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The nonlinear dynamics of corporate bond spreads: Regime-dependent effects of their determinants

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Non-technical summary

Research Question

Which factors determine corporate bond prices in which way? This question is highly relevant for investors and issuers, but also for financial supervisors. However, it has not been entirely answered by research to date. In this context, the global financial crisis highlighted again that the behavior of market participants, and thus the importance of particular price drivers, may change rapidly and considerably. Hence, it appears advisable to incorporate this aspect into models aimed at explaining the dynamics of corporate bond prices.

Contribution

This paper employs a so-called regime-switching approach when modeling US corporate bond spreads, defined as the excess yield corporate bonds as comparatively riskier assets have to pay over that of US treasuries with the same maturity. The regime-switching model allows the impact of the pricing factors on the spreads to differ between relatively calm market phases and periods of financial stress. During the model estimation, the two alternating market states are directly derived from the observed behavior of all variables in the model setup. The results provide new insight on the time-varying importance of individual risk factors not documented so far.

Results

Based on data for the 2004-2016 period, this study finds empirical evidence for corporate bond prices to be primarily driven by credit risk and interest rate risk during tranquil market conditions. During more anxious and volatile markets, however, the impact of these two factors abates, whereas liquidity risk becomes the salient issue. While representing a negligible factor during placid phases, market-wide illiquidity shocks appear to result in substantial and long-lived increases in risk premia on the corporate bond market when a bearish sentiment prevails. This considerable impact of illiquidity on corporate bond spreads has not been reported previously by similar empirical studies based on simpler models. Our results – which are shown to be robust against various modifications of the model setup – suggest that in highly unstable times like the global financial crisis liquidity risk may supersede credit risk as the most important determinant of corporate bond spreads.

Nichttechnische Zusammenfassung

Fragestellung

Die für Anleger und Emittenten im Markt, aber auch für die Finanzaufsicht relevante Frage, welche Faktoren auf welche Weise Einfluss auf die Preise von Unternehmensanleihen nehmen, kann von der Forschung bis heute nicht zur Gänze beantwortet werden. Die globale Finanzkrise rückte dabei erneut den Aspekt in den Fokus, dass sich das Verhalten von Finanzmarktakteuren und damit auch die Relevanz einzelner Einflussfaktoren im Zeitverlauf schnell und stark ändern können. Daher scheint es geboten, diesen bei der Entwicklung von Modellen zur Erklärung der Preisdynamik explizit abzubilden.

Beitrag

Die vorliegende Studie bedient sich zur Modellierung US-amerikanischer Unternehmensanleihepreise –ausgedrückt als Risikoprämie in Form eines Zinsaufschlags gegenüber US-Staatsanleihen gleicher Restlaufzeit – eines sogenannten Regime-Switching-Ansatzes. Dieser ermöglicht, dass sich die Stärke des Einflusses bepreisungsrelevanter Risikofaktoren auf die Zinsaufschläge zwischen Phasen ruhigerer Finanzmärkte und Phasen von Finanzmarktstress unterscheiden kann, wobei die beiden alternierenden Marktzustände direkt aus dem beobachteten Verhalten aller Modellvariablen abgeleitet werden. Die Modellschätzung liefert neue Erkenntnisse zur zeitabhängigen Relevanz einzelner Risikofaktoren, welche in der Form noch nicht nachgewiesen wurden.

Ergebnisse

Die den Zeitraum 2004 bis 2016 abdeckende Studie findet empirische Belege dafür, dass in ruhigen Marktphasen die Preise von Unternehmensanleihen hauptsächlich durch Kredit- und Zinsänderungsrisiken getrieben sind. Allerdings verlieren diese beiden Einflussfaktoren in Phasen nervöser, volatilerer Märkte relativ an Bedeutung zugunsten des Themas (mangelnder) Liquidität, welches dann stark in den Vordergrund rückt. Unbedeutend in normalen Marktphasen, zeigen sich marktweite Illiquiditätsschocks in Krisenzeiten als Ursache substantieller und langlebiger Ausweitungen der Risikoprämien am Unternehmensanleihemarkt, welche in diesem Ausmaß bisher in ähnlichen Studien bei Verwendung einfacherer Modelle noch nicht dokumentiert wurden. Die Ergebnisse, welche sich robust gegenüber diversen Änderungen im Modell-Setup zeigen, legen nahe, dass Kreditrisiken die Rolle als gewichtigster Einflussfaktor auf die Risikoprämien von Unternehmensanleihen in Krisenzeiten an Illiquiditätsrisiken verlieren können.

DEUTSCHE BUNDESBANK DISCUSSION PAPER NO 08/2019

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Abstract

This paper studies the behavior of corporate bond spreads during different market regimes between 2004 and 2016. Applying a Markov-switching vector autoregressive (MS-VAR) model, we document that the dynamic impact of spread determinants varies substantially with market conditions. In periods of high volatility, systematic credit risk—rather than interest rate movements—contributes to driving up spreads. Moreover, while market-wide liquidity risk is not priced when volatility is low, it becomes a crucial factor during stress periods. Our results challenge the notion that spreads predominantly capture credit risk and suggest it must be reassessed during periods of financial distress.

Keywords: Corporate bond spreads, regime dependency, Markov switching, vector autoregression, credit spread puzzle

JEL-Classification: C32, C34, C58, G12

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1. Introduction and related research

Understanding the determinants of corporate bond prices is crucial and has been even higher on the agenda ever since the global financial crisis, which was characterized by unprecedented levels and volatilities of corporate bond spreads. Learning about these spread dynamics is highly relevant for prudential supervisory authorities and central banks who trace aggregate spreads to assess financial stability and the effectiveness of monetary policies. Moreover, corporate bond investors and the treasury and risk management units of the corporates themselves benefit from a thorough analysis of the time-varying influence of spread determinants. Yet, a considerable fraction of the empirically observable variation in corporate bond spreads still remains unexplained. Even after including a host of non-default-related components into econometric models, predicted spreads are typically much too low to match actual levels, leading to the *corporate bond spread puzzle* (Chen et al., 2009; Guo, 2013; Huang and Huang, 2012).[1]

In this paper, we address this puzzle by modelling the relationship between spreads and their main drivers using a Markov-switching vector autoregressive (MS-VAR) model. By introducing the MS-VAR specification as an innovative econometric approach to model corporate bond spreads, we extend previously employed static single-equation models which do not allow for a data-driven separation of market regimes and neglect dynamic adjustments, time-varying correlations, and potential endogeneity issues.[2] At this, our research is closely related to the work of Acharya et al. (2013) and Kalimipalli et al. (2013).[3] Acharya et al. (2013) use a static MS model to analyze

[1] Structural credit risk models based on the Merton (1974) framework for valuing corporate debt are limited to variables which affect the firm's default probability and thus fail to explain empirically observed variation in corporate bond spreads (Duffee, 1998; Eom et al., 2004; Leland and Toft, 1996; Longstaff and Schwartz, 1995). Other contributions include liquidity concerns, tax effects, or business cycle dependencies to proxy for market-wide effects explaining non-default-related spread components (e.g. Collin-Dufresne et al., 2001; Duffie and Singleton, 1999; Elton et al., 2001). While incorporating non-default-related determinants increases explanatory power, it is still not fully understood which factors – and through which functional relationships – drive the dynamics of corporate bond spreads.

