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Abstract

Asset-backed securitisation (ABS) is an asset funding technique that involves the issuance of structured claims on the cash flow performance of a designated pool of underlying receivables. Efficient risk management and asset allocation in this growing segment of fixed income markets requires both investors and issuers to thoroughly understand the longitudinal properties of spread prices. We present a multi-factor GARCH process in order to model the heteroskedasticity of secondary market spreads for valuation and forecasting purposes. In particular, accounting for the variance of errors is instrumental in deriving more accurate estimators of time-varying forecast confidence intervals. On the basis of CDO, MBS and Pfandbrief transactions as the most important asset classes of off-balance sheet and on-balance sheet securitisation in Europe we find that expected spread changes for these asset classes tends to be level stationary with model estimates indicating asymmetric mean reversion. Furthermore, spread volatility (conditional variance) is found to follow an asymmetric stochastic process contingent on the value of past residuals. This ABS spread behaviour implies negative investor sentiment during cyclical downturns, which is likely to escape stationary approximation the longer this market situation lasts.

Keywords: Securitisation, MBS, CDO, CLO, CBO, ABS, Pfandbrief, GARCH model, structured finance

JEL: C12, C32, C53, G12, G21

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1 INTRODUCTION

1.1 Objective

Securitisation seeks to substitute capital market-based finance for credit finance by sponsoring financial relationships without the lending and deposit-taking capabilities of banks (disintermediation). Generally, securitisation represents a structured finance transaction, where receivables from a designated asset portfolio are sold as contingent claims on cash flows from repayment in the bid to increase the issuer's liquidity position and to support a broadening of lending business (refinancing) without increasing the capital base *(funding motive)*. Aside from being a funding instrument, securitisation also serves (i) to reduce both economic cost of capital and regulatory minimum capital requirements as a balance sheet restructuring tool *(regulatory and economic motive)*, (ii) to diversify asset exposures (especially interest rate risk and currency risk) as issuers repackage receivables into securitisable asset pools (collateral) underlying the so-called *asset-backed securitisation* (ABS) transactions *(hedging motive)*. Also the generation of securitised cash flows from a diversified asset portfolio represents an effective method of redistributing credit risks to investors and broader capital markets. These issuer incentives correspond to a certain investment appetites in ABS. As opposed to ordinary creditor claims in lending relationships, the liquidity of a securitised contingent claim on a promised portfolio performance in an structured transaction affords investors at low transaction costs to quickly adjust their investment holdings due to changes in personal risk sensitivity, market sentiment and/or consumption preferences.

Asset-backed securitisation (ABS) represents a growing segment of European structured finance. Efficient risk and asset allocation through seasoned trading in this relatively young fixed income market requires both investors and issuers to thoroughly understand the longitudinal properties of spread prices (over benchmark risk-free market interest rate) of traded securities, which reflect various risk factors of a transaction. Spreads are closely watched by investors and issuers alike, and by doing so, they create an efficient primary and secondary markets of informed investment. For loss of any technical study on secondary pricing in structured finance markets outside the U.S., examining the spread development of European structured transactions proves particularly interesting.

While recent research has generated essential information concerning the determination of ABS spreads (Goodman and Ho, 1997 and 1998; Arora et al. (2000)), the time series properties of these structured finance fixed income investments have been insufficiently addressed. Although research by Koutmos (2001 and 2002) develops a model for the spread dynamics of U.S. MBS transactions, it falls short of addressing other forms of ABS transactions (CDO) and quasi-ABS transactions (Pfandbriefe), with the latter deal type easily matches U.S. MBS by any standard of comparison, be it market volume, trading activity or historical track record.

In the following paper we conduct an empirical analysis of the spread change behaviour of European MBS and CDO transactions as well as Pfandbriefe in order to verify previous studies about certain time series properties of U.S. MBS spread data. Moreover, by using secondary market trading data of European ABS transactions we expand the existing empirical horizon of previous time series analysis of structured finance products. So far no study on the term structure of ABS spreads has been completed on European secondary market trading data. We develop a technical pricing and forecasting approach for the estimation of secondary market spreads of ABS transactions (and their constituent tranches) as a discrete approximation of a multi-factor continuous time model. We enlist modified GARCH(1,1) and GARCH(2,1) models in order to examine any volatility-induced future movements of logarithmic ABS spreads, their degree of symmetry and time variation as well as the corresponding volatility process. Hence, we aim to document the heteroskedasticity of ABS spread processes in order to learn about how past volatility of ABS spreads and changes in the spot rate (LIBOR) explain spread dynamics. We extend the approaches taken by Koutmos (2002) and Longstaff and Schwartz (1992) in order to find out whether spread volatility is constant or time-varying and whether observed spreads support either the existence and the dynamics of mean reversion or a random walk in level and first moment. Finally, we ensure the practical usefulness of the presented model for spread forecasting purposes in a correct model specification through various statistical diagnostics. The results could provide useful insights for adequate secondary market pricing of ABS issues with varying credit quality and an efficient management of ABS portfolios with respect to risk-return considerations.

The rest of the paper is organised as follows. In the subsequent section we examine selected statistical diagnostics of linear regression analysis (normality assumption and autocorrelation) after all descriptive statistics have been exhaustively analysed. In the next section, we discuss the effects of data transformation on time series dynamics before we determine the presence of level stationarity as an important requirement for simple hypothesis testing. In the subsequent section we crystallise in a number of formal statements a GARCH(1,1) and a GARCH(2,1) process of the heteroskedasticity for the spread series of CDO, MBS and Pfandbrief transactions. This is a necessary step to take in the process of translating continuous time models of the term structure of interest rates into a approximate two-factor model of spread dynamics. In the next section we present the estimation results of both GARCH models and verify the correct model specification by means of residual and coefficient tests. Following that, we discuss its econometric implications before we conclude in the last section.

1.2 Securitisation background

The flexible security design of asset-backed securitisation allows for a variety of asset types to be used ain securitised reference portfolios. *Mortgage-backed securities* (MBS), *real estate and non-real estate asset-backed securities* (ABS) and *collateralised debt obligations* (CDO) represent the three main strands of asset-backed securitisation in a broader sense. All ABS structures engross different criteria of legal and economic considerations, which all converge upon a basic distinction of security design: *traditional* vs. *synthetic* securitisation.

Traditional securitisation involves the legal transfer of assets or obligations to a third party that issues bonds as *asset-backed securities* (ABS) to investors via private placement or public offering. This transfer of title can take various forms (*novation*, *assignment*, *declaration of trust* or *subparticipation*), which ensures that the securitisation process involves a "clean break" (true sale, bankruptcy remoteness or "credit de-linkage" in loan securitisation) between the sponsoring bank (which originated the securitised assets) and the securitisation transaction itself. In most cases, however, the sponsor retains the servicing function of the securitised assets. Traditional securitisation mitigates regulatory capital requirements by trimming the balance sheet volume. In synthetic securitisation only asset risk (e.g. credit default risk, trading risk, operational risk) is transferred to a third party by means of derivatives without change of legal ownership, i.e. no legal transfer of the designated reference portfolio of assets.[1] Hence, any resulting regulatory capital relief does not stem from the actual transfer of assets off the balance sheet but the acquisition of credit protection against the default of the underlying assets through asset diversification and hedging.[2] Commonly, sponsors of synthetic securitisation issue debt securities supported by credit derivative structures, such as *credit-linked notes* (CLNs)[3], whose default tolerance amounts to total expected loan losses in the underlying reference portfolio. Hence, investors in CLOs are not only exposed to inherent credit risk of the reference portfolio but also operational risk of the issuer.[4] Recently, also traditional securitisation transactions included elements of synthetic securitisation (such as credit derivatives) in order to preserve the credit-linkage of issued securities to the originator and realise on-balance sheet financing to fund assets.[5]

In contrast to the U.S., where the market for ABS has had a longstanding tradition since the first half of the 1980s[6] (Klotter, 2000), European ABS has gained popularity only over the last several years –

[1] For instance, sellers of credit default swaps (CDS) receive a premium for their obligation of compensating buyers of credit protection for any default losses up to a specified amount. Since the compensation payment through credit default swaps (CDS) is contingent on a certain credit event, derivative components in the security design of synthetic transactions are termed "unfunded", while bonds directly issued to investors as "credit-linked notes" (CLN) are "funded".

[2] This property of synthetic CLOs is attractive to large banks, which tend to have access to on-balance sheet assets at competitive spreads.

[3] "Credit linkage" signifies credit risk transfer without a corresponding change of title (legal ownership) of the underlying asset claims.

[4] The absence of asset transfer to a special purpose vehicle (SPV) as in traditional CLOs aids the cost efficient administration of synthetic securitisation. Synthetic structures also garner issuers with a wider choice of leveraging the underlying reference portfolio, so that on average the nominal total value of issued debt securities of such transactions is significantly outstripped by the nominal tranche volume in conventional securitisation.

[5] The marginal difference in senior risk exposure between partially funded synthetic securitisation and traditional securitisation does not extent to junior noteholders with subordinated security interest. While partial funding structures bear more risk emerging from the sponsor's role, the credit enhancement (first loss provision) and subsequent junior tranches (the second loss position) are no more exposed to credit risk in synthetic deals than they are in traditional CLOs.

[6] The first asset-backed securitisation issue in its modern form was completed by *Sperry Corporation*, which issued computer lease backed notes in 1985 (Kendall, 1996).

notwithstanding the fact that *Pfandbrief* structures[7] (on-balance sheet mortgage-backed securities) have been an established method of securitising homogenous mortgage portfolios for more than two centuries.[8] Actually, the Pfandbrief market has developed into one of the largest fixed income markets in Europe. Recently, the issue volume of both mortgage-backed securities (MBS) and collateralised debt obligations (CDO) has surged at an impressive scale despite depressed expectations from interest-based income and the search for alternative asset funding mechanisms. Both types of ABS transactions have become an important segment of the European bond market as banks, non-bank financial intermediaries (NBFIs) and corporations favour more flexible funding mechanisms. Hence, ABS issues have caught up with Pfandbrief transactions as one of the largest (by outstanding volume) fixed income markets in Europe.

The distinct track record of on-balance sheet securitisation in European structured finance on the basis of the Pfandbrief scheme prohibits a comparison of European and U.S. asset-backed securitisation without consideration of the Pfandbrief market as control factor. With a nascent European ABS market yet falling short of attracting large secondary trading activity, only the Pfandbrief market in Europe matches the liquidity and maturity of U.S.-based securitisation. Hence, any analysis of ABS markets in Europe also needs to account for the existing investment behaviour of the Pfandbrief market.[9]

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[7] See also Böhringer, Lotz, Solbach and Wentzler (2001).

[8] The first *Pfandbrief* instrument was created by the executive order of Frederick the Great of Prussia in 1769 (Skarabot, 2002; Anonymous, 1999).

[9] Although MBS transactions and Pfandbrief transactions share the same type of reference assets, upon closer inspection several structural differences between these fixed income investments emerge. While the Pfandbrief is a classsical on-balance sheet refinancing tool (with both origination and issuance are completed by one and the same entity), MBS transactions involve at least one more party (besides the mortgage originator), which sells contingent claims on asset cash flows, so that the reference portfolio underlying the securitised assets is removed from balance sheet and legally segregated (bankruptcy remote). Pfandbrief transactions lack a direct relationship between mortgage cash flows and the promised repayments to investors, who rank *pari passu*, whose claims may be junior to other creditors of the Pfandbrief issuer. In comparison MBS transactions solely return cash flows generated from the pool performance of the designated reference portfolio. Investor claims rank either *pari passu* to each other in the sense of pass-through (PC) or are prioritised through subordination (but no other parties can declare a moratorium on assets). Hence, Pfandbrief ratings include an implicit financial strength rating of issuers, which are fully liable with their registered capital if the designated asset pools fail to generate sufficient cash flows for repayment of investors. Given this institutional guarantee and (legally defined) overcollateralisation Pfandbrief transactions generally receive high ratings. The downside of this legal arrangement is the fact that investors in Pfandbrief transactions are not insulated from an "originator event" (insolvency and bankruptcy), whereas MBS investors in a dedicated mortgage loan pool are. At the same time, MBS transactions are devoid of any institutional guarantee. So issuers of MBS transactions compensate issuers for the higher asset exposure due to deficient institutional protection by including various kinds of internal and external liquidity and credit support, such as bridge-over facilities, surety bonds, third-party guarantees, yields spreads/excess spread, overcollateralisation and reserve accounts. Finally, Pfandbrief issues are subject to stringent federal laws (requiring a weighted average loan-to-market or appraised value (LTV) of at least 60% as a statutory benchmark), whilst "private-label" MBS are free from these legal requirements, except in so-called "agency-MBS" in the U.S., where the quasi-government agencies Fannie Mae (FNMA), Freddie Mac (FHLMC) and Ginnie Mae (GNMA) provide institutional guarantees in return for certain restrictions imposed on mortgages eligible for purchase in MBS structures. In general, Pfandbrief transactions represent a very secure and liquid asset class of fixed income instruments with an established track record and cyclical resilience. MBS issues are equally liquid (at least in the U.S. market) and feature an unchallenged degree of flexibility allowing for customised features and investor arrangements, such as variations to amortising repayment (in contrast to bullet repayment structures of Pfandbrief issues). Pfandbriefe serve primarily as funding instruments, whereas MBSs are also employed for credit risk transfer and balance sheet restructuring with the aim of efficient management of economic and regulatory capital.

1.3 Characteristics of spreads

The pricing of fixed income obligations requires investors to determine the yield-to-maturity (YTM) measure or even an entire spot curve for discounting future cash flows. Depending on the nature of the obligation. Various factors influence the computation of the expected return of an fixed income security, such as the current market interest rate ("market spot rate"), the maturity of the obligation, the liquidity of the obligation, the current credit risk and the credit outlook of the obligation ("rating grade") and its volatility within a risk classification grade, asymmetric information, imbedded options, the size and tax treatment of the issued security.

The market interest rate enters into the calculation of the YTM as some benchmark yield curve or spot rate curve, e.g. the LIBOR or EURIBOR rate, which reflects the maturity dependence of interest rates. The (yield) spread over the benchmark yield of fixed income securities captures the risk contribution of the remaining aforementioned factors *in addition to the market interest rate*, which have to be taken into account for the mean-variance efficient pricing of fixed income securities. For instance, commonly imbedded options in MBS transactions feature spreads due to optionality, which is structured to the detriment of investors. So we observe that instruments that are imbedded trade at higher spreads than comparable securities without any option component ("option-adjusted spread analysis"). Also the lack of liquidity could depress the trading prices due to a liquidity spread, where highly liquid, recently issued issues are said to be "on-the-run" in a liquid secondary market and low associated liquidity spread, as opposed "off-the-run" issues that have less of a secondary market.

2 LITERATURE REVIEW

Recent research (Goodman and Ho, 1998; Koutmos, 2002) has indicated that government bond yields, the shape of the yield curve play an important role in the determination of fixed-rate MBS yields in the U.S.[10] In their study on the determinants of MBS-Treasury spreads Goodman and Ho (1998) also consider the five-year cap volatility and the ten-year swap spreads as a measure of some LIBOR effect as crucial factors, where the later having gained in importance over the recent past. Arora et al. (2000) propose a five-factor model that explains nearly 60% of mortgage spreads. Koutmos (2002) showed in an extended version of the Longstaff and Schwartz (1992) term structure model that U.S. MBS spreads over the maturity-matched treasury rate follow a mean-reverting stochastic process, which behaves asymmetrically in response to the direction of past spread change ("asymmetric mean reversion").

[10] Bhasin and Carey (1999) were the first to present an empirical study, which analysed – although in an admittedly rudimentary fashion, the trading behaviour of bank loans. In contrast to conventional wisdom of fixed income securities research, particularly credits with a low rating grade were traded most. This liquidity effect would of course affect the market price (i.e. the spread over some benchmark yield) *ex ceteris paribus* and its attendant volatility. However, it does not account for the pricing behaviour in ABS markets.

In the following paper we conduct an empirical analysis of the spread change behaviour of European MBS and CDO transactions as well as Pfandbriefe in order to ascertain previous studies about certain time series properties of U.S. MBS spread data. Research by Goodman and Ho (1998) indicates that MBS yields are by and large explained by the yield on government securities and the shape of the yield curve, even though the prepayment of principal and interest by mortgagors makes the duration of such transactions more volatile (compared to government bonds) due to an uncertain timing of cash flows.

We build on the factor approximation of a specialised Ito process of spread dynamics proposed by Koutmos (2002) and Longstaff-Schwartz (1992). We also consider Goodman and Ho (1998) as we control for LIBOR effects in both the mean and the conditional variance of spread change over time. Finally, we expands the empirical scope of previous studies by using a data set of European secondary market trading quotes of MBS, CDO and Pfandbrief transactions.

We test for asymmetric mean reversion by means of a multi-factor model. Empirical findings suggest all spread series follow an overall mean-reverting process. In contrast to Koutmos (2002), we find no statistical asymmetry of mean reversion during spread increases and decreases. However, the mean-reverting trend following spread decreases is economically stronger than the influence of past spread increases. The spread volatility is time-varying, depending on past variance forecasts, past squared errors of the mean equation (innovations) as well as past levels of spreads and the reference sport rate (LIBOR). Similar to Koutmos (2002) we can find that the conditional variance of spread change behaves largely asymmetric, rising more to positive innovations.

3 DATA DESCRIPTION

The primary data consists of aggregated secondary market spreads (with respect to the 3-month LIBOR rate) of European ABS transactions (Residential Mortgage-Backed Securities (RMBS),[11] Collateralised Debt Obligations (CDO) and Pfandbrief transactions) over almost two years (see Fig. 1). The spread series of RMBS and CDO transactions stems from the structured finance trading desk of a major European commercial bank, which generates an end-of-week indicative secondary spread benchmark from all traded transactions (classified by ABS type, rating and maturity) with the highest market quotes. The time series data of European Pfandbrief spreads are based on the *Merrill Lynch Pfandbrief Index* (see Appendix, Tab. 7). In Tab. 6 (Appendix) we spell out the nomenclature of the various time series in our ABS spread data base.

[11] We will use the generic expression of mortgage-backed securities (MBS) as short-hand for this asset class in the remainder of the paper.

3.1 Further specification

The data set underlying the aggregate secondary spreads (denominated in basis points above LIBOR) includes the majority of European ABS transactions classified as synthetic and traditional (true sale) CDO or RMBS with floating rate tranches of varying rating grades and maturities of 3, 5 and 7 years from 5 January 2001 to 18 October 2002 (93 weekly observations). As opposed to CDO spreads, MBS time series data does not consider synthetic and traditional structures individually but represents the weighted-average, aggregated spreads of both classifications. The dominance of traditional transactions in MBS spreads reflects the observed market preference for true sale structures of this kind of ABS. We chose the *Merrill Lynch (ML) EMU Pfandbrief Index* (via Bloomberg) as benchmark roughly matched in maturity (1-3 years, 3-5 years and 5-7 years) to the time series data of the selected CDO and RMBS tranches. Originally, daily Pfandbrief spreads were obtained for the time period from 13 April 1998 to 29 March 2002, which were later transformed into weekly spreads and shortened to fit the time period of observed CDO and RMBS spreads in order to ensure a reliable statistical analysis, whose results remain unaffected by disparate sample periods or higher data frequency of observations (see Fig. 1 in the Appendix). We replaced two missing observations on 14 April 2001 and 29 March 2002 (bank holidays) by the spreads of the previous day. The majority of Pfandbrief issues entering each maturity-based index benchmark were originated by German banks. Since the Pfandbrief indices contained different proportions of rating classes at the beginning and the end of the sample periods (see Appendix, Tab. 7) – on 5 January 2001 all Pfandbrief indices included more than 80% AAA-rated issues compared to 18 October 2002 when roughly 75% of all issues were rated AAA – we computed a mean weighted-average of rating classes for each maturity of Pfandbrief index and derived daily spreads according to this distribution of rating classes for each maturity classification of Pfandbriefe. We discarded the possibility of calculating the index composition for each daily spread observation due to short-term volatility jumps and level effects induced by the accounting scandals surrounding the U.S. corporations Enron and WorldCom.

