Time Varying Illiquidity of European Corporate Bonds

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Abstract

We study excess returns and liquidity of 17 European corporate bond indices during 2000-2014 using a threshold regime switching model. A genetic algorithm was employed to select the model variables and regime thresholds. The results identify changes in realized stock volatility as the best transition variable. In a regime with low volatility, illiquidity levels and shocks are mostly insignificant. In a stress regime with increasing volatility, illiquidity bares the most significant impact on bond index returns. We report significant differences in the illiquidity effects across bond indices for different maturities, ratings and industries.

Keywords: *Liquidity, European corporate bond indices, Threshold regime switching models, Genetic algorithms*

JEL classification: *C51, G01, G12, G32*

EFM classification: 340 (Fixed income); 140 (Capital structure).

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1. Introduction

There is growing evidence that expected returns and investors' risk attitudes tend to vary over time depending on the state of the economy. The above idea is, for example, empirically examined in bond literature utilizing different approaches such as: GARCH models (Chan and Wu, 1995), Gaussian models (Ang and Piazzesi, 2003), Markov regime-switching models (Guidolin and Timmermann, 2006), and smooth transition regression (STR) models (Lekkos and Milas, 2004; Chen and Maringer, 2011). The conditional pricing of liquidity risk in the bond market has also been documented more recently in the context of the recent financial crisis (Acharya et al., 2013; Friewald et al., 2012; Dick-Nielsen et al., 2012). The above studies, however, tend to focus on US government and corporate bonds.

Some recent US studies on corporate bond liquidity utilize TRACE data on corporate bond transactions (Mahanti et al., 2008; Jankowitsch et al., 2011; Dick-Nielsen et al., 2012; Bao et al., 2011; Friewald et al., 2012). Others are based on quotation data obtained from Bloomberg and Datastream (Chen et al., 2007) or the Lehman Brothers Fixed Income Database (Elton et al., 2001; Gebhardt et al., 2005; Acharya et al., 2013). All of the above mentioned US studies find the existence of a liquidity premium.

In this paper, we examine time-variation in excess returns and liquidity of 17 Euro denominated iBoxx bond indices from January 2000 to December 2014. The liquidity of the European corporate bond market is especially important given the phenomenal growth in recent years. The recent financial crisis and downturn in the European stock market contributed to expansion of the European bond market. Since 2009, the European bond market has acted as a lifeline for companies facing lending cuts from Eurozone banks. Estimates suggest that the European bond market provided 415 billion Euros of new lending to companies during the same period of time.[1] Increased corporate bond holdings by mutual funds together with the development of bond Exchange Traded Funds (ETFs) provided further impetus for growth of the European bond market. At the same time, recent regulatory changes in banking have increased the inventory holding costs, thus, raising illiquidity concerns.

[1] Financial Times, 18th November 2015.

Previous studies that examine samples consisting of individual European corporate bonds (Houweling et al., 2005; Galliani et al. 2014) echoed the results reported in studies on US bonds.[2] De Jong and Driessen (2012) and Aussenegg et al. (2015) are the only studies that examine European corporate bond indices.[3] De Jong and Driessen (2012) analyze Lehman Brothers Euro bond indices during August 2000 and December 2004. They consider liquidity risks originated from the equity market (measured by Amihud measure) and from the Treasury bond market (proxied by monthly changes in the bid-ask spread of long term US treasury bonds). The authors report that liquidity is priced in both US and European corporate bond yields. Aussenegg et al. (2015) examine 23 Euro-denominated iBoxx corporate bond indices from September 2003 to February 2011. The authors separated the level and slope components of term and default risk factors, and demonstrate different sensitivities of the risk factors before and after the recent financial crisis. The illiquidity factor, measured by the difference between the 6 months Euribor rate and the Euro Overnight Index Average (OIS) was found to be important only for short term bond indices, especially during the crisis.

Most related to our work are studies by Chen and Maringer (2011) and Acharya et al. (2013). The work of Chen and Maringer (2011) was the only previous study to examine time-varying corporate bond index returns within a Smooth Transition Regression (STR) model. They detected time variation in expected returns for high-grade US bond indices. The regime switching was mainly driven by the 3-quartered growth of industrial production. Acharya et al. (2013) investigate the exposure of US corporate bond returns to liquidity shocks of short term Treasury bonds and stocks over the period from 1973 to 2007. The results of a Markov regime-switching (MS) model suggest that the pricing of liquidity risk is conditional on the state of the economy. Consistent with episodes of flight-to-liquidity, returns on low rated bonds respond negatively to illiquidity whilst returns on investment grade bond respond positively during the "stress" regime.

Our research in this paper differs from prior papers in several ways. First, very little has been published on the comparison of different models that try to detect time-varying asset returns in a non-linear framework (see Chen and Maringer, 2011). For example, MS models attempt to identify, for each state, a conditional probability for remaining in that state or switching to another one and

[2] Houweling et al. (2005) examined a sample of 1,190 corporate bonds during 1999-2001. The data was obtained from combined sources (Lehman Brothers, Bloomberg, and Reuters 3000 Xtra). Authors use the following indirect liquidity proxies based on (individual) bond characteristics such as amount issued, yield volatility, and yield dispersion, etc. Galliani et al. (2014) examine 1,521 corporate and covered bonds during 2005 to 2012. The sample was taken from Bloomberg. They measure corporate bond liquidity with bid-ask spread, effective tick, LOT, the Roll measure and trade volume. They also use a composite measure based on Principal Component (PC) analysis.

[3] It is important to note that both studies were conducted in a linear setting.

then assign the individual observations based on what appears most likely (see Acharya et al., 2013). This approach is suitable whenever states or changes of regimes cannot be observed directly and when there is sound reason to believe that the likelihood of a state of a period depends on the state of the preceding period. These models are, therefore, popular when identifying structural breaks. However, by design, they offer little insights on factors driving regime changes. It is, however, plausible that the state depends on some observable external (i.e. market) events or conditions (e.g. market volatility or economic growth) which are then reflected in the state-indicator. The above scenario can be modelled through a Threshold regime switching (TS) model in which the transition mechanism is driven by observable state variables, and the transition between the regimes is abrupt at a threshold identified by the optimization procedure. We therefore develop a TS model with various candidate transition variables and a Genetic Algorithm (GA) that enables us to identify the most suitable factors that govern regime switches.[4] We make a further methodological contribution by addressing model over-fitting by using the Bayesian Information Criteria *(BIC).* By design, TS models link the different regimes directly to an observable variable as an integral part of the estimation process. This is particularly advantageous if one has prior assumptions about what distinguishes different effects, if the immediate effects of certain control variables are to be tested, or if one wants to isolate the effect of this particular variable on different regimes.

Second, we examine time-varying returns and liquidity of European corporate bond indices in a non-linear framework. A separate examination of the time-varying returns of different European bond indices is important since the cross-sectional effects of non-linearity on asset returns in large portfolios have been far less studied than the effects on one single risky asset (Ang and Timmermann, 2011). This is surprising given that, for example, individual assets and industry portfolios may differ in terms of their sensitivity and exposure to liquidity factors and regime changes.

Third, we measure liquidity risk at corporate bond level and then create aggregate measures of both illiquidity (level) and illiquidity risk for the respective bond indices. Previous related studies employ only corporate bond illiquidity risk measured by the bid-ask spread of US treasury bonds (e.g. Acharya et al., 2013) or do not consider an illiquidity risk factor (e.g. Chen and Maringer, 2011).

4 GA is the most popular type of Evolutionary Algorithms. They are efficient stochastic search techniques for solving complex optimization and search problems through a natural selection process that mimics natural selection (see Sastry et al., 2005).

Fourth, the availability of different iBoxx indices allows us to examine the systematic components of liquidity in portfolios constructed for different industries, which has not been done before.[5] Popularity of bond ETFs further highlights the importance of differences between underlying corporate bond indices. For example, there are notable differences between US and Euro dominated bond indices related to their construction and their suitability to provide benchmarks for various passive investment strategies (Brown, 2002; Goltz and Campani, 2011). A better understanding of the differences between alternative bond indices is, therefore, very important for retail investors, portfolio managers and regulators.

We identify changes in realized stock volatility as the best transition variable. In a regime with low volatility, illiquidity levels and shocks are mostly insignificant. In a stress regime with increasing volatility, illiquidity bares the most significant impact on bond index returns. We find significant differences in the illiquidity effects across bond indices for different maturities, ratings and industries. The reminder of this paper proceeds as follows. Section 2 reviews the relevant literature and motivates hypotheses. Section 3 describes the main characteristics of our data and the sample. Section 4 presents the methodology. The results are presented in section 5. Section 6 concludes the paper.

2. Literature review and hypotheses

A theoretical explanation for liquidity effects on asset prices is provided in Amihud and Mendelson (1986). The explanation is based on different expected returns (taking into account transaction costs over trading horizons) of investors with different trading horizons. Due to different expected returns, investors with longer horizons tend to hold more illiquid (and cheaper) assets compared to investors with shorter horizons. The negative association of illiquidity and contemporaneous returns is also in line with Acharya and Pedersen (2005). The authors suggest that in periods of a persistent illiquidity (i.e. negative liquidity shocks) contemporaneous returns tend to be lower whilst predicted future returns are higher. The negative liquidity shocks create additional demand (resulting in higher prices) for liquid assets and trigger flights to liquidity.

[5] For example, Dick-Nielsen et al. (2012) only compare finance and industrial sectors.

Previous US studies (Elton et al., 2001; Gebhardt et al., 2005; Chen et al., 2007; Mahanti et al., 2008; Jankowitsch et al., 2011; Dick-Nielsen et al., 2012; Bao et al., 2011; Friewald et al., 2012; Acharya et al., 2013) and European studies (Houweling et al., 2005; Galliani et al., 2014; De Jong and Driessen, 2012); Aussenegg et al., 2015) document the existence of a liquidity premium in bond markets. We, therefore, expect to detect a significant liquidity premium in our sample of European corporate bond indices. Thus,

H1: Illiquidity is negatively related to contemporaneous returns on European corporate bond indices.

The recent financial crisis resulted in an unprecedented liquidity shock in the European market. We expect that during the crisis investors' risk perceptions changed and consequently increased the demand for more liquid bonds, thus, resulting in a stronger liquidity effect. The motivation for this hypothesis is provided in Acharya and Pedersen (2005) and Brunnermeier and Pederson (2009). For example, Brunnermeier and Pederson's model predicts that market liquidity can suddenly dry up, is subject to "flight to quality", has commonality across securities, and co-moves with the market. Their model also predicts that volatility (measured by VIX) is one of state variables affecting market liquidity and risk premia.

Acharya et al. (2013) provide further empirical support for this hypothesis by examining the exposure of US corporate bond returns to liquidity shocks of short term US Treasury bonds and stocks within a Markov regime switching model. Similarly, Friewald et al. (2012) report the larger economic impact of a wide range of liquidity measures in periods of financial crisis. The authors also report that liquidity effects account for approximately 14% of explained corporate yield spread changes. Duffie et al. (2007) discuss the stronger effect of liquidity during crisis periods due to higher inventory holding costs and higher information asymmetry. Thus,

H2: The pricing of liquidity risk in the European corporate bond market is time-varying.

