicted positive sign and is highly significant. However, in terms of absolute value, it reduces from more than 1.6 in the first column to 1.3. Columns (6) and (7) show the results of applying the third empirical approach using mturnover. As expected, the coefficient for positive net return stocks is negative and significant. However, the coefficient for negative net return stocks is also negative and slightly significant.

Using Amihud's measure, the results of weekly analysis are strongly in support of the idea of asymmetric effect of illiquidity on returns. However, the effect of mturnover is not completely asymmetric. Although the results in table 1.3 exhibit a slight improvement in columns (3) and (5) compared to frist two columns in terms of coefficient on mturnover, they do not entirely reflect the predicted pattern of the effect of illiquidity on returns. More specifically, the effect is more significant both economically and statistically for positive net-return stocks, where the coefficient comes with the predicted negative sign. However, as will be shown, the results for monthly data are robust to using mturnover.

Table 1.4 presents the results of the estimation of the same specifications as in table 1.2 using monthly frequency data. The results, like in table 1.2 for weekly data, very strongly support the idea of asymmetric effect. Current return is still highly significant in all specifications with expected negative sign and absolute value roughly around 0.04. Unexpectedly, both beta and standard deviation of return come with negative sign and insignificant coefficients. Book to market equity is positive and significant as it was in tables 1.2 and 1.3. Interestingly, illiquidity without considering asymmetry is not a significant explanatory variable for monthly returns. More specifically, although the coefficients on $Illiq_t^i$ in columns (1) and (2) are positive, they are not statistically significant. Results in column (3) show that the product of current return and illiquidity affects the future return negatively and it is highly significant. Moreover, statistical significance and size of the effect of $Illiq_t^i$ as in column (2) becomes noticeably larger in column (5) where it is replaced by $Illiq_t^{i*}$. The last two specifications in columns (6) and (7) also confirm that the effect is asymmetric for negative and positive net return stocks.

[Table 1.4 here]

Just like table 1.3, I replicated the test for monthly data using mturnover as a measure for illiquidity. The results could be found in table 1.5. As shown in the first two columns of the table, the coefficient for mturnover is negative and does not have statistical significance. But, the results clearly show that when we take into account the asymmetry of the effect of mturnover, it becomes highly significant with predicted signs. The coefficient on return-mturnover interaction term in column (3) is as high as 20.16. in column (5), the coefficient on $mTrnvr_t^{i*}$ is positive and highly significant. The results in the last two columns are also in complete support of the idea of the asymmetry of the effect.

Overall, monthly analysis gives somewhat better estimations in terms of highlighting the asymmetric effect since it shows more compatible results when using mturnover. Individual stock analysis results are highly supportive for the paper's hypotheses. The results show that considering the asymmetry of the effect highly improves our understanding of the illiquidity-return relation. More specifically, we found a negative (and insignificant in case of monthly data) relation between mturnover and return, which seems to be surprising considering the existing literature. But after we disentangle the effect of turnover on winner and loser stocks, the coefficients come with predicted signs (and become significant).

[Table 1.5 here]

In case of Amihud's measure, the results show that the overall positive effect of illiquidity on returns found in the literature is mostly related to the effect of illiquidity on loser stocks, which is indeed stronger. Based on the model's intuition, this means that unsophisticated investors are more motivated to sell a poorly performing security rather than buying a highly performing one with the same liquidity status. As a results, the relatively higher strength of the effect on loser stocks offsets the effect on winner stocks and we observe a overall positive effect (see column (2) in tables 1.2 and 1.4). But we would measure the whole effect only if we add the two effects together. That way, the effect would be more pronounced and the results show that indeed it is more noticeable (see column (5) in 1.2 and 1.4).

1.3.5 Portfolio analysis

Most of the empirical studies in the literature perform portfolio analysis rather than individual stock analysis. The main reason is that the huge amount of noise existing in individual stocks data will balance out in portfolios. This gives a researcher the ability to get the results related to the research question while he cannot get such results using individual stocks data. In this section I rerun the tests based on the same empirical approaches mentioned above but with forming portfolios.

In each week (month), net return of each stock is computed as before and is grouped into two positive and negative net return sets. Then each positive and negative net return set of stocks are ranked by this variable separately, and five portfolios of each set (ten in total) are formed. Stocks of each portfolio are further sorted by their illiquidity measure into ten illiquidity portfolios. At the end a hundred net return-illiquidity portfolios are formed. Current and future returns, as well as other explanatory variables of portfolios are computed as simple average of the values for individual stocks in each of the portfolios. R-squared of each specification is obtained from average of R-squared of all the cross-sectional regressions.

[Table 1.6 here]

Table 1.6 presents the results of portfolio analysis for weekly frequency data. As the table shows, the effect of illiquidity is apparently not a explaining factor for future returns unless the asymmetry is taken into account. Interestingly, the coefficient on illiquidity in column (1) is not significant and is negative. In column (2) it remains insignificant and negative after size is included in the specification. On the other hand, the coefficient on the product of current return and illiquidity in columns (4) and (5) are negative and highly significant. The effect of $Illiq_t^{p*}$, with the same definition as before, is positive and significant. Finally, columns (6) and (7) clearly show that the effect of illiquidity exists and is asymmetric.

[Table 1.8 here]

Table 1.8 presents the results for portfolios analysis using monthly data. Just like the case for weekly data, all the results confirm the hypothesis that the effect of illiquidity on returns is asymmetric.

What could be understood from the results in this section is that, on the individual stock level data, between the two directions of the effect of illiquidity, the relative strength of the effect on loser stocks is higher. As a consequence, the outcome effect remains significant as an explaining variable for return even without considering asymmetry. In this case, considering the asymmetry of the effect makes the outcome effect more pronounced. But in portfolio level data (specially in monthly data) illiquidity dramatically loses its significance and the only way to revitalize the effectis to take into account the asymmetry of it. This finding is not sensitive to which measure of illiquidity we use. Tabulated regression results show that using mturnover as a measure for illiquidity doesn't change the conclusion. Hence, studding the illiquidity-return relation without considering the asymmetry would be misleading.

The power of the tests and the level of significance of the effect suggest that the same mechanism would exist and the same results should be observed in other markets like bond markets and option markets. The reason is that, based on the intuition of the model in section 4, the type of security is not a main determinant of the illiquidity-return relation. Hence, it may be possible that the reported positive effect of illiquidity on returns in these markets is nothing more than the two conflicting directions of the effect where the relative strength is higher for positive direction.

the effect of market illiquidity

In this section I study the effect of market illiquidity on return-illiquidity relation. The hypothesis to test is that the asymmetric effect of illiquidity on returns should be more pronounced in times of higher market illiquidity, because liquidity providing becomes worthier and more expensive for investors demanding it. As a result, returns should react more severely as a response to one unit of change in illiquidity when market is generally more illiquid. Acharya and Pedersen [2005] argue that the correlation between a stock's illiquidity and market illiquidity has a positive effect on expected returns because investors are willing to accept lower returns for stocks that become more liquid when market becomes illiquid. This lower return is what investors pay to have more liquid stocks in more illiquid market times. This reasoning has the same spirit as arguing that when market becomes illiquid, liquid stocks become more expensive.

To empirically test the hypothesis, I chose to use the portfolio analysis method. In each week (month) net return-illiquidity portfolios are formed as before but they are further sorted by the market illiquidity measure, which is the simple mean of illiquidity measure of all stocks in the sample for that week (month). All observations are clustered into quartiles based on market illiquidity. For example the first quartile corresponds to observations related to times of lowest market illiquidity and last quartile corresponds to observations related to times of highest market illiquidity. Using the same empirical approaches as above, I regress the portfolio's return in the next period on information in the current week (month) for all quartiles. The prediction is that the estimated coefficients for illiquidity are lager for higher market illiquidity quartiles.

Studying the effect of market illiquidity adds a time series dimension to previous tests. While Amihud's measure seems to be ideal for cross-sectional analysis, its dependency to price, volume and return makes it very sensitive to general market conditions. For example, suppose that in period t as a consequence of an economic boom, market return increases. Cross-sectionally, the relative illiquidity of individual stocks doesn't change. But, this has a direct effect on average market illiquidity measure without illiquidity being affected by return in reality. As a result, comparing Amihud's measure in two different market times may reflect non-liquidity changes in the market. The same could be said for price and volume. Although, the measure can be improved by controlling for price increase over time, the second illiquidity measure, mturnover, seems to be a more trustable measure in time series analysis as it is not dependent on other time-varying factors. To control for the inflation effect in Amihud's illiquidity measure, I multiply it by P^M_{t-1} which is the ratio of market capitalization at the end of week (month) $t-1$ and market capitalization at beginning of the sample period. In computing P^M_{t-1}, I do not require stocks to have trading activity boundaries. For the sake of brevity, I only report the results for the first and last market illiquidity quartiles.

[Table 1.10 here]

Table 1.10 reports the results for weekly portfolio data. Using the first empirical approach, columns (1) and (2) show that the negative coefficient on the illiquidity-return interaction term becomes noticeably larger when market is highly illiquid. The same is observable in columns (3) and (4) when the coefficient on $Illiq^{i*}_t$ is significantly different between two states of market. Columns (5) and (6) show that in times of market illiquidity, the effect is indeed larger on both loser and winner stocks.

Table 1.11 reports the results of replicating the same regressions using mturnover as a measure for illiquidity, where the estimated coefficients confirm all the previous findings.

[Table 1.11 here]

Replicating the analysis with monthly data gives two opposite results. The results using Amihud's measure for market illiquidity show that the effect of it is the reverse of what expected. In columns (1) and (2) of table 1.12, the coefficient on the interaction term of current return and illiquidity is more negative when market is less illiquid. It is also the case for other columns that the effect of illiquidity decreases with market illiquidity. However, untabulated results show that without considering P^M_{t-1}, the adjustment to control for inflation, the results become as expected. Moreover, table 1.14 shows that using mturnover as a measure for illiquidity, we get the predicted results. Comparing coefficients in columns (1) and (2) in this table, we see that the size of the effect of return-mturnover interaction term is quite larger in high mturnover market times and it is not even statistically significant in low mturnover market times. The same pattern is observable in other columns.

Overall, the results show that market illiquidity pronounces the effect of illiquidity on returns. Amihud's measure for illiquidity does not seem to be trustable for time series study because of its sensitivity to time varying factors. Even in case of weekly frequency data, where using Amihud's measure gives the expected results (see Table 1.10), the coefficient on current return decreases (in absolute terms) with market illiquidity which is surprising. Based on the model, when illiquidity increases, current return becomes a more important factor in describing the future return. This is what we see using mturnover and in both weekly and monthly frequency data.

1.3.6 Implications on Acharya and Pedersen [2005]

In this part of the paper, I present empirical evidence on how considering the asymmetry of the effect of illiquidity changes the results reported by Acharya and Pedersen [2005]. Before doing so, I briefly explain the paper's basic intuition and empirical methodology. However, I don't go deep into the details, which would be found in the original paper. Acharya and Pedersen [2005] (henceforth AP) study the effect of illiquidity risk on returns. To do so, they augment the capital asset pricing model to take into account illiquidity risk. Their simple model adds three new betas to the one conventional beta in CAPM model. The prediction of their model is that these newly introduced illiquidity-related betas affect the stocks' expected return as what follows. First, high levels of historical correlation between stock's illiquidity and market illiquidity increases the expected return.

This is similar to market beta in CAPM model which reflects the compensation investors ask for stocks that are highly correlated to market portfolio in terms of illiquidity. Second, investors are willing to accept lower return for stocks for which the historical correlation between the return and market illiquidity is high. The higher is this correlation, the return is higher in times of high illiquid market. Third, the expected return on stocks whose illiquidity is highly correlated with market return is lower because investors will benefit having a more liquid asset in down market periods. Using an overlapping generation framework, AP's solution for stock's conditional expected return becomes:

$$
\begin{aligned}
E_t(r^i_{t+1}) = r^f + E_t(c^i_{t+1}) + \lambda_t \frac{cov_t(r^i_{t+1}, r^M_{t+1})}{var_t(r^M_{t+1} - c^M_{t+1})} \\
+ \lambda_t \frac{cov_t(c^i_{t+1}, c^M_{t+1})}{var_t(r^M_{t+1} - c^M_{t+1})} \\
+ \lambda_t \frac{cov_t(r^i_{t+1}, c^M_{t+1})}{var_t(c^M_{t+1} - c^M_{t+1})} \\
+ \lambda_t \frac{cov_t(c^i_{t+1}, r^M_{t+1})}{var_t(r^M_{t+1} - c^M_{t+1})}
\end{aligned}
$$

Where c^i_{t+1},r^i_{t+1},c^m_{t+1} and r^M_{t+1} are individual stock's relative illiquidity cost, individual stock's return, market illiquidity cost and market return, respectively. What is new in this relation with respect to conventional CAPM is the last three parts, known as illiquidity betas. The first effect, $cov_t(c^i_{t+1}, c^M_{t+1})$ captures the premium investors want, to be compensated for holding a security that becomes illiquid when the market in general becomes illiquid. $cov_t(r^i_{t+1}, c^M_{t+1})$ captures the decrease in required return for investors that are willing to accept a lower return on an asset with a high return in times of market illiquidity. $cov_t(c^i_{t+1}, r^M_{t+1})$ captures the decrease in premium for investors willing to hold a liquid asset in times of low market return.

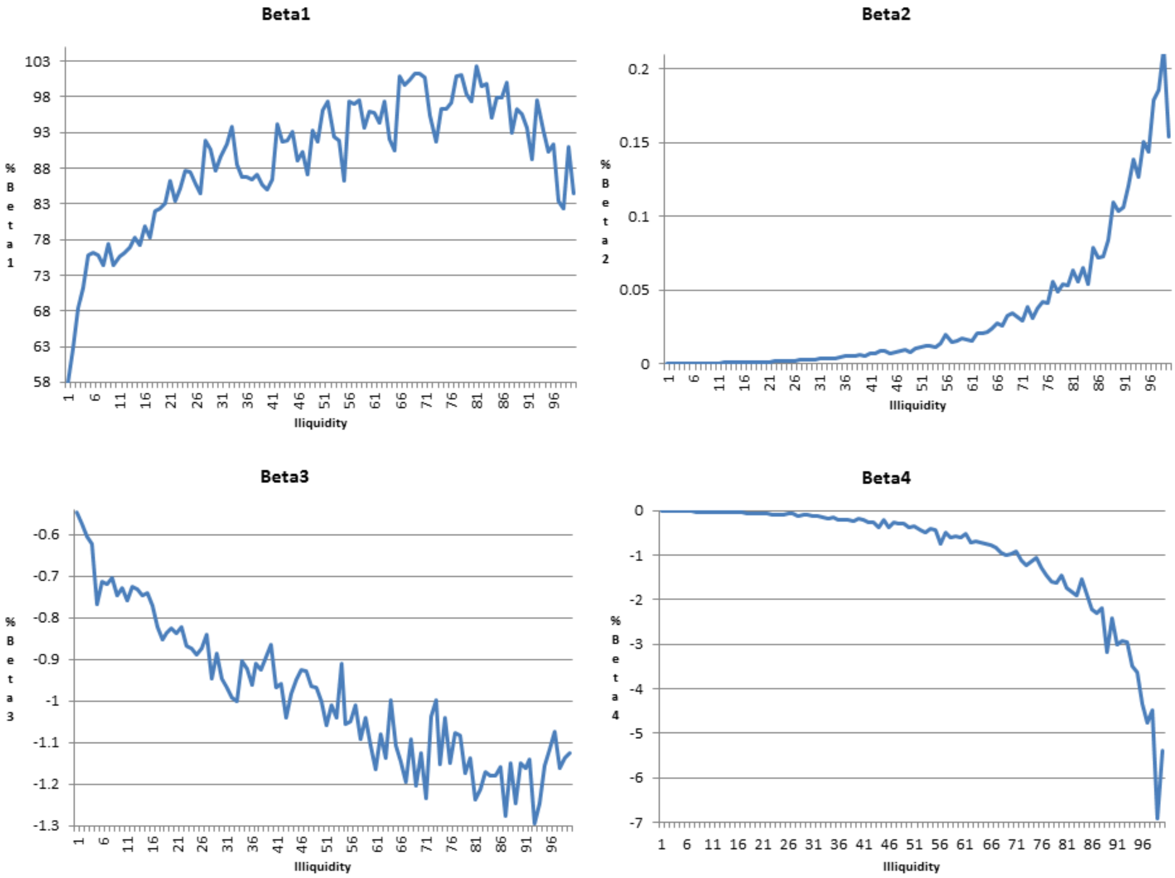
Using this relation, AP test their hypothesis on how expected return reacts to liquidity related risks. The illiquidity measure that is used by AP is Amihud's measure. However, AP make an adjustment to this measure to make it stationary and offset inflation effect. To do so, they introduce:

$$c^t_i = min(0.25 + 0.30 * ILLIQ^i_t * P^M_{t-1}, 30)$$

Where P^M_{t-1} is the ratio of the capitalizations of the market portfolio at the end of month $t-1$ and at the end of July 1962. Using c^t_i, in each year, all the stocks in the sample are ranked and 25 illiquidity portfolios are formed. Then illiquidity betas are computed for each portfolio as:

$$\beta^{1P} = \frac{cov_t(r^i_t, r^M_t - E_{t-1}(r^M_t))}{var_t(r^M_t - E_{t-1}(r^M_t) - [c^M_t - E_{t-1}(c^M_t)])}$$

Figure 1.2:



$$\beta^{2P} = \frac{cov_t(c_t^i - E_{t-1}(c_t^i), c_t^M - E_{t-1}(c_t^M))}{var_t(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])}$$

$$\beta^{3P} = \frac{cov_t(r_t^i, c_t^M - E_{t-1}(c_t^M))}{var_t(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])}$$

$$\beta^{4P} = \frac{cov_t(c_t^i - E_{t-1}(c_t^i, r_t^M - E_{t-1}(r_t^M))}{var_t(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])}$$

Finally, the following model is tested for portfolio returns using Fama-MacBeth regression analysis:

$$E(r_t^p - r_t^f) = \alpha + \kappa E(c_t^p) + \lambda\beta^{1P} + \lambda\beta^{2P} - \lambda\beta^{3P} - \lambda\beta^{4P}$$

Graph 1.2 presents the estimated betas following the same procedure as AP for the sample used in the previous section. There are only two differences between the procedures employed in this paper with respect to original procedure in AP. First, the sample period used in AP is 1962 to 1999, while in this paper; it is extended to 1960 to 2011. Second, I formed a hundred illiquidity portfolios instead of twenty five. This is because with a hundred illiquidity portfolios the changes in the results when asymmetry is introduced are more sensible. However, the estimated betas reported here are pretty much similar to what AP present.

Table 1.14 reports the estimated Fama-MacBeth regression for exactly the same specifications taken by AP. Except for the magnitude of coefficients, they are very similar to AP's results in other aspects like sign of the coefficient, statistical significance and goodness of the fit of the estimations. Note that:

$$\beta^{net,P} = \beta^{1P} + \beta^{2P} - \beta^{3P} - \beta^{4P}$$

and coefficient associated to $E(c^P)$ in specifications 1, 4 and 7 is a predetermined number equal to the average of turnover of all the stocks in the sample. This number equals to 0.034 in AP.

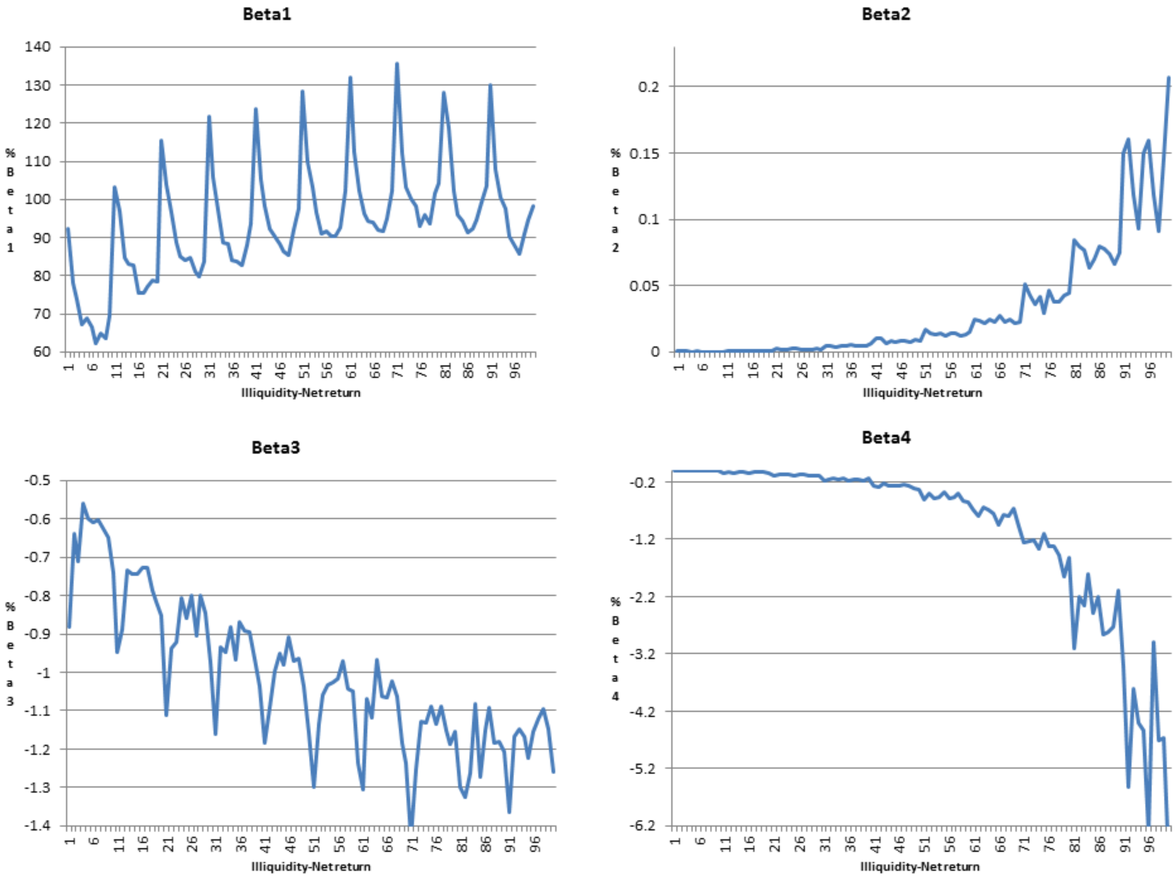
[Table 1.14 here]

The next step in this section is replicating the above analysis considering asymmetry in the effect on illiquidity. To do so, I make two changes to the procedure of forming the portfolios. The first change is that I form net return-illiquidity portfolios. In each month, net return of all stocks is computed and stocks are grouped into two positive and negative net return sets. Then each positive and negative net return set of stocks are ranked by this variable separately, and five portfolios of each set (ten in total) are formed. Stocks of each net return portfolio are further sorted by their illiquidity measure into ten illiquidity portfolios. At the end a hundred net return-illiquidity portfolios are formed. For example, portfolios 1 to 10 are associated to the first illiquidity deciles but correspond to lowest to highest net return portfolios. Similarly, portfolios 91 to 100 are highest illiquidity portfolios with portfolio 91 being the lowest and portfolio 100 being the highest net return portfolios. The second change that I made to the original procedure is reallocating portfolios within each month rather than within each year.

Graph 1.3 plots the estimated betas following the modified procedure. The changes for β^{1P} and β^{3P} with respect to graph 1.2 are very noticeable. For β^{1P}, illiquidity portfolio groups follow the same pattern as beta1 in graph 1.2. But obviously, within each illiquidity portfolio group, there is a negative trend. For β^{3P}, while there is an interesting hump-shape pattern within each illiquidity portfolio group, similar to graph 1.2, the trend across illiquidity groups is negative. There is no noticeable pattern for β^{2P} and β^{4P} with respect to graph 1.2.

Using the estimated betas, I rerun the Fama-MacBeth regressions with some modifications with respect to AP. The first modification is that I add each portfolio's return in month $t-1$ to all specifications. This variable, as I showed in previous sections, turns out to be a very powerful explanatory factor for portfolio's current return. The second modification is, using two dummy variables on negative and positive net return portfolios,

Figure 1.3:



I employed new variables generated by the product of the dummies and original explanatory variables in the regressions. More specifically, let NR^P_{t-1} be the portfolio P's net return in time $t-1$. Then, I define dummies as:

$$Dump^P_t \cong 1_{NR^P_t \geq 0} \quad , \quad Dumn^P_t \cong 1_{NR^P_t < 0}$$

Finally, the cross-sectional regression for Fama-MacBeth analysis gets the following specification:

$$E(r^p_t - r^f_t) = \alpha + \gamma r^P_{t-1} + Dump^P_t[\kappa E(c^p_t) + \lambda\beta^{1P} + \lambda\beta^{2P} - \lambda\beta^{3P} - \lambda\beta^{4P}]$$

$$+Dumn^P_t[\kappa E(c^p_t) + \lambda\beta^{1P} + \lambda\beta^{2P} - \lambda\beta^{3P} - \lambda\beta^{4P}]$$

I don't report the estimation results with pre-calculated κ since the assumption of this analysis is that κ has the opposite sign for negative and positive net return portfolios. Table 1.15 presents the results. Interestingly, confirming the findings in previous sections of this paper, the coefficient on r^P_{t-1} is negative and highly significant in all specifications.

Illiquidity cost, $E(c^P)$, has different signs for different net return portfolios in all specifications that it is incorporated in the regression. However, it is only partially significant and in none of the specifications, the coefficients on this variable for both groups are significant simultaneously.

In columns (1) and (2), although insignificant, the coefficients on beta1 and $\beta^{net,P}$ have the opposite signs for different net return portfolios. In column (3), the coefficients are significant for both groups but with noticeably different magnitudes. For both beta1 and beta-net, the size of the coefficient for positive net return group is one tenth of the size of the coefficient for negative net return group. Perhaps, the most interesting specification in table 13 is the one in column (4), where the coefficients on beta1 and beta-net have the opposite signs for different net return portfolios and are significant. This specification is comparable to column (6) in table 1.14, where the coefficients on β^{1P} and $\beta^{net,P}$ are -0.12 and 0.13 respectively. Apparently for the last two columns in table 1.15, disentangling two groups of portfolios does not improve our understanding of the expected return-illiquidity betas' relation. However, they are not meant to explain a lot the variation of expected returns, since AP's model implied restriction is the premium for all risk factors should be equal. Given this, the only relevant specifications in tables 1.14 and 1.15 are those with only $\beta^{net,P}$ as the risk factor.

[Table 1.15 here]

1.4 The Model

The aim of this section is to propose a model to describe the mechanism through which illiquidity affects stock returns. The model is kept as simple as possible and based only on standard basic assumptions. It is assumed that there are two assets in the economy, a risk-free and a risky asset. I employ the idea that some investors have misperception about the risky asset's value from DeLong et al. [1990]. Although maximizing their utility, in De Long et al paper these traders are called "unsophisticated" and are introduced to show that noise trading could be profitable and as a result, could be persistent in the market. Here I use this idea to simulate any reason that motivates some investors, apart from asset's fundamental value, to sell or buy it more aggressively.