3.2 Statistical descriptives

The quality of our estimation results of time series fundamentally depends on the statistical properties of ABS spread series in our data set, especially, the distribution of spreads and the degree of autocorrelation if applicable. We extract preliminary information about the descriptive statistics of the given spreads as a crucial piece of information for modelling the dynamics of spread changes in structured finance transactions (see Appendix, Fig. 1). On first inspection infrequent changes of spread data on level and first difference bears out strong evidence of distinct illiquidity in European MBS and CDO markets, which are commonly characterised as buy-and-hold markets. Moreover, in some cases the given spread time series of these asset types do not reflect actual transaction data but conflated bid/ask spreads. Pfandbrief spreads reflect reasonable stationarity of periodically mean-reverting cycles. In contrast, sporadically occurring hikes in level spread series of CDO and MBS transactions hint to arguably higher illiquidity of these markets compared to the Pfandbrief market. Although some interspersed idle periods in these spread series might jeopardise the appellation of even weak level stationarity, the frequently occurring volatility peaks in the first differences of spreads (both original and transformed) make a strong case for autoregressive constant heteroskedasticity models (ARCH). Nonetheless, bearing in mind the hazards of “stale time series”, we attach great importance to a robust preliminary analysis before we proceed to develop the proposed GARCH approach (see section 5.2 below).

Tab.1-Tab. 11 (Appendix) report several descriptive statistics of logarithmic and Johnson Fit-adjusted spread series. It can be seen that average spreads decrease with higher ratings and maturity. Relative spread volatilities (relative variation) are modest, ranging from 1.6% to 7% for the logarithmic spread series of asset classes in the data set. The *Jarque-Bera* test statistic (defined in section 3.3 below) shows that most spread series (with the exception of CSAAA3, CSBBB7, PAAA5 and PAAA7) reject the null hypothesis of normal distribution, given their values of skewness and kurtosis. The *Doornik-Hansen* diagnostic (see section 3.3 below) confirms this result about the spread process of observed data. All spread series fail to adhere to normality in their first differences.

According to the *Llung-Box Q-statistic* (defined in section 3.4 below) significant and high levels of autocorrelation exist in both observed spreads (up to 26 lags) and logspreads (up to 28 lags). The first moment of spreads sheds most of the serial correlation, with merely some spread series flagging autocorrelation at up to two lags (e.g. PAAA3 and PAAA5). Nonetheless, autocorrelation remains a pressing issue that needs to be addressed in the course of our preliminary statistical analysis. Even though autocorrelation is close to unity and fails to drop off quickly – hinting at non-stationarity – we will later see that the unit root hypothesis can be rejected for most spreads at level and first difference.

3.3 Test of normality

The proposed GARCH(1,1) and GARCH(2,1) models largely rely on the statistical assumptions of linear multivariate analysis for the coefficient estimates to be valid.[12] Although the endogenous variable is not required to fit certain distributional characteristics, once we valid parametric testing of the statistical significance of coefficients infers normally distributed residuals according for $e \sim N\left[0, s^{2}\mathbf{I}\right]$ (Greene, 1993, 172 and 184), which implicitly applies to dependent variables as well. Otherwise any resulting estimates would not be independent of the residuals and the critical values for parametric tests, such as the t-statistic, would lose their significance (Hair et al., 1998, 70f). However, countless empirical studies about investment instruments document that financial time series are hardly normally distributed – a common feature frequently ignored. Various kinds of transformation have been suggested in past research in order

[12] Assumptions for linear multivariate regression estimation (Greene, 1993, 170f) in matrix algebra: (i) linear relationship between exogenous and endogenous variables: $\mathbf{Y} = \mathbf{X}b + e$, (ii) zero expected residuals: $E(e) = 0$, (iii) homoskedasticity: $E(ee') = s^{2}\mathbf{I}$, (iv) independence of residuals: $E(e|\mathbf{X}) = 0$, (v) $\mathbf{X}$ represents a non-stochastic $n \times k$ matrix of rank k.

to adjust observed to data to fit desired distributional assumptions. For instance, Hartung (1987) suggests the logarithmic transformation, $g(x)=\ln(x+c)$, the reciprocal transformation, $g(x)=x^{-1}$, and the square root transformation, which comes in various forms, such as $g(x)=\sqrt{x+c}$. Alternatively, more complex ways of transformation exist, which promise higher flexibility at the loss of straightforward application, such as the so-called Johnson Fit (1949), which allows for transformation of any continuous distribution into a normal distribution. We apply both the logarithmic transformation and a statistical adjustment according to the Johnson algorithm to improve the distributional properties of the time series of our data set.

First, we conduct the test of normality on non-transformed data. In our preliminary descriptive statistic we first apply the Jarque-Bera (JB) test diagnostic to examine whether the null hypothesis of normally distributed spreads holds. The Jarque-Bera test statistic

$$JB=\frac{N-k}{6}\left(S^2-\frac{1}{4}(k-3)^2\right) \tag{0.1}$$

measures the degree to which a time series is normally distributed based on the difference of the skewness S and kurtosis K between the normal distribution and the spread series, where k represents the number of estimated coefficients used to create the series. The probability of the JB test indicates the likelihood of the JB statistic to exceed (in absolute value) the observed value of a normal distribution. Since the JB statistic is particularly suitable for large samples, our limited number of observations suggests an alternative test procedure, which would holds greater certainty as regards the normal distribution assumption. We apply the test procedure of Doornik and Hansen (1994), which was developed for small sample sizes. Similar to the Jarque-Bera test statistic, the Doornik-Hansen diagnostic (E_p) computes the deviations from the normal distribution on the basis of transformed higher moments of skewness z_1 and kurtosis z_2:

$$E_p = z_1^2 + z_1^2 \underset{app}{\sim} c^2_{df=2}. \tag{0.2}$$

Doornik and Hansen define the transformation of skewness S and kurtosis K for n number of observations as

$$z_1 = d\ln\left(y+\sqrt{y^2-1}\right), \tag{0.3}$$

where $d=\frac{1}{\sqrt{\ln(v)}}$, $y=S\sqrt{\frac{w^2-1}{2}\frac{(n+1)(n+3)}{6(n-2)}}$, $v^2=-1+\sqrt{2(b-1)}$,

$$b=\frac{3\left(n^2+27n-70\right)(n+1)(n+3)}{(n-2)(n+5)(n+7)(n+9)},$$

and

$$z_2 = \left(\left(\frac{c}{2a} \right)^{\frac{1}{3}} - 1 + \frac{1}{9a} \right) \sqrt{9a} \,, \qquad (0.4)$$

where $c = 2k\left(K - 1 - S^2\right)$, $a = a + S^2 c$, $k = \frac{(n+5)(n+7)\left(n^3 + 37n^2 + 11n - 313\right)}{12d}$,

$d = (n-3)(n+1)\left(n^2 + 15n - 4\right)$, $a = \frac{(n-2)(n+5)(n+7)\left(n^2 + 27n - 70\right)}{6d}$,

$c = \frac{(n-7)(n+5)(n+7)\left(n^2 + 2n - 5\right)}{6d}$.

Based on the Doornik-Hansen test the hypothesis of normally distributed spreads is rejected as the approximate $c^2_{df=2}$-distributed test statistic is significantly different from zero (see Appendix, Tab. 9-Tab. 11). Surprisingly, non-normality, which persists even after transformation, does not seem to stem from poor data quality in general and low levels of market liquidity in particular, e.g. if we contrast the spread distribution and the associated JB statistic and E_p statistic for PAAA2 and CSBBB7. Despite markedly higher liquidity of Pfandbriefe, the former time series deviates more from the normal distribution assumption than an illiquid, low-rated synthetic CDO tranche.

The normality assumption under both the Jarque-Bera statistic and the Doornik-Hansen approximation is also not satisfied for logarithmically transformed time series (marked by the acronym "L" added to the tranche specification), regardless of further adjustment by means of the Johnson Fit (marked by the acronym "AD"). The descriptive statistics show that the suggested transformation is successful in doing little more than improving the JB-statistic in some cases of extreme deviations from the normal distribution only, such as BBB-rated, traditional CDOs with maturity of seven years (CTBBB7_L) and AAA-rated Pfandbriefe with maturity of three years (PAAA3_L). On average the Doornik-Hansen test indicates even a worsening of the distributional properties of spreads after logarithmic transformation.

Although the logarithmic transformation does not improve the spread distribution across the board of all time series, we find evidence that extreme deviation from the normal distribution can be mitigated, whilst logspreads[13] generally tend to be more dissimilar to normality in the given data set. Besides improved distributional properties, logarithmic transformation also harmonises the spread variation coefficient $V = s_S / \overline{S}$, i.e. the ratio between standard deviation and mean of spreads, for all time series of weekly spreads. The variation coefficient also reveals the level effect of given ABS spreads – the standard deviation of spreads increases in the level of spreads. For non-transformed spreads we compute an average $\overline{S} = 16.67\%$ and a standard deviation $s_S = 5.66\%$, which are highly correlated at $r_{\overline{S},s_s} = 0.947$.

[13] Moreover, the additivity of logarithmic returns proves beneficial for our economic analysis.

Logarithmic transformation would mitigate this level effect and stabilise the variance of the entire spread sample for comparative analysis. The correlation of standard deviation and mean of weekly logspreads drops to $r_{\bar{S},s_s} = 0.289$. Further, we apply the *Johnson Fit* adjustment to align the continuous distribution of logspreads closer to normality. This transformation procedure is based on three kinds of frequency distribution functions (so-called *Johnson curves*) – an unbounded (S_U), a bounded (S_B) and a lognormal distribution (S_L) – with an associated transformation function $u = g + h k_i(x; l, x)$, where u denotes a standard normal target variable and x represents the original variable. Johnson specifies $k_i(x; l, x)$ for each type of distribution function (S_U, S_B, S_L), which is most suitable to transform an original variable to fit a normal distribution, with g, h, l and x as known parameters:

$$S_U: \quad k_1(x; l, x) = \sinh^{-1}\left(\frac{x - x}{l}\right), \tag{0.5}$$

$$S_B: \quad k_2(x; l, x) = \ln\left(\frac{x - x}{l + x - x}\right), \tag{0.6}$$

$$S_L: \quad k_3(x; l, x) = \ln\left(\frac{x - x}{l}\right). \tag{0.7}$$

Since S_L is lognormal distributed by definition, we can eliminate l from the last expression, so that the transformation function for this type of distribution function can be simplified to $u = g^* + h \ln(x - x)$ for $g^* = g - h \ln(l)$ (Slifker and Shapiro, 1980, 239). Johnson shows that parameters g and h define the shape of the fitted curve, the scale factor l defines the variance and x the expected value of the distribution. Slifer and Shapiro (1980, 240f) propose a simplified estimation procedure for all four parameters in each distribution function (S_U, S_B, S_L). First, the original variable data has to be assigned one of the three types of distribution functions. To this end, we pick a random value $z > 0$ of a standard normal distribution, where the values $-3z, -z, z$ and $3z$ constitute three intervals of equivalent distance. Commensurate to the cumulative densities of $-3z, -z, z$ and $3z$, we determine the corresponding values x_{-3z}, x_{-z}, x_z and x_{3z} for the distribution of the original variable x. These values of course do not form intervals of equivalent distance, because they stem from the original distribution function, which needs to be transformed. Depending on the relationship between the values x_{-3z}, x_{-z}, x_z and x_{3z} we determine the appropriate transformation function according to the following selection criteria:

S_U : $mn \times p^{-2} > 1$, S_B : $mn \times p^{-2} < 1$ and S_L : $mn \times p^{-2} = 1$,[14] where $m = x_{3z} - x_z$, $n = x_{-z} - x_{-3z}$ and $p = x_z - x_{-z}$. Once we have determined the adequate distribution function from the set of S_U, S_B and S_L, Slifker and Shapiro introduce a system of equations for each type of function in order to compute the four parameters g, h, l and x, with z small enough for small sample sizes,[15] so that the value of $x_{\pm 3z}$ can easily be calculated:

For S_U : $u = g + h \sinh^{-1}\left((x - x)\, l^{-1}\right)$ —

$$g = h \sinh^{-1}\left(\frac{(n-m)\, p^{-1}}{2\left(mn \times p^{-2} - 1\right)^{0.5}}\right),\ h = \frac{2z}{\cosh^{-1}\left(0.5(m+n)\, p^{-1}\right)} \quad \text{for } h > 0,$$

$$l = \frac{2\, p\left(mn \times p^{-2} - 1\right)^{0.5}}{\left((m+n)\, p^{-1} - 2\right)\left((m+n)\, p^{-1} + 2\right)^{0.5}} \quad \text{for } l > 0 \text{, and } x = \frac{x_z + x_{-z}}{2} + \frac{p\left((n-m)\, p^{-2}\right)}{2\left((m-n)\, p^{-1} - 2\right)}.$$

For S_B : $u = g + h \ln\left((x - x)(l + x - x)^{-1}\right)$ —

$$g = h \sinh^{-1}\left(\left[\left(pn^{-1} - pm^{-1}\right)\left(\left(1 + pm^{-1}\right)\left(1 + pn^{-1}\right) - 4\right)^{0.5}\right]\left(2\left(p^2 (mn)^{-1} - 1\right)\right)^{-1}\right),$$

$$h = z\left(\cosh^{-1}\left(0.5\left(\left(1 + pm^{-1}\right)\left(1 + pn^{-1}\right)\right)^{0.5}\right)\right) \quad \text{for } h > 0,$$

$$l = p\left(\left(\left(1 + pm^{-1}\right)\left(1 + pn^{-1}\right) - 2\right)^2 - 4\right)^{0.5}\left[p^2 (mn)^{-1} - 1\right]^{-1} \quad \text{for } l > 0 \text{, and}$$

$$x = \frac{x_z + x_{-z}}{2} - \frac{l}{2} + p\left(pn^{-1} - pm^{-1}\right)\left[2\left(p(mn)^{-1} - 1\right)\right]^{-1}$$

For S_L : $u = g^* + h \ln(x - x)$ —

$$g^* = h \ln\left(\left(mp^{-1} - 1\right)\left[p\left(mp^{-1}\right)^{0.5}\right]^{-1}\right),\ h = \frac{2z}{\ln\left(mp^{-1}\right)} \text{, and } x = \frac{x_z + x_{-z}}{2} - \frac{p}{2} \times \frac{mp^{-1} + 1}{mp^{-1} - 1}.$$

The application of the Johnson Fit routine on our data set of weekly spread series indicates that the quality of the desired adjustment to normality is highly sensitive to the choice of the random z-value. Hence, we resort to an iterative procedure to determine the optimal z-value at six decimals. First, we compute a preliminary z-value (preliminary optimal) for the best approximation of the original distribution to the normal distribution, measured by the Jarque-Bera statistic, as we count from 0 to 2 by staggered increments of 0.02. We refine the preliminary z-value through another cycle of increments of 0.001 within

[14] Since the probability of $mn/p^2 = 1$ to occur borders to zero, it seems reasonable to use certain tolerance levels around the critical value 1 for this selection process.
[15] Slifker and Shapiro (1980, 240f) recommend $z = 0.5$.

a band of +/-0.02 around its value in order to determine the optimal value of z. This iterative procedure continues until the parameterisation of z is sufficiently accurate for an optimal approximation of the normal distribution measured by the Jarque-Bera statistic of the original distribution after transformation. In our data set the transformation of the original spread time series via the Johnson Fit merely nears the standard normal. Moreover, the first two moments, m and s, of the adjusted spreads – which would describe a standard normal distribution under optimal transformation – deviate significantly from the original spread series across the sample. Consequently, we further adjust the Johnson-fitted spread series by matching mean and standard deviation to the original distribution; at the same time, however, we preserve the approximative normal distribution in the transformed spread series. In order to reinstate the variance of each original spread series we recalibrate the differences between fitted spreads and original spreads by means of multiplication with an adequate scaling factor. We also adjusted the mean of the fitted spread distribution to the original mean value by conditioning the new starting value.[16] The new adjusted spread series (marked by the acronym "_AD_L" in the rest of the paper) bear great resemblance to the original spread series for all asset classes in our data set. The correlation coefficient between both exceeds 90% in most cases. Only the matched pairs of one issue type of traditional CDOs (CTA5) and three out of four MBS time series (MAAA3, MAAA5 and MBBB7) exhibit weak correlation effects due to distorting effects by the transformation procedure. In Tab. 8 (Appendix) we illustrate the chosen z-values, the type of distribution underlying the transformation function, the correlation between the fitted spread series and the original spread series as well as the indicators of the normal distribution assumption, which include the Jarque-Bera statistic and the estimation results for the Doornik-Hansen test. We will consider these results when carrying out the GARCH estimation procedure.[17] We particularly address the violation of the normality assumption as we compute the heteroskedasticity consistent (quasi-maximum likelihood) covariance matrix, which is also needed for several model diagnostics (coefficient and residual tests) at a later stage of this paper.

Due to the disparate distributional characteristics and the varying goodness of adjustment through the Johnson Fit we continue to apply the proposed GARCH models on all spread series, i.e. non-adjusted spreads, logarithmic spreads and Johnson-fitted and adjusted logspreads. We postpone the conscious choice of eliminating certain spread data from our analysis at this stage, as the trade-off between lower levels of normality in all spread series (by retaining non-transformed time series) and sporadic distortions of actual spread change (in some Johnson-fitted spread series, e.g. CSAAA3) is not straightforward to this point.[18]

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[16] Both optimisations were conducted via the "goal seek" function supplied by the Microsoft Excel software package.

[17] Please note that we have not applied the Johnson Fit to LIBOR rates. So the LIBOR rates in later GARCH estimations with adjusted and Johnson Fit-adjusted spread series include logarithmic LIBOR rates only.

[18] Solely the MBBB7_AD_L spread series constitutes a strong case for disregarding the Johnson Fit of spreads and subsequent scaling, since this adjustment effects both a significant distortion of spread dynamics <u>and</u> a lower degree of normality.

3.4 Test of autocorrelation

The main statistical diagnostic for autocorrelation in time series is the Llung-Box test. Llung-Box Q-statistic at lag k represents the test statistic for the null hypothesis of no autocorrelation up to order k (i.e. whether the series is white noise) for

$$Q_{LB} = T(T+2)\sum_{j=1}^{k} r_j (T-j)^{-1}, \tag{0.8}$$

where r_j is the j^{th} autocorrelation and T is the number of observations. The Q-statistic is asymptotically distributed as c^2 with the degrees of freedom equal to the number of autocorrelations, since the observations are not the result of an ARIMA estimation. We augment this test statistic by the AC-value of autocorrelation (with the null hypothesis of no autocorrelation). The AC-value confirms the Q-statistic of absent serial correlation if it cannot be rejected at 5% level, i.e. falls within the two standard error bounds of $\pm 2T^{-0.5}$. We assume 36 lags as default test setting for all test statistics of autocorrelation for the given time series. We estimate the autocorrelation of series y with lag k and sample mean $\bar{y}$ as the correlation coefficient over k periods

$$r_k = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y}_{t-k})/(T-k)}{\sum_{t=1}^{T}(y_t - \bar{y})^2 / T}, \tag{0.9}$$

where $\bar{y}_{t-k} = \sum_{t=k+1}^{T}\left(y_{t-k} \times (T-k)^{-1}\right)$ relies on the same overall mean $\bar{y}$ as the mean of both y_{t-k} and y_t (which would bias the result towards zero for finite series) for matters of computational simplicity. Hence $r_k \neq 0$ means that the series is first order serially correlated. A geometric decrease of r_k in an increase of lags k would constitute a low-order autoregressive (AR) process, whereas as rapid decline of r_k to zero flags a low-order moving average (MA).