We are able to examine the interaction of bond rating and liquidity by comparing the results for European corporate bond indices with different credit ratings. Based on the results of previous studies (see Acharya et al., 2013; Chen et al., 2007; Friewald et al., 2012; Dick-Nielsen et al., 2012) we expect a significantly larger impact of illiquidity on bond indices with lower credit ratings. This hypothesis is in line with a flight-to-quality effect which results in a lower price reaction for highly rated bonds during the crisis. Thus, *H3: Liquidity effects are significantly larger in European corporate bond indices with lower credit ratings.*

We also expect a larger impact of illiquidity on bonds with greater duration (i.e. long-term bonds) due to their greater price elasticity (Acharya et al., 2013). Furthermore, long-term bonds tend to be less liquid compared to their short term counterparts, which further contributes to their higher sensitivity to liquidity shocks (Chen et al., 2007). Thus,

H4: Liquidity effects are significantly larger in European corporate bond indices with longer maturities.

Longstaff et al. (2005) report that bonds issued by US financial firms are more illiquid compared to bonds issued by their industrial counterparts. Friewald et al. (2012) however report no systematic liquidity difference between financial and industrial bonds. Dick-Nielsen et al. (2012) examine liquidity of US corporate bonds before and after the onset of the recent financial crisis. They find that bonds issued by financial firms tend to be more illiquid than industrial corporate bonds only during the financial crisis. In other periods, the differences in liquidity between financial and industrial bonds are not significant. Dick-Nielsen et al. (2012) explain these differences in liquidity by heightened information asymmetry regarding the state of financial firms during the crisis. Interestingly, when calculating the monthly averages of their composite illiquidity measures over longer periods of time the reported differences disappear. The above results highlight the importance of examining how liquidity affects different segments of the corporate bond market in times of financial crisis. Our sample includes corporate bond indices for 6 non-financial industry sectors, thus, allowing us to examine in more detail potential differences across industries that were not examined in previous studies.[6] Thus we expect differences in illiquidity effects in different European bond indices:

H5: Liquidity effects vary significantly across European corporate bond industry indices.

[6] Aussenegg et al. (2014) report a significant increase in levels, volatility, and diversity of Asset Swap Spreads (ASW) for 10 iBoxx industry indices (automobile and parts, chemicals, food and beverages, health care, oil and gas, personal and household goods, retail, telecommunications, utility, and banks) and composite indices stratified by industry grouping (Corporates, Financials, Non-Financials), during the financial crisis.

3. Data and sample description

Our main data source is the Markit iBoxx fixed income database. From the database we extract daily returns for 17 iBoxx corporate bond indices from 1st January 2000 to 31st December 2014. Our sample encompasses one composite index representing the entire European corporate bond market (Composite), two composite indices stratified by industry groupings (i.e. all bonds issued by financial firms and all bonds issued by non-financial firms), six industry indices (Automobiles and Parts, Industrial Goods & Services, Oil and Gas, Retail, Telecommunications, Utilities), three credit rating indices (AA, A, BBB) and five indices for different maturity tenors (1-3; 3-5; 5-7; 7-10; 10+ years).[7]

From the same database, we also collect bond specific characteristics (e.g. duration, rating, coupons, notional amounts, bid-ask prices, dirty prices, accrued interest, asset swap spreads, etc.) for a monthly average of 889 bonds that represent constituents of the respective sample indices during our investigation period.[8] Bonds included in the market capitalisation weighted indices have to be: investment grade rated with fixed coupons, a minimum amount outstanding of at least 500 million Euros and a minimum time to maturity of 1 year. Bonds with embedded options (e.g. sinking funds and amortizing bonds, callable and undated bonds, floating rate notes, convertible bonds, bonds with conversion options, and collateralized debt obligations) are all excluded by Markit from the iBoxx bond indices (Markit, 2010). In Table 1 we provide descriptive statistics for the selected sample of bond indices and their excess returns during our 15 year sample period.

Insert Table 1 about here

Among the six industry sectors the Utility index has the largest number of average constituents and the largest average market value (116 constituents and 105.7 billion Euros, respectively). In contrast, the Retail index is smallest both in terms of number of constituents and market value.

[7] It is worth noting that Markit provides only four credit rating categories: AAA, AA, A and BBB for investment grade bonds and indices. Until 1st January 2008 Markit used the lowest rating from Fitch, Moody's and S&P's to determine a bond's credit rating. From 1st January 2008 Markit's iBoxx investment grade indices use an average rating from the three leading credit rating agencies. The number of AAA rated bonds is very small throughout the sample period (less than 20), and is, therefore, not examined in our study. The relatively small number of AAA European corporate bonds in our sample is in line with samples used in some of previous studies (e.g. Biais et al., 2006).

[8] The number of constituents varies between a minimum number of 134 bonds in January 2000 and a maximum number of 1,544 bonds in December 2014.

Constituents of sample bond indices with the shortest time to maturity and best credit ratings tend to exhibit the highest average market values. Furthermore, constituents of different industry indices vary in terms of time to maturity and modified duration.[9] The average yield to maturity of index constituents ranges from 3.62% (Maturity 1-3 years index) to 4.98% (Maturity 10+ years index).

Monthly excess returns for bond indices are calculated by subtracting the one month EURIBOR rate at the end of the previous month from the corporate bond index total return of month t.[10] Overall the sample consists of 180 monthly excess returns for sample indices from January 2000 to December 2014. The mean (median) monthly excess return is highest for the Maturity 10+ years index (49 (82) basis points p.m.) and lowest for the Maturity 1-3 years index (16 (16) basis points p.m.). Amongst the six industry sector indices the index for Telecommunications exhibits the highest average (mean and median) excess return whilst its counterpart, the Automobiles and Parts industry, exhibits the lowest average (mean and median) returns. Overall, the composite index for the non-financial sector exhibits higher average excess returns compared to the composite index for the financial sector. Furthermore, the average excess returns of the index for BBB rated bonds is higher than that for the AA rated bonds index. Excess returns are highly leptokurtic for all sample indices except for the Utilities index. The skewness of excess returns is generally negative except for the Maturity 1-3 years index. The presence of excess kurtosis and skewness indicates the existence of outliers in our sample. This is expected given the fact that we cover the period of the recent financial crisis and include corporate bonds from different industries, maturities and credit ratings.

4. Methodology

4.1. Liquidity measures

Liquidity is not directly observable so the choice among alternative proxies represents an important topic for both practitioners and academics. Several papers measure liquidity using corporate bond characteristics (e.g. age, amount issued, industry, coupons, etc.) and trading activity proxies (e.g. bid-ask spreads, number of trades, trading volume, number of dealers, etc.) (see Houweling et al., 2005; Collin-Dufresne et al., 2001; Elton et al., 2001). Acharya et al. (2013) and De Jong and Driessen (2012) proxy for corporate bond liquidity risk by using government bonds bid-ask spreads. More recent papers on corporate bond liquidity employ (more direct) measures developed in the

[9] Average time to maturity ranges from 4.03 in the Automobiles and Parts to 6.67 years in the Utilities sector. The average of 5.5 years for the Composite index is in line with the reported average of 6 years in Biais et al. (2006).
[10] The Euribor rates are calculated on a continuous compounded basis.

literature on equity liquidity. The measures are based on transaction costs or price impact. For example, the most frequently used liquidity measures based on transaction costs proxies are: the Roll measure (Roll, 1984; Bao et al. 2011), the LOT measure (Lesmond et al., 1999), and the zero return measure (Lesmond et al., 1999). The best known price impact measure is the Amihud measure (Amihud, 2002).[11] Others include the measure of latent liquidity based on institutional holdings of corporate bonds (Mahanti et al., 2008) and a measure of price dispersion around the consensus market valuation (Jankowitsch et al., 2011).

There is, however, no consensus on how to measure the liquidity of an asset or what is the best liquidity proxy for corporate bonds. We, therefore, adopt two measures widely used in the liquidity literature (see Dick-Nielsen et al., 2012; Friewald et al., 2012; Goyenko et al., 2009, etc.): The Roll measure and the Fraction of trading days with zero return (FZR). FZR is a measure based on trading activities and Roll is a proxy for effective bid-ask spread.

4.1.1. Fraction of zero returns (FZR)

In the first step the fraction of zero returns in each month t is calculated for each constituent bond as:

$$FZR_{i,t} = \frac{NZR_{i,t}}{NTD_t} \tag{1}$$

$FZR_{i,t}$ is the fraction of trading days with zero returns during month t for bond i, $NZR_{i,t}$ is the number of zero return days in month t for bond i, and NTD_t is the number of (available) trading days in month t. A daily return is defined as zero return if it does not exceed the threshold of 0.01 basis points (i.e. 0.001%) in absolute terms.[12]

Daily returns are calculated using clean prices[13]:

$$r_{i,\tau} = \frac{P_{i,\tau} - P_{i,\tau-1}}{P_{i,\tau-1}} \tag{2}$$

[11] Goyenko et al. (2009) examine other transaction costs (i.e. spread) measures in equity market such as the Holden measures of effective tick and spread (Holden, 2009) and the Gibbs measure (Hasbrouck, 2004). Other price impact measures examined in this paper are the Pastor and Stambaugh (Pastor and Stambaugh, 2003) and the Amivest measures (Cooper et al., 1985).

[12] This threshold is used in order to avoid effect of potential rounding errors. We also exclude public holidays and dates when trading takes place only for a few hours on respective European exchanges.

[13] The clean price is the dirty price subtracted by accrued interest. The dirty prices provided by Markit are bid price quotes plus accrued interest. Thus, clean prices are equal to bid price quotes.

$r_{i,t}$ is the return of bond i on trading day τ and $P_{i,\tau}$ is the clean price of bond i on (trading) day τ.

In a second step, FZR is calculated for various bond indices by aggregating FZRs of constituent bonds in respective indices:

$$FZR_{k,t} = \sum_{i=1}^{n}\left(FZR_{i,t}\frac{MCap_{i,t}}{\sum_{i=1}^{n} MCap_{i,t}}\right) \tag{3}$$

$FZR_{k,t}$ is the fraction of trading days with zero returns for bond index k during month t and n is the number of bonds comprised in bond index k in month t. Thus, $FZR_{k,t}$ equals the market value weighted average fraction zero returns of all individual constituent bonds i. $MCap_{i,t}$ is the market value of bond i on the last trading day of month t.

4.1.2. Roll measure

First, we calculate the Kim and Lee (2014) version of Roll's (1984) liquidity measure for each constituent bond i in month t:

$$Roll_{i,t}^{KL} = 2\cdot\sqrt{\left|cov\left(r_{i,\tau}, r_{i,\tau-1}\right)\right|} \tag{4}$$

where $cov(r_{i,\tau},r_{i,\tau-1})$ is the first order autocovariance of daily returns in month t for bond i.

Then, for each sample bond index k the Roll measure is calculated by aggregating the liquidity measures of all bond index constituents, using market capitalization as weights:

$$Roll_{k,t}^{KL} = \sum_{i=1}^{n}\left(Roll_{i,t}^{KL}\frac{MCap_{i,t}}{\sum_{i=1}^{n} MCap_{i,t}}\right) \tag{5}$$

4.1.3. Composite liquidity measure (λ)

Some of the previous studies on liquidity utilize principal component (PC) analysis in order to identify a systemic liquidity component (Kim and Lee, 2014) or create a composite liquidity measure (Dick-Nielsen et al. 2012). For example, Dick-Nielsen et al. (2012) generate a new composite measure using PC factors that load evenly on four liquidity proxies (Amihud, Implicit trading costs, Turnover and Zero-traded day). We adopt a similar approach to Dick-Nielsen et al. (2012) and create a composite measure of liquidity based on our two liquidity proxies (FZR and Roll). First, we standardize FZR and Roll to a common scale. We then conduct a PC analysis and examine the factor loadings for the two measures. Finally, λ is defined as the sum of the standardised Roll measure multiplied by its first principal component loading and the standardised FZR measure multiplied by its first principal component loading.[14] Less liquid sample bonds are expected to have higher values for our three illiquidity measures (FZR, Roll, λ).

