Essays on Empirical Finance in Times of Crises – Fractional Integration, Structural Breaks, and Explosiveness

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Abstract

The 21st century – up to now – is characterized by numerous economically and financially relevant events. Just to name a few: The European Monetary Union was founded, the New Economy Bubble burst, Lehman Brothers collapsed, and the sovereign debt crisis in the euro zone arose. These occurrences had severe consequences for all economic entities. This collection of five essays applies or enhances methods from the field of time series analysis in order to get a better understanding of these events.

Following the introduction, Chapter 2 applies the structural break test by Sibbertsen and Kruse (2009) to falsify the uncovered interest rate parity theory in the euro area. This theory predicts a stationary long-run equilibrium between two interest rates. However, the results of this testing procedure suggest that the spread of government bonds issued by France, Italy, and Spain against Germany increased from nonstationary Long Memory to unit root behavior between 2006 and 2008.

The test by Phillips, Wu, and Yu (2011) exhibits severe size distortions if the residuals of the unit root or the explosive model contain stationary Long Memory. Chapter 3 proposes a modification of the test by Demetrescu, Kuzin, and Hassler (2008) to test against strong dependent innovation and an adjustment of the critical values of the test by Phillips, Wu, and Yu (2011) in the presence of Long Memory.

Chapter 4 applies the test by Phillips, Wu, and Yu (2011) to a time series which reflects the price development of the North American real estate sector and government bond yields as well as their spreads in the euro area. The results indicate explosiveness in the real estate market index and the yield spreads. Furthermore, the government bond yields of Greece and Portugal also show explosive behavior. In order to test against migration effects from the US real estate market to the yield(s) (spreads), the bubble migration test by Phillips and Yu (2011) is employed. The hypothesis of migration cannot be rejected coincident with the collapse of Lehman Brothers but there are no indications for these effects in the recent European debt crisis.

Chapter 5 uses techniques from the field of (fractional) cointegration analysis to falsify the theory of Goldreich, Hanke, and Nath (2005) about liquidity risk. The results here suggest that coincident with the advent of the financial crisis, the hypothesis of a long-run equilibrium of liquid and illiquid covered bonds must be rejected.

Finally, Chapter 6 compares the predictive power of neural networks forecasting interest rate spreads in the euro area with and without a term accounting for cointegration. This is motivated by interest rate convergence in the course of the advent of the Euro. The results suggest that adding a cointegration term might produce superior results.

Keywords: Sovereign Credit Risk, Liquidity Risk, Explosiveness, Structural Breaks, Fractional Integration

Zusammenfassung

Das 21. Jahrhundert war – bis jetzt – charakterisiert durch zahlreiche ökonomische und finanzwirtschaftliche Ereignisse. Um einige zu nennen: Die europäische Währungsunion wurde gegründet, die New Economy Blase platzte, Lehman Brothers meldete Konkurs an und die Staatsschuldenkrise in der Eurozone kam auf. Diese Vorkommnisse hatten schwerwiegende Konsequenzen für alle ökonomischen Einheiten. Im Rahmen der nachfolgenden fünf Aufsätze werden Methoden aus dem Feld der Zeitreihenanalyse angewandt oder erweitert, um die Ereignisse besser zu verstehen.

Nach der Einleitung wird in Kapitel 2 der Strukturbruchtest nach Sibbertsen und Kruse (2009) genutzt, um die ungedeckte Zinsparitätentheorie im Euroraum zu falsifizieren. Die Theorie impliziert ein stationäres langfristiges Gleichgewicht zwischen zwei Zinssätzen. Die Ergebnisse des Tests deuten allerdings darauf hin, dass die Zinsdifferentiale zwischen Staatsanleihen der Länder Frankreich, Italien und Spanien gegen Deutschland von nichtstationärem Long Memory zu Unit Root Verhalten zwischen 2006 und 2008 wechseln.

Der Test von Phillips et al. (2011) weist deutliche Verzerrungen der Size auf, wenn die Residuen des Unit Root oder des explosiven Modells stationäres Long Memory aufweisen. In Kapitel 3 wird eine Modifikation des Verfahrens von Demetrescu et al. (2008) vorgeschlagen, um gegen starke Abhängigkeiten der Residuen zu testen. Zusätzlich werden adjustierte kritische Werte des Tests von Phillips et al. (2011) für diesen Fall vorgeschlagen.

In Kapitel 4 wird der Test von Phillips et al. (2011) auf eine Zeitreihe, welche die Preisentwicklung am nordamerikanischen Immobilienmarkt repräsentiert, und auf die Rendite(spreads) der Staatsanleihen in der Eurozone angewandt. Die Ergebnisse geben Hinweise auf Explosivität am US Immobilienmarkt und in den Zinsdifferenzen. Darüber hinaus weisen die Renditen der Staatsanleihen aus Griechenland und Portugal explosives Verhalten auf. Um gegen Migrationseffekte vom US Immobilienmarkt zu den Staatsanleihen zu testen, wird der Test von Phillips und Yu (2011) genutzt. Die Hypothese der Migration kann, koinzident mit dem Konkurs von Lehman Brothers, nicht verworfen werden. Zur Zeit der europäischen Staatsschuldenkrise wird diese Hypothese allerdings abgelehnt.

Kapitel 5 nutzt Methoden der (fraktionalen) Kointegrationsanalyse, um die Theorie von Goldreich et al. (2005) zu Liquiditätsrisiken zu falsifizieren. Die Ergebnisse weisen darauf hin, dass, koinzident mit dem Aufkommen der Finanzkrise, die Hypothese eines langfristigen Gleichgewichts zwischen liquiden und illiquiden gedeckten Schuldverschreibungen verworfen werden muss.

Abschließend wird in Kapitel 6 die Qualität Neuronaler Netze zur Prognose der Zinsdifferentiale in der Eurozone untersucht. Es werden konventionelle Netze und Modelle, welche mögliche Kointegrationsbeziehungen berücksichtigen, miteinander verglichen. Motiviert ist dies durch das Konvergenzverhalten europäischer Staatsanleiherenditen während der Euroeinführung. Die Ergebnisse weisen darauf hin, dass ein Kointegrationsterm bessere Prognosen ermöglichen kann.

Schlagwörter: Sovereign Credit Risk, Liquiditätsrisiko, explosive Prozesse, Strukturbrüche, Fractional Integration

Contents

Chapter 1

Introduction

1 Introduction

"[G]iven that the structure of an econometric model consists of optimal decision rules of economic agents, and that optimal decision rules vary systematically with changes in the structure of series relevant to the decision maker, it follows that any change in policy will systematically alter the structure of econometric models." (Lucas, 1976, p. 41)

This often cited syllogism is the key element of the famous Lucas critique. Lucas (1976) argues that changes of economic policy systematically affect the behavior of economic agents. Therefore, any econometric model, trying to predict the effects of policy interventions, must fail. This argument seems to be particularly true in times of crisis. In the context of this thesis a crisis is related to the bursting of (financial) bubbles, recessions, inflation peaks, bank runs, currency crises and, most important here, arising sovereign credit risk as well as sovereign defaults. Thus, when a crisis occurs, parameters of econometric models might change dramatically due to varying plans and expectations of agents.

Therefore, from an econometrician's point of view the best solution seems to bury ones head in the sand. However, Basse (2006, p. 24) argues, that *"[t]he Lucas critique only shows that the consequences of government intervention cannot be analyzed by using econometrics. Applied in the right way econometrics in fact can be a very helpful research tool for economists studying historical events."* The following five chapters provide an application of econometrics *"in the right way"* or to enhance existing econometric approaches to fit reality better in order to understand the history of financial markets.

The uncovered interest rate parity theory predicts a stationary long-run equilibrium between the interest rates in the European Monetary Union (EMU). Numerous studies cannot falsify this theory empirically during the advent of the Euro (e.g., Baum and Barkoulas, 2006; Frömmel and Kruse, 2015). However, the results reported in Chapter 2, co-authored by Philipp Sibbertsen and Tobias Basse, provide evidence for breaks between 2006 and 2008 from mean-reverting to unit root behavior using the test by Sibbertsen and Kruse (2009). Thus, the persistence (measured by the long-memory parameter) of the yield spreads from French, Italian and Spanish against German government bonds has increased significantly after this period. This could be a sign of higher sovereign credit risk (and possibly liquidity and even redenomination risk) caused by the debt crisis in the euro area.

Chapter 3, co-authored with Robinson Kruse, considers the test by Phillips, Wu, and Yu (2011) under strong dependent innovations to test against explosiveness. This well established method is regarded to be a valuable alternative to other procedures identifying explosive behavior of a time series. However, the test by Phillips, Wu, and Yu (2011) exhibits severe size distortions if the residuals of the $AR(1)$ model contain strong dependent innovations. In order to overcome this shortcoming, we propose response curves to adjust the critical values of this test in the presence of residuals containing stationary long memory. To analyze the behavior of the innovations, we apply the test by Demetrescu, Kuzin, and Hassler (2008). However, this procedure also has a nonstandard limiting distribution in this setting. Therefore, we propose response curves depending on the autoregressive coefficient of the $AR(1)$ model to receive augmented critical values. We show by Monte Carlo simulation that the Prewhitening by Qu (2011) is an appropriate way to deal with short-run dynamics of the residuals for both tests.

Chapter 4, written with Robinson Kruse and Tobias Basse, considers the question whether the EMU crisis was triggered by the US subprime crunch by using recent methodologies suggested by Phillips, Wu, and Yu (2011) and Phillips and Yu (2011). We define crisis regimes by explosive behavior of interest rates and government bond yield spreads as a result of increasing sovereign credit, redenomination, and liquidity risk. As expected, we find clear evidence for explosive behavior in the spreads during the EMU crisis which coincides with the bankruptcy of Lehman Brothers. We estimate the time-varying persistence for a US house price proxy. Furthermore, we employ an explosiveness migration test and obtain indications for migration from the house price proxy to the spreads. We look at EMU interest rates in order to investigate whether the migration process is persistent during the EMU crisis. The results indicate that there is explosiveness migration caused by the Lehman Brothers bankruptcy, but no migration during the EMU crisis from US mortgage markets to EMU interest rates. The findings suggest that the EMU debt crisis is a homemade problem and remain essentially unchanged even after performing robustness checks.

Chapter 5, co-authored by Tobias Basse and Philipp Sibbertsen, is dedicated to liquidity risk. Liquidity risk describes the risk that an asset cannot always be sold without causing a fall in its price caused by a lack of demand for this asset. Many empirical studies examining liquidity premia have focused on government bonds (see Boudoukh and Whitelaw, 1993). Therefore, it might be of special interest to analyze yield differentials between liquid and illiquid German covered bonds. We examine the yields of rather liquid and more liquid Pfandbriefe with different maturities. In terms of credit risk the spreads between the yields of these two types of covered bonds should be zero. Moreover, assuming that the liquidity risk premium is a stationary variable, the yields of Pfandbriefe and Jumbo Pfandbriefe (which seem to be $I(1)$) should be cointegrated. We test this hypothesis by using a method proposed by Shimotsu (2012) to allow for fractional cointegration. Due to the financial crisis, it also seems to be appropriate to consider structural changes. Our results indicate fractional cointegrated yields before and after the crisis. However, during the crisis the degree of integration of the spread increases strongly.

Finally, Chapter 6, written with Christian von Spreckelsen, Tobias Basse, and Hans-Jörg von Mettenheim, discusses the implications of the interest rate parity theory on the prediction of government bond yields using neural network forecasting approaches. If there is a mean-reverting long-run equilibrium between government bond yields from different EMU countries during the advent of the Euro, an error correction term should improve the forecasting accuracy of neural networks which are applied to time series in first differences. This is motivated by a Monte Carlo simulation experiment by Qi and Zhang (2008) who show that differencing improves the prediction in the presence of unit root behavior of the data. Our approach can be interpreted as an analogy to the Vector Error Correction Model. We evaluate the model using bond yields from Germany and France from 1999 to 2007. The results indicate that neural networks accounting for cointegration can outperform conventional neural networks in this context.

Chapter 2

Testing for a Break in the Persistence in Yield Spreads of EMU Government Bonds

2 Testing for a Break in the Persistence in Yield Spreads of EMU Government Bonds

Co-authored with Philipp Sibbertsen and Tobias Basse.

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Chapter 3

Testing for Neglected Strong Dependence in Explosive Models

3 Testing for Neglected Strong Dependence in Explosive Models

Co-authored with Robinson Kruse.

3.1 Introduction

The test by Phillips, Wu, and Yu (2011) is a recent and widely applied procedure to test against explosive behavior in time series econometrics. There is fast-growing empirical literature, which applies the test to detect bubbles in real estate, commodity, and stock prices. However, there is a gap in the literature concerning strong dependent innovation processes in this framework. We consider the test by Phillips, Wu, and Yu (2011) under strong dependencies and find severe size distortions in case the residuals of the autoregressive model exhibit long memory. The unit root hypothesis is rejected far too often even for a mild form of strong dependence. We use the limit theory for mildly explosive models by Magdalinos (2012) to uncouple the consistent estimation of the autoregressive coefficient and the degree of persistence of the residuals. Thus, we are able to test the unit root hypothesis against an explosive alternative in the presence of long-range dependencies. We are particularly interested in small sample properties of all methods in this context, because explosive behavior seems to be a temporal phenomenon. In order to apply this method to detect explosive behavior, we suggest a modification of the procedure by Demetrescu, Kuzin, and Hassler (2008) to test against strong dependent innovations. This paper is structured as follows: Section 3.2 introduces the model and test procedures. The results of a Monte Carlo simulation are reported and discussed in Section 3.3. Section 3.4 concludes.

3.2 Model Specification and Testing Procedures

Let y_t be a stochastic process in discrete time of the form

$$y_t = \rho y_{t-1} + u_t \tag{1}$$

with $t = 0, 1, ..., T$, u_t as the innovation sequence, $\rho = 1 + \frac{c}{k_T}$ with $c \geq 0$ and $y_0 = 0$. $(k_T)_{T \geq 1}$ is a sequence which increases to infinity such that $k_T = o(T)$ when $T \to \infty$. We assume that u_t follows a fractionally integrated process of the form

$$\Phi(B)(1-B)^{d_u} u_t = \Psi(B)\epsilon_t \tag{2}$$

where all roots of the polynomials $\Phi(B)$ and $\Psi(B)$ are assumed to lie outside the unit circle and ϵ_t is independent and identically distributed with $E(\epsilon_t) = 0$, $sup_t E(\epsilon_t^2) < \infty$ and $\epsilon_t = 0$ for $t < 0$. The long-memory parameter $d_u \in [0, 0.5)$ determines the degree of integration of u_t and $(1-B)^d$ is defined by its binomial expansion

$$(1-B)^d = \sum_{j=0}^{\infty} \frac{\Gamma(j-d)}{\Gamma(-d)\Gamma(j+1)} B^j \tag{3}$$

with $\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}dt$ and B as the Backshift operator, i.e. $By_t = y_{t-1}$.