We determine the degree of autocorrelation at the statistical threshold of significant Q-statistics (p-value) and AC values (together with the partial correlation measure PAC) for the null hypothesis of no autocorrelation. This threshold level entails the maximum number of lags until which either the associated AC value or the Q-statistic no longer indicate a rejection of the null hypothesis of at least the 5 % level – whichever occurs first, with the Q-statistic being the primary criterion. For the given spread series the Llung-Box statistics (Appendix, Tab. 9-Tab. 11) indicate high levels of autocorrelation for up to more than twenty lags, which abate as the spread series are transformed into logspreads with/without the Johnson Fit procedure. Also the correlogram-generated partial correlation coefficients (PAC) between the current spread levels and past spread levels of up to five lags together with the associated Q-statistics for each period for non-transformed and transformed logspreads confirm this assessment. While partial correlation decreases substantially after one lag for synthetic and traditional CDO and MBS spread series (with the Johnson Fit reducing some of the correlation), Pfandbrief spreads retain partial correlation values of more than 20% up to three lags in some instances.

We attempt to strip all spread series of any autocorrelation effects by using the residuals of an AR(*p*) estimation of past spreads up to *p* number of (autocorrelative) lags. In an ordinary least squares regression (OLS) of lagged spreads (in keeping with the computation of abnormal returns in financial research) the residuals should not be correlated if past spreads as exogenous regressors absorb all serial correlation effects. We find that autocorrelation persists in the new spread time series of residuals, with autocorrelation and partial correlation test diagnostics only marginally different from the original spread series. Hence, we abstain from using new autocorrelation-adjusted spread series of AR estimated residuals. Nonetheless, the later GARCH estimation will include correction terms, which control for autoregressive effects up to lag two (see GARCH(2,1) model in section 5.2.2).

In some cases for CDO and MBS data this result might be primarily attributable to level effects as well as spread dynamics with "stale data" properties, where slight changes over time generate significant autocorrelation, which, at the same time, sustains a mean reverting process. However, in this case, "stale data" would mimic mean reversion, which would normally be a result of level stationarity in very liquid and volatile markets. This observation has important consequences for the later formulation of the multi-factor term structure model of structured spreads, where we control for past changes in LIBOR as spread reference base (so we could view the spread series as "excess returns" over LIBOR). We particularly take account of autocorrelation in the later GARCH estimation by computing heteroskedasticity consistent (quasi-maximum likelihood) covariance matrices, which are needed for several model diagnostics (coefficient and residual tests).

4 TIME SERIES DYNAMICS

In the section we examine the time series dynamics of the different asset class spreads of our sample. We first conduct a unit root test (in order to test for mean reversion) before we move on to introduce an approximative multi-factor model as an estimation of spread time series (GARCH specification), which allows us to determine asymmetric spread dynamics up to two lags while controlling for level effects induced by past spreads and changes in the base rate (LIBOR).

Various financial studies have shown that interest rates follow a random walk and, hence, do not succumb to a mean-reverting process, that is, they are not stationary in their levels (Nelson and Plosser, 1982). According to Koutmos (2001) U.S. MBS quotations and government bond yields have unit roots each, while the vector of U.S. MBS spreads and U.S. Treasury spreads appears co-integrated, i.e. both share a long-term relationship.[19] Koutmos (2002), however, finds that the unit root tests confirm stationarity (mean-reversion) of MBS spreads on a sample of weekly spreads of U.S. MBS transactions with maturities of five, seven and ten years over a time period of more than 30 years. Furthermore, his analysis concludes that spread changes exhibit asymmetric mean reversion, i.e. the first moment of spreads is strongly mean-reverting following spread decreases, but non-stationary following spread increases.

In order to determine the time trend and the presence of mean reversion of all CDO, MBS and Pfandbrief spread series (actual, adjusted and with/without Johnson Fit) in the data set, two methods emerge – the correlogram or the unit root test. In a finite data sample the correlogram testing procedure is imprecise, because sample autocorrelation will converge to zero for k elements (and indicate mean reversion) even if the time series is non-stationary. In practice it is difficult to tell whether a time series is non-stationary or slowly converging stationary. If values for autocorrelation drop to zero already after some periods, we can reject the random walk hypothesis (unit root). Hence, given the short spread time series in the data set, we opt for the classical unit root testing procedures by Dickey-Fuller (1981) and Phillips-Perron (1988), which detects the presence of serial correlation – the Augmented Dickey-Fuller (ADF) and the Phillips-Peron (PP) test statistics (Greene, 1993, 564f). The Augmented Dickey-Fuller Test (ADF) is defined in our case as

$$\ln(S_t) = m + r\ln(S_{t-1}) + e_t \quad \text{with } H_0 : r = 1 \, vs. \, H_1 : r < 1, \qquad (0.10)$$

where m and r are the test parameters, with e_t assumed to be white noise. The logarithmic spread $\ln(S_t)$ represents a stationary time series if $-1 < r < 1$, so that the hypothesis of stationarity is evaluated for r strictly lower than one. However, if $r = 1$, $\ln(S_t)$ follows a random walk with drift (non-stationarity), i.e. the variance of the spread process increases steadily with time and goes to infinity, and if $r > 1$ $\ln(S_t)$ is an explosive series. The PP test statistic is defined as the AR(1) process $\Delta\ln(S_t) = m + b\ln(S_{t-1}) + e_t$. Both the ADF and the PP test statistics assume the unit root of $H_0 : r = 1$ as null hypothesis, which can be rejected on the basis of the one-sided alternative hypothesis $H_1 : r < 1$. The ADF test controls for higher-order serial correlation by estimating $\Delta\ln(S_t) = m + g\ln(S_{t-1}) + e_t$, where $\ln(S_{t-1})$ (and higher order differences) is (are) subtracted from both sides, with $g = r - 1$, $H_0 : g = 0$ and $H_1 : g < 0$. In contrast, the PP test corrects the t-statistic of the g coefficient of the AR(1) process in order to account for serial correlation in the residuals e_t. This correction is implemented non-parametrically by estimating the spectrum of e_t at frequency zero under the Newey and West heteroskedastic and autocorrelation consistent estimator, where

[19] If observed variables grow together, spurious correlation might be measured erroneously. However, in the presence of co-integration they might share fundamental economic driver that gives rise to a long-term relationship.

$w^2 = g_0 + 2\sum_{j=1}^{q}\left(1-\frac{j}{q+1}\right)g_j$ and $g_j = T^{-1}\sum_{t=j+1}^{T}\tilde{e}_t\tilde{e}_{t-j}$ with the truncation lag q. The PP t-statistic is specified as

$$t_{PP} = \frac{\sqrt{g_0}t_b}{w} - \frac{\left(w^2 - g_0\right)Ts_b}{2w\hat{s}}, \tag{0.11}$$

where t_b and s_b are the t-statistic and the standard error of b respectively and $\hat{s}$ denotes the standard error of the test regression.

We run the ADF test statistic with a constant and a linear trend on level and first differences of spreads of up to two lags in order to control for serial correlation. We also complete the PP test diagnostic with a vector of three truncation lags of the autocorrelation consistent variance estimator for the Newey-West correction, that is, the number of periods of serial correlation to include. For both test we employ MacKinnon (1996) critical values for rejection of hypothesis of a unit root based on one-sided p-values.

Similar to Koutmos (2002) with respect to U.S. MBS Spreads we reject the unit root in most weekly spread time series for level data (see Tab. 1). Merely PAAA5 and PAAA7 spreads seem to be non-stationary (at least for the ADF test statistic), whereas the MAAA5 spreads yield inconclusive results. Autocorrelation effects can almost be entirely eliminated for a test specification of up to four lags. For the first difference of spreads both ADF and PP test diagnostics strongly reject the null hypothesis of a unit root in all cases. Hence, all spread series are integrated of the order zero or at least one. If spreads are mean-reverting, standard statistical hypothesis testing is applicable.

Generally, we find that LIBOR rates and spreads of European CDO, MBS and Pfandbrief transactions share a stationary co-integration vector, i.e. they have a long-term relationship, where most spread series themselves exhibit a I(0) process. We identify two possible causes for the discrepancies of mean-reverting properties across all spread series for level data: liquidity and data frequency. First, the fact that our results are less homogenous compared to Koutmos (2002) could be attributable to the poor data quality.[20] Whereas Koutmos used time series data of more than 30 years to substantiate his findings on the level stationary of U.S. MBS spreads, our limited number of observations over a time period of not even two years does not engross the same degree of measurability of long range cycles of mean-reversion.

[20] Higher ADF and PP test statistics of daily Pfandbrief spreads over the originally generated time period from September 1998 to October 2002 (not reported) indicates that better data quality with respect to data frequency and time period of observations, support the rejection of a unit root. Moreover, the spread series of Pfandbrief spreads over a four-year period include spread quotations of summer 2000, when some German Pfandbrief issues – for the first time in recent history – were downgraded amid the massive liquiditiy crises in global financial markets. While almost all German Pfandbrief transactions were AAA-rated and regarded similarly safe an investment as government bonds, a re-assessment of credit risk in Pfandbriefe sent spreads markedly higher during the second half of 2000. Also the shorter series of weekly Pfandbrief spreads used in this analysis might still suffer from lagged effects on spread volatility from January 2001 onwards.

Asset Class Spread Series	Augmented Dickey-Fuller (ADF)				Phillips-Peron (PP)			
	level		*on first difference*		*level*		*on first difference*	
	test stat. #	F-stat.	test stat.	F-stat.	test stat.	F-stat.	test stat.	F-stat.
Collateralised Debt Obligations (CDO), synthetic								
CSA5_AD_L	-3.367652***	2.8945	-6.253208***	23.6575	-2.727887***	3.5594	-9.919613***	49.1234
CSAAA3_AD_L	-2.115569**	1.3658	-5.439055***	21.9381	-2.104623**	2.4597	-9.574888***	45.8374
CSBBB7_AD_L	-2.152063**	1.2455	-5.886175***	23.3047	-2.338996**	2.5349	-9.590928***	45.9627
Collateralised Debt Obligations (CDO), traditional								
CTA5_AD_L	-1.4271	1.0235	-4.934276***	17.2697	-1.3810	1.1353	-8.614782***	36.8747
CTAAA3_AD_L	-1.807324*	1.0596	-7.036044***	26.7650	-1.85988*	2.0212	-8.925047***	39.9795
CTBBB7_AD_L	-3.868666***	3.8989	-7.199525***	28.3019	-3.507903***	5.2950	-8.927302***	39.9059
Mortgage-Backed Securities (MBS)								
MA7_AD_L	-2.293844**	4.1190	-6.616401***	21.2514	-2.71831***	3.6791	-8.431175***	35.9602
MAAA3_AD_L	-2.669565***	2.3823	-5.624701***	27.9576	-4.066767***	7.6201	-11.7885***	68.7735
MAAA5_AD_L	-3.9070	13.6306	-7.060149***	70.6754	-6.408603***	19.6483	-18.23404***	144.1522
MBBB7_AD_L	-6.035035***	10.9508	-7.239436***	35.9587	-5.76176***	16.8164	-12.14478***	68.2325
Pfandbriefe								
PAAA3_AD_L	-2.526267**	10.6802	-7.223362***	66.8306	-5.418308***	14.5363	-18.02513***	127.5861
PAAA5_AD_L	-1.5908	3.8489	-7.114721***	43.7777	-2.82416***	5.4351	-13.8917***	85.7927
PAAA7_AD_L	-1.5950	2.0476	-6.467876***	32.5846	-2.995738***	5.5289	-11.63695***	63.6673

Sample (adjusted): 21/01/2001-18/10/2002; 92 weekly observations; constant and linear time trend (shift) included in the text as exogenous variables. # MacKinnon (1996) critical values for rejection of hypothesis of a unit root based on one-sided p-values. Significance: * significant at 10% level, ** significant at 5% level, *** significant at 1% level. PP test completed with three-lag truncation for Bartlett (1981) kernel given Newey-West (1987) test.

Augmented Dickey-Fuller (ADF) test is based on: $\Delta y_{\tau} = \mu + \gamma_1 t + \gamma_2 y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \varepsilon_t$ with $H_0: \gamma_2 = 0$ vs. $H_1: \gamma_2 < 0$

Phillips-Peron (PP) test is based on: $\Delta y_t = \mu + \beta_1 (t - T/2) + \beta_2 y_{t-1} + \varepsilon_t$ with $H_0: \beta_2 = 1$ vs. $H_1: \beta_2 < 1$

Tab. 1. *Test of unit root – OLS regression of secondary market spreads of CDO, MBS and Pfandbrief transactions (only transformed and Johnson Fit adjusted spreads).*

Moreover, we need to view the level stationarity of spreads with great caution, given the quality of the data series. MBS and CDO markets on the one side and the Pfandbrief market on the other side differ significantly in investment liquidity. The "stale" nature of spread movements in the former combined with a persistent autoregressive effect in spread residuals for up to more than 20 lags for some CDO tranches (see Tab. 1) could bias the ADF and PP tests into rejecting the unit root. Yet, strong autocorrelation does not apply for first differences of spreads, so that at least first order integration (as suggested in the later model measuring spread dynamics on the basis of spread changes) yields satisfactory characteristics of mean reversion / stationarity.

5 THE MODEL

5.1 Model specification

The following model aims to describe the distribution and volatility of ABS spreads (CDO, MBS) and Pfandbrief spreads in Europe. Like the equilibrium models of the term structure of interest rates,[21] which are based on the stochastic process followed by a small number of state variables, each state variable S_t of ABS spreads follows a standard geometric Brownian motion (GBM),

$$S_t = S_0 \exp\left\{\left(m - s^2/2\right)t + s\sqrt{t}z_t\right\}, \qquad (0.12)$$

where the volatility process $s\sqrt{t}z_t$ – which could be also be written in a discrete sense as $\sqrt{t}z_t \equiv W_t - W_0$ – contains a Wiener process defined by the normally distributed variable $\Delta z \sim (0, \Delta t)$, whose mean change is zero and variance proportional to t. The dynamics of S_t, i.e. the instantaneous value, is identified by the stochastic differential equation

$$dS_t / S_t = m dt + s\, dW_t, \qquad (0.13)$$

of the Ito process $dS_t = m(S_t, t)dt + s(S_t, t)dW_t$ (generalised Wiener process), whose trend and volatility depend on the current spread level S_t and time. In the case of the GBM the drift m and the volatility s are proportional to the current value of S_t. W_t is a standard Brownian motion, with the infinitesimal increment of a Brownian motion denoted by a standard Wiener process $dz_{x,t} = e_j\sqrt{dt}$ and e_j as a standard normal random variable. This approach assumes that the normalised changes of spreads dS_t / S_t follow a standard normal distribution $N(0,1)$.

[21] These models are represented by Ito equations as in Hull (1995 and 1993) and others.

We measure the spread dynamics of $dS_{i,t}/S_{i,t} = mdt + s\,dW_t$ on the basis of a GARCH multi-factor term structure model as a discrete approximation of spread change, provided that the spread change follows a stationary process (see section 4). For this purpose we modify the approximative GARCH(1,1) model of U.S. MBS yields (over government bonds) by Koutmos (2002, 45),[22] as we describe the dynamics of spread change on the basis of additional endogenous factors in a refined GARCH model.

Generally a GARCH(*p*,*q*) process models the heteroskedasticity of a given time series x_T, whose distribution – conditionally on past observations of x_{t-q} – is specified by $F\left(x_t / s_t\right) \sim \left(0,1\right)$ of zero mean and variance of one. The conditional variance of the mean value follows a GARCH process defined by the volatility from the previous period(s), measured as the *q* lag(s) of the squared residual(s) from the mean equation (ARCH term(s)) and the forecast variance(s) of the last *p* periods (GARCH term(s)).

The adapted original two-factor GARCH(1,1) model by Longstaff and Schwartz (1992) as discrete approximation of continuous spread change would read

$$S_t - S_{t-1} \equiv \Delta S_t = a_0 + a_1 S_{t-1} + a_2 s_t^2 + e_t \qquad (0.14)$$

$$s_t^2 = b_0 + b_1 e_{t-1}^2 + b_2 S_{t-1} + b_3 s_{t-1}^2, \qquad (0.15)$$

for $F\left(\Delta S_t / s_t\right) \sim \left(0,1\right)$.

The equations of the mean and the conditional variance of spreads above capture any past influence on both spread change ΔS_t (mean equation) and conditional variance s_t^2. If the mean reversion parameter $a_1 < 0$, the spread series is considered level stationary. The conditional mean of spread change is dependent on the past spread level S_{t-1} and the level of the conditional variance, with error term e_t. The conditional variance follows a GARCH(1,1) process, which is defined by one lag squared errors e_{t-1}^2 in the mean equation, the autocorrelation term (forecast variance of the previous period) s_{t-1}^2 and the past spread level (as extension to the standard GARCH(1,1) model).

Since both equations do not recognise asymmetric spread dynamics, Koutmos (2002) proposes a two-factor model, which accommodates mean reversion in U.S. MBS yields after positive and negative past spread changes in line with Bali (2000). Koutmos breaks down both the mean reversion term a_1 (mean

[22] Building on the two-factor model by Longstaff and Schwartz (1992) and the work by Bali (2000, 192) on to stochastic volatility models of short-term interest rates, Koutmos considers frequently observed volatility clusters of yield curves (GARCH effect) in the context of asymmetric mean reversion. He finds that spreads commonly behave non-stationary if a positive spread change in the past had preceded an external shock, whilst mean reversion is statistically significant after negative spread change.

equation) into $a_{1,p} I_t S_{t-1} + a_{1,n} \left(1 - I_t\right) S_{t-1}$ by imposing the indicator function $I_t = \begin{cases} 1 & \text{if } S_t - S_{t-1} \geq 0 \\ 0 & \text{if } S_t - S_{t-1} < 0 \end{cases}$ on the first moment of one lag spreads. Moreover, he also introduces asymmetry in the conditional variance equation by discriminating between the coefficient value of positive and negative squared residuals of the previous period by means of an extended ARCH term $b_1 e_{t-1}^2 + b_2 u_{t-1}^2$ for $u_{t-1} = \min\left(0, e_{t-1}\right)$ instead of $b_1 e_{t-1}^2$ (ordinary ARCH term) only. Here, b_1 measures any general sensitivity of the conditional variance s_t^2 to past squared residuals, while the coefficient value of b_2 is limited to the contribution of negative past errors $e_{t-1} < 0$ to the variance and, hence, reflects any degree of potential asymmetries. This approach differs only formally from the so-called "threshold ARCH" (TARCH) process developed independently by Glosten et al. (1993) and Zakoian (1990), which allows asymmetric shocks to volatility through the ARCH term $b_1 e_{t-1}^2 + g e_{t-1}^2 d_{t-1}$ for $d = \begin{cases} 0 & \text{if } e_{t-1}^2 \geq 0 \\ 1 & \text{if } e_{t-1}^2 < 0 \end{cases}$. In the original TARCH setting introduced by Engle and Ng (1993) in their research on the impact of news on volatility (asymmetric News Impact Curve), good news $e_{t-1} < 0$ and bad news $e_{t-1} > 0$ have different effects on the conditional variance. Good news has an impact of b_1, while bad news has an impact of $b_1 + g$. If $g \neq 0$ the news impact is asymmetric, where $g > 0$ signifies a "leverage effect".

5.2 GARCH specification

In this paper we explain the heteroskedasticity spread change behaviour (term structure of spreads) by a multi-factor asymmetric GARCH process (GARCH(1,1) and GARCH(2,1)) on the basis of two equations for the mean and conditional variance. In extension to Koutmos' (2002) adaptation of Longstaff and Schwartz (1992), the conditional mean is influenced by past spread levels, the past LIBOR rate and the conditional variance. The latter follows a GARCH process defined by past variance (GARCH term), past squared residuals of the mean equation (ARCH term) as well as the LIBOR rate and past spreads as variance regressors. We find the LIBOR rate as an appropriate reference base for the given spread series (Goodman and Ho, 1998). In contrast to Koutmos, however, our sample size is limited to 93 weekly observations of actual secondary market spread data for traded tranches of theses asset types. In order to improve the statistical properties of the analysis we adjusted the spread series and transformed them, so that the subsequent examination could be completed on "raw" data, logarithmic spreads and spreads adjusted by the Johnson Fit. The spread series of LIBOR enters the estimation only as observed spot rates and logarithmic spot rate without Johnson Fit.

