Time-varying illiquidity and spillovers in the Eurozone

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Abstract

This paper aims to elucidate the behaviour of time-varying illiquidity and the intensity and direction of illiquidity spillovers in the Eurozone over the period 1990-2015. In the first part of the research, time-varying illiquidity is modelled using Markov regime switching (MRS) models that overcome most of the economic and econometric limitations of autoregressive (AR) processes, usually employed in the literature (Amihud, 2002; Korajczyk and Sadka, 2008; Foran et al., 2014). Results indicate that illiquidity shocks are persistent, that persistency is state-dependent and that multiple states exist. We find common patterns across all the countries that support the existence of interconnections. In the second part, this study examines the illiquidity interconnectedness among Eurozone countries, its direction and intensity, adapting recent models from Diebold and Yilmaz (2009, 2012). Using both a static and dynamic approach, evidence suggests that peripheral countries play a highly significant role in illiquidity transmission. The dynamic approach using rolling estimation, in line with the stochastic behaviour of illiquidity, reports also graphical evidence of net spillovers effects, thus providing a new contribution in this field.

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1 Introduction

The economic history witnessed a series of market downturns that destabilised global equilibria for a prolonged period of time and propagated across markets and asset classes. The global financial crisis (GFC) of 2007-2009 originated from the massive default of subprime borrowers in the American mortgage market and spread to the rest of the World with long-lasting effects on the financial and real economies. Although it caused persistent periods of illiquidity in the markets, it is just one of the most recent and known examples of local crises that propagated its effects to other economies. Market illiquidity is not just a persistent effect of financial turmoil in one country, but also its direct cause. More recently, the Irish banking sector and the Greek sovereign debt crises, driven by liquidity shortages, seriously challenged the Eurozone's stability, forcing policy makers to suddenly take counteractions to stem possible propagation to other economies with fundamental structural weaknesses. For example, the European Central Bank (ECB) began buying assets from commercial banks in March 2015 as part of its non-standard monetary policy measures to help economic growth of Eurozone nations. Sudden and pervasive liquidity drops might have also been the main player in otherwise puzzling market episodes (Chordia et al., 2000). For instance, Roll (1988) and Amihud et al. (1990) ascribe the 19^{th} of October 1987 market crash to be provoked by a widespread temporary reduction in liquidity. While certain events are indirectly related to liquidity drops, others, such as the Long Term Capital Management (LTCM) default, have been mainly caused by a failure of adequately accounting for liquidity considerations. For instance, Brunnermeier and Pedersen (2009) document that the collapse of the LTCM was mainly due to an excessive exposure to liquidity risk, even though market risk was hedged.

Two aspects directly derive from the above considerations. Firstly, that liquidity shocks are persistent. Secondly, that the liquidity channel constitutes a source of contagion among financial markets. Liquidity refers to the ability to buy and sell large amounts of a security at a low cost. Liquid securities, such as Treasury bills, can be sold instantaneously in blocks of several millions of dollars for a fraction of basis points. In contrast, highly illiquid securities are more difficult, time-consuming and costly to trade. As an example, consider the massive drop in value of nicely packaged junk bonds into collateralised debt obligations (CDO) that provoked the GFC in 2007. Their level of illiquidity became so high that selling them was possible only at a considerable discount. Previous research identifies two theoretical underpinnings that explain liquidity and its time-varying characteristic: asymmetric information and optimal inventory level. Asymmetric information implies that market makers apply a spread in order to control for the risk of the presence of informed traders (Copeland and Galai, 1983; Glosten and Milgrom, 1985). Inventory risk pertains the potential loss that market makers may suffer, because of a delay between the order and the execution, during the period of time needed to find a counterpart (Amihud and Mendelson, 1986). The optimal inventory level held by dealers is not static, but changes over time, according to stock-specific and market liquidity levels (Amihud et al., 2012). However, independently from the source, market microstructure literature finds ample evidence of pricing of liquidity risk. The initial asset-specific focus (Amihud and Mendelson, 1986) finds that illiquid securities have greater expected returns and thus investors require a premium for holding them. Subsequent works analyse liquidity from a market-wide perspective, as a priced risk factor (Chordia et al., 2000; Acharya and Pedersen, 2005; Brockman et al., 2009; Amihud et al., 2015). As a result, liquidity is of great interest for investors and academics and particularly in connection with the current level of uncertainty and financial turmoil. Despite the increasing interest around this topic in recent years, both the time-varying characteristic and the sources of illiquidity shocks remain largely unexplored. The former pertains the actual ability to model time-varying illiquidity, in order to adequately describe the effects of illiquidity shocks. The latter regards the sources of these shocks, which can be endogenous or exogenous. The present work tries to uncover new evidence on these two important aspects of illiquidity focusing on the stock market, given its importance for economic growth, social welfare and political reform (Andrikopoulos et al., 2014). In particular, we investigate a pool of eleven Eurozone countries that include core and peripheral economies.

It is widely accepted in the literature that liquidity is not a static phenomenon, but changes over time (Amihud, 2002). This time-varying characteristic is driven by several factors that directly affect the optimal inventory level held by market makers. Among others, it is worth mentioning the presence of informed traders, transparency of information, number of liquidity providers with their access to capital and overall uncertainty. In the first part of the present work, we investigate the time-varying characteristic of market liquidity. While financial reality vividly showed that illiquidity shocks can be persistent and therefor affect securities' returns, existing models are not fully capable of capturing these features. Therefor, the need for a deeper and more careful empirical scrutiny comes from the potential inappropriateness of the existing evidence in adequately depicting the effects of financial turmoil in the market. In fact, liquidity time-series have been usually modelled using autoregressive (AR) processes (Amihud, 2002; Korajczyk and Sadka, 2008; Foran et al., 2015). However, these models carry strict econometric assumptions. Amihud (2002) provides evidence of illiquidity persistency using an AR(1) process, which implies a unique state of illiquidity with unexpected and temporary shocks, assumed white noise. Similar methodologies and findings can be encountered in Korajczyk and Sadka (2008) and Foran et al. (2014). While these models can conveniently represent time-series of liquidity during tranquil periods of the economy, financial reality depicts a very different pattern during phases of greater uncertainty and financial turmoil. In fact, shocks become more persistent and markets can jump into prolonged periods of illiquidity. For instance, a shock in market liquidity causes higher margin requirements from liquidity providers with the effect of reducing even further overall market liquidity (Brunnermeier and Pedersen, 2009). In this context, alternative models should be taken into consideration to better describe an overall picture of illiquidity time-series, adequately accounting for tranquil and non-tranquil periods. We thus develop a set of important research questions that aim to shed some light on the persistency of illiquidity shocks: (i) are illiquidity shocks persistent? (ii) are there different illiquidity states? (iii) is each state characterised by a certain degree of persistency?. To investigate these research questions and to account for the time-varying behaviour of illiquidity, we employ Markov regime switching (MRS) models. Vastly used in the economics and financial literature, MRS models have only limited applications in this field (Watanabe and Watanabe, 2008; Acharya et al., 2013). This methodological contribution allows us to uncover new evidence on the time-varying characteristic of illiquidity. In fact, we find that shocks are persistent and characterised by well distinct states for all the countries in the sample. Moreover, we find that some countries are better represented by three states. These evidence provide new knowledge in this field by showing that the non-linear behaviour of illiquidity presents a trend coherent with liquidity spirals (Brunnermeier and Pedersen, 2009).

The second part of this paper is devoted to the investigation of the sources of illiquidity shocks. Sudden and pervasive illiquidity shocks can be endogenous or exogenous. The high degree of financial integration among markets at an international level indicate that what happens in one country is likely to affect other countries. For example, there are ample evidence of commonality in liquidity at a regional and global level (Brockman et al., 2009) and of illiquidity return premia (Amihud et al., 2015). When a shock in one country spreads its effects to other countries, this phenomenon is generally known as contagion. Since several meanings of contagion exist, in this paper we adopt the widely acknowledged definition of Forbes and Rigobon (2002*a*). Contagion can be interpreted as a significant increase in cross-market linkages after a shock to one country. This formalisation brings two significant implications. Firstly, that cross-market linkages have to increase as a result of a shock to one country. As noted also in Forbes and Rigobon (2002*a*), this implies that if two markets show a high degree of co-movements during periods of stability, even if markets continue to be highly correlated after a shock to one of them, this may not be contagion, but only interdependence. Moreover, a shock has to take place, in order to be transmitted. For example, if a shock originates in the US and spreads to the UK and Japan, is it possible to talk about contagion transmitted from the UK to the Japanese market? Some authors (Smimou and Khallouli, 2015) talk about shift-contagion, indicating exactly this type of dynamic, which does not disregard the necessary increase in cross-market linkages. The existing literature identifies three channels of contagion (Longstaff, 2010; Smimou and Khallouli, 2015). The information channel, which takes place when a shock in one market signals economic news that directly or indirectly impact security prices in other markets (King and Wadhwani, 1990). Another vector of transmission takes place via the liquidity channel. As outlined by Smimou and Khallouli (2015) liquidity shocks may be endogenous, those driven by economic fundamentals, or exogenous. Brunnermeier and Pedersen (2009) propose that investors who suffer losses in one market may have funding constraints also in other markets, so that overall market liquidity deteriorates. Furthermore, endogenous liquidity shocks in one market may increase uncertainty and episodes of investors' withdrawal in other markets, as in the case of the 19th October 1987 market crash. Lastly, a third mean of contagion can be realised through a risk channel, when a shock in one market is followed by an increase in the risk premia in other markets (Acharya and Pedersen, 2005). Consequently, contagion occurs when negative returns in the distressed market affect subsequent returns in other markets, also given the time-varying nature of risk premia (Amihud et al., 2015). Given the degree of global integration among markets, the Eurozone constitutes a more peculiar example to be investigated. In fact, with a shared monetary policy and a common currency, the Euro area has some unique features that differentiate it from other realities (Glick and Rose, 2016). It is a pool of heterogenous countries with core and peripheral economies that are characterised by a certain degree of interconnection and reciprocal influences. It is therefor necessary to investigate the internal dynamics of the Eurozone to enhance the understanding of illiquidity in an attempt to shed new lights on its time-varying components and sources of illiquidity shocks. Therefor, we develop a second set of important research questions: (i) is there a spillover effect through the liquidity channel among Eurozone countries? (ii) what is the intensity and direction of illiquidity shocks among heterogenous but integrated countries? (iii) is the spillover effect constant over time or does it suggest herd behaviour? The answers to these questions enhance the recent literature in this field (Andrikopoulos et al., 2014; Smimou and Khallouli, 2015), providing new and substantial methodological contributions. Adapting a model developed by Diebold and Yilmaz (2009, 2012), this paper seeks to elucidate the spillover dimension of illiquidity shocks across Eurozone markets. Firstly, with the introduction of an illiquidity spillover index (ISI), which captures the average contribution in the forecast error variance of illiquidity shocks. Moreover, to account for the time-varying aspect of illiquidity and to test for shift contagion during market downturns of both local and global origin, we provide a dynamic approach using rolling window estimation. Evidence reveal that the intensity of spillovers increases during phases of financial turmoil supporting the hypothesis of herd behaviour. Moreover, we find that some countries tend to be persistently net transmitters, while others mostly net receivers.

To sum up, this paper provides a threefold contribution. Firstly, we offer a methodological improvement to the knowledge of illiquidity shocks and their persistency, using MRS models, which provide empirical evidence of a non-linear behaviour of illiquidity time series. Secondly, we introduce a new measure that captures the average illiquidity spillover effect among countries belonging to a currency area. Lastly, we show that both the direction and the intensity of dynamic spillovers change over time, thus corroborating evidence of contagion. The rest of the paper is organised as follows. Section 2 reviews the existing literature and formulates the hypotheses. Section 3 explains the methodology and section 4 describes the data. The last two sections report the empirical analysis and concluding remarks.

2 Literature review and hypothesis

An impressive amount of microstructure literature regarding liquidity in asset pricing developed in the last decades, while its importance became increasingly popular in relation to market downturns. It is well known that the optimal inventory level that market makers hold is not static, but adjusted according to the speed and ability to find a counterpart for the order flow (Amihud and Mendelson, 1986). Moreover, dealers adjust their bid-ask spreads to hedge the potential loss deriving from informed traders (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Gârleanu and Pedersen, 2003). However, liquidity risk is not just affected by stock-specific characteristics, but also by market-wide shocks (Chordia et al., 2000) that potentially spread during market downturns (Brunnermeier and Pedersen, 2009). Whether these shocks are persistent has not been fully investigated. Moreover, even though the stochastic component of market liquidity has been addressed by several authors, there is little evidence regarding its endogenous and/or exogenous nature.

Amihud (2002) provides empirical evidence that liquidity is persistent and characterised by temporary unexpected shocks, using a trade impact measure, based on Kyle (1985)' λ, that captures the level of stock's illiquidity. He finds that illiquidity is highly persistent and assumes that shocks represent changes in overall market liquidity relative to investors' expectations. Similarly, Korajczyk and Sadka (2008) and Foran et al. (2015) estimate an AR(2) process on pre-whitened extracted principal components for several liquidity measures finding consistent results with Amihud (2002). Even though the estimation of time-varying illiquidity through AR(p) processes can adequately describe its evolution over time during tranquil periods, they rely on certain assumptions on illiquidity shocks. For instance, they have to be temporary and unexpected. However, other authors have often claimed that market downturns constitute a source of persistent liquidity shortages (Chordia et al., 2000; Brunnermeier and Pedersen, 2009). Chordia et al. (2000) indicate two channels through which liquidity affects asset pricing: one static and one dynamic. The static channel influences average trading cost and indicates the anticipated co-movement with the market, while the dynamic channel includes unexpected liquidity shocks and influences risk. However, the dynamic channel may result in persistent periods of illiquidity, coherently with the notion of liquidity spirals. This term, coined by Brunnermeier and Pedersen (2009), refers to the origination of liquidity crises from shortages in funding liquidity. While market liquidity regards the ease of trading and is related to the cost of buying and selling a security, funding liquidity is property of both securities and agents that trade. A security is considered to have a good funding liquidity if it is easy to borrow using the security as collateral. An agent has good funding liquidity if he is plenty of capital or has considerable access to financing with low margin requirements. When funding liquidity is largely available, market makers can satisfy even large orders with low margins and increase overall liquidity. This situation creates a positive effect on market liquidity due to favourable funding conditions. Similarly, also market liquidity affects funding. Periods of higher liquidity and lower volatility make easier to finance traders' positions with lower margins. Liquidity spirals work in reverse during market downturns and this interaction is potentially more violent (Brunnermeier and Pedersen, 2009). When funding liquidity is constrained, market makers reduce liquidity and increase transaction costs, which hamper even more the ability of liquidity to dry up. These dynamics were also at the basis for the GFC of 2007-2009 and provide a solid theoretical foundation for the persistency of liquidity shocks. Given this background, we test the following alternative hypotheses:

- H_0 a: Illiquidity shocks are temporary
- H_1 a: Illiquidity shocks are persistent and determine a new state of illiquidity

Our methodological contribution using Markov regime-switching models allows us to test if liquidity follows this non-linear pattern. The null hypothesis is in fact in line with the strand of literature that estimates illiquidity time-series with AR processes, since shocks are modelled as white noise. Limited applications of MRS models for illiquidity time series exist. Watanabe and Watanabe (2008) use a MRS model based on a detrended aggregate share turnover, adopting as time-series the liquidity betas obtained from mimicking portfolios to test liquidity risk. Acharya et al. (2013) consider 2 regimes of US corporate bonds, finding that unexpected rises in illiquidity have two different effects on bonds, particularly during periods of financial stress. On the one hand the price of junk bonds drops, but on the other hand, liquid high-grade bonds become more valuable. This effect is coherent with the so called flight to liquidity, already proposed in Amihud (2002) and Acharya and Pedersen (2005) for stocks, but not tested for time-series of market illiquidity.

Illiquidity shocks can be originated endogenously or transmitted from other markets or securities. During periods of greater uncertainty and generalised price drops, the exogenous channel can be particularly emphasised and commonly referred in the literature as contagion. Particularly in recent times, the high degree of financial integration among markets at a global level suggests that what happens in one country is likely to affect other economies. Moreover, the degree of interconnection rises during periods of financial turmoil, providing support for phenomena of contagion. For instance, the literature around financial contagion is immense and it is widely accepted in the literature that the financial channel dominates other channels (Smimou and Khallouli, 2015). Forbes and Rigobon (2002*a*) review several studies focusing on the various methodologies adopted to support evidence of contagion. They show that cross-market correlation is time-varying and dependent on volatility. Bae et al. (2003) present evidence of contagion associating this phenomenon to extreme returns, using a multinomial logistic regression model. King and Wadhwani (1990) test stock market cross-contagion between US, UK and Japan around the October 1987 crash, while Lee and Kim (1993) extend further the sample incorporating 12 major stock markets. The transmission of the endogenous dynamics specific of one country to others may be even more evident when markets are particularly integrated. This was the case of the GFC, where the increased uncertainty following the subprime crisis in the US hampered overall liquidity at a Global level. For instance, Mollah et al. (2016) identify the banking sector as the main transmission channel of the GFC between the US and the Eurozone countries. However, the endogenous channel, due to economic fundamentals, is not the only mean of contagion reported in the literature. In addition, exogenous liquidity shocks may constitute a source of contagion independently of macroeconomic news or noteworthy events, as in the case of the October 19th 1987 market crash (Roll, 1988; Amihud et al., 1990). Financial contagion, often associated with market downturns, does not mean that spillovers are a phenomenon that take place exclusively during financial or liquidity crises. The degree of integration and interdependence among stock markets posits interesting questions on how the intensity and direction of spillovers change between tranquil and turbulent periods. For instance, persistent illiquidity states can take place also during tranquil periods, when originated endogenously from other markets. The existing literature tends to classify two types of market integration across international stock exchanges. Part of the research analyses the impact of regional phenomena to a global perspective. An example of this is the introduction of the Euro or the Asian crisis (Gebka and Serwa, 2006). Another strand of literature explores financial integration between regional stock markets and leading stock exchanges. In both cases, financial contagion is often investigated in terms of returns and volatility spillovers. Hamao et al. (1990) study the effect of returns and volatility spillovers across international stock markets following the October 1987 market crash in a GARCH framework. Recent studies apply vector autoregressive (VAR) models to estimate the degree of causal relationship for pairwise countries. Beirne and Gieck (2014) examine interdependence and contagion across different asset classes for 60 economies using a global VAR model. Most of the literature that employs VAR models suffers from limitations due to the econometric constraints of VAR. An alternative approach is proposed by Diebold and Yilmaz (2009), who introduce an innovative measure of volatility spillovers that captures interconnections in a more dynamic setting. However, their initial model, based on Cholesky factorisation, suffers from econometric limitations due to the ordering of variables, which the authors overcome in a subsequent work (Diebold and Yilmaz, 2012).