[2] Although skewness, positive excess kurtosis, and persistence are robust stylized facts of the distribution of individual and aggregate corporate bond spreads (Gatfaoui, 2006; Pedrosa and Roll, 1998), early work on the corporate term structure assumes spreads to be normally distributed and uses simple linear regression models (e.g. Collin-Dufresne et al., 2001; Elton et al., 2001; Huang and Kong, 2003). Regression models with regime-switching, in particular those with Markov-switching (MS) as proposed by Hamilton (1989), account for non-normal distribution of spreads and persistence in their levels (Duffee, 1998; Timmermann, 2000). Moreover, MS models allow for explicit modeling of time-varying simultaneous correlations, thereby incorporating evidence that correlations between different financial asset returns typically increase during market downswings (Alexopoulou et al., 2009; Longin and Solnik, 2001, 1995). Consequently, MS models have recently been applied to study the corporate bond market (Acharya et al., 2013; Davies, 2008; Kalimipalli et al., 2013; Maalaoui Chun et al., 2014) as well as the related market of credit default swaps (Alexander and Kaeck, 2008; Chan and Marsden, 2014).

[3] Giesecke et al. (2011) study the determinants of U.S. corporate bond default rates for the 1866-2008 period. Regressing the actual annual default rates on financial and macroeconomic variables lagged by one year, their single-equation model allows the intercept term to be subject to Markovian regime switches, thereby providing for different default rate regimes. The authors find stock market returns and stock market return

regime-specific liquidity effects on corporate bond spreads. Their findings suggest that the negative impact of liquidity shocks on the spreads of speculative-grade bonds is limited to down market periods. In a related study, Kalimipalli et al. (2013) use a linear (single-regime) VAR model to examine the regime-specific impact of equity volatility and liquidity on corporate bond spreads and conclude that both volatility and liquidity shocks have a stronger effect on the spreads of low-rated bonds during crisis regimes.

Using weekly data covering the period from 2004 to 2016, we document significant differences in how default- and non-default-related factors impact aggregate corporate bond spreads conditional on the prevailing market regime. Specifically, our results suggest that the multivariate Markov-switching approach provides new insights into the time-varying role of illiquidity for pricing corporate bonds. Aggregate liquidity exhibits the most pronounced regime-specific differences in its effect on corporate bond spreads, and a shock to market-wide liquidity has the relatively largest impact on spreads in terms of magnitude and persistence during phases of high corporate bond and equity volatility. We conclude that, during highly unstable times like the global financial crisis, investors demand a substantially higher premium for taking on liquidity risk than previously assumed, thus providing novel evidence to rationalize the corporate bond spread puzzle.

Moreover, we find that during tense markets, shocks to credit risk trigger a disproportionately large and persistent increase in corporate bond spreads. Similarly, while interest rate risk plays a major role in normal times, it appears to have less of an impact relative to other risk factors when a bearish or generally anxious market sentiment prevails. In additional analyses, we show that our main results are robust to (i) the inclusion of more than one business cycle during the period under review, (ii) using alternative measures of illiquidity, and to (iii) the choice of the default risk measure.

2. The Markov-switching vector autoregressive model

2.1. Motivation

We choose the MS-VAR methodology to explain corporate bond spread dynamics and determinants as it allows us to analyze the regime-specific impact of the main determinants on the dynamic behavior of corporate bond index spreads within an interdependent system of equations. In fact, single-equation MS models selected in prior research might be missing important parts of the big picture since they are affected by potential endogeneity issues arising from simultaneous causality between the financial variables under review. Moreover, dynamic adjustments of the returns to shocks in a certain determinant cannot be analyzed in a static setting, either. Instead, all reactions

volatility to have significant forecasting power for default rates, whereas credit spreads do not feature predictive power.

are considered to be one-time adjustments that instantaneously take place within the same period.[4] Finally, a single-equation approach implies that all return determinants are assumed to be exogenous, i.e., do not allow for mutual causality between the variables that enter the model. However, due to their specific risk-return profile and correlations with other asset classes, corporate bonds lend themselves for hedging purposes and their returns can be expected to comove with, e.g., returns on Treasury and equity markets, i.e. variables typically deemed relevant determinants of corporate bond spreads.

Another methodological advantage of the MS-VAR approach is that prior knowledge about the exact regime changes –which might be recurring or caused by one-time events, and which can lead to either discrete or more gradual changes in the time series of the variables under review– is not required. Instead, the model estimation does not only provide the potentially differing regression coefficients, but at the same time also conditional regime probabilities for each point in time of the sample which allow conclusions to be drawn about when each submodel has most likely prevailed. Importantly, the distinct regimes are inferred endogenously by letting the sample data speak rather than being imposed ex ante by the researcher. Hence, the MS-VAR method enables us to have the differing regimes distinguished by a data-driven algorithm, such that the relevant spread drivers within each of these regimes can unambiguously be identified. This differentiates our approach from Kalimipalli et al. (2013), who compare (i) a shorter sample including the stress periods in 1998 (Asian and Russian crisis, LTCM collapse) and around the turn of the millennium in addition to all other non-stress periods between 1994 and 2007 to (ii) a longer sample that also covers the global financial crisis. Consequently, the regime-specific effects obtained from this exogenously imposed separation might in fact represent average effects of both crisis and non-crisis times prevailing between 1994 and 2010. Given that some of the determinants potentially have opposite effects on the spreads across regimes, effects could even average out in such a setting.

2.2. Model specification

Our model specification follows Krolzig (1997) who provides an elaborate discussion of the Markov-switching approach to (vector) autoregressive modeling. This methodology has the advantage of accommodating structural breaks or changes across regimes not only in the level of each time series in the multivariate system, but also with respect to the interdependent autoregressive dynamics and, moreover, the covariance structure between the shocks affecting the variables. A k-dimensional M-regime MS-VAR model of lag order p can be specified as

[4] Note that Timmermann (2000) shows that MS models with autoregressive dynamics are more flexible in modeling non-normally distributed data than those without autoregressive terms, since they can generate a greater variety of coefficients of skewness and kurtosis as well as patterns in autocorrelation and volatility dynamics.