In the GARCH(1,1) model we incorporate (i) the first moment of LIBOR changes (with indicator function) in the mean equation and (ii) the past LIBOR rate as variance regressor. In an alternative GARCH(2,1) process, we refine the GARCH(1,1) model as we (i) introduce a new set of mean reversion coefficients of lag two for positive and negative past spread levels mean equation (with a corresponding indicator function) and (ii) extend the past forecast variance to two lags in the estimation of conditional variance. Overall, we consider asymmetric effects of explanatory factors through (i) indicator functions for past spreads and past LIBOR rates in the mean equation as well as (ii) two coefficients for positive and negative errors in the expression for conditional variance.

5.2.1 *GARCH(1,1) model specification*

We specify the GARCH(1,1) model by the following mean equation and conditional variance equation:

$$\begin{aligned} S_t - S_{t-1} \equiv \Delta S_t = a_0 + I_t a_{1,1} S_{t-1} + (1 - I_t) a_{1,2} S_{t-1} + \\ K_t a_{2,1} L_{t-1} + (1 - K_t) a_{2,2} L_{t-1} + a_3 s_t^2 + e_t \end{aligned}, \qquad (0.16)$$

which specialises to

$$\begin{aligned} \Delta \ln(S_t) = a_0 + I_t a_{1,1} \ln(S_{t-1}) + (1 - I_t) a_{1,2} \ln(S_{t-1}) + \\ K_t a_{2,1} \ln(L_{t-1}) + (1 - K_t) a_{2,2} \ln(L_{t-1}) + a_3 s_t^2 + e_t \end{aligned} \qquad (0.17)$$

and

$$s_t^2 = b_0 + b_1 e_{t-1}^2 + b_2 u_{t-1}^2 + b_3 S_{t-1} + b_4 L_{t-1} + b_5 s_{t-1}^2, \qquad (0.18)$$

which specialises to

$$s_t^2 = b_0 + b_1 e_{t-1}^2 + b_2 u_{t-1}^2 + b_3 \ln(S_{t-1}) + b_4 \ln(L_{t-1}) + b_5 s_{t-1}^2, \qquad (0.19)$$

where S_t denotes the secondary market spreads of a certain asset class of CDO, MBS or Pfandbrief and L_t is the 3-month-LIBOR rate both at time *t*.[23] The indicator function of past innovations (negative and positive) is expressed as $u_{t-1} = \min(0, e_{t-1})$. The indicator functions for the first difference of spreads S_t and LIBOR rates L_t are $I_t = \begin{cases} 1 & \text{if } S_t - S_{t-1} \geq 0 \\ 0 & \text{if } S_t - S_{t-1} < 0 \end{cases}$ and $K_t = \begin{cases} 1 & \text{if } L_t - L_{t-1} \geq 0 \\ 0 & \text{if } L_t - L_{t-1} < 0 \end{cases}$ respectively.

In the above GARCH(1,1) expression the first order spread change depends on the spread level of the previous period (conditional on the direction of change), the change of the sport rate (LIBOR) of the previous period as reference base and the conditional variance with a past volatility forecast (GARCH term) and lagged squared residuals from the mean equation (ARCH term). The use of one lag spreads captures first-order autocorrelation. The inclusion of the LIBOR rate as proxy for the general interest rate level is crucial control factor of our analysis, because a statistically significant effect of LIBOR as the most prominent fixed income benchmark helps specify the nature of spread changes due to idiosyncratic effects in the ABS market. The squared residuals measure the part of spread changes that escape the explanatory

[23] Note that this specification could be modified to control for first differences in LIBOR changes. An extension of this paper incorporates this consideration.

power of independent factors in the mean equation. Hence, they measure mainly those parts of changes in the spread over time, which are common to the pricing of structured debt.

Moreover, model allows the examination of asymmetric effects of past spread levels and the squared errors on future spread dynamics. If the regression coefficients $a_{1,1} \neq a_{1,2}$ and $a_{1,1} + a_{1,2} < 0$ the given spread series is level stationary with asymmetric mean reversion at lag one. Analogously, the same applies for the relationship between $a_{2,1}$ and $a_{2,2}$ in the context of lag two. Moreover, past errors have different effects on the conditional variance. b_1 measures any general sensitivity of the conditional variance to past errors, whereas b_2 measures the impact of negative past error $e_{t-1} < 0$ on the conditional variance and, hence, reflects any degree of potential asymmetries for $b_2 \neq 0$. The contribution of an (overall) positive error $e_{t-1} > 0$ will be equal to $b_1 + b_2$. If $b_2 > 0$, the conditional variance of spread change is more sensitive to positive past errors (i.e. spread increases) than negative past errors (i.e. spread decreases). However, if $b_2 < 0$ negative residuals precede a negative reaction in spread change. b_3 and b_4 measure the sensitivity of variance to the spread level and the LIBOR rate, while b_5 represents its persistence.

5.2.2 GARCH(2,1) model specification

In extension to the GARCH(1,1) model we allow for a greater explanatory power by past volatility in a GARCH(2,1) process, as we expand the forecast variance of the conditional variance to the last two periods, which is matched by two lag spreads as additional independent variable in the mean equation to control for second-order autocorrelation. Squared errors in the conditional variance expression are kept at one lag.

$$\begin{aligned}\Delta \ln(S_t) = a_0 + I_t a_{1,1} \ln(S_{t-1}) + (1-I_t) a_{1,2} \ln(S_{t-1}) + J_t a_{2,1} \ln(S_{t-2}) + \\ (1-J_t) a_{2,2} \ln(S_{t-2}) + K_t a_{3,1} \ln(L_{t-1}) + (1-K_t) a_{3,2} \ln(L_{t-1}) + a_3 s_t^2 + e_t\end{aligned}, \qquad (0.20)$$

and

$$s_t^2 = b_0 + b_1 e_{t-1}^2 + b_2 u_{t-1}^2 + b_3 \ln(S_{t-1}) + b_4 \ln(L_{t-1}) + b_5 s_{t-1}^2 + b_6 s_{t-2}^2, \qquad (0.21)$$

where the indicator function for changes in the two lag spread difference of S_t is $J_t = \begin{cases} 1 \text{ if } S_t - S_{t-2} \geq 0 \\ 0 \text{ if } S_t - S_{t-2} < 0 \end{cases}$.

The estimation of the presented GARCH models requires a non-linear solution algorithm for conditional maximum likelihood (CML). We apply two kinds of maximum likelihood iterative estimation procedures – *Berndt-Hall-Hall-Hausman(BHHH)/Gauss-Newton* (1974)[24] and *Marquardt* (1963)[25]. Since the first moment

[24] The shared underlying approximative estimation algorithm is referred to as *Gauss-Newton* for general nonlinear least squares problems, and *Berndt, Hall, Hall, and Hausman (BHHH)* for maximum likelihood problems. For both types of

of logarithmic spreads of most time series in our data set does not follow a normal distribution (see Appendix, Tab. 9-Tab. 11) with the exception of some Pfandbrief issue spreads, we use the heteroskedasticity consistent covariance method by Bollerslev and Wooldridge (1992), which is needed for several model diagnostics (coefficient and residual tests). In this way, we derive robust estimators for quasi-maximum likelihood (QML) covariance and standard errors (Bollerslev and Woolridge, 1992, 145-150) even in absence of normally distributed spread differences.

Since both the maximum-neighbourhood procedure of the *Marquardt* ML algorithm and the approximation of the negative Hessian by the sum of the gradient vectors of the *Berndt, Hall, Hall, and Hausman (BHHH)* algorithm use random iterative components, the estimation for one and the same spread series could yield different results each time. This holds true especially for short time series, such as in our case of CDO, MBS and Pfandbrief spreads, where disparate local optima misrepresent the overall estimation result. In order to derive estimation results at parameter values that maximise the objective function (global optimum), we devise a specific estimation procedure. After N iterative cycles generates preliminary estimation results, we perpetuate the estimation process until the adjusted R^2-measure and the significance of estimators squares up with the best results after the first N number of estimations. The determination of N represents a trade-off between computational time and the consistency of the successive estimations given the length of the time series. We set $N = 1{,}000$ for the short time series of weekly spreads. The estimation procedure is conducted with simple OLS-estimators $\times 1, \times 0.7, \times 0.5, \times 0.3$ or $\times 0$ of the specified equation as three different starting values, where the starting value of $\times 0.7$ were used in cases when the estimation algorithm encountered a singular matrix due to multicollinearity of model factors.[26]

problems this estimation routine represents the substitution of the negative Hessian by an approximation derived from the summed outer product of the gradient vectors of each observation's contribution to the objective function. It is asymptotically equivalent to the actual Hessian when evaluated at the parameter values that maximise the objective function. Advantages of *Gauss-Newton/BHHH* are that only the first derivatives need to be evaluated and the outer product is necessarily positive definite. However, this approximation algorithm performs poorly and may provide a poor guide to the overall shape of the function, when evaluated at parameter values away from the maxium, so that more iterations may be needed for convergence.

[25] The *Marquardt* ML algorithm is based on a maximum-neighbourhood procedure, which combines the benefits of both Gauss algorithms and gradient procedures. According to Marquardt (Marquardt, 1963, 431) pure Gaussian estimation procedures frequently fail due to the divergence of successive iterative steps, whereas gradient procedures only gradually reach the necessary level of convergence if the approximate solution optimum has been determined already. The *Marquardt* ML estimation procedure does not share these drawbacks. Its algorithm quickly converges to the solution optimum (similar to Gauss algorithms) and pushes the updated parameter values in the direction of the gradient. Like in gradient procedures, the Marquardt estimation aims to find the optimum based on random solution values far removed from the area of convergence of other iterative estimation procedures (Marquardt, 1963, 441). The *Marquardt* algorithm modifies the *Gauss-Newton* algorithm in exactly the same manner as quadratic hill climbing modifies the *Newton-Raphson* method (by adding a correction matrix (or ridge factor) to the Hessian approximation). Note that in the Marquardt estimation we compute asymptotic standard errors from the unmodified *(Gauss-Newton)* Hessian approximation once convergence is achieved.

[26] As an alternative to applying SQR-GARCH estimation in cases, when multicollinearity of estimation yields a singular matrix only for any starting value of simple OLS-estimators, we could also skip the intercept term a_0 (i.e. the constant of spread differences) from the estimation equation. This remedial procedural, however, would only be commendable if the statistical significance of the intercept term is neglegible for the interpretion of the estimation results. Particularly in context of the GARCH(2,1) specification, high levels of significance of the intercept prohibit this approach.

Upon estimation of the two specifications of GARCH models, we examine the degree of level stationarity – the influence of past spread levels on future spread change that is – contingent on past positive and negative spread change (coefficient test). In order to attest overall mean reversion to the given spread dynamics we validate the hypotheses for the coefficient values $a_{1,1} + a_{1,2} < 0$ in GARCH(1,1) and $a_{1,1} + a_{1,2} < 0$ and $a_{2,1} + a_{2,2} < 0$ in GARCH(2,1) respectively. Each hypothesis is comprised of two sub-hypotheses: these are $H_{0,1} : a_{1,1} + a_{1,2} = 0$ and $H_{0,2} : a_{1,1} + a_{1,2} = \hat{a}_{1,1} + \hat{a}_{1,2}$ for both GARCH models as well as $H_{0,1} : a_{2,1} + a_{2,2} = 0$ and $H_{0,2} : a_{2,1} + a_{2,2} = \hat{a}_{2,1} + \hat{a}_{2,2}$ for GARCH(2,1) in order to account for past spread levels of up to lag two. The time series is overall stationary, if we cannot reject the second null hypothesis, i.e. sum of the coefficient values is not significantly different from the sum of the calculated test estimators, and the sum of the coefficients is smaller than zero, so that the first null hypothesis is rejected. Furthermore, in context of measuring the heteroskedasticity of spreads we also assess any asymmetry of spread dynamics. If $H_0 : a_{1,1} = a_{1,2}$ for GARCH(1,1) as well as $H_0 : a_{1,1} = a_{1,2}$ and $H_0 : a_{2,1} = a_{2,2}$ for GARCH(2,1) can be rejected, past spread change influences the effect the sensitivity of future spread change to past spread levels.

Both tests are completed on the basis of the *Wald coefficient test*, which computes the test statistic by estimating an unrestricted regression without imposing the coefficient restrictions specified by the null hypothesis. Hence, it tests the validity of linear coefficient restrictions as it measures how close the unrestricted estimates come to satisfying the restrictions under the null hypothesis. In matrix algebra the null hypothesis is generally written as $H_0 : \mathbf{R}b = r$, where r denotes the $m \times 1$ vector of the required results of the testable restrictions and m is the number of restrictions. The matrix $\mathbf{R}_{(m \times k)}$ represents the linear combinations of the restrictions, with b as the coefficient vector with k number of coefficients.[27] The Wald test diagnostic is calculated from

$$W = (\mathbf{R}b - r)' \times \left(s^2 \mathbf{R} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{R}'\right)^{-1} (\mathbf{R}b - r) \sim c^2_{df=m}, \quad (0.22)$$

[28]

where s^2 is the variance of unrestricted residuals.

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[27] For instance, the validity of the joint hypotheses of $b_1 + b_2 = 1$ and $b_3 = b_4$ would require the following specification of the Wald test for $m = 2$ and $k = 4$: $H_0 : \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & -1 \end{bmatrix} \otimes \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ (Hamilton, 1994, 205f).

[28] Under the assumption of independent and normally distributed residuals e, we calculate the F-statistic $F = (\mathbf{R}b - r)' \times \left(s^2 \mathbf{R} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{R}'\right)^{-1} \times (\mathbf{R}b - r) \times m^{-1}$, where $m = 1$ is equal to the value of W and s^2 poses as estimator of s^2 (Hamilton, 1994, 206).

Finally, we determine the correct specification of both modified GARCH models on the basis of three residual tests. We check the *Llung-Box (LB) Q-statistic* for standardised and squared standardised residuals of the estimation process in order to detect any remaining serial correlation in the mean equation and any remaining ARCH effect in the conditional variance equation respectively. If the mean equation is correctly specified, all Q-statistics for standardised residuals should be insignificant with no observable autocorrelation. Analogously, the same applies to the LB Q-statistic for squared standardised residuals of correctly specified conditional variance. Moreover, we resort to the *Jarque-Bera* statistic for standardised residuals as statistical diagnostic in order to test the null hypothesis of a normal distribution assumption of errors.

6 ESTIMATION RESULTS

Tab. 2 and Tab. 3 report the Berndt-Hall-Hall-Hausman (BHHH) estimation results for the multi-factor GARCH(1,1) and GARCH(2,1) models with asymmetric mean reversion on the basis of Johnson-Fit-adjusted and logarithmic spreads. Generally, the specified factors have relatively weak influence on conditional spread differences in GARCH(1,1) and conditional variance in GARCH(2,1) of MBS tranches, while all other spread series of other asset classes confirm the high degrees of explanatory power to designated model factors.

The intercept coefficient is significant for all spread series in the GARCH(2,1) model with the exception of all Pfandbrief tranches and MAAA5. In GARCH(1,1) the picture reverses, where the constant is only significant for CSAAA3, MBBB7 and PAAA7. The influence of past spreads on future spread change – be it at lag one $\left(a_{1,1}, a_{1,2}\right)$ in the GARCH(1,1) specification or up to two lags $\left(a_{1,1}, a_{1,2} \text{ and } a_{2,1}, a_{2,2}\right)$ in GARCH(2,1) – clearly supports the degree of mean reversion observed in the unit root test for the given coefficient values and the level of statistical significance. In all spread series the coefficients for past spreads levels with subsequent negative and positive spread change sum up to negative values, indicating level stationarity. Moreover, asymmetric mean reversion is more pronounced for low-rated MBS transactions and all Pfandbriefe time series, whose spread development and pricing pattern might be attributable to higher market liquidity and different asset-specific investor sentiment compared to CDO deals. The time series of all asset classes in the GARCH(1,1) model as well as all but the time series of traditional CDO transaction exhibit higher effects of negative spread change at lag one $\left(a_{1,2}\right)$. The coefficients $a_{1,1}$ and $a_{1,2}$ in both GARCH models share similar significance across the given spreads series, so that first order stationarity follows both negative and positive past spread change. In GARCH(1,1), however, the mean reversion coefficients are significant only for one out of six CDO tranche categories, two out of four MBS and all Pfandbrief transactions

Considering – where appropriate and statistically significant – the null hypothesis of future spread change irrespective of whether past spreads increased or declined, we find higher spread sensitivity to past spread levels associated with negative first moments (negative asymmetric mean reversion). All cases in GARCH(1,1) show this pattern of asymmetric mean reversion.

The asymmetric effect of past spread change reverses for second differences of past spread levels in the GARCH(2,1) specification, where the spread reaction after positive shocks is more pronounced. We detect exactly the opposite effect of two lag spread change in the GARCH(2,1) model, so that the response to positive spread changes $\left(a_{2,1}\right)$ dominates the negative effects $\left(a_{2,2}\right)$. This negative pricing bias might be attributable to the depressed economic outlook and cautious investor behaviour during the time the sample was taken. However, their statistical significance is the same for each type of spread series. All three traditional CDO and three out of four MBS spread series do not generate significant $a_{2,1}$ and $a_{2,2}$ coefficients. Level effects in a_0 seem to be limited to CDOs and MBSs in the GARCH(2,1) model only, where spread change remain almost unaffected by the LIBOR rate of the previous period (except for CDOs in the GARCH(2,1) model) as documented by coefficients $a_{2,1}$ and $a_{2,2}$ in GARCH(1,1) and $a_{3,1}$ and $a_{3,2}$ in GARCH(2,1) . The coefficients a_3 and a_4, which measure the direct influence of the conditional variance on spread change, are significant for PAAA7 spreads in GARCH(1,1) and CTAAA3 in GARCH(2,1). Surprisingly, neither the short time series nor the relative illiquid nature of CDO and MBS spreads in our data set induce pseudo-causalities – a situation that might reasonably explain why the z-statistics of CSAAA3 and MAAA5 in GARCH(1,1) as well as CSAAA3 and CSA5 in GARCH(2,1) are shy of reaching the 10% significance threshold by a margin only. No conclusive assessment can be made as regards the coefficient values of a_3 and a_4, whose signs do not seem to be associated with either a certain rating quality, maturity or asset class of the tranches (spread series).

We do not obtain a homogenous result for the estimator of the constant b_0 in either GARCH model. While most spread series generate positive intercept values, significant estimators are limited to CSA5, CTA5, MAAA3 and MA7 tranche types in GARCH(1,1) and CSAAA3, CTAAA3, CTA5 and PAAA7 in GARCH(2,1).

The coefficient b_1 measures any general sensitivity of the conditional variance to past residuals (ARCH effects) of estimated spread change. In all cases but BBB-rated traditional CDO transactions (CTBBB7) we cannot reject that the conditional variance of spread changes is not dependent on past errors b_1 (ARCH term) as spreads increase, whilst in both GARCH models negative past errors b_2 (ARCH term) for spread decline (negative ARCH effect) are significant in many instances, e.g. Pfandbriefe with short maturities and high-rated traditional CDOs. Since $b_1 + b_2$ measures the dependence on positive past errors and b_2 measures the influence of negative past errors, $b_2 \neq 0$ reflects potential asymmetries of how past errors generally affect conditional variance. We find $b_2 > 0$ in most spread series (with negative signs only for two out of three traditional CDO tranche types in GARCH(1,1) and two out of four MBS tranche types in GARCH(2,1)). Moreover, significant b_2 are always positive (with the only exception of the CTA5 spread series in GARCH(1,1)). Since negative effects of past squared residuals dominate the general effect of residuals by absolute value for both GARCH models, the conditional variance s_t^2 of spread change is more sensitive to negative past errors (i.e. spread declines).[29]

The predominantly positive influence of b_2 negative innovations (i.e. spread declines) on the conditional variance in both GARCH specifications documents that volatility is asymmetric, i.e. negative past errors increase spread volatility more than positive innovations (i.e. spread increases) – similar to stock price volatility. Apparently, the asymmetry of spread dynamics for the given time period captured by the sample size is not only limited to the mean equation alone but extends to the conditional variance, too. In our specific case, nearly all spread series exhibit an increase of conditional variance after a spread decrease and negative past innovations. Since our longer time series of Pfandbrief spreads (from 1998 to 2002) confirm this results to the extent that past errors (i.e. spread changes) have a positive effect or no effect at all on the conditional variance, we can rule out that asymmetric spread volatility merely reflects a specific pattern of spread dynamics with transitory validity.