The existence evidence of common market-wide determinants of liquidity within and across countries (Brockman et al., 2009; Amihud et al., 2015), implicitly raises the question of whether liquidity constitutes an exogenous source of shocks transmitted across markets. Furthermore, it is particularly insightful to investigate this issue when the degree of integration already constitutes an important factor that enhances the interdependence of stock exchanges. For this reason, this work examines the Eurozone, a currency union that makes particularly interesting to study not only the presence of liquidity spillovers, but what is also important their intensity and direction. Andrikopoulos et al. (2014) provide evidence of liquidity, return and volatility spillovers among the G7 stock markets. Even though their sample is constituted by the leading stock markets in the World and give interesting insights on the presence of spillovers, the Euro Area is an even more peculiar example of integration, where countries are pooled by a unique currency and a shared monetary policy. Furthermore, the presence of core and peripheral countries in the same currency union allows us to assess which economies work as transmitters and which as receivers of illiquidity shocks. A contribution similar to the present study can be found in Smimou and Khallouli (2015). The authors analyse illiquidity spillovers in the Eurozone, finding the existence of shift-contagion and pairwise causal relationship during the GFC. However, there are methodological limitation that the present study tries to address and further extend. In fact, even though they find evidence of liquidity spillovers using Granger causality test on VAR, their methodology can only capture pairwise time-invariant causality. In addition, Granger causality suffers from a series of limitations and critiques[1]. Differently from the existing literature on liquidity spillovers, we adapt a methodology developed by Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012) and we investigate the static and dynamic degree of interconnection among eurozone countries. We formulate the following non-mutually exclusive hypotheses:

- H_2: Illiquidity shocks are transmitted across member countries of the Eurozone
- H_3: The intensity and direction of illiquidity spillovers changes over time

The first hypothesis aims to better understand which countries contributed to the transmission of illiquidity shocks to other economies of the Union and which countries

[1] One formal discussion regarding possible drawbacks of this test is provided by Granger (1988) itself.

absorbed most of the shocks. This is important in order to enhance the awareness of the role played by core and peripheral economies toward the overall stability of the Eurozone. H_3 provides two further interesting implications by analysing the evolution of the spillovers effect in a more dynamic framework. Firstly, by looking at how the spillover effect changes over time, in order to provide evidence of contagion. Secondly, by testing how and if countries tend to be permanent net receivers or net transmitters, in order to detect the sources of shocks.

3 Methodology

The analysis of illiquidity persistency and spillovers in the Eurozone is carried out, using a sample of eleven countries, namely Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherland, Portugal and Spain. These countries constitute the 97% of the total gross domestic product (GDP) and 96% of the total market capitalisation of the Eurozone and thus can validly represent it[2]. Moreover, the sample analysed here is coherent with other studies in this field (Amihud et al., 2015; Smimou and Khallouli, 2015). There are several factors that make the Euro Area a peculiar example to investigate the interconnection of stock market illiquidity. In fact, the shared monetary policy and the unique currency are features that support the existence of a particularly strong degree of interconnection among these countries. For this reason, common patterns of time-varying illiquidity can emerge among linked markets, suggesting interesting implications for investors and policy makers. Furthermore, the predominant US-centric literature demands for further investigation of other contexts that can enhance the understanding of this relevant and growing phenomenon. The following sections describe the measure used for the analysis and the empirical methodologies employed to investigate time-varying illiquidity and spillovers.

All the stocks, dead and alive, listed in these eleven exchanges are analysed in

[2]The figures refer to 2015

order to account for survivorship biases and data regarding daily prices and volumes are gathered from Thomson DataStream for the period from 01/01/1990 to 31/12/2015. The length of the time span allows to highlight the evolution of illiquidity in each country, including remarkable events, such as, for example, the GFC or the euro crisis. Stock returns are obtained as the logarithmic difference of daily subsequent prices, $r_{i,t} = \ln(p_{i,t}) - \ln(p_{i,t-1})$.

3.1 The illiquidity measure

Several measures exist to proxy liquidity, both direct and indirect, mostly based on bid and ask prices and volumes. In the present work, illiquidity is measured following Amihud (2002), who captures the response of price to order flow, through the absolute price change per dollar of trading volume, based on (Kyle, 1985)' λ. In particular, Kyle (1985) proposes that prices are an increasing function of the imbalance in the order flow, caused by the fact that market makers can not distinguish between the order flow generated by informed and uninformed traders. Amihud (2002) studies the cross-sectional and time varying aspects of illiquidity, proposing a measure defined ILLIQ and finding that expected stock returns are an increasing function of expected illiquidity and that illiquidity is persistent over time. Since its introduction, Amihud (2002)'s price impact found strong support and wide applications. Goyenko et al. (2009) compare several liquidity measures in order to test whether they are actually appropriate to measure liquidity. They provide two important findings. Firstly, ILLIQ constitutes the best trade impact measure that proxies liquidity among those tested in their study, particularly in recent years. Secondly, the use of lower frequency data (e.g. weekly or monthly) can usefully estimate high-frequency measures, so that the effort of using high-frequency data is not worth the cost (and the econometric drawbacks). Indirect proxies are also often employed since other direct measures, such as those based on bid and ask prices, may not be available for large datasets or long time periods. Further support comes from Sadka (2006) who finds the highest pairwise correlation between ILLIQ and the fixed and variable components of its time-varying liquidity decomposition model. Algebraically, the daily illiquidity measure (ILL) for each stock i in each market s is given by:

$$ILL_{i,s,t} = \frac{|r_{i,s,t}|}{VOL_{i,s,t}} \tag{1}$$

where $r_{i,s,t}$ is the log return of stock i in market s at day t and $VOL_{i,s,t}$ is the volume of stock i in market s at day t. Aggregate stock market illiquidity is calculated, on a monthly basis[3] as the simple average of all the individual stock illiquidity measures in the market, consistently with other studies (see, for example, Brockman et al., 2009)[4]. Algebraically, the monthly illiquidity measure for each stock is calculated as:

$$ILLIQ_{i,s,m,t} = \frac{1}{D_{i,m}} \sum_{t=1}^{D_{i,m}} \frac{|r_{i,m,t}|}{VOL_{i,v,m,t}} \tag{2}$$

Where the subscript m indicates the month for which the average is calculated for each stock. Then, all these measures of individual stocks are averaged across all the stocks in each market, so that average illiquidity (AILLIQ) is defined as:

$$AILLIQ_{s,m} = \frac{1}{N_m} \sum_{t=1}^{N_m} ILLIQ_{i,m} \tag{3}$$

[3]I tested illiquidity with both annual and monthly data, consistently with Amihud (2002), but in the present study only monthly measures are reported for two reasons. Firstly, because there wouldn't be enough observations for all the countries and particularly for Ireland, for which data are available from 2000. Secondly, because the impact of illiquidity has more economic sense with frequencies of data higher than annual.

[4]Two different averages are computed, both equally weighted and volume-weighted. The former is consistent with most of the existing literature. For example, Brockman et al. (2009) use equally-weighted market measure in their study of commonality in a sample that includes EU countries. The latter follows the idea of Amihud et al. (2015), who notice that, in most European countries, the value of the free float available for trading is only part of the total market capitalisation of companies. Although both ways of averaging are computed, to facilitate the reader, only the equally-weighted average is reported in the main text. The second way of averaging is included in the appendix as robustness test and it is substantially coherent with the main findings using equally-weighted averages.

Where N_m is the number of stocks in each month in each market. The entire illiquidity time-series for each country is made of 312 monthly averages, except Ireland, for which the lack of data on volumes before the 2000 allows us to construct 187 monthly averages.

The use of monthly data is justified by several reasons. First of all, monthly data are particularly common in financial economics when MRS models are employed (Guidolin, 2011*b*). Moreover, in the specific context of the present research, lower frequency data may not be adequate to portrait the behaviour of illiquidity, which is often a phenomenon that explains its effects in the relatively short term. Finally, it must also be considered the econometric drawback in using high frequency proxies, so that monthly measures are usually employed to smooth the noise observed with daily or even tick-by-tick data.

3.2 Time-varying illiquidity

In the first part of the present study, the behaviour of illiquidity over time is analysed using Markov regime switching models. Even though the expectation about future illiquidity in tranquil periods, characterised by unexpected and temporary shocks, could be adequately be represented by AR(p) processes, during phases of increased uncertainty and generalised price drops high illiquidity can be more persistent. This spiral effect depicted by Brunnermeier and Pedersen (2009) takes place because in normal times liquidity shocks are absorbed by financial intermediaries, while in periods of adverse economic conditions and financial stress, intermediaries become more capital-constrained. Most of the extant literature (Amihud, 2002; Korajczyk and Sadka, 2008) models illiquidity time-series making use of AR(p) processes, but this methodology carries certain strong assumptions and implications. In fact, these models assume stationarity and constant parameters for the entire time-series and illiquidity shocks, captured by the error term, are assumed to be distributed as white noise. In particular, Amihud (2002) studies the time series effect of illiquidity, finding that it is persistent over time and that unexpected illiquidity has a negative effect on contemporaneous unexpected stock returns. In his model, monthly market illiquidity is assumed to follow an AR(1) process, of the form:

$$lnAILLIQ_{s,m} = c_0 + c_1 lnAILLIQ_{s,m-1} + v_m \tag{4}$$

Where $lnAILLIQ_{s,m}$ is the natural logarithm of monthly market illiquidity for market s in month m, c_0 and c_1 represent the coefficients and v_m is the residual. Individuals expect c_1 to be positive, since it indicates that the current level of illiquidity is based on its past value (one-period expectation), and it captures the expected component of illiquidity. The residual, v_m, represents the unexpected component of illiquidity and it is empirically demonstrated to have a negative impact on contemporaneous stock returns (Amihud, 2002). However, the error term v_m must be a white noise with mean zero and constant variance (ϵ_v^2), to support the claim that unexpected illiquidity is temporary. Moreover, this model implicitly identifies a unique state of illiquidity (c_0), characterised by unexpected and temporary deviations from the mean (v_m) and the whole time-series must be stationary to avoid spurious regressors. We test our null hypothesis H_0a that shocks are temporary and thus illiquidity time-series can be fully described by the model in equation 4 for each market in the sample.

Building on the notion of liquidity spirals (Brunnermeier and Pedersen, 2009) and the dual channel promoted by Chordia et al. (2000), we employ MRS models to detect whether illiquidity can be better explained in a non-linear framework, thus providing evidence in favour of our alternative hypotheses. In fact, MRS models can readily accommodate all the econometric limitations of AR(p) processes, providing a flexible representation of the time-series with switching parameters. Repeated MRS models are used for series that are believed to transition over a finite set of unobserved states and the process is allowed to evolve differently in each state (Brooks, 2014). All the possible outcomes are split into m regimes, but the time of transition and the duration between changes in states is random. As a result, the dependent variable y_t switches regime according to some unobserved variable, z_t, that takes integral values. The transition occurs according to a Markov process and described by the Markov property:

$$P(a < y_t < b | y_1, y_2, y_3, ..., y_m) = P(a < y_t < b | y_{t-1}) \tag{5}$$

The equation states that the probability distribution of the state at any time depends only on the state at time t-1, and not on the state in previous periods, such as t-2,t-3,t-n. We follow the method used by Hamilton (1989) to study the different behaviour of GDP growth in periods of expansion and contraction. His model, proposed for two regimes but easily extendable to multiple states, assumes that, given an unobserved state variable, z_t, it follows that:

$$\begin{aligned} p[z_t = 1 | z_{t-1} = 1] &= p_{11} \\ p[z_t = 2 | z_{t-1} = 1] &= 1 - p_{11} \\ p[z_t = 2 | z_{t-1} = 2] &= p_{22} \\ p[z_t = 1 | z_{t-1} = 2] &= 1 - p_{22} \end{aligned} \tag{6}$$

In the above equations, p_{11} and p_{22} are the probabilities that the variable stays in the same state, 1 and 2 respectively, while $1 - p_{11}$ and $1 - p_{22}$ are the probabilities of a switch to the second state from the first and to the first from the second. Under the above specifications, z_t evolves as an autoregressive process with equation:

$$z_t = (1 - p_{11}) + \rho z_{t-1} + \eta_t, \text{ with } \rho = p_{11} + p_{22} - 1 \tag{7}$$

The unknown parameters of the model $(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, p_{11}, p_{22})$ are estimated using maximum likelihood. We apply this methodology on the monthly illiquidity averages for each market. In particular, the estimation allows to release all the assumption of AR(p) processes, thus allowing intercepts, coefficients and variances to switch between states. The economics and financial literature that makes use of this methodology is immense. Hamilton (1989) presents the growth rate of GDP as a switching process to capture the asymmetrical behaviour of expansion and recession phases, while Garcia and Perron (1996) and Ang and Bekaert (2002) apply it on interest rates. Various applications also exist for exchange rates (Engel and Hamilton, 1990; Bergman and Hansson, 2005; Frömmel et al., 2005; Sylignakis and Kouretas, 2011). In the financial economics literature, Kim et al. (1998) analyse monthly stock returns, while Guidolin (2011*b*) and Guidolin (2011*a*) provide many applications to returns and portfolio choice. Forbes and Rigobon (2002*b*) analyse the joint distribution of equity and Treasury bond returns, while Elliott et al. (2005) focus on option pricing models. A few examples of this methodology exist also in the context of liquidity. Acharya et al. (2013) examine different states of US-corporate bonds and Watanabe and Watanabe (2008) investigates the time-varying liquidity risk betas[5].

3.3 Illiquidity spillovers

To analyse illiquidity spillovers across Eurozone's markets, we employ a modified version of Diebold and Yilmaz (2012, 2015). This methodology is based on a VAR modelling technique and the resulting estimation of variance decomposition. This approach, built on previous works from Koop et al. (1996) and Pesaran and Shin (1998), allows us to measure directional illiquidity spillovers in a generalised VAR framework that overcomes the possible effects of variable ordering. Previous evidence of financial contagion through the liquidity channel provide limited findings due to methodological constraints. Among others, Andrikopoulos et al. (2014) uncover evidence of Granger causal relationship between G7 stock markets in returns, volatility and illiquidity. A similar methodology is employed in Smimou and Khallouli (2015) for liquidity spillovers for a set of Eurozone countries. Although both studies adopt variance decomposition as robustness test, they are limited by the ordering of variables and only capture pairwise causation.

The present work differs from these recent contribution under several perspectives. First of all, it provides an innovative illiquidity spillover index (ISI) able to capture the contribution of spillovers of illiquidity shocks across markets. Secondly, differently from variance decomposition and Cholesky factorisation, the results are invariant by the ordering of variables. Lastly, this paper estimates the intensity and

[5]For a complete theoretical review of MRS models in economics and finance see Guidolin (2011*a*).

direction of gross and net spillovers. In fact, models based on Granger causality and variance decomposition can only capture pairwise correlation, which is constant for the full sample. Recent economic events, characterised by turbulence, growing integration and worldwide shocks, makes unlikely that fixed-parameter models apply over the entire sample, thus requiring a more dynamic approach. For this reason, we calculate a dynamic version of spillover analysis using rolling-window estimation that takes into account the time-varying component of illiquidity, consistently with the major literature (Chordia et al., 2000; Brunnermeier and Pedersen, 2009).

Consider a covariance-stationary N-variable VAR(p) with p lags, of the form:

$$X_t = \sum_{k=1}^{p} a_k X_{t-k} + \varepsilon_t \tag{8}$$

where X_t is a vector of log illiquidity measures, $\sum_{k=1}^{p} a_k$ is the matrix of the autoregressive parameters and ε_t is a vector of i.i.d error terms $\varepsilon \sim (0, \sigma^2)$ for each equation in the system. The moving average representation of the covariance-stationary VAR(p) is $X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the A_i is a $N \times N$ matrix of coefficients that follow the recursion $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \cdots + \varphi_p A_{i-p}$, with A_0 being a $N \times N$ identity matrix with $A_i = 0$ for $i < 0$.

Following Diebold and Yilmaz (2012), who use their model on a generalised VAR approach based on Koop et al. (1996) and Pesaran and Shin (1998), in which variance decomposition is invariant on variable ordering, it results in an h-step-ahead forecast error variance decomposition $\theta^g_{ij}(H)$ with $H = 1, 2, \ldots$ we have:

$$\theta^g_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e\prime A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i\prime A_h \sum A_h\prime e_i)} \tag{9}$$

$\sum$ represents the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the jth equation and $e\prime$ is a selection vector, with one as the ith element and zeros otherwise. The entries of the variance decomposition matrix are normalised based on the row sum, in order to satisfy the condition $\sum_{i,j}^{N} \tilde{\theta}^g_{i,j}(H) = 1$, where the superscript $\tilde{\theta}$ indicates the normalised error variance. The total illiquidity spillover index is then constructed as:

$$ISI = \frac{\sum_{i,j=1;i\neq j}^{N} \tilde{\theta}_{i,j}^{g}(H)}{\sum_{i,j=1}^{g} \tilde{\theta}_{i,j}^{g}(H)} * 100 \tag{10}$$

And, under the above condition of normalisation, it is equal to:

$$ISI = \frac{\sum_{i,j=1;i\neq j}^{N} \tilde{\theta}_{i,j}^{g}(H)}{N} * 100 \tag{11}$$

This measure describes the average contribution of illiquidity spillovers from shocks due to all variables to the total forecast error variance and constitutes a sufficient tool to estimate how much of shocks to illiquidity spillover among Eurozone's markets. However, the normalised elements of the matrix provide further information on the direction of spillovers, transmitted from market i to all other markets:

$$ISI_{i\rightarrow j} = \frac{\sum_{j=1;j\neq i}^{N} \tilde{\theta}_{j,i}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{j,i}^{g}(H)} * 100 = \frac{\sum_{j=1;j\neq i}^{N} \tilde{\theta}_{j,i}^{g}(H)}{N} * 100 \tag{12}$$

As well as received by market i from all other markets:

$$ISI_{i\leftarrow j} = \frac{\sum_{j=1;j\neq i}^{N} \tilde{\theta}_{i,j}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{i,j}^{g}(H)} * 100 = \frac{\sum_{j=1;j\neq i}^{N} \tilde{\theta}_{i,j}^{g}(H)}{N} * 100 \tag{13}$$

A further interesting feature is the computation of the net spillover, which shows whether a market is a net receiver or transmitter. The net illiquidity spillover from market i to all other markets j is obtained as:

$$NISI_i = ISI_{i\rightarrow j} - ISI_{i\leftarrow j} \tag{14}$$

The above measures capture total and net directional spillovers in a simple but effective measure. Even though they provide valuable information to the transmission of illiquidity shocks, the present study is not limited to a static representation of spillovers. Given the time-varying nature of illiquidity and the market-wide events that characterised recent history, it is necessary to include more dynamic models in the analysis. In fact, single fixed-parameters may omit valuable information on illiquidity transmission. To address this issue, illiquidity spillovers are estimated in a dynamic setting, using a 60-months rolling windows.