$$\boldsymbol{y}_t = \boldsymbol{v}(s_t) + \sum_{i=1}^{p} \boldsymbol{A}_i(s_t)\boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where $\boldsymbol{y}_t$, $\boldsymbol{v}(s_t)$ and $\boldsymbol{\varepsilon}_t$ are $k\times 1$ vectors, the $\boldsymbol{A}_i(s_t)$ are $k\times k$ matrices containing the autoregression coefficients, and $\boldsymbol{\varepsilon}_t \overset{iid}{\sim} N(\mathbf{0}, \Sigma_{\varepsilon}(s_t))$ follows a multivariate normal distribution with zero mean, $t = 1, \ldots, T$. In case $\Sigma_{\varepsilon}(s_t)$ is nondiagonal, it captures simultaneous co-movements between the k variables in $\boldsymbol{y}_t$, whereas the $\boldsymbol{A}_i(s_t)$ may capture lagged dynamic interdependencies between them. $s_t \in \{1, 2, \ldots, M\}$ is a state variable whose unobservable realization is assumed to evolve according to a discrete-time, discrete-state homogeneous first-order Markov process which is irreducible ergodic and defined by the transition probabilities

$$p_{ij} = \Pr(s_{t+1} = j \mid s_t = i), \qquad 0 \leq p_{ij} \leq 1, \qquad \sum_{j=1}^{M} p_{ij} = 1 \qquad \forall i,j \in \{1, 2, \ldots, M\}. \tag{2}$$

These conditional probabilities determine how likely a certain regime i at time t will be followed by (the same or a different) regime j in the next period, and they can be conveniently collected in the transition matrix

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1M} \\ p_{21} & p_{22} & \cdots & p_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ p_{M1} & p_{M2} & \cdots & p_{MM} \end{bmatrix} \tag{3}$$

with the components in each row of the matrix summing to unity. The first-order property of the Markovian regime-generating process implies that all relevant information about its future is contained in its present state. Hence, the probability of a certain regime realization at time period $t+1$ is dependent on the past only through the regime realization in t.[5]

In specification (1) the intercept vector, the autoregressive parameter matrices, and the covariance matrix of the error term vector are all subject to Markov-switching, i.e., they might adopt distinct values according to the regime prevailing at time t. Thus, using the notation of Krolzig (1997) the process can be labeled as an MSIAH-VAR(p) model, with the letter H referring to Markov-switching heteroskedasticity through regime-specific (co)variances. In contrast to a so-

[5] The (first-order) Markov regime-generating process is what differentiates MS-VAR models from the mixture-of-normals models (Clark, 1973; Granger and Orr, 1972; Pearson, 1894) which are characterized by serially independently distributed regimes, i.e., the transition probabilities are independent from the history of the regimes such that they coincide with the unconditional ("ergodic") regime probabilities. Since the transition matrix $\mathbf{P}$ has rank one if $\Pr(s_{t+1} = j \mid s_t = i) = \Pr(s_{t+1} = j \mid s_t = j) = \Pr(s_{t+1} = j)$, $\forall i \neq j$, the mixture-of-normals model can be considered a restricted version of the MS-VAR model. The latter is more advantageous to modeling non-normally distributed financial time series, since mixture-of-normals cannot bring about time-varying conditional variances, and *"the Markovian dependency in the mixture probabilities significantly expands the scope for asymmetry and fat tails that can be generated by time-independent mixture models"* (Timmermann, 2000; p. 100).

called MSMAH-VAR(p) specification in which $\boldsymbol{\mu}_y(s_t)$, i.e., the mean of $\boldsymbol{y}_t$, is subject to regime shifts, the MSIAH-VAR(p) model cannot only accommodate immediate one-time jumps in the process mean, but is also appropriate for modeling gradual dynamic adjustments of $\boldsymbol{y}_t$ after the transition from one regime to the other (Knüppel, 2009; Krolzig, 1997).[6] Thus, its flexibility makes the MSIAH the specification of choice when no prior knowledge about the specific intra- and inter-regime dynamic interdependencies between the variables is available.

3. Data and variables

3.1. Sample

We analyze weekly data constructed as averages over the observations for all trading days on the NYSE within a week during the sample period. We do so in order to try to circumvent that our results may be driven by potential day-of-the-week or weekend effects in the data, which Nippani and Arize (2008) found to be inherent in corporate bond indices. Using weekly data might also mitigate the index rebalancing effects observed at the end of each month, which is due to corporate bond indices being refreshed indices that hold the credit rating as a measure of credit quality constant over time through frequent portfolio rebalancing (Bierens et al., 2005; Duffee, 1998).

Our final sample spans the period from January 2004 until December 2016, covering a total of 679 weekly observations for each time series. We choose our period under review such that it starts in 2004, i.e. shortly after Phase II of the TRACE (Trade Reporting and Compliance Engine) system was implemented by the National Association of Securities Dealers (NASD) in an effort to increase transparency and, in turn, liquidity on the U.S. corporate bond market.[7] Before TRACE, the secondary corporate bond market was a largely intransparent decentralized broker-dealer market (Chacko, 2006; Hong and Warga, 2000; Schultz, 2001). The TRACE transaction reporting led to an increased competition between market makers and a decline in price dispersion for transactions completed in the same bond (Bessembinder et al., 2006; Cici et al., 2011; Edwards et al., 2007). Hence, it will be interesting to see if, for instance, liquidity shocks in today's more transparent corporate debt markets still play the same role for spreads. The evidence in Kalimipalli et al. (2013), for their sample starting in 1994, and Acharya et al. (2013), who study the 1973–2007

[6] The letters 'I' and 'A' in MSIAH stand for Markov-switching in the intercept vector (I) and the autoregressive parameter matrices (A), respectively. The second 'M' in MSMAH denotes that – as opposed to an MSI-AH setup – not the intercept vector, but the mean of $\boldsymbol{y}_t$ is permitted to vary between regimes (Krolzig, 1997; ch. 1.2.2).

[7] The TRACE system allows for the reporting and real-time dissemination of data concerning transactions taking place in the OTC corporate bond market. Regulatory laws established by the Securities and Exchange Commission (SEC) require brokers dealing with specific fixed-income securities to report their transactions. For further details, please refer to the TRACE Fact Book available online at *http://www.finra.org/TRACE*.

period, suggests so; however, both analyses mainly comprise the less transparent and highly illiquid pre-TRACE times.

Additionally, the 2004–2016 period includes spread movements of unprecedented magnitude which occurred during the global financial crisis as well as the sovereign debt crisis in Europe. To the extent that unforeseen crisis times coincide with significantly different spread reactions to changes in market conditions, our analysis based on spread data including the global financial crisis should paint an up-to-date picture of how spread movements differ from their normal values when the market enters a stress regime.

The MS-VAR model used in our analysis of the regime-specific dynamics of aggregate U.S. corporate bond spreads comprises six variables. Besides the spread time series, we include the time series of five important spread determinants that capture various sources of risk premia relevant for corporate bond market investors.