As we define positive contribution of past errors as $b_1 + b_2$ the degree of the asymmetric effect of past errors on spread volatility is captured by the metric $(b_1 + b_2)/b_1$ ("asymmetry factor" of conditional variance). Across most ARCH terms in both GARCH models the asymmetry factor is greater than one (with the exception of negative values for CSAAA3, CSA5 and CTAAA3 in both models, i.e. no asymmetry in conditional variance, and values between 0 and 1 for MAAA3 in GARCH(1,1) as well as CTBBB7 and MBBB7 in GARCH(2,1). It also decreases the longer the maturity and the lower the rating grade of the given spread series. In general, the GARCH(2,1) specification seems to produce a more consistent degree of asymmetry than the GARCH(1,1) model. Particularly in the former specification, the asymmetry factor of more than two in most spread series indicates that negative past errors of spread estimates (negative innovations/spread decline) increase the spread volatility twice as much than positive past errors (spread increase).

[29] See also Bali (2000), 210f.

	Collateralised Debt Obligations (CDO)						Mortgage-Backed Securities (MBS)				Pfandbriefe		
	Synthetic			*Traditional*									
	CSAAA3[#]	CSA5	CSBBB7	CTAAA3[#]	CTA5	CTBBB7	MAAA3[#]	MAAA5	MA7[§,#]	MBBB7	PAAA3	PAAA5[#]	PAAA7[#]
α_0	0.5673**	0.8561	1.0612	0.2943	0.1866	0.4390	0.3424	0.7994	-0.0068	2.2816***	0.3371*	0.1029	0.8264***
	(2.3169)	(0.6994)	(0.9432)	(1.0250)	(0.7681)	(0.6291)	(1.1870)	(0.8033)	-(0.0403)	(3.2228)	(1.9480)	(0.7087)	(3.5174)
$\alpha_{1,1}$	-0.0861**	-0.1161	-0.1325	-0.0511	-0.0280	-0.0769	-0.18967**	-0.2908	-0.0047	-0.4655***	-0.1328**	-0.0562	-0.3019***
	-(2.1500)	-(0.8382)	-(1.0774)	-(0.7022)	-(0.7225)	-(0.6902)	-(2.0648)	-(0.9405)	-(0.1170)	-(3.4630)	-(2.1319)	-(1.5046)	-(3.5624)
$\alpha_{1,2}$	-0.1069**	-0.1266	-0.1404	-0.0758	-0.0391	-0.0892	-0.1916**	-0.2910	-0.0104	-0.4904***	-0.1576**	-0.0936**	-0.3270***
	-(2.4369)	-(0.9098)	-(1.1281)	-(1.0653)	-(0.9835)	-(0.7861)	-(2.0874)	-(0.9406)	-(0.2618)	-(3.6885)	-(2.5466)	-(2.5064)	-(3.8437)
$\alpha_{2,1}$	-0.1686**	-0.1990	-0.2061	-0.0813**	-0.0369	-0.0196	0.1656	0.0682	0.0185	0.0256	0.0439	0.0787	0.2143
	-(2.2852)	-(0.5777)	-(0.7286)	-(2.3773)	-(0.7351)	-(0.2799)	(1.4387)	(1.3586)	(0.3221)	(0.2682)	(1.4013)	(0.9720)	(1.5737)
$\alpha_{2,2}$	-0.1554**	-0.1812	-0.1955	-0.0762**	-0.0362	-0.0178	0.1630	0.0690	0.0210	0.0262	0.0483*	0.0849	0.2277*
	-(2.3193)	-(0.5291)	-(0.6962)	-(2.3188)	-(0.7214)	-(0.2563)	(1.4285)	(1.3693)	(0.3683)	(0.2754)	(1.6853)	(1.0786)	(1.6733)
α_3	2.4101	-0.5681	-9.0706	11.7871	2.5065	7.9509	-8.5146	0.8947	-0.0001	1.0513	0.1799	-0.0091	-43.8189**
	(1.3336)	-(0.0374)	-(1.1289)	(1.0322)	(1.0794)	(0.9429)	-(1.3835)	(1.3162)	(0.0000)	(0.5716)	(0.0838)	-(0.0014)	-(1.8944)
β_0	0.0036	0.0402**	0.0212	0.0012	0.0243**	0.0129	-0.0104*	-0.0594	-0.0006**	-0.2476	0.0128*	-0.0001	0.0045***
	(0.0560)	(2.0382)	(0.6551)	(0.1793)	(2.4426)	(0.7765)	-(1.6789)	-(0.3204)	-(1.9298)	-(1.2934)	(7.2262)	-(0.0276)	(3.6997)
β_1	-0.0224	-0.0026	0.0744	-0.0246	0.1741	0.3558*	-0.0013	0.7060	0.1401	-0.0509	0.1103	-0.0367	0.0446
	-(0.6368)	-(0.1131)	(1.1934)	-(1.2860)	(0.9792)	(1.6544)	-(0.0077)	(0.5045)	(0.6356)	-(0.4679)	(0.8971)	-(0.2232)	(1.0182)
β_2	0.1569	0.5707	0.0623	0.2851	-0.6778**	-0.1365	0.0494	-0.0634	0.0509	1.1432*	2.2513***	-0.0728	0.14646*
	(0.6341)	(0.3310)	(0.1393)	(1.3934)	-(2.5173)	-(0.4364)	(0.2688)	-(0.0422)	(0.0550)	(1.7963)	(2.7118)	-(0.5866)	(1.6698)
β_3	-0.0005	-0.0047**	-0.0026	-0.0008	-0.0036**	-0.0020	0.0005	0.0193	-0.0001***	0.0502	-0.0020*	0.0000	-0.0020***
	-(0.0424)	-(1.9611)	-(0.7561)	-(0.5056)	-(2.4146)	-(0.7841)	(1.3507)	(0.3210)	-(7.3532)	(1.3390)	-(1.9074)	(0.0526)	-(10.2139)
β_4	0.0001	-0.0110**	-0.0041	0.0013	-0.0046**	-0.0014	0.0006**	-0.0002	0.0008***	0.0051	-0.0038***	0.0001	0.0018**
	(0.0114)	-(2.0897)	-(0.4896)	(0.9064)	-(2.3085)	-(0.7085)	(1.8720)	-(0.5719)	(2.8981)	(0.4003)	-(3.2261)	(0.0273)	(2.3578)
β_5	0.5772	0.5468**	0.5387***	0.5115*	0.5237**	0.4624	0.3978***	0.3918***	0.5962***	-0.1378	0.0428	1.0295***	0.6096***
	(0.8391)	(2.0165)	(2.8658)	(1.8500)	(2.2190)	(1.2741)	(2.9750)	(6.1298)	(4.6666)	-(0.3178)	(0.4804)	(3.0848)	(6.5966)

Time series are transformed by the Johnson Fit over logarithmic ("AD_L")basis point spreads of ABS tranche indices, where M="Residential Mortgage-Backed Securities (RMBS)", P="Pfandbrief", CS="Synthetic Collateralised Debt Obligation (synthetic CDO)" and CT="Traditional/True Sale Collateralised Debt Obligation (traditional CDO)"; letters "AAA" to "BBB" reflect the Standard&Poor's investment grade rating system. The number associated with each time series reflects the maturity in years. Z-statistics in parentheses; ***=1% significance, **=5% significance, *=10% significance. All GARCH (1,1) parameters have been estimated according to the Berndt-Hall-Hall-Hausman algorithm, except in cases marked [#] (Marquardt quasi-maximum likelihood estimation procedure); [§] no Bollerslev-Woolridge robust standard errors and variance.

Tab. 2. *Estimation Results of GARCH(1,1) model (only transformed and Johnson Fit adjusted spreads).*

	Collateralised Debt Obligations (CDO)						Mortgage-Backed Securities (MBS)				Pfandbriefe		
	Synthetic			*Traditional*									
	CSAAA3	CSA5#	CSBBB7	CTAAA3	CTA5	CTBBB7	MAAA3	MAAA5	MA7	MBBB7#	PAAA3	PAAA5#	PAAA7
α_0	0.4512*	0.9770**	1.1291**	-1.3025***	0.4565***	0.9452*	0.5331***	-0.0208	1.2504***	1.5252*	-0.1462	-0.0888	0.0688
	(1.7998)	(2.0314)	(2.0673)	-(2.5877)	(3.2101)	(1.7063)	(2.9439)	-(0.1026)	(2.8365)	(1.6310)	-(0.4601)	-(0.8203)	(0.7261)
$\alpha_{1,1}$	-0.5265***	-0.1521***	-0.3345***	0.2034*	-0.1127	0.1230	-0.1691**	-0.0425	-0.6625***	-0.4129**	-0.4316***	-0.1856***	-0.2950***
	-(3.3951)	-(2.6568)	-(3.2618)	(1.7791)	-(1.0673)	(0.4810)	-(2.0991)	-(0.2263)	-(6.1594)	-(2.3341)	-(5.4273)	-(2.7298)	-(4.0992)
$\alpha_{1,2}$	-0.5232***	-0.1541***	-0.3362***	0.1891*	-0.1256	0.1139	-0.2210***	-0.0433	-0.6949***	-0.4286**	-0.4636***	-0.2155***	-0.3139***
	-(3.4540)	-(2.7158)	-(3.2779)	(1.6724)	-(1.2021)	(0.4452)	-(2.8149)	-(0.2306)	-(6.6998)	-(2.4563)	-(6.0432)	-(3.2446)	-(4.4373)
$\alpha_{2,1}$	0.4876***	0.0398**	0.2047***	0.1029	0.0494	-0.2595	0.0017	0.0536	0.2645**	0.0849	0.4935***	0.2231***	0.2860***
	(2.8917)	(2.5641)	(3.7188)	(1.1419)	(0.5199)	-(1.1244)	(0.0169)	(0.2551)	(2.2946)	(1.1748)	(5.6383)	(2.8094)	(3.8173)
$\alpha_{2,2}$	0.4675***	0.0364**	0.1979***	0.0957	0.0435	-0.2601	-0.0007	0.0515	0.2356**	0.0700	0.4677***	0.2084***	0.2669***
	(2.8508)	(2.4113)	(3.5631)	(1.0706)	(0.4661)	-(1.1316)	-(0.0069)	(0.2472)	(2.0586)	(1.0239)	(5.4355)	(2.7004)	(3.6558)
$\alpha_{3,1}$	-0.2089***	-0.2695**	-0.2557**	0.1374*	-0.0991***	-0.1412**	-0.0058	-0.0117	0.0292	0.0720**	0.0206	0.0112	-0.0023
	-(2.6787)	-(2.0732)	-(2.2377)	(1.8453)	-(3.1577)	-(2.2327)	-(0.0822)	-(0.6220)	(0.3767)	(2.0411)	(0.5280)	(0.1851)	-(0.0449)
$\alpha_{3,2}$	-0.1718***	-0.2629**	-0.2506**	0.1479**	-0.0957***	-0.1340**	0.0132	-0.0096	0.0370	0.0658**	0.0219	0.0266	0.0090
	-(2.2718)	-(2.0562)	-(2.2008)	(1.9641)	-(3.1995)	-(2.2001)	(0.1907)	-(0.4651)	(0.4998)	(2.0702)	(0.5753)	(0.4511)	(0.1774)
α_4	0.2385	-10.6189	-8.8101	32.3039***	-1.6554	-10.3923	-5.7329	-7.3350	-1.2715	5.4482	-2.3015	-0.1315	7.1095
	(0.1367)	-(1.5540)	-(1.5093)	(2.7027)	-(0.4600)	-(1.1939)	-(1.1109)	-(0.6728)	-(0.5421)	(1.1447)	-(0.2789)	-(0.0680)	(0.9129)
β_0	0.0918**	0.0032	0.0067	0.0222***	0.0237***	0.0171	0.0047	0.0013	-0.0458	-0.0072	0.0062	-0.0097	0.0070*
	(2.1182)	(0.5237)	(0.7215)	(140.1111)	(2.5758)	(1.2880)	(0.1959)	(0.2029)	-(1.3632)	-(0.0688)	(1.1436)	-(0.7166)	(1.8599)
β_1	0.4130	-0.0319	0.0611	-0.0285	0.1772	0.2941*	0.2584	0.0966	0.0841	0.5061	-0.0030	0.0785	0.0441
	(1.2536)	-(1.4870)	(0.6275)	-(1.4088)	(1.3784)	(1.6461)	(1.2549)	(0.8433)	(1.1114)	(0.8352)	-(0.0499)	(1.2205)	(1.0463)
β_2	-0.4774	0.3497	0.1205	0.2067***	0.9762	-0.2284	-0.3180	0.0962	0.4669*	-0.1015	0.4379	0.2777*	0.0408
	-(1.4226)	(0.7898)	(0.3837)	(2.5649)	(1.2649)	-(0.7793)	-(1.4177)	(0.2275)	(1.8585)	-(0.2302)	(1.5409)	(1.8896)	(0.9146)
β_3	-0.0133**	-0.0003	-0.0007	-0.0051***	-0.0037**	-0.0026	-0.0047	-0.0004	0.0135	-0.0013	-0.0030	-0.0006	-0.0032***
	-(2.0757)	-(0.8885)	-(0.6463)	-(1468.4230)	-(2.5371)	-(1.2705)	-(0.7130)	-(0.2241)	(1.1257)	-(0.0645)	-(1.4466)	-(0.5880)	-(3.5052)
β_4	-0.0254**	-0.0010	-0.0017	-0.0028***	-0.0047**	-0.0020	0.0101	0.0002	0.0040	0.0100	0.0018**	0.0092	0.0037***
	-(2.1487)	-(0.4001)	-(0.8310)	-(28.4047)	-(2.5382)	-(1.3047)	(1.1039)	(0.6192)	0.8448	(1.4080)	(1.8611)	(1.1068)	(3.0172)
β_5	-0.0053	0.7662***	0.6896	0.5079**	0.11379***	0.5414	-0.3226	0.5880	0.8476***	-0.3269	0.2033	0.6453***	0.8942***
	-(0.0209)	(3.7768)	(0.4944)	(2.0074)	(3.7852)	(0.8417)	-(1.3091)	(0.4339)	(5.0418)	-(1.3036)	(0.8088)	(2.7110)	(11.1602)
β_6	0.1209	0.2048**	0.1188	0.0224	0.6477***	-0.0211	-0.0735	0.0412	-0.3504***	0.1383	0.5787**	-0.4895***	-0.7964***
	(0.9002)	(2.0187)	(0.0953)	(0.1435)	(6.2909)	-(0.0464)	-(0.3724)	(0.0379)	-(2.7044)	(1.2283)	(2.5586)	-(2.6539)	-(10.2685)

Time series are transformed by the Johnson Fit over logarithmic ("AD_L") basis point spreads of ABS tranche indices, where M="Residential Mortgage-Backed Securities (RMBS)", P="Pfandbrief", CS="Synthetic Collateralised Debt Obligation (synthetic CDO)" and CT="Traditional/True Sale Collateralised Debt Obligation (traditional CDO)"; letters "AAA" to "BBB" reflect the Standard&Poor's investment grade rating system. The number associated with each time series reflects the maturity in years. Z-statistics in parentheses; ***=1% significance, **=5% significance, *=10% significance. All GARCH (2,1) parameters have been estimated according to the Berndt-Hall-Hall-Hausman algorithm, except in cases marked # (Marquardt quasi-maximum likelihood estimation procedure); § no Bollerslev-Woolridge robust standard errors and variance.

Tab. 3. *Estimation Results of GARCH(2,1) model (only transformed and Johnson Fit adjusted spreads).*

The coefficient b_3 measures the sensitivity of the conditional variance to the spread level of the previous period ("level effect"). We find no coherent results for a significant level effect. b_3 carries a negative sign for the majority of spread series in GARCH(1,1) and all spread series in GARCH(2,1) with the exception of MA7. The level effect is most significant for Pfandbrief transactions in GARCH(1,1) and traditional CDOs in GARCH(2,1), where b_3 is negative as well. The coefficient b_4 measures the level effect of the underlying reference spot rate (LIBOR rate) of the previous period on conditional variance of spreads. Past LIBOR rates seem to play some role only for traditional CDOs and Pfandbriefe in both GARCH models, whereas evidence of possible influence on synthetic CDO structures and MBS is inconclusive.

Finally, we estimate the coefficients b_5 for both GARCH specifications and b_6 for GARCH(2,1) only in order to control the estimation of the conditional variance for possible GARCH effects at lag one (and lag two for GARCH(2,1)). Past variance levels at lag one $\left(s_{t-1}^2\right)$ are almost always positive (with the exception of the spread series for MBBB7) and highly significant for almost all time series in the GARCH(1,1) set-up. In GARCH(1,1) the coefficient values of b_5 are positive in most cases of spread series (with CSAAA3, MAAA3 and MBBB7 carrying negative signs) and are significant especially for traditional CDO and Pfandbrief transactions. The coefficient b_6 documents that most of the explanatory power of the GARCH term carries over even into the second lag variance forecast in GARCH(2,1). Our estimation fails to reject the null hypothesis that b_6 has no effect on the conditional variance in all Pfandbrief spreads and in one of each spread series of CDO (traditional and synthetic) and MBS tranche types at a significance level of at least 5%. In contrast to s_{t-1}^2 evidence of how past forecast variance s_{t-2}^2 at lag two influences the conditional variance is mixed. Most Pfandbrief spreads and two out of four MBS spread series exhibit negative GARCH effects for b_6, whereas positive GARCH effects dominate for CDO transactions in GARCH(2,1). Hence, both b_5 and b_6 point to the fact that the direction and the significance of any GARCH effect might depend on the liquidity of the transaction type (with Pfandbrief transactions being the most liquid and CDO tranches the most illiquid) and, to some extent, data frequency – the degree of significance and coefficient values of b_5 and b_6 increase for an extended series of Pfandbrief spreads (results are not reported in this paper; see also section 3).

Generally, the ARCH and GARCH effects of the conditional variance seem to have greatest statistical significance for Pfandbriefe and high-rated traditional CDO transactions, while the mean equation with asymmetric effects of past spread and LIBOR levels generates the closest estimation for the time series of synthetic CDOs and Pfandbriefe.

We further need to determine the statistical classification of the spread dynamics. We examine the specification of level stationarity as well as the statistical validity of asymmetric mean reversion based on the coefficients $a_{1,1}, a_{1,2}$ (ARCH terms) in the mean equation of GARCH(1,1) and $a_{1,1}, a_{1,2}$ and $a_{2,1}, a_{2,2}$

in the mean equation of the GARCH(2,1) model. To this end we resort to the Wald coefficient to test the null hypothesis $\mathrm{H}_0: a_{1,1} + a_{1,2} < 0$ ($\mathrm{H}_0: a_{2,1} + a_{2,2} < 0$ for GARCH(2,1) only) for overall mean reversion of the GARCH models. If $a_{1,1} + a_{1,2} = 0$ the trend has a unit root (random walk) and if $a_{1,1} + a_{1,2} > 0$ the spread development is explosive, which does not make economic sense. So spread change is level stationary if we can reject H_0. We apply the Wald coefficient test to validate the assumption of $a_{1,1} + a_{1,2} < 0$ on the basis of two separate sub-hypotheses $H_{0,1}: a_{1,1} + a_{1,2} = 0$ and $H_{0,2}: a_{1,1} + a_{1,2} = \hat{a}_{1,1} + \hat{a}_{1,2}$ for both GARCH models as well as $H_{0,1}: a_{2,1} + a_{2,2} = 0$ and $H_{0,2}: a_{2,1} + a_{2,2} = \hat{a}_{2,1} + \hat{a}_{2,2}$ for GARCH(2,1). As shown in Tab. 2 for GARCH(1,1) only one out of six CDO spread series (CSA5), two out of four MBS spread series (MAAA3 and MBBB7) and two out of three Pfandbrief spread series (PAAA3 and PAAA5) produce Wald statistics of at least 5% significance, so that the sum of coefficients $a_{1,1}, a_{1,2}$ equals the sum of their estimators and differs from zero in all estimations. Moreover, the trend of each spread series can be determined based on the sign of $\hat{a}_{1,1} + \hat{a}_{1,2}$. All spread series clearly exhibit negative mean reversion coefficients at lag one.