We are interested in the hypothesis

$$\mathcal{H}_0 : \rho = 1 \quad \text{against} \quad \mathcal{H}_1 : \rho > 1$$

using the t_ρ-statistic

$$t_\rho = \frac{\rho - 1}{\sigma_\rho} \tag{4}$$

of the regression model

$$y_t = \mu + \rho y_{t-1} + u_t \tag{5}$$

where σ_ρ is the standard deviation of ρ. Sowell (1990) proves that for $\rho = 1$, $(1-B)^{d_u}u_t = \epsilon_t, \epsilon_t \sim NID(0, \sigma_\epsilon^2)$ and $y_0 = 0$,

$$t_\rho \Rightarrow \frac{\int_0^1 \widetilde{W}_{d_u} dW_{d_u}}{\left(\int_0^1 \widetilde{W}_{d_u}^2\right)^{1/2}} \text{ if } d_u \in [0, 0.5) \tag{6}$$

as $T \to \infty$ with W_{d_u} as the fractional Brownian motion as defined by Mandelbrot and Van Ness (1968) and $\widetilde{W}_{d_u}$ as the demeaned fractional Brownian motion. From the results of Sowell (1990) it follows that the ordinary least squares estimator (OLS) of ρ is consistent under the null hypothesis. Under the alternative, Magdalinos (2012) shows that the asymptotic behavior of the sample moments $\sum_{t=1}^T y_{t-1}^2$ and $\sum_{t=1}^T y_{t-1}u_t$ are affected by a stationary long memory innovation sequence. However, this effect is canceled out in least squares regression theory. This result enables us to estimate ρ consistently by OLS and to analyze the persistence of the residuals d_u. Thus, we are able to construct a right tailed unit root test which allows a stationary long memory process as the innovation sequence. To deal with short-run dynamics, we use the Prewhitening as proposed by Qu (2011).

Furthermore, we simulate quantiles of the limiting distribution of t_ρ depending on d_u with $10,000$ Monte Carlo repetitions with d_u in the interval of $[0, 0.5)$ by steps of 0.01 and estimate response curves of the form

$$cv_\alpha(d_u) = \sum_{i=0}^{s} \beta_i d_u^i. \tag{7}$$

Here, cv_α is the α-quantile of the simulated distribution and s denotes the maximal polynomial order. Figure 1 shows the simulated quantiles (y-axis) depending on d_u (x-axis).

As described before, the limiting distribution of the t_ρ-values depends on the memory parameter of the innovation process of model 1. Thus, we might test against strong dependent residuals. The following exposition is based on Demetrescu, Kuzin, and Hassler (2008). The authors suggest a lag augmented version of the Lagrange multiplier test by Robinson (1995). This procedure is based on the regression

$$x_t = \phi x_{t-1}^* + a_1 x_{t-1} + a_2 x_{t-2} + ... + a_p x_{t-p} + \varepsilon_t \text{ for } t = p+1, ..., T \tag{8}$$

with $x_{t-1}^* = \sum_{j=1}^{t-1} \frac{x_{t-j}}{j}$, x_t as an univariate time series, p as the number of lags in the augmentation,

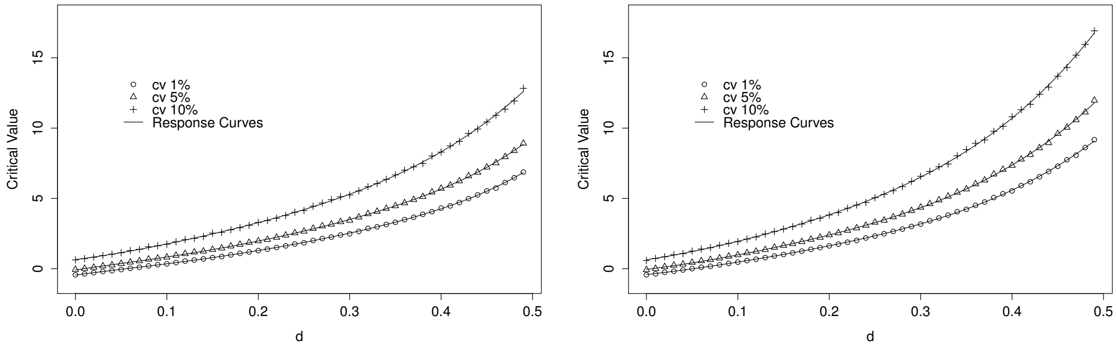

Figure 1: Simulated quantiles of t_ρ with $T = 250$ (left) and $T = 500$ (right).

which grows with the sample size, and ε_t as an innovation process. In its classical form, the authors retain limiting normality of the t_ϕ-statistic, which is used to test the null hypothesis $H_0 : \phi = d = 0$. However, we investigate the persistence of the residuals in model (1)

$$u_t = y_t - \mu - \rho y_{t-1} \tag{9}$$

using the $t_{\hat{\phi}}$-values of the regression

$$u_t = \hat{\phi} u^*_{t-1} + \hat{a}_1 u_{t-1} + \hat{a}_2 u_{t-2} + ... + \hat{a}_p u_{t-p} + \hat{\varepsilon}_t \text{ for } t = p+1, ..., T \tag{10}$$

to test $H_0 : \hat{\phi} = d_u = 0$. Thus, $t_{\hat{\phi}}$ has a nonstandard limiting distribution which depends on ρ, because for $c > 0$ the serial correlation coefficient has a $k_T \rho$ convergence as shown by Phillips and Magdalinos (2007). This also holds in the case of $d_u \in (0, 0.5)$ as shown by Magdalinos (2012). Therefore, using $10,000$ Monte Carlo repetitions, we simulate the limiting distribution of $t_{\hat{\phi}}$ which depends on the estimated ρ and we estimate response curves as in equation (7). Figure 2 shows the upper quantiles of the limiting distribution (x-axis) depending on the estimate of ρ (y-axis).

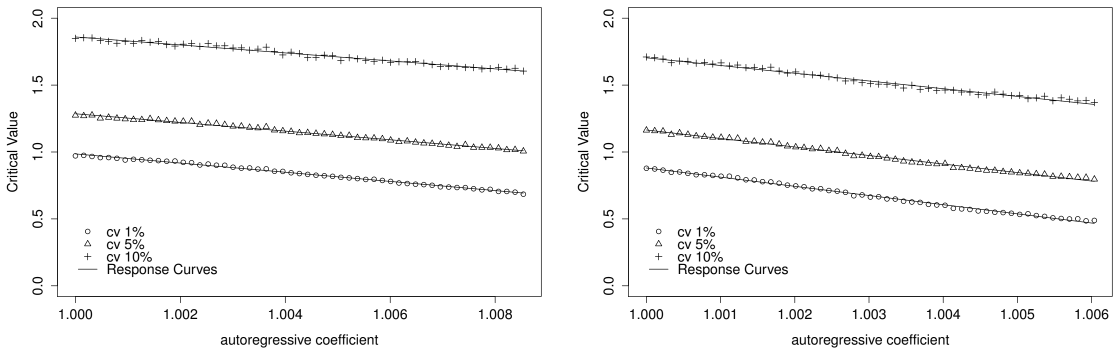

Figure 2: Simulated quantiles of $t_{\hat{\phi}}$ with $T = 250$ (left) and $T = 500$ (right).

3.3 Monte Carlo Simulation

We evaluate the 5% size and power of the procedure by Demetrescu, Kuzin, and Hassler (2008) applied to the residuals u_t in both the unit root and in the explosive case using $1,000$ Monte Carlo runs each. Here, the data generating process is designed as $(1-L)^{d_u} u_t = \epsilon_t$, $c = 0$ (see table 1), and $c = 0.135$ (see table 2) respectively with augmented critical values depending on the estimate of ρ.

Table 1: Size and power (5%) of the ALM test (1).

	$T = 250$			$T = 500$		
d_u	$p = 0$	$p = \tilde{p}$	*prewhitened*	$p = 0$	$p = \tilde{p}$	*prewhitened*
0.00	0.0545	0.0175	0.0465	0.0510	0.0290	0.0530
0.05	0.1185	0.0325	0.1205	0.1915	0.0545	0.1800
0.10	0.2350	0.0326	0.2435	0.4095	0.0840	0.4156
0.15	0.3785	0.0570	0.3780	0.6595	0.1305	0.6545
0.20	0.4965	0.0570	0.5015	0.8310	0.1760	0.8320
0.25	0.6455	0.0580	0.6315	0.9240	0.2235	0.9245
0.30	0.7205	0.0625	0.7230	0.9595	0.2620	0.9675
0.35	0.7940	0.0600	0.7900	0.9825	0.2660	0.9880
0.40	0.8360	0.0515	0.8320	0.9935	0.2880	0.9905
0.45	0.8560	0.0420	0.8480	0.9975	0.2495	0.9890

We consider three cases in order to deal with short-run dynamics. We set the lag augmentation to its true value ($p = 0$), to the deterministic lag length selection $\tilde{p} = \left[4 * (T/100)^{0.25}\right]$ as suggested by Demetrescu, Kuzin, and Hassler (2008) and to $p = 0$ after a Prewhitening of u_t (labeled *prewhitened* in both tables) using the procedure by Qu (2011). The later works as follows: We estimate an ARFIMA(p, d, q) model with $p, q = 0, 1$ determining the lag order by the Bayesian Information Criterion (BIC) with a_p as the autocorrelation coefficients and b_q as the moving average coefficients of u_t. Subsequently, we use a_p and b_q to construct $u_t^* = (1 - a_p B)(1 + b_q B)^{-1} u_t$. Afterwards, the test by Demetrescu, Kuzin, and Hassler (2008) is applied to u_t^* with $p = 0$ lags.

Table 2: Size and power (5%) of the ALM test (2).

	$T = 250$			$T = 500$		
d_u	$p = 0$	$p = \tilde{p}$	*prewhitened*	$p = 0$	$p = \tilde{p}$	*prewhitened*
0.00	0.0480	0.0140	0.0480	0.0510	0.0205	0.0505
0.05	0.1150	0.0225	0.1150	0.1995	0.0450	0.2070
0.10	0.2240	0.0295	0.2230	0.4380	0.0790	0.4235
0.15	0.3675	0.0375	0.3515	0.6856	0.1285	0.6750
0.20	0.5325	0.0400	0.5040	0.8630	0.1840	0.8580
0.25	0.6460	0.0600	0.6365	0.9360	0.2430	0.9430
0.30	0.7475	0.0660	0.7370	0.9685	0.2880	0.9805
0.35	0.8125	0.0675	0.8150	0.9890	0.3145	0.9915
0.40	0.8485	0.0665	0.8755	0.9960	0.3275	0.9935
0.45	0.8770	0.0505	0.8810	0.9995	0.3410	0.9870

The results indicate conservative size and nonmonotonic power in the case of the deterministic lag selection. However, setting p to its expected true value ($p = 0$) after applying the Prewhitening to the residuals u_t, leads to correct size and monotonic increasing power. The power properties are quite similar to the case where p is known, which belongs to the most preferable but unrealistic cases. Thus, the Prewhitening seems to be superior compared to the deterministic lag selection approach.

Table 3: Size and power (5%) of the test against explosiveness.

	$T = 250$			$T = 500$		
c	$d = 0$	$d = 0.2$	$d = 0.4$	$d = 0$	$d = 0.2$	$d = 0.4$
0.000	0.0450	0.3156	0.4670	0.0480	0.3360	0.4663

Furthermore, we consider the 5% size of the test by Phillips, Wu, and Yu (2011) using $1,000$ Monte Carlo replications. This procedure is correctly sized for $I(0)$ residuals but shows strong distortions for $d_u \in (0, 0.5)$ as reported by table 3. Thus, we evaluate the 5% size and power of t_ρ with augmented critical values depending on d_u. The data generating process is given by equation (1) with $c \geq 0$, $k_T = T^{0.5}$ and $(1 - L)^{d_u} u_t = \epsilon_t$ with $d_u \in [0, 0.5)$. To deal with short-run dynamics, we estimate the residuals $\tilde{u}_t$ from regression $y_t = \tilde{\rho} y_t + \tilde{u}_t$ and apply the Prewhitening by Qu (2011) to $\tilde{u}_t$. We use the prewhitened residuals u_t to construct the series $y_t^* = \tilde{\rho} y_{t-1}^* + u_t$ with $y_0 = 0$. Furthermore, we estimate the parameters of the regression $y_t^* = \mu + \rho y_{t-1}^* + u_t$ to receive t_ρ. The parameter d_u is estimated by a Maximum Likelihood estimator applied to u_t. All results are generated by using response curves as depicted by figure 1. The size and power properties are reported in table 4. The test holds its size ($\alpha = 0.05$) and exhibits monotonic power. For strong dependent residuals, the test improves power properties which might be caused by the more efficient estimations of ρ.

Table 4: Size and power (5%) of the test against explosiveness with augmented critical values.

	$T = 250$			$T = 500$		
c	$d = 0$	$d = 0.2$	$d = 0.4$	$d = 0$	$d = 0.2$	$d = 0.4$
0.000	0.0450	0.0495	0.0530	0.0480	0.0520	0.0510
0.027	0.0850	0.0965	0.1025	0.0880	0.1270	0.1430
0.040	0.0855	0.1145	0.1525	0.1150	0.1550	0.2420
0.054	0.1230	0.1525	0.2360	0.1690	0.2500	0.4060
0.068	0.1735	0.2115	0.3370	0.3180	0.3340	0.5185
0.081	0.2460	0.2705	0.4215	0.4240	0.5270	0.6610
0.095	0.3220	0.3750	0.5270	0.6000	0.6300	0.7280
0.108	0.4160	0.4610	0.6255	0.6920	0.7090	0.1130
0.122	0.5145	0.5435	0.6895	0.7870	0.8050	0.8700
0.135	0.6610	0.6400	0.7640	0.8645	0.8810	0.8910

3.4 Conclusion

We use the theory by Sowell (1990) and Magdalinos (2012) to uncouple the consistent estimation of the autoregressive coefficient of an $AR(1)$ model and the degree of integration of its residuals in the unit root or the explosive case. From these results we are able to propose response curves to augment the test by Phillips, Wu, and Yu (2011) under strong dependent innovations. To test against $I(d)$ with $d \in (0, 0.5)$ behavior of the residuals, we propose augmented critical values for the test by Demetrescu, Kuzin, and Hassler (2008). The utility of all methods in finite samples is illustrated by Monte Carlo simulations.