4 Data and descriptive statistics

The overall sample is constituted by daily adjusted closing prices and volumes, for each stock in each market. Past literature reports that equity data from Thomson DataStream must be handled with care (Andrikopoulos et al., 2014). A frequent procedure to filter data from this source is proposed by Ince and Porter (2006). In this study several filters are applied in order to minimise the risk of data errors following Ince and Porter (2006) and Lee (2011). Specifically, only domestic stocks recorded as equity in DataStream and listed in the main stock exchange for which data are available are included. Moreover, data are cleaned from possible biases using the following filters:

- Zero daily returns are coded as missing;
- Daily returns are coded as missing if they are greater than 200% and if $(1 + r_{i,d}) * (1 + r_{i,d-1}) - 1 \leq 50\%$;
- Daily returns are coded as missing if their drop in value is greater than 97%;
- Stocks with daily volume greater than number of share outstanding are deleted;
- Daily volumes are coded as missing if their value is smaller than 100€;
- Market days in which more than 90% stocks have zero returns are excluded.

Tables 1 and 2 show the summary statistics of the illiquidity measures for each market, obtained as the equally-weighted average of individual stocks' measures. Table 1 reports the number of observations, mean, standard deviation, minimum and maximum values of the monthly averages illiquidity time-series. The number of observations (number of months) changes according to the availability of data. Ireland, for example, has 187 observations, since data on volumes are available only from 2000 on Datastream. Portugal is the most illiquid market and Italy is the least illiquid. From table 2, it can be noticed that illiquidity time series are positively skewed and show an excess kurtosis substantially greater than 3, indicating a deviation from the normality assumption. In addition, the p-values of the Shapiro-Wilk test (S-W) indicate that the null hypothesis of normal distribution is significantly rejected for all markets. The features of skewness and kurtosis are consistent with the existing findings around the characteristics of illiquidity. In particular, regarding kurtosis, it is extensively reported in the literature that sudden and pervasive drops characterise financial markets, as in the case of the October 1987 crash (Roll, 1988).

Table 1: Summary statistics

The table presents the mean, standard deviation, minimum and maximum values for the stock market average illiquidity calculated across each stock in each country. The sample runs from January 1, 1990 to December 31, 2015. The number of observation depends on the availability of data. Each observation corresponds to a monthly average.

	Austria	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Netherland*	*Portugal*	*Spain*
Observations	312	312	312	312	312	311	187	312	312	312	311
Mean	8.764	14.535	3.766	11.748	8.73	5.942	3.133	0.571	2.962	16.979	1.015
Std. Dev.	5.906	9.662	2.211	3.019	4.24	5.391	3.009	0.309	1.713	9.812	0.627
Min	0.934	0.063	0.697	3.605	1.47	0.543	0.483	0.018	1.020	2.849	0.269
Max	43.688	44.852	11.905	20.707	21.03	25.197	20.056	1.469	15.095	56.503	4.925

Table 2: Normality features

The table presents the mean, median, skewness, kurtosis and the p-value of the Shapiro-Wilk test for the stock market average illiquidity of each country. It can be seen that for all the countries the assumption of normality can be rejected.

Statistic	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Netherland*	*Portugal*	*Spain*
Mean	8.76	14.53	3.77	11.75	8.73	5.94	3.13	0.57	2.96	16.98	1.02
Median	8.23	15.39	3.21	11.22	8.72	3.79	2.17	0.56	2.50	14.59	0.86
Skewness	1.75	0.08	0.85	0.47	0.47	1.33	2.63	0.25	2.83	1.33	2.38
Kurtosis	8.66	2.29	3.35	3.33	2.53	3.94	12.13	2.94	15.10	5.02	11.10
p-value S-W test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 3 reports the correlation coefficients. Many countries indicate positive correlations, supporting the idea of integration among Eurozone markets. The most evident exception to this trend can be seen for Greece, which shows negative pairwise correlation with the majority of the other countries.

Table 3: Correlation analysis

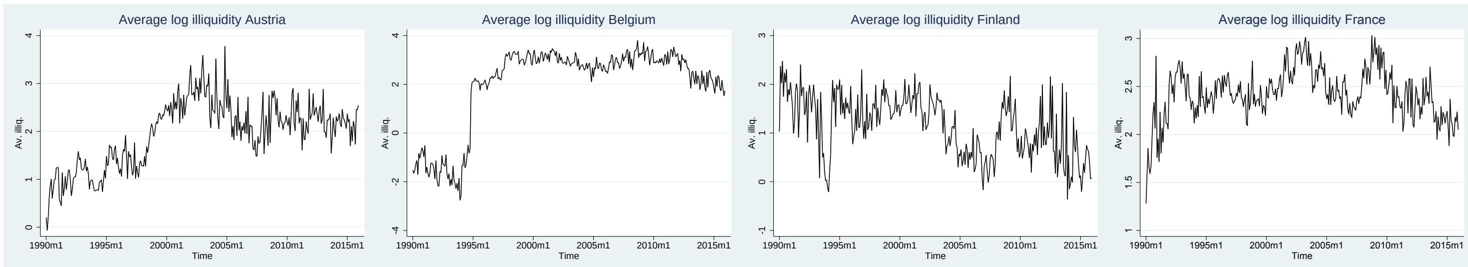
The table presents the correlation matrix of the time-series of illiquidity measures. Illiquidity is measured using the Amihud measure for each stock and is averaged across all the stocks in each country. The sample runs from January 1, 1990 to December 31, 2015.

	Austria	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Netherland*	*Portugal*	*Spain*
Austria	1										
Belgium	0.089	1									
Finland	0.328	0.479	1								
France	0.431	0.395	0.514	1							
Germany	0.200	0.283	0.110	0.469	1						
Greece	-0.243	-0.395	-0.207	-0.487	-0.044	1					
Ireland	0.153	-0.052	0.086	0.039	0.002	0.177	1				
Italy	0.282	0.206	0.441	0.454	0.348	0.188	0.203	1			
Netherland	0.298	0.168	0.236	0.480	0.436	-0.097	0.163	0.340	1		
Portugal	0.036	0.172	0.092	-0.060	-0.051	0.060	0.035	0.070	-0.007	1	
Spain	-0.009	0.273	0.249	0.213	0.206	0.016	0.044	0.325	0.190	0.036	1

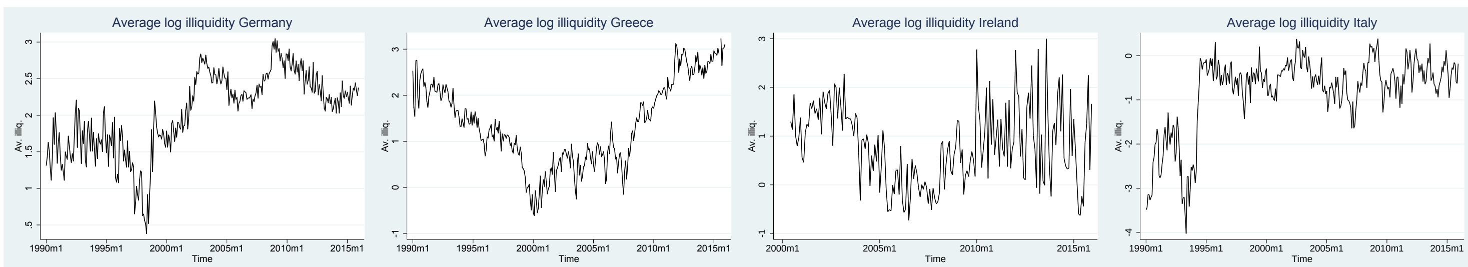
Figure 1 describes, for each market, the trend of ln-illiquidity, likewise to Amihud and Mendelson (2015), who report a similar pattern for the US market. From this graphical overview, a few considerations can be inferred. All the markets present well defined states of high and low illiquidity that last for several months. The most evident can be noted for Belgium and Italy, where a clear change around January 1996 indicates a switch from low to high illiquidity. Common to most of the markets depicted is the increase in illiquidity around the GFC of 2007-2009. However, illiquidity peaks are not highlighted only in conjunction with the GFC. In fact, coherently with the existing literature (see Acharya and Pedersen, 2005), jumps in illiquidity take place in connection with the most remarkable events of the last 25 years. Constitute examples of this evidence the Asian crisis, the Russian and the Long Term Capital Management default and also the "dotcom" bubble. However, even though common patterns across markets can be identified, other events are specific of each single economy, such as the Irish banking sector crisis after the GFC, or the Greek sovereign debt crisis. Another interesting feature can be noticed in connection with the introduction of the Euro as a common currency. In fact, it can be observed a general increase in illiquidity after the 2000 for almost all the markets, corresponding to the introduction of the Euro and the dotcom bubble. However, the increase in illiquidity is somewhat unexpected, since greater interconnection across capital markets should be a motive for an improvement in market liquidity. A further point of interest refers to the relation between illiquidity and volatility. Periods of greater illiquidity show also higher volatility, consistently with Brunnermeier and Pedersen (2009).

Figure 1: Log illiquidity time-series

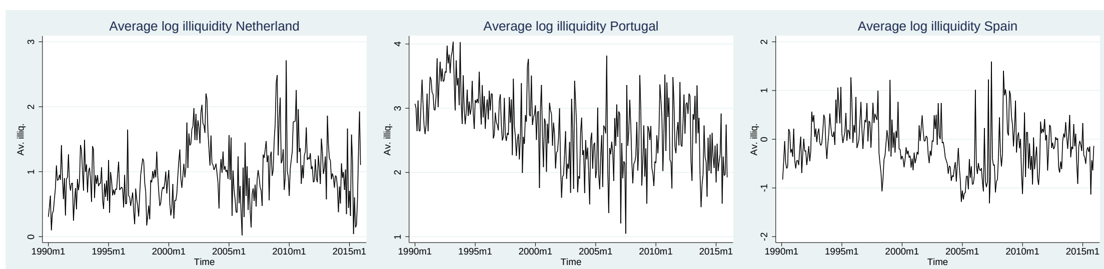
(a) Austria (b) Belgium (c) Finland (d) France



(e) Germany (f) Greece (g) Ireland (h) Italy



(i) Netherland (j) Portugal (k) Spain



The central point of the reported plots is the evidence that more than one state of illiquidity can be identified. In particular, liquidity shocks tend to persist for several months, determining an illiquidity state different form the previous period. Therefor, these graphs propose interesting insights and econometric implications that have to be considered and that will be addresses later. The idea of Chordia et al. (2000), who notice that illiquidity measures are subject to econometric problems, is a valid point from the graphical investigation. We thus test stationarity with an augmented Dickey-Fuller test (table 4). The null hypothesis of a unit root can be rejected for Finland and Spain, with marginal rejection for France, Italy, Netherland and Portugal.

Table 4: ADF test on lnilliq

The table presents the p-values of the Augmented Dickey-Fuller test for the presence of a unit root. The test is performed on the logarithm of monthly average of illiquidity for each country and the alternative hypothesis is stationarity of the time.series.

Country	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Netherland*	*Portugal*	*Spain*
p-value	0.4189	0.9039	0.0000	0.0367	0.4253	0.9254	0.2398	0.0342	0.0215	0.0186	0.0000

Although the ADF test reports evidence of non-stationarity for 5 markets in the sample, this test may not be appropriate in detecting structural breaks. The issue of testing structural changes for unknown break dates is extensively examined in Andrews (1993). Moreover, Garcia and Perron (1996) analyse the supremum Wald test, for the specific case of two regimes. Table 5 reports the p-values of the supremum Wald test for unknown break dates, which strongly rejects the null hypothesis of no structural changes for each country. Even though this test is limited to the specific case of two states, for the purpose of the present study, the evidence of structural breaks justifies the adoption of MRS models as alternative to AR(p) models.

Table 5: Sup. Wald test for structural breaks

The table presents the p-value of the supremum Wald test for the presence of structural breaks in the series. The test is performed on the log of monthly illiquidity averages for each country. The test has as null hypothesis the absence of structural breaks against the alternative of one structural break.

Country	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Netherland*	*Portugal*	*Spain*
Sup Wald (p-value)	0.000	0.000	0.000	0.000	0.000	0.009	0.000	0.000	0.002	0.000	0.015

5 Empirical results

In this section, we investigate the time-varying nature of illiquidity and its channels of transmission for our pool of 11 Eurozone countries. We begin by testing our initial hypotheses on the characteristics of illiquidity time series. In section 5.1, the standard AR(1) process is compared to a MRS model with multiple states, where all the parameters are allowed to switch between regimes. We start with a 2-regimes MRS model, where the two states indicate high and low levels of market illiquidity. Then, we test a 3-regimes MRS model, where the three states indicate normal, high and low illiquidity. Next, in sections 5.2 and 5.3 we look at illiquidity spillovers to investigate if the financial channel constitutes a source of transmission of illiquidity shocks among markets belonging to a currency area. To achieve this, we implement our innovative illiquidity spillover index (ISI) together with a dynamic approach using rolling estimation. The latter allows to better understand the intensity and direction of spillovers in tranquil periods and during accentuated financial turmoil.

5.1 Autoregressive illiquidity: one vs multiple states

Time-varying illiquidity is firstly analysed using the AR(1) model depicted in equation 4 for each Eurozone's monthly illiquidity time-series. Table 6 reports the empirical estimation and includes intercepts and coefficients (with t-stats in parentheses), r^2 and score of the Akaike's information criterion (AIC). It can be noticed that all the coefficients are positive and significant, indicating common patterns in terms of illiquidity persistency in the Eurozone. Furthermore, even though the magnitude of the AR coefficients changes from country to country, it is generally consistent with previous evidence for the US market[6] (Amihud, 2002) and also greater in most cases. Generally, core economies show high persistency, with the case of Germany particularly emblematic, with a highly significant coefficient of 0.91. In contrast, peripheral markets, such as Ireland, Portugal and Spain report lower persistency. The intercepts substantially support our descriptives reported in table 1, which identify Italy as the least illiquid country and Portugal as the most illiquid. Diagnostics plots for the residuals [7] indicate that errors do not seem to be white noise and that they have autocorrelation. These diagnostics, together with the evidence of non-stationarity and presence of structural changes reported in tables 4 and 5 suggest that non-linear models would be more appropriate to describe illiquidity time-series, in lieu of AR processes.

To better understand time-varying illiquidity, we start by using a MRS model with 2 states, which can be interpreted as high and low illiquidity. For each regime, both the intercept and the AR coefficient are allowed to change, in order to detect the degree of persistency of illiquidity shocks. Moreover, the matrix of transition probabilities estimates the likelihood of a switch in regime between one period and the following. Table 7 shows the estimated output. It reports, for each country, the intercept and the AR coefficient for states 1 and 2. It can be seen that almost all the coefficients are positive and highly significant, indicating that shocks identify a new state of illiquidity and that each state is persistent. Further support to this claim is provided by the matrix of transition probabilities. In particular, the probability of a switch in regime conditional on the regime in the previous period (p_{12} and p_{21}) is very close to zero for the majority of countries. This evidence testifies that after a shock it is unlikely for the random variable to revert in the following period to the other state. In contrast, Belgium, Germany and Greece report a higher probability of a switch compared to the probability of non-switching. The case of Belgium is

[6] Amihud (2002) finds a highly significant autoregressive coefficient of 0.768 and an r^2 of 0.53.

[7] Reported in the Appendix 1 to conserve space

Table 6: Illiquidity persistency with AR(1) processes

The table shows results from a AR(1) process for each country in the sample of the ln of the equally-weighted averages of individual illiquidity measures, $AILLIQ_{s,m} = c_0 + c_1 AILLIQ_{s,m-1} + v_m$, where c_0 and c_1 represent the coefficients and v_m is the residual. Intercepts and autoregressive coefficients with their relative t-stats are reported in the first two columns of the table, together with the R^2 of the regression and the Akaike information criterion (AIC) in the third and fourth columns.

	constant	*coeff. AR(1)*	R^2	*AIC*
Austria	0.294***	0.853***	0.741	228.8
	(4.96)	(29.76)		
Belgium	0.0648*	0.973***	0.959	230.4
	(2.15)	(84.80)		
Finland	0.365***	0.679***	0.457	404.1
	(6.65)	(16.11)		
France	0.720***	0.705***	0.525	-188.3
	(7.72)	(18.48)		
Germany	0.186***	0.910***	0.832	-43.87
	(3.80)	(39.09)		
Greece	0.0456	0.968***	0.932	0.390
	(1.85)	(64.91)		
Ireland	0.445***	0.448***	0.2	409.1
	(-5.93)	(-6.78)		
Italy	-0.0622*	0.910***	0.854	187.8
	(-2.45)	(42.46)		
Netherland	0.468***	0.520***	0.272	293.4
	(9.04)	(10.75)		
Portugal	1.454***	0.456***	0.207	457.4
	(10.46)	(8.98)		
Spain	-0.0669*	0.456***	0.209	398.9
	(-2.49)	(-9.03)		

trivial. In fact, despite a positive and significant AR coefficient of 0.874 for regime 1, the matrix indicates that the probability of being in state 1 at time t, conditional on being in regime 1 at time t-1 is only 0.04%. In order to assess whether this non-linear approach better fits to the data, we use the AIC as decision criterion, following Perron (1997). In particular, we look at the model that minimises the AIC for each market, comparing the last column of table 6 with the last row of table 7. It can be seen that the AIC is minimised for all the countries in the sample when the MRS model is employed. Thus, we can conclude in favour of our alternative hypothesis (H_1) that more than one illiquidity state is identified and that each state is persistent. As a further support to our findings, we look at the residuals of the MRS model (Appendix 2). They show that residuals tend to be normally distributed and the autocorrelation considerably decays. Figure 2 depicts the estimated regimes on the illiquidity time-series for each country, together with the smoothed transition probabilities. Regime 1 is represented by the grey area, while the white area refers to regime 2. The behaviour of illiquidity time series considerably varies among markets, in terms of switches in regime. Finland, France, Ireland, Italy and Portugal report long periods where the sate variable is in regime 1, with associated probabilities very close to the unit. In contrast, other countries show more frequent switches, both in tranquil phases of the economy and during financial turmoil.