In the current model, misperception about the risky asset's value will be one of the drivers of fluctuations of its price, whereas in De Long et al (1990) it is the only one. I include this variable in the model to simulate "unsophisticated " traders' behavior of impatience. Whenever this variable is positive, these type of traders buy the risky asset more aggressively and vice versa. Another source of risky asset's price change in the market is supply shocks. The idea behind this assumption is that not all market participants are available in the market all the time. Amihud et al. [2005] considers this as a source of illiquidity. In the model, illiquidity arises when selling (or buying) pressure is accompanied by a positive (or negative) supply shock. In the opposite case, for example when selling pressure exists in the market, negative supply shock absorbs the pressure and there would be no reward on liquidity providing. The combination of these two random variables is the most important determinant of the price process.

The intuition of the model is as follows. Suppose that unsophisticated investors become bullish and increase their demand for the risky asset. In case the risky asset is liquid enough, i.e. the random supply is positive, there is no reason to expect that the expected return of sophisticated investors is higher than that of unsophisticated investors. This is because, liquidity providing is not worthy at all and there is no reward on that. But in case the risky asset is illiquid, i.e. the random supply is negative, sophisticated investors would provide liquidity to unsophisticated investors and as a consequence, they would ask for a raise in their expected return. Note that the higher expected return is brought about by selling an overpriced asset to unsophisticated investors which in turn increases the current return and decreases the future return. The opposite case is when unsophisticated investors become bearish and potential sellers. When the random supply is negative, there is no reason for sophisticated investors to have higher expected return than unsophisticated investor. Otherwise, sophisticated investors would buy the underpriced asset and in turn, increase their expected return.

1.4.1 The economy and the solution

Risk-free asset pays the guaranteed amount $R = 1+r$ where $r > 0$. The supply of risk-free asset is assumed to be demand-elastic. Risky asset pays a random amount of dividend in each period:

$$D_t = \hat{D} + d_t \quad where \quad \hat{D}_t > 0$$

$\hat{D}$ is the constant over time part of the dividend process and d_t is the random part. It is assumed that d_t follows and AR(1) process:

$$d_{t+1} = \alpha_d d_t + u_{t+1} \quad where \quad 0 \leq u_d < 1$$

In each period, all investors receive a signal, s_t, about the future dividend shock:

$$u_{t+1} = s_t + \varepsilon_{t+1}$$

$$s_t \sim N(0, \sigma_s^2)$$

$$\varepsilon_t \sim N(0, \varepsilon_s^2)$$

It is also assumed that s_t and ε_{t+1} are independent processes. As mentioned earlier, the model assumes that two types of investors exists in the market. w percent of investors are sophisticated (type A) and others are unsophisticated (type B) investors. While both types are utility maximizers, the difference between the two types is that type B investors misperceive the risky asset's value by a random process:

$$k_t \sim N(0, \sigma_k^2)$$

Both types have constant absolute risk aversion parameter ρ. In each period both types solve the following optimization problem:

$$\max_X \quad E_t[-exp(-\rho W_{t+1})]$$

Type A investors solve the above problem subject to:

$$W_{t+1} = RW_t + X_t^A(P_{t+1} + D_{t+1} - RP_t)$$

Type B investors solve it subject to:

$$W_{t+1} = RW_t + X_t^B(P_{t+1} + D_{t+1} - RP_t + k_t)$$

Where W_t and P_t is the wealth and risky asset's price processes and X_t^A and X_t^B are demands for the risky asset by type A and type B investors, respectively. Moreover, it is assumed that in each period, there is a random supply of the risky asset which shapes the market clearing condition in each period:

$$wX_t^A + (1-w)X_t^B = X_t$$

Where

$$X_t = \hat{X} + x_t$$

$$x_{t+1} = \alpha_x x_t + z_{t+1} \quad where \quad 0 \leq \alpha_x < 1$$

$$z_t \sim N(0, \sigma_x^2)$$

Negative or positive random supply means that there is a random demand or supply for the risky asset, respectively. Given the assumptions about the economy, the fundamental value of the risky asset, F_t, could be obtained by:

$$F_t = E_t[\sum_{n=0}^{\infty} \frac{1}{R^n} D_{t+n}|s_t, d_t] = \frac{R\tilde{D}}{r} + \frac{1}{R-\alpha_d} s_t + \frac{R}{R-\alpha_d} d_t$$

and its variance is given by:

$$\sigma_F^2 = \frac{1}{(R-\alpha_d)^2}\sigma_s^2 + \frac{R^2}{(R-\alpha_d)^2}\sigma_\varepsilon^2$$

The fundamental value, however, is different than equilibrium price of the risky asset. In this economy, the equilibrium price is given by

$$P_t = F_t - D_t + \gamma_0 + \gamma_k k_t + \gamma_X X_t$$

As a proof, assume that price is a function exactly like above. Then it is possible to define excess return as:

$$ER_{t+1} = P_{t+1} + D_{t+1} - RP_t$$

Using the function for price and fundamental value we can obtain the following for excess return in time $t+1$:

$$ER_{t+1} = -r\gamma_0 + \gamma_X(X_{t+1} - RX_t) + \gamma_k(k_{t+1} - Rk_t) + \frac{1}{R-\alpha_d}s_{t+1} + \frac{R}{R-\alpha_d}\varepsilon_{t+1} \quad (1.1)$$

Then its expectation and variance conditional on information at time t are:

$$E_t(ER_{t+1}) = -r(\gamma_0 + \gamma_X\hat{X}) + \gamma_X(\alpha_x - R)x_t - \gamma_k Rk_t \quad (1.2)$$

$$var_t(ER_{t+1}) = \sigma_F^2 + \gamma_X^2\sigma_x^2 + \gamma_k^2\sigma_k^2$$

Based on model's assumptions, type A and B investors' demand for risky asset are:

$$X_t^A = \frac{-r(\gamma_0 + \gamma_X X) + \gamma_X(\alpha_x - R)x_t - \gamma_k Rk_t}{\rho(\sigma_F^2 + \gamma_X^2\sigma_x^2 + \gamma_k^2\sigma_k^2)}$$

$$X_t^B = \frac{-r(\gamma_0 + \gamma_X X) + \gamma_X(\alpha_x - R)x_t - \gamma_k Rk_t + k_t}{\rho(\sigma_F^2 + \gamma_X^2\sigma_x^2 + \gamma_k^2\sigma_k^2)}$$

Market clearing condition gives:

$$r(\ gamma_0 + \gamma_X\hat{X}) + \gamma_X(\alpha_x - R)x_t - \gamma_k Rk_t = \rho\sigma_{ER}^2 X_t - (1-w)k_t \quad (1.3)$$

Where

$$\sigma_{ER}^2 = \sigma_F^2 + P_X^2\sigma_x^2 + P_k^2\sigma_k^2$$

This equation gives the sufficient conditions to solve for parameters in the price equation. More specifically it gives following three conditions:

$$\begin{cases} \gamma_k = \frac{1-w}{R} \\ \gamma_X = \frac{c}{2\sigma_x^2}[-1 \pm \sqrt(1 - \frac{\sigma_x^2}{\sigma_x^{2*}})] \quad s.t. \quad \sigma_x^2 \leq \sigma_x^{2*} \\ \gamma_0 = \frac{\hat{X}(\gamma_X - \rho\sigma_{ER}^2)}{r} \end{cases} \quad (1.4)$$

where

$$c = \frac{R-\alpha_x}{\rho} \quad \sigma_x^{2*} = \frac{c^2}{4q^2} \quad and \quad q^2 = \sigma_F^2 + \gamma_k^2\sigma_k^2$$

γ_k is positive since $w < 1$. γ_X is negative for both roots. But the root with positive sign is more consistent with the fact that when σ_F^2 and σ_k^2 converge to zero, γ_X should converge to zero. This is because as σ_F^2 and σ_k^2 converge to zero, σ_x^2 remains the only source of risk in the model and since both types of investors' exposure to this risk is identical, its importance in determining the price should fade out. The same (γ_X converging to zero) should happen in case σ_x^2 converges to zero and this is another reason to accept the root with positive sign. Provided that the mean supply $\hat{X}$ is positive, γ_0 is also negative since γ_X is negative.

1.4.2 Interpretations

When the mean supply is positive, the results imply that all types of risk decrease the price through P_0. This includes the asset's fundamental risk, supply risk and the risk that type B investors will become bearish. This could be called "abundance" effect: any source of risk would decrease demand and price when supply is positive (risky asset is abundant). On the other hand, when the mean supply is negative, the price is increasing in risk. Contrary to the previous case, negative supply makes the supply worthier and risk would farther decrease it and pushes up the price. Likewise, this could be called "scarcity"effect.

The model implies that bullishness raises the price and bearishness decreases it. It is intuitive since positive misperception increases type B investors' demand as well as aggregate demand, while negative misperception decreases both. The size of the effect is a direct function of the ratio of type B investors. On the extreme cases where all investors are sophisticated, the effect is zero and where all investors are unsophisticated, the effect is just the discounted value of the misperception.

Positive random supply also decreases the price and negative one increases it. Random supply's effect is a decreasing non-linear function of type B investor's ratio, $1 - w$ with negative second order effect. This means that, ceteris paribus, smaller values for random supply would be enough to offset the effect of certain amount of misperception, as the type B investor's ratio increases.

Given the solution for the model, demand function for both investor types are the following:

$$X_t^A = X_t - \frac{(1-w)k_t}{\sigma_{ER}^2} \tag{1.5}$$

$$X_t^B = X_t + \frac{wk_t}{\sigma_{ER}^2} \tag{1.6}$$

As expected, type A investor's demand for risky asset is decreasing in misperception value and it is increasing for type B investor. Using equation 1.1, excess return's unconditional autocorrelation is given by:

$$\rho_{ER} = \frac{1}{\sigma_{ER}^2}[-\frac{\gamma_X^2\sigma_x^2(R-\alpha_x)(1-\alpha_x R)}{1-\alpha_x^2} - R\gamma_k^2\sigma_k^2]$$

With $\alpha_x < \frac{1}{R}$, the autocorrelation value is negative and otherwise the sign is unknown. Moreover, σ_{ER} is a highly nonlinear function of $1 - w$, the ratio of unsophisticated investors.

1.4.3 Relative expected returns

What could be interesting in this setup is analyzing sophisticated investors' expected excess return relative to unsophisticated investors. The expected relative excess return could be defined as the product of the two investor types' holding of the risky asset and the expected excess return defined in 2.4:

$$\Delta ER_t = E_t(ER_{t+1})(X_t^A - X_t^B) = \frac{(1-w)k_t^2}{\rho\sigma_{ER}^2} - k_t X_t$$

ΔER_t has two parts. The first part is positive and captures the increase in sophisticated investor's expected return as a result of unsophisticated investors' misperception. It could be also regarded as the penalty that type B investors incurs because of their misperception. The second part captures the increase in expected return coming from liquidity providing behavior. But this term really increases ΔER_t when k_t and X_t have different signs i.e. when illiquidity arises. Suppose that type B investors have positive misperception but the random supply is negative. What happens in this case is that type B investors will demand a large amount of the risky asset and type A investors will provide more liquidity and increase their expected return relative to expected return of the other type. The opposite case is the same. When unsophisticated investors' misperception is negative (enough) and random supply is positive, they sell more aggressively and it is type A investors who absorb this supply and in turn will ask for higher expected return.

From the setup above, it may seem that these are always the sophisticated investors that have superior position compared to the other type, in the sense that they always have higher expected return. However, it is not the case. ΔER_t is a quadratic function of k_t and takes its lowest value when:

$$k_t^* = \frac{\sigma_{ER}^2}{2(1-w)}$$

Interestingly, with this value for misperception we will have:

$$\Delta ER_t(k_t^*) = \frac{\rho\sigma_{ER}^2 X_t^2}{4(1-w)}$$

Which is decreasing in the random supply, no matter it is positive or negative, and always negative unless the random supply is zero. In this situation unsophisticated inventors, although having misperception about the price, perform absolutely better. However, a necessary condition for this to happen is X_t and k_t having the same sign and this is equivalent to have liquid risky asset. To see this better, note that positive misperception increases the price (since P_k is positive) and positive random supply decreases it (since P_X is negative). When the net effect is negative, the price of the risky asset falls below the fundamental value. At the same time from equations 1.5 and 1.6 we see that unsophisticated investors ask more of the risky asset which is underpriced. Especially when $k_t = k_t^*$, from 1.3 we have:

$$E_t(ER_{t+1})(k_t^*) = \frac{\rho\sigma_{ER}^2 X_t}{2}$$

which is positive since random supply is assumed to be positive. The case when both random supply and misperception are negative is pretty much the same. In this case unsophisticated investors will sell the overpriced asset more aggressively and the expected return of type A investors would be negative.

1.4.4 Model implications

According to the results of the model, two key points that determine who is going to have higher expected return are how liquid is the asset and how large is the misperception. For sophisticated investors to be rewarded for liquidity providing, illiquidity is a necessary condition. The reward for liquidity providing is an increasing function of illiquidity and also how motivated unsophisticated investors are to trade the asset as a result of price misperception. As mentioned earlier, the research question of this paper is not the sources of the price misperception. However, there two key assumptions about the underlying process that generates the price misperception. The first assumption is that it exists and is specific to a part of investors and not all of them. If all of the investors always remain wise or patient enough, or if all of them become foolish or impatient, the model doesn't work. The second assumption is that misperception should be independent of the risks that affect the cash flow process of the risky asset. Otherwise, liquidity providers would incorporate it to re-compute the present value of the future cash flows of the risky asset and adjust their demand function. A reasonable motivation to generate misperception, which characterizes the asymmetry of the illiquidity effect, is the current performance net of market return. Impatient investors would sell a security that is currently underperforming and buy an outperforming security, in a more aggressive manner. Based on the model's framework, two conclusions could be drawn:

- Controlling for market return, illiquid and currently positive (negative) return stocks will face a(n) decrease (increase) in their return and
- The amount by which the return decreases (increases) is related positively to security's illiquidity and negatively to its current performance.

These two conclusions describe the situations in which the liquidity providing becomes worthier in the model. But it is natural to think of possible similar situations outside the model. One of these situations is when market becomes more illiquid. Obviously, in times of more illiquid market, the reward on liquidity providing would be higher because liquidity supply is lower. Hence, it is expected that the relation described in the second prediction above is more pronounced in times of illiquid market. It leads us to make the third conclusion as:

- The effect of illiquidity and current performance on expected utility as described above, is more pronounced in times of more illiquid market.

More specifically, the first two conclusions talk about the sign of the effect and the third talks about the magnitude: for the same level of illiquidity and current return, expected return is higher when market is more illiquid.

1.4.5 Conclusion

In this paper I study the effect of illiquidity on stock returns using a new view point. While current literature generally concludes that the positive effect exists not only in the US stock market but also in other markets and also other countries, using data on NYSE-AMEX individual stocks, this paper provides strong evidence supporting that the effect is asymmetric and not always positive. I employed two widely used measures for illiquidity which are Amihud's (2002) illiq and turnover. The results highly confirm the existence of asymmetric effect of illiquidity in cross-sectional analysis. Moreover, using turnover which is a less sensitive measure for liquidity relative to Amihud's measure, I find that market illiquidity increases the asymmetric effect of illiquidity on returns. Moreover, the empirical evidence suggests that not considering the asymmetry of the effect, may result in finding illiquidity not significant in explaining returns, or finding a negative effect of illiquidity on returns. The theoretical model gives a consistent explanation of the mechanism through which illiquidity affects stock returns. Simply put, the model says that the effect is the change in expected return that could be considered as the price for liquidity and is paid by investors demanding it. When demand for illiquidity is initiated by investors willing to buy a stock, the change in expected return is negative and vice versa. Based on this reasoning, when there is an incentive for buying an illiquid stock, there should be a consecutive negative return and when there is an incentive for selling an illiquid stock, there should be a consecutive positive return, and this relation is more pronounced when market is less liquid.

Table 1.2: Cross-sectional relation between stock returns and Amihud's illiq, weekly Fama-MacBeth regression

	(1) Ret_{t+1}^i	(2) Ret_{t+1}^i	(3) Ret_{t+1}^i	(4) Ret_{t+1}^i	(5) Ret_{t+1}^i	(6) Ret_{t+1}^i	(7) Ret_{t+1}^i
Ret_t^i	-0.0805***	-0.0806***	-0.0738***	-0.0721***	-0.0770***	-0.0763***	-0.0764***
	(-46.66)	(-46.75)	(-41.39)	(-41.10)	(-44.29)	(-43.95)	(-44.04)
$Beta_t^i$	-0.000291	-0.000292	-0.000299	-0.000301	-0.000292	-0.000288	-0.000289
	(-1.69)	(-1.70)	(-1.71)	(-1.76)	(-1.66)	(-1.68)	(-1.69)
SD_t^i	0.0299**	0.0298**	0.0292**	0.0315**	0.0279*	0.0304**	0.0303**
	(2.61)	(2.62)	(2.58)	(2.77)	(2.48)	(2.65)	(2.66)
BE/ME_t^i	4.22e-4***	4.29e-4***	4.47e-4***	4.42e-4***	4.37e-4***	4.25e-4***	4.32e-4***
	(4.95)	(5.12)	(5.15)	(5.31)	(5.00)	(5.01)	(5.18)
$devyld_t^i$	-1.94e-5	-3.60e-5	-3.43e-5	-3.61e-5	-3.51e-5	-1.98e-5	-3.59e-5
	(-0.90)	(-1.17)	(-1.13)	(-1.19)	(-1.15)	(-0.92)	(-1.17)
$Illiq_t^i$	0.0732	0.0727		-0.0419			
	(1.83)	(1.82)		(-0.92)			
$Size_t^i$		-0.0192	-0.0207	-0.0206	-0.0198		-0.0202
		(-0.75)	(-0.82)	(-0.81)	(-0.78)		(-0.80)
$(Illiq * Ret)_t^i$			-7.677***	-10.18***			
			(-15.66)	(-19.37)			
$Illiq_t^{i*}$					0.400***		
					(14.96)		
$(Dump * Illiq)_t^i$						-0.517***	-0.517***
						(-9.05)	(-9.03)
$(Dumn * Illiq)_t^i$						0.491***	0.489***
						(9.77)	(9.74)
_cons	0.00201***	0.00203***	0.00202***	0.00200***	0.00205***	0.00200***	0.00202***
	(6.28)	(6.35)	(6.23)	(6.31)	(6.27)	(6.27)	(6.34)
N	4,174,497	4,174,497	4,174,497	4,174,497	4,174,497	4,174,497	4,174,497
R^2	0.0421	0.0431	0.0434	0.0469	0.0421	0.0446	0.0456

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table contains the results of estimating weekly NYSE-AMEX stock returns on its determinants for the period 1962 to 2011. $Illiq_t^i$ is Amihud's (2002) liquidity measure for stock i at period t and $Illiq_t^{i*}$ is defined as:

$Illiq_t^{i*} \cong Illiq_t^i * (-1) * 1_{R_t^i - R_t^m \geq 0} + Illiq_t^i * 1_{R_t^i - R_t^m < 0}$

and $Dump_t^i$ and $Dumn_t^i$ are defined as:

$Dump_t^i \cong 1_{R_t^i - R_t^m \geq 0}$ and $Dumn_t^i \cong 1_{R_t^i - R_t^m < 0}$ where R_t^i and R_t^m are individual stock and market returns on period t, respectively. p-values are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.3: Cross-sectional relation between stock returns and turnover, weekly Fama-MacBeth regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ret^i_{t+1}	Ret^i_{t+1}	Ret^i_{t+1}	Ret^i_{t+1}	Ret^i_{t+1}	Ret^i_{t+1}	Ret^i_{t+1}
Ret^i_t	-0.0826***	-0.0826***	-0.0919***	-0.0920***	-0.0925***	-0.0933***	-0.0933***
	(-48.00)	(-48.09)	(-49.09)	(-49.09)	(-52.21)	(-52.28)	(-52.35)
$Beta^i_t$	-4.97e-4**	-5.00e-4**	-2.90e-4	-4.95e-4**	-2.94e-4	-4.97e-4**	-0.000499**
	(-2.96)	(-2.98)	(-1.65)	(-2.95)	(-1.67)	(-2.96)	(-2.99)
SD^i_t	0.0235*	0.0235*	0.0282*	0.0225*	0.0302**	0.0232*	0.0232*
	(2.12)	(2.13)	(2.51)	(2.04)	(2.70)	(2.10)	(2.11)
BE/ME^i_t	4.81e-4***	4.87e-4***	4.23e-4***	4.78e-4***	4.24e-4***	4.75e-4***	0.000480***
	(5.56)	(5.72)	(4.86)	(5.62)	(4.89)	(5.50)	(5.66)
$devyld^i_t$	-1.15e-6	-1.43e-5	-2.47e-5	-1.24e-5	-2.31e-5	9.15e-7	1.16e-5
	(-0.05)	(-0.46)	(-0.78)	(-0.39)	(-0.73)	(0.04)	(-0.37)
$mTrnvr^i_t$	-1.636***	-1.632***		-1.602***			
	(-12.35)	(-12.34)		(-11.23)			
$Size^i_t$		-0.0188	-0.0177	-0.0184	-0.0187		-0.0193
		(-0.75)	(-0.70)	(-0.73)	(-0.74)		(-0.77)
$(mTrnvr * Ret)^i_t$			-10.22***	-9.111***			
			(-13.31)	(-11.24)			
$mTrnvr^{i*}_t$					1.330***		
					(18.50)		
$(Dump * mTrnvr)^i_t$						-2.936***	-2.932***
						(-19.88)	(-19.87)
$(Dumn * mTrnvr)^i_t$						-0.350*	-0.348*
						(-2.15)	(-2.14)
_cons	0.00153***	0.00155***	0.00204***	0.00157***	0.00199***	0.00151***	0.00153***
	(4.86)	(4.93)	(6.24)	(5.02)	(6.08)	(4.80)	(4.87)
N	4186208	4186208	4186208	4186208	4186208	4186208	4186208
R^2	0.044	0.045	0.043	0.048	0.042	0.046	0.047

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table contains the results of estimating weekly NYSE-AMEX stock returns on its determinants for the period 1962 to 2011. $mTrnvr^i_t$ is turnover for stock i at period t and $mTrnvr^{i*}_t$ is defined as:

$$Illiq^{i*}_t \cong Illiq^i_t * (-1) * 1_{R^i_t - R^m_t \geq 0} + Illiq^i_t * 1_{R^i_t - R^m_t < 0}$$

$$mTrnvr^{i*}_t \cong mTrnvr^i_t * (-1) * 1_{R^i_t - R^m_t \geq 0} + mTrnvr^i_t * 1_{R^i_t - R^m_t < 0}$$

and $Dump^i_t$ and $Dumn^i_t$ are defined as:

$Dump^i_t \cong 1_{R^i_t - R^m_t \geq 0}$ and $Dumn^i_t \cong 1_{R^i_t - R^m_t < 0}$ where R^i_t and R^m_t are individual stock and market returns on period t, respectively. p-values are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.4: Cross-sectional relation between stock returns and Amihud's illiq, monthly Fama-MacBeth regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ret^i_{t+1}	Ret^i_{t+1}	Ret^i_{t+1}	Ret^i_{t+1}	Ret^i_{t+1}	Ret^i_{t+1}	Ret^i_{t+1}
Ret^i_t	-0.0488***	-0.0490***	-0.0434***	-0.0395***	-0.0446***	-0.0437***	-0.0439***
	(-12.40)	(-12.48)	(-11.00)	(-10.18)	(-11.44)	(-11.20)	(-11.29)
$Beta^i_t$	-0.00137	-0.00138	-0.00144	-0.00145	-0.00134	-0.00140	-0.00141
	(-1.60)	(-1.60)	(-1.64)	(-1.69)	(-1.50)	(-1.64)	(-1.64)
SD^i_t	-0.0151	-0.0155	-0.0205	-0.00717	-0.0278	-0.0113	-0.0118
	(-0.25)	(-0.26)	(-0.33)	(-0.12)	(-0.45)	(-0.19)	(-0.20)
BE/ME^i_t	0.00166***	0.00170***	0.00181***	0.00173***	0.00175***	0.00167***	0.00171***
	(4.19)	(4.36)	(4.41)	(4.44)	(4.23)	(4.21)	(4.38)
$devyld^i_t$	-0.000178	-0.000289	-0.000307*	-0.000287	-0.000297	-0.000175	-0.000288
	(-1.61)	(-1.89)	(-2.01)	(-1.89)	(-1.95)	(-1.59)	(-1.89)
$Illiq^i_t$	0.204	0.204		-0.258			
	(0.87)	(0.87)		(-0.89)			
$Size^i_t$		-0.0336	-0.0434	-0.0388	-0.0401		-0.0362
		(-0.30)	(-0.38)	(-0.34)	(-0.35)		(-0.32)
$(Illiq$ $*Ret)^i_t$			-7.505***	-14.38***			
			(-5.85)	(-10.51)			
$Illiq^{i*}_t$					1.200***		
					(7.84)		
$(Dump$ $*Illiq)^i_t$						-1.622***	-1.620***
						(-5.27)	(-5.26)
$(Dumn$ $*Illiq)^i_t$						1.259***	1.256***
						(4.60)	(4.59)
_cons	0.0118***	0.0119***	0.0120***	0.0117***	0.0120***	0.0117***	0.0118***
	(8.19)	(8.21)	(8.14)	(8.13)	(8.11)	(8.15)	(8.17)
N	962173	962173	962173	962173	962173	962173	962173
R^2	0.057	0.058	0.058	0.062	0.057	0.060	0.061

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table contains the results of estimating monthly NYSE-AMEX stock returns on its determinants for the period 1962 to 2011. $Illiq^i_t$ is Amihud's (2002) liquidity measure for stock i at period t and $Illiq^{i*}_t$ is defined as:

$$Illiq^{i*}_t \cong Illiq^i_t * (-1) * 1_{R^i_t - R^m_t \geq 0} + Illiq^i_t * 1_{R^i_t - R^m_t < 0}$$

and $Dump^i_t$ and $Dumn^i_t$ are defined as:

$Dump^i_t \cong 1_{R^i_t - R^m_t \geq 0}$ and $Dumn^i_t \cong 1_{R^i_t - R^m_t < 0}$ where R^i_t and R^m_t are individual stock and market returns on period t, respectively. p-values are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.5: Cross-sectional relation between stock returns and turnover, monthly Fama-MacBeth regression