4.2. Transaction vs. quoted prices

Previous studies highlight potential issues with the use of dealer quotes (i.e. bid prices) rather than actual transaction prices. For example, Collin-Dufresne et al. (2001) suggest that bid quotes may be slow in responding to changes in relevant information thus creating a so called "bid factor". This delay may affect liquidity proxies trying to capture transitory price movements (e.g. Roll measure). Furthermore, the lack of changes in quoted prices could also mean incomplete data coverage by a data provider thus introducing a bias into the FZR measure (see Friewald et al., 2012).

Although we use quoted prices we do not believe that our estimates would be seriously impacted by a "bid factor" and incomplete data coverage. First, Markit is a leading global (bond) information provider applying very strict rules in creating iBoxx indices. Markit collects actively quoted bond prices from ten leading brokers and applies rigorous controls to exclude erroneous and stale prices. Incoming bank quotes are consolidated into a single (bid) price before entering into the index calculation in real time. Markit publishes closing index values and midday fixing levels for bonds and indices. These valuations are considered as a market-wide average and are widely used by market participants and researchers. For example, Friewald et al. (2012) used consolidated Markit prices as a consensus market valuation to complement TRACE transaction data for US corporate bonds.[15] Biais et al. (2006) also studied Euro-denominated bonds from the iBoxx composite index during 2003-2004. The authors are also able to collect complete high frequency transaction data for sample bonds from TRAX. Their findings suggest that bid and ask quotes are meaningful prices and that they change in line with transaction costs. The quoted spreads are also consistent with effective spreads obtained from high frequency transaction data (TRAX). Overall, Biais et al. (2006) conclude that bonds from iBoxx are representative for European investment grade bonds. Their results are consistent with the results reported for the US market (e.g. Goldstein et al., 2007; Edwards et al., 2007) thus suggesting that the economics of the secondary markets for bonds are not fundamentally different in Europe and in the US.

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[14] We were not able to estimate some of alternative measure such as the Specialist spread (Lesmond et al., 1999) due to data availability.

[15] TRACE does not provide bid-offer prices which are required for computation of the percent effective spread, which in turn requires the bid-offer midpoint (see Holden et al., 2013).

Yet another potential concern is related to the frequency of data and the possibility that some liquidity effects maybe captured only by high frequency (intraday) data. Goyenko et al. (2009) provide evidence that liquidity proxies (among them Roll and FZR) perform reasonably well regardless of whether they use low (i.e. daily or monthly) or high frequency (i.e. intraday) equity data. For example, both monthly and annual low-frequency measures capture high-frequency measures of transaction costs. Goyenko et al. (2009) also report a reasonably good performance of Roll and Fraction Zero Return (FZR) liquidity measures relative to their 'competitors'.

4.3. Model specification and estimation procedure

4.3.1. Base model

We start with liquidity augmented Fama and French (1993) model:

$$EBR_{t,k} = \alpha_{k,0} + \beta_{k,1} \cdot TERM_t + \beta_{k,2} \cdot DEFRATE_t + \beta_{k,3} \cdot \lambda_t + \varepsilon_{s,t,k} \qquad (6)$$

The dependent variable, $EBR_{t,k}$ is the excess return of corporate bond index k in month t. β_k is a vector of coefficients of the *kth* sector. *TERM* represents a term risk premium, defined as the difference between the monthly log return on the iBoxx German Government Bond Index (maturity of 7 to 10 years) and the one month Euribor rate in the previous month. *DEFRATE* is the monthly ratio of the number of defaulted issuers of (all) corporate bonds over the number of active companies in Euro-zone countries (plus: UK, Switzerland, Norway and Sweden).[16] We also estimate the model with *DEF* as the difference in returns between a composite index of corporate bonds and a maturity-matched composite of German government bonds.[17] The correlation of *DEF* and λ however is high (0.33), thus creating multicollinearity issues.[18] The high correlation is also an indication that *DEF* tends to capture both the default and liquidity risk of corporate bonds. Further motivation to use *DEFRATE* rather than alternative proxies of default risk (e.g. firm specific characteristics) is that aggregate factors appear much more important than firm-specific factors in determining credit spread changes (Collin-Dufresne, 2001) and that we examine bond indices (i.e.

[16] *DEFRATE* was provided by Moody's.
[17] This measure is frequently used in the literature (see Aussenegg et al., 2015; Acharya et al., 2013).
[18] It is worth noting that the correlation between DEF and the liquidity measure used in Acharya et al. (2013) is only -0.057. Acharya et al. (2013), however, proxy liquidity in the corporate bond market by using the bid-ask spread of US government bonds.

portfolios) rather than individual bonds.[19] We also run the model with illiquidity innovations (i.e. shocks) proxied by residuals from an autoregressive model ($AR\lambda_t$).[20] Thus,

$$EBR_{t,k} = \alpha_{s,k,0} + \beta_{k,1} \cdot TERM_t + \beta_{k,2} \cdot DEFRATE_t + \beta_{k,3} \cdot AR\lambda_t + \varepsilon_{s,t,k} \tag{7}$$

To test the prediction of Acharya and Pedersen (2005) that illiquidity negatively affects contemporaneous bond returns and positively affects future returns, we re-run models (6) and (7) with lagged illiquidity and illiquidity shocks.

4.3.2. Threshold regime switching (TS) model

In regime switching models, it is assumed that different scenarios exist. Within the scenarios, the parameters are constant, but across scenarios they can differ. Assuming linear relationships and two distinct regimes, this can be written as:

$$EBR_{t,k} = \begin{cases} \alpha_{1,0} + \sum_i \beta_{1,i,k} x_{ti} + \varepsilon_t & \text{period } t \text{ belongs to regime 1} \\ \alpha_{2,0} + \sum_i \beta_{2,i,k} x_{ti} + \varepsilon_t & \text{period } t \text{ belongs to regime 2} \end{cases} \tag{8}$$

In the TS model, the two equations for regimes 1 and 2 are joined by a step function G_t, and the transition between the two regimes is abrupt at $s_t = c$, where s_t is a transition variable. If $s_t > c$, the system is in one regime, otherwise in another (e.g. high-volatility and low-volatility regimes):[21]

$$G_t = \begin{cases} 0 & s_t \leq c \text{ (regime 1)} \\ 1 & s_t > c \text{ (regime 2)} \end{cases} \tag{9}$$

For potential transition variables, s_t, we use the macroeconomic indicators proposed in the previous literature. For example, the level and first order difference of the following potential transition variable (TV) are used:[22] Monthly growth rate of industrial production (see Chen, 1991; Chen and Maringer, 2011), short-term interest rates (see Chen, 1991), realised volatility of stock market returns (Bao et al., 2011), implied volatility of stock market returns (Brunnermeier and Pedersen, 2009; Bao et al., 2011), volatility risk premia of the stock market (Bollereslev et al., 2009), realized

[19] Potential use of Credit Default Swap (CDS) would restrict the sample to only very large firms with frequently traded CDS contracts.
[20] The model is specified as AR (3) or AR (2). The lags are selected to ensure no serial correlation of the residuals. The procedure is adopted from Acharya et al. (2013).
[21] To avoid abrupt switches, it is possible to use continuous functions such as the S-shaped sigmoid function (see, Chen and Maringer, 2011). This extension allows for more flexibility, yet at the cost of additional parameters.
[22] An exception is the monthly grow rate of industrial production, where only levels are used.

volatility of bond index returns and the illiquidity measure λ.[23] Overall, we examine 13 (6x2 plus 1) potential candidates for our transition variable (TV). The winner of the 'horse race' is the transition variable that yields the lowest estimated *BIC*.

4.3.3 Estimation process

The TS model is flexible and can include several (i.e. more than two) regimes allowing for more than one threshold. Including additional regimes increases the number of parameters noticeably. In particular for data sets where the number of observations is small in relation to the number of parameters, over-fitting might occur. To consider this (flexibility of TS models regarding the number of regimes and our dataset of 180 monthly observations) we allow for up to three regimes in the estimation process. However, our results reveal that no more than two regimes have appeared to be optimal in the TS model optimization process.[24] This paper, therefore, proceeds with a two-regime TS model. In the optimization process the parameters $\beta_{r,i,k}$, $r = 1, 2$ (see eq. (8)) and the corresponding threshold *c* are estimated in minimizing the Bayesian information criterion (BIC):

$$BIC = \log\left(\sum_{t=1}^{T} \hat{\varepsilon}_t^2\right) + k \cdot \frac{\log(T)}{T} - \log(2\pi) \tag{10}$$

where T is the number of observations and k is the number of parameters included in the estimation, where k also reflects the degrees of freedom lost. BIC consists of three parts: (i) the first part measures the goodness-of-fit in terms of the remaining errors; (ii) the second part is a "punishment term" for the size of the model in relation to the sample size; and (iii) the last part is a constant term $(-\log(2\pi))$ that stems from the normality assumption for the residuals.[25] While it does not make much sense to compare the BIC's for different time series (i.e. in our case for different bond indices) or dependent variables (i.e. different model magnitudes), this measure can be used to compare different models when applied to the same dependent variables. This *BIC* measure rewards parsimonious models: the inclusion of an explanatory variable is then only desirable if it reduces the sum of squared errors noticeably. A variable that adds little extra explanatory power tends to be excluded: if the lost degrees of freedom (and the chance of overfitting) weigh heavier than the improvement in the goodness-of-fit, then the more parsimonious

[23] Monthly growth rate of industrial production and short-term interest rates are from Thomson Reuters Datastream. Realised volatility of stock market returns is based on daily EuroStoxx 50 returns. Implied volatility of stock market returns is based on daily VStoxx values. Daily EuroStoxx 50 index and Euro Stoxx 50 volatility index (VStoxx) data are obtained from the stoxx.com website. Realized volatility of bond index returns is based on daily returns of the Markit European Corporate Composite bond index.

[24] Models with three regimes were found to provide little extra insights if any. Unreported results are available from authors upon request.