3.2. Variables

3.2.1. Corporate bond spread

Our key variable under review, SPREAD, denotes the option-adjusted spread calculated for the Bank of America Merrill Lynch U.S. High Yield Master II index. Spread data are available in daily frequency through the Federal Reserve Economic Data (FRED) system on the web page of the Federal Reserve Bank of St. Louis. The underlying corporate bond index is designed to track the performance of U.S. dollar-denominated debt that is publicly issued in the domestic corporate cash market and has a rating below investment grade based on an average of Moody's, S&P, and Fitch. The index is actively watched by market participants and based on a database of secondary market prices for a large group of bonds, each of which must have a fixed coupon schedule, at least one year of remaining maturity, and a minimum amount outstanding of USD 100m to be included in the index.[8] The spreads are calculated as the yield differential between the corporate bond index and a spot Treasury curve, corrected for the value of any embedded options as well as coupon and index rebalancing effects. Calculating option-adjusted spreads (OAS) gives us the correct yield differentials, which are not distorted by time variation observed only due to variations in the value of embedded options.[9] This correction is particularly important for our period under review, when the vast majority of corporate debt which constitutes Bank of America Merrill Lynch corporate bond indices was subject to a call provision (Faust et al., 2013; p. 1505).

[8] For further details on the index calculation, see *http://fred.stlouisfed.org/series/BAMLH0A0HYM2* and Bank of America Merrill Lynch's 'Index Rules & Definitions' at *http://www.mlindex.ml.com*.

[9] For details on how the present value of the securities' potential cash flows is evaluated when the securities exhibit embedded options, see the calculation methodologies in Bank of America Merrill Lynch's 'Bond Index Almanac' available at *http://www.mlindex.ml.com*.

3.2.2. Yield curve

With respect to the remaining variables entering y_t, we review the theoretical and empirical evidence in order to define the set of potential determinants that affect – and might, in turn, be affected by – aggregate corporate bond spreads. Duffee (1998), e.g., shows that corporate bond spreads are exposed to the level and the slope of the Treasury yield curve, since both variables capture current as well as expected changes in (risk-free) interest rate levels.[10] According to structural credit risk models, an increase in the short-term risk-free rate should result in a lower spread via an increase in the risk-neutral drift of the firm value process which decreases the default probability (Longstaff and Schwartz, 1995). Similarly, a decrease in the slope may signal the danger of an economic downturn accompanied by a higher default rate and, thus, higher market-wide spread levels (Collin-Dufresne et al., 2001). We proxy the slope of the Treasury yield curve, which is a suitable forward-looking indicator for the state of the economy (Estrella and Hardouvelis, 1991; Estrella and Trubin, 2006), by the difference between the 10-year and the 3-month constant maturity Treasury (CMT) rates provided by the Federal Reserve, and denote this difference by YC_SLOPE.[11] At this, the 10-year CMT rate represents the level of the yield curve (YC_LEVEL). The level is often referred to as the relatively more persistent, long-run component of the yield curve, which is closely related to inflation expectations (e.g. Diebold et al., 2006).

3.2.3. Stock market development

A corporate bond can be viewed as a combination of a default-free bond and a short position in a put option on the value of the firm's stock with a strike price equal to the face value of the bond (Merton, 1974). Thus, just like equities, corporate bond spreads are exposed to movements in the aggregate stock market representing a forward-looking measure of the macroeconomic performance (Campello et al., 2008; Elton et al., 2001; Huang and Kong, 2003). Stock market index returns can also be interpreted as an aggregate gauge of the firms' leverage ratios, since negative returns imply a decreasing value of the firms' assets for a given level of debt. Hence, consistent with structural credit risk models, an increase in the market-wide leverage ratio through negative stock market index returns implies a higher probability of default[12], which should in turn induce a

[10] Interestingly, Ang and Bekaert (2002) find short- and long-term Treasury rates to be characterized by regime-switching behavior, with the regimes reflecting states of the U.S. business cycle. Hence, it makes sense to assume that the two yield curve measures can also exert a regime-dependent influence on the spreads, which the MS-VAR model can detect.

[11] Treasury rate time series were retrieved in daily frequency from the 'H.15 Statistical Release of Selected Interest Rates issued by the Board of Governors of the Federal Reserve System', available at http://www.federalreserve.gov/releases/h15/.

[12] Giesecke et al. (2011) find stock market index returns to be significant predictors for subsequent default rates. The authors also highlight that *"credit risk represents a systematic risk in the macroeconomic environment that is priced in financial markets"* and review relevant research in the field (ibid.: p. 243).

higher spread level. We include log returns of the S&P500 index (STOCK_RET) which we obtain from Thomson Reuters Datastream.

Moreover, structural credit risk models also imply that spreads should increase in stock market volatility, since larger fluctuations in firm value increase the probability of hitting the default barrier. Corroborating the intuition that more extreme spread movements happen during more volatile stock market cycles, Bierens et al. (2005) find the Chicago Board Options Exchange (CBOE) Market Volatility Index –commonly known by its ticker symbol VIX– to be a good indicator of the probability of jumps in the spreads. In addition, Tang and Yan (2010) document implied volatility as the most significant default-risk determinant of corporate bond spreads. Thus, following Campbell and Taksler (2003) and Cremers et al. (2008), among others, we include the VIX in our model setup. The VIX measures the expected market-wide stock return volatility over the next 30 days as conveyed by a range of S&P500 stock index option prices. We obtain the time series of the VIX –which is quoted as an annualized standard deviation given in percentage points– in daily frequency from the CBOE's website.[13]

3.2.4. Market liquidity

Finally, beyond default and market risk, spreads have also been shown to incorporate a significant liquidity premium since the trading frequency of corporate bonds is low as compared to Treasury bonds (e.g. Chen et al., 2007; Dick-Nielsen et al., 2012; Hu et al., 2013). Since we use index-level (instead of bond-specific) spread data, we cannot resort to liquidity measures at the security level, i.e. bid-ask spreads, trade size, or the number of non-trading days. Instead, we utilize a market-wide illiquidity measure in order to capture the systematic illiquidity component in the corporate bond market. Indeed, prior research documents that many bonds become illiquid around the same time, leading to market-wide illiquidity spikes that can be witnessed after shock events such as the bankruptcy of Lehman Brothers (Bao et al., 2011; Bongaerts et al., 2012). We choose the 'noise measure' recently proposed by Hu et al. (2013) to proxy for aggregate illiquidity. This metric depicts pricing errors in U.S. Treasury bonds calculated as the root mean squared distance between their market yields and the yields implied by a smooth estimate of the zero-coupon yield curve. Intuitively, the smaller the observed "noise" in the yields, the larger the amount of arbitrage capital available and, in turn, the higher the provision of liquidity in the market. The key advantage of the noise measure as opposed to previously used aggregate illiquidity measures[14] is that Hu et

[13] See http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index for further details on the methodology.