	(1) Ret^i_{t+1}	(2) Ret^i_{t+1}	(3) Ret^i_{t+1}	(4) Ret^i_{t+1}	(5) Ret^i_{t+1}	(6) Ret^i_{t+1}	(7) Ret^i_{t+1}
Ret^i_t	-0.0485***	-0.0487***	-0.0685***	-0.0697***	-0.0624***	-0.0624***	-0.0625***
	(-12.29)	(-12.37)	(-15.41)	(-15.65)	(-15.30)	(-15.24)	(-15.31)
$Beta^i_t$	-0.00176*	-0.00176*	-0.00145	-0.00145	-0.00146	-0.00164	-0.00164
	(-2.07)	(-2.07)	(-1.63)	(-1.72)	(-1.64)	(-1.94)	(-1.94)
SD^i_t	-0.00698	-0.00739	-0.0285	-0.00938	-0.0169	-0.00363	-0.00405
	(-0.11)	(-0.12)	(-0.46)	(-0.15)	(-0.27)	(-0.06)	(-0.06)
BE/ME^i_t	0.00182***	0.00186***	0.00180***	0.00183***	0.00182***	0.00180***	0.00184***
	(4.39)	(4.56)	(4.33)	(4.46)	(4.39)	(4.34)	(4.50)
$devyld^i_t$	-0.000182	-0.000298*	-0.000305*	-0.000310*	-0.000299	-0.000189	-0.000305*
	(-1.69)	(-1.99)	(-1.97)	(-2.07)	(-1.95)	(-1.76)	(-2.04)
$mTrnvr^i_t$	-0.844	-0.837		0.569			
	(-1.37)	(-1.36)		(0.85)			
$Size^i_t$		-0.0304	-0.0269	-0.0341	-0.0325		-0.0294
		(-0.27)	(-0.24)	(-0.30)	(-0.29)		(-0.26)
$(mTrnvr *Ret)^i_t$			-20.16***	-24.02***			
			(-10.15)	(-11.41)			
$mTrnvr^{i*}_t$					2.843***		
					(8.79)		
$(Dump *mTrnvr)^i_t$						-3.537***	-3.531***
						(-5.37)	(-5.36)
$(Dumn *mTrnvr)^i_t$						2.870***	2.869***
						(3.65)	(3.65)
_cons	0.0115***	0.0115***	0.0123***	0.0120***	0.0120***	0.0116***	0.0117***
	(7.85)	(7.87)	(8.26)	(8.20)	(8.09)	(7.94)	(7.95)
N	962,215	962,215	962,215	962,215	962,215	962,215	962,215
R^2	0.058	0.059	0.058	0.062	0.056	0.060	0.061

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table contains the results of estimating monthly NYSE-AMEX stock returns on its determinants for the period 1962 to 2011. $mTrnvr^i_t$ is turnover for stock i at period t and $mTrnvr^{i*}_t$ is defined as:

$$Illiq^{i*}_t \cong Illiq^i_t * (-1) * 1_{R^i_t - R^m_t \geq 0} + Illiq^i_t * 1_{R^i_t - R^m_t < 0}$$

$$mTrnvr^{i*}_t \cong mTrnvr^i_t * (-1) * 1_{R^i_t - R^m_t \geq 0} + mTrnvr^i_t * 1_{R^i_t - R^m_t < 0}$$

and $Dump^i_t$ and $Dumn^i_t$ are defined as:

$Dump^i_t \cong 1_{R^i_t - R^m_t \geq 0}$ and $Dumn^i_t \cong 1_{R^i_t - R^m_t < 0}$ where R^i_t and R^m_t are individual stock and market returns on period t, respectively. p-values are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.6: This table presents results of Fama-MacBeth cross-sectional analysis for weekly frequency data of portfolios formed using NYSE-AMEX individual stocks for sample period 1962-2011. $Illiq_t^{p*}$ is defined as:
$Illiq_t^{p*} \cong Illiq_t^p * (-1) * 1_{R_t^p - R_t^m \geq 0} + Illiq_t^p * 1_{R_t^p - R_t^m < 0}$
and $Dump_t^p$ and $Dumn_t^p$ are defined as:
$Dump_t^p \cong 1_{R_t^p - R_t^m \geq 0}$ and $Dumn_t^p \cong 1_{R_t^p - R_t^m < 0}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p
Ret_t^p	-0.0796***	-0.0798***	-0.0666***	-0.0646***	-0.0726***	-0.0716***	-0.0719***
	(-45.44)	(-45.65)	(-35.05)	(-34.95)	(-39.68)	(-39.74)	(-39.94)
$Beta_t^p$	0.000480	0.000477	0.000729*	0.000530	0.000669*	0.000520	0.000517
	(1.60)	(1.60)	(2.39)	(1.79)	(2.16)	(1.72)	(1.72)
SD_t^p	0.0782***	0.0802***	0.0625***	0.0847***	0.0633***	0.0760***	0.0781***
	(4.57)	(4.72)	(3.89)	(4.98)	(3.95)	(4.41)	(4.56)
BE/ME_t^p	-6.54e-4**	-6.78e-4**	-6.56e-4**	-6.73e-4**	-6.26e-4*	-6.56e-4**	-6.86e-4**
	(-2.90)	(-3.00)	(-2.72)	(-3.01)	(-2.56)	(-2.92)	(-3.05)
$devyld_t^p$	7.47e-5	4.38e-5	5.58e-5	7.27e-5	3.72e-5	7.17e-5	5.25e-5
	(1.18)	(0.41)	(0.53)	(0.70)	(0.35)	(1.15)	(0.50)
$Illiq_t^p$	-0.0622	-0.0622		-0.152**			
	(-1.30)	(-1.31)		(-3.00)			
$Size_t^p$		-7.68e-11	-8.41e-11	-7.82e-11	-7.92e-11		-7.94e-11
		(-1.24)	(-1.35)	(-1.29)	(-1.27)		(-1.30)
$(Illiq$							
$*Ret)_t^p$			-10.04***	-11.52***			
			(-21.05)	(-23.32)			
$Illiq_t^{p*}$					0.516***		
					(17.52)		
$(Dump$							
$*Illiq)_t^p$						-0.651***	-0.647***
						(-10.51)	(-10.50)
$(Dumn$							
$*Illiq)_t^p$						0.492***	0.488***
						(8.51)	(8.48)
_cons	0.000627	0.000625	0.000809	0.000494	0.000854	0.000664	0.000662
	(1.34)	(1.33)	(1.64)	(1.06)	(1.70)	(1.43)	(1.42)
N	266,100	266,100	266,100	266,100	266,100	266,100	266,100
R^2	0.807	0.807	0.910	0.910	0.853	0.853	0.853

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.7: This table presents results of Fama-MacBeth cross-sectional analysis for weekly frequency data of portfolios formed using NYSE-AMEX individual stocks for sample period 1962-2011. $mTrnvr_t$ is simply the product of minus one and turnover. $mTrnvr_t^{i*}$ is defined as:
$mTrnvr_t^{i*} \cong mTrnvr_t^i * (-1) * 1_{R_t^i - R_t^m \geq 0} + mTrnvr_t^i * 1_{R_t^i - R_t^m < 0}$
and $Dump_t^i$ and $Dumn_t^i$ are defined as:
$Dump_t^i \cong 1_{R_t^i - R_t^m \geq 0}$ and $Dumn_t^i \cong 1_{R_t^i - R_t^m < 0}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p
Ret_t^p	-0.0818***	-0.0822***	-0.0921***	-0.0958***	-0.102***	-0.104***	-0.104***
	(-46.85)	(-47.00)	(-45.55)	(-45.94)	(-52.03)	(-52.29)	(-52.32)
$Beta_t^p$	-2.78e-4	-2.92e-4	4.31e-4	-3.17e-4	4.95e-4	-2.26e-4	-2.38e-4
	(-0.94)	(-0.99)	(1.41)	(-1.08)	(1.62)	(-0.78)	(-0.82)
SD_t^p	0.0725***	0.0746***	0.0660***	0.0712***	0.0705***	0.0779***	0.0800***
	(4.56)	(4.72)	(4.15)	(4.51)	(4.42)	(4.89)	(5.05)
BE/ME_t^p	4.65e-5	5.85e-5	-5.36e-5*	6.85e-5	-6.00e-4*	-1.06e-5	-1.06e-5
	(0.21)	(0.26)	(-2.21)	(0.31)	(-2.46)	(-0.05)	(-0.05)
$devyld_t^p$	5.18e-5	1.40e-5	4.95e-5	4.68e-5	1.17e-5	8.12e-5	0.000117
	(0.78)	(0.13)	(0.46)	(0.43)	(1.12)	(1.23)	(1.12)
$mTrnvr_t^p$	-1.696***	-1.750***		-1.868***			
	(-9.05)	(-9.34)		(-8.29)			
$Size_t^p$		-8.07e-11	-7.52e-11	-9.24e-11	-9.49e-11		-1.23e-10*
		(-1.32)	(-1.22)	(-1.51)	(-1.58)		(-2.05)
$(mTrnvr * Ret)_t^p$			-11.62***	-15.60***			
			(-9.78)	(-11.73)			
$mTrnvr_t^{p*}$					1.940***		
					(20.63)		
$(Dump * mTrnvr)_t^p$						-3.838***	-3.906***
						(-18.42)	(-18.63)
$(Dumn * mTrnvr)_t^p$						0.641**	0.614**
						(2.94)	(2.83)
_cons	7.85e-6	-4.93e-5	9.15e-4	-5.85e-5	7.45e-4	-1.51e-4	-2.01e-4
	(0.02)	(-0.10)	(1.81)	(-0.13)	(1.45)	(-0.32)	(-0.42)
N	266,100	266,100	266,100	266,100	266,100	266,100	266,100
R^2	0.820	0.824	0.841	0.845	0.880	0.886	0.886

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.8: This table presents results of Fama-MacBeth cross-sectional analysis for monthly frequency data of portfolios formed using NYSE-AMEX individual stocks for sample period 1962-2011. $Illiq_t^{p*}$ is defined as:
$Illiq_t^{p*} \cong Illiq_t^p * (-1) * 1_{R_t^p - R_t^m \geq 0} + Illiq_t^p * 1_{R_t^p - R_t^m < 0}$
and $Dump_t^p$ and $Dumn_t^p$ are defined as:
$Dump_t^p \cong 1_{R_t^p - R_t^m \geq 0}$ and $Dumn_t^p \cong 1_{R_t^p - R_t^m < 0}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p
Ret_t^p	-0.0525***	-0.0530***	-0.0420***	-0.0382***	-0.0457***	-0.0443***	-0.0449***
	(-13.42)	(-13.58)	(-10.59)	(-9.83)	(-11.72)	(-11.43)	(-11.60)
$Beta_t^p$	-6.69e-4	-6.06e-4	-5.47e-4	-9.87e-4	-7.01e-4	-9.71e-4	-9.05e-4
	(-0.46)	(-0.41)	(-0.36)	(-0.67)	(-0.45)	(-0.67)	(-0.62)
SD_t^p	-0.0875	-0.0878	-0.100	-0.0678	-0.109	-0.0799	-0.0809
	(-1.01)	(-1.02)	(-1.17)	(-0.79)	(-1.30)	(-0.92)	(-0.94)
BE/ME_t^p	0.00246**	0.00251**	0.00311**	0.00300**	0.00257**	0.00255**	0.00259**
	(2.67)	(2.72)	(3.28)	(3.27)	(2.67)	(2.75)	(2.77)
$devyld_t^p$	-2.31e-4	-7.72e-4	-7.19e-4	-5.98e-4	-7.54e-4	-1.88e-4	-6.44e-4
	(-0.84)	(-1.77)	(-1.73)	(-1.45)	(-1.75)	(-0.70)	(-1.53)
$Illiq_t^p$	0.00223	0.0106		-0.232			
	(0.01)	(0.04)		(-0.79)			
$Size_t^p$		2.66e-10	3.10e-10	2.37e-10	2.98e-10		2.19e-10
		(1.04)	(1.21)	(0.97)	(1.15)		(0.88)
$(Illiq * Ret)_t^p$			-10.97***	-13.72***			
			(-9.30)	(-10.65)			
$Illiq_t^{p*}$					1.247***		
					(8.87)		
$(Dump * Illiq)_t^p$						-1.483***	-1.453***
						(-4.89)	(-4.81)
$(Dumn * Illiq)_t^p$						1.109***	1.101***
						(3.93)	(3.95)
_cons	0.0125***	0.0126***	0.0123***	0.0121***	0.0130***	0.0125***	0.0126***
	(6.04)	(6.12)	(5.76)	(5.93)	(6.06)	(6.05)	(6.15)
N	61,100	61,100	61,100	61,100	61,100	61,100	61,100
R^2	0.637	0.677	0.751	0.765	0.704	0.694	0.718

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.9: This table presents results of Fama-MacBeth cross-sectional analysis for monthly frequency data of portfolios formed using NYSE-AMEX individual stocks for sample period 1962-2011. $mTrnvr_t$ is simply the product of minus one and turnover. $mTrnvr_t^{p*}$ is defined as:
$mTrnvr_t^{p*} \cong mTrnvr_t^p * (-1) * 1_{R_t^p - R_t^m \geq 0} + mTrnvr_t^p * 1_{R_t^p - R_t^m < 0}$
and $Dump_t^p$ and $Dumn_t^p$ are defined as:
$Dump_t^p \cong 1_{R_t^p - R_t^m \geq 0}$ and $Dumn_t^p \cong 1_{R_t^p - R_t^m < 0}$

	(1) Ret_{t+1}^p	(2) Ret_{t+1}^p	(3) Ret_{t+1}^p	(4) Ret_{t+1}^p	(5) Ret_{t+1}^p	(6) Ret_{t+1}^p	(7) Ret_{t+1}^p
Ret_t^p	-0.0434***	-0.0432***	-0.0699***	-0.0767***	-0.0612***	-0.0615***	-0.0615***
	(-11.19)	(-11.18)	(-15.37)	(-16.55)	(-15.22)	(-15.24)	(-15.26)
$Beta_t^p$	0.00108	0.00104	0.00125	0.00320*	0.00138	0.00132	0.00126
	(0.71)	(0.68)	(0.77)	(2.16)	(0.86)	(0.88)	(0.83)
SD_t^p	0.0355	0.0411	-0.0782	-0.0309	0.0269	0.0372	0.0403
	(0.45)	(0.52)	(-1.01)	(-0.39)	(0.34)	(0.46)	(0.50)
BE/ME_t^p	0.00196*	0.00213*	0.00168	0.00129	0.00162	0.00163	0.00178
	(2.17)	(2.32)	(1.82)	(1.44)	(1.75)	(1.83)	(1.96)
$devyld_t^p$	-4.08e-4	-7.24e-4	-0.00109*	-0.00103*	-8.98e-4	-4.62e-4	-7.69e-4
	(-1.08)	(-1.41)	(-2.00)	(-2.00)	(-1.68)	(-1.23)	(-1.51)
$mTrnvr_t^p$	-0.0299	-0.0463		2.069**			
	(-0.05)	(-0.07)		(3.03)			
$Size_t^p$		7.00e-12	-6.23e-11	-8.10e-11	-5.34e-11		2.32e-12
		(0.02)	(-0.19)	(-0.25)	(-0.16)		(0.01)
$(mTrnvr * Ret)_t^p$			-21.37***	-27.40***			
			(-11.25)	(-13.71)			
$mTrnvr_t^{p*}$					2.871***		
					(10.52)		
$(Dump * mTrnvr)_t^p$						-2.701***	-2.750***
						(-4.12)	(-4.18)
$(Dumn * mTrnvr)_t^p$						2.802***	2.787***
						(4.06)	(4.05)
_cons	0.00748***	0.00747***	0.0107***	0.00942***	0.00823***	0.00785***	0.00792***
	(4.02)	(4.00)	(5.66)	(5.02)	(4.35)	(4.21)	(4.24)
N	61,100	61,100	61,100	61,100	61,100	61,100	61100
R^2	0.640	0.666	0.868	0.904	0.748	0.738	0.749

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.10: This table presents results of Fama-MacBeth cross-sectional analysis for weekly frequency data of portfolios formed using NYSE-AMEX individual stocks for sample period 1962-2011, for different market illiquidity times. When $Milliq_t = 1$, observations are associated to lowest market illiquidity times (first market illiquidity quartile) and when $Milliq_t = 4$ observations are associated to highest market illiquidity times (last market illiquidity quartile). $Illiq_t^{p*}$ is defined as:
$Illiq_t^{p*} \cong Illiq_t^p * (-1) * 1_{R_t^p - R_t^m \geq 0} + Illiq_t^p * 1_{R_t^p - R_t^m < 0}$
and $Dump_t^p$ and $Dumn_t^p$ are defined as:
$Dump_t^p \cong 1_{R_t^p - R_t^m \geq 0}$ and $Dumn_t^p \cong 1_{R_t^p - R_t^m < 0}$

	(1)		(2)		(3)	
$Milliq_t$:	1	4	= 1	4	1	4
	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p
Ret_t^p	-0.0962***	-0.0518***	-0.102***	-0.0581***	-0.1000***	-0.0575***
	(-22.99)	(-13.51)	(-25.64)	(-15.63)	(-25.75)	(-15.65)
$Beta_t^p$	-0.000168	0.00153*	-0.000406	0.00150*	-0.000301	0.00107
	(-0.31)	(2.04)	(-0.73)	(2.00)	(-0.59)	(1.43)
SD_t^p	0.144***	0.0337	0.153***	0.0371	0.146***	0.0610
	(3.62)	(1.10)	(3.83)	(1.25)	(3.71)	(1.75)
BE/ME_t^p	0.000291	-0.00114**	0.000363	-0.00106*	-0.0000130	-0.000885*
	(0.46)	(-2.74)	(0.56)	(-2.49)	(-0.02)	(-2.20)
$devyld_t^p$	-0.000392	0.000181	-0.000396	0.000178	-0.000403	0.000210
	(-1.18)	(1.44)	(-1.19)	(1.36)	(-1.22)	(1.64)
$Size_t^p$	1.50e-10	-1.93e-10	1.64e-10	-1.86e-10	1.39e-10	-1.91e-10
	(0.90)	(-1.83)	(0.97)	(-1.76)	(0.85)	(-1.82)
$(Illiq * Ret)_t^p$	-7.935***	-12.36***				
	(-7.74)	(-12.89)				
$Illiq_t^{p*}$			0.247***	0.765***		
			(4.56)	(11.03)		
$(Dump * Illiq)_t^p$					-0.147	-1.071***
					(-1.24)	(-7.88)
$(Dumn * Illiq)_t^p$					0.401***	0.683***
					(3.81)	(5.02)
_cons	-0.00121	0.000353	-0.00116	0.000275	-0.000942	-0.000146
	(-1.28)	(0.33)	(-1.20)	(0.25)	(-1.09)	(-0.14)
N	66,600	66,500	66,600	66,500	66,600	66,500
R^2	0.946	0.856	0.922	0.786	0.923	0.787

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.11: This table presents results of Fama-MacBeth cross-sectional analysis for weekly frequency data of portfolios formed using NYSE-AMEX individual stocks for sample period 1962-2011, for different market mturnover times. When $MmTrnvr_t = 1$, observations are associated to lowest market mturnover times (first market mturover quartile) and when $MmTrnvr_t = 4$ observations are associated to highest market mturnover times (last market mturover quartile). $mTrnvr_t$ is simply the product of minus one and turnover. $mTrnvr_t^{p*}$ is defined as:
$mTrnvr_t^{p*} \cong mTrnvr_t^p * (-1) * 1_{R_t^p - R_t^m \geq 0} + mTrnvr_t^p * 1_{R_t^p - R_t^m < 0}$
and $Dump_t^p$ and $Dumn_t^p$ are defined as:
$Dump_t^p \cong 1_{R_t^p - R_t^m \geq 0}$ and $Dumn_t^p \cong 1_{R_t^p - R_t^m < 0}$

	(1)		(2)		(3)	
$MmTrnvr_t$:	1	4	1	4	1	4
	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p
Ret_t^p	-0.0424***	-0.144***	-0.0440***	-0.158***	-0.0437***	-0.162***
	(-10.23)	(-38.27)	(-11.22)	(-45.12)	(-11.45)	(-44.63)
$Beta_t^p$	-0.0000389	0.000685	-0.00000743	0.000974	0.0000653	-0.000559
	(-0.05)	(1.08)	(-0.01)	(1.53)	(0.09)	(-0.97)
SD_t^p	0.0930**	-0.0425	0.0976**	-0.0406	0.105**	-0.0328
	(2.88)	(-1.35)	(3.00)	(-1.29)	(3.22)	(-1.06)
BE/ME_t^p	-0.000351	-0.000865	-0.000415	-0.000952*	-0.000179	-0.000107
	(-0.81)	(-1.86)	(-0.96)	(-2.04)	(-0.45)	(-0.25)
$devyld_t^p$	0.00000220	0.000724*	-0.00000541	0.000784*	0.00000824	0.000872**
	(0.04)	(2.30)	(-0.10)	(2.58)	(0.16)	(2.89)
$Size_t^p$	-1.32e-11	-4.23e-10*	-9.94e-12	-4.19e-10*	-2.15e-11	-4.64e-10**
	(-0.58)	(-2.31)	(-0.43)	(-2.33)	(-0.90)	(-2.59)
$(mTrnvr *Ret)_t^p$	-9.006**	-16.04***				
	(-3.24)	(-7.43)				
$mTrnvr_t^{p*}$			0.990***	2.566***		
			(4.20)	(16.97)		
$(Dump *mTrnvr)_t^p$					-2.097***	-5.390***
					(-3.94)	(-14.99)
$(Dumn *mTrnvr)_t^p$					0.873	0.390
					(1.54)	(1.17)
_cons	0.0000158	0.00167	-0.000245	0.00136	-0.000873	0.000332
	(0.01)	(1.88)	(-0.21)	(1.50)	(-0.86)	(0.38)
N	66,500	66,600	66,500	66,600	66,500	66,600
R^2	0.701	0.896	0.679	0.936	0.704	0.936

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.12: This table presents results of Fama-MacBeth cross-sectional analysis for monthly frequency data of portfolios formed using NYSE-AMEX individual stocks for sample period 1962-2011, for different market illiquidity times. When $Milliq_t = 1$, observations are associated to lowest market illiquidity times (first market illiquidity quartile) and when $Milliq_t = 4$ observations are associated to highest market illiquidity times (last market illiquidity quartile). $Illiq_t^{p*}$ is defined as:
$Illiq_t^{p*} \cong Illiq_t^p * (-1) * 1_{R_t^p - R_t^m \geq 0} + Illiq_t^p * 1_{R_t^p - R_t^m < 0}$
and $Dump_t^p$ and $Dumn_t^p$ are defined as:
$Dump_t^p \cong 1_{R_t^p - R_t^m \geq 0}$ and $Dumn_t^p \cong 1_{R_t^p - R_t^m < 0}$

	(1)		(2)		(3)	
$Milliq_t$:	1	4	1	4	1	4
	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p
Ret_t^p	-0.0409***	-0.0417***	-0.0414***	-0.0456***	-0.0388***	-0.0445***
	(-5.10)	(-4.24)	(-5.63)	(-4.61)	(-5.15)	(-4.47)
$Beta_t^p$	-0.00869***	0.00795	-0.00838**	0.00876*	-0.00602*	0.00382
	(-3.49)	(1.84)	(-3.30)	(2.00)	(-2.47)	(0.92)
SD_t^p	0.186	0.238	0.162	0.208	0.108	0.419*
	(0.95)	(1.46)	(0.84)	(1.26)	(0.55)	(2.59)
BE/ME_t^p	0.00801**	-0.00129	0.00762**	-0.00120	0.00762***	-0.000605
	(3.34)	(-0.78)	(3.27)	(-0.71)	(3.41)	(-0.36)
$devyld_t^p$	-0.00406**	0.000785	-0.00533**	0.000903	-0.00498**	0.000759
	(-2.72)	(1.28)	(-3.28)	(1.47)	(-3.21)	(1.28)
$Size_t^p$	1.03e-09	-6.51e-10	1.41e-09	-7.37e-10	1.11e-09	-5.81e-10
	(1.47)	(-0.91)	(1.94)	(-0.97)	(1.49)	(-0.78)
$(Illiq * Ret)_t^p$	-21.19***	-11.71***				
	(-4.26)	(-3.98)				
$Illiq_t^{p*}$			2.541***	1.351**		
			(5.51)	(3.03)		
$(Dump * Illiq)_t^p$					-1.781	-4.374***
					(-1.91)	(-5.37)
$(Dumn * Illiq)_t^p$					4.375***	-0.679
					(4.71)	(-0.84)
_cons	0.00419	-0.000985	0.00451	-0.00105	0.00266	-0.00162
	(1.12)	(-0.22)	(1.23)	(-0.23)	(0.73)	(-0.35)
N	15,300	15,200	15,300	15,200	15,300	15,200
R^2	0.671	0.786	0.649	0.722	0.667	0.735

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.13: This table presents results of Fama-MacBeth cross-sectional analysis for monthly frequency data of portfolios formed using NYSE-AMEX individual stocks for sample period 1962-2011, for different market mturnover times. When $MmTrnvr_t = 1$, observations are associated to lowest market mturnover times (first market mturover quartile) and when $MmTrnvr_t = 4$ observations are associated to highest market mturnover times (last market mturover quartile). $mTrnvr_t$ is simply the product of minus one and turnover. $mTrnvr_t^{p*}$ is defined as:
$mTrnvr_t^{p*} \cong mTrnvr_t^p * (-1) * 1_{R_t^p - R_t^m \geq 0} + mTrnvr_t^p * 1_{R_t^p - R_t^m < 0}$
and $Dump_t^p$ and $Dumn_t^p$ are defined as:
$Dump_t^p \cong 1_{R_t^p - R_t^m \geq 0}$ and $Dumn_t^p \cong 1_{R_t^p - R_t^m < 0}$

	(1)		(2)		(3)	
$MmTrnvr_t$:	1	4	1	4	1	4
	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p	Ret_{t+1}^p
Ret_t^p	-0.0239**	-0.119***	-0.0243**	-0.109***	-0.0235**	-0.111***
	(-2.81)	(-12.05)	(-3.25)	(-12.37)	(-3.14)	(-12.67)
$Beta_t^p$	0.000237	0.00242	-0.000231	0.00302	0.000988	0.00207
	(0.07)	(0.83)	(-0.07)	(1.02)	(0.28)	(0.76)
SD_t^p	0.0513	-0.179	0.100	-0.0582	0.0513	-0.0646
	(0.35)	(-1.15)	(0.66)	(-0.37)	(0.34)	(-0.41)
BE/ME_t^p	0.00270	0.00311	0.00258	0.00300	0.00274	0.00344*
	(1.76)	(1.97)	(1.59)	(1.83)	(1.80)	(2.27)
$devyld_t^p$	0.000191	0.000722	0.000301	0.000928	0.000266	0.000978
	(1.14)	(0.51)	(1.79)	(0.67)	(1.66)	(0.77)
$Size_t^p$	-7.42e-11	-9.17e-10	-1.02e-10	-9.35e-10	-1.11e-10	-7.17e-10
	(-0.85)	(-0.98)	(-1.16)	(-0.99)	(-1.28)	(-0.79)
$(mTrnvr * Ret)_t^p$	-10.58*	-26.04***				
	(-2.41)	(-7.55)				
$mTrnvr_t^{p*}$			2.305***	3.438***		
			(3.38)	(8.10)		
$(Dump * mTrnvr)_t^p$					-1.719	-4.227***
					(-1.00)	(-3.86)
$(Dumn * mTrnvr)_t^p$					2.623	2.591*
					(1.55)	(2.37)
_cons	0.00375	0.00777*	0.00252	0.00474	0.00336	0.00494
	(0.95)	(1.99)	(0.62)	(1.23)	(0.85)	(1.31)
N	15,200	15,300	15,200	15,300	15,200	15,300
R^2	0.320	0.887	0.289	0.827	0.295	0.827

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.14: This table reports the estimated Fama-MacBeth regression for exactly the same specifications taken by AP using NYSE-AMEX individual stocks for sample period 1962-2011.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$r_t^p - r_t^f$	$r_t^p - r_t^f$	$r_t^p - r_t^f$	$r_t^p - r_t^f$	$r_t^p - r_t^f$	$r_t^p - r_t^f$	$r_t^p - r_t^f$	$r_t^p - r_t^f$
$E(c^p)$	0.068	0.000807**		0.068	-0.00436***		0.068	-0.462***
	(-)	(2.83)		(-)	(-7.89)		(-)	(-8.34)
$\beta^{net,p}$	0.0226***	0.0243***		0.0562*	0.483***	0.132***		
	(4.94)	(5.79)		(2.07)	(9.30)	(4.89)		
β^{1p}			0.0247***	-0.0366	-0.480***	-0.116***	0.0145**	-0.0454
			(5.35)	(-1.37)	(-9.12)	(-4.36)	(2.70)	(-0.09)
β^{2p}							2.97	-1.2
							(1.22)	(-0.48)
β^{3p}							-0.419	-0.702*
							(-1.23)	(2.10)
β^{4p}							0.0660	-0.553***
							(0.80)	(-5.64)
_cons	-0.0101**	-0.0114***	-0.0108**	-0.00812**	0.00274	-0.00584	-0.00685*	0.00402
	(-2.73)	(-3.36)	(-3.02)	(-2.65)	(0.91)	(-1.91)	(-2.39)	(1.42)
N	61,200	61,200	61,200	61,200	61,200	61,200	61,200	61,200
R^2	0.715	0.807	0.508	0.746	0.857	0.855	0.760	0.858

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.15: This table reports the estimated Fama-MacBeth regression coefficients for modified version of the procedure taken by AP using NYSE-AMEX individual stocks for sample period 1962-2011. $Dump_t^P \cong 1_{NR_t^P \geq 0}$, $Dumn_t^P \cong 1_{NR_t^P < 0}$.