[25] This third part can be (and often is) dropped as it has no impact on the estimation.

model has the better BIC. This trade-off (reduction in the sum of squared errors and increase of the "punishment term") depends on the sample size: the fewer observations (T) there are, the greater the peril of over-fitting and, hence, the greater the margin costs of including a variable. By the same reasoning, this measure helps to identify whether there are different regimes in the first place: If the second regime is not substantially different from the first, the respective parameters, $\beta_{r=1,i,k}$ and $\beta_{r=2,i,k}$, should not differ significantly. Hence, dropping the second regime allows for more degrees of freedom; the reduction in the punishment term outweighs the drop in the goodness-of-fit term. The single-regime model will then have the lower and more favourable BIC. This measure typically prefers more parsimonious models than other criteria for model selection, including the adjusted R^2.[26]

No closed-form solution exists for the selection of variables or the choice of threshold. We, therefore, use a Genetic Algorithm (GA) to determine the threshold values and, for each regime, which of the available variables to include.[27] For any given selection, the parameters $\beta_{r,i,k}$ are estimated using the standard ordinary least squares approach, which then provides the estimates for the error terms, and the respective BIC. Due to the GA's evolutionary principles, the search process converges to the lowest possible BIC. To ensure solid convergence behaviour, a generous calibration has been chosen and each setting has been solved repeatedly. To avoid overfitting, multiple regimes are allowed only if either regime includes at least twenty percent of the observations. If the GA suggest a threshold that leaves one of the regimes with fewer observations, that regime is dropped and the number of lost degrees of freedom, k, is reduced accordingly.[28]

5. Results

5.1. Liquidity of European corporate bond indices

Descriptive statistics for our three liquidity measures are presented in Table 2. The median fraction of zero return days (FZR) for the Composite index is 0.717% (Table 2 - Panel A) thus suggesting

[26] Compared to other criteria for model selection, including the adjusted R^2, the BIC is typically faster in excluding variables. Hence, a model that minimizes the BIC is not necessarily the one maximizing the adjusted R^2.

[27] For more details on using evolutionary methods for model estimation, see, e.g. Gilli et al. (2011) and the literature discussed therein.

[28] During the optimization process independent variables (i.e. *TERM, DEFRATE,* λ) can also be dropped if this contributes to minimize the *BIC.*

very good overall liquidity of European corporate bonds.[29] Recent studies for the US corporate bond market report FZR values that are strongly sample dependent. For example, Dick-Nielsen et al. (2012) document a very high median number of bonds' zero-trading days of 60.7% in their sample of 5,376 US bonds, during the 2005 to2009 period.[30] This evidence is in strong contrast to the mean FZR value of 0.03% reported in Friewald et al. (2012) for US-corporate bonds during the period October 2004 until December 2008.[31]

Insert Table 2 about here

Across credit ratings, the AA bond index exhibits a much lower average (median) FZR value compared to the BBB bond index (0.83% (0.37%) vs 1.38% (1.23%)). Furthermore, the median FZR decreases almost monotonically with maturity. For example, the median FZR for 1-3 years maturities is 1.143% whilst it is only 0.490% for bonds with a maturity of more than 10 years.[32] Bonds issued by financial institutions exhibit a more than two times higher median FZR compared to their non-financial counterparts. Among different industries, the highest median FZR is recorded in the Oil & Gas sector (1.708%) and the lowest in the Retail sector (0.000), thus highlighting significant differences in bond liquidity across industries.

The median Roll measure for the Composite index is 0.167% p.m. (Table 2 – Panel B). This median is smaller compared to the median values reported in recent US studies. For example, Dick-Nielsen et al. (2012) report a Roll median value of 0.53% on a quarterly basis. Friewald et al. (2012) report a median Roll measure of 1.56%.[33]

[29] Huberman and Stanzl (2005) and Dick-Nielsen et al (2012) report that dealers tend to split big sell orders for illiquid bonds in several trades in order to reduce the price impact of trades. All else equal, this behaviour would increase frequency of trades and potentially reduce FZR for the most illiquid bonds. Given strict Markit rules and absence of very illiquid bonds in our sample, we do not expect that the above practices are of great importance for calculation of FZR in our sample.

[30] It is worth noting that Dick-Nielsen et al. (2012) use TRACE data that include investment and non-investment grade bonds during a much shorter period dominated by the financial crisis.

[31] Notably, this study also uses Markit data for calculation of FZR for US bonds.

[32] It is, however, worth noting that the mean FZR for the 10+ maturity bracket is rather high and more similar to the mean value reported for 1-3 years than for any other maturity bracket.

[33] Due to differences in adjustments for positive serial covariances, a direct comparison of Roll measures reported in various studies is typically not directly possible (see Corwin, 2014).Researches typically make one of four adjustments to the Roll measure in cases where serial covariance of returns is positive: (i) treat the measure as missing (e.g. Dick-Nielsen et al., 2012); (ii) set the measure to zero (Friewald et al., 2012); (iii) take the square root without applying the negative sign and treat the result as negative (Roll, 1984); or iv) treat positive covariances as if they are negative by taking the square root from absolute values, resulting in positive values for the Roll measure (Kim and Lee, 2014;

The median Roll measure (Table 2 - Panel B) ranges from 0.074% (Index for 1-3 years maturity) to 0.347% (Index for 10+ years). Bonds issued by financial institutions exhibit higher (mean and median) Roll measures compared to their counterparts from non-financial sectors. Amongst different industries, the Retail sector exhibits (again) nearly the highest liquidity (lowest Roll measure of 0.135%) whilst Industrial Good & Services and Utilities exhibit similarly high illiquidity based on the Roll measure.[34]

Results for our composite liquidity measure (λ) are presented in Table 2 (Panel C). The unreported results of the PC analysis resulted in a composite measure that loads evenly on the standardized FZR and Roll measure.[35] Median values for our composite liquidity measure (λ) are predominantly negative for sample indices, ranging from -0.393 (AA rating) to -0.142 (Oil & Gas).[36] The results suggest good liquidity for the European corporate bond market, consistent with recent media reports and some earlier evidence (see Biais et al., 2006).[37]

5.2. Results of TS model

Figure 1 presents excess returns and risk factors for the Corporate Composite Index during the sample period. As expected, we document higher values for our illiquidity and default factors during 2001 (dot.com crisis) and 2008-09 period (recent financial crisis). This was accompanied with a sharp drop in excess returns during the respective crisis periods. The previously reported leptokurtic distribution of excess returns (Table 1), together with the time-varying properties of the common factors justify consideration of nonlinearity and regime shifts.

Figure 1 about here

Table 3 presents the mean and median ranks of 13 potential transition variables (TV). The ranks are based on the *BIC* in the TS model optimization process. The TV with the lowest BIC for a

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Lesmond, 2005). Corwin (2014) shows that mean Roll spreads are approximately twice as large when positive serial return covariances were treated as negative instead of being treated as zero.

[34] Our sample Roll and FZR measures are highly correlated at 43%.

[35] The results are available from authors upon request.

[36] The autocorrelation of λ is high at 0.77 suggesting high persistency.

[37] For example, recent media reports highlight record numbers of new bond deals in Europe (see, The Wall Street Journal, 15-17th May and 8th September 2015). Our Euro-corporate-bond composite liquidity measure also evolves in a very close pattern to the US-corporate-bond composite liquidity measure calculated based on the same method by Federal Reserve Bank of New York (see Adrian et al., 2015).

particular bond index is assigned a rank of 1, the TV with the second lowest BIC receives a rank of 2, and so forth. During this analysis each TV receives 17 rank numbers (one for each of the 17 sample bond indices). Δ_rv, defined as the first order differences of realized stock market monthly volatility, achieved the highest overall rank. Our result is in line with the Brunnermeier and Pedersen (2009) model which predicts that volatility (measured by VIX) is a state variable affecting market liquidity and risk premium. Bao et al. (2011) also document a close relationship between their illiquidity measure for the US corporate bond market and (contemporaneous) changes in the VIX index, a variable that covers shocks to market risk and/or to the risk appetite of market participants.

Insert Table 3 about here

Table 4 presents the estimates for our TS model. The results suggest that for all bond indices, the change in realized stock market volatility can be used to identify two distinct regimes.[38] For example, in regime 1, (when changes in realized stock volatility are below the estimated threshold *c*, the coefficients for illiquidity are predominantly insignificant (and, therefore, dropped in the estimation process).[39] As expected, *TERM* and *DEFRATE* exhibit statistical significance and positive signs, respectively.[40] Coefficients for λ are mostly insignificant in regime 1.

Insert Table 4 about here

In the second regime, however, illiquidity coefficients are predominantly negative and statistically significant. Together with *TERM* they explain most variations in excess returns. The effect of *TERM* is (again) positive, yet with much stronger economic significance (i.e. coefficients for the

[38] All models include a constant term; mostly for statistical reasons. It seems noteworthy, however, that in regime 1 it is almost always insignificant, while in regime 2, it is almost always significant. Interpreting this phenomenon, however, is difficult, as the constant might well absorb some aspects of the dropped variables.

[39] For example, the threshold of $c = -0.35$ (Composite index) corresponds to the 47.8% percentile of the transition variable, implying that in 47.8% (or 86) of the considered 180 periods, the system was considered to be in regime 1, while for the remaining 94 periods (52.5%) regime 2 applies.

[40] Notably, in regime 1 statistically significant and positive illiquidity coefficients are, e.g., reported for the BBB bond index and the 1-3 years bond index. For these two indices *TERM* is not statistically significant in the first regime. For the Automobiles and Parts index all three coefficients are positive and statistically significant. *TERM* is the only statistically significant (and positive) factor for the Telecommunication index.

term spread are typically much higher in regime 2 than they are in regime 1). *DEFRATE* coefficients are statistically significant (and positive) only for BBB, 7-10, 10+ and Telecommunication indices. This implies that in the second regime (i.e. a stress regime with mostly increasing stock market volatility) illiquidity is (for most bonds) more important than a default factor. The correlation of λ and *DEFRATE* is low at -0.076 over the sample period, implying that λ is a relatively clean measure of market illiquidity that is separated from the default risk. The switching importance of λ and *DEFRATE* is in line with our hypothesis 2. When illiquidity soars, illiquidity can harm excess returns much more than its default risk. The dominant negative sign of the coefficients of λ across various indices in regime 2 is also consistent with the volatility feedback explanation proposed by Campbell and Hentschel (1992). Increases in aggregate volatility lead to a reduction in investor holdings of risky assets, which in turn lowers contemporaneous returns.

The results presented in Table 4 also provide support for hypothesis 3 and 4. Illiquidity effects are larger for lower rated bonds in regime 2. The λ coefficient for BBB rated bonds is -0.683 vs -0.315 for AA rated bonds. Illiquidity effects are stronger for long-term bonds in regime 2. For example, the λ coefficient for short-term bonds (1-3 year maturity) is -0.241, whereas it is -0.801 for long-term bonds (10+ year maturity).

In addition, the coefficient for λ is negative and statistically significant for all industries in regime 2. Automobile and Parts exhibit the smallest coefficient of -0.245 and the Retail sector the largest coefficient (-0.530). Thus, the effect of illiquidity seems to be smallest in the Automobile and Parts industry and largest in the Retail sector. The adjusted R^2 is largest for Utilities (69.5%) and smallest for the Oil and Gas sector (45.2%). Interesting, in regime 2 the effect of illiquidity is more pronounced for financial sector bonds (λ coefficient of -0.673 vs -0.383 for non-financial industry bonds). On the other hand, the adjusted R^2 of the financial sector is much smaller compared to the non-financial sector (35.8% vs 62.2%). Thus, our TS model can explain much more of return variations for bonds from the non-financial industries. This could be due to increased uncertainty regarding bailouts of some of leading financial institutions during financial crisis. Bond prices of financial institutions were consequently influenced more by other factors (i.e. other than *TERM, DEFRATE,*λ) compared to their counterparts from non-financial sectors.

Overall, the thresholds might differ, but in times of (strongly) decreasing realised stock volatility, excess bond returns are more responsive to default rates than to liquidity. But in periods of (strongly) increasing volatility, excess bond returns are driven by liquidity rather than default rates.

This is consistent with results of Acharya et al. (2013) who report that default risk is distinct from liquidity risk, especially in the stress regime.