Chapter 4

The Walking Debt Crisis

4 The Walking Debt Crisis

Co-authored with Robinson Kruse and Tobias Basse.

4.1 Introduction

US house prices peaked in the years 2005 and 2006. As a consequence, the availability of credit for potential buyers of real estate decreased and borrowers experienced more and more problems to refinance their loans. This new environment increased the pressure on real estate prices. The resulting dramatic fall of US house prices, of course, had massive negative effects on the prices of US subprime mortgage-backed securities. These collateralized bonds had also been bought by financial institutions in Europe and Asia. Therefore, not only US banks (e.g., Lehman Brothers and Washington Mutual) all of a sudden found themselves to be in deep trouble. The collapse of Lehman Brothers intensified the problems. At this point one of the central questions (see Eichengreen, Mody, Nedeljkovic, and Sarno, 2012) seems to be how the Subprime Crisis – a problem in a rather small segment of US financial markets – was able to have such serious negative consequences for the global economy. One of the key answers to this important question clearly is the global banking system. In fact, international banks have played a critical role in the transmission of the crisis from the US to Europe and other parts of the world. Most importantly, banks have been responsible for causing some additional fiscal problems in some European countries. Basse, Friedrich, and Kleffner (2012), for example, have identified structural changes in the relationship between German and Italian government bond yields. They have found two structural breaks that can be explained by changes in sovereign credit risk. While the first structural break coincides with the US Subprime Crisis and the resulting bank rescue programs in Europe, the second structural break might be a consequence of a phenomenon that could be called the European sovereign debt crisis. Three countries (namely Greece, Portugal and Ireland) played a special role in this second part of the crisis. The sudden increase of the importance of sovereign credit risk in Europe has had major consequences for the pricing of fixed income securities in one of the biggest bond markets of the world. Sibbertsen, Wegener, and Basse (2014), for example, have argued that the crisis at least for the moment has ended the process of interest rate convergence in the European Monetary Union (EMU). Solely in Ireland the fiscal problems of the government can be explained by the costs resulting from measures to stabilize the financial system of the country. Moreover, there also have been dangerous imbalances within the Eurozone between surplus nations with higher exports than imports and deficit nations with more goods and services imported than exported. Given that the existence of the common currency made it impossible for deficit nations to devalue and thereby improve their competitiveness Varoufakis (2013), for example, has argued that even without the credit crunch in the US and the subsequent events in 2008 something bad simply had to happen. Therefore, it could also be argued that this second part of the crisis actually was no second part but a crisis of its own. Ludwig (2014) already has presented an interesting discussion of this issue. We try to find new relevant empirical evidence. More specifically, we use a methodology that recently has been suggested by Phillips, Wu, and Yu (2011) and Phillips and Yu (2011) to shed new light on this question.

The paper is structured as follows: Section 4.2 gives a short review of the relevant literature focusing on interest rate convergence in the EMU. Section 4.3 discusses methodological issues and introduces the data examined. The empirical evidence is presented in Section 4.4. Section 4.5 concludes.

4.2 Literature Review

The introduction of the Euro in 1999 has been very important for the bond markets of the EMU countries because the new common currency has eliminated exchange rate risk among the member states. Therefore, it is no surprise that Kim, Moshirian, and Wu (2006) have been able to document that the Euro has caused structural change in the bond market. Lund (1999) has argued that a binding time table for the introduction of the common currency existed before 1999. Consequently, the prospects of the monetary union should already have fixed income markets before the introduction of the Euro. Laopodis (2008) has reported an increase in the correlation of the returns on Euro government bonds after the introduction of the new currency. Using techniques of cointegration analysis this empirical study also has identified the existence of two groups of EMU countries – a core group (including Germany and France) and some peripheral countries (including Italy and Ireland). In addition, employing methods of cointegration analysis Jenkins and Madzharova (2008) were able to find cointegration among nominal government bond yields in the Euro area after the introduction of the Euro. Thus, they have argued convincingly that interest rates in EMU countries have converged. Meanwhile, the European debt crisis has caused some concerns about sovereign credit risk and possibly even redenomination risk (which means the return of currency risk due to the breakdown of the EMU) in the market for fixed income securities. This is a relatively new strand of literature. Gruppe and Lange (2014) have shown that higher sovereign credit risk has caused structural change among government bond yields in Germany and Spain. Moreover, using a similar approach Basse (2014) has reported that government bond yields in Austria, Belgium, Finland and the Netherlands seem to be cointegrated with German government bond yields and that there has been no sign for structural change caused by the crisis. Gómez-Puig and Sosvilla-Rivero (2014) also have searched for structural change in EMU government bond markets and have argued that more than half of the breakpoints identified seem to be connected to the Euro sovereign debt crisis. Moreover, Sibbertsen, Wegener, and Basse (2014) have tested for a break in the persistence of EMU government bond yield spreads examining data from France, Italy and Spain using German sovereign bonds as benchmark. Their results indicate that there are structural breaks. The persistence of the examined time series has increased significantly during the crisis. This could be a sign of higher sovereign credit risk and of redenomination risk.

4.3 Data and Methodology

4.3.1 Data

We use daily data from 8/31/2001 until 7/31/2015 taken from the Bloomberg Database. All series are normalized to 1 at the beginning of the sample. Spreads – marked by $\tilde{\Delta}$ – are computed as the simple difference between Germany and Greece (GR_t), Italy (IT_t), Spain (ES_t) and Portugal (PT_t) in levels. The daily house price proxy is indicated by REI_t. This is the Dow Jones Equity REIT price index. Equity REITs invest in properties. Therefore, a broad index consisting of US Equity REITs should be regarded as a useful measure of economic activity in the North American real estate sector. Data on the share price index is available on a daily basis.[1]

4.3.2 Testing Explosiveness

We are interested in whether our time series show explosive behavior. This paper deals with a mildly form of explosiveness as analyzed by Phillips and Magdalinos (2007) defined by the model

$$y_t = \rho y_{t-1} + \varepsilon_t \tag{11}$$

with y_t as a stochastic process in discrete time, $t = 1, ..., T$, ε_t as the innovation sequence and $\rho = 1 + \frac{c}{k_T}$ with $c > 0$. $(k_T)_{T \geq 1}$ is a sequence which increases to infinity such that $k_T = o(T)$ when $T \to \infty$. ε_t is an independent and identical random variable or weakly dependent with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t^2) < \infty$.

In order to identify explosiveness, we apply the procedure by Phillips, Wu, and Yu (2011) to each of our time series. The regression of the augmented Dickey-Fuller (ADF) test

$$y_t = \mu + \rho y_{t-1} + \sum_{j=1}^{J} \theta_j \Delta y_{t-j} + \varepsilon_t, \varepsilon_t \sim NID\left(0, \sigma^2\right) \tag{12}$$

is estimated by Ordinary Least Squares (OLS) for some lag length J. Δ indicates first differences and NID denotes independent and normal distribution. We are interested in the hypothesis of a unit root process $H_0 : \rho = 1$ against the right tailed alternative $H_1 : \rho > 1$.

We assume a temporary limited mildly explosive model of the form as analyzed by Phillips and Yu (2009)

$$y_t = y_{t-1} 1\left\{t < \tau_e\right\} + \rho y_{t-1} 1\left\{\tau_e \leq t \leq \tau_f\right\} + \left(\sum_{k=\tau_f+1}^{T} \varepsilon_k + y^*_{\tau_f}\right) 1\left\{t > \tau_f\right\} + \varepsilon_t 1\left\{t \leq \tau_f\right\}, \tag{13}$$

[1] Concerning our assumption that REITs are adequate as a house price market proxy, we investigated the number of cointegration relations between REITs and the S&P Case-Shiller Home Price Index using the procedure suggested by Johansen (1988, 1991). The hypothesis of zero relations has been rejected while the hypothesis of one relation can not be rejected on a 1% significance level. The S&P Case-Shiller Home Price Index examined here is a very popular measure of residential real estate prices in 20 US metropolitan areas.

with $\rho = 1 + \frac{c}{T^\alpha}$, $c > 0$ and $\alpha \in (0, 1)$. This model switches from a unit root to an explosive regime at τ_e and back to unit root behavior at τ_f. It comes to a new level $y^*_{\tau_f}$ with a re-initialization at τ_f. Furthermore, a short transitional period is allowed when it switches from explosive to unit root behavior in which the process is mean reverting.

Thus, we use a forward recursive approach to test against explosiveness. This procedure, proposed by Phillips, Wu, and Yu (2011), deals with the estimation of model (12) involving subsamples of the data by the expansion of one observation at each run. The first estimation includes $\tau_0 = [Tr_0]$ observations. r_0 is some fraction of the whole sample and $[x]$ indicates the integer part of x. Thus, the regression involves $\tau = [Tr]$ observations for $r_0 \leq r \leq 1$. Denoting the t-statistic by ADF_r, Phillips, Wu, and Yu (2011) specify the limiting distribution under the null as

$$ADF_r \Rightarrow \frac{\int_0^r \widetilde{W} dW}{\left(\int_0^r \widetilde{W}^2\right)^{1/2}} \quad \text{and} \quad \sup_{r \in [r_0, 1]} ADF_r \Rightarrow \sup_{r \in [r_0, 1]} \frac{\int_0^r \widetilde{W} dW}{\left(\int_0^r \widetilde{W}^2\right)^{1/2}},$$

with W as the standard Brownian motion and $\widetilde{W}(r) = W(r) - \frac{1}{\tau}\int_0^1 W$. To stamp the origination $\hat{r}_e$ and the collapse date $\hat{r}_f$ of the explosive behavior, Phillips and Yu (2011) construct the estimates as

$$\hat{r}_e = \inf_{s \geq r_0} \left\{ s : ADF_s > cv^{adf}_{\beta_T}(s) \right\} \ , \hat{r}_f = \inf_{s \geq \hat{r}_e + \gamma \ln(T)/T} \left\{ s : ADF_s < cv^{adf}_{\beta_T}(s) \right\}. \tag{14}$$

$\gamma \ln(T)$ ensures that a short episode after the origination is not considered for a collapse date stamping and $cv^{adf}_{\beta_T}(s)$ is the right-sided critical value with a significance level of β_T. For practical implementation the authors suggest to set the critical value to $cv^{adf}_{\beta_T}(s) = -0.08 + \ln([Tr])/C$. This helps to ensure the consistent estimation of both parameters by a slowly varying rate of $cv^{adf}_{\beta_T}(s)$. We set C to $1,000$, thus, for large sample sizes, we are close to the ADF_r 5% critical values.

4.3.3 Testing the Migration of Explosiveness

The following exposition draws heavily from Phillips and Yu (2011). The authors propose a test procedure that makes use of the recursive estimation of ρ as introduced in the previous section to test against migration of explosive behavior from one variable to another. We have two time series y_t and x_t with mildly and timely limited explosive autoregressive regimes as in equation (13). Suppose that the start of explosiveness is denoted by $\tau_{ey} = [Tr_{ey}]$ and $\tau_{ex} = [Tr_{ex}]$, respectively. Furthermore, the estimated autocorrelation coefficient $\hat{\rho}_y$ peaks at $\tau_{py} = [Tr_{py}]$ and $\hat{\rho}_x$ peaks at $\tau_{px} = [Tr_{px}]$. Additionally, it is assumed that $r_{py} > r_{px}$.

We obtain for ρ_y under the null

$$\rho_y(\tau) = \begin{cases} 1, & \tau < \tau_{ey} = [Tr_{ey}] \\ 1 + \frac{c_y}{T^\alpha}, & \tau > \tau_{ey} = [Tr_{ey}] \end{cases}, \tag{15}$$

and under the alternative

$$\rho_y(\tau) = \begin{cases} 1, & \tau < \tau_{ey} = [Tr_{ey}] \\ 1 + \frac{c_y}{T^\alpha} + d\frac{c_x}{T^\alpha}\left(\frac{\tau - \tau_{px}}{m}\right)^2, & \tau > \tau_{ey} = [Tr_{ey}] \end{cases}, \tag{16}$$

with $m = \tau_{py} - \tau_{px} = [Tr_{py}] - [Tr_{px}]$. ρ_x is defined under both hypotheses as

$$\rho_x(\tau) = \begin{cases} 1, & \tau < \tau_{ex} = [Tr_{ex}] \\ 1 + \frac{c_{ex}}{T^\alpha}, & \tau > \tau_{ex} = [Tr_{ex}] \\ 1 + \frac{c_x}{T}\left(\frac{\tau - \tau_{px}}{m}\right), & \tau > \tau_{px} = [Tr_{px}] \end{cases}. \tag{17}$$

We assume $c_{ex} > 0$ and a negative localizing coefficient function $c_x(\cdot) < 0$. Thus, ρ_x is local-to-unity upon the explosive regime which influences the behavior of ρ_y. Phillips and Yu (2011) assume a linear relation for ρ_x with a constant $c_x < 0$. This leads to $dc_x = 0$ under the null and to $dc_x > 0$ under the alternative and enables us to test the hypothesis

$$H_0 : \beta_1 = 0 \text{ vs. } H_1 : \beta_1 < 0 \tag{18}$$

with β_1 from the regression model

$$\hat{\rho}_y(\tau) - 1 = \beta_0 + \beta_1(\hat{\rho}_x(\tau) - 1)\frac{\tau - \tau_{px}}{m} + \epsilon(\tau), \tag{19}$$

where β_0 and β_1 are OLS estimates and $\epsilon(\tau)$ is the error sequence for $\tau = [Tr_{px}] + 1, ..., [Tr_{py}]$. Figures 3 and 4 show the trajectory of ρ_x and ρ_y under both hypotheses.