	(1)	(2)	(3)	(4)	(5)	(6)
	$r_t^p - r_t^f$	$r_t^p - r_t^f$	$r_t^p - r_t^f$	$r_t^p - r_t^f$	$r_t^p - r_t^f$	$r_t^p - r_t^f$
r_{t-1}^p	-0.0383***	-0.0384***	-0.0408***	-0.0380***	-0.0414***	-0.0397***
	(-10.23)	(-10.24)	(-10.87)	(-10.08)	(-10.65)	(-10.14)
$(E(c) * Dump)_t^p$	-0.0133	-0.00548	-0.174***		-0.196***	
	(-0.44)	(-0.17)	(-6.01)		(-6.41)	
$(E(c) * Dumn)_t^p$	1.800*	1.797*	0.525		0.726	
	(2.47)	(2.48)	(0.68)		(0.89)	
$\beta^{net,p} * Dump_t^p$	0.00269		0.103***	-0.0567*		
	(0.89)		(4.34)	(-2.54)		
$\beta^{net,p} * Dumn_t^p$	-0.00551		0.898***	0.679***		
	(-1.70)		(3.65)	(3.46)		
$\beta^{1p} * Dump_t^p$		0.00255	-0.105***	0.0591**	-0.00619	-0.00411
		(0.82)	(-4.37)	(2.62)	(-1.60)	(-1.05)
$\beta^{1p} * Dumn_t^p$		-0.00572	-0.913***	-0.688***	-0.00483	-0.00124
		(-1.74)	(-3.68)	(-3.46)	(-0.97)	(-0.25)
$\beta^{2p} * Dump_t^p$					2.807**	-1.602
					(2.76)	(-1.68)
$\beta^{2p} * Dumn_t^p$					12.96	2.882
					(0.35)	(0.08)
$\beta^{3p} * Dump_t^p$					-0.560	-0.545
					(-1.86)	(-1.79)
$\beta^{3p} * Dumn_t^p$					0.278	0.163
					(0.61)	(0.37)
$\beta^{4p} * Dump_t^p$					-0.0183	0.0232
					(-0.62)	(0.79)
$\beta^{4p} * Dumn_t^p$					-1.331	-1.139
					(-1.06)	(-0.93)
_cons	0.551*	0.566*	0.860***	0.630**	0.840***	0.642**
	(2.46)	(2.50)	(4.00)	(3.10)	(3.95)	(3.16)
N	62,200	62,200	62,200	62,200	62,200	62,200
R^2	0.742	0.741	0.755	0.744	0.745	0.765

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 2

Asymmetric effect of illiquidity on corporate bond yield spreads

Chapter Two:

Asymmetric effect of illiquidity on corporate bond yield spreads

2.1 Introduction

The effect of both liquidity level and liquidity-related risks on corporate bond yield spreads is acknowledged by a large number of studies. The existing literature mainly concludes that liquidity is priced in corporate bond yield spreads. Being highly related to this literature, the literature on liquidity-return relation in stock markets is very rich and the positive relation between illiquidity[1] and stock returns is documented by numerous numbers of papers. The author's recent study on the other hand, documents empirical evidence on the existence of nonlinearity in illiquidity- return relation in US stock market, which explores the role of stocks' current performance in determining the direction of the illiquidity effect on returns. More specifically, empirical evidence presented in the paper shows that the effect of illiquidity on stock returns is positive if the stock underperforms the market and negative otherwise. The results are robust to using weekly and monthly frequency data, employing different illiquidity measures (turnover and Amihud [2002]'s measure) and both individual and portfolio analysis.

The natural question that arises is that whether the same pattern in data is observable in corporate bond market. Since the theoretical models proposed in both literatures to explain why illiquidity derives the fluctuations in returns in stock markets and yield spread in bond markets have the same intuition, it is highly expected for corporate bonds to exhibit the same nonlinearity in yield spread-illiquidity relation. The strong evidence on the existence of nonlinearity in liquidity-return relation in stock markets is a motivation to perform the same analysis on corporate bond markets.

The main objective of this paper is to identify asymmetry of the effect of liquidity on corporate bond yield spreads. More specifically, I test whether the current performance of the bonds has an impact on how liquidity affects the yield spreads. The current performance of a bond is measured by the comparison of the bond yield and average market yield. Based on the evidence from the stock market, it is expected to observe that liquidity affects positively the bond that have better performance compared to market and vice versa.

2.2 Review of the Literature

There is a fairly substantial literature that relates liquidity to asset pricing providing strong evidence regarding positive premium for illiquidity, not only in stock markets, but also in other security markets like options and bond markets. The research in this field is based of the idea that investors would ask for a premium on assets that are illiquid, in order to compensate for the transaction cost incurred when trading the assets. Amihud and

[1] In this paper, I use the words liquidity and illiquidity interchangeably as the refer to the same basic idea

Mendelson [1986] is one of the very first papers studding the illiquidity effect on returns in the US equity market and present evidence on the positive effect of illiquidity on stock returns. Acharya and Pedersen [2005] present an augmented capital asset pricing model that takes into account illiquidity risk and find that expected liquidity is an important determinant of expected returns in US equities market.

Amihud and Mendelson [1991] study the U.S. treasury market and find that less liquid treasury notes are cheaper than treasury bills which are more liquid. Following Amihud and Mendelson [1991], several authors study the impact of liquidity on corporate bond yields and virtually all of these papers find that liquidity is priced in bond yields. Some of the researcher have contributed to this literature by analyzing how the yield spread-liquidity relation is dependent to market regime. For example, Beber et al. [2009] find that while liquidity is a very significant driver of the sovereign bond market, its effect on the yield spreads is more pronounced in market distress times. Nils et al. [2012] find that the economic impact of the liquidity is significantly larger in periods of crisis.

Beside the importance of the reported findings about the illiquidity effect, one of the major concerns in the literature is how to measure illiquidity. In the existing literature, illiquidity is (mostly) defined as the ease of trading a security. But there are many ways to interpret the word "ease". The disagreement on how to measure illiquidity is reflected in the fairly big number of measures that are proposed to proxy it. Each of the measures captures one aspect of illiquidity (or meaning of the word "ease"). Some of the papers use indirect proxies based on bond characteristics such as age. Some papers add to their regressions other indirect market-related proxies like trade volume, number of trades and number of days without trade. Some papers contribute to the literature by introducing new liquidity measures. Good examples are Amihud [2002] and Pastor and Stambaugh [2003]. Discussing about details of these measures or the advantages or disadvantages of each of them is not the aim of this paper. A good reference on illiquidity sources and its aspects is Amihud et al. [2005].

There are two main approaches in the literature to study the effect of illiquidity on returns. The first approach takes illiquidity as one of the deterministic characteristics that affects the security's price. In this approach there is no illiquidity risk involved and in most cases, it is used to examine the explanatory power of illiquidity level toward cross-sectional differences in returns. Among others, Amihud and Mendelson [1986], Swan and Westerholm [2002] and Amihud [2002] follow this approach. As mentioned above, the authors using this approach generally report that less liquid securities have higher returns.

The second approach on the other hand, takes illiquidity as systematic risk. In this approach, securities with higher exposure to illiquidity related-risks are expected to have higher returns. Hence, unlike the previous approach, expected return of securities would be higher depending on how much they are subject to illiquidity risk, even though their illiquidity level is not high. For example Pastor and Stambaugh [2003] argue that stocks with greater sensitivity to market-wide liquidity, exhibit higher expected returns. Acharya and Pedersen [2005]'s study adjusts the capital asset pricing model to take into account illiquidity risk. Their simple model introduces three new betas and add them to the one conventional beta in CAPM model. They also present empirical evidence supporting their model implied predictions.

In this paper the first approach is taken. I use individual bond's illiquidity to explain cross-sectional differences in yield spreads. But unlike the previous studies, I take into account the asymmetry of the effect and show how it improves the explanatory power of the models studding the effect of illiquidity on bond yield spreads.

2.3 Intuition and Hypothesis

In this section, I provide an overview of the intuition underlying the research questions and the hypotheses I test. The fundamental assumption taken in this paper is that there are impatient investors in the market that would trade a security as a response to its current performance. The intuition is that liquidity providers change their required return for the liquidity they provide to impatient investors. Liquidity providing may increase or decrease the expected return of liquidity providers depending on whether liquidity is provided to impatient traders who want to sell a security that has faced a negative price change, or traders willing to buy a security that has a recent price appreciation. In the former case where a security has a current negative return but is liquid enough, there is no reason to expect a change in the expected return. But in case the security is illiquid, liquidity providers that accommodate the selling pressure caused by traders trying to get rid of that security, will ask for higher return. Hence, we would expect an increase in return as a reward to liquidity providing. This reward is increasing in how much worthy the provided liquidity is, i.e. trader's selling pressure. Two factors may affect selling pressure. First, securities that have a recent poor performance are subject to be sold more aggressively by impatient traders and those with poorer performance face stronger selling pressure. Second, for higher illiquidity levels selling pressure is higher because it makes it more difficult to sell the unwanted security.

In the latter case where the security has a recent good performance the story is almost the same. Demand pressure would be caused by impatient traders willing to buy the security which is increasing in security's illiquidity and its level of good performance. Likewise, liquidity providers who fulfill such demand would ask for higher return, which in this case translates in a negative change in security's return. The distinction between the cases where illiquidity affects loser or winner securities would add a lot of explanatory power to the liquidity measures. The proposed intuition suggests that underlying process that generates such asymmetry in liquidity-yield spread relation is the premium asked by liquidity providers to impatient investors.

Based on the intuition explained above, we test two hypotheses. The first hypothesis is naturally to investigate the effect of liquidity on bong yield spreads.

H1: Liquidity is an important price factor in the corporate bond market.

I test the first hypothesis to make sure that the results of the estimations match those of the current literature. I will replicate the results of Nils et al. [2012] to perform the comparison. The main hypothesis tested in this analysis is however the second one.

H2: The effect Liquidity on bond yield spreads is function of the bond's current performance.

In other words, I test how the effect of liquidity on yield spreads is different when the bond's performance is better than the average market performance compared to to time that its performance is worse than average market performance.

2.4 Methodology

As I mentioned before first step to test the second hypothesis is to test the first research question by replicating Nils et al. [2012]'s results. This paper investigates the effect of illiquidity on US corporate bonds yield spreads using a number of liquidity measures including Amihud [2002]'s measure, Roll [1984]'s measure, including bond characteristics such as amount issued, age, *etc.* which are conventionally taken as proxies for liquidity. The authors also examine how the explanatory power of liquidity towards yield spreads differs in normal market times versus times of financial distress. The empirical findings of the paper illustrate the strong positive effect of illiquidity on yield spreads which becomes significantly larger in times of crisis.The main focus of the current paper is on replicating the cross-sectional analysis of Nils et al. [2012] and then, test the existence of asymmetry using Fama-MacBeth methodology.

To perform their analysis, Nils et al. [2012] test the following specification:

$$\begin{aligned}(yield\ spread)_{it} = a_0 &+ a_1(bond\ characteristics)_{it}\\ &+ a_2(trading\ activity\ variables)_{it}\\ &+ a_3(liquidity\ measures)_{it}\\ &+ a_4(rating\ dummies)_{it} + \varepsilon_{it}\end{aligned}$$

Where yield spread is each bond's yield differential with respect to risk free rate and bond characteristics are age, coupon, maturity and amount issued. Trading activities consist of volume traded and number of trades in a given period of time as well as trading interval which is the period in which the bond is not traded.

To test the existence of nonlinearity in the effect of liquidity on bond yield spreads I need to augment the specification in equation 1.1. In case of stock returns, the determinant of the direction of the effect of illiquidity is the performance of the stock compared to market performance. Accordingly, bond yield spreads would be clustered into two sets: spreads which are greater than average market yield spread and those which are less than this value. The market yield spread is simply defined as the average yield spread of bonds with the same maturity and rating. The expectation is to observe asymmetry in the effect of illiquidity, which is, positive effect on bond yield spreads if spreads are greater than average market spread and negative effect otherwise. Note that in case of bond yields, a price appreciation is equivalent to a reduction in yield whereas for stocks it means an increase in return. Hence, yields and returns have an opposite image in terms of price change.

To test the existence of asymmetry on the effect of liquidity on bond yield spreads, the following specification will be estimated:

$$\begin{aligned}(yield\ spread)_{it} = a_0 &+ a_1(bond\ characteristics)_{it} \\ &+ a_2(trading\ activity\ variables)_{it} \\ &+ a_3 1_{y_s it \geq ys_{mt}}(liquidity\ measures)_{it} \\ &+ a_4 1_{y_s it \leq ys_{mt}}(liquidity\ measures)_{it} \\ &+ a_5(rating\ dummies)_{it} + \varepsilon_{it}\end{aligned}$$

Where $1_{ys_{it} \leq ys_{mt}}$ is the indicator function and is equal to unity if the bond yield spread, is greater than average market yield spread, and zero otherwise. A negative and significant estimation is expected for a_3 and a positive and significant estimation is expected for a_4.

We regress equations 1.1 and 2.4 using Fama-MacBeth procedure and using weekly data obtained from averages of the daily data of all variables.

2.5 Liquidity measures

One of the liquidity measures employed in this paper is Amihud [2002]'s measure. The Amihud's measure for a certain bond over a particular time period with N_t observed returns is defined as the average of the absolute value of these returns divided by the bond's trading volume ν_j over the same period of time:

$$Amihud_t = \frac{1}{N_t} \sum_{j=1}^{N_T} \frac{|r_j|}{\nu_j}$$

For this analysis, daily volume-weighted average prices are used to compute returns and the Amihud measure is generated on a day-by-day basis.
Roll measure is developed by Roll [1984] and concerns with bid-ask bounce that results in transitory price movements which are serially negatively correlated. The strength of

this co-variation is a proxy for the round-trip costs for a particular bond and hence is a measure of liquidity. More precisely, the Roll measure is defined as:

$$Roll_t = 2\sqrt{-cov(\Delta p_t, \Delta p_{t-1})}$$

Where Δp_t is the volume-weighted price change from period $t-1$ to t. This measure is computed for a rolling window of 60 days, where at least eight observations are required for each window. Another illiquidity measure employed in this paper is recently introduced by Jankowitsch et al.. This measure is based on the dispersion of traded prices around the marketwide consensus valuation. A low dispersion around the valuation suggests that the security can be traded close to its fair value and therefore, represents low trading costs and illiquidity. Nils et al. [2012] take market valuations from Markit and use them as market wide consensus valuation. In this study, average daily traded prices are used as market valuation because the data from Markit is not available. More specifically, the price dispersion measure for a particular day and bond is computed as:

$$price\ dispersion_t = \sqrt{\frac{1}{\sum_{k=1}^{K_t} \nu_k} \sum (p_k - m_t)^2 \nu_k}$$

Where p_k and ν_k represent the K_t observed traded prices and their trade volumes on date t and m_t is the daily average price (market-wide valuation for that day from Markit in the original study).

Finally, the zero-return measure indicates whether price movements occur between trading days. The zero-return measure is equal to one, if we find an unchanged price, and is set to zero, otherwise. The intuition behind this measure is that bonds that have prices that stay constant over long time are likely to be less liquid. Nils et al. [2012] take Markit quotations as indicators of price movement over time. In this study, because the market valuation data from is not available, I use daily average price fluctuations to generate zero-return measure.

2.6 Data

The data on intraday bond transactions is obtained from TRACE which covers the period June 2002 to July 2012. The corporate bond yield spread will be measured relative to the US constant maturity Treasury bond yield curve which is obtained from Federal Reserve System. Bond characteristics as well as credit ratings are obtained from Bloomberg and Fixed Income Securities Database (FISD). $S\&P$ Credit ratings provided by FISD are used in the regressions since this database provide bond rating changes over time. There are some conflicts between data on bond maturity, coupon and amount issued reported by FISD and Bloomberg. After comparing hand collected data from FINRA and those from

Bloomberg and FISD, it seemed that maturity and coupon from FISD and amount issued from Bloomberg are more trustable.
The cross-sectional analysis will be based on weekly frequency data which are simple average of daily observations. Following the original study, I use the filters proposed by Dick-Nielsen [2009] for the TRACE data to eliminate potentially erroneous data points. Observations associated to negative yields and yields greater than 50 percent are eliminated.
To investigate how the explanatory power of the independent variables differs in financial crises compared to normal market environments, Nils et al. [2012] define the following three subperiods: The GM/Ford crisis (March 2005-January 2006) when a segment of the corporate bond market was affected, the subprime crisis (July 2007-December 2008), which was much more pervasive across the corporate bond market, and the normal period in between (February2006-June2007).

2.7 Original and replication results

Table 2.1 compares the results of estimating equation 1.1 reported in Nils et al. [2012] to those found in this study. The last column of table 2.1 presents the result of estimation using our whole sample period, 2002-2012, which is absent in Nils et al. [2012]. Results obtained in this study and those of Nils et al. [2012] are generally very similar and totally support the hypotheses proposed in the paper. Especially, the coefficients on Amihud's liquidity measure are quite similar (in terms of magnitude and statistical significance) and have the same order. All liquidity measure are highly significant and are greater in market stress times compared to normal times. However, there are some differences in the results. For example, the coefficient on volume in Gm/Ford period is not significant in Nils et al. [2012] while it is significant in my estimations.

The next step is to investigate whether there is nonlinearity in illiquidity-yield spread relation. To find the answer, in each week, observations are split into two sets. The first set consists of observations for which the yield spread is greater than the average yield spread of all bonds with that same rating and maturity. Otherwise the observations are allocated to the second set. Based on this clustering, new illiquidity measures are generated as follows:

$$Pos.Price\ dispersion_t = Price\ dispersion_t * 1_{Yield\ spread_t \geq Ave.Yield\ spread_t}$$

$$Neg.Price\ dispersion_t = Price\ dispersion_t * 1_{Yield\ spread_t \leq Ave.Yield\ spread_t}$$

Where 1 is the indicator function. The same formula is applied to generate $Pos.Amihudilliq$, $Neg.Amihudilliq$, $Pos.Roll$ and $Neg.Roll$. and equation 2.4 is estimated.

The results of estimating equation 2.4 are reported in table 2.2. As expected, the sign for coefficients are different for two yield spread status and have strong statistical significance. The results suggest that the effect of current performance on liquidity-yield spread relation is asymmetric, not only in the sign of the effect, but also in the magnitude. The estimated coefficients of all the liquidity measures are greater in absolute value for the case of bonds with greater yield with respect to market. This implies that bonds which are cheaper compared to the average price of bonds of the same maturity and credit rating are more affected by liquidity.

2.2 also displays a huge improvement in terms of goodness of fit for all the regressions when nonlinearity is taken into account. For instance, comparing the results in tables 2.1 and 2.2 shows that when nonlinearity is considered, the R-squared raises from 48 to 56 percent in subprime crisis period and from 41 percent to 49 percent for the whole sample period. The same improvement is observable for other columns as well.

Introducing asymmetry to the Nils et al. [2012] specification has another effect on the results. Results in table 2.1 confirms Nils et al. [2012]'s hypothesis that the effect of liquidity is more pronounced in market stress time. This can be seen by comparing the magnitude of the coefficients on liquidity measures in normal times versus GM/Ford or Subprime crisis. However, among three liquidity measures, it is only price dispersion that confirms this hypothesis in table 2.2. This puts a question mark on whether the findings of Nils et al. [2012] is credible or not.

2.8 conclusion

In this paper I test the existence of nonlinearity in illiquidity-yield spread relation in US corporate bond market. To validate the results and before I test the main hypothesis of this paper, I replicated the results reported by Nils et al. [2012]. Nils et al. [2012] study the US corporate bond market and find that liquidity is an important pricing factor for corporate bonds. Moreover, they find that the effect of liquidity on bond yield spreads is more pronounced during crisis. The estimation results of this paper confirm those of Nils et al. [2012]. The results of testing for nonlinearity in illiquidity-yield spread in bond market on the other hand suggest that illiquidity asymmetrically affects bond yields spreads. Moreover, introducing the asymmetry to Nils et al. [2012]'model generates results that contradicts the conclusion that the effect of liquidity on bond yield spreads is more pronounced during crisis.

Table 2.1: The relation between US corporate bond yield spreads and liquidity, Fama-MacBeth regression

	GM/Ford Crisis Yield spread		Normal Period Yield spread		Subprime crisis Yield spread		06/2002-07/2012 Yield spread
	This study	Friewald *et al*	This study	Friewald *et al*	This study	Friewald *et al*	
Price dispersion	0.191***	0.35***	0.175***	0.27***	0.255***	0.452***	0.234***
	(15.98)	(14)	(27.83)	(18.88)	(31.6)	(7.89)	(19.67)
Amihud illiq	0.0618***	0.086***	0.0528***	0.0718***	0.0806***	0.169***	0.0668***
	(17.75)	(28.45)	(16.47)	(29.44)	(12.18)	(12.57)	(18.07)
Roll	0.311***	0.072***	0.211***	0.081***	0.421***	0.1133*	0.320***
	(16.34)	(8.25)	(14.49)	(23.44)	(12.23)	(1.92)	(14.95)
Coupon	0.193***	0.157***	0.157***	0.1142***	0.130***	0.35**	0.173***
	(14.74)	(5.64)	(10.74)	(27.9)	(11.02)	(2.37)	(24.13)
Volume	0.027***	0.0013	0.0288***	-0.0113**	0.0123***	0.0432**	0.0123***
	(4.91)	(0.28)	(7.99)	(-2.42)	(4.51)	(2.47)	(7.03)
Maturity	-0.0266***	0.011***	-0.00541***	0.017***	-0.0335***	-0.0599***	-0.0259***
	(-7.69)	(3.66)	(-3.55)	(11.65)	(-9.96)	(-3.64)	(-11.42)
Amount issued	-0. 488***	-0.2539***	-0. 217***	-0.1824***	-0. 181***	-0.325***	-0. 237***
	(-11.26)	(-27.23)	(-8.82)	(-14.58)	(-19.02)	(-10.06)	(-20.49)
Trading interval	-0.00047	0.0073***	0.00884***	0.0025**	0.0780***	0.0062	0.0560***
	(-0.13)	(6.084)	(3.45)	(1.93)	(12.59)	(1.064)	(10.05)
Num. of trades	0.0383***	0.045***	0.0135***	0.0316***	0.0172***	0.035*	0.0199***
	(10.53)	(16.78)	(9.15)	(13.43)	(19.06)	(1.81)	(20.26)
Zero return	-0.396***	0.237***	-0.276***	0.0387	0.360***	0.6128	0.107
	(-4.73)	(4.13)	(-4.58)	(0.78)	(3.41)	(1.57)	(0.83)
Age	-0.0606***	0.0053***	-0.0247***	-0.0038	0.0139***	-0.043***	-0.0121***
	(-13.03)	(2.41)	(-6.41)	(-0.81)	(6.26)	(-3.29)	(-5.12)
Rating Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	8.749***	1.8476***	7.760***	1.44***	7.958***	4.44***	8.109***
	(10.47)	(16.24)	(14.65)	(24.75)	(12.080)	(3.77)	(20.89)
N	231,849	-	423,976	-	1,119,110	-	2,470,244
R2	0.435	0.59	0.317	0.6	0.486	0.49	0.409

This table presents the estimation results of regressing the yield spread of weekly US corporate bonds on three liquidity measures as well as bond characteristics (equation 1.1). Bond spread is computed as the difference between individual bonds yield and treasury bill rate of the same maturity. Odd columns except are the results of this paper and even columns are reported by Nils et al. [2012] in table 6. GM/Ford crisis correspond to 01/05/2005 to 01/02/2006, normal period corresponds to 02/02/2006 to 01/07/2007 and subprime srisis corresponds to 02/07/2007 to 01/01/2009. t-statistics are reported in parentheses and are calculated from Newey and West (1987) standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.2: The relation between US corporate bond yield spreads and liquidity with non-linearity, Fama-MacBeth regression

	GM/Ford Crisis Yield spread	Normal Period Yield spread	Subprime crisis Yield spread	06/2002-07/2012 Yield spread
Pos.Price dispersion	0.289***	0.280***	0.629***	0.494***
	(19.85)	(27.22)	(17.1)	(22.68)
Neg.Price dispersion	-0.184***	-0.181***	-0.288***	-0.235***
	(-19.24)	(-24.68)	(-13.80)	(-23.75)
Pos.Amihud illiq	0.0636***	0.0646***	0.0857***	0.0803***
	(15.31)	(13.23)	(12.58)	(16.7)
Neg.Amihud illiq	-0.0383***	-0.0526***	-0.0386***	-0.0371***
	(-8.89)	(-15.55)	(-11.93)	(-17.14)
Pos.Roll	0.629***	0.460***	0.698***	0.618***
	(36.83)	(16.84)	(14.89)	(20)
Neg.Roll	-0.379***	-0.307***	-0.244***	-0.302***
	(-16.65)	(-19.91)	(-19.25)	(-28.09)
Coupon	0.0984***	0.0797***	0.0822***	0.115***
	(8.91)	(6.46)	(7.81)	(17.79)
Volume	0.0254***	0.0269***	0.0103***	0.00947***
	(4.85)	(7.95)	(3.94)	(5.85)
Maturity	-0.0421***	-0.0238***	-0.0315***	-0.0304***
	(-16.41)	(-12.69)	(-16.71)	(-24.83)
Amount issued	-0.271***	-0.0216	-0.110***	-0.150***
	(-7.83)	(-1.10)	(-17.17)	(-14.41)
Trading interval	-0.0117**	0.00225	0.0572***	0.0366***
	(-3.30)	(0.89)	(11.5)	(9.49)
Num. of trades	0.0299***	0.00394**	0.0113***	0.0128***
	(9.62)	(2.74)	(16.35)	(15.89)
Zero return	-0.341***	-0.251***	0.163	0.0322
	(-4.53)	(-4.33)	(1.67)	(0.27)
Age	-0.0269***	-0.00733**	0.00720***	-0.00522**
	(-9.92)	(-3.01)	(4.12)	(-2.85)
Rating Dummies	Yes	Yes	Yes	Yes
Constant	10.05***	8.862***	8.728***	8.976***
	(12.05)	(16.21)	(13.26)	(23.05)
N	231,849	423,976	1,119,110	2,470,244
R2	0.517	0.388	0.564	0.492

This table presents the estimation results of regressing the yield spread of weekly US corporate bonds on three liquidity measures as well as bond characteristics (equation 2.4). Bond spread is computed as the difference between individual bonds yield and treasury bill rate of the same maturity. Liquidity measures are clustered based on bond performance (for complete description refer to paper's text). GM/Ford crisis correspond to 01/05/2005 to 01/02/2006, normal period corresponds to 02/02/2006 to 01/07/2007 and subprime srisis corresponds to 02/07/2007 to 01/01/2009. t-statistics are reported in parentheses and are calculated from Newey and West (1987) standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 3

Unconventional Monetary Policy and Government bond spreads in the euro area

Chapter Three:

Unconventional Monetary Policy and Government bond spreads in the euro area

3.1 Introduction

Long-term yields differentials between Euro area government bonds and German government bonds co-move with an unstable pattern over time. Yield spreads on the safe benchmark in the area converged significantly with the introduction of the euro, narrowing from highs in excess of 300 basis points in the pre-EMU period to less than 30 basis points about one year after the introduction of the euro. Yet, bonds issued by Euro area Member States have never been regarded as perfect substitutes by market participants: interest rate differentials co-moved synchronously at the very low-level between the introduction of EMU and the subprime loans crisis, they became sizeable during the course of 2008 and 2009 with some separation in co-movement between high-debt and low debt countries. The debt crisis from the end of 2009 onwards brought about differentials of the same, or even greater magnitude, than those of the pre-euro era and more heterogeneity in co-movement. Yields have been progressively going back to a convergence pattern after the ECB has implemented three policies involving bond purchases: the Securities Market Programme (SMP), the Outright Monetary Transactions (OMT), and the 3-year Long-Term Refinancing Operations (LTRO).