When using illiquidity shocks rather than levels (Table 5), the results are similar: in periods with (strong) increases in realised stock volatility, an increase in illiquidity has a noticeable negative impact on excess bond returns. When volatility is decreasing, it is the default rate that drives excess returns. Akin to the results for levels of the illiquidity, the constant terms are more relevant in regime 2 than their regime 1 counterparts, and the parameters for *TERM* are typically larger than in regime 1. By and large, the model with illiquidity shocks seems to work similarly well when compared to the model with illiquidity levels.

Insert Table 5 about here

All industries have a significant and negative coefficient for the illiquidity shock measure. Again, the Automobile and Parts industry exhibits the smallest coefficient (-0.589), now the Industrial Goods and Services industry has the largest negative coefficient (-0.820). Again, illiquidity is more important for financial firms (λ coefficient of -1.085 vs -0.481 for non-financial companies). Also the adjusted R^2 is again much larger for non-financial bonds (62.2% vs. 36.9%).

Acharya and Pedersen (2005) predict that illiquidity negatively affects contemporaneous bond returns and positively affects future returns. We re-run models (6) and (7) with lagged illiquidity levels (Table 6) and lagged illiquidity shocks (Table 7). The results reported in Table 6 are in line with the Acharya and Pedersen (2005) predictions. The coefficients for λ remain negative and significant with positive and statistically significant lagged illiquidity levels λ_lag6 in the second regime.[41] The results for lagged illiquidity shocks ($AR\lambda\_lag6$) are reported in Table 7. The coefficients for ARλ_lag6 are insignificant across most of the sample indices in both regimes. This result is expected given ARλ's lack in persistency.[42]

[41] Given relatively small sample size, we tried 3 and 6 months lags. The unreported results for 3 months lagged λ are available from authors upon request.
[42] ARλ exhibits correlation with its 1st lag close to zero. On the other hand, λ's correlation is 0.77 and persists up to the 9th lag.

6. Conclusion

In this paper, we examine the time-variation in excess returns and liquidity of 17 Euro denominated iBoxx bond indices from January 2000 to December 2014. We combine a threshold regime switching model with a genetic algorithm to select the model variables and regime thresholds. Illiquidity is examined at corporate bond level and then aggregated to measure illiquidity levels and shocks for the respective corporate bond indices. The availability of different iBoxx indices allows us to examine the systematic components of liquidity in portfolios constructed for different industries, which has not been done before.

We identify changes in realized stock volatility as the best transition variable. Although our composite illiquidity measure varies significantly across ratings, maturities and industries, the change in realized stock market volatility identifies two distinct regimes for all sample indices. In times of decreasing realised stock volatility, excess bond returns are more responsive to default rates than to liquidity. But in periods of increased volatility, excess bond returns are driven by illiquidity rather than default rates. Overall, our TS model explains more of return variations for bonds from the non-financial industries.

List of references

Acharya, V., and Pedersen L.H., 2005. Asset pricing with liquidity risk, *Journal of Financial Economics*, 77, 375-410.

Acharya, V.V., Amihud Y., and Bharath S., 2013. Liquidity risk of corporate bond returns: A conditional approach, *Journal of Financial Economics*, 110, 358–386.

Adrian, T., Fleming, M., Shachar, O., Stackman, D., and Vogt, E., 2015. Has Liquidity Risk in the Corporate Bond Market Increased? Liberty Street Economics, Federal Reserve Bank of New York, October 6th, 2015.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series Effects, *Journal of Financial Markets*, 5, 31-56.

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

Ang, A., and Piazzesi, M., 2003. A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables, *Journal of Monetary Economics*, 50, 745–787.

Ang, A., and Timmerman, A., 2011. Regime changes and financial markets. Unpublished working paper, Columbia University and University of California at San Diego.

Aussenegg W., Götz, L., and Jelic, R., 2014. European asset swap spreads and the credit crisis, *European Journal of Finance,* DOI: 10.1080/1351847X.2014.935869

Aussenegg, W., Götz, L., and Jelic, R., 2015. Common factors in the performance of European corporate bonds – Evidence before and after the financial crisis, *European Financial Management,* 21, No. 2, 265–308.

Bao, J., Pan. J, and Wang J., 2011, The illiquidity of corporate bonds, *Journal of Finance*, 66, No. 3, 911-946.

Biais, B., Declerck, F., Dow, J., Portes, R., and von Thadden, E.-L., 2006. European corporate bond markets: Transparency, liquidity, efficiency, Centre for Economic Policy Research and City of London.

Bollerslev, T., Tauchen, G., and Zhou. H., 2009. Expected stock returns and variance risk premia, *Review of Financial Studies*, 22, 4463–4492.

Brown, P., 2002. Constructing and calculating bond indices – Guide to the EFFAS European bond commission standardized rules, GDP, Cambridge.

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

Campbell, J.Y., and Hentschel, L., 1992. No news is good news: An asymmetric model of changing volatility in stock returns, Journal of Financial Economics, 31, No. 3, 281-318.

Chan, K. C. and Wu, H.K., 1995. Another look on bond market seasonality: A note, *Journal of Banking and Finance*, 19, 1047-1054.

Chen, L., Lesmond, D., Wei, J., 2007. Corporate yield spreads and bond liquidity, *Journal of Finance,* 62, 119–149.

Chen, N.F., 1991. Financial investment opportunities and the macroeconomy, Journal of Finance, 46, 529-553.

Chen, X.H., D. Maringer, 2011. Detecting time-variation in corporate bond index return: A smooth transition regression model, *Journal of Banking and Finance*, 35, 95–103.

Collin-Dufresne, P., Goldstein, R.S., Martin, J., 2001. The determinants of credit spread changes, *Journal of Finance*, 56, 2177–2207.

Cooper, S., Groth, K., Avera, W., 1985. Liquidity, exchange listing and common stock performance, *Journal of Economics and Business,* 37, 19–33.

Corwin, S.A., 2014. Dealing with negative values in the high-low spread estimator, A comment on "Pricing of liquidity risks: Evidence from multiple liquidity measures" by Soon-Ho Kim, S-H. and K-H. Lee, *Journal of Empirical Finance*, 25, 112-133.

De Jong, F. and Driessen, J., 2012. Liquidity risk premia in corporate bond markets, *Quarterly Journal of Finance*, 2, No. 2, forthcoming.

Dick-Nielsen, J.D., Feldhutter P., and Lando D., 2012. Corporate bond liquidity before and after the onset of the subprime crisis, *Journal of Financial Economics,* 103, 471-492.

Duffie, D., Garleanu, N., Pedersen, L.H., 2007. Valuation in over the counter markets, *Review of Financial Studies,* 20, 1865–1900.

Edwards, A., Harris, L., Piwowar, M., 2007. Corporate bond market transaction costs and transparency, Journal of Finance, 62, 1421–1451.

Elton, E., Gruber, M., Agrawal, D., Mann, C., 2001. Explaining the rate spread on corporate bonds, *Journal of Finance*, 56, 247–277.

Fama, E.F., and French, K.R., 1993. Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics,* 33, 3–56.

Financial Times, Stress tests needed for European bond funds, 18th November 2015.

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

Galliani, C., Petrella G., and Resti, A., 2014. The liquidity of European corporate and government bonds: drivers and sensitivity to different market conditions, European Commission, JRC Technical Reports, JRC81644.

Gebhardt, W.R., Hvidkjaer, S., and Swaminathan, B., 2005. The cross-section of expected corporate bond returns: betas or characteristics? *Journal of Financial Economics*, 75, 1, 85–114.

Gilli, Maringer, D., and Schumann, 2011. Numerical Methods and Optimization in Finance, 1st Ed. Academic press.

Goldstein, M., Hotchkiss, E., and Sirri, E., 2007. Transparency and liquidity: a controlled experiment on corporate bonds, *Review of Financial Studies*, 20, 2, 235–73.

Goltz, F. and Campani, C. H., 2011, A review of corporate bond indices: Construction principles, return heterogeneity, and fluctuations in risk exposures, EDHEC-Risk institute.

Goyenko, R.Y., Holden, G.W., and Trzcinka, C.A., 2009. Do liquidity measures measure liquidity? *Journal of Financial Economics*, 92, 153-181.

Guidolin, M., and Timmermann, A., 2006. An econometric model of nonlinear dynamics in the joint distribution of stock and bond returns, *Journal of Applied Econometrics*, 21, No. 1, 1-22.

Hasbrouck, J., 2004. Liquidity in the futures pits: inferring market dynamics from incomplete data, *Journal of Financial and Quantitative Analysis*, 39, 305–326.

Holden, C. W., Jacobsen, S., and Subrahmanyam, A., 2013. The Empirical Analysis of Liquidity, *Foundations and Trends in Finance*, 8, No. 4, 263-365

Holden, C.W., 2009. New low-frequency liquidity measures, *Working Paper*, Indiana University.

Houweling, P., Mentink, A., and Vorst, T., 2005. Comparing possible proxies of corporate bond liquidity, *Journal of Banking and Finance*, 29, 1331-1358.

Huberman, G., and Stanzl, W., 2005. Optimal Liquidity Trading, Review of Finance, 9, 165-200.

Jankowitsch, R., Nashikkar, A., Subrahmanyam, M., 2011. Price dispersion in OTC markets: a new measure of liquidity, *Journal of Banking and Finance*, 35, 343–357.

Kim, S-H., and Lee, K-H., 2014. Pricing of liquidity risks: Evidence from multiple liquidity measures, *Journal of Empirical Finance*, 25, 112–133.

Lekkos, I. and Milas, C., 2004. Common risk factors in the U.S. and UK interest rate swap markets: Evidence from a nonlinear vector autoregression approach, *Journal of Futures Markets*, 24, No. 3, 221–250.

Lesmond, D., 2005. Liquidity of emerging markets, *Journal of Financial Economics*, 77, 411–452.

Lesmond, D., Ogden, J., and Trzicinka, C., 1999. A new estimate of transaction costs, *Review of Financial Studies*, 12, 1113-1141.

Longstaff, F., Mithal, S., Neis, E., 2005. Corporate yield spreads: default risk or liquidity? New evidence from the credit-default swap market, *Journal of Finance*, 60, 2213–2253.

Mahanti, S., Nashikkar, A., Subrahmanyam, M., Chackod, G., and Mallik, G., 2008. Latent liquidity: A new measure of liquidity, with an application to corporate bonds, *Journal of Financial Economics*, 88, 272–298.

Markit, 2010, iBoxx EUR Benchmark Index Guide, April.

Pástor, L., and Stambaugh, R.F., 2003. Liquidity Risk and Expected Stock Returns, *Journal of Political Economy*, 111, 642-685.

Roll, R., (1984), A simple implicit measure of the effective bid-ask spread in an efficient market, *Journal of Finance*, 39, 1127-1139.

Sastry K., Goldberg D., and Kendall G., 2005. Genetic algorithms, in: Edmund K.B., Graham K. editors. Search methodologies: Introductory tutorials in optimization and decision support techniques. New York: Springer Science+Business Media, 97-127.

The Wall Street Journal, Corporate Bonds Hold Up, 15-17th May 2015.

The Wall Street Journal, US Firms Race to Sell Bonds in Europe, 8th September 2015.