[14] Previously employed aggregate illiquidity measures for the corporate bond market include the swap spread calculated as the yield differential of the 10-year interest rate swap index over the 10-year Treasury (Collin-Dufresne et al., 2001; Feldhütter and Lando, 2008), the Treasury-Eurodollar (TED) spread, defined as the difference between the 3-month London Interbank Offered Rate (LIBOR) and the 3-month Treasury Bill rate (Campbell and Taksler, 2003; Kalimipalli et al., 2013), and the LIBOR-OIS (overnight index swap) spread, i.e. the difference between the 3-month LIBOR and the OIS rate for the same maturity (e.g. Sengupta and

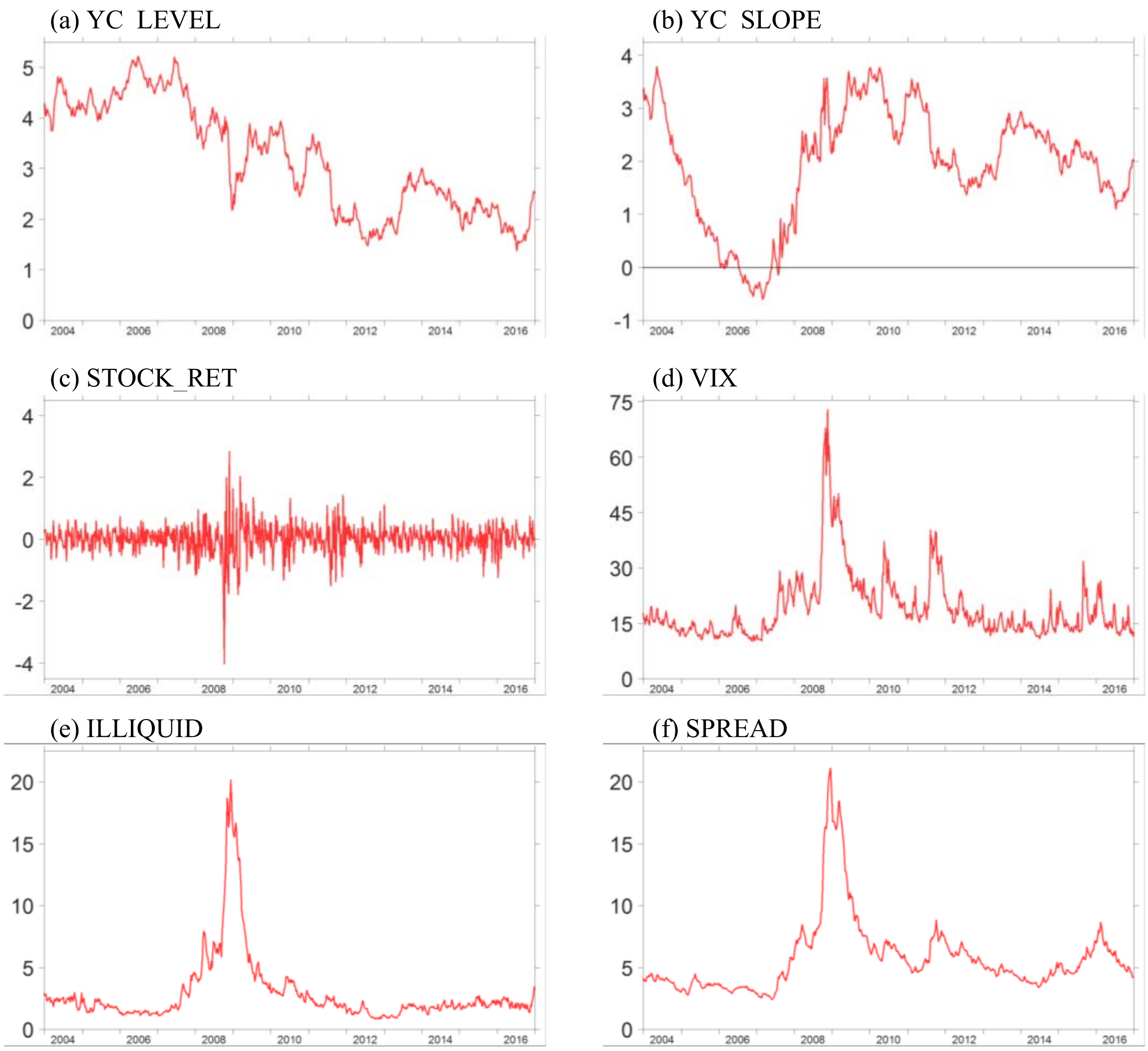
al. (2013) are able to show that – despite originating in the Treasury market – it carries information about general illiquidity conditions on the financial markets, capturing "*liquidity crises of varying origins and magnitudes*" during the 1987–2011 period (p. 2344). Specifically, based on arbitrage capital allocated across different financial market segments, the measure allows for spillovers of liquidity shocks between them and thus addresses general and systematic illiquidity issues. We obtain the noise measure time series from Jun Pan's homepage and denote this final component of the vector $\boldsymbol{y}_t$ in our model as ILLIQUID.[15]

Figure 1 shows the time series of all six variables entering the MS-VAR model for the period under review and will be discussed along with the results of the model estimation in the next section.

Tam, 2008). However, all three market-wide illiquidity measures are closely connected with the interbank lending market, which came close to failure in the global financial crisis. Specifically, Krishnamurthy (2010) shows that the swap spread is biased towards anomalous negative values ever since. Moreover, the interbank market was later involved in the rate-rigging scandal which resulted in distorted LIBOR rates between 2005 and 2009 (e.g. Monticini and Thornton, 2013). Hence, one should be cautious when using any of these aggregate illiquidity measures. In section 5.2, we investigate if our findings are robust to the choice of the illiquidity measure.

[15] See http://www.mit.edu/~junpan/.

Figure 1
Time series of variables used in MS-VAR model



Notes: The graph plots the time series of all six variables used in the MS-VAR system for the 2004-2016 sample period under review as described in section 3.2.

4. Results

4.1. Regime number and lag length specification

We model the dynamics in the vector of the $k = 6$ variables presented in section 3.2 by means of an MS-VAR model with two regimes. The restriction in terms of the number of possible different states M is made in order to obtain a parsimonious model, since the curse of dimensionality already present in a classical (one-regime) linear VAR model is potentiated with each additional Markov-switching regime allowed. For given values of k and p, the flexibility of letting all VAR model parameters be subject to regime-dependent time-variation takes its toll in the number of parameters to be estimated, which grows rapidly in M.[16] Moreover, statistical tests for the number of regimes are problematic since the test statistics do not follow standard distributions. Standard likelihood ratio (LR) test statistics, e.g., are not asymptotically distributed as a χ_2. This is due to conventional regularity conditions being violated because of components in the transition probability matrix which represent nuisance parameters identified only under the alternative, as discussed in Davies (1987), Hansen (1992), and Cho and White (2007). Hence, it is common to specify the number of regimes – typically to two – rather than deciding based on econometric tests. Finally, once we introduce a third regime to our MS-VAR setup, we find that it cannot be clearly distinguished from one of the other two regimes (Regime 1, discussed below). The probability of having observed Regime 3 ex post does not differ much from that of Regime 1, both probabilities are either close to zero or oscillate around 0.5, i.e. do not allow for an unambiguous regime classification. This finding corroborates our choice of only two regimes, which is consistent with the number of regimes set or identified in the majority of other studies (e.g. Davies, 2008; Maalaoui Chun et al., 2014; Pavlova et al., 2015).