During the 2010-12 Euro area crisis government bond spreads reached levels that cannot be predicted by standard models (Favero [2013]). There are two potential explanations for this fact: the models linking bond spreads to fundamentals were missing some important variables, or prices deviated substantially from fundamentals. The identification of the relative importance of the two alternative explanations of this evidence carries important policy implications. Is the unconventional monetary policy implemented by the ECB shielding high debt country from market discipline and therefore providing them the wrong incentives? The answer depends on how much prices deviated from fundamentals due to contagion and market turbulence and on the impact of ECB policies on the different components of yield spreads.

Given tax harmonization within the euro area, interest rates differentials across different countries should price three factors: default risk, liquidity risk and expectations of exchange rate fluctuations. Sovereign issuers that are perceived as having a greater solvency risk, must pay investors a default risk premium. Liquidity risk is the risk of having to sell (or buy) a bond in a thin market and, thus, at an unfair price and with higher transaction costs. Small issuers with low volumes of bonds outstanding and thus small markets must compensate investors with a liquidity premium. The introduction of the euro in January 1999 initially eliminated the expectations on exchange rate fluctuations, but the subprime loan crisis first and then the generalized surge in the debt to GDP and deficit to GDP ratios for all Euro area countries that has been observed after 2009, has induced markets to reconsider the possibility of the exit from the euro for some of the countries and even of a collapse of the common currency.

Interventions on the liquidity risk and the redenomination risk are without doubt within the mandate of the ECB, while default risk is most appropriately dealt with by fiscal rather than monetary policy.

In this paper we propose a four factor model of yield spreads in the euro area where local default risk, liquidity risk and redenomination risk are augmented by a global factor that in turn depends on default risk, liquidity risk and redenomination risk in the whole area. Such a model allows us to assess the impact of ECB interventions on area wide liquidity, redenomination and default risk and therefore to provide new evidence for judging how appropriate were the interventions on the bond market.

3.2 Determinants of Sovereign Spreads on Bunds

Most of the research on sovereign bond market can be categorized into two strands. The first strand's research question is how government bond yield spread is affected by its driving factors and how this effect is changed in different market regimes. Liquidity risk, credit risk, redenominatoin risk, contagion, ECB interventions *etc* are among determinants that are reported to contribute in variations in bond yield spreads. For example, using euro area data, Beber et al. [2009] conclude that the impact of liquidity risk on the sovereign yield spread increases with market uncertainty and the increase in more significant for longer maturity bonds. Favero and Missale [2012] find that liquidity plays a partial role in euro area yield differentials while credit risk is always priced. Favero et al. [2010] introduces a global variable in euro area suggesting that the channel through which contagion affects yield spreads is fiscal fundamentals in a sense that countries with closer fiscal fundamentals tend to have stronger co-movement. Krishnamurthy et al. [2014] study the relative effectiveness of ECB interventions on yield spreads and find that they have been effective in decreasing the spreads mostly through reducing the default risk. De Santis [2014] introduces a measure to quantify redenomination risk and shows that the measure is priced in the sovereign bond market. The second strand of the research on government bonds is focused on the dynamic interactions between the determinants of government bond yields. For example, Pelizzon et al. [2014] examine the dynamic relationship between credit risk and liquidity in the European sovereign bond market considering ECB interventions. He and Milbradt [2014] study the interaction between default and liquidity for corporate bonds that are traded in an over-the-counter secondary market. Bai et al. [2012] examine how credit risk and liquidity risk evolve in the European sovereign bond market during the sovereign debt crisis.

In this paper, we apply a combination of these approaches. We study nine Euro area countries bond yield spreads relative to German Bund. The key assumption taken in this study is that the yield spread is a function of liquidity risk, credit risk and redenomination risk plus the global factor. It is also assumed that the dynamics of the risk factors can be described within a vector autoregressive framework. The aim of employing such a framework is to assess the relative importance of each risk factor for the dynamics of bond spreads by means of historical decomposition of the spreads. Such a framework allows us to analyse the interaction of the factors which are driven by three structural shocks and the ultimate effect of the shocks on yield spreads. Default shock, liquidity shock and redenomination shock are assumed to drive the dynamics of three risk factors of each country. Accordingly, a structural vector autoregressive model is set to capture the fluctuations in risk factors. This setup is also convenient to analyze the ECB policies implications on risk factors and eventually on yield spreads.

The historical decomposition methodology is applied to analyze the observed series of the endogenous variables in terms of the structural shocks and the evolution of the exogenous variables. The relative strength of this tool over the conventional impulse response analysis is that historical decomposition does not assume that structural shocks are one time shocks, but it takes the series of structural shocks that evolve through time, allowing us to make a judgement over what has actually happened to the series of interest in the sample period.

3.2.1 Data construction

To do the analysis, we use MTS (Mercato dei Titoli di Stato) intraday interdealer fixed-income securities data, which covers European bonds wholesale transactions and limit-order books, for the period April 2003 to December 2012. MTS data includes bonds issued by treasuries and local governments, international public institutions and structured securities issued in forty countries. This database contains all the transaction information such as price, trade direction, date, time and quantity with a unique bond identifier. Moreover, the limit-order book contains information of best three bid and ask quote prices and corresponding quantities. Our sample period covers pre and post US subprime crisis as well as Euro-zone crisis, providing an ideal ground for analyzing the connection between yields and liquidity, credit and redenomination risks. In this study, we apply the government bond data associated to ten European countries namely Italy, Germany, France, Spain, Portugal, Ireland, Austria, The Netherlands, Belgium and Finland, which are the most frequently traded bonds in local and Euro MTS markets. We drop from the sample non euro currency bonds, structured and quasi-government bonds, floating and indexed coupon bonds, bonds traded prior to issue to avoid any complexities these type of bonds introduce to bond pricing.

Bond yields are taken from Datastream. Interestingly, the yields calculated from transaction prices of MTS dataset perfectly match those from Datastream. The reason we apply the bond yields from a different source is that using MTS dataset results in a lot of missing values for yields, raising from the fact that MTS is not the only venue for bond trading.

Figure 3.1 graphs the 10 year maturity bond yields of the countries under analysis. The graph suggests that the European sovereign bond market has experienced three different episodes. Prior to 2009, bond yields tend to co-move very highly and the variation of the yields is fairly low. After the European sovereign debt crisis started in 2008, the bond yields started to depart. The gap between the yields has been increasing until 2011. Beginning 2012, the bond yields started to respond to the ECB interventions and the gap started to shrink. During 2012, European sovereign bond market faced a market segmentation. Bonds could be classified into high yield, Italy, Spain, Portugal and Ireland and low yield, Germany, France, Finland, Austria, Belgium and the Netherlands. This segmentation is very important in explaining the dynamics of the yield spreads with respect to its driving factors, which will be elaborated in the next sections.

[Figure 3.1 here]

We supplement MTS data with the Credit Default Swap (CDS) data from Markit. This database covers daily CDS quotes for all countries under analysis and various maturities. Figure 3.2 presents the graph of the 10 year maturity CDS rates for the countries under analysis. The Figure displays the same up and down episodes as for the bond yields.

[Figure 3.2 here]

We use MTS market book data to compute the liquidity measures. To do so, we partition our sample in two dimensions. First, we group the bonds according to their country and benchmark status. Benchmark bonds are those traded on both Euro MTS and local MTS markets while non-benchmark bonds are traded only on local MTS markets. Second, bonds are further grouped based on time to maturity. Bonds with 2.5-3.5 years, 4.5-5.5 years, 6.5-7.5 years, and 9.5-10.5 years to maturity are considered as 3, 5, 7 and 10 year maturity groups. Liquidity measures are computed as follows. For each bond each day all the liquidity measures are computed in each five minute windows and averaged through the day to make the daily measure. Then, measures associated to bonds of the same country/benchmark/maturity group are averaged and set as the daily liquidity measure. One of the liquidity measures that is employed in this paper is the quoted bid-ask spread which is defined as:

$$Bidask_t^i = \frac{2}{T}\Sigma_{t=1}^{T}\frac{A_t^i - B_t^i}{A_t^i + B_t^i}$$

where i and t stand for each country and time, respectively, and A and B are best ask and bid prices. Quoted spread estimates the transaction cost an investor incurs for a round-trip trade that is a sale followed by a buy. This measure is widely used in empirical studies, including papers on sovereign debt market. Effective bid-ask spread is another liquidity measure used in this analysis. The definition of this variable is given by De Jong and Rindi [2009] as:

$$Effective_t^i = \frac{1}{T}\Sigma_{t=1}^{T} 2Q_t^i(p_t^i - m_t^i)$$

where Q_t^i in the transaction direction, p_t^i is the transaction price and m_t^i is midpoint of the quoted bid-ask spread at the time of the transaction. Effective bid-ask spread estimates the transaction cost as the difference between the transaction price and the fundamental value of the asset estimated by the midpoint of the prevailing quoted bid-ask spread. The third liquidity measure is the quoted spread which is introduced by Bollen and Whaley (1998):

$$QSpread_t^i = \frac{Depth_t^i}{\frac{Ask_t^i + Bid_t^i}{2}}$$

where $Depth_t^i$ is the quantity as the best bid and ask prices of the limit order book. $Depth_t^i$ and cumulative depth, $CDepth_t^i$, defined as cumulative quantity at the best three bid and ask prices of the limit order book, are two other liquidity measures that are used in this study.

Quanto CDS, defined as the spread between the dollar denominated and Euro denominated CDS quote is used as a proxy for the redenomination risk. This measure becomes non zero on August 2010, and is always zero before this date. Figure 3.3 graphs 10 year maturity quanto CDS rates for the countries under analysis.

[Figure 3.3 here]

Following Favero et al. [2010], contagion is measured for each country by a weighted average of bond yields of other countries. Weights are the the inverse of the fiscal distance which is defined as the absolute value of the difference between the fiscal fundamentals of two countries. Fiscal fundamentals, namely debt to GDP and deficit to GDP are the European Commission Forecasts, that are released every six months. These variables enter the specification in terms of the difference between each country's forecast and the forecast of the same variables for Germany.

Table 3.1 presents the summary statistics of the data employed in this study. This table displays for each country and each maturity, the number of bonds traded on MTS, yield, CDS rate, quoted bid-ask spread and quoted depth. According to table 3.1, Germany and Italy have the highest number of bond issues (traded on MTS) while Ireland and Austria have the lowest number.

[Table 3.1 here]

One of the challenges of the empirical literature of the sovereign bond market is to choose a benchmark to construct the yield spreads. Some of the empirical papers have employed Euro-swap rates as benchmark (Beber et al. [2009]). Figure 3.4 graphs the 10 year German bund rates versus the Euro-swap rates of the same maturity. The figure shows that the Bund rates are historically below the swap rates which makes the German bund a credible choice for the risk free benchmark compared to Euro-swap. Moreover, while the gap between the two series is fairly low until 2007, it widens to its highest levels around 2008, when the Euro crisis started, suggesting that market perception of risk was higher for Euro-swap. Given these facts, we believe that German Bund makes a better choice for the benchmark to construct the yield spreads. Accordingly, CDS rates and all the liquidity measures enter the specifications in terms of the difference between each country's rate and the same for Germany.

3.3 The ECB unconventional monetary policy

ECB has taken a number of actions in response to distortions in Euro sovereign bond market and widening yield spreads across the Eurozone, specially during the debt crisis. Here we briefly review some the most important actions of the ECB[1]. In May 9, 2010, the ECB announced the Securities Markets Programme (SMP) and officially started it a day later. Under the SMP, the ECB intervened sovereign debt market by buying, on the secondary market and on market prices, the bonds of distressed countries. The ECB announced a reactivation of the SMP on August 7, 2011. According to market consensus, during the first phase, the ECB mainly purchased the debt of Greece, Ireland, and Portugal and during the second phase bonds of Italy and Spain were purchased. The last SMP purchases took place in February 2012 and the programme was terminated in September 2012. In August 2012 ECB announced the possibility of Outright Monetary Transactions (OMTs). In contrast to the SMP, a necessary condition for OMTs is that a country has to commit to a certain fiscal reforms indicated by the ECB in order to benefit the intervention. A further difference to the SMP is that OMTs are ex ante unlimited and would focus on bonds with maturities of one to three years. On September 6, 2012, the ECB announced the start of the OMT but no bonds had been purchased under the OMT program until 2014. In addition to SMPs and OMTs, On December 8, 2011 the ECB announced its long-term refinancing operation (LTRO), which is a process by which the ECB provides financing to banks in Euro zone. The ECB have been providing the liquidity to the banks via its Main Refinancing Operations (MROs). MROs have one week and one month maturities while LTROs are designed to have three year maturity. Two LTROs have been announced by the ECB as of today. The first LTRO was announced

[1]For a full description please refer to the ECB Press Release.

on December 20, 2011 and according to market participants Eurozone banks from Italy, Spain, Ireland and Greece heavily subscribed for it. On February 28, 2012, the second LTRO was announced. The magnitude of the ECB lending through the second LTRO had a small increase compared to the first one, but it was taken as an indicator of the health of Eurozone banks because the number of banks borrowed was below expectations.

Clearly the ECB interventions had a large impact on the yield of the sovereign bonds. The channel through which the ECB interventions affects the bond yields and the relative effectiveness the interventions however is still a debate. Most of the recent papers studding the European sovereign bond market that have analyzed the effect of the ECB interventions on yield spreads are focused on direct effect. In this paper, we analyse the effect of the ECB interventions through the effect on the yield spread determinants. In other words, we study the direct effect of the ECB policies on default risk, liquidity risk and redenomination risk and then, through the factors, the indirect effect of the interventions on the yield spreads. In the next section, we explain in detail how we proceed with the analysis.

3.4 An empirical dynamic four-factor model

In this section, the empirical framework of this study is explained. Existing studies of the relationship between bond yield spreads and its driving factors have two limitations. First, many previous empirical models of the link between spreads and stock prices have been postulated on that the risk factors do not give feedback to each other. In other words, risk factors are assumed to be strictly exogenous. On the other hand, some of the empirical studies provide evidence that factors actually do give feedback to each other (Pelizzon et al. [2014]). Hence, the assumption that the risk factors are strictly exogenous does not seem to be credible. Second, and raising from the first limitation, the driving force of the fluctuations in yield spreads are not identified correctly. For example, a shock to default risk may affect the yield spread positively, but it may have a negative effect on liquidity as well. This issue makes the the inference of the regressions where the dynamics of the factors are not taken into account misleading. In this article, we address both of these limitations with the help of a structural VAR model, where the dynamics of risk factors are modeled within a vector autoregressive framework. The vector of risk factors, z_t^i, consists of default risk measure by first difference of CDS, redenomination risk measured by first difference of quanto CDS and liquidity risk measured by one of the liquidity measures. Applying the first difference makes CDS and quanto CDS series stationary. The structural representation of this VAR is given by:

$$A_0 z_t^i = \alpha + \sum_j A_i z_{t-j}^i + ECBDummies_t + \epsilon_t^i$$

$$z_t^i = \begin{pmatrix} \Delta CDS_t^i \\ \Delta quanto\ CDS_t^i \\ liquidity_t^i \end{pmatrix} \tag{3.1}$$

where i stands for each country and ϵ_t^i is a vector of serially and mutually uncorrelated structural shocks which are identified from the reduced form VAR model, $e_t^i = A_0^{i^{-1}} \epsilon_t^i$ by imposing short run restriction on $A_0^{i^{-1}}$. We assume that there are three structural shocks that drive the risk factors: the default shock, ϵ_{1t}^i, redenomination shock, ϵ_{2t}^i and liquidity shock ϵ_{2t}^i. The short run restrictions imposed on $A_0^{i^{-1}}$ is as follows:

$$\begin{pmatrix} e_{1t}^{\Delta CDS^i} \\ e_{2t}^{\Delta QCDS^i} \\ e_{3t}^{liquidity^i} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{default\ shock} \\ \varepsilon_{2t}^{rdnmntn\ shock} \\ \varepsilon_{3t}^{liqdty\ shock} \end{pmatrix} \tag{3.2}$$

where zeros represent the restrictions. The restriction of the identification matrix implies that default risk is not affected by both liquidity and redenomination shocks. The latter is consistent with Pelizzon et al. [2014] who, using the Italian government bond data, find that CDS granger causes liquidity but not the other way around. The former is inspired by the observation that redenomination risk is higher for countries with high default risk. In other words, exiting from euro is more probable for countries with higher default risk. The last row of the identification matrix implies that liquidity risk is affected by both redenomination and default shocks as well as liquidity shocks.

Yield spreads are assumed to a function of risk factors, as well as the global variable. the full specification of the yield spread is as follows:

$$\begin{aligned} yieldspread_t^i = \alpha^i &+ \beta 1^i * yieldspread_{t-1}^i + \beta 2^i * \Delta CDS_t^i + \beta 3^i * CDS_{t-1}^i \\ &+ \beta 4^i * \Delta QuantoCDS_t^i + \beta 5^i * QuantoCDS_{t-1}^i + \beta 6^i * liquidity_t^i \\ &+ \beta 7^i * \Delta Global_t^i + \beta 8^i * Global_{t-1}^i + \epsilon_t^i \end{aligned} \tag{3.3}$$

which is specified in a cointegrated autoregressive distributed lag, ARDL(1,1), representation. ARDL model deals with studding cointegration and is introduced originally by Pesaran and Shin [1999] and further extended by Pesaran et al. [2001]. This econometrics tool is becoming increasingly popular in empirical research due to its econometric advantages. First, it can be employed regardless of whether the underlying variables are stationary i.e. I(0), integrated of order one i.e. I(1) or of higher degrees and second, the long-run and short-run parameters of the empirical specification can be estimated simultaneously. While we are not particularly interested in finding a cointegration relation between yield spreads and its drivers, it is really important to control for short run and long run impact of the factors on yield spreads.

3.4.1 Estimation

The estimation procedure has two steps which are as follows: ARDL(1,1) model in 3.3 is estimated as a system of equations for the whole sample period (2003-2012) for all countries. System estimation would account for any cross correlation between the error terms of each country's equation. For a technical reason, the structural VAR is estimated separately for each country but only for a sub-sample of the available data, i. e. for 2010-2012. The reason of cutting the sample is that the redenomination risk becomes active after August 2010 and therefore its proxy is always zero before this date. This makes is difficult to interpret the simulation of the yield spreads resulted from the historical decomposition of the redenomination shocks while we know that basically there was no such shocks. To control for the effect of the ECB interventions on risk factors we include a number of dummies in the the structural VAR specification as external variables. Each of these dummies capture two days window (the announcement day and a day after) of each of the ECB policies. Since there are two SMPs, one OMT and two LITROs, overall there are five ECB intervention dummies.

The second step is the simulation of the yield spreads applying the historical decomposition methodology. Based on 3.3, the yield spreads are a function of three risk factors in addition to the global factor. Risk factors make the yield spreads an indirect function of the structural shocks. Moreover, yield spreads of each country are a function of the measurement error of all ARDL specifications including the country in question.

The aim of the simulation is to compare the relative importance of each structural shocks in explaining the yield spreads. The simulation of the yield spreads using the structural shocks are very straightforward. For each country and each maturity, we simulate the risk factors using the estimated coefficients of the structural VAR where we keep only one structural shock in each simulation. The simulated risk factors are then applied to simulate the yield spreads in 3.3. The resulted simulation series would be interpreted as the explaining power of the structural shock relative to the other shocks: the more fluctuations captured by the simulated series, the more important is the structural shock in explaining the dynamics of the yield spreads. We have done an additional simulation for each country and maturity using the global factor. The idea here is to visualise how shocks to the global factor can explain the variations in yield spreads, where a shock to the global factor is measured by the measurement errors. In other words, to do this simulation, we simulate the factors without the structural shocks, but the simulation of the yield spreads is done with all the measurement errors that contribute to construct the global factor.

It is important to notice that normally to get a consistent interpretation of the simulated series one necessary condition is that the structural shocks are orthogonal to the measurement errors. Otherwise, the impact of the structural shocks on the yield spreads would be attributable to the measurement errors. Interestingly, the correlation between the measurement errors and the structural shocks for all countries in all maturities are very low and pronominalization is not needed. The highest correlation observed in our sample is between the Italian 10 year maturity measurement error and the liquidity shock which is 10 percent.

We perform the empirical analysis for the all 3, 5, 7 and 10 year maturities and all liquidity measures but only the results for the 10 year maturity using the quoted bid-ask spread as liquidity measure are reported.

Conditional VS Unconditional Estimation

One of the contributions of this paper is that it shows there is a considerable heterogeneity across countries in response of the yield spreads to factors. Therefore, imposing panel restrictions on coefficients may mask such heterogeneity and the consequent interpretation of the results may be erroneous. To better explore the issue, we replicate the results reported in table 3 of Beber et al. [2009] and present the results in 3.2.

[Table 3.2 here]

To replicate the Beber et al. [2009] results we follow all the procedure explained in the paper and use exactly the same sample period as the original paper.[2]. Beber et al. [2009] estimate the following specification using MTS daily data for ten European countries and the sample period 2003-2004 at four different maturities and using four liquidity measures:

$$Yield_t^i - EuroSwap_t = \alpha + \beta(CDS_t^i - CDS_t^{AVE}) + \gamma(Liq_t^i - Liq_t^{AVE}) \tag{3.4}$$

where $EuroSwap_t$ is the Euro-swap rate at time t, CDS_t^i and Liq_t^i are the credit default swap rate and liquidity measure for country i at time t and CDS_t^{AVE} and Liq_t^{AVE} are the cross-sectional averages of the CDS_t^i and Liq_t^i variables, respectively during period t. Comparing our results with Beber et al. [2009] suggests that we have been fairly successful in replicating the results. All the signs of the coefficients of liquidity measures are as expected and the goodness of fit improves as maturity increases. One of the limitations of the equation 3.4, apart from the imposing the panel restrictions, is that it omits the lag dependent variable. Figure 3.5 graphs the 10 year maturity yield spreads of the countries under analysis for the whole sample period. This figure shows that persistence is one of the properties of the yield spread series, specially during 2003-2004. This property necessities the inclusion of the lag dependent variable in the right hand side of the equation 3.4.

[2]Please refer to the original paper for detailed procedure of variable definitions and data construction

Therefore, we augment the equation 3.4 in two directions. First we remove the panel restrictions and allow the coefficients to vary across countries and second, we include the lag dependent variable in the RHS of equation 3.4:

$$\begin{aligned} Yield_t^i - EuroSwap_t = \alpha_i &+ \lambda_i(Yield_{t-1}^i - EuroSwap_{t-1}) \\ &+ \beta_i(CDS_t^i - CDS_t^{AVE}) \\ &+ \gamma_i(Liq_t^i - Liq_t^{AVE}) \end{aligned} \tag{3.5}$$

Table 3.3 reports the system estimation results of equation 3.5 for 10 year maturity bond rates for 2003-2004 where effective bid-ask spread is used as the liquidity measure. The results illustrate the importance of the lag dependent variable. It is always highly statistically significant and its magnitude varies from 0.17 in of Austria to 0.75 in the case of Greece. Interestingly, the coefficient of CDS is negative and significant for Portugal, Spain and Belgium and insignificant for Greece. This result makes it clear how restrictive the panel restrictions are and how misleading the results would be if one does not take into account the heterogeneity across countries. The case of the liquidity measure is even worse as it comes with statistical significance and predicted sign only for Spain.

[Table 3.3 here]

Baseline Model Estimation

In this section we present the results of the estimation of equation 3.3. The results are reported in table 3.4. The results clearly show the importance of unrestricted estimation as the variation of the magnitude of the coefficients across countries is significant.

[Table 3.4 here]

The last column of the table presents the results imposing the panel restrictions. Not surprisingly, the lag dependent variable is close to unity and highly significant for all countries, resulted from the unit root property of the yield spreads. The short-run effect of the default risk is highly significant as well. The variation of the coefficient of ΔCDS_t across countries suggest that the effect of this variable is more pronounced for high yield countries. It gets its highest values for the case of Italy and Spain, 0.65 and 0.67 respectively, while it is as low as 0.05 for the case of The Netherlands. The long-run effect of the default risk follows the same pattern as the short-run effect. Its value is higher for troubled countries and lower for low yield countries. Surprisingly, the short-run effect of the redenomination risk is negative for high yield countries and insignificant for low yield countries, and the long-run is only significant for three countries out of nine. We interpret this result as an evidence that controlling for the default risk would capture the effect of the redenomination risk as well. Historically, the redenomination risk have been higher for troubled countries, countries with g=higher default risk. Liquidity risk is an interesting case among other factors. It is highly significant with positive sign when we impose the panel restrictions, but unrestricted coefficients shows that it is only significant for three out of nine countries. The global variable seems to be another important factor in explaining the yield spreads. The short-run effect follows he same pattern as the default risk. It tends to be higher for troubled countries like Italy and Spain and lower for low yield countries like France and The Netherlands.