Table 1: Sample descriptive statistics

This table presents descriptive statistics of our sample of 17 Euro-denominated iBoxx corporate bond indices and their constituents for the sample period from January 2000 to December 2014. The sample consists of one composite index, three indices for different rating classes (AA, A, BBB), 5 maturity indices (1-3 years, 3-5 years, 5-7 years, 7-10 years, 10+ years), financial and non-financial corporate bond indices, and six industrial indices. Overall the sample contains 180 monthly observations for each sample bond index. Presented characteristics of the sample indices (Number of bonds and Market value per index) and their constituents (Market value per bond, Yield to maturity, Time to maturity and Modified duration) are averages (means) during the sample period. Data on index constituents' names and (end of month) characteristics are extracted from Markit's annual files. The constituents' characteristics are their end-of-month characteristics aggregated (using constituents' market capitalisation) at level of the respective indices. Excess returns of a particular bond index for month t are obtained by subtracting the one month Euribor rate at the end of the previous month (t-1) from the total bond index return of month t. Euribor rate is from Datastream, calculated on a continuous compounded basis. Total bond index returns are monthly log returns, in percentage terms, based on the last trading day of the corresponding month. **, * are 1% and 5% significance levels, respectively.

Bond Index	Number of bonds	Market value per index (billion €)	Market value per bond (million €)	Yield to maturity (% p.a.)	Time to maturity (years)	Modified duration (years)	Excess return (% p.m.)						
							Mean	Median	St. deviation	Min	Max	Excess kurtosis	Skewness
Composite	889	858.8	956.0	4.24	5.49	4.42	0.26	0.36	1.10	-5.25	3.53	3.53**	-0.71**
Rating AA	150	172.5	1,120.4	3.72	5.67	4.68	0.24	0.35	0.98	-4.38	2.48	2.05**	-0.70**
Rating A	426	403.7	924.2	4.20	5.60	4.51	0.22	0.34	1.20	-6.77	3.83	6.69**	-1.20**
Rating BBB	295	259.1	912.8	4.82	5.24	4.13	0.30	0.36	1.36	-6.96	4.60	5.26**	-0.87**
Maturity 1-3 years	238	240.0	999.0	3.62	2.03	1.87	0.16	0.16	0.52	-1.52	2.02	2.57**	0.37*
Maturity 3-5 years	247	242.5	972.1	4.07	4.01	3.51	0.24	0.25	0.96	-4.56	3.16	3.53**	-0.53**
Maturity 5-7 years	177	165.9	924.5	4.49	6.02	5.01	0.30	0.38	1.40	-7.17	4.50	4.91**	-0.86**
Maturity 7-10 years	170	159.9	945.1	4.85	8.49	6.63	0.34	0.56	1.80	-9.10	5.47	5.12**	-1.03**
Maturity 10+ years	57	50.5	851.4	4.98	14.97	10.08	0.49	0.82	1.98	-7.65	5.55	1.35**	-0.46*
Financial	395	392.7	958.0	4.42	5.51	4.50	0.26	0.33	1.42	-7.84	4.79	6.73**	-0.91**
Non-Financial	494	466.1	955.8	4.05	5.54	4.41	0.28	0.40	0.96	-4.34	2.55	2.09**	-0.70**
Automobiles & Parts	49	51.9	1,046.4	3.85	4.03	3.37	0.21	0.30	0.92	-6.56	2.62	14.87**	-2.19**
Industrial G&S	56	47.1	863.9	4.25	5.70	4.57	0.26	0.40	1.10	-3.48	3.60	0.85*	-0.39*
Oil & Gas	32	31.6	922.7	4.16	5.66	4.58	0.25	0.32	1.23	-7.63	4.11	9.51**	-1.59**
Retail	24	19.0	797.8	3.89	5.08	4.08	0.25	0.32	1.07	-6.34	3.45	7.61**	-1.34**
Telecommunications	82	93.5	1,217.2	4.18	5.95	4.53	0.33	0.47	1.10	-3.42	3.42	0.94*	-0.32
Utilities	116	105.7	878.7	4.02	6.67	5.18	0.32	0.46	1.06	-3.00	3.11	-1.90	-0.28

Table 2: Liquidity measures

This table reports descriptive statistics for FZR (Panel A), Roll (Panel B) and Composite (λ) (Panel C) measures of illiquidity from January 2000 to December 2014. FZR and Roll are estimated using equations (1) and (2). FZR is a percentage of days with zero returns, per month. To estimate FZR and Roll illiquidity measures, we use daily bond (clean) price data of the corresponding bond index constituents provided by Markit. FZR and Roll illiquidity measures were calculated for each of bond index constituents' and are then aggregated to an illiquidity measure for the respective bond indices using bonds' end of month market values. FZR and Roll are, therefore, value weighted average illiquidity measures for the respective bond indices. Our Composite measure of illiquidity (λ) is constructed as the sum of the standardised Roll measure multiplied by its first principal component loading and the standardised FZR measure multiplied by its first principal component loading. **, * are 1% and 5% significance levels, respectively.

Panel A: FZR measure (%)

Bond Index	Mean	Median	St.dev.	Min	Max
Composite	1.114	0.717	1.383	0.067	10.577
Rating AA	0.827	0.372	1.247	0.000	6.397
Rating A	1.057	0.591	1.619	0.000	13.730
Rating BBB	1.377	1.235	1.633	0.000	13.705
Maturity 1-3 years	1.639	1.143	1.757	0.000	9.849
Maturity 3-5 years	0.960	0.612	1.401	0.018	9.578
Maturity 5-7 years	1.086	0.578	1.516	0.000	10.107
Maturity 7-10 years	0.811	0.305	1.624	0.000	13.344
Maturity 10+ years	1.398	0.490	2.514	0.000	14.047
Financial	1.462	1.123	1.643	0.019	12.661
Non-Financial	0.799	0.443	1.233	0.029	8.258
Automobiles & Parts	0.672	0.145	2.793	0.000	35.022
Industrial G&S	1.108	0.296	2.513	0.000	20.660
Oil & Gas	2.297	1.708	2.187	0.000	10.350
Retail	0.508	0.000	1.252	0.000	6.529
Telecommunications	0.418	0.179	0.901	0.000	5.682
Utilities	0.625	0.208	1.293	0.000	8.727

Panel B: Roll measure

Bond Index	Mean	Median	St.dev.	Min	Max
Composite	0.194	0.167	0.117	0.054	0.933
Rating AA	0.176	0.156	0.100	0.040	0.786
Rating A	0.191	0.164	0.130	0.052	1.112
Rating BBB	0.223	0.183	0.142	0.054	0.900
Maturity 1-3 years	0.091	0.074	0.068	0.016	0.475
Maturity 3-5 years	0.166	0.137	0.108	0.030	0.754
Maturity 5-7 years	0.228	0.197	0.151	0.055	1.214
Maturity 7-10 years	0.286	0.244	0.191	0.074	1.455
Maturity 10+ years	0.387	0.347	0.213	0.131	1.846
Financial	0.210	0.173	0.156	0.054	1.123
Non-Financial	0.178	0.163	0.090	0.053	0.729
Automobiles & Parts	0.145	0.122	0.100	0.039	0.805
Industrial G&S	0.207	0.174	0.134	0.062	0.956
Oil & Gas	0.199	0.157	0.149	0.053	1.227
Retail	0.157	0.135	0.102	0.024	0.887
Telecommunications	0.181	0.162	0.089	0.047	0.668
Utilities	0.189	0.173	0.093	0.055	0.611

Panel C: Composite measure (λ)

Bond Index	Mean	Median	Std.dev.	Min	Max
Composite	-0.034	-0.400	1.211	-1.365	7.520
Rating AA	-0.045	-0.393	1.183	-1.265	6.379
Rating A	-0.033	-0.367	1.228	-1.162	8.395
Rating BBB	-0.051	-0.347	1.203	-1.437	6.611
Maturity 1-3 years	-0.010	-0.296	1.068	-1.322	5.577
Maturity 3-5 years	-0.002	-0.364	1.169	-1.381	7.037
Maturity 5-7 years	-0.031	-0.358	1.194	-1.321	7.506
Maturity 7-10 years	-0.025	-0.339	1.226	-1.126	7.734
Maturity 10+ years	-0.046	-0.390	1.075	-1.211	6.867
Financial	-0.016	-0.343	1.198	-1.292	6.949
Non-Financial	-0.056	-0.392	1.189	-1.426	7.123
Automobiles & Parts	-0.005	-0.371	1.177	-1.359	7.259
Industrial G&S	0.004	-0.376	1.278	-1.092	7.413
Oil & Gas	0.026	-0.142	1.058	-1.368	6.218
Retail	-0.048	-0.373	1.047	-1.212	4.739
Telecommunications	-0.049	-0.302	1.095	-1.353	7.473
Utilities	-0.136	-0.331	0.870	-1.217	3.958

Figure 1: Excess returns and risk factors during the sample period

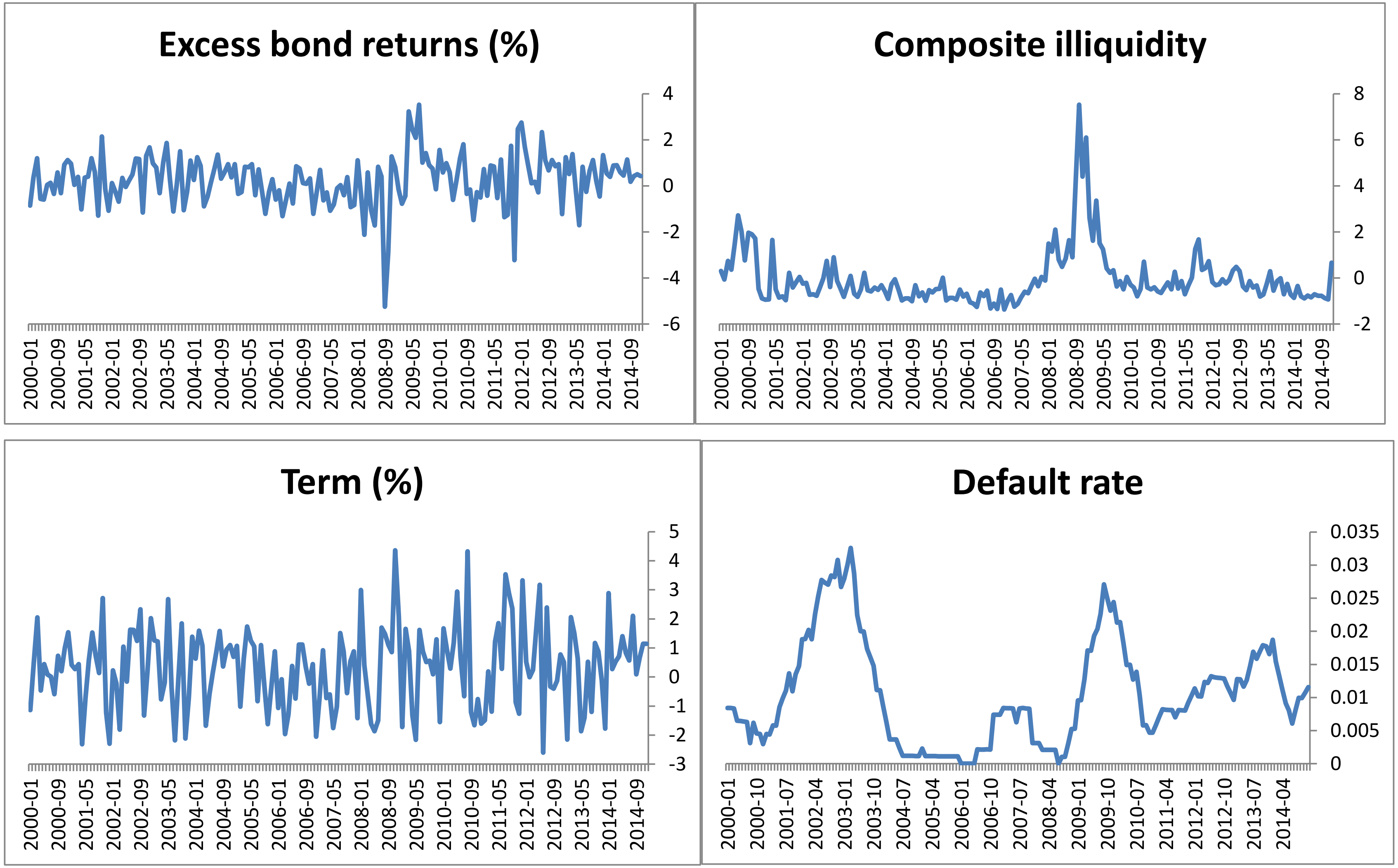

Table 3: Ranks of transition variables

This table presents the mean and median ranks of 13 potential transition variables (TV) analyzed. Ranks are based on the *BIC* in the TS model optimization process. The TV with the lowest *BIC* for a particular bond index (e.g. the corporate composite index) is assigned a rank of 1, the TV with the second lowest BIC receives a rank of 2, and so forth. During this analysis, each TV receives 17 rank numbers (one for each of the 17 sample bond indices). Based on these 17 rank numbers mean and median values are reported for each TV below.