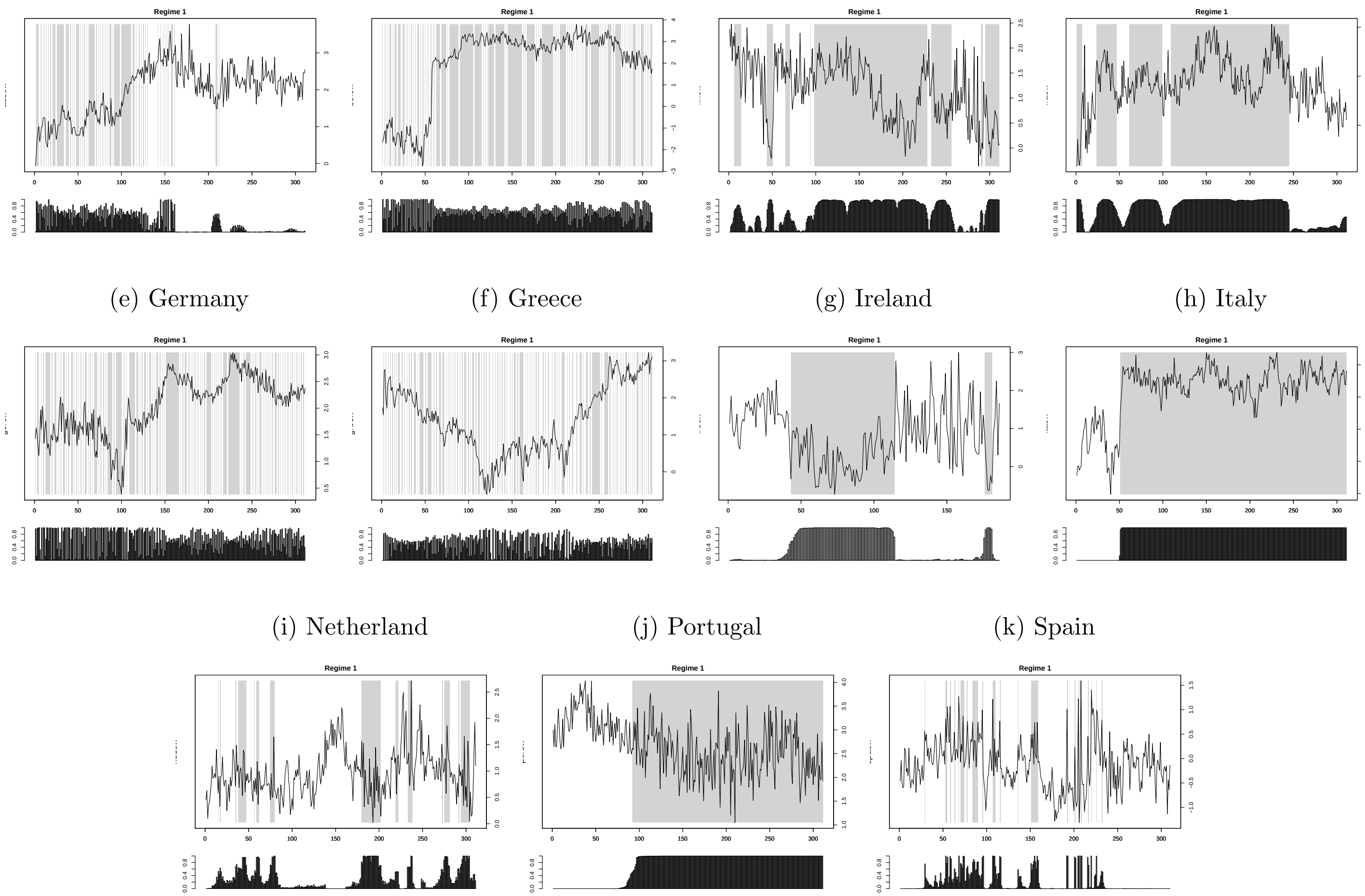
Even though the description of illiquidity time-series using a 2-states Markov model substantially improves the understanding of its behaviour, we extend the robustness of the findings by testing for the existence of more regimes. In fact, past research argues that MRS model should not be constrained to a predetermined number of states (Guidolin, 2011*a*). This is because the theoretical justification to the use of MRS models implies that there should not be a mere trade-off decision between these models and two-state nonlinear frameworks. Instead, the data themselves should provide information on the most suitable number of states. As a result, we do not confine our analysis to the arbitrary imposition of 2 states, as in Watanabe and Watanabe (2008) and Acharya et al. (2013), but we also test for 3 states and we report the estimation in table 8.

Table 7: MRS model: 2 states

The table reports the results of the MRS model for switching intercepts and AR coefficients, tested for the presence of 2 states for each country for equally-weighted averages of the ln of individual illiquidity measures, over the period from January 1, 1990 to December 31, 2015. The first four rows indicate the states identified with the corresponding intercepts and AR coefficients. The following four rows report the estimated matrix of transition probabilities of a switch in regime. The last two rows of each panel indicates the Schwarz-Bayesian and Akaike's information criteria. The stars (*) next to each estimated intercepts and coefficients indicate the significance level: 10%(*), 5%(**) and 1%(***).

MRS: 2 states	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Netherland*	*Portugal*	*Spain*
State 1											
Constant	0.106*	0.33*	0.892***	0.554***	0.639***	0.245***	1.251***	-0.16***	0.3***	1.622***	0.384*
Coefficient	0.946***	0.874***	0.31*	0.781***	0.768***	0.872***	-0.022	0.656***	0.677***	0.483***	-0.594*
State 2											
Constant	1.853***	-0.128**	0.124**	1.735***	-0.127*	-0.199**	0.096	-0.583*	0.739***	2.011***	-0.087***
Coefficient	0.198*	1.046***	0.876***	0.234*	1.015***	1.091***	0.502***	0.758***	0.315**	0.19**	0.646***
p11	98.35%	0.04%	91.27%	97.93%	9.95%	35.72%	97.75%	99.62%	95.93%	99.99%	50.72%
p12	1.65%	99.96%	8.73%	2.07%	90.05%	64.28%	2.25%	0.38%	4.07%	0.01%	49.28%
p21	2.44%	68.1%	5.55%	5.08%	52.37%	64.2%	3.1%	0.01%	10.81%	0.46%	9.4%
p22	97.56%	31.9%	94.45%	94.92%	47.63%	35.8%	96.9%	99.99%	89.19%	99.54%	90.6%
SBIC	192.4	232.4	380.7	-183.5	-47.3	16.65	395.9	189.8	297.7	446.8	372.2
AIC	158.5	198.5	346.8	-217.4	-81.3	-17.3	366.1	155.9	263.8	412.9	338.4

Figure 2: Regimes and transition probabilities



(a) Austria (b) Belgium (c) Finland (d) France

(e) Germany (f) Greece (g) Ireland (h) Italy

(i) Netherland (j) Portugal (k) Spain

Table 8: MRS model: 3 states

The table reports the results of the MRS model for switching intercepts and AR coefficients, tested for the presence of 3 states for each country for equally-weighted averages of the ln of individual illiquidity measures, over the period from January 1, 1990 to December 31, 2015. The first six rows indicate the states identified with the corresponding intercepts and AR coefficients. The following six rows report the estimated matrix of transition probabilities of a switch in regime. The last two rows of each panel indicates the Schwarz-Bayesian and Akaike's information criteria. The stars (*) next to each estimated intercepts and coefficients indicate the significance level: 10%(*), 5%(**) and 1%(***).

MRS: 3 states	*Austria*	*Belgium*	*Finland*	*France*	*Germany*	*Greece*	*Ireland*	*Italy*	*Netherland*	*Portugal*	*Spain*
State 1											
Constant	-0.215*	-0.37	0.984***	1.982***	0.608***	-0.249**	1.265***	0.005	0.644***	1.628***	0.316
Coefficient	1.139***	1.029***	0.211	0.13	0.799***	1.124***	-0.029	0.944***	0.256***	0.482***	-0.55*
State 2											
Constant	0.312***	0.063	0.058	0.491***	-0.039	2.083***	-0.266*	-0.176***	0.900***	2.148***	0.13
Coefficient	0.817***	0.987***	0.804***	0.843***	0.996***	0.03	0.365*	0.563***	-0.012	0.157*	0.961
State 3											
Constant	1.859***	0.575***	0.175*	0.281***	-0.618***	0.245***	0.355	-0.291	0.126	1.662	-0.23
Coefficient	0.191*	0.883***	1.007***	0.841***	1.151***	0.870***	0.585*	1.088***	0.917***	0.273	0.515***
p11	19.14%	2.13%	89.47%	91.31%	18.49%	34.41%	97.59%	72.27%	0.60%	100.00%	44.53%
p12	77.50%	45.38%	9.40%	8.68%	4.91E-01	0.70%	2.38%	9.45%	23.55%	4.73E-08	1.23%
p21	63.21%	17.87%	7.54%	3.05%	33.61%	4.50E-05	7.72%	7.03%	15.17%	3.58E-05	0.31%
p22	36.79%	76.51%	20.00%	28.59%	59.74%	100.00%	36.95%	87.05%	84.83%	76.25%	21.00%
p31	2.45%	75.54%	1.03%	2.61E-05	73.83%	57.59%	0.13%	60.85%	27.35%	1.65%	13.25%
p32	3.22E-10	24.42%	89.26%	78.88%	17.91%	1.12E-09	42.60%	26.13%	2.22E-05	61.73%	72.65%
SBIC	206.4	226.7	384.1	-188.1	-60.4	12.3	410.2	214.2	299.2	468.8	382.8
AIC	164.5	184.8	342.2	-229.9	-102.3	-29.5	374.4	172.3	261.1	426.8	340.9

Table 8 reports the estimation using MRS methodology for 3 states of illiquidity time-series with switching parameters, similarly to table 7. By allowing the model to identify 3 distinct states, our aim is to capture one normal state of illiquidity, one persistent period of high illiquidity and one persistent period of low illiquidity. In fact, when an illiquidity shock takes place, the level of funding illiquidity deteriorates with negative effects on market illiquidity (Brunnermeier and Pedersen, 2009). In contrast, highly liquid markets result in better margin requirements that increase funding liquidity, hence improving market liquidity and corresponding to the low illiquid state. It can be noted that most of the parameters are positive and significant, except for Spain, where all the constants are not significantly different from zero. Although having one constant statistically equal to zero is not an issue per se, since it constitutes a state itself, in the case of Spain we deduct that the model is not able to detect different regimes when three switching states are estimated. However, our overall results provide further robustness to the 2-states estimation and the employment of Markov methodology. Regarding the AR coefficients, it can be seen that high persistency of each state is found for almost all the countries and all the states. There are some contexts where the probability of a switch is very low even though the AR coefficient is not significantly different from zero. For example, state 1 for France, which indicates high illiquidity (1.982), reports an insignificant coefficient of 0.13, but the probability (p_{11}) is 91.31%. Similarly, state 2 of Greece and state 1 of Ireland, which also correspond to high illiquidity, have insignificant coefficients but a very low probability of a switch. These counterintuitive evidence can be interpreted in terms of sources of persistent illiquidity shocks. In fact, the AR coefficient may not capture exogenous shocks originated from other markets that cause illiquidity to be persistent in a given market.

At this point it is legitimate to ask which model is preferable between those with 2 and 3 regimes. The adopted decision criterion to firstly provide evidence that MRS model better explain illiquidity time-series compared to AR processes was the AIC. However, Perron (1997) finds that AIC performs badly compared to the Schawrz-

Bayesian Information Criterion (SBIC) in detecting the number of changes in a time series. Therefor we look at the SBIC criterion to detect for which models it is minimised, comparing the penultimate row of tables 7 and 8. From the comparison, it can be noticed that for the majority of markets the SBIC is minimised with three switching states. The only exceptions are Austria, Ireland, Italy Portugal and Spain, where the best model is a 2-regimes Markov model. As a further robustness test, we perform the empirical estimation for 4 and 5 states. Table 9 reports the comparison in terms of AIC and shows that MRS models minimise the decision criterion and therefor are preferred to analyse time-varying illiquidity. In untabulated results, we find that the SBIC is minimised for none of the countries with a number of states greater than 3. We do not extend the analysis to a greater number of states in order to preserve economic significance of our results. In fact, an excessively high number of states may be meaningless in terms of interpretation of the economic significance.

Table 9: Comparison of the models

Comparison of the Akaike's information criterion for the three models and for each country in the sample. The star (*) indicates the model that minimises the information criterion.

	AR(1)	*MRS 2 regimes*	*MRS 3 regimes*
Austria	228.8	158.5	155.5*
Belgium	230.4	198.5	175.8*
Finland	404.1	346.8	333.2 *
France	-188.3	-217.4	-239.0*
Germany	-43.87	-81.3	-111.3*
Greece	0.39	-17.3	-38.6*
Ireland	409.1	366.1	365.5*
Italy	187.8	155.9*	163.4
Netherland	293.4	263.8	248.3*
Portugal	457.4	412.9*	417.9
Spain	398.9	338.4	332.0*

To sum up, we find that illiquidity time series should not be approached using linear methodologies, since illiquidity shocks are more persistent than previously thought and their effect tend to last for some time. These results are also consistent with the notion of liquidity spirals (Brunnermeier and Pedersen, 2009) and the dual channel theorised by Chordia et al. (2000).

5.2 Illiquidity spillovers: static analysis

In this section, we report the full-sample spillover analysis, which estimates the average illiquidity spillover effect across Eurozone stock markets. Table 10, that we call illiquidity spillover table, shows the average contribution of illiquidity shocks to and from each country. Every ij^{th} entry represents the estimated contribution to the forecast error variance of country i coming from innovations to country j. The last column of the table, labelled "From Others" indicates the sum of the total contribution to country i from all other countries j. Similarly, the row labelled "To Others" is the column sum of the total contribution from country i to all other countries j. Finally, the main feature of this table is our new measure ISI in the lower right corner, which represents the average illiquidity forecast error variance in all 11 countries, coming from spillovers.

To start with, the column sum shows that Finland, Italy and the Netherland are, in this order, the countries that contribute the most to illiquidity shocks to the other nations. In contrast, peripheral countries such as Portugal, Ireland and Greece are are amongst the lowest contributors of gross directional spillovers. This evidence suggests that economies in financial distress contribute to illiquidity spillovers in proportion to their size. It can be noted, from the row sum "From Others", that France is the country where most of the spillover is transmitted. Moreover, some peripheral countries that include Austria, Belgium, Greece and Portugal, are also those that receive the lowest spillovers. Lastly, the average non-directional spillover, which reflects the various measures into a single index, is 53.7%. This number is interpreted as the total illiquidity forecast error variance in all the 11 markets coming from spillover for the 53.7%, corroborating the evidence of interconnectedness among Eurozone economies. Smimou and Khallouli (2015) report Granger causality among Eurozone countries with respect to illiquidity. The evidence reported here are not only consistent with previous studies (Smimou and Khallouli, 2015), but they also add new and valuable information. First of all in terms of the overall spillover effect, captured by the measure ISI. Moreover, in terms of pairwise direction and intensity of the contribution. Although we find clear evidence of transmission across interrelated economies of illiquidity shocks, the present methodology is limited in capturing the evolution of spillovers, which require a more dynamic approach. Furthermore, only gross directional spillovers are reported in the table, so that the actual net contribution can not be fully understood. In the next section, we extend our static analysis using rolling-window estimation to describe the evolution of total and directional spillovers.

5.3 Illiquidity spillovers: dynamic analysis

Several global and local macroeconomic events took place during the sample period under analysis, including the GFC and the euro crisis. In this context, it is reasonable to expect that financial turbulence can not adequately be represented by a static model captured by a single parameter. In order to grasp the potentially important changes in illiquidity spillovers, the estimation is repeated using a 60-months rolling analysis. This length of the rolling windows allows reliable estimates with minor losses in terms of truncation of the sample. In fact, wider windows would substantially reduce the starting point of the graphical representation of the index. However, the 10-years window depicted in the Figure 3 indicates higher levels of spillovers, particularly during recent periods of financial turmoil. Moreover, it describes the time variation of the spillover index.

Since the second half of 2005, the graph already shows higher illiquidity spillovers across stock markets, slightly below 70%. The downward trend of the following two years is interrupted by a spike around the end of 2007, which formally constitutes the beginning of the GFC. However, the index reaches its peak of 75% in late 2008,

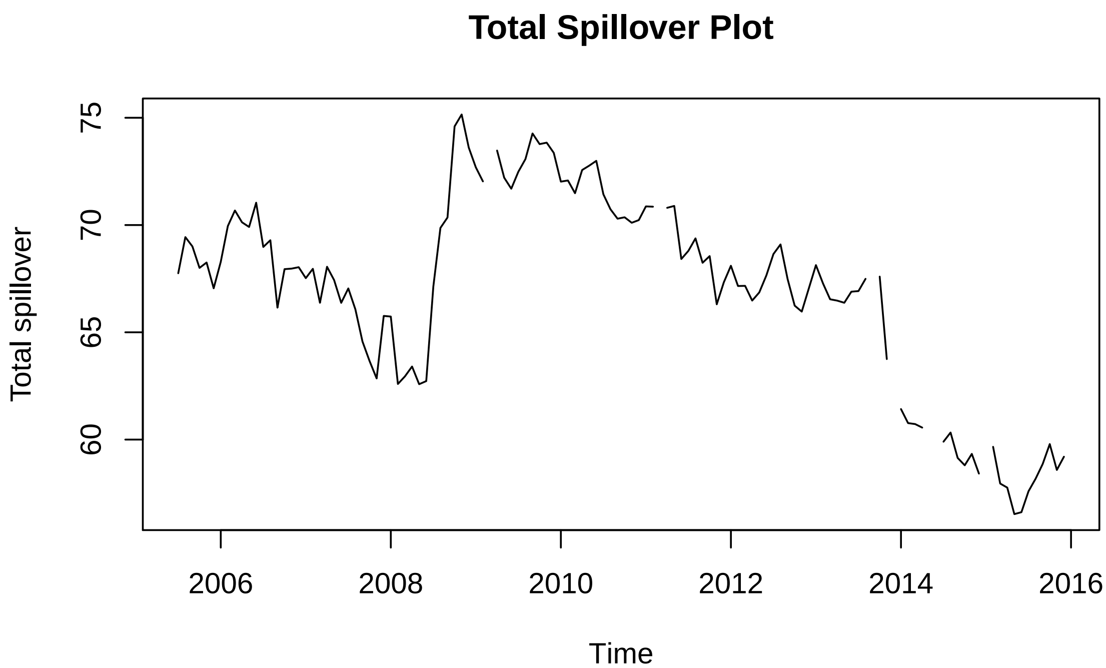
Table 10: Illiquidity spillover table

The table shows the illiquidity spillovers to and from each market in the sample, namely Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherland, Portugal and Spain form 01/01/2000 to 31/12/2015. Each ij^{th} entry represents the estimated contribution to the forecast error variance and elements in the diagonal report the own contribution. The column "From Others" reports the row sum and the row "To Others" reports the column sum, both excluding own contribution. The number on the bottom right is the illiquidity spillover index and is reported in percentage.