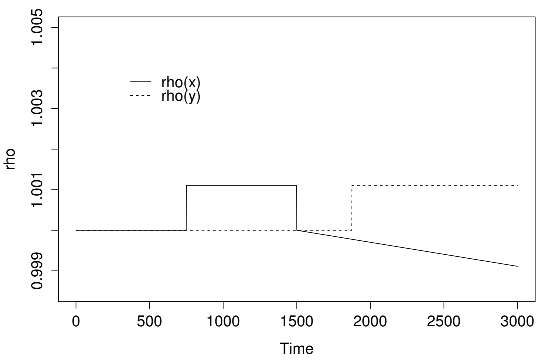

Figure 3: ρ_x and ρ_y under H_0.

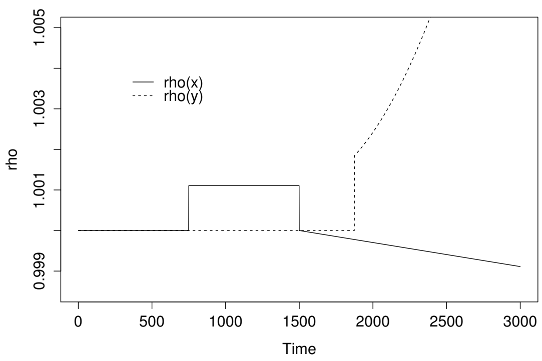

Figure 4: ρ_x and ρ_y under H_1.

Phillips and Yu (2011) constructed an asymptotically conservative and consistent test for the hypothesis in equation (18) based on the statistic

$$Z_\beta = \frac{\hat{\beta}_1}{L(m)}, \text{ with } \frac{1}{L(m)} + \frac{L(m)}{n^e} \to 0 \text{ as } n \to \infty \text{ for any } e > 0. \tag{20}$$

The test has asymptotically zero size because $\hat{\beta}_1/L(m) \to_p 0$ under the null and unit power because $Z_\beta = O_p\left(T^{1-\alpha}/L(m)\right)$ under the alternative for some slowly varying function $L(m)$. Z_β is compared to critical values from the standard normal distribution $cv_{N,\alpha}$ and rejects the H_0 if $|Z_\beta| > cv_{N,\alpha}$. The authors suggest to set $L(m) = a\log(m)$ with $1/3 \leq a \leq 3$ to control the size of the test. Figure 5 shows the density of Z_β with $L(m) = 3\log(m)$, $m = 100$ under the null. The dotted line is the density of the $N(0,1)$ distribution and the vertical line indicates the 0.95 quantile. This result is obtained by Monte Carlo Simulation with $mc = 10,000$ iterations. We have $n = 3,631$ observations for our empirical application. Thus, we use another Monte Carlo Simulation with $n = 3,000$, $m = 600$ and the same settings as in the case before. The result indicates that the test holds its size with $a = 1/3$.

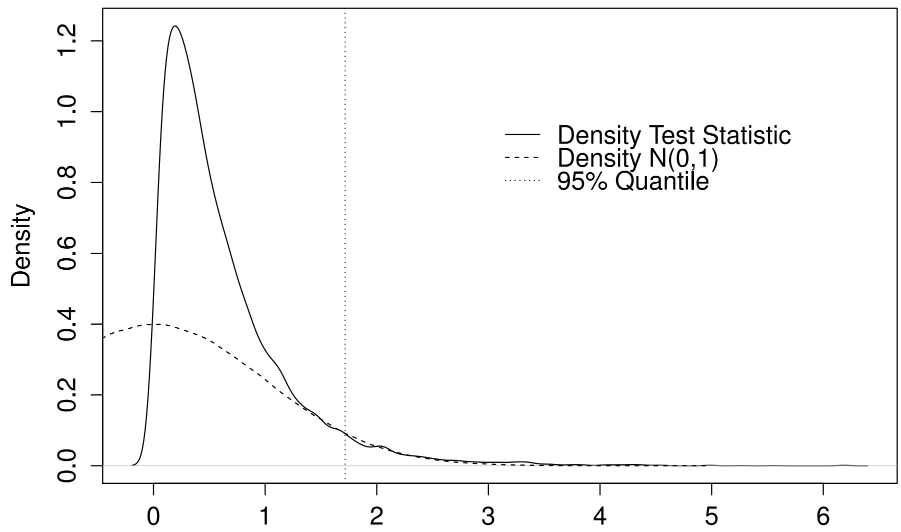

Figure 5: Density of $|Z_\beta|$

4.4 Empirical Results

4.4.1 Testing against Explosiveness and Migration Effects

At first, we apply the test procedure by Phillips, Wu, and Yu (2011) to REI_t. Figure 6 shows arising and collapsing explosiveness from the beginning of our sample until 2007. The recursive estimated $\hat{\rho}_{REI_t}$ peaks at 2/8/2007, when HSBC announced higher provisions for bad mortgage loans. Now, we apply the procedure to the spreads of Greece, Spain, Italy and Portugal against Germany as reported by figures 7 to 10. The values of the maximal autocorrelation coefficient are reported in table 5.

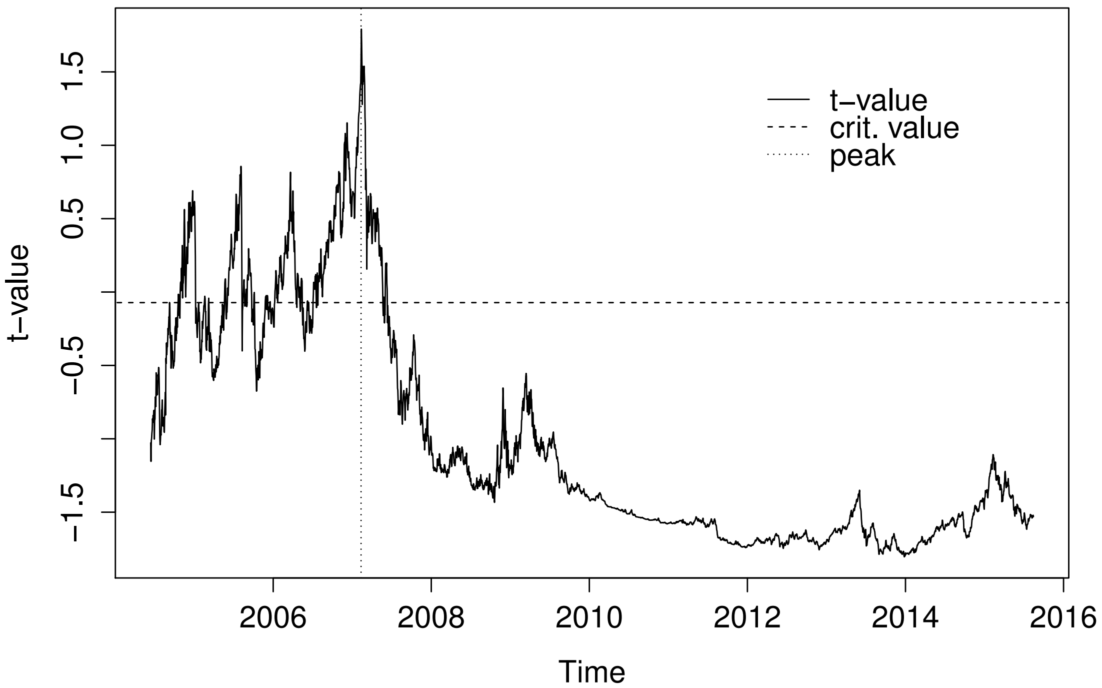

Figure 6: Trajectory of $t_{\rho_{REI}}$.

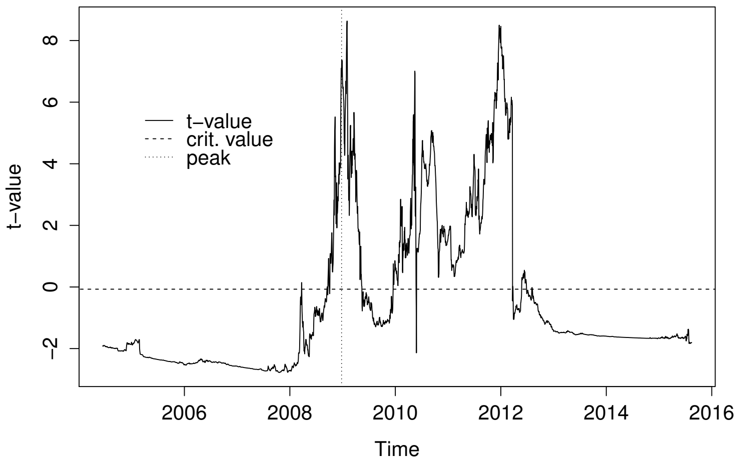

Figure 7: Trajectory of $t_{\hat{\rho}_{\tilde{\Delta}GR_t}}$.

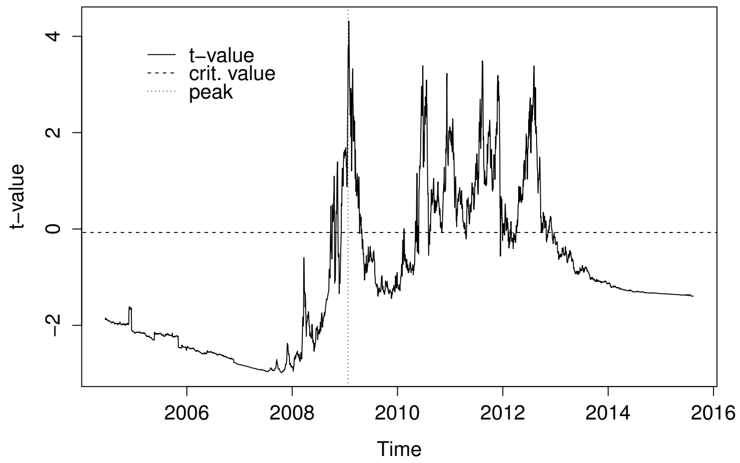

Figure 8: Trajectory of $t_{\hat{\rho}_{\tilde{\Delta}ES_t}}$.

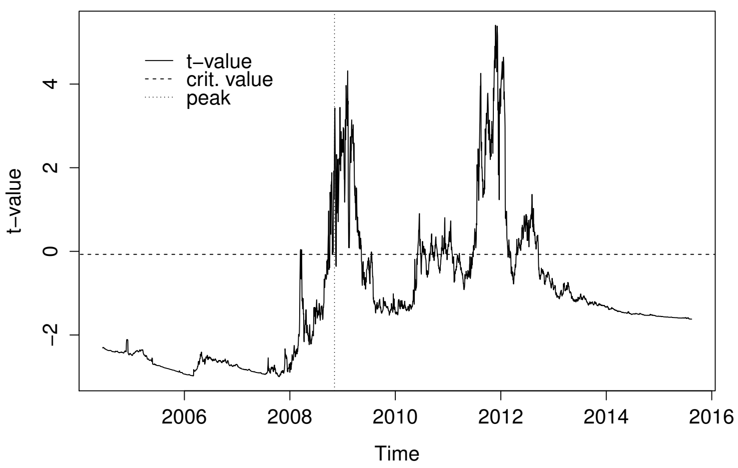

Figure 9: Trajectory of $t_{\hat{\rho}_{\tilde{\Delta}IT_t}}$.

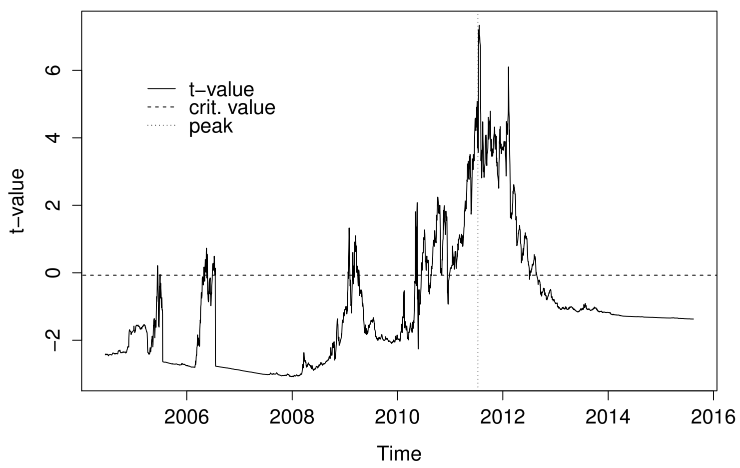

Figure 10: Trajectory of $t_{\hat{\rho}_{\tilde{\Delta}PT_t}}$.

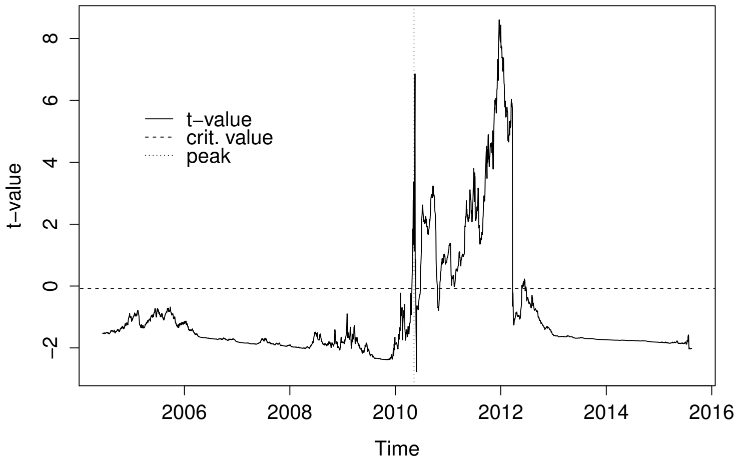

Figure 11: Trajectory of $t_{\hat{\rho}_{GR_t}}$.

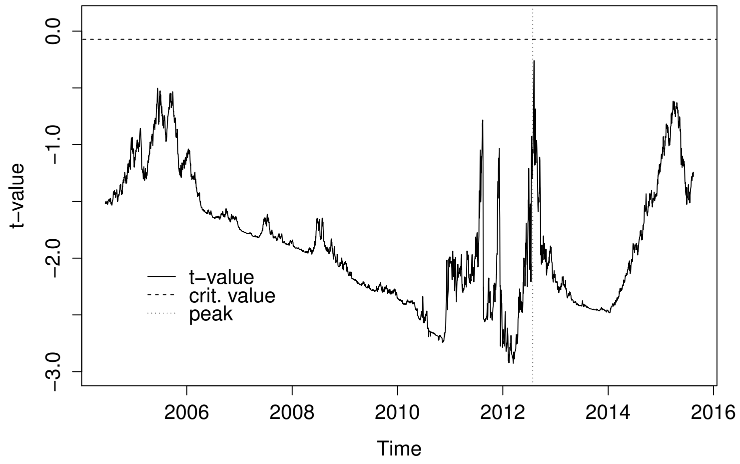

Figure 12: Trajectory of $t_{\hat{\rho}_{SP_t}}$.