Tab. 5 reports the results of the Wald-testing procedure for the GARCH(2,1) model coefficients $a_{1,1}, a_{1,2}$ and $a_{2,1}, a_{2,2}$. Here, almost all spread series (with the exception of CSBBB7, CTA3 and MA7) – more than in the GARCH(1,1) specification – reject the null hypothesis $H_{0,1}: a_{1,1} + a_{1,2} = 0$ at high levels of significance. Moreover, the sum of coefficients equals the sum of estimators $\left(H_{0,2}: a_{1,1} + a_{1,2} = \hat{a}_{1,1} + \hat{a}_{1,2}\right)$ at a 99% confidence level, and the sum of estimators $\hat{a}_{1,1} + \hat{a}_{1,2}$ is negative for all spread series. Hence, the Wald test for mean reversion for both GARCH models at lag one confirms our results obtained from the unit root test, which generates the most robust results for Pfandbrief and MBS spreads. At the same time the degree of mean reversion weakens for the coefficients $a_{2,1}, a_{2,2}$ at lag two in GARCH(2,1). In comparison to the coefficient values $a_{1,1}, a_{1,2}$, all traditional CDO spread series as well as two out of three Pfandbrief spread series lose their significance of mean reversion at lag two, so that $H_{0,1}: a_{2,1} + a_{2,2} = 0$ can no longer be rejected. Moreover, the sum of estimators $\hat{a}_{2,1} + \hat{a}_{2,2}$ is positive for all spread series. Hence, in GARCH(2,1) the Wald coefficient test indicates that CDO transactions fail to unequivocally support mean reversion at lag one and non-stationarity at lag two for first and second spread differences, whilst MBS spread series show significant level stationarity in $a_{1,1} + a_{1,2} < 0$ but not for $a_{2,1} + a_{2,2} < 0$.

We also assess the degree of asymmetry of spread dynamics in context of measuring the heteroskedasticity of spreads. We test the null hypothesis of no asymmetry for the first spread differences $\mathrm{H}_0: a_{1,1} = a_{1,2}$ for both GARCH model ($\mathrm{H}_0: a_{2,1} = a_{2,2}$ for GARCH(2,1) only). The results of both test are reported in Tab. 4 and Tab. 5.

In both GARCH models the null hypothesis of no asymmetry, i.e. future spreads are equally sensitive to positive or negative first differences of past spreads (spread declines/spread increases), can be rejected at high confidence intervals for nearly all asset classes for the coefficients $a_{1,1}, a_{1,2}$. Merely two MBS spread series (MAAA3 and MAAA5) and one Pfandbrief type (PAAA7) in GARCH(1,1), and one CDO spread series (CSBBB7) and one MBS tranche type (MA7) in GARCH(2,1) generate probability values for the H_0 as coefficient restriction, which makes the Wald test statistics not significant.[30] The significance of asymmetric effects of previous spread change also persist in the second difference of past spreads of GARCH(2,1) in Tab. 5 – though at an admittedly lower degree of significance especially for traditional CDO transactions.

Our estimation results for the mean equation are in general agreement with the findings by Koutmos (2002) on U.S. MBS spreads. However, in contrast to Koutmos (2002), we find that all spread time series at one lag (with the exception of traditional AAA-rated CDOs in GARCH(2,1)) generate negative $a_{1,1}$ and $a_{1,2}$ coefficients of different explanatory power (with greater effects of negative past spread change compared to positive changes). Hence, future spreads show varying sensitivity to the direction of past spread change, while spreads exhibit mean reversion in each case. Consequently, overall mean reversion for both $a_{1,1}$ and $a_{1,2}$ is maintained. Interestingly, each time series exhibits the same direction of asymmetric spread response to both positive and negative past spread differences in both GARCH models. This observation also holds true for second differences in GARCH(2,1). However, whilst the absolute coefficient values for negative past spread change $(a_{1,2})$ are consistently higher than for negative past spread change $(a_{1,1})$ in both GARCH models as in Koutmos (2002), asymmetric mean reversion of spread change at two lags indicates positive bias if $a_{2,1}$ and $a_{2,2}$ are compared in GARCH(2,1), where we also observe a complete sign reversal as $a_{2,1}$ and $a_{2,2}$ coefficients carry positive signs in all cases. Considering the high speed of mean reversion, this result seems plausible. The estimation results for asymmetric mean reversion of Pfandbrief spreads are contradictory given strong evidence of mean reversion in the estimation of the GARCH model, while the ADF test (see Tab. 1) indicates the existence of a unit root in level data, so co-integration is limited to the order of one (I(1) process). The estimation results in both GARCH models also affirm the high significance of the previous period's variance forecast (GARCH term) for the conditional variance (b_5). The extended approach of GARCH(2,1) hints to an even stronger historical effect of past volatility, where two lag past variance (b_6) exerts a durable influence on future spread change. Judging by the estimation results for Pfandbriefe, market liquidity apparently facilitates this effect.

[30] The *p*-value indicates the probability of the tested restriction to be significant for the estimation. In this case, the c^2-distributed Wald-statistic would not deviate from zero at a commonly accepted level of significance.

By and large we corroborate the estimation results of conditional variance in Koutmos (2002). Although we find that negative past errors (b_2) increase volatility of spread series more than positive past errors (b_1), in contrast to Koutmos (2002) asymmetric squared residuals (ARCH term) from the mean equation are only significant for negative past errors (b_2) in several MBS, traditional CDO and Pfandbrief spread time series. The statistical irrelevance of past positive errors (as spreads increase) is striking and leads to reservations regarding preliminary statistical interpretation asset classes with particularly low t-statistics of coefficient estimates, such as MBS in both GARCH models. The model specification in the following section will address this issue in detail.

If we take into account all estimation results only coefficient values b_1 and b_2 for Pfandbriefe in GARCH(1,1) and all CDOs in GARCH(2,1) deliver clear support for asymmetric effect of past errors. Also for MBS transactions in both GARCH models and Pfandbriefe under the GARCH(2,1) process the effect of negative past errors (in cases of spread decline) is more prevalent than any positive past errors. Nonetheless, merely traditional CDO transactions and Pfandbriefe in the GARCH(2,1) model display high but not sufficiently significant t-statistics for b_1. Moreover, we find that spread levels and LIBOR rates of the previous period play a modest role in explaining conditional variance as variance regressors, whose coefficients b_3 and b_4 show evidence of significance mostly for CDO and Pfandbrief time series. Only in the GARCH(1,1) model do our estimation results for MBS transactions (7-year maturity) tally with the findings by Koutmos (2002).

7 MODEL SPECIFICATION

The correct (model) specification of the mean and conditional variance of spread dynamics by means of standardised residuals – volatility no explained by the model – is vital to the pricing of structured finance transactions and the management of spread risk. Hence, we apply model diagnostics to both GARCH specifications in order (i) to detect any remaining non-linear structure/autocorrelation (Llung-Box (LB) Q-statistic) of estimated standardised errors $E(e_t/s_t)$ and squared standardised errors $E(e_t/s_t)^2$, and (ii) to test the normality (Jarque-Bera statistic) of standardised residuals (with first and second moments equal to zero and unity respectively).

Highly significant LB Q-statistics in Tab. 4 and Tab. 5 testify to an almost complete absence of higher order serial correlation even at lag one in both standardised residuals of the mean equation (i.e. specification of mean equation) and squared standardised residuals of conditional variance (i.e. specification of conditional variance equation). Only some MBS spread time series in both GARCH model specifications retain statistically significant serial correlation in squared standardised residuals up to six lags. Since the LB Q-statistics for standardised residuals indicate no significant autocorrelation, the inclusion of one lag spread levels in the in the mean equation of the GARCH(1,1) model and up to two lag spreads in the mean equation of GARCH(2,1) model prove sufficient for the correct specification of the mean equation, so that no further inclusion of appropriate lagged endogenous variables in the equation at the cost of losing degrees of freedom is warranted. Also in the specification of conditional variance we can rule out ARCH effects (significant Q-statistic) in squared standardised residuals for all asset types but high-rated MBS transactions. With regard to the Jarque-Bera statistic, we find that the null hypothesis of normally distributed standardised residuals is rejected for all time series with estimation results (see Tab. 4 and Tab. 5).

Although the Llung-Box (LB) and Jarque-Bera (JB) statistics are commonly accepted and well established model diagnostics to examine the degree of autocorrelation and normality of standardised residuals,[31] they fail to test how well the proposed GARCH models capture the asymmetric effects on spread volatility, i.e. the contribution of positive and negative past estimation errors/innovations to changes in conditional variance (Koutmos, 2002). Since the GARCH processes explain the heteroskedasticity of observed spread behaviour, the correct specification of the conditional variance equation and any patterns of asymmetric change is imperative.

In the spirit of the diagnostics developed by Engle and Ng (1993) to test asymmetric effects in the news impact curve implied by the model estimates of conditional variance, we examine the correct specification of the asymmetric volatility process of spread dynamics by means of three testing procedures: the (negative) sign bias test, the negative size bias test and the positive sign bias test. All test rest on the assumption that the conditional variance is correctly specified only if the squared standardised residuals escape any predictability through observed variables, which distinguish between positive and negative past errors (null hypothesis). Hence, if the t-statistics for all three tests are statistically insignificant, the estimated volatilities from the GARCH models fully incorporate past information (at one lag).

The (negative) sign bias test $(e_t/s_t)^2 = m + gK + e_t$ measures any statistically significant influence of past errors e_{t-1} (at one lag) on squared standardised residuals $(e_t/s_t)^2$, which is the volatility not predicted by conditional variance of the model estimation. Since we define the dummy variable $K = 1$ for $e_{t-1} < 0$ else $K = 0$ in order to account for asymmetric influences of past errors, a significant t-statistic of K signifies that the impact of positive and negative past errors on spread volatility is not fully specified in the asymmetric ARCH terms of the conditional variance equation; unexplained spread volatility still contains some positive/negative effect by past errors.

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[31] The Llung-Box Q-statistic of standardised residuals is deemed sufficient for the correct specification of the mean equation at this point, as it merely confirms the estimation results obtained from the OLS regression and the Wald coefficient statistics. However, the correct specification of conditional variance requires a further refinement of autocorrelation tests.

	Collateralised Debt Obligations (CDO)					
	synthetic			*traditional*		
	CSAAA3	CSA5#	CSBBB7	CTAAA3#	CTA5	CTBBB7
Wald-test H_0: $\alpha_{1,1}=\alpha_{1,2}$ (t-stat.)	6.784**	16.657***	13.368***	83.384***	15.296***	15.725***
Wald-test H_0: $\alpha_{1,1}+\alpha_{1,2}=0$ (t-stat.)	0.0050	6.920**	1.2165	0.7780	0.7310	0.5460
LB-Q Statistic (lags)	0.539 (1)	0.000 (1)	NA	2.009 (1)	0.099 (1)	NA
LB^2-Q Statistic (lags)	0.007 (1)	0.246 (1)	NA	0.232 (1)	0.021 (1)	NA
Jarque-Bera	3164.16***	1695.81***	NA	660.55***	5902.84***	NA
Sign Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K+e_t$ (t-stat.)	0.620	0.381	-0.439	-1.207	-2.048**	0.135
Negative Size Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K\varepsilon_{t-1}+e_t$ (t-stat.)	0.089	0.160	0.331	1.157	1.803*	0.773
Positive Size Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K\varepsilon_{t-1}+e_t$ (t-stat.)	-0.524	0.327	1.040	0.660	1.440	-0.118

	Pfandbriefe			*Mortgage-Backed Securities (MBS)*			
	PAAA3	PAAA5#	PAAA7#	MAAA3#	MAAA5	MA7#	MBBB7
Wald-test H_0: $\alpha_{1,1}=\alpha_{1,2}$ (t-stat.)	109.426***	164.506***	101.6270	1.4260	0.3890	22.392***	12.497***
Wald-test H_0: $\alpha_{1,1}+\alpha_{1,2}=0$ (t-stat.)	5.471**	4.028**	13.7180	4.311***	0.8850	0.0356	12.790***
LB-Q Statistic (lags)	8.809*** (1)	0.309 (1)	NA	0.0378 (1)	1.561 (1)	0.004 (1)	0.435 (1)
LB^2-Q Statistic (lags)	0.765 (1)	0.002 (1)	NA	0.420 (1)	0.484 (1)	0.016 (1)	4.867* (2)
Jarque-Bera	145.98***	3635.51***	NA	329.03***	246.32***	18763.83***	742.83***
Sign Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K+e_t$ (t-stat.)	1.025	0.466	-0.523	-0.228	0.620	0.461	-2.056**
Negative Size Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K\varepsilon_{t-1}+e_t$ (t-stat.)	-1.135	-0.007	-0.196	1.646	-2.033**	-0.039	0.426
Positive Size Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K\varepsilon_{t-1}+e_t$ (t-stat.)	-2.250**	-2.023**	1.131	1.270	-0.353	-0.108	2.443**

All GARCH (1,1) parameters have been estimated from the time series - transformed by the Johnson Fit and the natural logarithm ("AD_L") - according to the Berndt-Hall-Hall-Hausman algorithm, except in cases marked # (Marquardt quasi-maximum likelihood estimation procedure); § no Bollerslev-Woolridge robust standard errors and variance.***=1% significance, **=5% significance, *=10% significance. *NA* indicates that no results could be generated by the statistics software due to data overflow. The values $(\varepsilon_\tau/$ and $(\varepsilon_\tau/\sigma_\tau)^2$ are the mean and the conditional variance of standardised residuals obtained from the GARCH (1,1) model. LB(x) denotes the Llung-Box Q-statistic (autocorrelation) for $(\varepsilon_\tau/\sigma_\tau)$ up to *x* lags and LB^2(x) denotes the Llung-Box Q-statistic for $(\varepsilon_\tau/\sigma_\tau)^2$ up to *x* lags. Number of observations: 93. In the sign bias and size bias tests we included 91 observations (instead of 93) after adjusting for

Tab. 4. *Coefficient and residual tests of GARCH(1,1) model (only transformed and Johnson Fit adjusted spreads).*

	Collateralised Debt Obligations (CDO)					
	synthetic			traditional		
	CSAAA3	CSA5#	CSBBB7	CTAAA3	CTA5	CTBBB7
Wald-test H_0: $\alpha_{1,1}=\alpha_{1,2}$ (t-stat.)	0.1270	6.848**	0.0490	5.401**	39.682***	7.108***
Wald-test H_0: $\alpha_{1,1}+\alpha_{1,2}=0$ (t-stat.)	11.734***	7.216***	2.6880	2.982*	1.2870	0.2140
Wald-test H_0: $\alpha_{2,1}=\alpha_{2,2}$ (t-stat.)	4.296**	3.640*	0.9580	2.2900	7.801***	0.0750
Wald-test H_0: $\alpha_{2,1}+\alpha_{2,2}=0$ (t-stat.)	8.251***	6.213**	0.6820	1.2250	0.2430	1.2720
LB-Q Statistic (lags)	0.539 (1)	1.406 (1)	NA	NA	100.840*** (6)	NA
LB^2-Q Statistic (lags)	0.007 (1)	1.367 (1)	NA	NA	11.935*** (2)	NA
Jarque-Bera	1712.16***	1339.42***	NA	NA	808.52***	NA
Sign Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K+e_t$ (t-stat.)	-0.005	-1.084	-0.439	-0.111	-3.135***	-1.931
Negative Size Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K\varepsilon_{t-1}+e_t$ (t-stat.)	1.181	0.979	0.331	0.540	1.728*	-0.608
Positive Size Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K\varepsilon_{t-1}+e_t$ (t-stat.)	0.481	1.042	1.040	0.330	2.259**	1.316

	Pfandbriefe			Mortgage-Backed Securities (MBS)			
	PAAA3	PAAA5#	PAAA7	MAAA3	MAAA5	MA7	MBBB7#
Wald-test H_0: $\alpha_{1,1}=\alpha_{1,2}$ (t-stat.)	72.088***	60.295***	82.747***	10.857***	5.139**	0.2980	6.845*
Wald-test H_0: $\alpha_{1,1}+\alpha_{1,2}=0$ (t-stat.)	32.838***	8.912***	18.209***	6.072**	41.453***	0.0520	5.736**
Wald-test H_0: $\alpha_{2,1}=\alpha_{2,2}$ (t-stat.)	65.610***	18.616***	52.904***	0.0960	22.757***	0.9570	4.092**
Wald-test H_0: $\alpha_{2,1}+\alpha_{2,2}=0$ (t-stat.)	30.675***	7.596***	13.972***	0.0000	4.743**	0.0630	1.2160
LB-Q Statistic (lags)	0.432 (1)	0.850 (1)	0.385 (1)	12.739*** (1)	0.110 (1)	0.643 (1)	NA
LB^2-Q Statistic (lags)	0.029 (1)	1.178 (1)	1.224 (1)	13.025*** (1)	95.831*** (6)	0.011 (1)	NA
Jarque-Bera	603.620***	1557.34***	4.253	72.171***	29.063***	12551.25***	NA
Sign Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K+e_t$ (t-stat.)	-0.463	0.739	-1.213	-1.863*	-1.213	0.564	-2.555*
Negative Size Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K\varepsilon_{t-1}+e_t$ (t-stat.)	0.348	0.771	0.850	3.000***	2.399	0.111	1.960*
Positive Size Bias Test H_0: $(\varepsilon_t/\sigma_t)^2=\mu+\gamma K\varepsilon_{t-1}+e_t$ (t-stat.)	0.596	-0.607	0.167	1.355	0.259	0.441	-0.347

All GARCH (2,1) parameters have been estimated from the time series - transformed by the Johnson Fit and the natural logarithm ("AD_L") - according to the Berndt-Hall-Hall-Hausman algorithm, except in cases marked # (Marquardt quasi-maximum likelihood estimation procedure); § no Bollerslev-Woolridge robust standard errors and variance.***=1% significance, **=5% significance, *=10% significance. *NA* indicates that no results could be generated by the statistics software due to data overflow. The values $(\varepsilon_\tau/\sigma_\tau)$ and $(\varepsilon_\tau/\sigma_\tau)^2$ are the mean and the conditional variance of standardised residuals obtained from the GARCH (2,1) model. LB(x) denotes the Llung-Box Q-statistic (autocorrelation) for $(\varepsilon_\tau/\sigma_\tau)$ up to *x* lags and $LB^2(x)$ denotes the Llung-Box Q-statistic for $(\varepsilon_\tau/\sigma_\tau)^2$ up to *x* lags. Number of observations: 93. In the sign bias and size bias tests we included 91 observations (instead of 93) after adjusting for endpoints.

Tab. 5. *Coefficient and residual tests of GARCH(2,1) model for all spread series (only transformed and Johnson Fit adjusted spreads).*

The negative size bias tests extends the sensitivity analysis of squared standardised residuals to negative past errors to include the size of past estimation errors as well. This means that we regress the squared standardised residuals on past residuals conditioned by the dummy variable *K*, so that $\left(e_t / s_t\right)^2 = m + g\,K e_{t-1} + e_t$. Significant t-values for the regression coefficient g mean that the specification of the conditional variance does not account for the asymmetric effect of small or large negative errors. The same logic applies analogously to the positive size bias test $\left(e_t / s_t\right)^2 = m + g\,(1-K) e_{t-1} + e_t$.