	AUS	BEL	FIN	FRA	GER	GRE	IRE	ITA	NET	POR	SPA	From Others
AUS	68.3	1.5	4.7	13.4	0.7	0.5	1.1	3.6	2.2	1.3	2.7	32
BEL	1.1	70.2	9.2	2.5	7.6	1.5	0.2	2.4	1.3	0.1	4	30
FIN	4.3	9.5	38.5	11.5	6.1	2.4	0.7	10.4	7.4	1.5	7.6	61
FRA	5.5	5.6	17.2	22.7	8.2	0.5	0.3	15	12.7	0.8	11.4	77
GER	1.3	6.2	9.1	4.9	37.5	1.8	0.3	16.4	10.1	1.4	11.1	63
GRE	0.6	0.8	3.2	0.7	3.9	64.7	3.6	12.5	4.8	0.2	5	35
IRE	2.2	8.5	11.9	7.4	2.5	5.1	33	7.6	12.3	1.5	8	67
ITA	2.4	3.3	15	7.4	8	5.5	0.8	32.8	12.5	0.3	12	67
NET	1.1	7.6	12.3	10.8	9.9	2.1	1.8	10.4	34.8	0.6	8.7	65
POR	1.4	3.5	3.7	2.3	2.8	4	1.4	1.4	6.9	71.2	1.3	29
SPA	3.9	2.7	11.7	10.5	5.1	4.2	1.4	13.2	10.4	0.8	36.1	64
Contribution to others	24	49	98	71	55	28	12	93	81	8	72	590
Contribution including own	92	119	137	94	92	92	45	126	115	80	108	ISI: 53.70%

indicating the greater level of interconnection of eurozone nations during the GFC of 2007-2009 and suggesting proofs of contagion. Thereafter, the index reports other two declining maxima that correspond to the euro crisis. In fact, noticeable events like the Greek sovereign debt crisis and the Irish banking sector instability took place in the year immediately following the GFC. In addition, it is interesting to notice that the spillovers gradually reduce to their mean level with the introduction of the quantitative easing programme by the European Central Bank on September 2012. Even though this graphical analysis reports the total spillover plots, valuable pieces of information regarding the direction are not investigated. To account for this, the rolling estimation is repeated for each market to retrieve information regarding gross

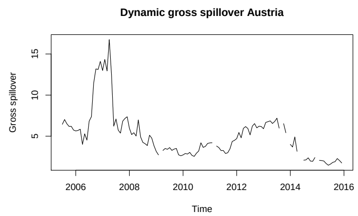
Figure 3: Total illiquidity spillover



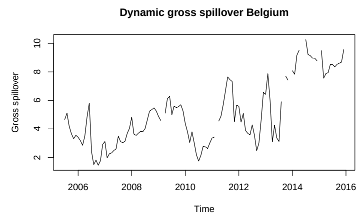
directional spillovers. This analysis simply corresponds to the dynamic version of the row sum reported in table 10. Figure 4 shows the illiquidity spillover from each country to the others. On the y-axis, it is reported the intensity, which varies from country to country. Moreover, it can be noted that spillovers considerably fluctuate over time for all the economies.

Figure 4: Gross directional spillovers

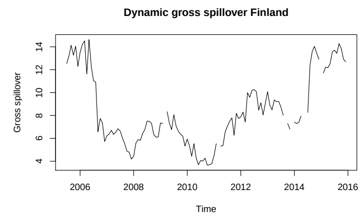
(a) Austria



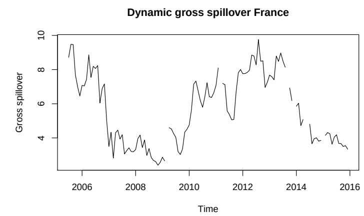
(b) Belgium



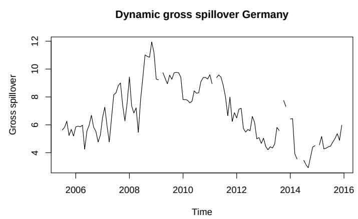
(c) Finland



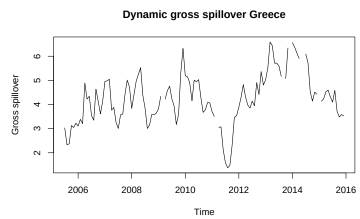
(d) France



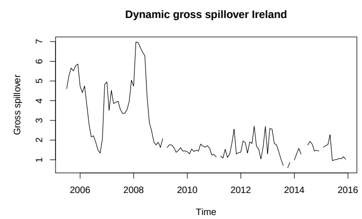
(e) Germany



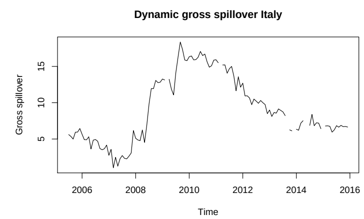
(f) Greece



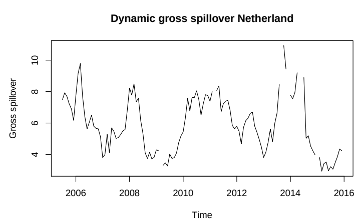
(g) Ireland



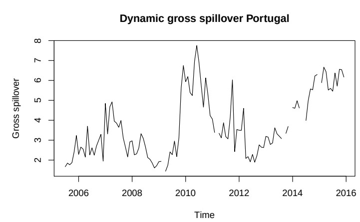
(h) Italy



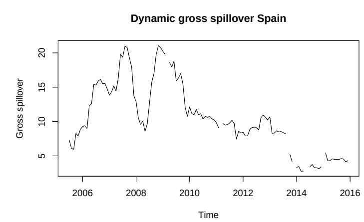
(i) Netherland



(j) Portugal



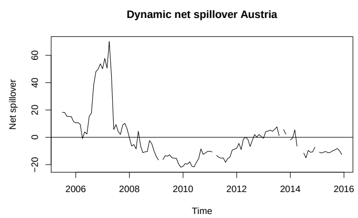
(k) Spain



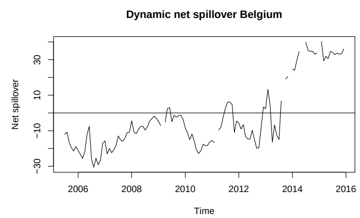
In terms of magnitude, Italy and Spain are amongst the nations with the highest transmission levels, consistently with our static analysis (table 10), reaching peaks around 20% during the GFC. Greater intensity of spillovers during the GFC can be also seen for other markets, both core, such as Germany, and peripheral, including Greece and Ireland. However, there is not a unique common pattern across all the markets, probably due to country-specific sources of uncertainty. These evidence using a dynamic spillovers analysis provide evidence of greater interdependence during periods of financial instability that other studies unexpectedly fail to grasp. For instance, Andrikopoulos et al. (2014) do not provide supportive findings of greater spillover effects using a dummy variable accounting for the GFC period (see Andrikopoulos et al., 2014, p. 123). Although these plots provide valuable information, the core of our analysis relies on net directional illiquidity spillovers, in order to investigate which countries are net transmitters or receivers. Figure 5 shows, for each market, the net spillover effect, which corresponds to the difference between the column sum "From Others" and the row sum "To others" in table 10. It uncovers interesting evidence in terms of interconnection among Eurozone countries. In fact, it can be clearly seen that most of the illiquidity transmission comes from Italy and Spain, the two biggest peripheral countries. Italy is net receiver until mid-2008, while from that point forth becomes transmitter, reaching the peak of 60% before the end of 2009. Similarly, Spain is transmitter for almost the entire time period under analysis, with spikes that exceed 80% during the GFC. Germany turned to be a transmitter during the crisis period, while overall it absorbed most of the shocks during the rest of the sample, while France was a net receiver during 2007-2009. It is interesting to notice that core countries are counterintuitively the channels of shock transmission to peripheral countries during phases of financial turmoil, while net receiver in tranquil periods. For instance, small and peripheral economies, which include Greece, Ireland, Portugal and Belgium were receivers during the GFC. One of the benefits of this dynamic analysis can be appreciated with respect to the case of Finland. It substantially contributed to illiquidity shocks only at the beginning and end of the time period, while we saw that on average it is the grater transmitter (see table 10). These findings enhance other studies in this field by providing a picture of which countries are mostly net transmitters and net receivers. Smimou and Khallouli (2015) observe a the transmission of local shocks to other markets of the Eurozone for a limited time window. However, they fail to empirically demonstrate both the impact of the shock in the receiver country and the net contribution of the transmitter. We overcome these limitations by showing the overall and net effect of illiquidity shocks.

Figure 5: Net directional spillovers

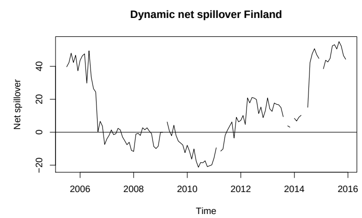
(a) Austria



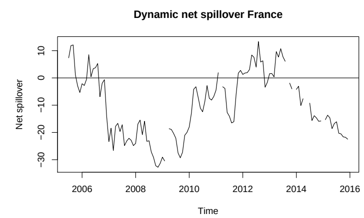
(b) Belgium



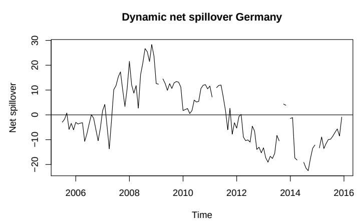
(c) Finland



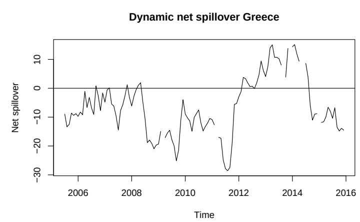
(d) France



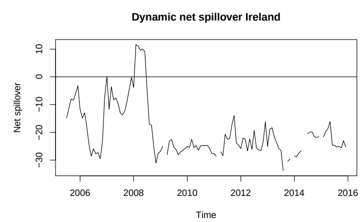
(e) Germany



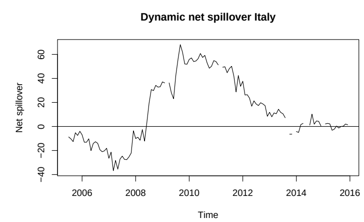
(f) Greece



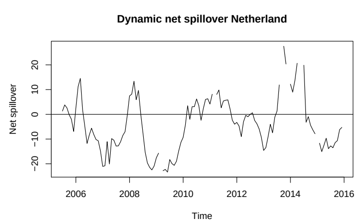
(g) Ireland



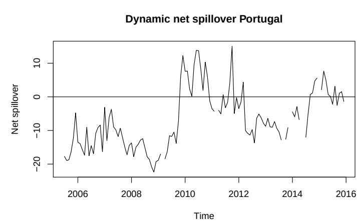
(h) Italy



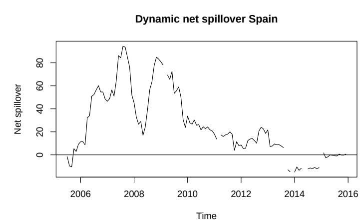
(i) Netherland



(j) Portugal



(k) Spain



6 Conclusions, implications and future research

The present study investigates stock market illiquidity, by looking at its time-varying behaviour and at the sources of illiquidity shocks for a pool of Eurozone countries form January 1, 1990 to December 31, 2015. In the first part, we provide a methodological contribution that uncovers interesting features of time-varying illiquidity, employing MRS models. This non-linear approach overcomes most of the econometric limitations of the widely employed AR processes in the existing literature (Amihud, 2002; Korajczyk and Sadka, 2008; Foran et al., 2014). Consistently with the effects of the GFC and other local and global market downturns and coherently with the notion of liquidity spirals (Brunnermeier and Pedersen, 2009), we find that the dynamic channel identified by Chordia et al. (2000) is generated by illiquidity shocks that persist over time. For instance, our results show that a new persistent state of illiquidity exists as a result of illiquidity shocks, characterised by positive and highly significant AR coefficient and a very low probability of a switch. To our knowledge, this is the first study that provides these evidence for stock market illiquidity for the Euro Area. Previous applications look at the bond market (Acharya et al., 2013) and the liquidity betas from mimicking portfolios (Watanabe and Watanabe, 2008). However, we also extend these previous applications, by testing for the presence of multiple states, without limiting the contribution to the arbitrary imposition of two states. For instance, we find that most of the countries under analysis are better explained with three-regimes Markov models.

In the second part of this work, we look at the source of illiquidity shocks, by analysing interconnections and spillovers. This paper investigates endogenous and exogenous channels of transmission within the Eurozone under both a static and a dynamic settings. Firstly, this work introduces a new measure that captures interconnectedness, defined illiquidity spillover index (ISI), built following Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012). It captures the forecast error variance received and transmitted from and to each country in the sample and over the entire time period. Secondly, given the time-varying nature of illiquidity, the estimation is repeated in a dynamic framework using rolling window analysis. Results indicate strong spillover effects across countries in the sample, with Italy and Spain which constitute the major sources of illiquidity within the Euro area. The dynamic analysis reveals that the transmission is not constant over time and that some countries are net transmitters, while others are net receivers during phases of market turmoil.

This study provides new evidence that enhance the understanding of the characteristics of market illiquidity within the most important currency area. By looking at its variation over time and the transmission channel, future research can benefit from the findings presented here, by investigating the implications in terms of pricing of liquidity risk. In line with recent trends within this field (see, for example, Amihud et al., 2015), the inclusion of time-varying components and exogenous effects may shed new lights on the illiquidity premia across countries, with natural implications for investors and regulators.

Bibliography

Acharya, V. V., Amihud, Y. and Bharath, S. T. (2013), 'Liquidity risk of corporate bond returns: conditional approach', *Journal of financial economics* **110**(2), 358–386.

Acharya, V. V. and Pedersen, L. H. (2005), 'Asset pricing with liquidity risk', *Journal of Financial Economics* **77**(2), 375–410.

Amihud, Y. (2002), 'Illiquidity and stock returns: cross-section and time-series effects', *Journal of Financial Markets* **5**(1), 31–56.

Amihud, Y., Hameed, A., Kang, W. and Zhang, H. (2015), 'The illiquidity premium: international evidence', *Journal of financial economics* **117**(2), 350–350.

Amihud, Y. and Mendelson, H. (1986), 'Asset pricing and the bid-ask spread', *Journal of Financial Economics* **17**(2), 223–249.

Amihud, Y. and Mendelson, H. (2015), 'The pricing of illiquidity as a characteristic and as risk'.

Amihud, Y., Mendelson, H. and Pedersen, L. H. (2012), *Market Liquidity: Asset Pricing, Risk, and Crises*, Cambridge University Press, New York.

Amihud, Y., Mendelson, H. and Wood, R. (1990), 'Liquidity and the 1987 stock market crash', *Journal of Portfolio Management* pp. 65–69.

Andrews, D. W. (1993), 'Tests for parameter instability and structural change with unknown change point', *Econometrica: Journal of the Econometric Society* pp. 821–856.

Andrikopoulos, A., Angelidis, T. and Skintzi, V. (2014), 'Illiquidity, return and risk in g7 stock markets: Interdependencies and spillovers', *International Review of Financial Analysis* **35**, 118–127.

Ang, A. and Bekaert, G. (2002), 'Regime switches in interest rates', *Journal of Business Economic Statistics* **20**(2), 163–182.

Bae, K.-H., Karolyi, G. A. and Stulz, R. M. (2003), 'A new approach to measuring financial contagion', *The Review of Financial Studies* **16**(3), 717–763.

Beirne, J. and Gieck, J. (2014), 'Interdependence and contagion in global asset markets', *Review of International Economics* **22**(4), 639–659.

Bergman, U. M. and Hansson, J. (2005), 'Real exchange rates and switching regimes', *Journal of International Money and Finance* **24**(1), 121–138.

Brockman, P., Chung, D. Y. and Pérignon, C. (2009), 'Commonality in liquidity: A global perspective', *Journal of Financial and Quantitative Analysis* **44**(4), 851–882.

Brooks, C. (2014), *Introductory econometrics for finance*, Vol. Thirdition., Cambridge University Press, Cambridge, United Kingdom.

Brunnermeier, M. K. and Pedersen, L. H. (2009), 'Market liquidity and funding liquidity', *The Review of Financial Studies* **22**(6), 2201–2238.

Chordia, T., Roll, R. and Subrahmanyam, A. (2000), 'Commonality in liquidity', *Journal of Financial Economics* **56**(1), 3–28.

Copeland, T. E. and Galai, D. (1983), 'Information effects on the bid-ask spread', *The Journal of Finance* **38**(5), 1457.

Diebold, F. X. and Yilmaz, K. (2009), 'Measuring financial asset return and volatility spillovers, with application to global equity markets', *The Economic Journal* **119**(534), 158–171.

Diebold, F. X. and Yilmaz, K. (2012), 'Better to give than to receive: Predictive directional measurement of volatility spillovers', *International Journal of Forecasting* **28**(1), 57–66.

Diebold, F. X. and Yilmaz, K. (2015), *Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring*, Oxford University Press, USA.

Elliott, R. J., Chan, L. and Siu, T. K. (2005), 'Option pricing and esscher transform under regime switching', *Annals of Finance* **1**(4), 423–432.

Engel, C. and Hamilton, J. D. (1990), 'Long swings in the dollar: Are they in the data and do markets know it?', *The American Economic Review* **80**(4), 689–713.

Foran, J., Hutchinson, M. C. and O'Sullivan, N. (2014), 'The asset pricing effects of uk market liquidity shocks: evidence from tick data', *International Review of Financial Analysis* **32**, 85–94.

Foran, J., Hutchinson, M. C. and O'Sullivan, N. (2015), 'Liquidity commonality and pricing in uk equities', *Research in International Business and Finance* **34**, 281–293.

Forbes, K. J. and Rigobon, R. (2002*a*), 'No contagion, only interdependence: measuring stock market comovements', *The journal of Finance* **57**(5), 2223–2261.

Forbes, K. J. and Rigobon, R. (2002*b*), 'No contagion, only interdependence: Measuring stock market comovements', *The Journal of Finance* **57**(5), 2223–2261.

Frömmel, M., MacDonald, R. and Menkhoff, L. (2005), 'Markov switching regimes in a monetary exchange rate model', *Economic Modelling* **22**(3), 485–502.

Garcia, R. and Perron, P. (1996), 'An analysis of the real interest rate under regime shifts', *The Review of Economics and Statistics* **78**(1), 111–125.

Gârleanu, N. and Pedersen, L. H. (2003), 'Adverse selection and the required return', *The Review of Financial Studies* **17**(3), 643–665.