Potential Transition Variable	Mean Rank	Median Rank
First order differences of realized stock market volatility	1.18	1
First order differences of implied stock market volatility	3.65	3
First order differences of variance risk premium of the stock market	3.88	4
First order differences of composite illiquidity measure	4.94	5
Variance risk premium of the stock market	5.00	4
Short term interest rate	5.71	5
First order differences of realized volatility of the bond market	7.65	8
Realized volatility of the bond market	8.59	7
Implied volatility of the stock market	8.65	9
First order differences of short term interest rate	8.76	9
Composite illiquidity measure	10.94	11
Monthly growth rate of industrial production	11.00	11
Realized stock market volatility	11.06	12

Table 4: Threshold model estimates with level of illiquidity

This table presents results for our TS model with level of illiquidity. Columns 2-5 provide the regression coefficients (with their p-values) for regime 1. Columns 7-10 contain the parameters (p-values) for state 2. If cells for parameter-values are empty, then these variables where excluded for the sake of improving BIC; if the cell the threshold is empty, then no two distinct regimes could be identified and the parameters reported under regime 1 apply for the entire time window. The values for the threshold (based on Δ_rv) are presented in column 6. The values in brackets next to c represent a percentage of the sample observations allocated to regime 1, based on the c value. For example, for Composite index, 47.8% (or 86) of the considered 180 months were considered to be in regime 1. For the remaining 94 months (52.5%), regime 2 applies.

	Regime 1: $\Delta rv_t \le c$					**Regime 2:** $\Delta rv_t > c$					
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bond Index	**Const.**	**TERM**	**DEFR.**	**λ**	***c***	**Const.**	**TERM**	**DEFR.**	**λ**	**BIC**	**Ad.R^2 (%)**
Composite	-0.001	0.305	45.201		-0.35	-0.276	0.509		-0.529	2.882	51.4
	(0.994)	(0.000)	(0.000)		(47.8%)	(0.001)	(0.000)		(0.000)		
Rating AA	0.013	0.445	26.384		-0.36	-0.149	0.563		-0.315	2.346	64.7
	(0.903)	(0.000)	(0.001)		(47.8%)	(0.015)	(0.000)		(0.000)		
Rating A	-0.064	0.294	46.926		-0.36	-0.306	0.526		-0.649	3.004	50.6
	(0.665)	(0.000)	(0.000)		(47.8%)	(0.000)	(0.000)		(0.000)		
Rating BBB	0.159		57.627	0.335	-0.36	-0.759	0.450	33.284	-0.683	3.434	44.0
	(0.379)		(0.000)	(0.001)	(47.8%)	(0.000)	(0.000)	(0.006)	(0.000)		
Maturity 1-3	-0.051		30.582	0.105	-0.35	-0.063	0.187		-0.241	1.670	36.4
	(0.501)		(0.000)	(0.016)	(47.8%)	(0.149)	(0.000)		(0.000)		
Maturity 3-5	-0.003	0.222	42.259		-0.36	-0.214	0.426		-0.452	2.696	47.1
	(0.982)	(0.000)	(0.000)		(47.8%)	(0.004)	(0.000)		(0.000)		
Maturity 5-7	-0.020	0.340	57.571		-0.36	-0.345	0.619		-0.659	3.377	49.2
	(0.909)	(0.000)	(0.000)		(47.8%)	(0.001)	(0.000)		(0.000)		
Maturity 7-10	0.059	0.491	61.820		-0.36	-0.848	0.763	35.808	-0.939	3.816	52.2
	(0.787)	(0.000)	(0.000)		(47.8%)	(0.000)	(0.000)	(0.014)	(0.000)		
Maturity 10+	0.165	1.027	40.126		0.47	-0.973	0.983	43.405	-0.801	3.727	67.4
	(0.334)	(0.000)	(0.003)		(63.9%)	(0.000)	(0.000)	(0.010)	(0.000)		
Financial	-0.075	0.244	57.072		-0.36	-0.296	0.486		-0.673	3.597	35.8
	(0.704)	(0.005)	(0.000)		(47.8%)	(0.011)	(0.000)		(0.000)		
Non-Financial	0.081	0.378	33.367		-0.36	-0.218	0.531		-0.383	2.380	62.2
	(0.451)	(0.000)	(0.000)		(47.8%)	(0.001)	(0.000)		(0.000)		
Auto. & Parts	0.000	0.165	44.970	0.276	-1.24	-0.100	0.396		-0.245	2.422	48.9
	(0.999)	(0.002)	(0.000)	(0.000)	(27.8%)	(0.063)	(0.000)		(0.000)		
Industrial	-0.090	0.240	52.907		-0.38	-0.256	0.550		-0.490	2.960	51.5
	(0.542)	(0.000)	(0.000)		(46.7%)	(0.002)	(0.000)		(0.000)		
Oil & Gas	0.019	0.334	43.305		-0.36	-0.238	0.494		-0.525	3.079	45.2
	(0.902)	(0.000)	(0.000)		(47.8%)	(0.008)	(0.000)		(0.000)		
Retail	0.072	0.451	24.795		0.47	-0.222	0.535		-0.530	2.494	61.8
	(0.436)	(0.000)	(0.001)		(63.9%)	(0.005)	(0.000)		(0.000)		
Telecom.	0.648	0.404			-0.71	-0.531	0.530	34.518	-0.435	2.943	52.6
	(0.000)	(0.000)			(37.8%)	(0.000)	(0.000)	(0.000)	(0.000)		
Utilities	0.103	0.586	20.047		0.47	-0.191	0.628		-0.401	2.448	69.5
	(0.258)	(0.000)	(0.006)		(63.9%)	(0.014)	(0.000)		(0.000)		

Table 5: Threshold model estimates with illiquidity shocks

This table presents results for our TS model with illiquidity shocks. Columns 2-5 provide the regression parameters (with their p-values) for regime 1. Columns 7-10 contain the parameters (p-values) for state 2. If cells for parameter-values are empty, then these variables where excluded for the sake of improving BIC; if the cell the threshold is empty, then no two distinct regimes could be identified and the parameters reported under regime 1 apply for the entire time window. The values for the threshold are presented in column 6. The values in brackets next to c represent a percentige of the sample observations allocated to regime 1, based on the c value. For example, for Composite index, 46.7% of the considered 180 months were considered to be in state 1. For the remaining 53.3% months, regime 2 applies.

	Regime 1: $\Delta rv_t \leq c$					**Regime 2:** $\Delta rv_t > c$					
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bond Index	**Const.**	**TERM**	**DEFR.**	**ARλ**	***c***	**Const.**	**TERM**	**DEFR**	**ARλ**	**BIC**	**Ad.R^2 (%)**
Composite	0.015	0.293	44.261		-0.38	-0.135	0.518		-0.764	2.897	50.7
	(0.915)	(0.000)	(0.000)		(46.7%)	(0.089)	(0.000)		(0.000)		
Rating AA	0.013	0.445	26.384		-0.36	-0.086	0.568		-0.464	2.351	64.5
	(0.903)	(0.000)	(0.001)		(47.8%)	(0.164)	(0.000)		(0.000)		
Rating A	-0.043	0.282	45.768		-0.38	-0.152	0.529		-0.949	3.015	50.1
	(0.775)	(0.000)	(0.000)		(46.7%)	(0.073)	(0.000)		(0.000)		
Rating BBB	0.115		60.844		-0.36	-0.234	0.441		-0.831	3.496	37.6
	(0.546)		(0.000)		(47.8%)	(0.034)	(0.000)		(0.000)		
Maturity 1-3	-0.063	0.122	16.822	-0.351						1.611	35.7
	(0.208)	(0.000)	(0.000)	(0.000)							
Maturity 3-5	-0.003	0.222	42.259		-0.36	-0.113	0.423		-0.618	2.695	47.1
	(0.982)	(0.000)	(0.000)		(47.8%)	(0.122)	(0.000)		(0.000)		
Maturity 5-7	-0.008	0.328	56.847		-0.38	-0.194	0.626		-0.869	3.423	46.8
	(0.967)	(0.000)	(0.000)		(46.7%)	(0.061)	(0.000)		(0.000)		
Maturity 7-10	0.094	0.474	59.796		-0.38	-0.249	0.807		-1.498	3.822	50.8
	(0.678)	(0.000)	(0.001)		(46.7%)	(0.049)	(0.000)		(0.000)		
Maturity 10+	0.165	1.027	40.126		0.47	-0.937	0.998	53.106	-1.097	3.714	67.8
	(0.331)	(0.000)	(0.003)		(63.9%)	(0.000)	(0.000)	(0.002)	(0.000)		
Financial	-0.062	0.226	56.319		-0.38	-0.126	0.495		-1.085	3.580	36.9
	(0.757)	(0.009)	(0.000)		(46.7%)	(0.261)	(0.000)		(0.000)		
Non-Financial	0.197	0.338	27.851		-0.72	-0.266	0.531	17.447	-0.481	2.402	62.2
	(0.102)	(0.000)	(0.002)		(37.8%)	(0.002)	(0.000)	(0.010)	(0.000)		
Auto. & Parts	0.151	0.182	32.746		-0.96	-0.290	0.384	18.091	-0.589	2.266	56.3
	(0.201)	(0.000)	(0.000)		(33.9%)	(0.000)	(0.000)	(0.004)	(0.000)		
Industrial	-0.104	0.286	48.628	-0.419	-0.38	-0.157	0.559		-0.820	2.902	55.3
	(0.466)	(0.000)	(0.000)	(0.001)	(46.7%)	(0.047)	(0.000)		(0.000)		
Oil & Gas	0.053	0.316	41.341		-0.38	-0.185	0.488		-0.660	3.088	44.7
	(0.736)	(0.000)	(0.001)		(46.7%)	(0.034)	(0.000)		(0.000)		
Retail	0.072	0.451	24.795		0.47	-0.202	0.561		-0.668	2.515	61.0
	(0.441)	(0.000)	(0.001)		(63.9%)	(0.012)	(0.000)		(0.000)		
Telecom.	0.113	0.454	28.949		0.63	-0.182	0.569		-0.738	2.947	52.4
	(0.316)	(0.000)	(0.001)		(68.9%)	(0.105)	(0.000)		(0.000)		
Utilities	0.103	0.586	20.047		0.47	-0.120	0.639		-0.454	2.481	68.5
	(0.266)	(0.000)	(0.006)		(63.9%)	(0.143)	(0.000)		(0.000)		

Table 6: Threshold model estimates with lagged level of illiquidity

This table presents results for our TS model with 6 months lagged level of illiquidity. Columns 2-6 provide the regression parameters (with their p-values) for regime 1. Columns 8-11 contain the parameters (p-values) for state 2. If cells for parameter-values are empty, then these variables where excluded for the sake of improving BIC; if the cell the threshold is empty, then no two distinct regimes could be identified and the parameters reported under regime 1 apply for the entire time window. The values for the threshold are presented in column 7. The values in brackets next to c represent a percentige of the sample observations allocated to regime 1, based on the c value. For example, for Composite index, 63.9% of the considered 180 months were considered to be in state 1. For the remaining 36.1% months, regime 2 applies.