With respect to the choice of the lag length p in the two-state MS-VAR model, we rely on the commonly used Hannan-Quinn (HQ) information criterion (Hannan and Quinn, 1979). Following the modification of Chan et al. (2004) AIC criterion for regime-switching autoregressive models proposed by Mittnik and Semmler (2013), we first calculate an overall HQ criterion for the two-state MS-VAR model specified as

$$\mathrm{HQ} = \sum_{i=1}^{2} T_i HQ_i \tag{4}$$

where

$$HQ_i = ln\left|\widehat{\sum}_i\right| + \frac{2clnlnT_i}{T_i}K \quad , \tag{5}$$

with c = 1.1 and $K=pk^2 + k(k+2)/2$. Here, p is the autoregressive order assumed to be the same in both regimes, T_i reflects the number of observations associated with regime i, and $\widehat{\sum}_i$ is the estimated residual covariance matrix of regime i. Second, we also compute the HQ criterion as given above for single-equation two-regime Markov-switching autoregressive (MS-AR) models that are specified for each of the six variables in the MS-VAR system, for which we replace $\widehat{\sum}_i$ in (5) by an unbiased estimate of the regime-specific single equation's residual variance. For all models, we assume lag orders of $p = 0, 2, \dots, 8$ to be possible choices.

[16] We refrain from considering time-varying transition probabilities, which would further increase computational complexity. See, e.g., Durland and McCurdy (1994), Filardo (1994), Filardo and Gordon (1998), and Kim et al. (2008) for approaches in which the elements of **P** are subject to time-variation. However, even with constant transition probabilities, the number of components in **P** to be estimated is already growing quadratically in M.

Table 1
Lag order selection analyses – HQ criteria

p	$\boldsymbol{y}_t$	YC_LEVEL	YC_SLOPE	STOCK_RET	VIX	ILLIQUID	SPREAD
0	6,214.58	-996.92	-692.12	**4,883.27**	1,919.51	-149.30	517.48
1	-6,387.07	-3,283.50	**-3,197.22**	4,885.09	687.11	-1,996.12	-2,368.84
2	**-6,490.97**	**-3,308.75**	-3,182.15	4,886.67	**542.26**	**-2,014.14**	**-2,553.46**
3	-5,543.61	-3,279.94	-3,172.94	4,891.84	706.16	-1,960.13	-2,523.95
4	-5,652.74	-3,266.49	-3,162.87	4,887.72	726.72	-1,954.67	-2,517.00
5	-5,128.23	-3,240.25	-3,127.43	4,897.00	667.38	-1,966.78	-2,496.26
6	-4,637.79	-3,226.01	-3,132.15	4,890.57	691.51	-1,976.69	-2,492.61
7	-4,044.36	-3,233.88	-3,137.68	4,893.31	698.65	-1,980.06	-2,487.85
8	-3,307.14	-3,171.32	-3,125.19	4,961.38	752.99	-1,950.43	-2,471.16

Notes: Column $\boldsymbol{y}_t$ contains the HQ criterion as specified in equations (4) and (5). The remainder of columns contains the HQ criterion evaluated for a reduced version of the vector $\boldsymbol{y}_t$ which contains the respective column variable as the only element. Bold figures denote the minimum value within the respective column. See section 4.1 for a detailed description of measures and methods.

The results for the different lag order selection analyses reported in Table 1 suggest that a lag length of two is appropriate for the MS-VAR model. The estimation of the two-regime MS-VAR(2) model comprising T = 677 observations for each of the six variables as specified in section 3.2 is conducted employing the Expectation-Maximization (EM) algorithm.[17] The statistical properties of the standardized residuals resulting from the estimation support our model specification.

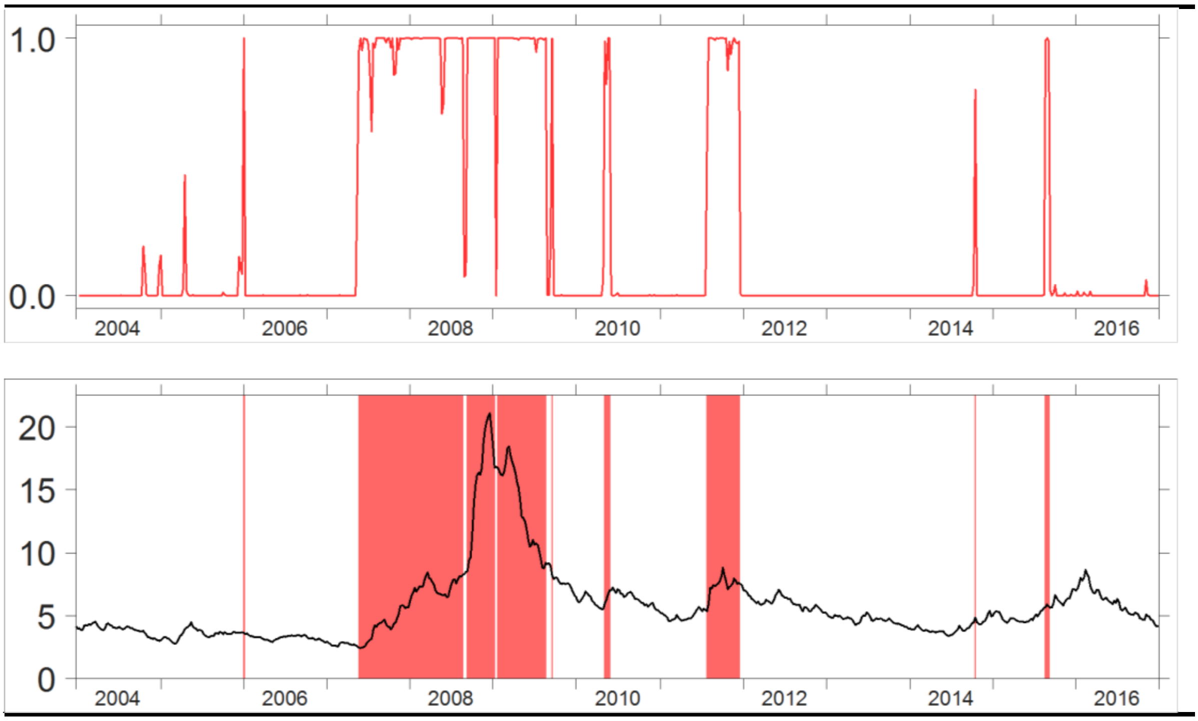
4.2. Analysis and interpretation of identified regimes