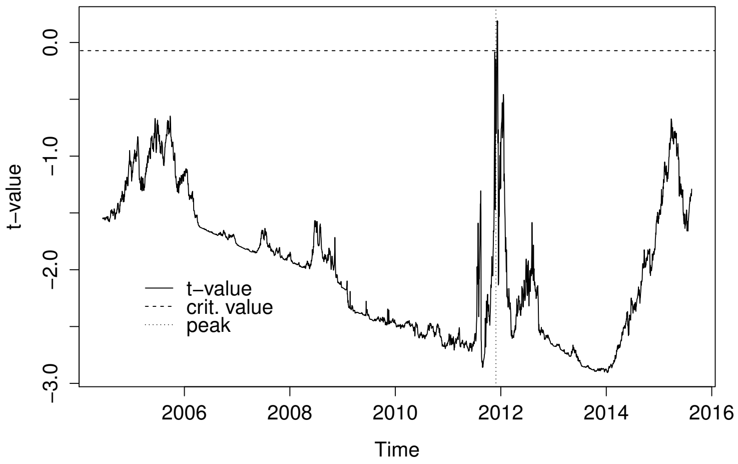

Figure 13: Trajectory of $t_{\hat{\rho}_{IT_t}}$.

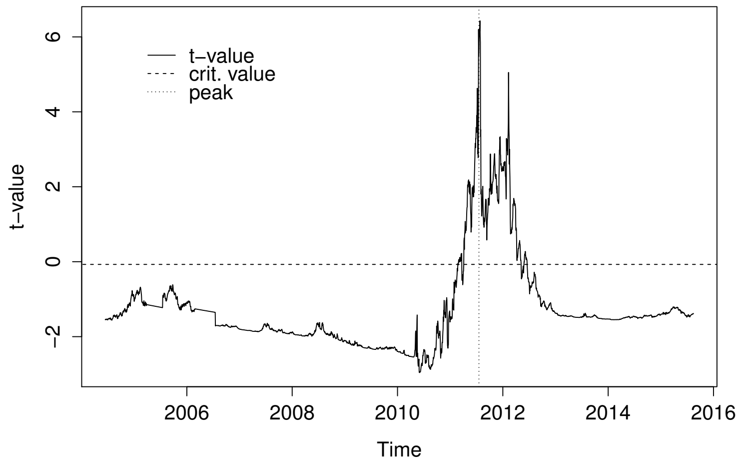

Figure 14: Trajectory of $t_{\hat{\rho}_{PT_t}}$.

Table 5: Value of the maximal autocorrelation coefficient.

Country	Date	$\max_t\{\hat{\rho}_t\}$
$\tilde{\Delta}GR_t$	12/22/2008	1.014
$\tilde{\Delta}IT_t$	11/3/2008	1.008
$\tilde{\Delta}ES_t$	1/23/2009	1.007
$\tilde{\Delta}PT_t$	7/13/2011	1.008

Table 6: Value of the maximal autocorrelation coefficient.

Country	Date	$\max_t\{\hat{\rho}_t\}$
GR_t	5/10/2010	1.015
IT_t	11/29/2011	1.000
ES_t	7/26/2012	1.000
PT_t	7/19/2011	1.009

The results indicate explosive behavior of the spreads between 2008 and 2009 apart from Portugal. Here, we have explosiveness in 2011. Furthermore, we apply the procedure to the interest rate time series as reported by table 6 and figures 11 to 14 to isolate the regimes after the subprime crisis. The t-value is not considerable larger than the critical value in the case of Italy and Spain. However, we see explosiveness for Greece and Portugal. Now, we apply the migration test as described in the foregone section to the REI_t and the spreads against Germany. Tables 7 and 8 show the results of the test.

Table 7: Migration test applied to spreads.

Country	Test statistic	$\hat{\beta}_1$
GR_t	10.338	-9.261
IT_t	6.971	-6.172
ES_t	5.199	-4.693
PT_t	6.807	-6.948

Table 8: Migration test applied to interest rates.

Country	Test statistic	$\hat{\beta}_1$
GR_t	0.622	-0.607
PT_t	0.934	-0.954

We see that the spread seems to be strongly affected by the explosiveness of REI_t. All results are significant on a level of 0.01. However, the test applied to the interest rates indicates no explosiveness migration. Thus, theses findings underline the hypothesis that the EMU crisis is a homemade problem by the countries while the first explosive regime was triggered by the bankruptcy of Lehman Brothers.

4.4.2 Robustness Checks

We evaluate the robustness of our results in three ways: First, we use an alternative way to stamp the dates of explosiveness by Harvey, Leybourne, and Sollis (2015). This is motivated by the fact, that the authors receive better power properties of this procedure compared to the recursive approach in order to stamp explosive regimes. Second, we use a procedure by Kruse and Wegener (2016) to test against strong dependent innovations in the explosive regime. The authors show that the right tailed unit root test has severe size distortions under strong dependent innovations. They propose adjusted critical values to overcome this problem and a procedure to test against fractional integrated residuals. Third, we use an indirect inference estimator to estimate the autoregressive coefficient of model (12) as proposed by Phillips, Wu, and Yu (2011). This is motivated by the well known bias of the conventional OLS estimator in the vicinity of unity in small samples. Kruse and Kaufmann (2015) show by simulation, that the indirect inference estimator is a valuable alternative to other procedures.

Harvey, Leybourne, and Sollis (2015) consider the following data generating process for y_t with $t = 1, ..., T$,

$$y_t = \mu + u_t \tag{21}$$

$$u_t = \begin{cases} y_{t-1} + \epsilon_t \text{ for } t = 2, ..., [r_1 T] \\ (1+\delta_1) y_{t-1} + \epsilon_t \text{ for } t = [r_1 T] + 1, ..., [r_2 T] \\ (1-\delta_2) y_{t-1} + \epsilon_t \text{ for } t = [r_2 T] + 1, ..., [r_3 T] \\ y_{t-1} + \epsilon_t \text{ for } t = [r_3 T] + 1, ..., T \end{cases} \tag{22}$$

with $\delta_1 \geq 0$ and $\delta_2 \geq 0$, ϵ_t as an error term. This process has a unit root up to $\tau_1 = [r_1 T]$, followed by explosive behavior for $\delta_1 > 0$ up to $\tau_2 = [r_2 T]$, collapse of the explosiveness up to $\tau_3 = [r_3 T]$ for $\delta_2 > 0$ and finally unit root behavior until the end of the sample. The authors use a Bayesian Information Criterium to chose the optimal OLS estimated model from the following data generating processes:

1. $0 < r_1 < 1$, $r_2 = 1$: unit root, explosiveness to sample end
2. $0 < r_1 < r_2 < 1$, $r_2 = r_3$: unit root, explosiveness, unit root to sample end
3. $0 < r_1 < r_2 < 1$, $r_3 = 1$: unit root, explosiveness, collapse to sample end
4. $0 < r_1 < r_2 < r_3 < 1$: unit root, explosiveness, collapse, unit root to sample end

We use the estimated breakpoints to test against explosiveness using the t_ρ-statistic

$$t_\rho = \frac{\rho - 1}{\sigma_\rho} \tag{23}$$

of the regression model

$$y_t 1 \{\tau_i < t \leq \tau_{i+1}\} = \mu + \rho y_{t-1} 1 \{\tau_i < t \leq \tau_{i+1}\} + \epsilon_t \tag{24}$$

for $i = 1, 2$. Here, σ_ρ is the standard deviation of ρ. Kruse and Wegener (2016) account for short-run dynamics of the error term ϵ_t using the Prewhitening procedure by Qu (2011). To test against strong dependent innovations, they suggest to use the test by Demetrescu, Kuzin, and Hassler (2008) with adjusted critical values depending on the estimate of ρ. If the results of this test show indications for strong dependent residuals, we employ a local Whittle estimator to estimate the degree of integration $I(d)$ with $d \in [0, 0.5)$. Kruse and Wegener (2016) suggest response curves depending on d to adjust the critical values of the right tailed unit root test.

Furthermore, it is well known that the OLS estimator has a bias in the region of unity in finite samples (see Phillips, Wu, and Yu, 2011; Kruse and Kaufmann, 2015). The authors suggest to use the indirect inference estimator

$$\hat{\rho}_H^{II} = \underset{\rho\in\Theta}{\operatorname{argmin}} \|\hat{\rho} - \frac{1}{H}\sum_{h=1}^{H}\hat{\rho}^h(\rho)\| \tag{25}$$

by Phillips, Wu, and Yu (2011). Here, $\hat{\rho}^h(\rho)$ is the OLS estimator from a simulated series with $AR(1)$ coefficient ρ. H is the number of available simulation paths, Θ is a compact parameter space and $\|\cdot\|$ is a distance metric. For $H \to \infty$ Phillips, Wu, and Yu (2011) obtain

$$\hat{\rho}_H^{II} = \underset{\rho\in\Theta}{\operatorname{argmin}} \|\hat{\rho} - q(\rho)\| \tag{26}$$

where $q(\rho) = E\left(\hat{\rho}^h(\rho)\right)$ is the binding function. Thus, the idea is to compare the estimates $\hat{\rho}$ from a grid of true values for ρ with its average OLS estimates. The indirect inference estimator leads to the minimal distance between $\hat{\rho}$ and the average OLS estimator. See Kruse and Kaufmann (2015) for details and simulation studies for different bias correction procedures.

Table 9: Results of the robustness check.

	$\hat{\rho}$	$\hat{\rho}^{II}$	Breakpoints		ALM	t_ρ	Prewhitening
REI_t	1.0188	1.0192	10/19/2006	11/20/2008	0.1889**	2.4700***	$ARFIMA(1,0.07,1)$
$\tilde{\Delta}GR_t$	1.0003	1.0054	3/23/2007	4/22/2009	-1.0385	0.1297**	$ARFIMA(1,0,1)$
$\tilde{\Delta}IT_t$	1.0048	1.0075	5/16/2006	6/13/2008	-0.9015	13.9398***	$ARFIMA(1,0,1)$
$\tilde{\Delta}ES_t$	1.0004	1.0055	8/25/2006	9/25/2008	-0.5721	0.0961**	$ARFIMA(1,0,1)$
$\tilde{\Delta}PT_t$	0.9983	1.0047	5/11/2010	7/25/2012	2.8503***	-2.3465	$ARFIMA(1,0.30,1)$
GR_t	1.0024	1.0063	1/8/2010	3/8/2012	-0.7464	1.1105***	$ARFIMA(1,0,1)$
IT_t	0.9977	0.9997	11/8/2012	7/31/2015	-0.7479	-1.9408	$ARFIMA(1,0,1)$
ES_t	0.9892	0.9996	12/31/2012	7/31/2015	-0.9774	-1.9102	$ARFIMA(1,0,1)$
PT_t	0.9878	0.9983	11/19/2012	7/31/2015	-0.8616	-2.0848	$ARFIMA(1,0,1)$

Table 9 reports the results of the robustness checks. Firstly, all the beginnings and the ends of all explosive periods are validated by the procedure proposed by Harvey, Leybourne, and Sollis (2015). Furthermore, the second explosive regimes as indicated by the recursive right tailed unit root test for the spreads do not seem to be explosive using this alternative stamping procedure. In order to conserve space, we report the respective regimes with the highest autoregressive coefficient. Secondly, in the case of REI_t and $\tilde{\Delta}PT_t$ we receive indications for strong dependent innovations. The test statistic of the augmented version of the procedure of Demetrescu, Kuzin, and Hassler (2008) is indicated by ALM using a Prewhitening and $p = 0$ lags to account for short-run dynamics. The result that REI_t shows explosive behavior is not affected while the result of the right tailed unit root test for $\tilde{\Delta}PT_t$ does no longer indicate explosiveness. Thirdly, the indirect inference estimator indicates explosiveness for all spreads and the government bond yield from Greece. Thus, the required condition of migrations of explosiveness from REI_t is fulfilled for all the spreads and the yield from Greece. To summarize the findings of the robustness checks: The results of the procedure by Harvey, Leybourne, and Sollis (2015) and the indirect inference estimator underline the findings of the recursive right tailed unit root test. Strong dependent innovations are only relevant in the case of the spread between Portugal and Germany.

4.5 Conclusion

Employing a test procedure recently introduced by Phillips, Wu, and Yu (2011) we searched for explosive behavior in the US housing market and the EMU government bond market. With regard to EMU bonds, we considered interest rates of a number of countries and government bond yield spreads (with German government bond yields as benchmark) in order to distinguish between two explosive regimes: First, explosiveness initiated by the bankruptcy of Lehman Brothers as a result of the bursting of the US housing market bubble and second, explosive behavior provoked by the EMU sovereign debt crisis. Further, we used a procedure of Phillips and Yu (2011) to investigate migration effects from the US house price bubble to EMU government bond yield spreads and to EMU interest rates. Examining the spreads, our results seem to indicate that there are two crises. The first crisis reflected in the yield differentials – as expected – is a result of the collapsing US housing market. Phrased somewhat differently, the results reported here indicate the existence of a migration process. Therefore, the first problems encountered in Europe most probably should indeed be regarded as a result of the US Subprime Crisis. However, the second crisis seems to be a consequence of the explosiveness of yields caused by the sudden appearance of sovereign credit risk and redenomination risk in EMU government bond markets. These observations indeed do suggest that the EMU debt crisis is a homemade problem. Consequently, the crisis originating in the US housing market really has moved from US mortgage backed securities to European banks and (most probably via bank rescue programs) to EMU government bonds. This crisis therefore really is some sort of a walking debt crisis but does not seem to be a long distance runner because it most probably is not the cause of the EMU sovereign debt crisis. Thus, the results of our empirical investigations do support the point of view that the second part of the crisis was no second part but a major crisis of its own.