Glick, R. and Rose, A. K. (2016), 'Currency unions and trade: a post-emu reassessment', *European Economic Review* **87**, 78–91.

Glosten, L. R. and Milgrom, P. R. (1985), 'Bid, ask and transaction prices in a specialist market with heterogeneously informed traders', *Journal of Financial Economics* **14**(1), 71–100.

Goyenko, R. Y., Holden, C. W. and Trzcinka, C. A. (2009), 'Do liquidity measures measure liquidity?', *Journal of Financial Economics* **92**(2), 153–181.

Granger, C. W. (1988), 'Some recent development in a concept of causality', *Journal of econometrics* **39**(1-2), 199–211.

Guidolin, M. (2011*a*), *Markov Switching in Portfolio Choice and Asset Pricing Models: A Survey*, Vol. 27 Part 2, Emerald Group Publishing Limited, pp. 87–178.

Guidolin, M. (2011*b*), *Markov Switching Models in Empirical Finance*, Vol. 27 Part 2, Emerald Group Publishing Limited, pp. 1–86.

Hamao, Y., Masulis, R. W. and Ng, V. (1990), 'Correlations in price changes and volatility across international stock markets', *The Review of Financial Studies* **3**(2), 281–307.

Hamilton, J. D. (1989), 'A new approach to the economic analysis of nonstationary time series and the business cycle', *Econometrica* **57**(2), 357–384.

Ince, O. S. and Porter, R. B. (2006), 'Individual equity return data from thomson datastream: Handle with care', *Journal of Financial Research* **29**(4), 463–479.

Kim, C.-J., Nelson, C. R. and Startz, R. (1998), 'Testing for mean reversion in heteroskedastic data based on gibbs-sampling-augmented randomization', *Journal of Empirical Finance* **5**(2), 131–154.

King, M. A. and Wadhwani, S. (1990), 'Transmission of volatility between stock markets', *The Review of Financial Studies* **3**(1), 5–33.

Koop, G., Pesaran, M. H. and Potter, S. M. (1996), 'Impulse response analysis in nonlinear multivariate models', *Journal of econometrics* **74**(1), 119–147.

Korajczyk, R. A. and Sadka, R. (2008), 'Pricing the commonality across alternative measures of liquidity', *Journal of Financial Economics* **87**(1), 45–72.

Kyle, A. S. (1985), 'Continuous auctions and insider trading', *Econometrica* **53**(6), 1315–1335.

Lee, K.-H. (2011), 'The world price of liquidity risk', *Journal of Financial Economics* **99**(1), 136–161.

Lee, S. B. and Kim, K. J. (1993), 'Does the october 1987 crash strengthen the co-movements among national stock markets?', *Review of Financial Economics* **3**(1), 89.

Longstaff, F. A. (2010), 'The subprime credit crisis and contagion in financial markets', *Journal of financial economics* **97**(3), 436–450.

Mollah, S., Quoreshi, A. S. and Zafirov, G. (2016), 'Equity market contagion during global financial and eurozone crises: Evidence from a dynamic correlation analysis', *Journal of International Financial Markets, Institutions and Money* **41**, 151–167.

Perron, P. (1997), 'L'estimation de modeles avec changements structurels multiples. (with english summary.)', *L'Actualite Economique/Revue D'Analyse Economique* **73**(1-2-3), 457–505.

Pesaran, H. H. and Shin, Y. (1998), 'Generalized impulse response analysis in linear multivariate models', *Economics letters* **58**(1), 17–29.

Roll, R. (1988), 'The international crash of october 1987', *Financial Analysts Journal* **44**(5), 19–35.

Sadka, R. (2006), 'Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk', *Journal of Financial Economics* **80**(2), 309–349.

Smimou, K. and Khallouli, W. (2015), 'On the intensity of liquidity spillovers in the eurozone', *International Review of Financial Analysis* .

Syllignakis, M. N. and Kouretas, G. P. (2011), 'Markov-switching regimes and the monetary model of exchange rate determination: evidence from the central and eastern european markets', *Journal of International Financial Markets, Institutions and Money* **21**(5), 707–723.

Watanabe, A. and Watanabe, M. (2008), 'Time-varying liquidity risk and the cross section of stock returns', *The Review of Financial Studies* **21**(6), 2449–2486.

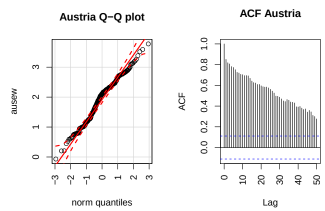
7 Appendix

7.1 Appendix 1

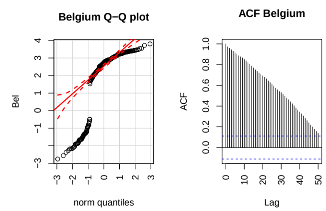
In this section we report the diagnostic tests for the residuals of the AR(1) process estimated using equation 4. For each AR(1) estimation on the time-series of log illiquidity, figure 6 shows the quantile-quantile plot and the autocorrelation function of the residuals. The diagnostics plots for the residuals show that they does not seem to be white noise and that they have autocorrelation for each market in the sample. Together with the evidence of non-stationarity and presence of structural breaks, these empirics support the non-linearity of illiquidity time-series.

Figure 6: AR(1) Diagnostics

(a) Austria



(b) Belgium



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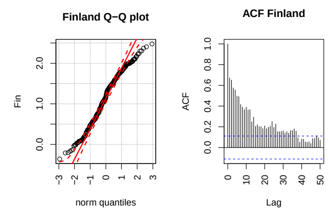
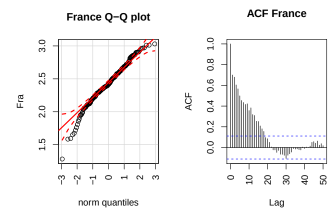
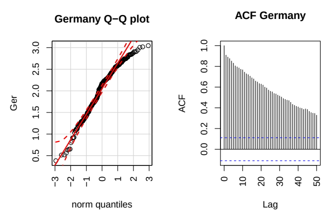