In MS models, the identified regimes do not necessarily have an obvious interpretation, but instead are subject to an identification problem (Krolzig, 1997) which stems from the interchangeability of the regime labels and, in turn, the respective linear submodels. Since one can arbitrarily reclassify the unobservable states without changing the law of the process $\boldsymbol{y}_t$, the MS-VAR model is not unambiguously identified. However, following many other studies, we identify one regime (henceforth Regime 1) as the "normal" state. Regime 1 is characterized by relatively low volatility levels as measured by the estimated regime-specific variances of the innovations in all six equations of the VAR model. By contrast, Regime 2 marks the high-volatility or "stress" state since it exhibits larger values on the main diagonal of its regime-specific residual covariance matrix. Additionally, Regime 2 features higher average levels of corporate bond spreads, the VIX, and the illiquidity

[17] The EM algorithm was proposed by Dempster et al. (1977) for situations in which the likelihood is intractable or difficult to deal with due to incomplete or latent data. Its application for MS models was initially suggested by Hamilton (1990, 1989) for simple MS regression models and revised for the more complex case of vector systems with autoregressive dynamics by Krolzig (1997).

measure as compared to Regime 1. The respective values are discussed below.

Figure 2
Underlying regimes in corporate bond index spreads



Notes: The upper graph plots the smoothed probability of being in Regime 2, $\Pr(s_t=2|\boldsymbol{Y}_T)$, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) and using the variables introduced in section 3.2. The bottom graph presents the time series of the corporate bond index spread, with the shaded areas indicating periods when Regime 2 prevails, i.e. the smoothed probability of being in Regime 2 is 0.5 or greater.

Figure 2 plots an estimate of the unobservable regime indicator function s_t obtained in the MS-VAR model estimation, i.e. the smoothed probability of being in Regime 2, $\Pr(s_t = 2|\boldsymbol{Y}_T)$. This probability draws on the information contained in the entire sample of size T used for model estimation, denoted by $\boldsymbol{Y}_T=\{\boldsymbol{y}_\tau\}_{\tau=1}^{T}$, in order to make an inference about the unobserved regimes ex post and, thus, gives the best estimate of the latent state at any point in time within the sample. It is calculated via the Baum-Lindgren-Hamilton-Kim (BLHK) filter and smoother, which is employed in the expectation step in each iteration of the EM algorithm during the ML estimation of the two-state MS-VAR model.[18] Following standard practice, we assume periods of high volatility to be identified by values of 0.5 or greater for $\Pr(s_t = 2|\boldsymbol{Y}_T)$, while the low-volatility regime is assumed to prevail when $\Pr(s_t = 1|\boldsymbol{Y}_T) = 1 - \Pr(s_t = 2|\boldsymbol{Y}_T)$ is greater than 0.5. The resulting distinction of regimes proves

[18] The BLHK filter might be considered a discrete version of the Kalman filter. Its smoothing part makes use of the backward recursions suggested by Kim (1994), which present a major improvement – particularly for VAR specifications – over the computationally demanding algorithm introduced by Hamilton (1990, 1989). The BLHK smoother provides the calculation of the likelihood function as a by-product, which enables ML estimation of the model parameters in the first place; see Krolzig (1997) for details.

clear-cut, as shown by the values of $\Pr(s_t = 1 | \boldsymbol{Y}_T)$ and $\Pr(s_t = 2 | \boldsymbol{Y}_T)$, respectively, which are almost always close to either one or zero.

In support of the results, the regime classification measure (RCM) proposed by Ang and Bekaert (2002) confirms an unambiguous discrimination between the two regimes.[19] Specifically, the RCM value of 2.99 suggests a remarkably conclusive regime distinction, i.e. proving that the MS-VAR model performs very well in discriminating between the regimes based on the time series dynamics.

Regarding the interpretation of the regimes identified, the resulting classification as reported in Figure 2 clearly reflects periods of financial market stress. Among the phases assigned to Regime 2, we identify the start of the global financial crisis in June/July 2007 when the first subprime mortgage defaults became publicly known, as well as spreads skyrocketing triggered by the collapse of Lehman Brothers in September 2008 and subsequently fueled by the money market liquidity crisis. In March 2009, markets were supported by the expansion of the Fed's first Quantitative Easing program ("QE1"). This intervention led to a steady decline in financial stress with markets apparently returning to normal after the third quarter of 2009. However, the beginning of the eurozone debt crisis in April 2010 marked new turmoil which even intensified in the second half of 2011 due to (i) worries about the resilience of the eurozone banking system, (ii) Standard & Poor's downgrading U.S. Treasury bonds from their AAA status, and (iii) growing fears of another U.S. recession. The high-volatility regime phases inferred by the MS-VAR model indeed capture all of these periods of actual turbulences in financial markets. Since we cannot think of severe historical crisis periods mistakenly assigned to the low-volatility regime, we will henceforth refer to Regime 2 as the stress regime.[20]

Further inquiry into the behavior of the six time series in $\boldsymbol{y}_t$ during the stress regimes reveals that all of them exhibit a pronounced volatility and/or considerable level shifts. Naturally, however, not all variables behave the same during all stress regimes. For instance, Figure 1 reveals that the increase in values of the illiquidity measure in the second half of 2011 does not coincide with any

[19] This metric uses the smoothed regime probabilities and is defined as

$$\mathrm{RCM} = \frac{400}{T} \sum_{t=1}^{T} \Pr(s_t = 1 \mid \boldsymbol{Y}_T) \Pr(s_t = 2 \mid \boldsymbol{Y}_T)$$

for a two-regime model. The standardization leads to an RCM value of 100 for the worst classification possible, when each of the two regimes has a probability of 0.5 at each point t in the sample, whereas a value of zero indicates a perfect regime separation, i.e., in each period t, the two regime probabilities equal one and zero, respectively.

[20] Note that, at first glance, the switch to the high-volatility regime in the first week of January 2006 appears to be an assignment mistake. However, as shown in Figure 1(b), it corresponds to a dramatic drop in the yield curve slope (leading to an inverted yield curve shortly afterwards) and rapid declines or surges in either slope or level of the yield curve prove typical for the crisis periods during our period under review. Reasons for this relation likely include the monetary policy interventions by the Federal Open Market Committee (i.e. QE1-QE3 or the maturity extension program "Operation Twist"), which all had significant effects on longer-term market interest rates, see, e.g., Gilchrist and Zakrajšek (2013), or flight-to-quality effects as many investors rebalanced their portfolios away from risky assets towards safe haven securities.

extraordinary spread development. Similarly, all variables except for the yield curve slope do not look significantly different in January 2006 as compared to their dynamics in the months prior to and after that period. Thus, the VAR approach to sorting the regime switches seems able to detect an overall picture of the relevant crisis regimes most likely unattainable via single-equation spread modeling.

4.3. Comparison of regime-specific dynamic systems

4.3.1. MS model parameters

In this section, we will have a closer look at the ML estimates of the parameters of our MS-VAR model. Table 2 presents the estimates for the Markov chain parameters, which correspond to the regime classification discussed in section 4.2.