In all three residual tests we find strong evidence that the number of explanatory variables generating the GARCH model estimates for spread heteroskedasticity correctly specify the asymmetric influences on conditional variance. Hence, we cannot reject the null hypothesis that past errors influence the spread volatility (squared standardised residuals) not predicted my GARCH models. However, the residual tests of two spread series (MBBB7 and CTA5) in both GARCH models indicate that some explanatory power of past errors is not captured by the conditional variance equation. While standardised residuals of MBBB7 spreads flag a significant sign bias and positive size bias of past innovations, the specification of conditional variance also seems to be insufficient for the spread volatility of CTA5 spreads. The estimation errors of the latter reveal significant sign bias and positive size bias.

Overall, the model diagnostics based on common coefficient and residual tests as well as the sign bias and size bias testing procedures for asymmetric conditional variance suggest that the specification of spread volatility in either a GARCH(1,1) or GARCH(2,1) process generates adequate results of relatively high statistical validity, which could be relied upon for forecasting purposes. The maximum likelihood estimated multi-factor model approximation of the given spread series describe the spread dynamics particularly well for Pfandbriefe and to a lesser extent for CDOs. However, while asymmetric mean reversion and the asymmetric impact of past errors on conditional variance are statistically and economically significant in most cases, the model specification under GARCH(2,1) seems to leave doubts as to its appropriateness for mortgage-backed securities (MBS).

After logarithmic transformation in combination with the Johnson Fit procedure, all CDO, MBS and Pfandbrief spread series in the data set exhibit strong mean reversion in both the simple OLS regression analysis and unit root tests (Augmented Dickey-Fuller (ADF) and Phillips-Peron (PP)) – except for CTA5, MAAA5 and two out of three Pfandbrief spread series (PAAA5 and PAAA7).[32] Hence, hypothesis testing is statistically viable. We also found a level effect in the degree of mean reversion, where higher mean spreads of a certain asset time series would entail higher levels of mean

[32] The non-stationary of the latter two spread series can only be eliminated by using daily observations over the original time period of four years (with the exclusion of all observations during the second half of 2000 in order to control for exogenous distortions to any mean-reverting trend due to the financial crises in summer 2000).

reversion than spread series with lower sample mean. Although the unit root tests explain any serial correlation in spread dynamics on the basis of only some shift and time trend without recognition of level effects, the model diagnostic of general level stationarity are consistent with later estimation results of the multi-factor GARCH models.

Although the significance of the estimated maximum-likelihood parameters varies among the series of asset types, we can clearly identify a strong statistical influence of endogenous factors on spread series of MBS and Pfandbrief transactions in the GARCH(1,1) model and on traditional CDO and Pfandbrief deals in the proposed GARCH(2,1) framework.. In both GARCH processes model diagnostics bear out asymmetric spread change behaviour, i.e. divergent effects of past spreads on future spread change, with MBS spread series generating economically stronger results (i.e. level of mean reversion) than CDOs in spite of lower average mean spreads. All spread series exhibit asymmetric mean reversion to the extent that spread changes are mostly level stationary following either increases or decreases of past spreads lagged by one period. However, the effect of negative past spread change is economically and statistically stronger. This observation runs counter findings about non-stationary behaviour in recent of MBS spreads in Koutmos (2002), who qualifies overall asymmetric mean reversion based on stationary spread change after spread decreases dominating random spread change after spread decreases. Moreover, MBS

Our model estimates also consider asymmetries of expected future spread change for more than one period. If we extend the asymmetric effects of past spread change to two lags we find that the observation of varying degrees of mean reversion completely reverses and spread change – regardless of the direction of past spread change – follows a random walk. The statistical diagnostics (Wald test) of estimated coefficients in both GARCH(1,1) and GARCH(2,1) processes confirm mean reversion. Hence, the mean equation seems to be correctly specified and hypothesis testing can be justifiably applied. We also observe significant asymmetric effects of past errors on spread volatility. Past negative innovations (associated with spread decline) seem to have a greater effect on the conditional variance than positive past errors.

Standard residual tests for normality (Jarque-Bera statistic) and autocorrelation (Lung-Box Q-statistic) confirm reliable model specification of the mean and the conditional variance of standardised residuals of most spread series in the data set. However, theses tests fall short of measuring how well the proposed GARCH models measure the asymmetric nature of spread volatility. We examine the contribution of small and large past negative and past errors to squared standardised residuals by means of the so-called sign bias and size bias test statistics. In almost all cases, past innovations fail to have an effect on estimation errors, i.e. spread volatility not explained by the specification of the model. Hence, the specification of conditional variance in both GARCH model estimations incorporates all explanatory power of past innovations.

Although we do not consider a "horse-race" of GARCH model specifications, the GARCH(2,1) process seems to be more robust than the GARCH(1,1) model. Not only do we find economically and statistically stronger asymmetric contribution of past spread changes in GARCH(2,1), but also a more profound and consistent asymmetric effects of past errors on spread volatility (conditional variance). Additionally, despite the loss of degrees of freedom in the estimation procedure it engenders, the inclusion of more explanatory factors in GARCH(2,1) promotes higher levels of significance for almost all spread series of CDO, MBS and Pfandbrief transactions (especially for spread series that matter most in our analysis, e.g. the mean equation of synthetic CDOs and MBSs as well as the conditional variance equation of synthetic CDOs and MBSs). In contrast, the GARCH(1,1) model not succeed in generating significant estimation results for most mean equations of CDO and MBS spread series. And yet, the proof of the pudding of whether such different levels of statistical significance actually matter lies in the correct model specification. Standard residual diagnostics for the detection of any remaining non-linear structure and non-normality in estimation errors (normalised residual spreads) indicate that the GARCH(2,1) model offers more reliable model estimates for the mean and the conditional variance of spread change, i.e. estimation errors exhibit little or no serial correlation and follow a normal distribution. Also statistical tests of a correct specification of asymmetries in the volatility process – asymmetries in conditional variance (sign bias test) and the influence of varying degrees of positive and negative past errors on spread volatility (size bias test) – attest lower influence of past errors on standardised residuals in the GARCH(2,1) compared to the GARCH(1,1) process. Hence, the inclusion of an asymmetric GARCH term with lag two is a statistically preferable extension to the GARCH(1,1) specification.

However, we need to interpret the estimated results of both GARCH models with caution due to the low data frequency and short time period of our data set compared to more than 30 years of U.S. MBS trading data used as spread history Koutmos (2002). Since the European ABS market has seen active secondary trading only for little more than three years, the data history of this study is limited by systemic constraints. The results of the unit root test and GARCH models are certainly influenced by the data quality of the sample. Additionally, the relative illiquidity of CDO and MBS transaction tranches in Europe exacerbates any distorting effect induced by data limitations. Nonetheless, the presented GARCH models yield estimation results with fairly robust model estimators.

The quality of the data sample and the authenticity of the spread series in the data set could also be compromised by the rating volatility and asset liquidity included in the composition of in the secondary spread benchmarks. For one, some GARCH effects of spreads might be induced by varying rating volatility between spread series, e.g. AAA rating show less volatility than BBB ratings. Furthermore, our data set of secondary market prices does not control for liquidity, because only the transactions with the "tightest" spreads are routinely selected to make up the benchmark for the secondary market prices for each asset class.[33] Hence, the combination of rating volatility and liquidity considerations distort actual spread dynamics.

8 DISCUSSION

After logarithmic transformation in combination with the Johnson Fit procedure, all CDO, MBS and Pfandbrief spread series in the data set exhibit strong mean reversion in both the simple OLS regression analysis and unit root tests (Augmented Dickey-Fuller (ADF) and Phillips-Peron (PP)) – except for CTA5, MAAA5 and two out of three Pfandbrief spread series (PAAA5 and PAAA7).[34] Hence, hypothesis testing is statistically viable. We also found a level effect in the degree of mean reversion, where higher mean spreads of a certain asset time series would entail higher levels of mean reversion than spread series with lower sample mean. Although the unit root tests explain any serial correlation in spread dynamics on the basis of only some shift and time trend without recognition of level effects, the model diagnostic of general level stationarity are consistent with later estimation results of the multi-factor GARCH models.

Although the significance of the estimated maximum-likelihood parameters varies among the series of asset types, we can clearly identify a strong statistical influence of endogenous factors on spread series of MBS and Pfandbrief transactions in the GARCH(1,1) model and on traditional CDO and Pfandbrief deals in the proposed GARCH(2,1) framework.. In both GARCH processes model diagnostics bear out asymmetric spread change behaviour, i.e. divergent effects of past spreads on future spread change, with MBS spread series generating economically stronger results (i.e. level of mean reversion) than CDOs in spite of lower average mean spreads. All spread series exhibit asymmetric mean reversion to the extent that spread changes are mostly level stationary following either increases or decreases of past spreads lagged by one period. However, the effect of negative past spread change is economically and statistically stronger. This observation runs counter findings about non-stationary behaviour in recent of MBS spreads in Koutmos (2002), who qualifies overall asymmetric mean reversion based on stationary spread change after spread decreases dominating random spread change after spread decreases.

[33] The creation of seondary spread benchmark also smoothes out price variations across different transactions in the same rating category. Ideally, one would wish to control for liquidity by setting the trading volume of transactions entering the secondary market spread benchmark each week in relation to the total volume of outstanding transactions in the same asset class, which have not been traded. We also do not control for jumps/level effects in the spread series beyond the inclusion of the LIBOR rate as variance regressor in the conditional variance equation.

[34] The non-stationary of the latter two spread series can only be eliminated by using daily observations over the original time period of four years (with the exclusion of all observations during the second half of 2000 in order to control for exogenous distortions to any mean-reverting trend due to the financial crises in summer 2000).

Our model estimates also consider asymmetries of expected future spread change for more than one period. If we extend the asymmetric effects of past spread change to two lags we find that the observation of varying degrees of mean reversion completely reverses and spread change – regardless of the direction of past spread change – follows a random walk. The statistical diagnostics (Wald test) of estimated coefficients in both GARCH(1,1) and GARCH(2,1) processes confirm mean reversion. Hence, the mean equation seems to be correctly specified and hypothesis testing can be justifiably applied. We also observe significant asymmetric effects of past errors on spread volatility. Past negative innovations (associated with spread decline) seem to have a greater effect on the conditional variance than positive past errors.

Standard residual tests for normality (Jarque-Bera statistic) and autocorrelation (Lung-Box Q-statistic) confirm reliable model specification of the mean and the conditional variance of standardised residuals of most spread series in the data set. However, theses tests fall short of measuring how well the proposed GARCH models capture the asymmetric nature of spread volatility. We examine the contribution of small and large past negative and past errors to squared standardised residuals by means of the so-called sign bias and size bias test statistics. In almost all cases, past innovations fail to have an effect on estimation errors, i.e. spread volatility not explained by the specification of the model. Hence, the specification of conditional variance in both GARCH model estimations incorporates all explanatory power of past innovations.

Although we do not consider a "horse-race" of GARCH model specifications, the GARCH(2,1) process seems to be more robust than the GARCH(1,1) model. Not only do we find economically and statistically stronger asymmetric contribution of past spread changes in GARCH(2,1), but also a more profound and consistent asymmetric effects of past errors on spread volatility (conditional variance). Additionally, despite the loss of degrees of freedom in the estimation procedure it engenders, the inclusion of more explanatory factors in GARCH(2,1) promotes higher levels of significance for almost all spread series of CDO, MBS and Pfandbrief transactions (especially for spread series that matter most in our analysis, e.g. the mean equation of synthetic CDOs and MBSs as well as the conditional variance equation of synthetic CDOs and MBSs). The GARCH(2,1) model estimates point towards more reliable time series properties of MBS spread changes compared to CDO spreads. In contrast, the GARCH(1,1) model does not succeed in generating significant estimation results for most mean equations of CDO and MBS spread series. And yet, the proof of the pudding of whether such different levels of statistical significance actually matter lies in the correct model specification. Standard residual diagnostics for the detection of any remaining non-linear structure and non-normality in estimation errors (normalised residual spreads) indicate that the GARCH(2,1) model offers more reliable model estimates for the mean and the conditional variance of spread change, i.e. estimation errors exhibit little or no serial correlation and follow a normal distribution. Also statistical tests of a correct specification of asymmetries in the volatility process –

asymmetries in conditional variance (sign bias test) and the influence of varying degrees of positive and negative past errors on spread volatility (size bias test) – attest lower influence of past errors on standardised residuals in the GARCH(2,1) compared to the GARCH(1,1) process. Hence, the inclusion of an asymmetric GARCH term with lag two is a statistically preferable extension to the GARCH(1,1) specification.

However, we need to interpret the estimated results of both GARCH models with caution due to the low data frequency and short time period of our data set compared to more than 30 years of U.S. MBS trading data used as spread history Koutmos (2002). Since the European ABS market has seen active secondary trading only for little more than three years, the data history of this study is limited by systemic constraints. The results of the unit root test and GARCH models are certainly influenced by the data quality of the sample. Additionally, the relative illiquidity of CDO and MBS transaction tranches in Europe exacerbates any distorting effect induced by data limitations. Nonetheless, the presented GARCH models yield estimation results with fairly robust model estimators.

The quality of the data sample and the authenticity of the spread series in the data set could also be compromised by the rating volatility and asset liquidity included in the composition of in the secondary spread benchmarks. For one, some GARCH effects of spreads might be induced by varying rating volatility between spread series, e.g. AAA rating show less volatility than BBB ratings. Furthermore, our data set of secondary market prices does not control for liquidity, because only the transactions with the "tightest" spreads are routinely selected to make up the benchmark for the secondary market prices for each asset class.[35] Hence, the combination of rating volatility and liquidity considerations distort actual spread dynamics.

9 CONCLUSION

Based on modified GARCH multi-factor models (GARCH(1,1) and GARCH(2,1)) we explored the spread dynamics of four different asset types of structured finance transactions: synthetic and traditional CDOs, MBSs and Pfandbriefe. A simple OLS regression to test for mean reversion without shift and time trend and the Augmented Dickey-Fuller (ADF)/Phillips-Peron (PP) statistics of unit root tests verify that almost all spread time series are level stationary. The first differences of all spreads series in the data set describe a highly significant mean reverting process. This also implies

[35] The creation of seondary spread benchmark also smoothes out price variations across different transactions in the same rating category. Ideally, one would wish to control for liquidity by setting the trading volume of transactions entering the secondary market spread benchmark each week in relation to the total volume of outstanding transactions in the same asset class, which have not been traded. We also do not control for jumps/level effects in the spread series beyond the inclusion of the LIBOR rate as variance regressor in the conditional variance equation.

a high degree of co-integration between the asset type (security) and the benchmark yield (spread) at least at the order of one.

The conditional ML likelihood estimation of our GARCH models yield statistically significant results for most spread series in the data set. We observe asymmetric mean reversion for past spread change at one lag, where the contribution of negative first moments of past spreads was stronger than positive first moments. The stationarity of spreads does not extend to two lags of past spread changes, although asymmetry is preserved. According to the Wald coefficient test the mean reversion coefficients for positive and negative past spread levels are statistically different from each other. Moreover, spread volatility also exhibits asymmetric time series properties. Past negative innovations (associated with spread decline) appear to have a greater effect on the conditional variance than positive past errors.

Standard residual model diagnostics (Jarque-Bera statistic and Lung-Box Q-statistic) testify to a correct specification of the mean and the conditional variance of spread change on the basis of standardised residuals and the squared standardised residuals (i.e. the mean and the variance of estimation errors). We also examine the influence of small and large past negative and positive errors on the spread volatility not captured by the model estimates. Both the sign bias and the size bias tests confirm that the specification of spread volatility in the estimation model recognises all explanatory power of past innovations, so that past errors do not have any influence on the degree of standardised residuals in any statistically meaningful way.

In conclusion, we find that the proposed GARCH approach to modelling the heteroskedasticity of European ABS spreads convincingly corroborates previous findings about the spread dynamics of U.S. MBS transactions. The spread change behaviour obviously responds asymmetrically to past innovations (errors) and the direction of past spread change. At the same time, we also consider (i) level effects induced by changes in the LIBOR rate as reference spot rate and (ii) a longer history of past variance forecasts to influence spread volatility, which improves the model specification compared to previous studies. To our knowledge, this study presents the first attempt to analyse market pricing for ABS transactions in Europe on the basis of actual trading data. Nonetheless, due to some inconsistent estimation results caused by the limited data set, higher data frequency and deal-based secondary market trading data to of several issues that remain to be solved in a further refinement of the model.

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11 APPENDIX

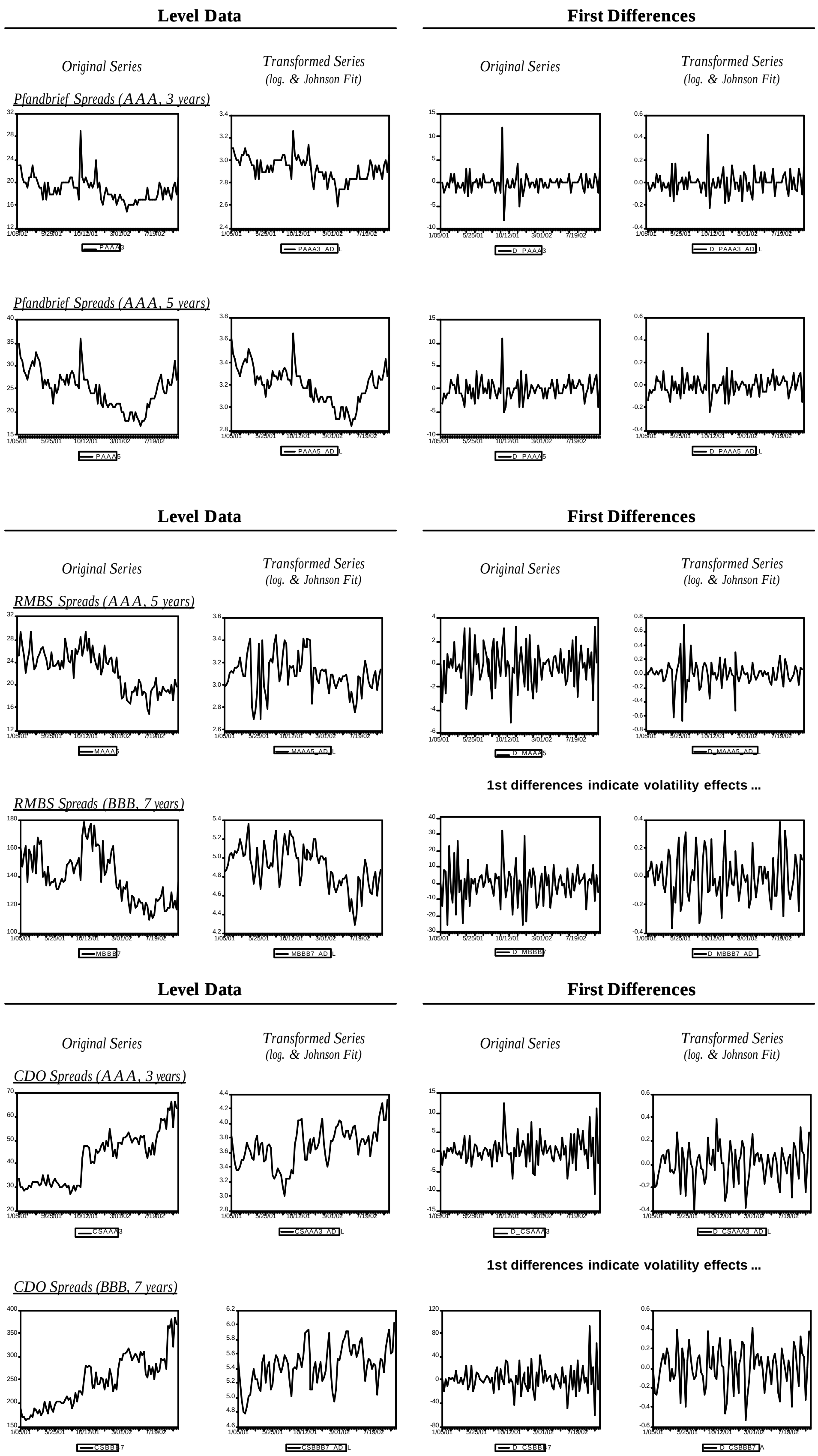

Fig. 1. *Data overview of selected spread series.*

Acronym	ABS Type	Rating Class (S&P)	Maturity	Deal Structure
CSAAA3	CDO	AAA	3 years	synthetic
CSA5	CDO	A	5 years	synthetic
CSBBB7	CDO	BBB	7 years	synthetic
CTAAA3	CDO	AAA	3 years	traditional, balance sheet
CTA5	CDO	A	5 years	traditional, balance sheet
CTBBB7	CDO	BBB	7 years	traditional, balance sheet
MAAA3	RMBS	AAA	3 years	synthetic & trad.
MAAA5	RMBS	AAA	5 years	synthetic & trad.
MA7	RMBS	A	7 years	synthetic & trad.
MBBB7	RMBS	BBB	7 years	synthetic & trad.
PAAA3	Pfandbrief	AAA	3 years	on-balance
PAAA5	Pfandbrief	AAA	5 years	on-balance
PAAA7	Pfandbrief	AAA	7 years	on-balance