We also present the results of the estimation of the structural VAR specification in relation 3.1. The estimation is done using data from 2010 to 2012. As stated earlier, in the VAR specification we include five dummies as exogenous variables to control for the ECB interventions effect on the risk factors. These dummy variables match two SMPs, two LTROs and a OMT intervention. The results are presented in tables 3.5 to 3.7. Table 3.5 shows the estimation results for ΔCDS equation. This variable shows an autoregressive property for high yield countries (Italy, Spain, Portugal and Ireland) and a partial autoregressive property for other countries. ΔCDS also shows a minor dependence to the first and second lags of the liquidity and redenomination risks, being significant only for Italy and Belgium. The coefficients on dummies suggest that all the ECB interventions have been effective to decrease the default risk on impact. Among all programs, SMPs have been the most successful interventions and they mostly affect troubled countries. LTROs had milder effect compared to SMPs and they affected the default risk of Italy the most. While not practically exercised, the announcement of the MTO is shown to have a positive effect on the default risk of Italy and Spain.

The estimation results for $\Delta QuantoCDS$ is presented in table 3.6. The coefficients on the autoregressive variables suggest that this variable is negatively auto-correlated for all countries. Moreover, the results suggest that this variable receives a feedback from the first and second lags of the both default and liquidity risks. Unlike ΔCDS, the effect of the ECB policies on $\Delta QuantoCDS$ is not conclusive. The coefficients of the the two SMPs are never significant and the first LTRO has increased the redenomination risk of Spain.

Table 3.7 presents the estimation of the last equation of the relation 3.1. The results show that *liquidity* is highly auto-correlated and receives a minor feedback from default and redenomnation risks first and second lags. Like the case of the default risk, SMPs are shown to have a the most significant effects on *liquidity*. But interestingly, the sign of the coefficients of SMPs are positive meaning that these interventions have decreased the liquidity. On the other hand, the coefficients of the LTROs are negative but insignificant.

Overall, the results of the VAR estimation show that default risk had the highest effect on the other factors in the sample period under analysis. Moreover, the ECB intervention have affected default risk more that other risk factors.

[Table 3.5 here]

[Table 3.6 here]

[Table 3.7 here]

3.4.2 Historical Decomposition

Historical decomposition is a very strong econometric tool that makes it possible to analyze the cumulative effect of structural shocks on yield spreads. The relative strength of this tool over the conventional impulse response analysis is that historical decomposition does not assume that structural shocks are one time shocks. In reality, shocks affecting the yield spreads belong to a sequence, often with different signs at different points in time. We use the historical decomposition by simulating the path of the yield spreads under the assumption that only one of the structural shocks is non-zero. Comparing the simulated series with actual yield spread series illustrates the explaining power of the structural shock. Another set of simulations are carried out for all countries to analyse the response of yield spreads to contagion. This set of simulations are performed for each under the assumption that all the structural shocks are zero while all the measurement errors of other countries (contributing to the global factor) are non-zero.

Figures 3.6 to 3.14 presents the historical decomposition of the yield spreads of all countries under analysis. Two different patterns could be identified from the simulations. Expectedly, high yield countries namely Italy, Spain, Portugal and Ireland present a very clear image: the default risk takes up all the fluctuations of the yield spreads of these countries. The case of Spain and Ireland are very interesting as the simulated series closely move with the actual series. However, there is a gap between the simulated series and actual yield spreads for Portugal and Italy, which widens after the second SMP. We interpret this result as an evidence of lowered market perception of risk for these two countries. Liquidity shock tends to play a very minor role for Portugal after the second SMP, but it does not seem to capture any fluctuations of the yield spreads for other high yield countries. The same statement could be applied to redenomination risk and contagion as they seem to play no role in explaining the yield spreads.

On the other hand, the results for low yield countries are not conclusive. Yield spreads of France does not seem to respond to any of the structural shocks. Therefore, most of the fluctuations of the series is taken up by the measurement error. Finland and the Netherlands have a very similar case to France with the exception that default shock tends to become active after the second LTRO. Belgium and Austria are the most responsive low yield countries to the default risk. Other structural shocks does not seem to paly any important role in explaining the yield spreads.

Overall, the results of yield spread simulation are in line with the estimation of the baseline model: default risk is the main driving factor of the yield spreads of the troubled countries and it partially explains the fluctuations os the yield spreads of low yield countries.

3.5 Conclusions

This paper develops a new methodology for analyzing sovereign bond market. Our methodology identifies the fundamental risk factors that drive the yield spreads. The flexibility of our methodology allows capturing the dynamic interaction between the risk factors and studding the ultimate effect of the factors on yield spreads.

One of the contributions of this paper is that it shows that countries are very different in responding to the changes in the risk factor. Ignoring the heterogeneity among countries would make the interpretations misleading. The results of this paper show that while imposing panel restrictions would result in finding liquidity risk an important factor describing the yield spread, unrestricted analysis suggest that this factor plays a minor role.

Our results suggest that the default risk is the most responsible factor for yield spreads, specially after 2010. This result has important implications for the ECB policy makers. While the results confirm the effectiveness of the ECB interventions on yield spreads on impact, their effect does not seem to last very long. Our results therefore may be useful to give a hint to policy makers on that whether they should target liquidity or quality.

Figure 3.1: Daily 10 year maturity bond yields (percent) of ten European countries for the sample period 2003-2012. Data source is DataStream.

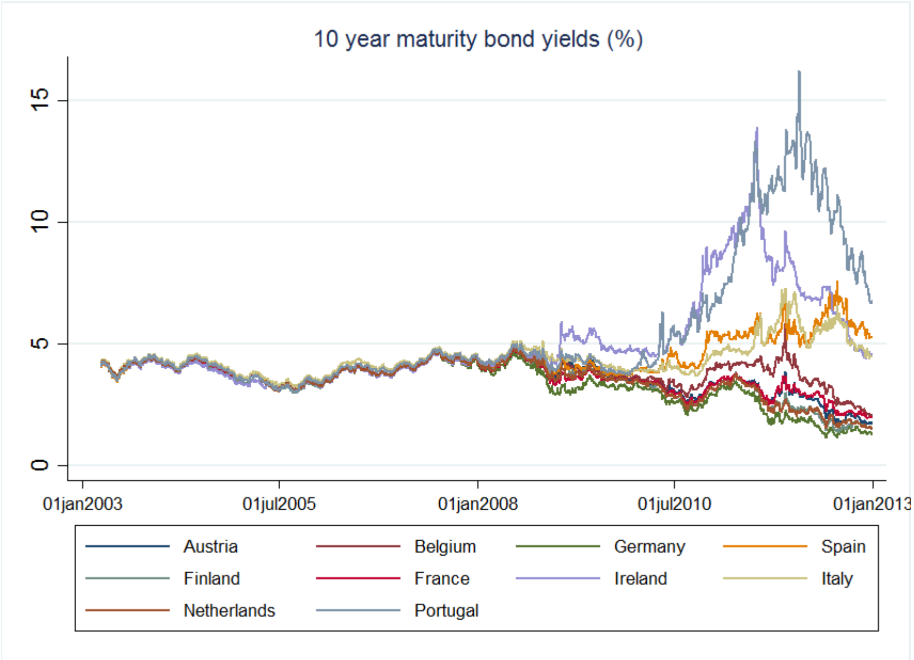


Figure 3.2: Daily 10 year maturity Credit Default Swap (level) rates of ten European countries for the sample period 2003-2012. Data source is Markit.

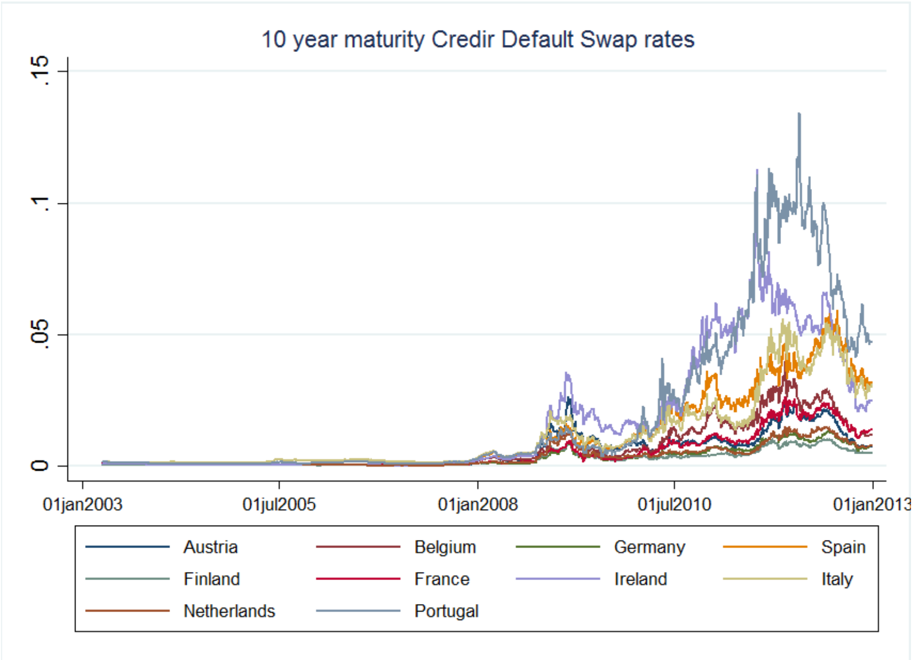


Figure 3.3: Daily 10 year maturity quanto CDS (basis points) rates of ten European countries for the sample period 2010-2012. Data source is Markit.

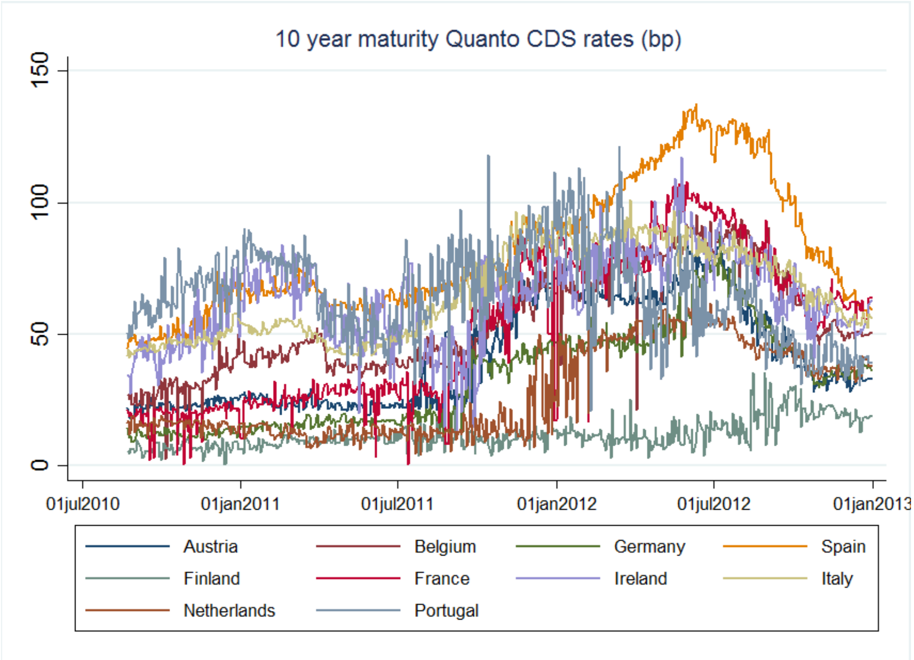


Figure 3.4: Daily 10 year maturity German benchmark bond yields versus Euro-Swap rates for the sample period 2003-2012. Data source is DataStream.

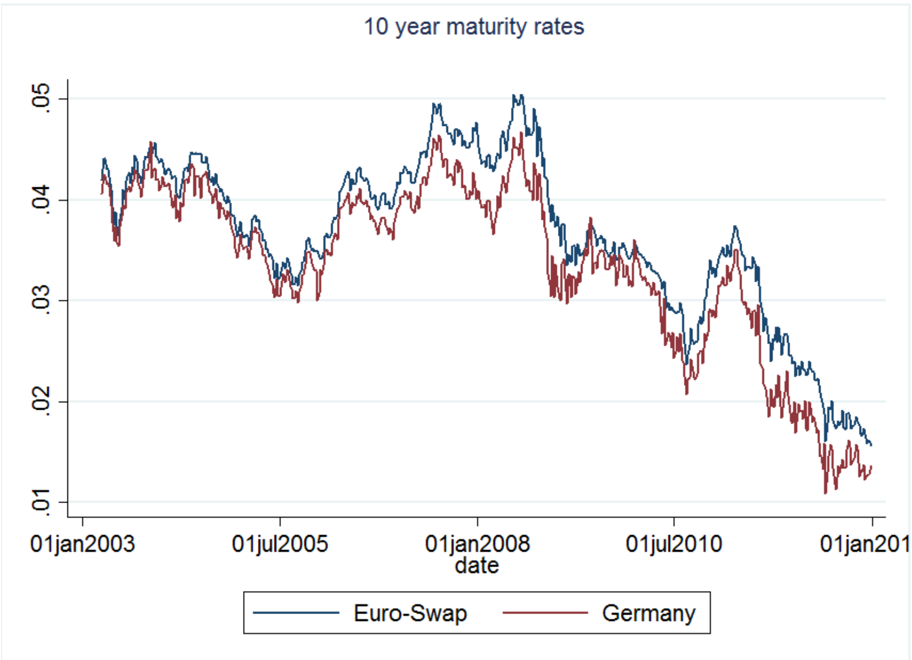


Figure 3.5: Daily 10 year maturity bond yields rates differential versus Germany for the sample period 2003-2012. Data source is DataStream.

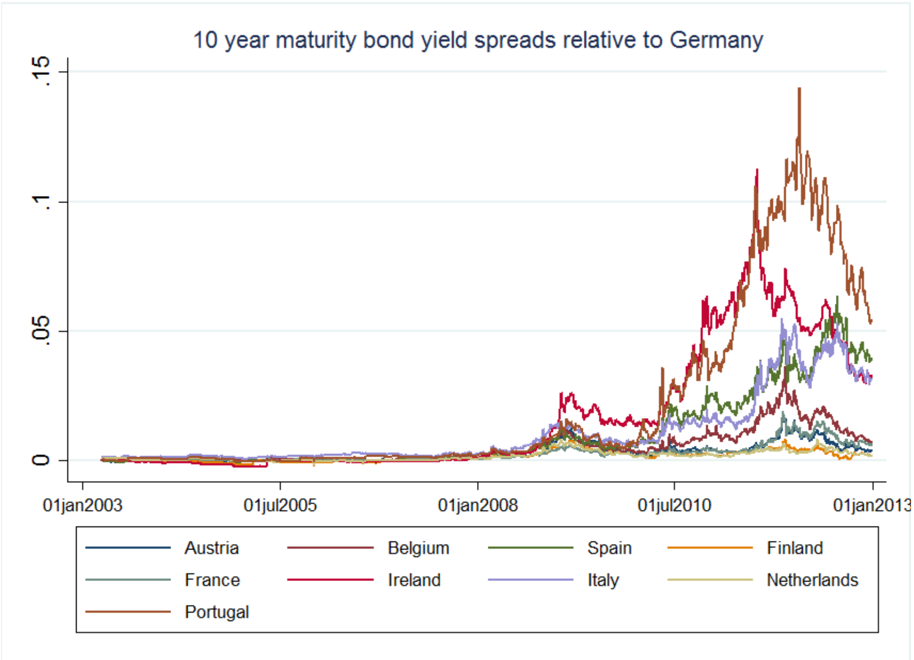


Table 3.1: This table presents summary statistics for our sample data. N is the number of bonds in each country/maturity category traded on the MTS. Yield is the average of the bond yield. CDS is the average Credit Default Swap rate expressed in basis points. Quoted spread is the average quoted bid-ask spread and Depth is the average quoted depth for each country/maturity expressed in millions of euros.

3 year							**5 year**						
Country	N	Yield	CDS	Q_CDS	Quoted spread	Depth	**Country**	N	Yield	CDS	Q_CDS	Quoted spread	Depth
Austria	13	2.87	34.44	20.27	0.0022	162.91	Austria	14	3.02	45.72	29.54	0.0034	166.98
Belgium	26	2.50	49.76	31.39	0.0016	154.68	Belgium	23	3.02	62.17	42.02	0.0022	177.46
Germany	103	2.72	16.08	12.60	0.0006	107.39	Germany	62	2.93	25.03	22.16	0.0008	151.33
Spain	71	3.18	108.52	59.13	0.0034	150.78	Spain	60	3.54	120.59	66.21	0.0048	141.78
Finland	13	2.80	15.44	6.07	0.0010	200.65	Finland	13	3.17	21.05	9.56	0.0017	243.33
France	58	2.40	31.81	25.71	0.0012	119.28	France	50	2.84	45.01	38.82	0.0017	138.38
Ireland	8	3.87	180.17	45.16	0.0137	69.00	Ireland	7	4.29	173.11	50.90	0.0157	118.17
Italy	92	3.14	104.80	45.28	0.0014	222.51	Italy	40	3.64	119.36	52.44	0.0018	243.39
Netherlands	29	2.18	30.66	13.42	0.0006	146.21	Netherlands	19	2.64	37.10	22.16	0.0010	203.55
Portugal	19	3.20	243.70	51.57	0.0207	163.37	Portugal	16	3.83	232.74	53.91	0.0230	208.59
7 year							**10 year**						
Austria	14	3.41	50.67	34.32	0.0036	161.37	Austria	12	3.59	54.96	37.77	0.0040	166.21
Belgium	18	3.35	67.31	46.98	0.0026	170.84	Belgium	16	3.73	71.04	50.35	0.0023	211.84
Germany	34	3.36	30.12	26.92	0.0010	130.50	Germany	32	3.34	34.89	30.86	0.0010	173.17
Spain	44	3.76	124.34	68.73	0.0069	130.73	Spain	52	4.19	125.97	70.57	0.0099	152.91
Finland	8	3.46	25.13	11.82	0.0018	244.62	Finland	7	3.96	28.32	13.34	0.0020	230.72
France	32	3.19	51.62	44.66	0.0021	127.53	France	34	3.37	56.95	48.50	0.0025	172.87
Ireland	9	4.27	178.04	52.94	0.0216	77.72	Ireland	8	4.47	164.67	54.07	0.0153	101.85
Italy	21	3.82	124.60	55.11	0.0023	253.02	Italy	31	4.32	128.17	56.86	0.0025	275.83
Netherlands	13	3.42	46.47	26.84	0.0014	214.40	Netherlands	16	3.21	51.12	30.42	0.0012	224.59
Portugal	12	3.82	224.98	55.03	0.0265	229.31	Portugal	12	4.09	214.65	56.14	0.0275	226.66

Table 3.2: Panel restricted relation between yield spreads, credit quality and liquidity

	Effective bid ask spread	Depth at the best bid or ask	Liquidity index	Cumulative limit order book depth
		3 year		
Constant	-0.00150***	-0.00151***	-0.00150***	-0.00151***
	(0.000)	(0.000)	(0.000)	(0.000)
CDS	0.0175***	0.0167***	0.0166***	0.0164***
	(0.000)	(0.000)	(0.000)	(0.000)
Liquidity	0.0169	-0.00000117	-0.000362	-4.57e-08
	(0.082)	(0.315)	(0.137)	(0.139)
Overal_R2	0.062	0.059	0.060	0.061
		5 year		
Constant	-0.00131***	-0.00131***	-0.00131***	-0.00131***
	(0.000)	(0.000)	(0.000)	(0.000)
CDS	0.00536***	0.00509***	0.00512***	0.00473***
	(0.000)	(0.000)	(0.000)	(0.001)
Liquidity	0.0120**	-0.00000279***	-0.000599***	-6.27e-08***
	(0.002)	(0.000)	(0.000)	(0.000)
Overal_R2	0.121	0.121	0.112	0.112
		7 year		
Constant	-0.00108***	-0.00108***	-0.00107***	-0.00108***
	(0.000)	(0.000)	(0.000)	(0.000)
CDS	0.00255**	0.00259**	0.00280**	0.00251**
	(0.010)	(0.008)	(0.004)	(0.010)
Liquidity	0.0110***	-0.00000396***	-0.00139***	-8.86e-08***
	(0.000)	(0.000)	(0.000)	(0.000)
Overal_R2	0.286	0.183	0.142	0.154
		10 year		
Constant	-0.00102***	-0.00103***	-0.00103***	-0.00103***
	(0.000)	(0.000)	(0.000)	(0.000)
CDS	0.00340***	0.00392***	0.00383***	0.00378***
	(0.000)	(0.000)	(0.000)	(0.000)
Liquidity	0.00630	-0.00000211***	-0.000514***	-3.85e-08***
	(0.062)	(0.000)	(0.000)	(0.000)
Overal_R2	0.378	0.308	0.318	0.315

This table contains the results of replicating Beber *et al* who estimated the following regression using daily observations from 2003 to 2004:
$Yield_t^i - EuroSwap_t = \alpha + \beta(CDS_t^i - CDS_t^{AVE}) + \gamma(Liq_t^i - Liq_t^{AVE})$
where $Yield_t^i$, CDS_t^i and Liq_t^i represent the yield, Credit Default Swap, and liquidity measures for the given maturity and country i over period t. CDS_t^{AVE} and Liq_t^{AVE} are the corresponding cross-sectional averages at time period t. The $EuroSwap_t$ is the constant maturity fixed leg yield for the given maturity over period t. p-values are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.3: Unrestricted relation between yield spread, lag yield spread, credit quality and liquidity

	Italy	France	Belgium	Netherlands	Spain
Constant	-0.000217***	-0.000905***	-0.000749***	-0.000602**	-0.000915***
	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)
Yld_sprd_{t-1}	0.489***	0.269***	0.322***	0.499***	0.288***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CDS_t	0.00225*	0.000561	-0.00219**	0.0156*	-0.00474***
	(0.017)	(0.642)	(0.009)	(0.024)	(0.001)
$Liquidity_t$	0.0129	0.00193	-0.000280	-0.0459	0.0238***
	(0.082)	(0.459)	(0.926)	(0.092)	(0.000)
adj. (R^2)	0.319	0.054	0.092	0.382	0.263

	Austria	Portugal	Germany	Greece	Finland
Constant	-0.000863***	-0.000454***	-0.000795***	0.0000259	-0.000927***
	(0.000)	(0.000)	(0.000)	(0.845)	(0.000)
Yld_sprd_{t-1}	0.165**	0.282***	0.487***	0.746***	0.234*
	(0.003)	(0.000)	(0.000)	(0.000)	(0.010)
CDS_t	0.000879	-0.00238*	0.00668**	-0.000936	0.00435
	(0.652)	(0.021)	(0.002)	(0.635)	(0.224)
$Liquidity_t$	-0.0139**	0.00679	-0.00307	0.0111	0.00811
	(0.002)	(0.117)	(0.770)	(0.082)	(0.585)
adj. (R^2)	0.043	0.130	0.302	0.641	0.077

This table contains the results of estimating the following regression using daily observations from 2003 to 2004:
$Yield_t^i - EuroSwap_t = \alpha^i + \lambda^i(Yield_{t-1}^i - EuroSwap_{t-1})$
$+\beta^i(CDS_t^i - CDS_t^{AVE}) + \gamma^i(Liq_t^i - Liq_t^{AVE})$
where $Yield_t^i$, CDS_t^i and Liq_t^i represent the yield, Credit Default Swap, and liquidity measures (quoted bid-ask spread) for the given maturity and country i over period t. CDS_t^{AVE} and Liq_t^{AVE} are the corresponding cross-sectional averages at time period t. The $EuroSwap_t$ is the constant maturity fixed leg yield for the given maturity over period t. Data corresponds to 10 year maturity bond, CDS and Euro-Swap rates. p-values are reported in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4: Unrestricted relation between yield spread, credit risk, liquidity risk and redenomination risk

	Italy	Belgium	France	Spain	Netherlands	Austria	Finland	Portugal	Ireland	Panel
Constant	0.0000238*	0.0000160*	0.0000124*	-0.0000145	0.0000163**	0.0000115	0.00000551	-0.0000108	0.00000118	0.00000907**
	(0.038)	(0.034)	(0.033)	(0.183)	(0.009)	(0.059)	(0.140)	(0.656)	(0.942)	(0.007)
Yld_sprd_{t-1}	0.966***	0.981***	0.976***	0.975***	0.983***	0.976***	0.992***	0.966***	0.975***	0.990***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔCDS_t	0.645***	0.488***	0.329***	0.667***	0.0527**	0.213***	0.0752***	0.526***	0.526***	0.459***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CDS_{t-1}	0.0304***	0.0151***	0.0174***	0.0296***	0.0104*	0.00736*	0.00661	0.0281***	0.0285***	0.00988***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.048)	(0.028)	(0.217)	(0.000)	(0.000)	(0.000)
$\Delta Quanto\_CDS_t$	-0.145***	-0.0194	0.0116	-0.154***	0.00898	-0.00855	0.00799	-0.121***	-0.0449	-0.0146**
	(0.000)	(0.171)	(0.222)	(0.000)	(0.416)	(0.577)	(0.573)	(0.000)	(0.078)	(0.008)
$Quanto\_CDS_{t-1}$	0.0240***	0.00208	0.000262	0.00728	0.000749	0.0104**	0.0221*	0.0119	0.00365	-0.00191
	(0.001)	(0.606)	(0.945)	(0.283)	(0.848)	(0.002)	(0.029)	(0.425)	(0.722)	(0.263)
$Liquidity_t$	0.00594	0.00654*	0.00104	0.00119	0.00396	0.00648***	0.00217	0.00474***	0.00131	0.00166***
	(0.179)	(0.042)	(0.445)	(0.459)	(0.256)	(0.000)	(0.093)	(0.000)	(0.295)	(0.000)
$\Delta Global\_Yld_t$	0.923***	0.286***	0.222***	0.650***	0.207***	0.0439***	0.243***	0.312**	0.0427	0.0725***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.137)	(0.000)
$Global\_Yld_{t-1}$	0.0383**	0.00878*	0.00978*	0.00468	0.00446	0.00442**	0.00125	0.0740***	0.00915*	0.00273**
	(0.004)	(0.042)	(0.026)	(0.551)	(0.170)	(0.003)	(0.723)	(0.000)	(0.030)	(0.004)
(N)	2539	2539	2539	2539	2539	2539	2539	2539	2539	2529
adj. (R^2)	0.999	0.998	0.996	0.999	0.999	0.991	0.994	0.999	0.999	0.998

This table contains the results of estimating the following regression using daily observations from 2003 to 2012:

$$yieldspread^i_t = \alpha^i + \beta 1^i * yieldspread^i_{t-1} + \beta 2^i * \Delta CDS^i_t + \beta 3^i * CDS^i_{t-1}$$
$$+\beta 4^i * \Delta QuantoCDS^i_t + \beta 5^i * QuantoCDS^i_{t-1} + \beta 6^i * liquidity^i_t$$
$$+\beta 7^i * \Delta Global^i_t + \beta 8^i * Global^i_{t-1} + \epsilon^i_t$$

where $yieldspread^i_t$, CDS^i_t, $QuantoCDS^i_t$, $Global^i_t$ and $Liquidity^i_t$ represent the yield, Credit Default Swap, quanto CDS, global variable and liquidity measures (quoted bid-ask) for the given maturity and country i over period t. Δ represents the first difference operator. All the variables except quanto CDS enter the specification in terms of the difference between each country's rate and the same for Germany. Data corresponds to 10 year maturity rates. p-values are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5: VAR(2) estimation of credit risk, redenomination risk and liquidity risk with the ECB interventions dummies, part 1