Chapter 5

Liquidity Risk Premia in Times of Crisis - Empirical Evidence from the German Covered Bond Market

5 Liquidity Risk Premia in Times of Crisis - Empirical Evidence from the German Covered Bond Market

Co-authored with Tobias Basse and Philipp Sibbertsen.

5.1 Introduction

Liquidity risk is defined as the risk that an asset cannot always be sold without causing a strong fall in its price because of a lack of demand for this asset. The liquidity premium compensates investors for bearing liquidity risk. Many empirical studies examining liquidity premia have focused on government bonds. In fact, there are numerous relevant papers. Boudoukh and Whitelaw (1993), for instance, have examined price differentials among liquid and illiquid Japanese government bonds. More recently, Sibbertsen, Wegener, and Basse (2014) have, for example, suggested that the existence of liquidity premia to compensate investors for the lower liquidity of the Italian and Spanish government bond markets relative to the German government bond market could help to explain their empirical findings that show deviations from the uncovered interest rate parity condition. In order to gain additional insights with regard to interest rates and liquidity premia it could be of interest to analyze data from the German covered bond market, that incorporates two types of bonds with differences regarding their liquidity. Moreover, the financial crisis seems to have caused a kind of re-pricing of liquidity risk in the European covered bond market. Therefore, it might be of special interest to examine yield differentials between liquid and illiquid German covered bonds using techniques of time series analysis.

The paper is structured as follows: The next section describes the features of covered bonds and their particular importance for the global bond markets. The third part introduces the term of liquidity risk. Section 5.4 describes the data and provides a first insight about their time series properties. Section 5.5 introduces a methodology to estimate a fractional cointegrated system. The following section presents the results of an application of covered bond yields. Section 5.6 concludes.

5.2 Covered Bonds

Covered bonds are one of the most important segments of the global bond market. These fixed income securities are fully collateralized bonds issued by authorized banks and are backed by a pool of assets that in general consists of mortgage loans or public sector loans. There are some country specific differences with regard to the assets that are eligible to back covered bonds. Meanwhile, German covered bonds (so-called Pfandbriefe), for example, may also be secured by ship and aircraft loans. In marked contrast to asset-backed securities the assets backing covered bonds remain on the balance sheet of the issuer. Only in the case of an insolvency of the issuing bank the assets belonging to the cover pool are separated from the balance sheet of the insolvent bank to meet the claims of the bondholders (e.g., Tolckmitt and Walburg, 2002; Lorenz, 2006).

Covered bonds are usually seen as an important source of funding for the European banking industry. This is especially true for German banks, where covered bonds have a long tradition. In fact, the Pfandbrief can look back upon a history of more than 200 years (e.g., Hagen, 2003; Lorenz, 2006). Therefore, it is hardly surprising that the market for Pfandbriefe is by far the most important segment of the European covered bond market.

There are different types of German covered bonds. Most importantly, there are so-called traditional Pfandbriefe and Jumbo Pfandbriefe. While both types of bonds are governed by the same requirements with regard to credit risk, traditional Pfandbriefe are issued in smaller sizes. Therefore, the market for these securities is regarded to be less liquid than Jumbo Pfandbriefe. The first Jumbo Pfandbrief was issued in 1995 (e.g., Hagen, 2003). This special type of covered bond with a minimum issuing volume of 1 billion EUR was created to provide a more liquid financial instrument for institutional investors. Besides the regulations with regard to issue size, there are additional minimum standards for a Jumbo Pfandbrief in order to increase market liquidity. They must, for example, be placed by a syndicate consisting of at least five banks. These banks act as market makers. Given that both traditional and Jumbo Pfandbriefe are very secure investments, yield spreads between these two types of German covered bonds usually are interpreted as pure liquidity premia by market participants.

5.3 Liquidity Risk

Liquidity is an important concept in financial economics and measures how easy financial assets can be converted into cash. It is hard to find a generally accepted definition of liquidity. Goldreich, Hanke, and Nath (2005), for example, have noted that the term liquidity is often used to describe the narrowness of the bid-ask spread; however, they have also argued that there are broader definitions (e.g., trading volume, market depth or other measures of market activity). Boudoukh and Whitelaw (1993) have argued convincingly that the value of liquidity results from the uncertainty about future trading needs of current investors. Assuming that all bondholders are buy-and-hold investors, liquidity obviously would not matter when there is no need to engage in additional bond market transactions after the fixed income securities have been purchased. Investors would simply hold the bonds until maturity - in other words for one period (which, of course, is not necessarily one year). However, investors might be hit by liquidity shocks that force bondholders to sell assets (see Goldreich, Hanke, and Nath, 2005). Lucas (1990) has argued that these liquidity shocks have the capacity to induce sudden large drops in the prices of bonds and other illiquid securities. The probability for the emergence of such a shock that causes a flight to liquidity is given by λ. In order to focus on the liquidity premium it does make sense to examine two types of bonds that are identical with only one exception - their liquidity. Under the assumption that fully liquid assets can be sold without costs while selling illiquid bonds leads to trading costs of c and examining one period bond risk neutral investors, the relationship among yields is given by the following equation:

$$i_A = i_B + \lambda \times c \tag{27}$$

where an investor would be indifferent between holding liquid bond A or illiquid bond B. Obviously, the liquidity premium should be higher when investors are assumed to be risk-averse. Then there also would be a risk premium compensating bondholders for liquidity risk. Moreover, Goldreich, Hanke, and Nath (2005) have suggested to generalize the model by considering trading costs for liquid and illiquid bonds (c_A and c_B). In this case the relationship is given by:

$$i_A = i_B + \lambda \times (c_A - c_B). \tag{28}$$

5.4 Data and Initial Analysis

We examine the yields of traditional Pfandbriefe and Jumbo Pfandbriefe with the maturities of five, seven and ten years. Our sample starts at 01-01-1999 and ends at 12-30-2011. Therefore we investigate 679 weekly observations taken from Bloomberg Database.

If the spread between the yields z_t is a risk measure as discussed in section 5.3, it should be zero for the same amount of risk in both yields. Because of this, we assume z_t to be stationary or phrased somewhat differently: $I(d)$ with $d = 0$. In this case, the yields of Pfandbriefe and Jumbo Pfandbriefe should be cointegrated with the vector $\vec{\beta} = (1, -1)$. Two $I(1)$ variables are said to be cointegrated if they share a common stochastic trend. Thus, first of all, we use the approach suggested by Ng and Perron (2001) to test for $I(1)$ behavior of the yields.

Table 10: Ng Perron Test for unit roots

	Akaike		Schwarz	
	Intercept	Intercept and Trend	Intercept	Intercept and Trend
Pfandbrief 5Y	-1.00107	-1.31612	-1.00107	-1.31612
Pfandbrief 7Y	-1.10745	-1.46411	-1.10745	-1.46411
Pfandbrief 10Y	-1.13057	-1.48812	-1.13057	-1.48812
Jumbo Pfandbrief 5Y	-1.01021	-1.29734	-1.01021	-1.29734
Jumbo Pfandbrief 7Y	-1.10774	-1.41607	-1.10774	-1.41607
Jumbo Pfandbrief 10Y	-1.17924	-1.58644	-1.17924	-1.58644

Table 10 shows the test statistics of the unit root test. Comparing the critical values of -1.98 (intercept) and -2.91 (intercept and trend) with the test statistics indicates that the null hypothesis of a unit root for the six time series cannot be rejected.

However, a look at figure 15 causes reasonable doubt that the assumption about z_t is fulfilled. The autocorrelation functions of the spreads decline very slowly which is an indication of $I(d)$ behavior with $d > 0$. Thus, we employ a modified GPH estimator for d to investigate the order of integration of the yield differentials in more detail. This modification by Phillips and Magdalinos (2007) has been shown to have better power properties than the original suggested by Geweke and Porter-Hudak (1983).

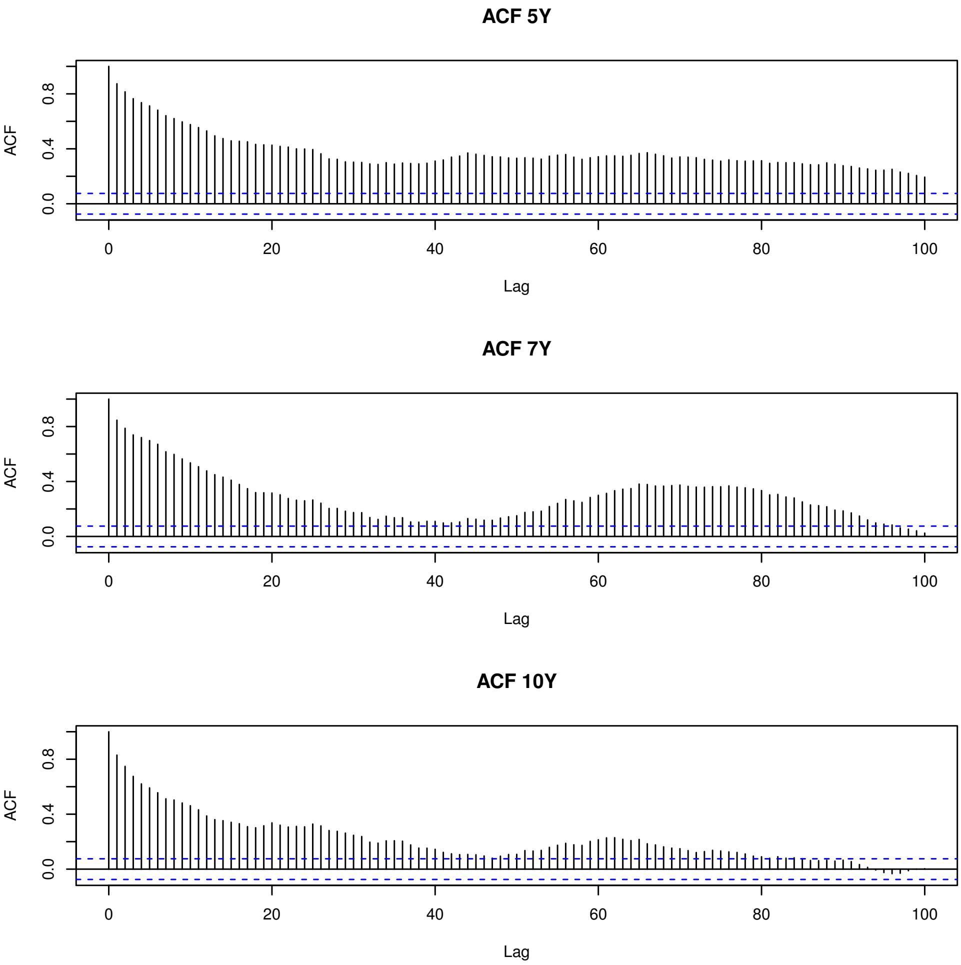

Figure 15: Autocorrelation functions of the 5, 7, and 10 years spread.

Table 11: Modified GPH

Maturity	Bandwidth	d	StdErr	$t(H_0 : d = 0)$	$P > \|t\|$	$t(H_0 : d = 1)$	$P > \|t\|$
	0.50	0.5124997	0.0981141	5.2235	0.000	-3.8763	0.000
5 Years	0.60	0.6784042	0.0783983	8.6533	0.000	-3.5461	0.000
	0.70	0.6253090	0.0563143	11.1039	0.000	-5.7249	0.000
	0.80	0.6911256	0.0446706	15.4716	0.000	-6.5335	0.000
	0.50	0.4961688	0.1413929	3.5091	0.002	-4.0062	0.000
7 Years	0.60	0.6914198	0.0874687	7.9048	0.000	-3.4026	0.001
	0.70	0.7059399	0.0589845	11.9682	0.000	-4.4929	0.000
	0.80	0.6793011	0.0491622	13.8176	0.000	-6.7836	0.000
	0.50	0.6960751	0.1865023	3.7323	0.001	-2.4166	0.016
10 Years	0.60	0.7190957	0.1107111	6.4952	0.000	-3.0974	0.002
	0.70	0.7117394	0.0713346	9.9775	0.000	-4.4043	0.000
	0.80	0.7303082	0.0568460	12.8471	0.000	-5.7047	0.000

Also this procedure suggests $I(d)$ behavior with $0 < d < 1$ of z_t as reported in table 11. If the assumption of $\vec{\beta}$ holds, this might be an indication that the yields of the traditional Pfandbrief and the Jumbo Pfandbrief are fractionally cointegrated. Shimotsu (2012) highlights two examples of bivariate fractionally cointegrated systems: The first refers to the case with two time series x_t and y_t which have the same memory parameter $d_x < 1$ and the equilibrium error u_t is integrated of order d_u with $d_u < d_x$ for $t = 1, 2, ...T$. See e.g. Bandi and Perron (2006), Christensen and Nielsen (2006) and Nielsen and Frederiksen (2011) for empirical applications of fractional cointegration matching the foregone case. The second example refers to the case where x_t and y_t are $I(d_x)$ with $d_x = 1$ and u_t is integrated with $0 < d_u < 1$. This one seems to match our case: The yields are individually $I(1)$ and the equilibrium error for $\vec{\beta} = (1, -1)$ is integrated of order $0.45 < d_u < 0.75$. Moreover, using the procedure by Phillips and Magdalinos (2007) to test against $d_x = 0$ and against $d_x = 1$ indicates evidence that x_t and y_t are $I(1)$. However, results are not reported in order to conserve space.

Furthermore, we are particularly interested in whether d_u remains constant over time. Thus, we use the methodology proposed by Sibbertsen and Kruse (2009) to test the hypothesis

$$H_0 : d_u = d_{u,0},\ \forall\ t \text{ vs. } H_1 : \begin{cases} d_u = d_{u,1} \text{ for } t = 1, ..., [\tau T] \\ d_u = d_{u,2} \text{ for } t = [\tau T] + 1, ..., T \end{cases} . \tag{29}$$

Here, $[\tau T]$ denotes the biggest integer smaller than τT with τ as the relative breakpoint estimator and T as the number of observations. The test by Sibbertsen and Kruse (2009) modifies the procedure proposed by Leybourne, Taylor, and Kim (2007) to test against a break in persistence under long-range dependencies of univariate time series. They restricted $0 \leq d_0 < \frac{3}{2}$ under H_0 and $0 \leq d_1 < \frac{1}{2}$ and $\frac{1}{2} \leq d_2 < \frac{3}{2}$ under the alternative. Moreover, d_1 and d_2 can be exchanged, so a break from stationary to non-stationary long-memory and vice versa can be investigated. Thus, we test against a break in the persistence in the spread of traditional and Jumbo Pfandbriefe using the estimated d under the null hypothesis by the modified GPH estimator. In this case there is clear evidence for a break between 2006 and 2007 for all maturities. Table 12 shows the results of this test.