Tab. 6. *Definition of nomenclature for the spread series associated with a certain asset type in the data set.*

Pfandbrief (Rating Grade)	Mean Weighted-Average Index Portion	*05-Jan-01*		*18-Oct-02*	
		Weighted-Average Index Portion	No. of Issues	Weighted-Average Index Portion	No. of Issues
with maturity 1-3 years					
AAA	78.11%	81.51%	989	74.39%	815
AA	20.81%	17.91%	191	23.71%	180
A	1.08%	0.45%	10	1.71%	29
Cash		0.12%		0.19%	
Total	100.00%	100.00%	1190	100.00%	1024
with maturity 3-5 years					
AAA	79.63%	82.78%	722	76.48%	536
AA	19.76%	17.04%	126	22.48%	144
A	0.61%	0.18%	4	1.04%	15
Cash		0.00%		0.00%	
Total	100.00%	100.00%	852	100.00%	695
with maturity 5-7 years					
AAA	81.03%	87.07%	431	74.91%	329
AA	18.31%	12.72%	53	23.90%	83
A	0.67%	0.22%	2	1.11%	11
Cash		0.00%		0.07%	
Total	100.00%	100.00%	486	100.00%	423

Tab. 7. *Definition of the Merrill Lynch EMU Pfandbrief Index and its rating class composition over time.*

Asset Class Spread Series	z-value	Selected distribution	ρ with original	Skewness	Kurtosis	JB	p_{JB}	E_P	p_E
CSAAA3_AD_L	0.9515	S_B	0.9597	0.0461	3.5767	1.3359	0.5128	3.1429	0.2077
CSA5_AD_L	0.8292	S_B	0.9173	-0.0914	3.2128	0.3051	0.8585	1.1243	0.5700
CSBBB7_AD_L	0.8341	S_B	0.9679	0.0972	3.3628	0.6636	0.7176	1.8504	0.3965
CTAAA3_AD_L	0.3029	S_U	0.4504	0.2781	2.2272	3.5511	0.1694	5.4736	0.0648
CTA5_AD_L	0.4108	S_B	0.9330	-0.2280	2.7507	1.0582	0.5891	1.0287	0.5979
CTBBB7_AD_L	0.9119	S_B	0.9317	0.0360	3.0430	0.0276	0.9863	0.4472	0.7996
MAAA3_AD_L	0.2864	S_B	0.9912	0.3847	2.5218	3.2142	0.2005	4.9582	0.0838
MAAA5_AD_L	0.2765	S_U	0.2511	-0.1348	2.0911	3.5201	0.1720	4.6662	0.0970
MA7_AD_L	0.0902	S_U	0.2592	0.0701	3.3462	0.5463	0.7610	1.7428	0.4184
MBBB7_AD_L	0.1507	S_U	-0.0331	0.1279	7.3745	75.2062	0.0000	49.1697	0.0000
PAAA3_AD_L	0.8342	S_B	0.9808	-0.1098	3.6506	1.8466	0.3972	3.6514	0.1611
PAAA5_AD_L	0.6446	S_B	0.9967	0.0258	2.8617	0.0854	0.9582	0.0657	0.9677
PAAA7_AD_L	0.8041	S_B	0.9902	0.0599	3.0421	0.0631	0.9689	0.4690	0.7910

Tab. 8. *Data transformation of spread series for each asset class by means of the Johnson Fit procedure.*

	Collateralised Debt Obligations (CDO), synthetic								
	CSAAA3	CSAAA3_L	CSAAA3_AD_L	CSA5	CSA5_L	CSA5_AD_L	CSBBB7	CSBBB7_L	CSBBB7_AD_L
Mean	43.1624	3.7314	3.7314	125.7536	4.8060	4.8060	252.0388	5.5049	5.5049
Median	46.0000	3.8286	3.8192	137.0000	4.9200	4.8697	256.0000	5.5452	5.5449
Maximum	65.0000	4.1744	4.3118	175.0000	5.1648	5.3492	375.0000	5.9269	6.0047
Minimum	30.0000	3.4012	3.2583	72.0000	4.2767	4.1993	174.0000	5.1591	5.0301
Std. Dev.	11.1472	0.2617	0.2617	28.8914	0.2447	0.2447	56.4064	0.2236	0.2236
Rel. Variation	25.83%	7.01%	7.01%	22.97%	5.09%	5.09%	22.38%	4.06%	4.06%
Skewness	0.2464	-0.0271	-0.0914	-0.2057	-0.4738	0.0461	0.3951	0.0181	0.0972
Kurtosis	1.9558	1.5821	3.2128	1.8318	1.9614	3.5767	2.4892	2.0100	3.3628
Jarque-Bera	5.1664	7.8022	0.3051	6.0075	7.7426	1.3359	3.4679	3.8437	0.6636
Prob. JB	0.0755	0.0202	0.8585	0.0496	0.0208	0.5128	0.1766	0.1463	0.7176
E_p	9.3451	16.5417	1.1243	11.3919	20.9996	3.1429	5.5840	5.0403	1.8504
Prob. E	0.0093	0.0003	0.5700	0.0034	0.0000	0.2077	0.0613	0.0804	0.3965
LB-Q (lags)*	815.09 (26)	882.6 (26)	437.37 (14)	902.86 (27)	909.24 (27)	587.16 (26)	822.25 (28)	911.34 (28)	609.65 (25)
AC value	0.1870	0.1850	0.1990	0.1860	0.1730	0.1980	0.1870	0.1710	0.1980
Observations	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*

	Collateralised Debt Obligations (CDO), traditional								
	CTAAA3	CTAAA3_L	CTAAA3_AD_L	CTA5	CTA5_L	CTA5_AD_L	CTBBB7	CTBBB7_L	CTBBB7_AD_L
Mean	29.7670	3.3846	3.3846	94.8936	4.5263	4.5263	199.2566	5.2839	5.2839
Median	28.0000	3.3322	3.3769	90.0000	4.4998	4.5700	185.2200	5.2215	5.2672
Maximum	39.0000	3.6636	3.6240	150.0000	5.0106	5.0782	300.0000	5.7038	5.6205
Minimum	25.6000	3.2426	3.0413	72.0000	4.2767	4.2178	170.0000	5.1358	4.9377
Std. Dev.	4.0718	0.1313	0.1313	22.4846	0.2284	0.2284	31.0592	0.1428	0.1428
Rel. Variation	13.68%	3.88%	3.88%	23.69%	5.05%	5.05%	15.59%	2.70%	2.70%
Skewness	0.7577	0.6853	-0.2280	0.6303	0.3858	0.2781	1.5057	1.2042	0.0360
Kurtosis	1.9730	1.8238	2.7507	2.2566	1.7907	2.2272	4.8686	3.7495	3.0430
Jarque-Bera	13.1245	12.7770	1.0582	8.3887	8.0601	3.5511	49.1922	24.9182	0.0276
Prob. JB	0.0014	0.0017	0.5891	0.0151	0.0178	0.1694	0.0000	0.0000	0.9863
E_p	61.6615	59.8116	1.0287	24.0032	21.3419	5.4736	69.3523	49.9135	0.4472
Prob. E	0.0000	0.0000	0.5979	0.0000	0.0000	0.0648	0.0000	0.0000	0.7996
LB-Q (lags)*	581.14 (15)	583.9 (15)	420.4 (13)	1002.3 (27)	1072.8 (27)	655.46 (16)	674.81 (25)	768.14 (26)	739.28 (28)
AC value	0.1740	0.1740	0.1790	0.1600	0.1800	0.1840	0.1820	0.1710	0.1690
Observations	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*

Time series are stated in basis point spreads of ABS tranche indices, where M="Residential Mortgage-Backed Securities (RMBS)", P="Pfandbrief", CS="Synthetic Collateralised Debt Obligation (CDO), and CT="Traditional/True Sale Collateralised Debt Obligation". Letter "AAA" to "BBB" reflect the Standard&Poor`s investment grade rating system. The number associated with each time series reflects the maturity in years. * Llung-Box Q-statistic significant at 5% level for the given number of lags and suitable AC value. AC value denotes when the H_0 of no autocorrelation can no longer be rejected at 5% level at a certain number of lags, i.e. the test statistic falls within the two standard error bounds of $+/-2T^{-0.5}$.

Tab. 9. *Descriptive statistics of all CDO spread series (level data).*

	Mortgage-Backed Securities (MBS)											
	MAAA3	MAAA3_L	MAAA3_AD_L	MAAA5	MAAA5_L	MAAA5_AD_L	MA7	MA7_L	MA7_AD_L	MBBB7	MBBB7_L	MBBB7_AD_L
Mean	20.7234	3.0217	3.0217	22.9782	3.1244	3.1244	65.1915	4.1751	4.1751	140.3138	4.9367	4.9367
Median	22.0000	3.0910	2.9947	24.0000	3.1781	3.0854	66.0000	4.1897	4.1829	142.0000	4.9558	4.9514
Maximum	25.0000	3.2189	3.2047	28.0000	3.3322	3.3879	75.0000	4.3175	4.3678	175.0000	5.1648	5.2871
Minimum	17.0000	2.8332	2.7988	17.5000	2.8622	2.8285	60.0000	4.0943	4.0988	120.0000	4.7875	4.4829
Std. Dev.	2.8099	0.1404	0.1404	3.2387	0.1446	0.1446	4.3854	0.0673	0.0673	16.9122	0.1207	0.1207
Rel. Variation	13.56%	4.65%	4.65%	14.09%	4.63%	4.63%	6.73%	1.61%	1.61%	12.05%	2.44%	2.44%
Skewness	-0.3854	-0.4277	-0.1348	-0.2056	-0.2931	0.0701	0.0774	0.0080	0.3847	0.1416	0.0127	0.1279
Kurtosis	1.3751	1.3694	2.0911	1.4860	1.4694	3.3462	1.7472	1.6577	2.5218	1.8052	1.6713	7.3745
Jarque-Bera	12.6680	13.2799	3.5201	9.6394	10.5222	0.5463	6.2409	7.0582	3.2142	5.9050	6.9174	75.2062
Prob. JB	0.0018	0.0013	0.1720	0.0081	0.0052	0.7610	0.0441	0.0293	0.2005	0.0522	0.0315	0.0000
E_p	53.6208	62.5617	4.6662	26.1014	32.9179	1.7428	11.2472	13.7045	4.9582	10.5874	13.2351	49.1697
Prob. E	0	0	0.097	0	0	0.4184	0.0036	0.0011	0.0838	0.005	0.0013	0
LB-Q (lags)*	886.74 (22)	905.08 (22)	164.22 (7)	934.77 (23)	967.94 (23)	35.073 (3)	752.65 (20)	785.63 (21)	645.58 (19)	699.72 (17)	733.1 (17)	22.393 (2)
AC value	0.1710	0.1820	0.1270	0.1760	0.1810	0.1410	0.1890	0.1720	0.1760	0.1570	0.1890	0.1300
Observations	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*

	Pfandbriefe								
	PAAA3	PAAA3_L	PAAA3_AD_L	PAAA5	PAAA5_L	PAAA5_AD_L	PAAA7	PAAA7_L	PAAA7_AD_L
Mean	18.7766	2.9268	2.9268	24.9894	3.2045	3.2045	31.8192	3.4437	3.4437
Median	19.0000	2.9444	2.9571	25.0000	3.2189	3.2111	31.5000	3.4499	3.4540
Maximum	29.0000	3.3673	3.2652	36.0000	3.5835	3.6690	47.0000	3.8501	3.9766
Minimum	15.0000	2.7081	2.5928	17.0000	2.8332	2.8406	22.0000	3.0910	2.9558
Std. Dev.	2.1056	0.1065	0.1065	4.1543	0.1691	0.1691	5.8217	0.1819	0.1819
Rel. Variation	11.21%	3.64%	3.64%	16.62%	5.28%	5.28%	18.30%	5.28%	5.28%
Skewness	1.4225	0.8305	-0.1098	0.1397	-0.2348	0.0258	0.3768	0.0708	0.0599
Kurtosis	7.6301	4.9100	3.6506	2.6313	2.4766	2.8617	2.3737	2.0795	3.0421
Jarque-Bera	115.6686	25.0950	1.8466	0.8381	1.9371	0.0854	3.7609	3.3975	0.0631
Prob. JB	0.0000	0.0000	0.3972	0.6577	0.3796	0.9582	0.1525	0.1829	0.9689
E_p	22.4233	10.8896	3.6514	0.5585	2.1983	0.0657	6.3592	4.2158	0.469
Prob. E	0	0.0043	0.1611	0.7564	0.332	0.9677	0.0416	0.1215	0.791
LB-Q (lags)*	151.67 (10)	189.51 (12)	226.06 (12)	415.8 (15)	459.52 (15)	410.94 (14)	584.97 (20)	617.95 (19)	543.62 (17)
AC value	0.1940	0.0710	0.1090	0.1760	0.1820	0.1950	0.1810	0.1910	0.2130
Observations	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*

Time series are stated in basis point spreads of ABS tranche indices, where M="Residential Mortgage-Backed Securities (RMBS)", P="Pfandbrief", CS="Synthetic Collateralised Debt Obligation (CDO), and CT="Traditional/True Sale Collateralised Debt Obligation". Letter "AAA" to "BBB" reflect the Standard&Poor`s investment grade rating system. The number associated with each time series reflects the maturity in years. * Llung-Box Q-statistic significant at 5% level for the given number of lags and suitable AC value. AC value denotes when the H_0 of no autocorrelation can no longer be rejected at 5% level at a certain number of lags, i.e. the test statistic falls within the two standard error bounds of $+/-2T^{-0.5}$.

Tab. 10. *Descriptive statistics of all MBS and Pfandbrief spread series (level data).*

	Collateralised Debt Obligations (CDO), synthetic								
	CSAAA3	CSAAA3_L	CSAAA3_AD_L	CSA5	CSA5_L	CSA5_AD_L	CSBBB7	CSBBB7_L	CSBBB7_AD_L
Mean	43.1624	3.7314	3.7314	125.7536	4.8060	4.8060	252.0388	5.5049	5.5049
Median	46.0000	3.8286	3.8192	137.0000	4.9200	4.8697	256.0000	5.5452	5.5449
Maximum	65.0000	4.1744	4.3118	175.0000	5.1648	5.3492	375.0000	5.9269	6.0047
Minimum	30.0000	3.4012	3.2583	72.0000	4.2767	4.1993	174.0000	5.1591	5.0301
Std. Dev.	11.1472	0.2617	0.2617	28.8914	0.2447	0.2447	56.4064	0.2236	0.2236
Rel. Variation	25.83%	7.01%	7.01%	22.97%	5.09%	5.09%	22.38%	4.06%	4.06%
Skewness	0.2464	-0.0271	-0.0914	-0.2057	-0.4738	0.0461	0.3951	0.0181	0.0972
Kurtosis	1.9558	1.5821	3.2128	1.8318	1.9614	3.5767	2.4892	2.0100	3.3628
Jarque-Bera	5.1664	7.8022	0.3051	6.0075	7.7426	1.3359	3.4679	3.8437	0.6636
Prob. JB	0.0755	0.0202	0.8585	0.0496	0.0208	0.5128	0.1766	0.1463	0.7176
E_p	9.3451	16.5417	1.1243	11.3919	20.9996	3.1429	5.5840	5.0403	1.8504
Prob. E	0.0093	0.0003	0.5700	0.0034	0.0000	0.2077	0.0613	0.0804	0.3965
LB-Q (lags)*	815.09 (26)	882.6 (26)	437.37 (14)	902.86 (27)	909.24 (27)	587.16 (26)	822.25 (28)	911.34 (28)	609.65 (25)
AC value	0.1870	0.1850	0.1990	0.1860	0.1730	0.1980	0.1870	0.1710	0.1980
Observations	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*

	Collateralised Debt Obligations (CDO), traditional								
	CTAAA3	CTAAA3_L	CTAAA3_AD_L	CTA5	CTA5_L	CTA5_AD_L	CTBBB7	CTBBB7_L	CTBBB7_AD_L
Mean	29.7670	3.3846	3.3846	94.8936	4.5263	4.5263	199.2566	5.2839	5.2839
Median	28.0000	3.3322	3.3769	90.0000	4.4998	4.5700	185.2200	5.2215	5.2672
Maximum	39.0000	3.6636	3.6240	150.0000	5.0106	5.0782	300.0000	5.7038	5.6205
Minimum	25.6000	3.2426	3.0413	72.0000	4.2767	4.2178	170.0000	5.1358	4.9377
Std. Dev.	4.0718	0.1313	0.1313	22.4846	0.2284	0.2284	31.0592	0.1428	0.1428
Rel. Variation	13.68%	3.88%	3.88%	23.69%	5.05%	5.05%	15.59%	2.70%	2.70%
Skewness	0.7577	0.6853	-0.2280	0.6303	0.3858	0.2781	1.5057	1.2042	0.0360
Kurtosis	1.9730	1.8238	2.7507	2.2566	1.7907	2.2272	4.8686	3.7495	3.0430
Jarque-Bera	13.1245	12.7770	1.0582	8.3887	8.0601	3.5511	49.1922	24.9182	0.0276
Prob. JB	0.0014	0.0017	0.5891	0.0151	0.0178	0.1694	0.0000	0.0000	0.9863
E_p	61.6615	59.8116	1.0287	24.0032	21.3419	5.4736	69.3523	49.9135	0.4472
Prob. E	0.0000	0.0000	0.5979	0.0000	0.0000	0.0648	0.0000	0.0000	0.7996
LB-Q (lags)*	581.14 (15)	583.9 (15)	420.4 (13)	1002.3 (27)	1072.8 (27)	655.46 (16)	674.81 (25)	768.14 (26)	739.28 (28)
AC value	0.1740	0.1740	0.1790	0.1600	0.1800	0.1840	0.1820	0.1710	0.1690
Observations	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*	*93*

Time series are stated in basis point spreads of ABS tranche indices, where M="Residential Mortgage-Backed Securities (RMBS)", P="Pfandbrief", CS="Synthetic Collateralised Debt Obligation (CDO), and CT="Traditional/True Sale Collateralised Debt Obligation". Letter "AAA" to "BBB" reflect the Standard&Poor`sinvestment grade rating system. The number associated with each time series reflects the maturity in years. * Llung-Box Q-statistic significant at 5% level for the given number of lags and suitable AC value. AC value denotes when the H_0 of no autocorrelation can no longer be rejected at 5% level at a certain number of lags, i.e. the test statistic falls within the two standard error bounds of $+/-2T^{-0.5}$.

Tab. 11. *Descriptive statistics of all CDO spread series (first differences).*

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