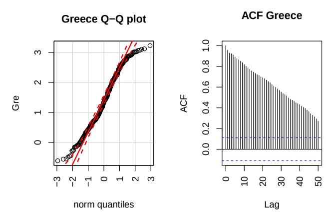
(d) France



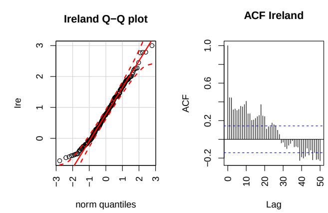
(e) Germany



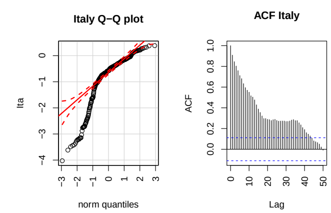
(f) Greece



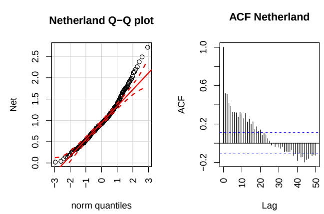
(g) Ireland



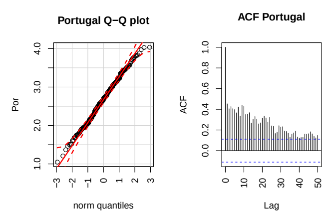
(h) Italy



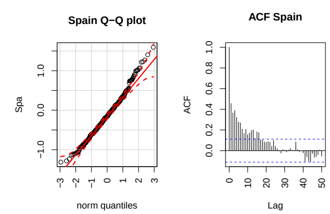
(i) Netherland



(j) Portugal



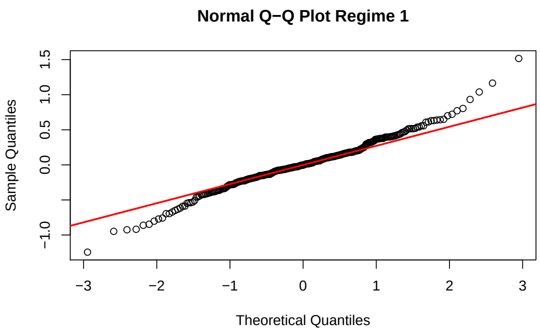
(k) Spain



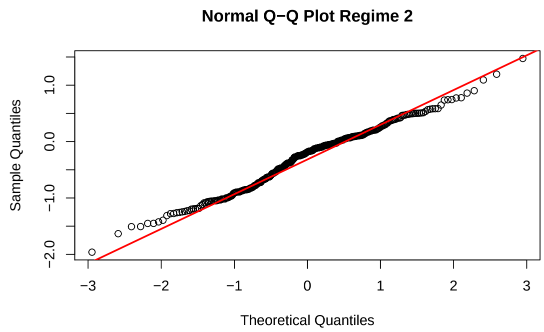
7.2 Appendix 2

Figure 7: Diagnostics on Residuals

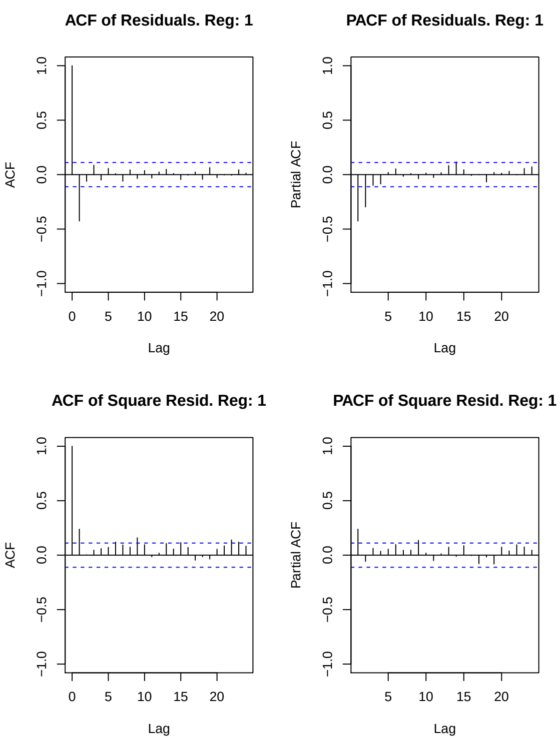
(a) Austria regime 1



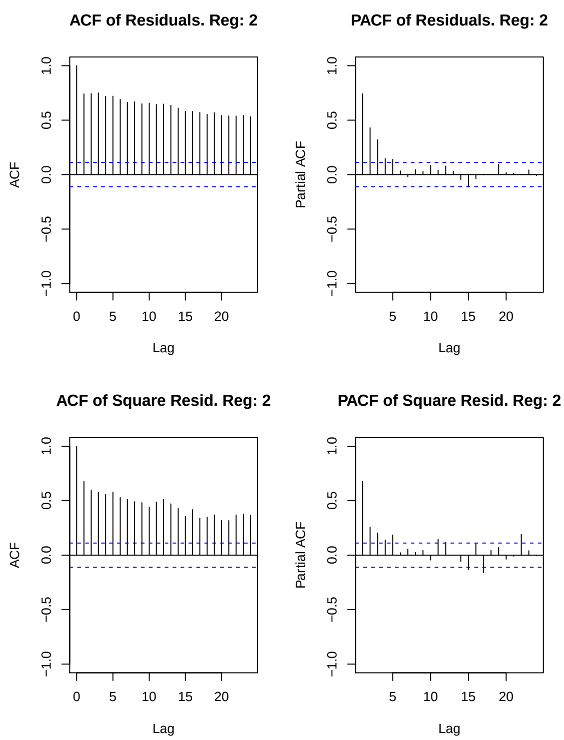
(b) Austria regime 2

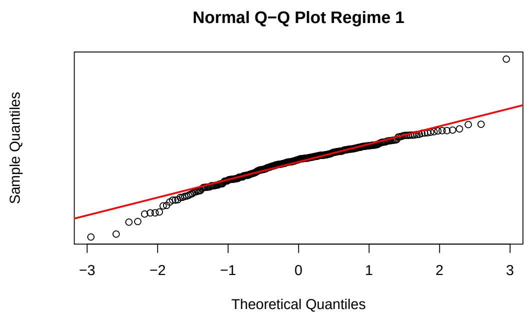


(c) Autocorrelation regime 1

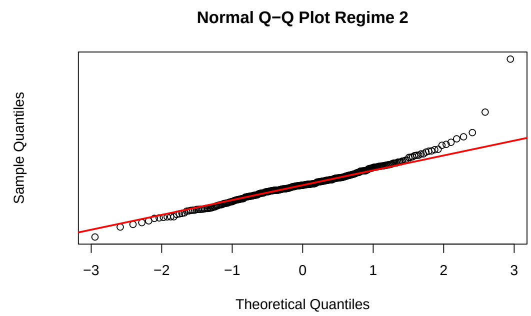


(d) Autocorrelation regime 2

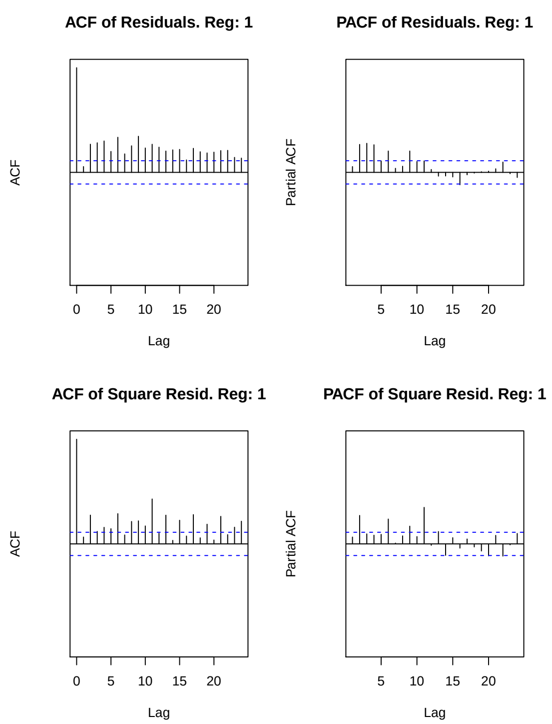




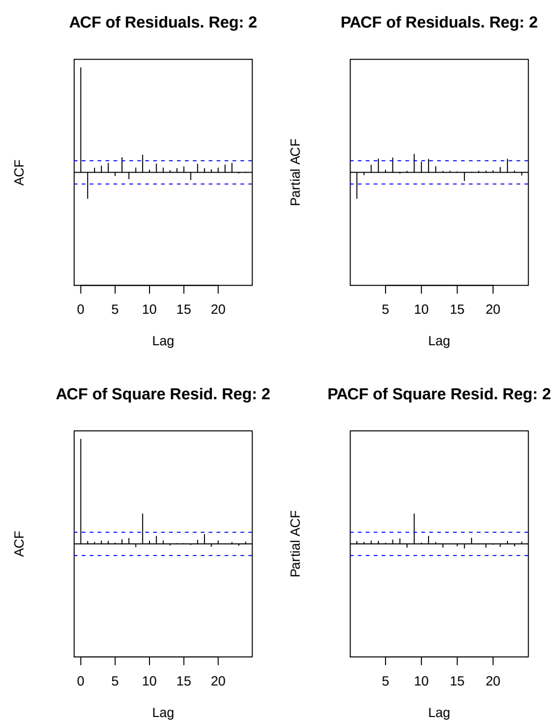
(e) Belgium regime 1



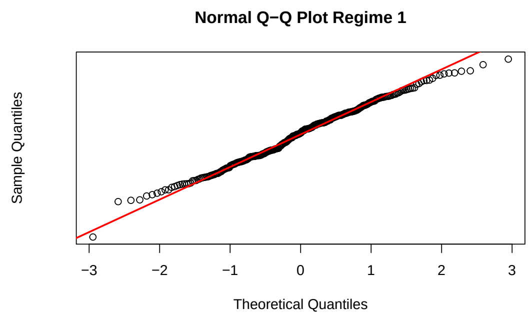
(f) Belgium regime 2



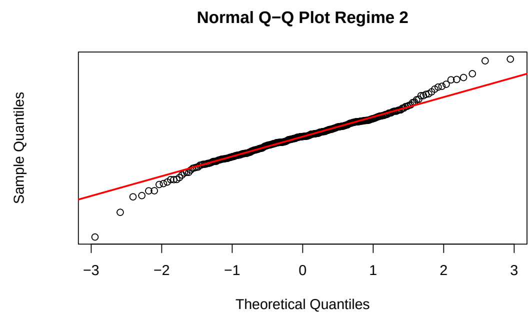
(g) Autocorrelation regime 1



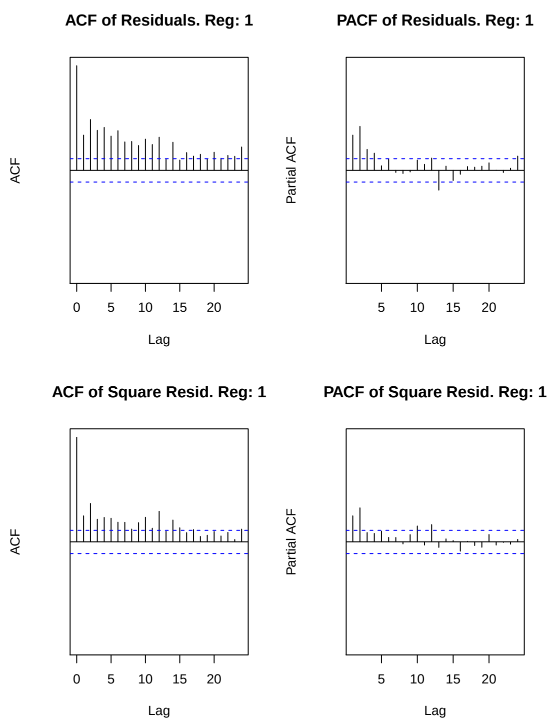
(h) Autocorrelation regime 2



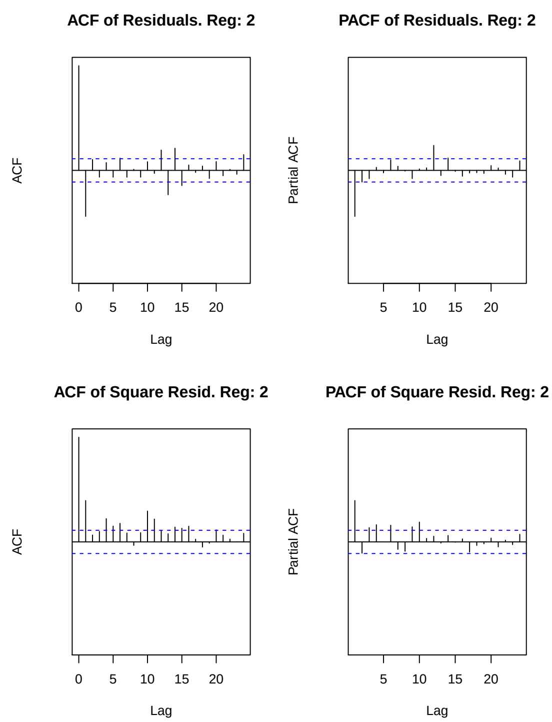
(i) Finland regime 1



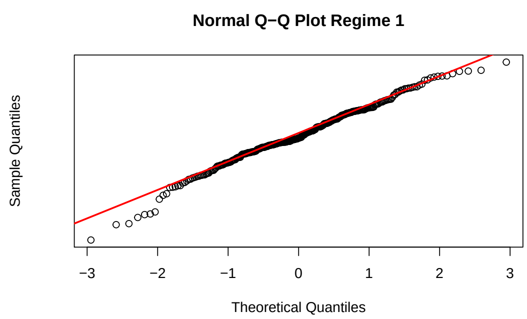
(j) Finland regime 2



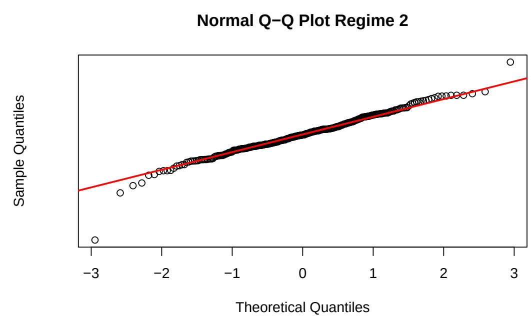
(k) Autocorrelation regime 1



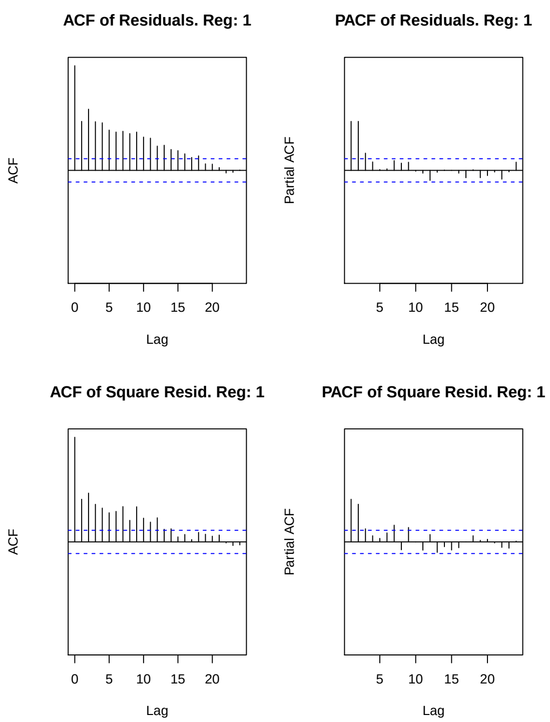
(l) Autocorrelation regime 2



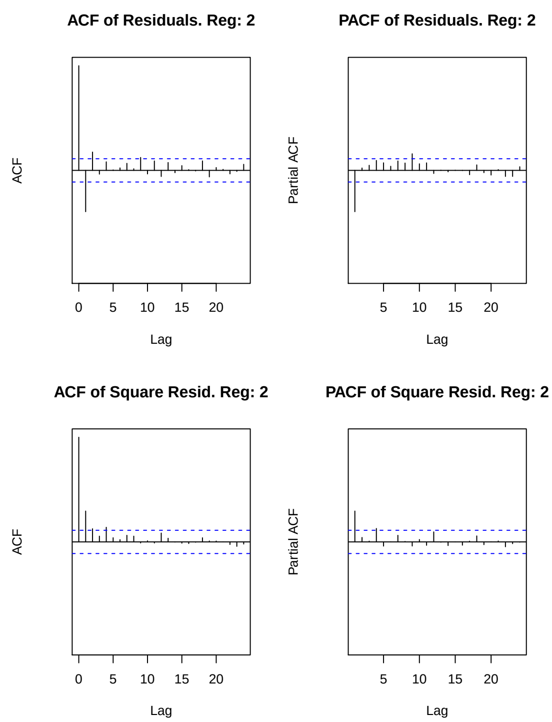
(m) France regime 1



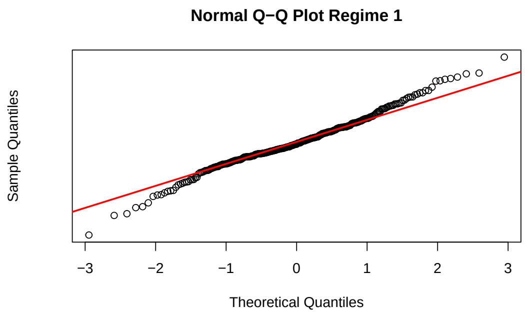
(n) France regime 2



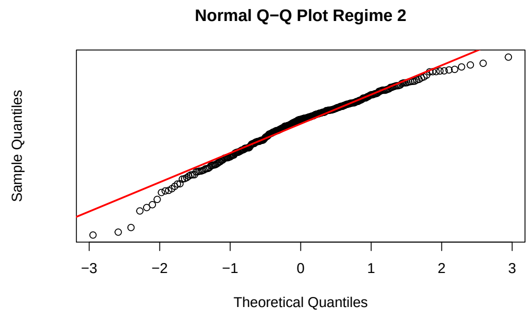
(o) Autocorrelation regime 1



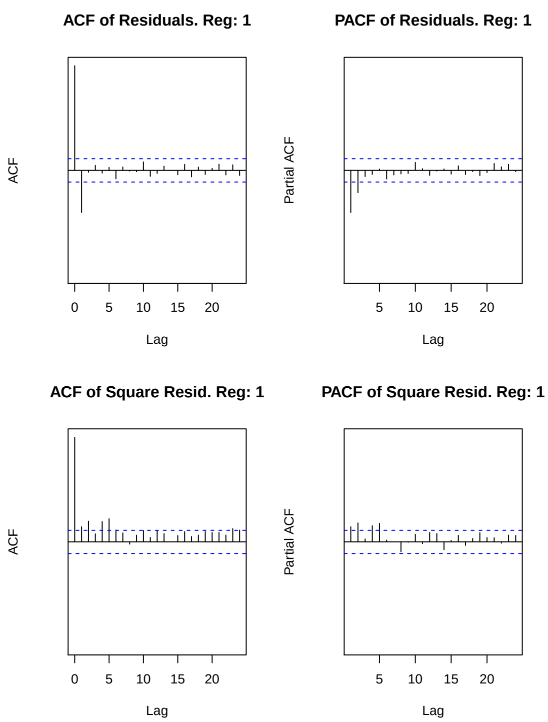
(p) Autocorrelation regime 2



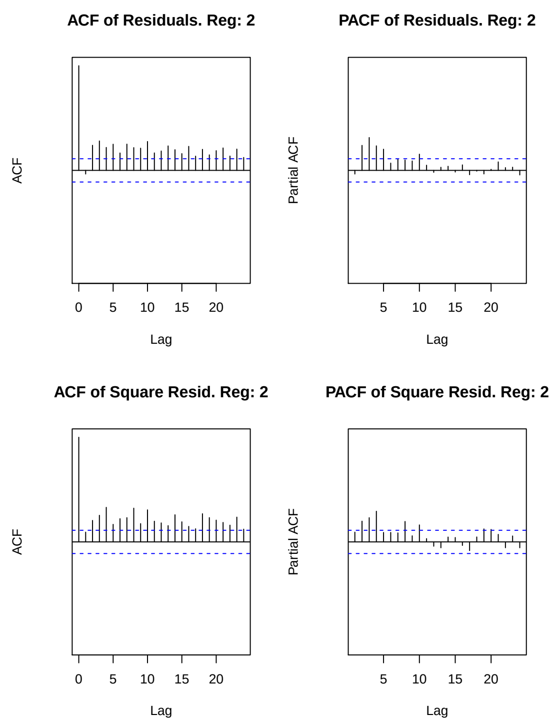
(q) Germany regime 1



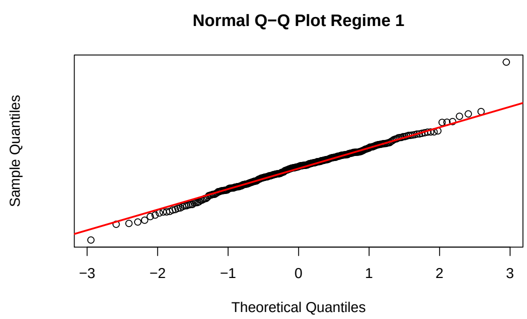
(r) Germany regime 2



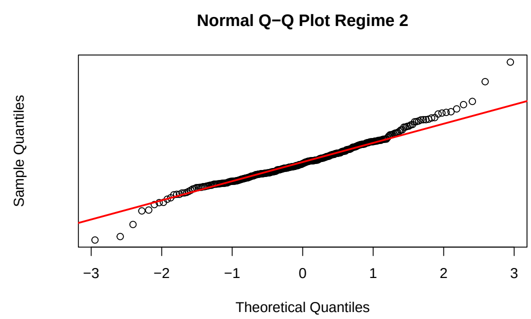
(s) Autocorrelation regime 1



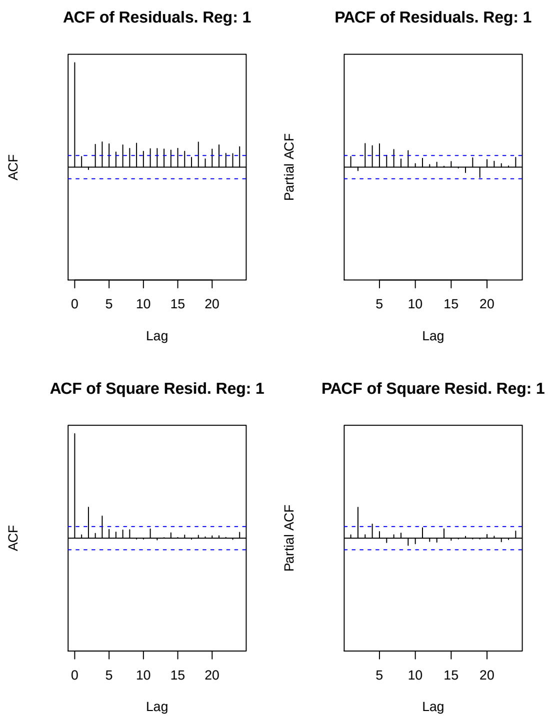
(t) Autocorrelation regime 2



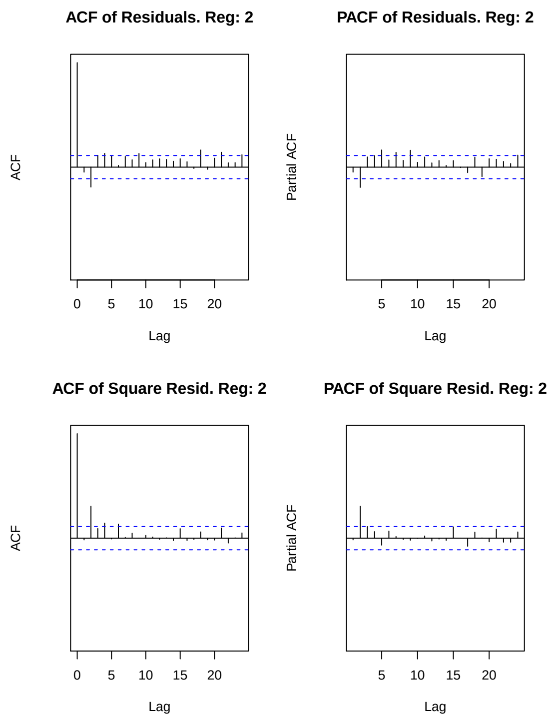
(u) Greece regime 1



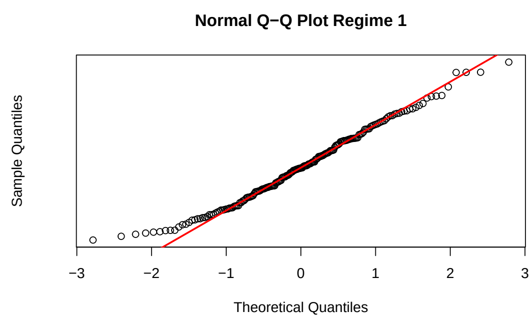
(v) Greece regime 2



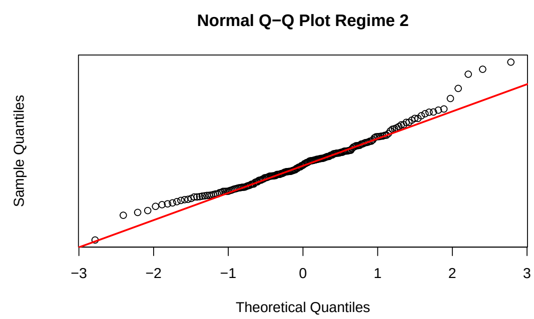
(w) Autocorrelation regime 1



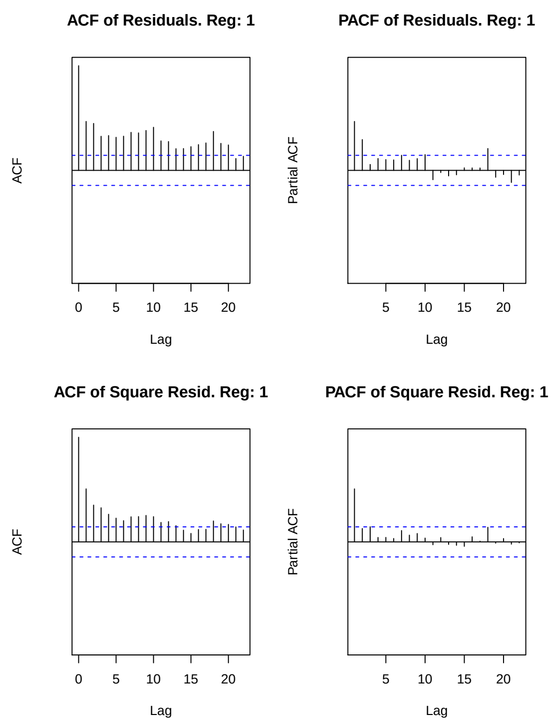
(x) Autocorrelation regime 2



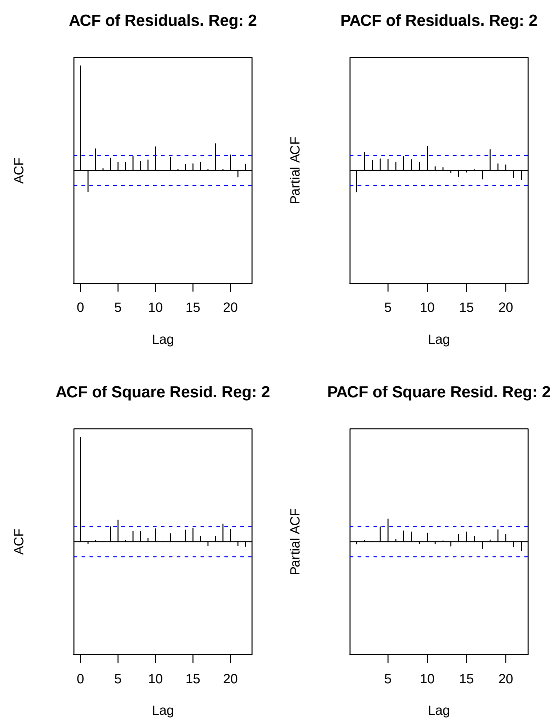
(y) Ireland regime 1



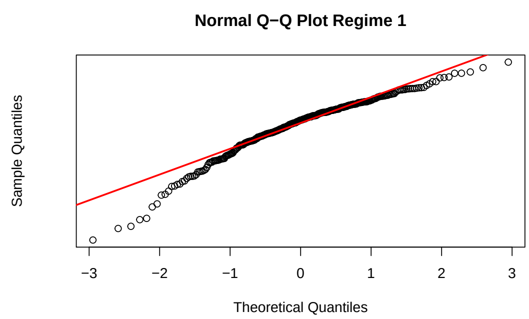
(z) Ireland regime 2



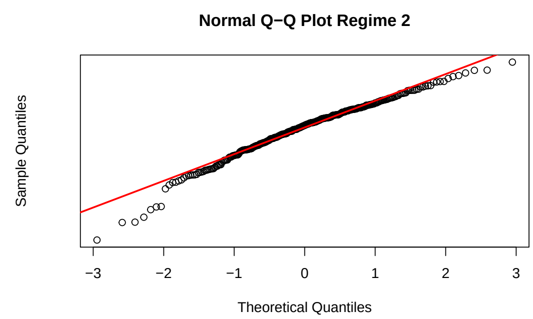
() Autocorrelation regime 1



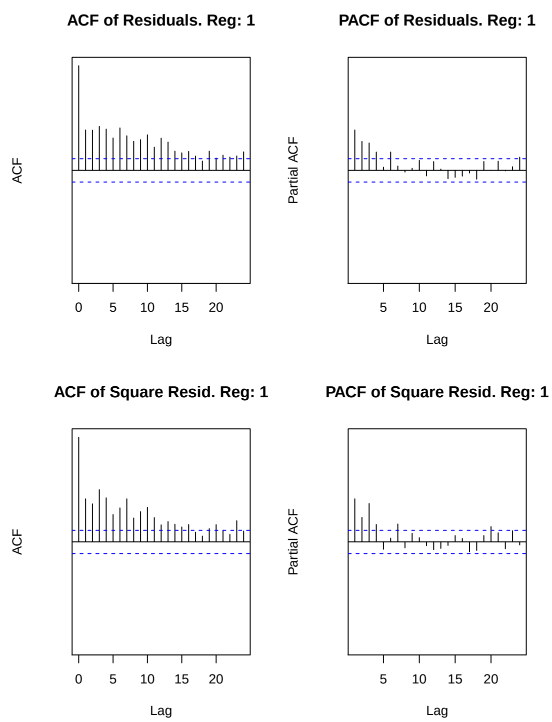
() Autocorrelation regime 2



() Italy regime 1



() Italy regime 2



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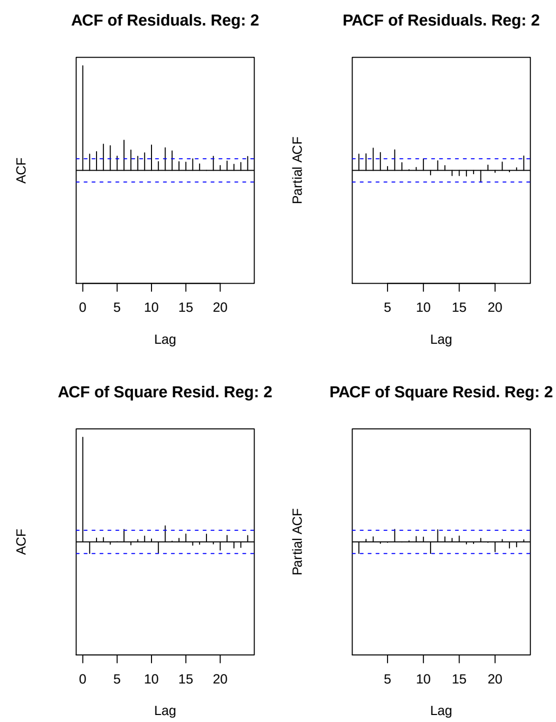