Table 12: Results of the test against changing persistence (1)

Maturity	Bandwidth	Test Statistic	CV low	CV up	Test Decision	Break Date
5 Years	0.5	0.271	0.579	1.704	Increasing Persistence	2006-02-17
	0.8	0.270	0.631	1.588	Increasing Persistence	2006-02-17
7 Years	0.5	0.348	0.508	1.963	Increasing Persistence	2006-10-13
	0.8	0.348	0.620	1.609	Increasing Persistence	2006-10-13
10 Years	0.5	0.513	0.620	1.61	Increasing Persistence	2007-07-27
	0.8	0.513	0.641	1.569	Increasing Persistence	2007-07-27

However, the European Central Bank established the *Covered Bond Purchase Programme* in order to stabilize the covered bond market in Europe. This intervention might have caused decreasing persistence in 2009. Thus, we test against a break in d_u after the first break. Table 13 shows the results and figure 16 shows the chart of the simple spreads with marked breaks. Thus, it seems that, coincident with the financial crisis, the persistence of the spread increased strongly. This might cause spurious results in order to explain the behavior of the covered bond spreads using regression models (see, for example, Prokopczuk, Siewert, and Vonhoff (2013)).

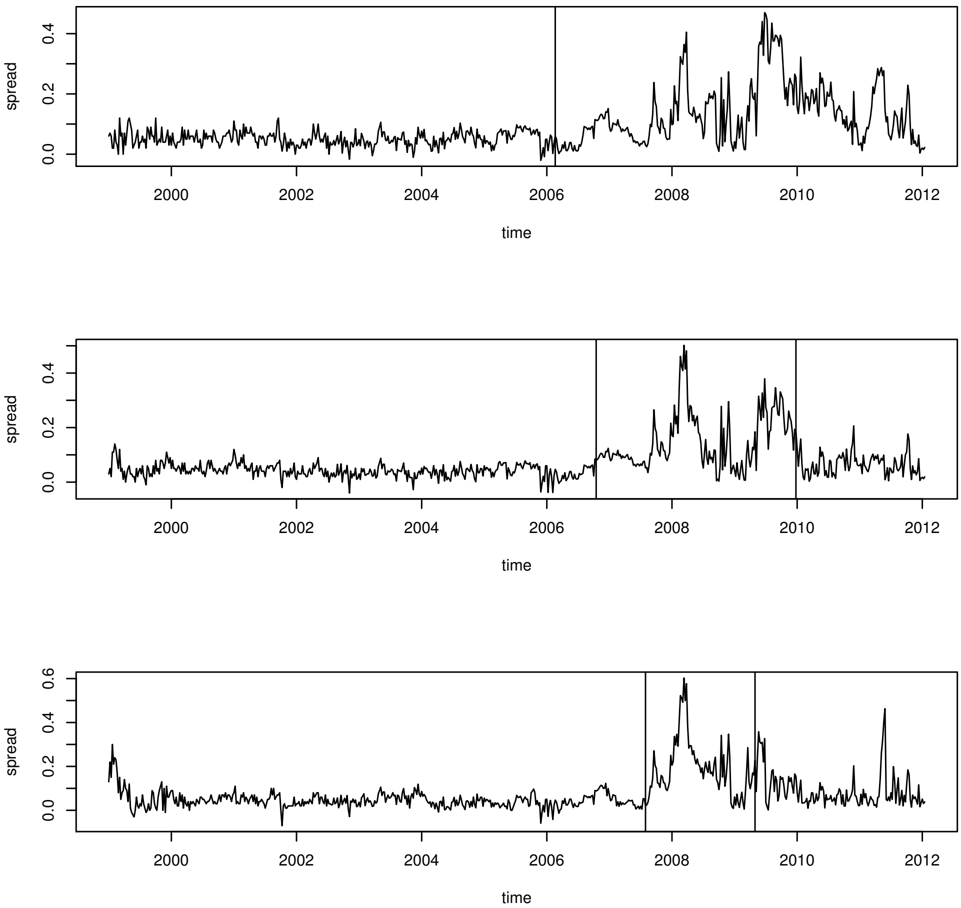

Figure 16: Spreads of the traditional Pfandbriefe and Jumbo Pfandbriefe. The lines indicate the estimated breakpoints.

Table 13: Results of the test against changing persistence (1)

Maturity	Bandwidth	Test Statistic	CV low	CV up	Test Decision	Break Date
5 Years	0.5	0.894	0.579	1.704	Cannot reject H_0	
	0.8	0.894	0.599	1.652	Cannot reject H_0	
7 Years	0.5	1.637	0.459	2.202	Cannot reject H_0	
	0.8	1.637	0.620	1.608	Decreasing Persistence	2009-12-18
10 Years	0.5	2.336	0.825	1.276	Decreasing Persistence	2009-03-20
	0.8	2.336	0.641	1.569	Decreasing Persistence	2009-03-20

Furthermore, additional breaks or smooth trends might cause spurious long memory before the first breakpoint and after the second break. For this reason we test against a further break in the persistence as proposed above and in addition we use the test by Qu (2011). The procedure by Qu (2011) tests the null hypothesis of stationary long memory against short memory with level shifts or smooth trends. This test evaluates the derivative of the local Whittle likelihood at the first $[\kappa r]$ Fourier frequencies κ with $r \in [\epsilon, 1]$. Here, we consider a bandwidth from $T^{0.55}$ to $T^{0.75}$ and we apply this procedure until the first break in d_u for all maturities with $\epsilon = 0.02$. See Sibbertsen, Leschinski, and Holzhausen (2015) for a multivariate version of this procedure. Regarding the ten years spread we estimate $d_u > 0.5$. Thus, the results in this case might be questionable for a bandwidth between $T^{0.60}$ and $T^{0.75}$.

Table 14: Results of Qu's Test (1)

Spread	$T^{0.55}$	$T^{0.60}$	$T^{0.70}$	$T^{0.75}$
5 Years	0.51	0.84	0.84	0.77
7 Years	0.63	0.76	0.65	0.61
10 Years	0.82	(1.07)	(1.31)	(1.36)

Table 15: Results of Qu's Test (2)

Spread	$T^{0.55}$	$T^{0.60}$	$T^{0.70}$	$T^{0.75}$
7 Years	0.68	0.45	0.38	0.60
10 Years	0.34	0.37	0.43	0.25

Neither the test by Sibbertsen and Kruse (2009) (results are not reported in order to conserve space) nor the results of the procedure by Qu (2011) (results are reported in table 14) indicate doubts that the behavior of the particular spreads until the breaks between 2006 and 2007 might be caused by spurious long memory at a confidence level of $\alpha = 0.1$. Additionally, we apply the test by Qu (2011) to the spreads after the second break. As reported in table 15, we do not find any indications about long range dependencies caused by level shifts or smooth trends on a confidence level of $\alpha = 0.1$ regarding the seven and ten year spread. We do not consider the five year spread because we do not find decreasing persistence in this case. Motivated by these results, we estimate a fractionally cointegrated system for subsamples to control for breaks in d_u and for the full sample in order to investigate the cointegrating vector $\vec{\beta}$ in the following section.

5.5 Estimating a Fractionally Cointegrated System for Covered Bond Yields

5.5.1 Methodology

Shimotsu (2012, pg. 266) noted, that if the standard $I(0)/I(1)$ cointegration techniques are applied to fractionally cointegrated time series, "it leads to either (i) a false rejection of the existence of an equilibrium relationship, or (ii) misspecification of the degree of persistence of the stochastic trend and/or the equilibrium error." Thus, considering the results of section 5.4, it seems to be appropriate to employ fractional cointegration methods.

A lot of studies examined estimation techniques of fractional cointegrated systems (e.g. Velasco, 2003; Robinson, 2008; Nielsen and Frederiksen, 2011). Robinson (2008) showed that the local Whittle estimator is consistent and has an asymptotic Gaussian distribution if $0 \leq d_u < d_x < 0.5$. Shimotsu (2012) used a tapered version of this estimator on the first stage and the exact local Whittle approach proposed by Shimotsu and Phillips (2005) on the second stage. This two-step estimation procedure accommodates the stationary and the nonstationary case of x_t and u_t, respectively. The estimator of the memory parameters is asymptotic normally distributed in both cases. Moreover, Shimotsu (2012) noted, that the distribution and the convergence rate of β

depends on the difference between d_x and d_u. Thus for $d_x - d_u < 0.5$, β is asymptotic normally distributed.

We use the procedure proposed by Shimotsu (2012) to estimate $\vec{\beta} = (1, -\beta)$, d_x and d_u of the bivariate fractionally cointegrated system

$$\begin{cases} (1-L)^{d_u}(y_t - \beta x_t) = \varepsilon_{1,t}, \\ (1-L)^{d_x} x_t = \varepsilon_{2,t} \end{cases} \tag{30}$$

with $t = 1, 2, ..., T$, $\beta \neq 0$, and $\varepsilon_{1,t}$, $\varepsilon_{2,t}$ are stationary with zero mean. However, we use the estimator by Shimotsu (2010) on the second stage to deal with an unknown mean. Shimotsu (2012) noted that the asymptotic distribution remains the same.

5.5.2 Empirical Results

First of all, we estimate the cointegrated system as proposed in equation 30 for the whole sample $T = 679$ and bonds with the maturity of 5, 7 and 10 years. We consider bandwidths $m = T^{\zeta}$ and $\zeta = 0.55, 0.60, 0.65, 0.70, 0.75$. The results are reported in table 16. Here and in the following, ρ is the correlation between $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$. For $\rho \neq 0$ the most estimation procedures of fractional cointegrated systems fail. However, the procedure by Shimotsu (2012) overcomes this problem.

(Insert table 16 here)

The hypothesis of $d_x = 1$ cannot be rejected on a confidence level of $\alpha = 0.05$ for most m and all maturities. This finding is consistent with the results of the test proposed by Ng and Perron (2001) reported in table 10. Furthermore, $H_0 : \beta = 1$ cannot be rejected in most cases and $\alpha = 0.05$. However, for 5 and 10 years maturity and $m = 0.55$, $d_x - d_u > 0.5$ applies, thus the asymptotic distribution theory for β is not available. For this reason we use a subsampling method with subsamples of size $b = 200$. Also in this case, $H_0 : \beta = 1$ cannot be rejected. Depending on m, d_u is between 0.5 and 0.8 and even the upper bounds of the confidence intervals are smaller than 1. All these findings indicate fractional cointegration with $\{d_u, d_x, \beta\} = \{[0.5, 0.8]), 1, (1, -1)\}$. To investigate the behavior before and after the breaks in d_u, we estimate the cointegrated system as proposed in equation 30 for subsamples based on the results of the test by Sibbertsen and Kruse (2009) as described in section 5.4. Considering the time before the particular break date, the results are reported in table 17.

(Insert table 17 here)

The estimation results indicate that the system is fractionally cointegrated with $\{d_u, d_x, \beta\} = \{[0.2, 0.7]), 1, (1, -1)\}$. Most surprisingly, d_u is still significantly different from zero. However, the degree of integration is smaller than for the whole sample. In most cases $d_x - d_u > 0.5$ applies, thus we also use the subsampling method as described above with $b = 100$. Furthermore, we estimate a fractionally cointegrated system after the breakpoints to quantify the change of the parameters. Table 18 shows the results.

(Insert table 18 here)

It is obvious that d_u has increased for all bandwidths and all bonds and d_x and β have remained constant since 2006 and 2007, respectively.

For $\beta = (1, -1)$ and in the case of the seven year spread the test shows decreasing persistence in 2009 for the bandwidth of $T^{0.75}$. This also holds for the ten year spread and all considered bandwidths. Thus, we consider the time from 2006 and 2007, respectively until 2009 and from 2009 to 2011. So we use 166 (87) observations regarding the the seven year spread (ten year spread) before and 106 (144) after the particular break points. Table 19 shows the results of the estimated fractionally cointegrated system.

(Insert table 19 here)

The finding that d_u has increased significantly since 2006 and 2007 is confirmed. This is consistent with the results reported by Sibbertsen et al. (2014) who have examined European government bond yields. Their results can be explained by higher credit risk and possibly even with redenomination risk (a special version of exchange rate risk). Sibbertsen et al. (2014) also have argued that liquidity might matter. With regard to the examined time series, increased risk premia due to changes to credit risk and redenomination risk obviously are of no relevance. However, the reported findings can definitely be explained by higher absolute or relative trading costs c or $c_B - c_A$, an increased probability for the emergence of a shock (see equation 27 and equation 28) or a higher liquidity risk premium.

The hypothesis that $\beta = (1, -1)$ and $d_x = 1$ cannot be rejected in most cases. However, confidence intervals have become broader. This might be caused by small sample sizes. Furthermore, we estimate $\{d_u, d_x, \beta\}$ after 2009. The results are reported in table 20.

(Insert table 20 here)

It is obvious that d_u decreased and the hypothesis of $d_x = 1$ cannot be rejected. However, due to broader differences between d_x and d_u the asymptotic distribution theory for β is not available. Nonetheless, we waive the subsampling method due to small sample sizes.

To briefly resume our results, we found fractional cointegration between Pfandbriefe and Jumbo Pfandbriefe with $\{d_u, 1, (1, -1)\}$. We further tested against structural breaks in d_u and found that the relations between the two covered bonds have changed over time. These results might be caused by the financial crisis. Surprisingly, when d_u was low or decreased, which could be a characteristic of moderate economic times, it was still not zero. Figure 17 shows the autocorrelation functions of the spreads in the particular regimes.