	Regime 1: $\Delta rv_t \leq c$						**Regime 2: $\Delta rv_t > c$**						
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Bond Index	**Const.**	**TERM**	**DEFR.**	**λ**	**λ_lag6**	***c***	**Const.**	**TERM**	**DEFR.**	**λ**	**λ_lag6**	**BIC**	**Ad.R^2 (%)**
Composite	0.172	0.367	25.375		0.315	0.47	-0.289	0.455		-0.686	0.365	2.749	59.3
	(0.109)	(0.000)	(0.003)		(0.000)	(63.9%)	(0.001)	(0.000)		(0.000)	(0.000)		
Rating AA	0.037	0.469	20.951		0.155	0.25	-0.153	0.569		-0.428	0.186	2.313	67.4
	(0.671)	(0.000)	(0.003)		(0.003)	(58.9%)	(0.021)	(0.000)		(0.000)	(0.004)		
Rating A	0.101	0.295	35.656		0.301	-0.92	-0.229	0.495		-0.848	0.436	2.863	59.0
	(0.513)	(0.000)	(0.003)		(0.000)	(35.0%)	(0.001)	(0.000)		(0.000)	(0.000)		
Rating BBB	0.362	0.272	26.471		0.451	0.47	-0.439	0.377		-0.833	0.441	3.330	50.7
	(0.014)	(0.000)	(0.024)		(0.000)	(63.9%)	(0.000)	(0.000)		(0.000)	(0.000)		
Maturity 1-3 years	0.036	0.105	18.504		0.189	0.30	-0.044	0.190		-0.360	0.240	1.488	49.4
	(0.541)	(0.000)	(0.000)		(0.000)	(60.6%)	(0.323)	(0.000)		(0.000)	(0.000)		
Maturity 3-5 years	0.181	0.274	21.434		0.329	0.47	-0.214	0.383		-0.582	0.319	2.525	57.4
	(0.063)	(0.000)	(0.006)		(0.000)	(63.9%)	(0.007)	(0.000)		(0.000)	(0.000)		
Maturity 5-7 years	0.215	0.419	32.447		0.401	0.47	-0.402	0.536		-0.811	0.315	3.265	56.6
	(0.124)	(0.000)	(0.003)		(0.000)	(63.9%)	(0.001)	(0.000)		(0.000)	(0.003)		
Maturity 7-10 years	0.656	0.602			0.573	0.47	-0.527	0.700		-1.220	0.567	3.709	57.0
	(0.000)	(0.000)			(0.000)	(63.9%)	(0.000)	(0.000)		(0.000)	(0.000)		
Maturity 10+ years	0.165	1.027	40.126			0.47	-0.547	0.934		-1.007	0.569	3.669	69.3
	(0.319)	(0.000)	(0.002)			(63.9%)	(0.000)	(0.000)		(0.000)	(0.000)		
Financial	0.111	0.295	43.465		0.390	-0.87	-0.212	0.451		-0.871	0.463	3.529	42.7
	(0.608)	(0.001)	(0.009)		(0.001)	(35.6%)	(0.032)	(0.000)		(0.000)	(0.000)		
Non-Financial	0.184	0.423	19.405		0.242	0.47	-0.237	0.480		-0.463	0.239	2.253	68.2
	(0.028)	(0.000)	(0.003)		(0.000)	(63.9%)	(0.001)	(0.000)		(0.000)	(0.001)		
Automobiles & Parts	0.000	0.165	44.970	0.276		-1.24	-0.076	0.398		-0.276	0.214	2.403	51.0
	(0.999)	(0.002)	(0.000)	(0.000)		(27.8%)	(0.151)	(0.000)		(0.000)	(0.005)		
Industrial G&S	-0.090	0.240	52.907			-0.38	-0.227	0.532		-0.572	0.226	2.954	52.9
	(0.536)	(0.000)	(0.000)			(46.7%)	(0.006)	(0.000)		(0.000)	(0.015)		
Oil & Gas	0.140	0.342	30.342		0.332	-0.36	-0.220	0.482		-0.616	0.260	3.024	50.5
	(0.348)	(0.000)	(0.011)		(0.001)	(47.8%)	(0.010)	(0.000)		(0.000)	(0.004)		
Retail	0.131	0.460	20.772		0.193	0.47	-0.242	0.521		-0.624	0.279	2.406	66.6
	(0.139)	(0.000)	(0.003)		(0.000)	(63.9%)	(0.001)	(0.000)		(0.000)	(0.000)		
Telecommunications	0.563	0.485			0.382	-0.38	-0.508	0.524	29.191	-0.422		2.898	55.7
	(0.000)	(0.000)			(0.000)	(46.7%)	(0.000)	(0.000)	(0.002)	(0.000)			
Utilities	0.161	0.599	16.148		0.168	0.47	-0.203	0.603		-0.445	0.216	2.411	71.9
	(0.072)	(0.000)	(0.022)		(0.005)	(63.9%)	(0.007)	(0.000)		(0.000)	(0.003)		

Table 7: Threshold model estimates with lagged illiquidity shocks

This table presents results for our TS model with 6 months lagged illiquidity shocks. Columns 2-6 provide the regression parameters (with their p-values) for regime 1. Columns 8-11 contain the parameters (p-values) for state 2. If cells for parameter-values are empty, then these variables where excluded for the sake of improving BIC; if the cell the threshold is empty, then no two distinct regimes could be identified and the parameters reported under regime 1 apply for the entire time window. The values for the threshold are presented in column 7. The values in brackets next to c represent a percentage of the sample observations allocated to regime 1, based on the c value. For example, for Composite index, 46.7% of the considered 180 months were considered to be in state 1. For the remaining 53.3% months, regime 2 applies.

	Regime 1: $\Delta rv_t \leq c$						**Regime 2: $\Delta rv_t > c$**						
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Bond Index	**Const.**	**TERM**	**DEFR.**	**ARλ**	**ARλ_lag6**	***c***	**Const.**	**TERM**	**DEFR.**	**ARλ**	**ARλ_lag6**	**BIC**	**Ad.R^2 (%)**
Composite	0.015	0.293	44.261			-0.38	-0.135	0.518		-0.764		2.8966	50.7
	(0.915)	(0.000)	(0.000)			(46.7%)	(0.089)	(0.000)		(0.000)			
Rating AA	0.013	0.445	26.384			-0.36	-0.086	0.568		-0.464		2.3514	64.5
	(0.903)	(0.000)	(0.001)			(47.8%)	(0.164)	(0.000)		(0.000)			
Rating A	-0.043	0.282	45.768			-0.38	-0.152	0.529		-0.949		3.0147	50.1
	(0.775)	(0.000)	(0.000)			(46.7%)	(0.073)	(0.000)		(0.000)			
Rating BBB	0.115		60.844			-0.35	-0.234	0.441		-0.831		3.4956	37.6
	(0.546)		(0.000)			(47.8%)	(0.034)	(0.000)		(0.000)			
Maturity 1-3 years	-0.061	0.122	16.912	-0.345	0.116							1.6094	37.3
	(0.212)	(0.000)	(0.000)	(0.000)	(0.021)								
Maturity 3-5 years	-0.003	0.222	42.259			-0.36	-0.113	0.423		-0.618		2.6954	47.1
	(0.982)	(0.000)	(0.000)			(47.8%)	(0.122)	(0.000)		(0.000)			
Maturity 5-7 years	-0.008	0.328	56.847			-0.38	-0.194	0.626		-0.869		3.4229	46.8
	(0.967)	(0.000)	(0.000)			(46.7%)	(0.061)	(0.000)		(0.000)			
Maturity 7-10 years	0.094	0.474	59.796			-0.38	-0.249	0.807		-1.498		3.8217	50.8
	(0.678)	(0.000)	(0.001)			(46.7%)	(0.049)	(0.000)		(0.000)			
Maturity 10+ years	0.165	1.027	40.126			0.47	-0.937	0.998	53.106	-1.097		3.7143	67.8
	(0.331)	(0.000)	(0.003)			(63.9%)	(0.000)	(0.000)	(0.002)	(0.000)			
Financial	-0.062	0.226	56.319			-0.38	-0.126	0.495		-1.085		3.5797	36.9
	(0.757)	(0.009)	(0.000)			(46.7%)	(0.261)	(0.000)		(0.000)			
Non-Financial	0.214	0.316	26.202		0.235	-1.03	-0.252	0.527	18.643	-0.478		2.3882	63.6
	(0.085)	(0.000)	(0.005)		(0.006)	(32.8%)	(0.003)	(0.000)	(0.004)	(0.000)			
Automobiles & Parts	0.151	0.182	32.746			-0.97	-0.290	0.384	18.091	-0.589		2.2657	56.3
	(0.201)	(0.000)	(0.000)			(33.9%)	(0.000)	(0.000)	(0.004)	(0.000)			
Industrial G&S	-0.104	0.286	48.628	-0.419		-0.38	-0.157	0.559		-0.820		2.9015	55.3
	(0.466)	(0.000)	(0.000)	(0.001)		(46.7%)	(0.047)	(0.000)		(0.000)			
Oil & Gas	0.053	0.316	41.341			-0.38	-0.185	0.488		-0.660		3.0875	44.7
	(0.736)	(0.000)	(0.001)			(46.7%)	(0.034)	(0.000)		(0.000)			
Retail	0.072	0.451	24.795			0.47	-0.202	0.561		-0.668		2.5153	61.0
	(0.441)	(0.000)	(0.001)			(63.9%)	(0.012)	(0.000)		(0.000)			
Telecommunications	0.658	0.394			0.436	-1.06	-0.407	0.534	31.517	-0.505		2.9197	54.7
	(0.000)	(0.000)			(0.001)	(32.8%)	(0.000)	(0.000)	(0.000)	(0.000)			
Utilities	0.103	0.586	20.047			0.47	-0.120	0.639		-0.454		2.4811	68.5
	(0.266)	(0.000)	(0.006)			(63.9%)	(0.143)	(0.000)		(0.000)			