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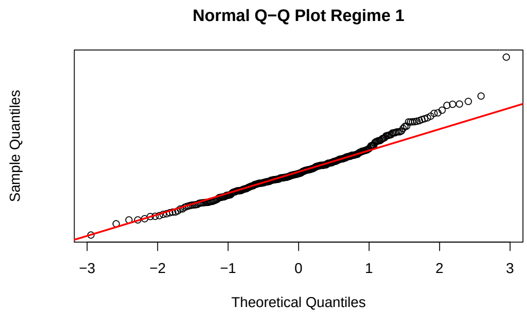
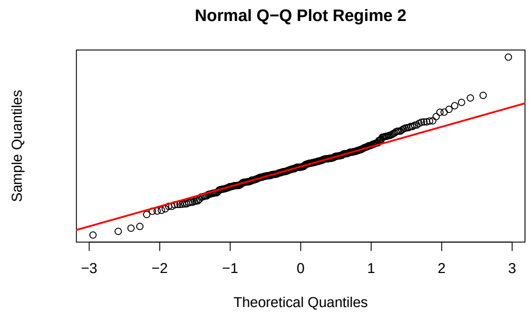


() Netherland regime 1



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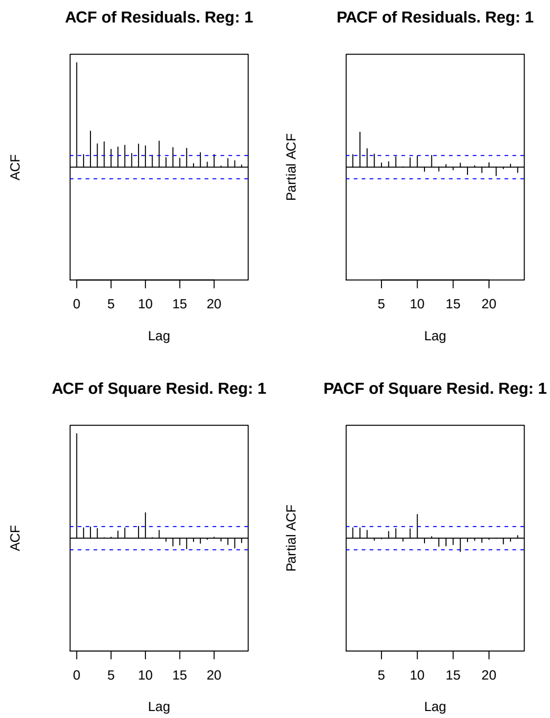
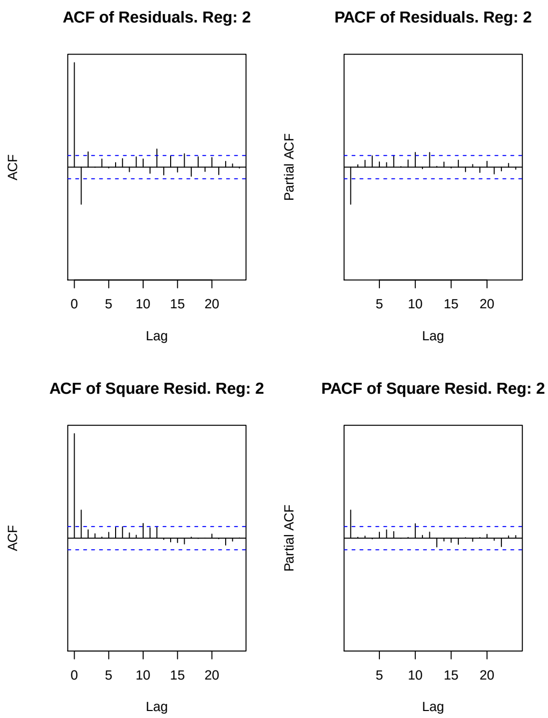
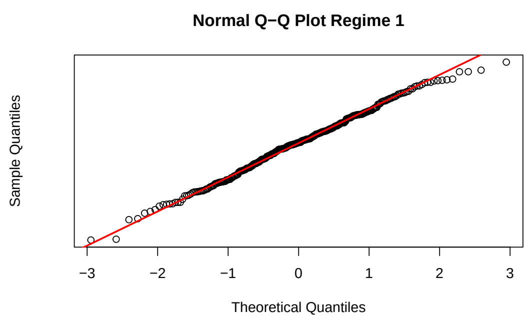


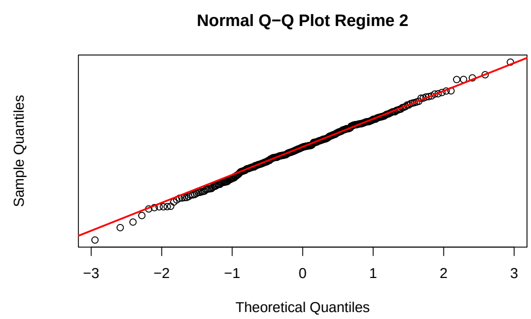
() Autocorrelation regime 1



() Autocorrelation regime 2



() Portugal regime 1



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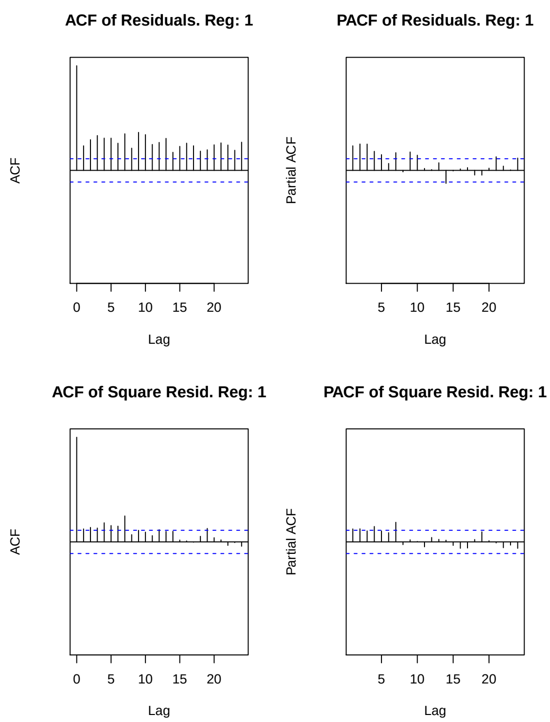
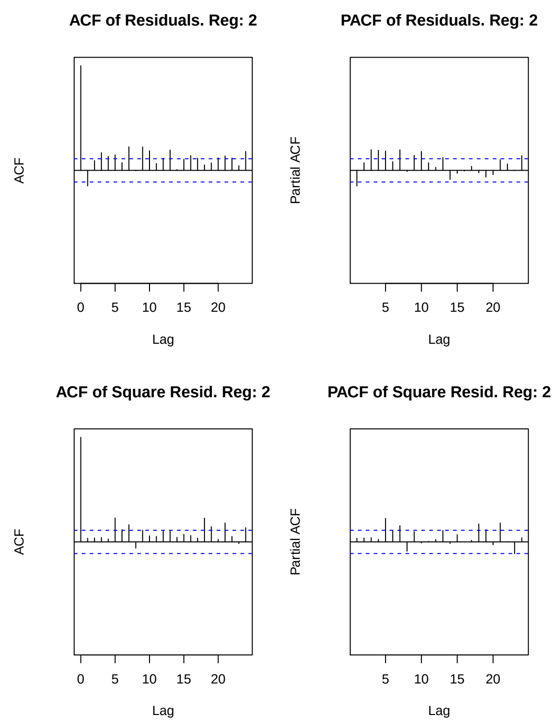
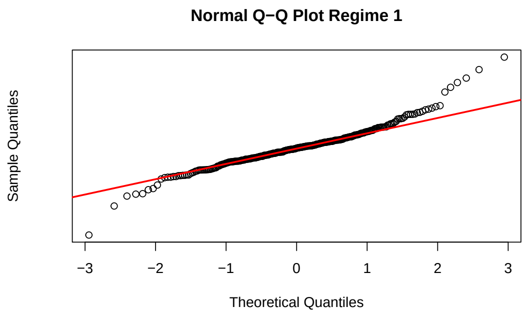


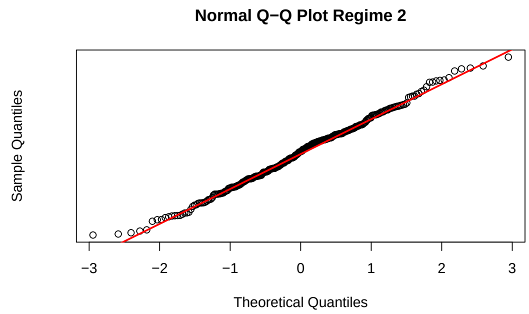
() Autocorrelation regime 1



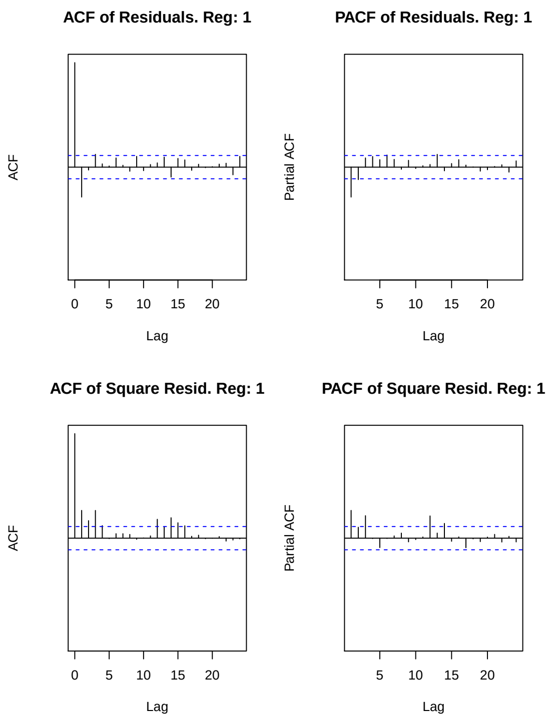
() Autocorrelation regime 2



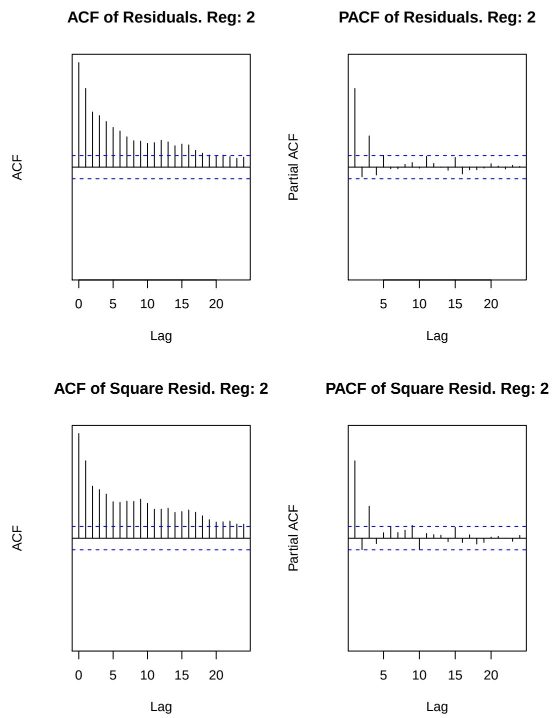
() Spain regime 1



() Spain regime 2



() Autocorrelation regime 1



() Autocorrelation regime 2

7.3 Appendix 3

This appendix reports the results obtained with the volume-weighted averages of individual illiquidity measures. The volume-weighted monthly average is calculated firstly calculating daily volume-weighted averages for each stock and then averaging across each month and for all the stock in the market. Monthly averages are multiplied by 100. Algebraically:

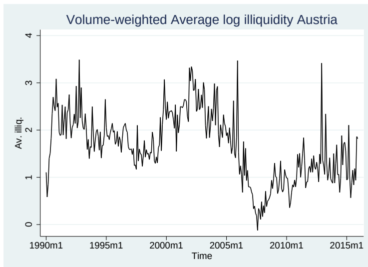
$$\text{Volume-weighted average: } VAILLIQ_{s,m} = \frac{1}{N_m}\sum_{t=1}^{N_m} ILLIQ_{i,m} * \frac{VOLD_{i,m}}{VOLD_{s,m}} \tag{15}$$

As a robustness test, we report the estimation obtained with the AR(1) process, which show results consistently similar to those reported in table 6 with equally-weighted averages. Figure -2 shows the behaviour of market illiquidity over time for the 11 markets under considerations. Although the plots appear slightly different from those reported in figure 1, the graphical evidence of multiple regimes is still very clear.

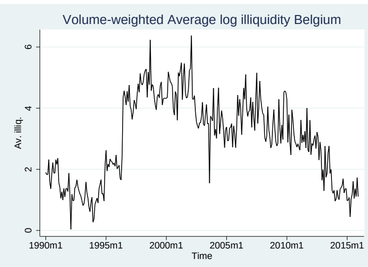
x

Figure -2: Volume-weighted market illiquidity

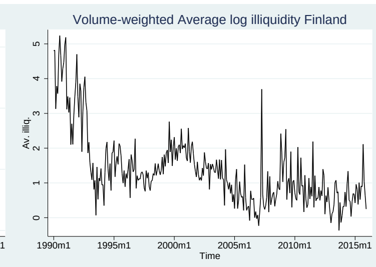
(a) Austria



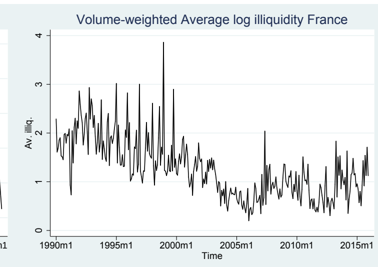
(b) Belgium



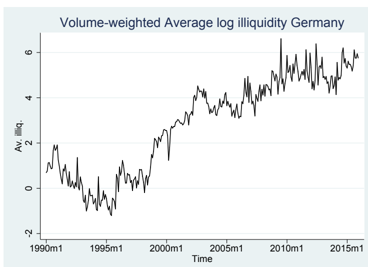
(c) Finland



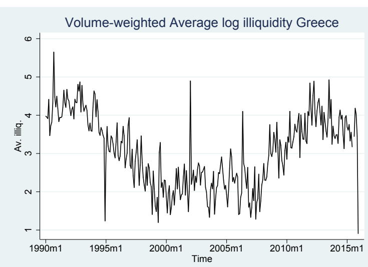
(d) France



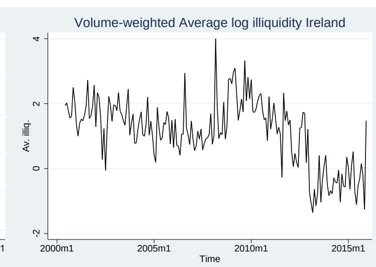
(e) Germany



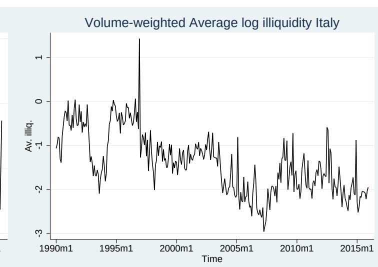
(f) Greece



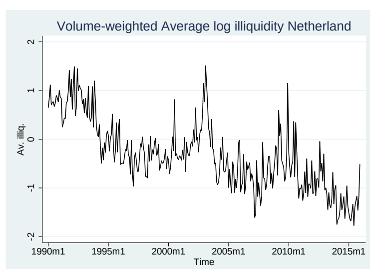
(g) Ireland



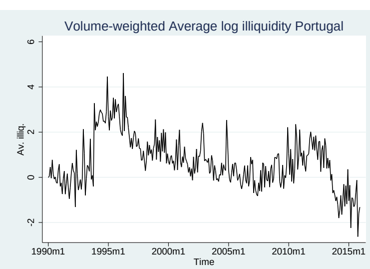
(h) Italy



(i) Netherland



(j) Portugal



(k) Spain

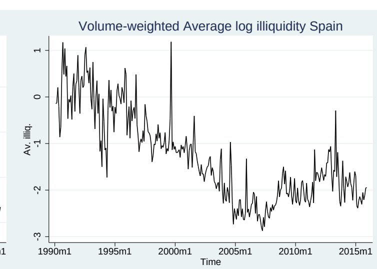


Table 11: Illiquidity persistency with AR(1) processes

The table shows results from a AR(1) process for each country in the sample of the ln of the volume-weighted averages of individual illiquidity measures, $AILLIQ_{s,m} = c_0 + c_1 AILLIQ_{s,m-1} + v_m$, where c_0 and c_1 represent the coefficients and v_m is the residual. Intercepts and autoregressive coefficients with their relative t-stats are reported in the first two columns of the table, together with the R^2 of the regression and the Akaike information criterion (AIC) in the third and fourth columns.

	constant	*coeff. AR(1)*	R^2	*AIC*
Austria	0.355***	0.788***	0.622	230.8
	(5.612)	(22.552)		
Belgium	0.284***	0.905***	0.815	232.4
	(3.513)	(36.899)		
Finland	0.28***	0.787***	0.639	406.1
	(4.792)	(23.363)		
France	0.459***	0.635***	0.407	-186.3
	(7.474)	(14.568)		
Germany	0.085	0.976***	0.948	-41.87
	(1.886)	(75.713)		
Greece	0.586***	0.806***	0.640	2.389
	(5.318)	(23.454)		
Ireland	0.332***	0.703***	0.495	411.1
	(4.184)	(13.434)		
Italy	-0.238***	0.830***	0.689	189.8
	(-4.835)	(26.148)		
Netherland	-0.061*	0.821***	0.678	295.4
	(-2.40)	(25.49)		
Portugal	0.169***	0.752***	0.561	459.4
	(3.362)	(19.852)		
Spain	-0.152***	0.886***	0.787	400.9
	(-3.632)	(33.691)		