ΔCDS_t	Italy	Belgium	France	Spain	Netherlands	Austria	Finland	Portugal	Irland
Constant	0.0000351	0.00000958	0.0000101	0.0000495	0.000000281	0.000000315	-0.00000306	0.000160	0.0000625
	(0.466)	(0.699)	(0.432)	(0.385)	(0.977)	(0.987)	(0.746)	(0.099)	(0.435)
ΔCDS_{t-1}	0.255***	0.229***	0.0505	0.242***	-0.186***	0.142***	-0.136***	0.264***	0.255***
	(0.000)	(0.000)	(0.123)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔCDS_{t-2}	-0.0874**	-0.0524	0.0741*	-0.133***	-0.0959**	-0.0187	0.0452	0.000281	0.0320
	(0.009)	(0.103)	(0.023)	(0.000)	(0.003)	(0.565)	(0.166)	(0.993)	(0.323)
$\Delta Q.\ CDS_{t-1}$	-0.337**	-0.0911*	-0.00387	-0.0881	-0.00195	0.0393	0.00151	-0.0135	0.0773
	(0.004)	(0.015)	(0.832)	(0.424)	(0.910)	(0.202)	(0.934)	(0.859)	(0.271)
$\Delta Q.\ CDS_{t-1}$	-0.0807	-0.0524	0.0248	0.117	0.0130	0.0838**	0.00406	0.00495	0.00926
	(0.496)	(0.163)	(0.176)	(0.289)	(0.454)	(0.006)	(0.825)	(0.948)	(0.895)
$Liquidity_{t-1}$	-0.117***	-0.0612***	-0.00494	-0.00236	-0.00496	0.00212	-0.000826	-0.00353	0.00455
	(0.000)	(0.000)	(0.251)	(0.723)	(0.624)	(0.805)	(0.901)	(0.122)	(0.251)
$Liquidity_{t-1}$	0.119***	0.0605***	0.00330	0.00203	0.00382	-0.00322	0.000298	0.00179	-0.00594
	(0.000)	(0.000)	(0.443)	(0.760)	(0.709)	(0.708)	(0.964)	(0.436)	(0.133)
SMP1	-0.00338***	-0.000504	-0.000297	-0.00397***	0.000124	-0.000155	0.000206	-0.00852***	-0.00355***
	(0.000)	(0.187)	(0.194)	(0.000)	(0.406)	(0.483)	(0.091)	(0.000)	(0.001)
SMP2	-0.00260***	-0.000736	0.000322	-0.00404***	-0.000123	0.0000885	-0.0000400	-0.00435**	-0.00377***
	(0.000)	(0.055)	(0.160)	(0.000)	(0.414)	(0.688)	(0.741)	(0.004)	(0.000)
LTRO1	-0.00176*	-0.000344	-0.000131	-0.000789	-0.00000523	-0.0000977	0.000135	-0.000914	-0.000624
	(0.016)	(0.373)	(0.570)	(0.275)	(0.972)	(0.661)	(0.268)	(0.543)	(0.560)
LTRO2	-0.000529	-0.000269	-0.000202	0.0000249	-0.000104	-0.000168	-0.00000219	0.00344*	0.00174
	(0.454)	(0.482)	(0.391)	(0.972)	(0.483)	(0.445)	(0.985)	(0.024)	(0.102)
OMT	-0.00246***	-0.000434	-0.000193	-0.00292***	-0.000117	-0.000162	0.00000336	-0.000618	-0.00135
	(0.001)	(0.258)	(0.402)	(0.000)	(0.430)	(0.461)	(0.978)	(0.682)	(0.206)

This table contains the results of estimating a VAR(2) specification of ΔCDS_t^i, $\Delta Q.CDS_t^i$ and $Liquidity_t^i$, representing the first difference of CDS, first difference of quanto CDS and liquidity measures (quoted bid-ask spread) for the given maturity and country i over period t. The VAR specification also includes five dummy variables that correspond to each of the ECB interventions. All the variables except quanto CDS enter the specification in terms of the difference between each country's rate and the same for Germany. This table presents the results associated to the ΔCDS_t equation. Data corresponds to 10 year maturity rates and sample period is form 2010 to 2012. p-values are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6: VAR(2) estimation of credit risk, redenomination risk and liquidity risk with the ECB interventions dummies, part 2

$\Delta Q.\ CDS_t$	Italy	France	Belgium	Netherlands	Spain	Austria	Finland	Portugal	Irland
Constant	0.00000394	0.00000194	0.00000662	0.0000165	-0.00000656	-0.0000114	0.00000595	0.0000114	0.00000994
	(0.781)	(0.926)	(0.763)	(0.341)	(0.709)	(0.577)	(0.720)	(0.781)	(0.785)
ΔCDS_{t-1}	0.0371***	0.0693*	-0.00419	0.0369***	0.0769	0.00741	0.0637	0.0584***	0.0469**
	(0.000)	(0.010)	(0.941)	(0.000)	(0.181)	(0.830)	(0.264)	(0.000)	(0.002)
ΔCDS_{t-2}	-0.00342	0.0269	0.248***	-0.0204*	0.0683	-0.0112	-0.0526	-0.0296*	-0.0151
	(0.729)	(0.318)	(0.000)	(0.040)	(0.237)	(0.745)	(0.358)	(0.030)	(0.306)
$\Delta Q.\ CDS_{t-1}$	-0.369***	-0.596***	-0.376***	-0.364***	-0.622***	-0.559***	-0.504***	-0.629***	-0.566***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta Q.\ CDS_{t-2}$	-0.0798*	-0.259***	-0.292***	-0.106**	-0.269***	-0.0974**	-0.232***	-0.253***	-0.290***
	(0.022)	(0.000)	(0.000)	(0.002)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
$Liquidity_{t-1}$	-0.0143	-0.0307**	0.0135	-0.00123	0.00754	-0.00384	-0.0248*	-0.00253**	0.000781
	(0.147)	(0.005)	(0.068)	(0.544)	(0.678)	(0.673)	(0.032)	(0.009)	(0.665)
$Liquidity_{t-2}$	0.0160	0.0337**	-0.0119	0.000934	0.0112	0.00775	0.0223	0.00248*	-0.000771
	(0.107)	(0.002)	(0.107)	(0.646)	(0.540)	(0.393)	(0.053)	(0.011)	(0.668)
SMP1	-0.0000554	-0.0000568	-0.0000440	0.0000244	0.0000113	-0.0000131	0.0000179	0.000115	-0.0000127
	(0.791)	(0.859)	(0.911)	(0.911)	(0.966)	(0.955)	(0.933)	(0.856)	(0.979)
SMP2	-0.0000797	-0.000216	-0.000266	-0.000110	-0.0000888	0.000211	-0.000213	0.000142	0.000196
	(0.702)	(0.500)	(0.498)	(0.616)	(0.741)	(0.366)	(0.317)	(0.822)	(0.689)
LTRO1	0.0000406	0.0000417	-0.0000962	-0.0000837	0.000905***	-0.000370	0.000208	-0.00139*	0.0000179
	(0.850)	(0.897)	(0.807)	(0.704)	(0.001)	(0.116)	(0.330)	(0.029)	(0.971)
LTRO2	-0.000195	0.0000719	0.000338	-0.000194	-0.000811**	-0.000104	0.000133	0.000820	0.000516
	(0.346)	(0.822)	(0.402)	(0.376)	(0.002)	(0.654)	(0.531)	(0.200)	(0.288)
OMT	-0.000257	-0.000562	-0.000451	-0.000730***	-0.0000928	-0.000304	0.000448*	0.0000343	-0.000323
	(0.219)	(0.080)	(0.251)	(0.001)	(0.727)	(0.191)	(0.039)	(0.957)	(0.507)

This table contains the results of estimating a VAR(2) specification of ΔCDS_t^i, $\Delta Q.CDS_t^i$ and $Liquidity_t^i$, representing the first difference of CDS, first difference of quanto CDS and liquidity measures (quoted bid-ask spread) for the given maturity and country i over period t. The VAR specification also includes five dummy variables that correspond to each of the ECB interventions. All the variables except quanto CDS enter the specification in terms of the difference between each country's rate and the same for Germany. This table presents the results associated to the $\Delta Q.\ CDS_t$ equation. Data corresponds to 10 year maturity rates and sample period is form 2010 to 2012. p-values are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

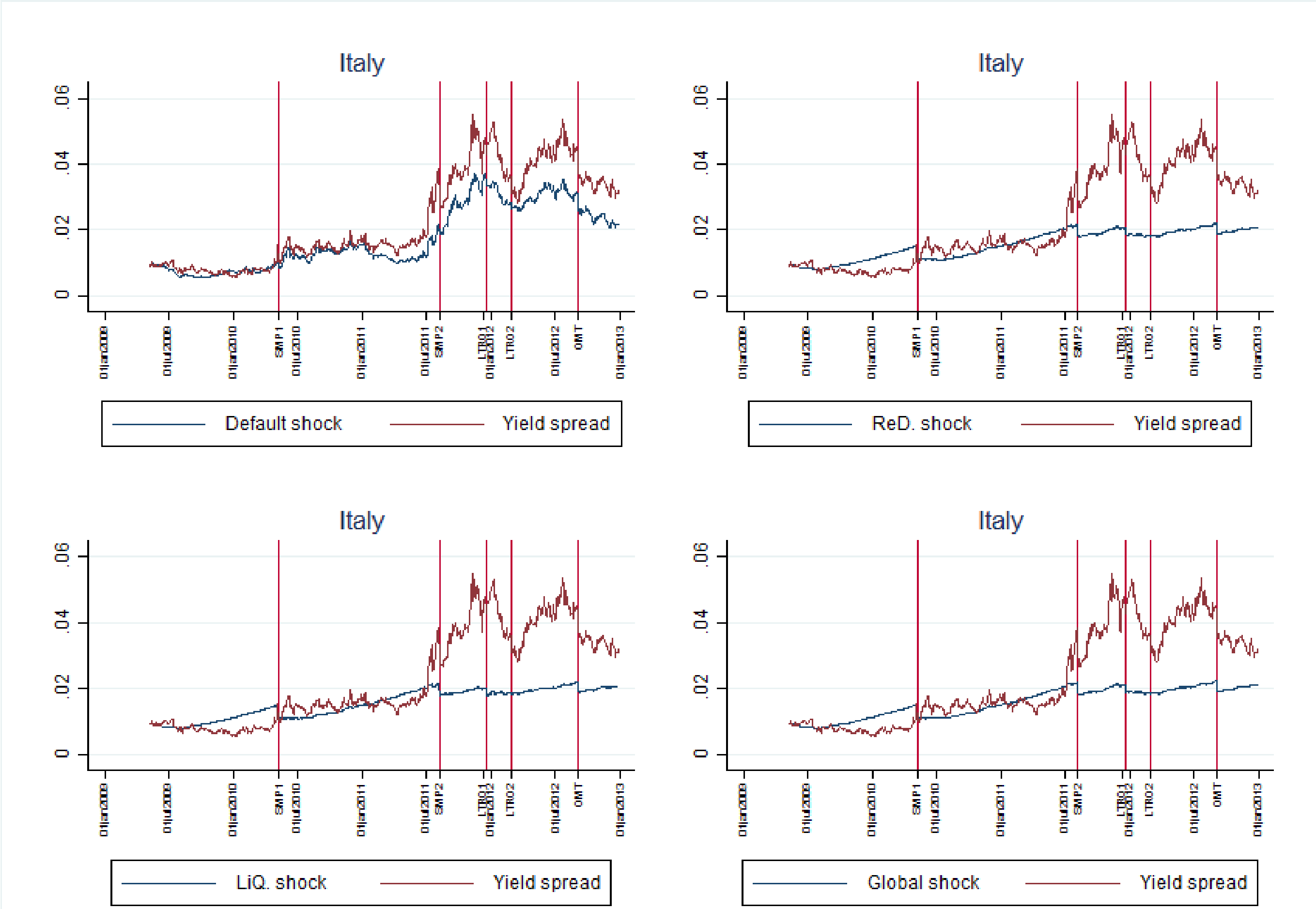
Table 3.7: VAR(2) estimation of credit risk, redenomination risk and liquidity risk with the ECB interventions dummies, part 3

$Liquidity_t$	Italy	France	Belgium	Netherlands	Spain	Austria	Finland	Portugal	Ireland
Constant	0.0000851*	0.000174**	0.000435***	0.000805**	0.000199***	0.000256***	0.000273***	0.00476***	0.00273***
	(0.040)	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔCDS_{t-1}	0.0668*	0.201**	0.215	0.00475	0.0743	0.00559	-0.0702	0.622	0.272
	(0.021)	(0.006)	(0.369)	(0.973)	(0.459)	(0.962)	(0.635)	(0.158)	(0.286)
ΔCDS_{t-2}	0.0544	0.0262	0.457	-0.146	-0.0233	0.228*	-0.191	-0.444	-0.00882
	(0.061)	(0.722)	(0.055)	(0.303)	(0.817)	(0.050)	(0.199)	(0.309)	(0.972)
$\Delta Q.\ CDS_{t-1}$	0.228*	0.0786	0.0899	0.169	-0.0813	0.141	0.239**	-2.279*	-0.539
	(0.026)	(0.362)	(0.500)	(0.726)	(0.132)	(0.200)	(0.004)	(0.026)	(0.321)
$\Delta Q.\ CDS_{t-2}$	0.0297	0.109	-0.0429	-0.00730	-0.101	0.139	0.186*	-0.236	0.217
	(0.772)	(0.204)	(0.749)	(0.988)	(0.064)	(0.204)	(0.026)	(0.817)	(0.689)
$Liquidity_{t-1}$	0.553***	0.564***	0.552***	0.509***	0.470***	0.641***	0.485***	0.576***	0.600***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Liquidity_{t-2}$	0.414***	0.374***	0.257***	0.445***	0.282***	0.300***	0.329***	0.349***	0.313***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMP1	0.000356	0.000281	-0.000226	0.00140	-0.000105	0.00250**	0.00279***	0.00618	0.00318
	(0.562)	(0.748)	(0.892)	(0.657)	(0.822)	(0.001)	(0.000)	(0.760)	(0.701)
SMP2	0.00446***	0.00396***	0.00218	0.00303	0.000739	0.00272***	0.00247***	0.0113	0.0251**
	(0.000)	(0.000)	(0.191)	(0.337)	(0.115)	(0.001)	(0.000)	(0.577)	(0.002)
LTRO1	-0.000844	-0.00104	0.000600	-0.000629	0.0000404	-0.000172	0.000364	0.0256	0.00902
	(0.181)	(0.242)	(0.720)	(0.842)	(0.932)	(0.828)	(0.509)	(0.205)	(0.276)
LTRO2	-0.000107	-0.000575	0.00360*	-0.00126	0.0000727	-0.000177	-0.0000695	-0.0431*	0.0238**
	(0.861)	(0.512)	(0.035)	(0.688)	(0.875)	(0.821)	(0.899)	(0.035)	(0.004)
OMT	0.00129*	0.000464	0.000287	0.0000143	0.000533	0.000880	-0.00146**	-0.0150	0.0126
	(0.036)	(0.598)	(0.864)	(0.996)	(0.250)	(0.262)	(0.009)	(0.459)	(0.128)

This table contains the results of estimating a VAR(2) specification of ΔCDS_t^i, $\Delta Q.CDS_t^i$ and $Liquidity_t^i$, representing the first difference of CDS, first difference of quanto CDS and liquidity measures (quoted bid-ask spread) for the given maturity and country i over period t. The VAR specification also includes five dummy variables that correspond to each of the ECB interventions. All the variables except quanto CDS enter the specification in terms of the difference between each country's rate and the same for Germany. This table presents the results associated to the $Liquidity_t$ equation. Data corresponds to 10 year maturity rates and sample period is form 2010 to 2012. p-values are reported in parentheses.

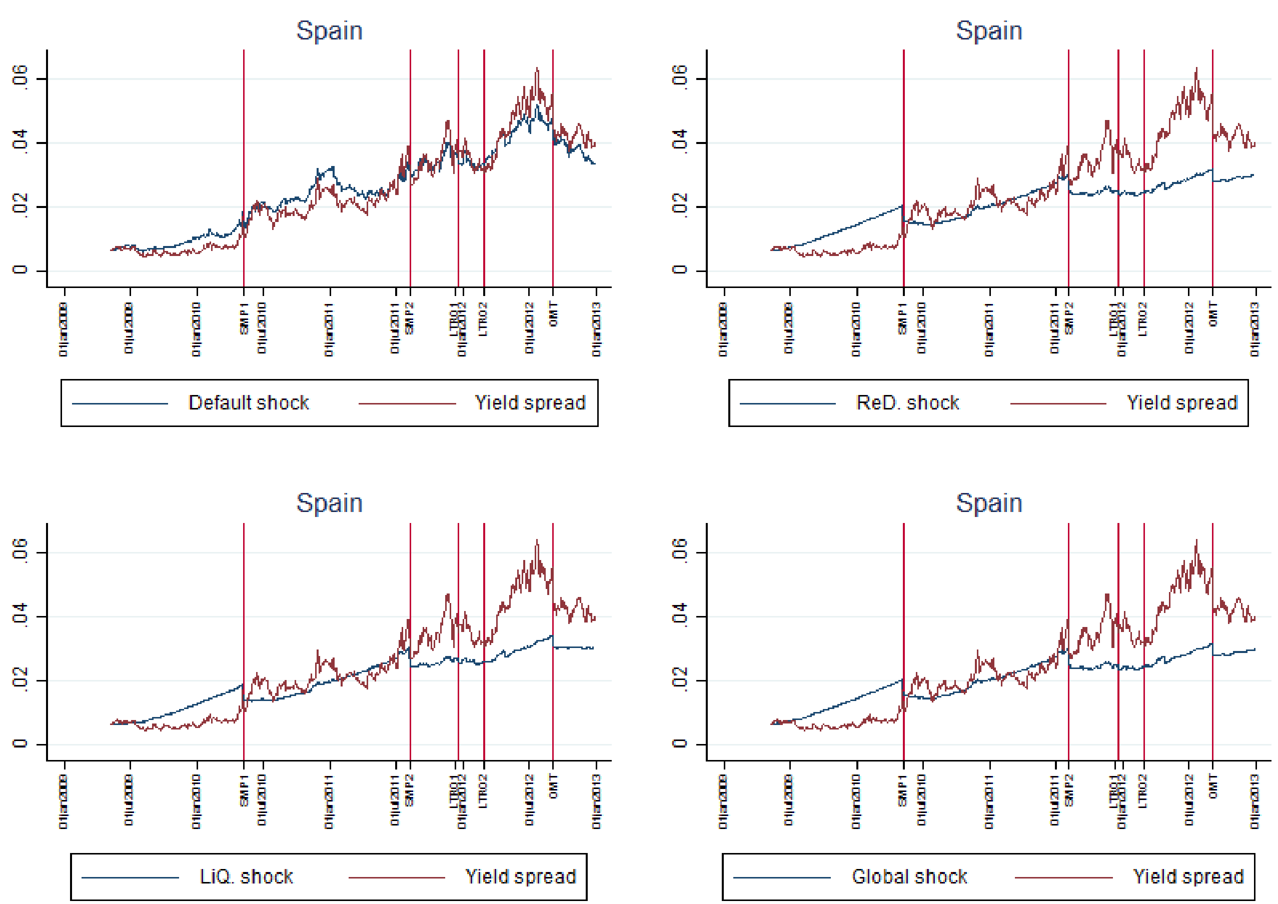
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3.6: Historical decomposition of Italy's 10 year maturity bond yield spread



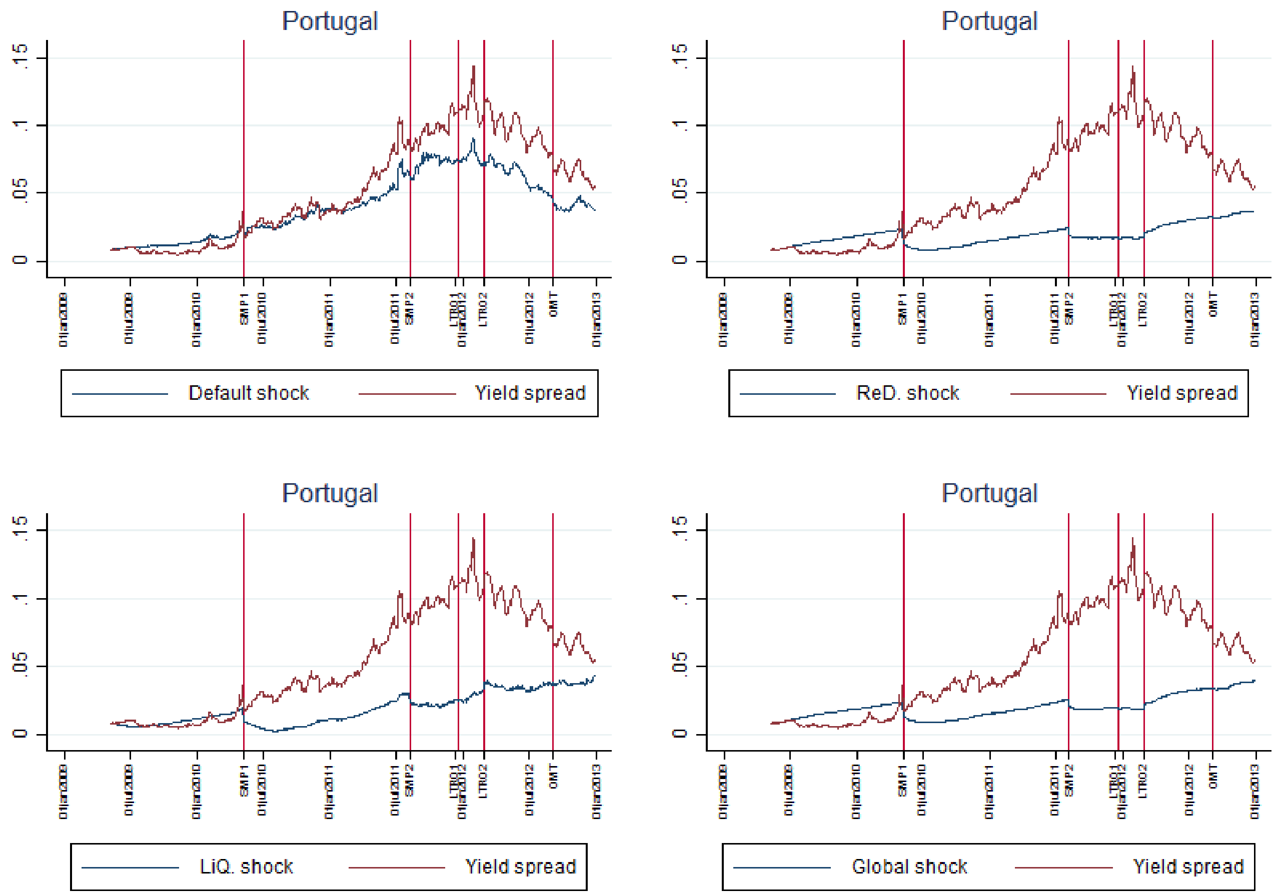
This figure graphs the historical decomposition of the Italy's 10 year maturity yield spread from 2010 to 2012. The upper left, upper right and lower left panels present the simulation of the yield spread based on default shock, redenomination shock and liquidity shock, respectively. Simulation based on a structural shock is accomplished by assuming that only the structural shock under consideration in non-zero. The lower left panel presents the simulation under the assumption that all the measurement errors of the countries are non-zero while all the structural shocks are zero.

Figure 3.7: Historical decomposition of Spain's 10 year maturity bond yield spreads



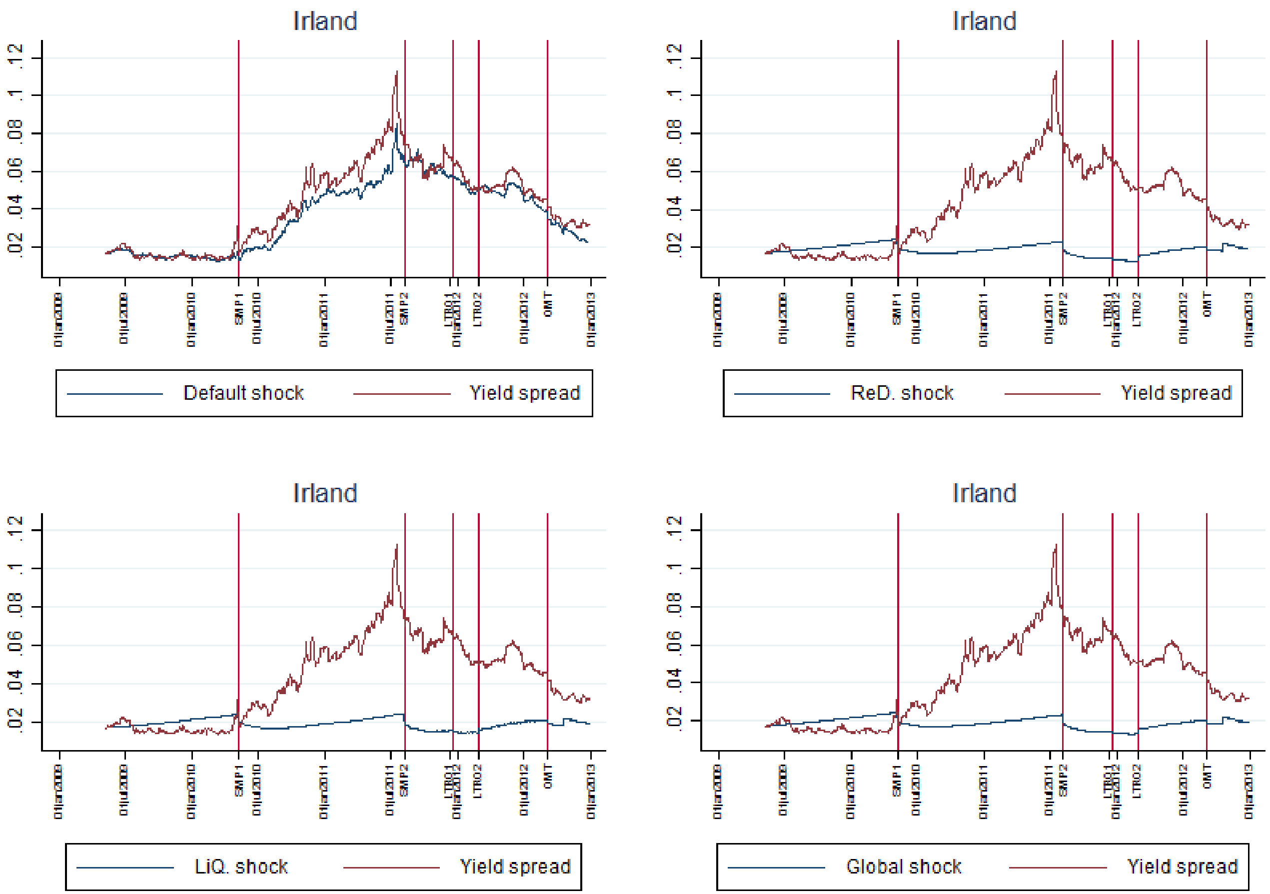
This figure graphs the historical decomposition of the Spain's 10 year maturity yield spread from 2010 to 2012. The upper left, upper right and lower left panels present the simulation of the yield spread based on default shock, redenomination shock and liquidity shock, respectively. Simulation based on a structural shock is accomplished by assuming that only the structural shock under consideration in non-zero. The lower left panel presents the simulation under the assumption that all the measurement errors of the countries are non-zero while all the structural shocks are zero.