5.6 Conclusion

We examined the relationship between yields of traditional Pfandbriefe and Jumbo Pfandbriefe using techniques of time series analysis. Both seem to be $I(1)$. Accepting that the two types of covered bonds only differ with regard to liquidity risk and assuming that the liquidity risk

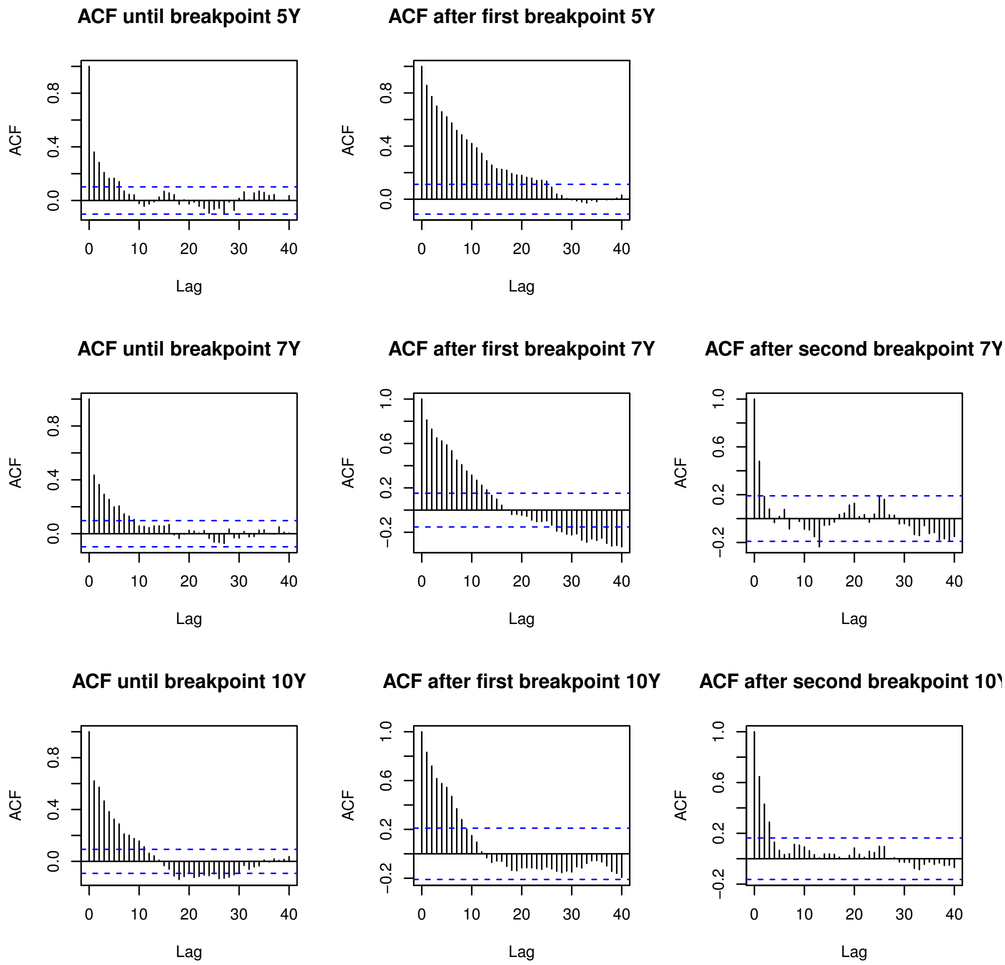

Figure 17: Autocorrelation functions of the subsamples indicated by the structural break test of the 5, 7, and 10 years spread.

premium is a stationary variable, the bond yields - under certain plausible assumptions - should be cointegrated with $\beta = (1, -1)$. The latter cannot be rejected while the simple cointegration framework does not take account for the properties of the considered system. Thus, we used the procedure suggested by Shimotsu (2012) to allow for fractional cointegration. We estimated fractionally cointegrated systems with $([0.5, 0.8], 1, (1, -1))$, therefore the assumption of a stationary liquidity premium could not be confirmed. This result might be spurious due to structural changes in the persistence indicated by the test proposed by Sibbertsen and Kruse (2009). We found increasing persistence for all maturities which coincides with the financial crisis. Regarding seven and ten years bonds, we further examined a second breakpoint with decreasing d_u. Altogether, we considered three regimes: A quite low persistence of the spread before, a high d_u in the crisis and a low d_u after the crisis. In the first and third regime, d_u was not equal to zero but stationary. We used the procedure by Qu (2011) to test against spurious long memory and found true long memory within these regimes. The hypothesis of $\beta = (1, -1)$ cannot be rejected for all three subsamples. These results can be explained by at least three factors. First of all, the trading costs, represented by c or by $(c_B - c_A)$ respectively, might have increased dramatically, thus the process of convergence of both yields has changed. Furthermore, flight-to-liquidity effects, represented by λ, might have caused a higher d_u. Finally, the investors might have become more risk averse. A mixture of the last two points might be particularly plausible, considering the timing of the breakpoints.

Appendix to Chapter 5

Table 16: Estimated fractional cointegrated system (1)

m	$T^{0.55}$	$T^{0.60}$	$T^{0.65}$	$T^{0.70}$	$T^{0.75}$
5 Years					
d_u	0.6194	0.7154	0.6862	0.7034	0.6725
	[0.461 0.777]	[0.583 0.848]	[0.570 0.802]	[0.605 0.802]	[0.589 0.756]
d_x	1.1290	1.0942	1.1075	1.1030	1.0925
	[0.971 1.287]	[0.962 1.227]	[0.992 1.224]	[1.004 1.202]	[1.009 1.176]
β	1.0190	1.0409	1.0201	1.0193	1.0190
	[0.998 1.074]*	[1.006 1.076]	[0.993 1.047]	[0.989 1.049]	[0.994 1.044]
ρ	-0.3022	-0.3774	-0.2326	-0.2274	-0.2174
7 Years					
d_u	0.6715	0.7943	0.7668	0.7580	0.6832
	[0.514 0.829]	[0.660 0.929]	[0.650 0.884]	[0.660 0.857]	[0.600 0.767]
d_x	1.0697	1.0458	1.0737	1.0872	1.0748
	[0.912 1.227]	[0.911 1.180]	[0.956 1.191]	[0.988 1.187]	[0.991 1.159]
β	1.0173	1.0296	0.9996	1.0051	1.0080
	[0.984 1.051]	[0.965 1.095]	[0.952 1.047]	[0.964 1.046]	[0.979 1.037]
ρ	-0.3453	-0.3301	-0.1641	-0.1705	-0.1985
10 Years					
d_u	0.4930	0.6746	0.6080	0.6227	0.6620
	[0.331 0.654]	[0.539 0.810]	[0.491 0.725]	[0.524 0.721]	[0.579 0.745]
d_x	1.0628	1.0245	1.0512	1.0666	1.0590
	[0.902 1.224]	[0.889 1.160]	[0.934 1.168]	[0.968 1.165]	[0.976 1.142]
β	1.0198	1.0395	1.0253	1.0308	1.0411
	[1.008 1.135]*	[0.991 1.088]	[0.998 1.052]	[1.004 1.057]	[1.005 1.077]
ρ	-0.2051	-0.2757	-0.1873	-0.2206	-0.2580

Table 17: Estimated fractional cointegrated system (2)

m	$T^{0.55}$	$T^{0.60}$	$T^{0.65}$	$T^{0.70}$	$T^{0.75}$
5 Years					
d_u	0.2117	0.2918	0.3119	0.3325	0.3376
	[0.026 0.397]	[0.129 0.455]	[0.172 0.452]	[0.212 0.453]	[0.234 0.442]
d_x	1.1518	1.0689	1.1772	1.1771	1.1102
	[0.967 1.337]	[0.906 1.232]	[1.038 1.317]	[1.057 1.298]	[1.006 1.214]
β	0.9991	1.0003	0.9997	0.9999	1.0007
	[0.997 1.007]*	[0.997 1.009]*	[0.999 1.006]*	[1.000 1.007]*	[1.000 1.009]*
ρ	-0.3483	-0.2832	-0.2796	-0.2443	-0.2626
7 Years					
d_u	0.2529	0.3512	0.4592	0.4142	0.4233
	[0.068 0.438]	[0.190 0.512]	[0.321 0.597]	[0.295 0.534]	[0.321 0.525]
d_x	1.0633	1.0381	0.9978	1.1878	1.0729
	[0.879 1.248]	[0.877 1.199]	[1.013 1.289]	[1.068 1.307]	[0.971 1.175]
β	1.0015	1.0001	0.9978	0.9973	1.0002
	[1.001 1.010]*	[0.997 1.011]*	[0.997 1.006]*	[0.998 1.008]*	[0.997 1.008]*
ρ	-0.2243	-0.2049	-0.1918	-0.1019	-0.1922
10 Years					
d_u	0.3900	0.6939	0.7045	0.6850	0.6686
	[0.207 0.573]	[0.536 0.852]	[0.570 0.839]	[0.571 0.799]	[0.571 0.766]
d_x	1.0410	1.1891	1.0838	1.1669	1.0942
	[0.858 1.224]	[1.032 1.347]	[0.949 1.218]	[1.053 1.281]	[0.997 1.192]
β	0.9938	0.9905	0.9969	0.9966	1.0059
	[0.988 1.022]*	[0.986 0.995]	[0.969 1.025]	[0.987 1.007]	[0.985 1.027]
ρ	-0.1945	-0.1801	-0.1958	-0.2529	-0.2564

Table 18: Estimated fractional cointegrated system (3)

m	$T^{0.55}$	$T^{0.60}$	$T^{0.65}$	$T^{0.70}$	$T^{0.75}$
5 Years					
d_u	0.8294	0.7222	0.7251	0.7377	0.7083
	[0.640 1.019]	[0.549 0.895]	[0.575 0.875]	[0.606 0.869]	[0.595 0.821]
d_x	1.1449	1.1483	1.0723	1.0548	1.0730
	[0.955 1.334]	[0.975 1.321]	[0.922 1.222]	[0.923 1.186]	[0.960 1.186]
β	1.0941	1.0355	1.0439	1.0374	1.0367
	[0.988 1.200]	[0.980 1.092]	[0.960 1.127]	[0.947 1.128]	[0.966 1.108]
ρ	-0.5019	-0.2452	-0.2750	-0.2497	-0.2407
7 Years					
d_u	0.9555	0.8422	0.8038	0.7275	0.6786
	[0.804 1.108]	[0.657 1.028]	[0.646 0.962]	[0.590 0.865]	[0.559 0.798]
d_x	0.9529	1.0875	1.041	1.0321	1.0532
	[0.801 1.105]	[0.902 1.273]	[0.883 1.199]	[0.895 1.169]	[0.933 1.173]
β	-9.3965	0.9723	1.0059	1.0122	1.0064
	[-30.158 11.365]	[0.829 1.116]	[0.868 1.144]	[0.916 1.108]	[0.938 1.075]
ρ	0.9997	-0.0986	-0.1850	-0.2204	-0.1900
10 Years					
d_u	0.5612	0.5105	0.5842	0.6195	0.6551
	[0.348 0.775]	[0.320 0.701]	[0.421 0.748]	[0.478 0.761]	[0.529 0.782]
d_x	1.0322	1.0978	0.9912	1.0035	1.0484
	[0.819 1.246]	[0.907 1.288]	[0.828 1.155]	[0.862 1.145]	[0.922 1.175]
β	1.0997	1.0636	1.0925	1.1055	1.0783
	[1.060 1.139]	[1.030 6.021]*	[1.016 1.169]	[1.022 1.189]	[0.999 1.157]
ρ	-0.4000	-0.1836	-0.3144	-0.3439	-0.2024

Table 19: Estimated fractional cointegrated system (4)

m	$T^{0.55}$	$T^{0.60}$	$T^{0.65}$	$T^{0.70}$	$T^{0.75}$
7 Years					
d_u	0.7549	0.8318	0.7216	0.6791	0.7106
	[0.838 1.105]	[0.620 1.044]	[0.539 0.904]	[0.513 0.845]	[0.566 0.855]
d_x	1.0940	1.0790	1.0615	1.1152	1.1085
	[0.850 1.338]	[0.867 1.291]	[0.879 1.244]	[0.949 1.281]	[0.964 1.253]
β	0.9711	1.0013	1.0328	0.9861	1.0018
	[0.838 0.836]	[0.809 1.194]	[0.914 1.152]	[0.918 1.054]	[0.917 1.087]
ρ	-0.2046	-0.2348	-0.3491	-0.1271	-0.1372
10 Years					
d_u	0.9453	1.0253	0.6709	0.6944	0.8949
	[0.716 1.174]	[0.837 1.213]	[0.451 0.891]	[0.498 0.891]	[0.734 1.056]
d_x	1.0609	1.0350	1.0007	0.9676	1.0393
	[0.832 1.290]	[0.847 1.223]	[0.781 1.221]	[0.771 1.164]	[0.879 1.200]
β	1.9938	16.8853	1.2000	1.2429	1.5414
	[0.990 2.998]	[6.029 27.742]	[0.981 1.419]	[0.978 1.507]	[0.984 2.099]
ρ	-0.9139	-0.9997	-0.4429	-0.4949	-0.7297

Table 20: Estimated fractional cointegrated system (5)

m	$T^{0.55}$	$T^{0.60}$	$T^{0.65}$	$T^{0.70}$	$T^{0.75}$
7 Years					
d_u	-0.1180	0.0256	0.2958	0.3176	0.4991
	[-0.375 0.139]	[-0.212 0.263]	[0.075 0.517]	[0.123 0.512]	[0.327 0.672]
d_x	1.2107	1.1638	1.0320	1.0849	1.1310
	[0.954 1.468]	[0.927 1.401]	[0.811 1.253]	[0.891 1.279]	[0.958 1.304]
β	1.0013	0.9930	0.9913	0.9848	0.9800
	[- -]*	[- -]*	[- -]*	[- -]*	[- -]*
ρ	0.4318	0.2762	-0.0928	0.0264	-0.0118
10 Years					
d_u	0.1254	0.1537	0.3223	0.4691	0.5782
	[-0.127 0.378]	[-0.073 0.381]	[0.127 0.518]	[0.296 0.643]	[0.425 0.732]
d_x	1.1051	1.2546	0.9927	1.0660	1.1138
	[0.853 1.358]	[1.028 1.481]	[0.797 1.188]	[0.893 1.240]	[0.960 1.267]
β	1.0581	1.0552	1.0581	1.0591	1.0550
	[- -]*	[- -]*	[- -]*	[- -]*	[- -]*
ρ	-0.1592	-0.0561	-0.1814	-0.1591	-0.1428

Chapter 6

Forecasting Government Bond Yields with Neural Networks Considering Cointegration

6 Forecasting Government Bond Yields with Neural Networks Considering Cointegration

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