Figure 3.8: Historical decomposition of Portugal's 10 year maturity bond yield spreads



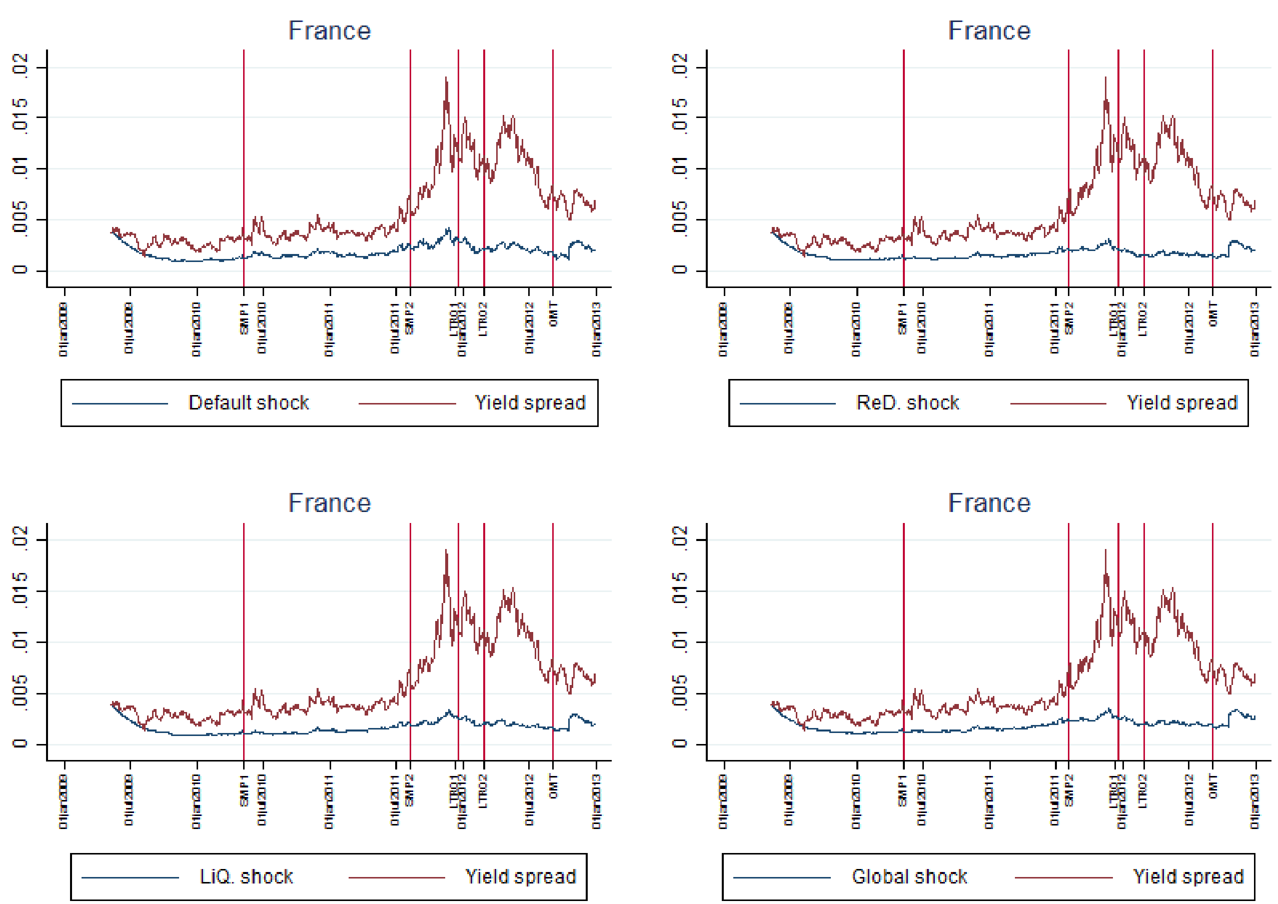
This figure graphs the historical decomposition of the Portugal's 10 year maturity yield spread from 2010 to 2012. The upper left, upper right and lower left panels present the simulation of the yield spread based on default shock, redenomination shock and liquidity shock, respectively. Simulation based on a structural shock is accomplished by assuming that only the structural shock under consideration in non-zero. The lower left panel presents the simulation under the assumption that all the measurement errors of the countries are non-zero while all the structural shocks are zero.

Figure 3.9: Historical decomposition of Ireland's 10 year maturity bond yield spreads



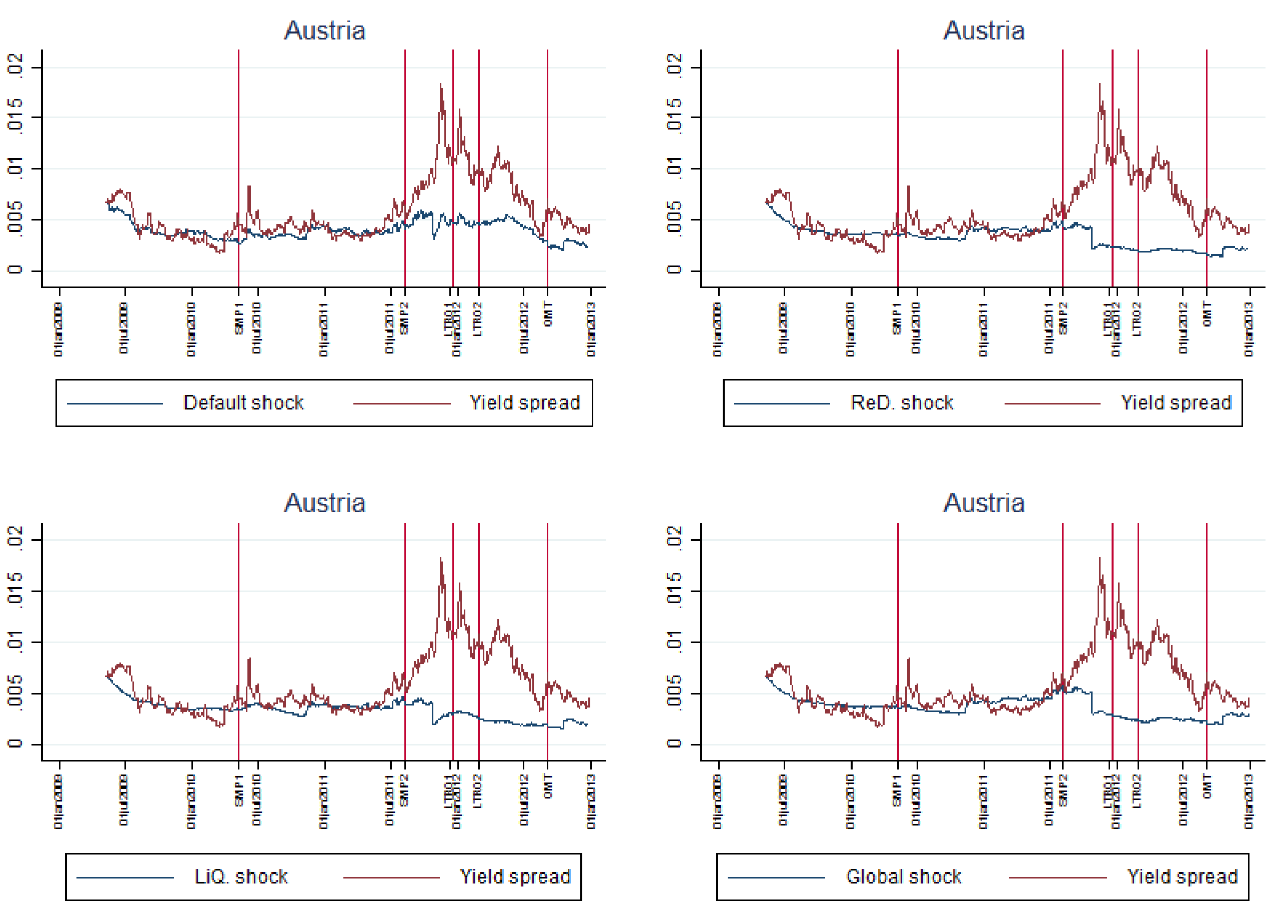
This figure graphs the historical decomposition of the Ireland's 10 year maturity yield spread from 2010 to 2012. The upper left, upper right and lower left panels present the simulation of the yield spread based on default shock, redenomination shock and liquidity shock, respectively. Simulation based on a structural shock is accomplished by assuming that only the structural shock under consideration in non-zero. The lower left panel presents the simulation under the assumption that all the measurement errors of the countries are non-zero while all the structural shocks are zero.

Figure 3.10: Historical decomposition of France's 10 year maturity bond yield spreads



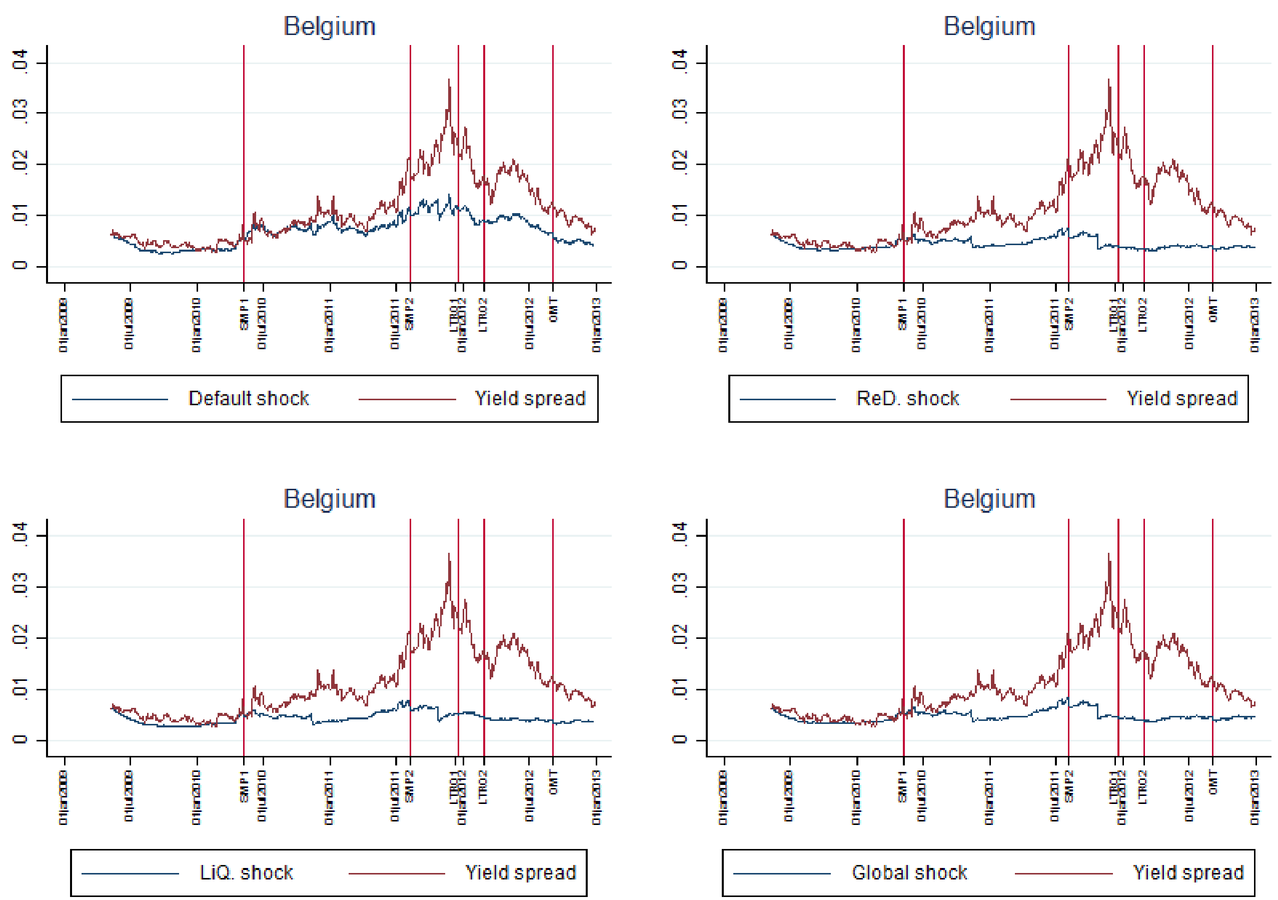
This figure graphs the historical decomposition of the France's 10 year maturity yield spread from 2010 to 2012. The upper left, upper right and lower left panels present the simulation of the yield spread based on default shock, redenomination shock and liquidity shock, respectively. Simulation based on a structural shock is accomplished by assuming that only the structural shock under consideration in non-zero. The lower left panel presents the simulation under the assumption that all the measurement errors of the countries are non-zero while all the structural shocks are zero.

Figure 3.11: Historical decomposition of Austria's 10 year maturity bond yield spreads



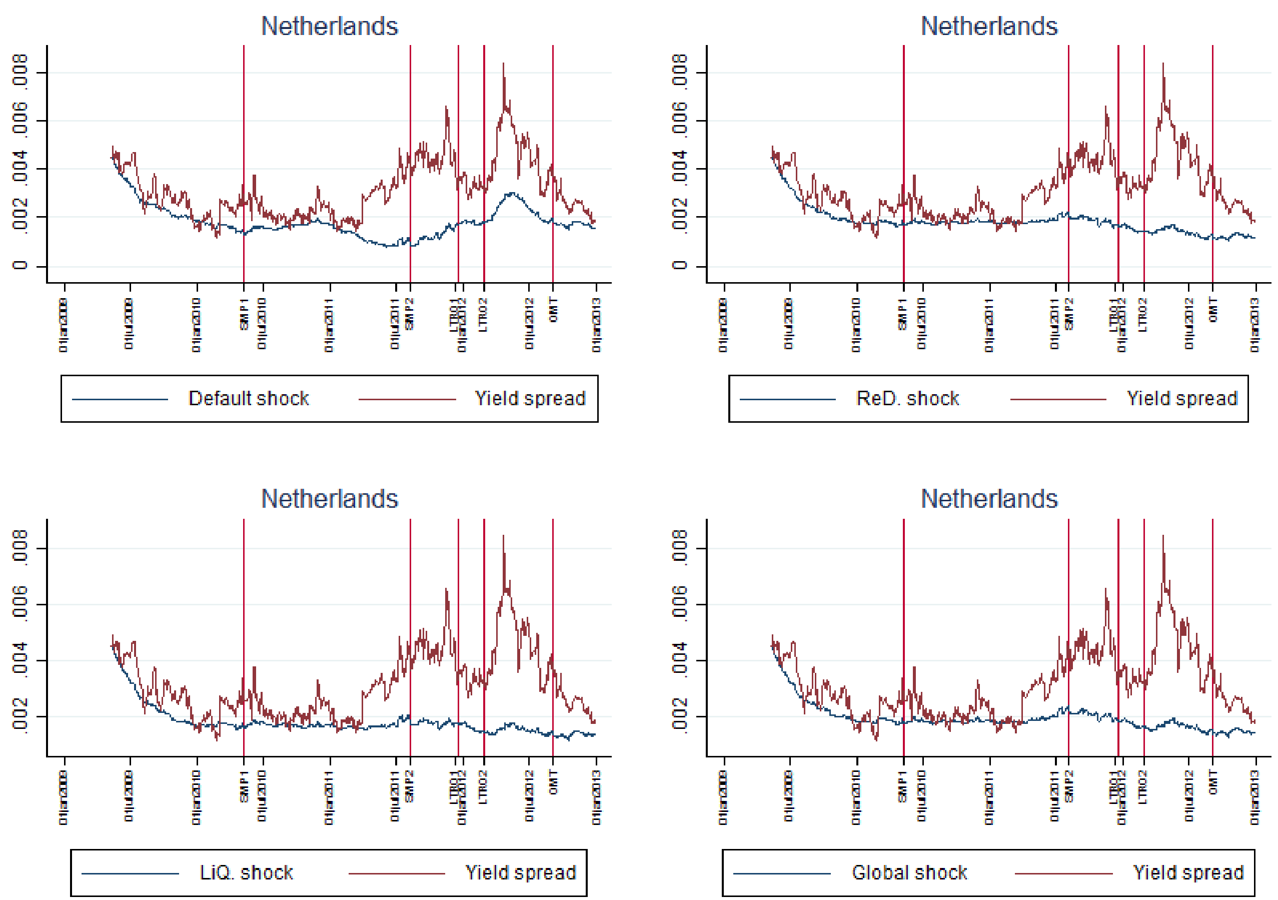
This figure graphs the historical decomposition of the Austria's 10 year maturity yield spread from 2010 to 2012. The upper left, upper right and lower left panels present the simulation of the yield spread based on default shock, redenomination shock and liquidity shock, respectively. Simulation based on a structural shock is accomplished by assuming that only the structural shock under consideration in non-zero. The lower left panel presents the simulation under the assumption that all the measurement errors of the countries are non-zero while all the structural shocks are zero.

Figure 3.12: Historical decomposition of Belgium's 10 year maturity bond yield spreads



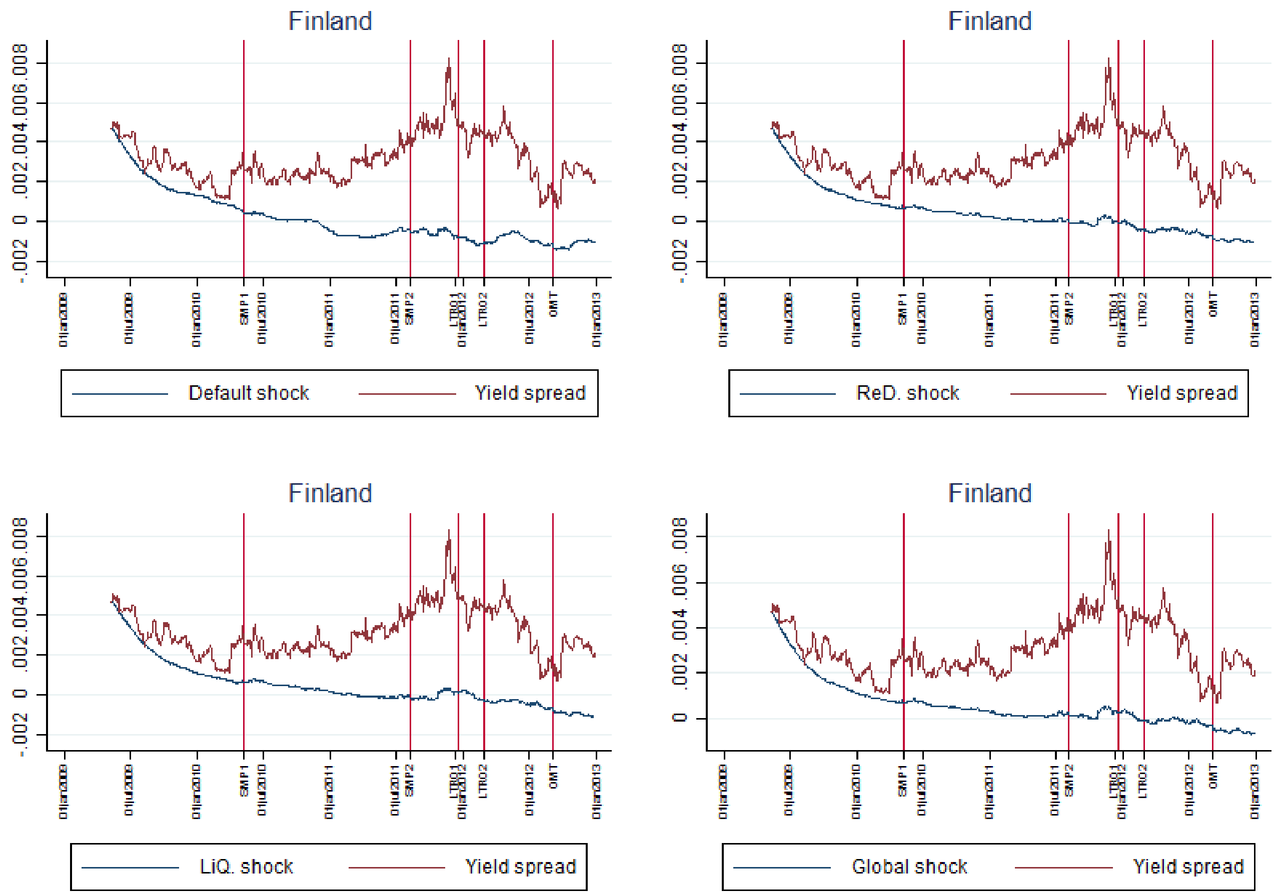
This figure graphs the historical decomposition of the Belgium's 10 year maturity yield spread from 2010 to 2012. The upper left, upper right and lower left panels present the simulation of the yield spread based on default shock, redenomination shock and liquidity shock, respectively. Simulation based on a structural shock is accomplished by assuming that only the structural shock under consideration in non-zero. The lower left panel presents the simulation under the assumption that all the measurement errors of the countries are non-zero while all the structural shocks are zero.

Figure 3.13: Historical decomposition of the Netherlands's 10 year maturity bond yield spreads



This figure graphs the historical decomposition of the the Netherlands's 10 year maturity yield spread from 2010 to 2012. The upper left, upper right and lower left panels present the simulation of the yield spread based on default shock, redenomination shock and liquidity shock, respectively. Simulation based on a structural shock is accomplished by assuming that only the structural shock under consideration in non-zero. The lower left panel presents the simulation under the assumption that all the measurement errors of the countries are non-zero while all the structural shocks are zero.

Figure 3.14: Historical decomposition of Finland's 10 year maturity bond yield spreads



This figure graphs the historical decomposition of the Finland's 10 year maturity yield spread from 2010 to 2012. The upper left, upper right and lower left panels present the simulation of the yield spread based on default shock, redenomination shock and liquidity shock, respectively. Simulation based on a structural shock is accomplished by assuming that only the structural shock under consideration in non-zero. The lower left panel presents the simulation under the assumption that all the measurement errors of the countries are non-zero while all the structural shocks are zero.

Bibliography

V. Acharya and L.H. Pedersen. Asset Pricing with Liquidity Risk. *Journal of Financial Economics*, (77):375–410, 2005.

Y. Amihud. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Economics*, (17):223–249, 2002.

Y. Amihud and H. Mendelson. Asset pricing and the bid-ask spread. *Journal of Finance*, (46):1411–1425, 1986.

Y. Amihud and H. Mendelson. Liquidity, Maturity, and the Yields on U.S. Treasury Securities. *Journal of Finance*, (46):1411–1425, 1991.

Y. Amihud, H. Mendelson, and L.H. Pedersen. Liquidity and Asset Prices. *Foundations and Trends in Finance*, (1):269–364, 2005.

D. Avarmov, T. Chordia, and A. Goyal. Liquidity and Autocorrelations in Individual Stock Returns. *The Journal of Finance*, (61):2365–2394, 2006.

J. Bai, C. Julliard, and K. Yuan. Eurozone Sovereign Bond Crisis: Liquidity or Fundamental Contagion. *Working paper*, 2012.

A. Beber, M. Brandt, and K. Kavajecz. Flight-to-quality or flight-to-liquidity? Evidence from the euro-area bond market. *Review of Financial Studie*, (22(3)):925–957, 2009.

G. Bekaert, C.R. Harvey, and C. Lundblad. Liquidity and expected returns: Lessons from emerging markets. *Review of Finanical Studies*, pages 1783–1831, 2005.

J.Y. Campbell, J.G Sanford, and W. Jiang. Trading Volume and Serial Correlation in Stock Returns. *Quarterly Journal of Economics*, (108):905–939, 1993.

P. Christoffersen, R. Goyenko, K. Jacobs, and M. Karoui. Illiquidity Premia in the Equity Options Market. *Working pape*, 2012.

V.T. Datar, N.Y. Naik, and R. Radcliffe. Liquidity and stock returns: an alternative test. *Journal of Finance*, (1):205–219, 1998.

F. De Jong and B. Rindi. *The Microstructure of Financial Markets.* Cambridge University Press, 2009.

R.A. De Santis. Redenomination Risk. *Working paper*, 2014.

J. B. DeLong, A. Shleifer, L.H. Summers, and R.J. Waldmann. Noise Trader Risk in Financial Markets. *Journal of Political Economy*, (98):703–738, 1990.

J. Dick-Nielsen. Liquidity biases in TRACE. *Journal of Fixed Income*, 19:43–55, 2009.

C. Favero. Modelling and forecasting government bond spreads in the euro area: A GVAR model. *Journal of Econometrics*, (177(2)):343–356, 2013.

C. Favero and A. Missale. Sovereign Spreads in the Euro area.Which Prospects for a Eurobond? *Economic Policy*, (70):231–273, 2012.

C. Favero, M. Pagano, and E.-Lu. von Thadden. How does liquidity affect government bond yields? *Journal of Financial and Quantitative Analysis*, (45(1)):107–134, 2010.

Z. He and K. Milbradt. Endogenous Liquidity and Defaultable Bonds. *Econometrica*, (82), 2014.

R. Jankowitsch, A. Nashikkar, and M. Subrahmanyam. Price disper sion in OTC markets: a new measure of liquidity. *Journal of Banking and Finance*, 35:343–357.

S. Koch. Noise Trader Risk in Financial Markets. *Working paper*, 2010.

A. Krishnamurthy, S. Nagel, and A. Vissing-Jorgensen. ECB Policies involving Government Bond Purchases: Impact and Channels. *Working Paper*, 2014.

W. Liu. A liquidity-augmented capital asset pricing model. *Journal of Financial*, pages 631–671, 2006.

F. Nils, R. ankowitsch, and M.G. Subrahmanyam. Illiquidity or credit deterioration: A study of liquidity in the US corporate bond market during financial crises. *Journal of Financial Economics*, 105:18–36, 2012.

L. Pastor and R. Stambaugh. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, (111):642–685, 2003.

L. Pelizzon, M.G. Subrahmanyam, D. Tomio, and J. Uno. Sovereign Credit Risk, Liquidity, and ECB Intervention: Deus ex Machina? *Working paper*, 2014.

M.H. Pesaran and Y. Shin. An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis, in: Strom, S., and P. Diamond (eds.). *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium, Chapter 11, Cambridge, Cambridge University Press.*, 1999.

M.H. Pesaran, Y. Shin, and R.J. Smith. Bounds Testing Approaches to the Analysis of Level Relationships, in: Hendry, D.F., and M.H. Pesaran (eds.), Special Issue in Honour of J.D. Sargan - Studies in Empirical Macroeconometrics. *Journal of Applied Econometrics*, (16):289–326, 2001.

R. Roll. A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance*, (4):1127–1139, 1984.

M. Scholes and J. Williams. Estimating betas from non-synchronous data. *Journal of Financial Economics*, (5):309–327, 1977.

T. Shumway. The delisting bias in CRSP data. *Journal of Finance*, (52):327–340, 1997.

P.L. Swan and J.J. Westerholm. Asset prices and liquidity: The impact of endogenous trading. *Working Paper, University of New South Wales*, 2002.