Table 2
Results of the ML estimation: log-likelihood values and Markov chain parameters

max. $\ln L(\boldsymbol{\theta}\vert \boldsymbol{Y}_T)$	
linear VAR(2)	-8,207.80
2-regime MS-VAR(2)	988.38
LR	18,392.36
$p(LR)_{Davies}$	0.00
transition probabilities	
p_{11}	0.97
p_{22}	0.91
expected durations	
d_1	39.93
d_2	10.69
ergodic regime probabilities	
π_1	0.79
π_2	0.21

Notes: This table reports the maximum log-likelihood function value for the 2-regime MS-VAR(2) model in equation (1) and a simple linear (single-regime) VAR(2) model when employed for modeling the 6-variate vector $\boldsymbol{y}_t$ as specified in section 3.2, respectively. LR=2($\ln L(\boldsymbol{\theta_1}/\boldsymbol{Y}_T)$- $\ln L(\boldsymbol{\theta_0}/\boldsymbol{Y}_T)$) is the likelihood ratio statistic for the test of the null hypothesis that the maximum log-likelihood function value of the 2-regime MS-VAR(2) model is significantly larger than that of its single-regime counterpart, with $\boldsymbol{\theta_0}$ ($\boldsymbol{\theta_1}$) denoting the set of parameters of the model under the null (alternative) hypothesis. An estimate for the significance level of the LR test statistic as obtained from Davies (1987) upper bound test is denoted by $p(LR)_{Davies}$, with $\Pr\left(\chi^2_q > LR\right) + 2\left(\frac{LR}{2}\right)^{q/2} \exp\left(-\frac{LR}{2}\right)/\Gamma(q/2)$, where $\Gamma(\cdot)$ is the standard gamma function. The transition probabilities p_{11} and p_{22} reported are estimates for the elements on the main diagonal of **P** as defined in (3). Estimates for the expected duration of regime 1 and 2 are given by $d_1=1/p_{12}=1/(1-p_{11})$ and $d_2=1/p_{21}=1/(1-p_{22})$. π_1 and π_2 denote estimates for the ergodic regime probabilities in (6).

Based on the smoothed regime probabilities filtered by the EM algorithm, estimates for the transition probabilities in **P** can be derived. They show that both regimes are very persistent, with probabilities of staying in the respective regime, p_{11} and p_{22}, of close to one. However, the probability of shifting from the high-volatility to the low-volatility regime (p_{21}=1-p_{22}=0.09) appears to be three times as large as the probability that a shift from the low-volatility to the high-volatility regime will occur (p_{12}=1-p_{11}=0.03). This indicates that the low-volatility Regime 1 is more persistent than Regime 2, which translates to a relatively higher expected duration calculated as the reciprocal of the probability of leaving the regime, i.e., $d_1=1/p_{12}$. The expected duration of a continuous period of high volatility is about 11 weeks, whereas a less volatile normal market phase is estimated to last 40 weeks on average. With the transition probabilities on hand, one can also calculate the unconditional probabilities that the process is in one of the two regimes, which are given by

$$\pi_1=\Pr(s_t=1)=\frac{1-p_{22}}{2-p_{11}-p_{22}} \qquad \text{and} \qquad \pi_2=\Pr(s_t=2)=\frac{1-p_{11}}{2-p_{11}-p_{22}} \quad . \tag{6}$$

Since these probabilities define the stationary or unconditional probability distribution of the regimes, they are also referred to as *ergodic*, *long-run*, or *steady-state* probabilities. Here, roughly four in five weekly observations are supposed to belong to the low-volatility regime in the long run, while the high-volatility regime is likely to be observed less frequently. Finally, the maximized log-likelihood function value of the two-regime MS-VAR(2) model is considerably higher than that of a classical linear VAR(2) model. This difference in the two goodness-of-fit measures supports our choice of the two-state MS model, since the nonlinear specification features a much better fit. Testing the null hypothesis of one regime against the alternative of two regimes by means of a likelihood ratio (*LR)* is somehow problematic since the asymptotic distribution of the test statistic is nonstandard. However, the value of the common test statistic is substantially larger than any conservative choice of a critical value for all conventional confidence levels, i.e. the null of only one regime is comfortably rejected.[21] Moreover, the estimate $p(LR)_{Davies}$ obtained from Davies (1987) upper bound test for the significance level of the *LR* test statistic, which accounts for the nuisance parameters under the alternative, corroborates our test decision.[22] Consequently, we note that the MS-VAR model provides a significantly better fit than the linear VAR specification.

4.3.2. Regime-specific moments

[21] The value of the respective test statistic is computed as

$$LR=2(\ \ln L(\boldsymbol{\theta_1}/\boldsymbol{Y_T})-\ln L(\boldsymbol{\theta_0}/\boldsymbol{Y_T})\ ),$$

where $\boldsymbol{\theta_0}$ ($\boldsymbol{\theta_1}$) denotes the set of parameters of the model under the null (alternative) hypothesis.

[22] Davies (1987) shows that for a single-peaked likelihood function, a valid estimate of the upper bound for the significance level of the standard *LR* test statistic is given by

$$\Pr\left(\chi^2_q > LR\right)+2\left(\frac{LR}{2}\right)^{q/2} exp\left(-\frac{LR}{2}\right)/\Gamma(q/2)$$

where $\Gamma(\cdot)$ is the standard gamma function.

We continue by analyzing the regime-specific differences of the spreads and their five potential determinants in more detail. To this end, Table 3 reports estimates for the regime-specific unconditional means and variances of all six variables of the MS vector process. It also shows the estimated error term variance for each variable's equation in the VAR, again for both the low-volatility Regime 1 and the high-volatility Regime 2.[23]

Table 3
Results of the ML estimation: regime-specific moments

	YC_LEVEL	YC_SLOPE	STOCK_RET	VIX	ILLIQUID	SPREAD
uncond. means						
$\boldsymbol{\mu}_y(s_t=1)'$	3.116	1.929	5.042	16.070	2.041	4.902
$\boldsymbol{\mu}_y(s_t=2)'$	3.495	2.018	-8.087	30.488	6.064	8.904
uncond. variances						
$diag(\boldsymbol{\Sigma}_y(s_t=1))'$	1.218	1.191	1,182.520	17.981	0.865	2.547
$diag(\boldsymbol{\Sigma}_y(s_t=2))'$	0.794	1.081	7,188.987	152.185	22.843	22.087
$diag(\boldsymbol{\Sigma}_\varepsilon(s_t=1))'$	0.006	0.006	0.113	2.368	0.097	0.018
$diag(\boldsymbol{\Sigma}_\varepsilon(s_t=2))'$	0.018	0.041	0.653	15.156	0.181	0.133

Notes: This table reports estimates for the vectors of regime-specific unconditional means $\boldsymbol{\mu}_y(s_t=1)$ and $\boldsymbol{\mu}_y(s_t=2)$ and variances diag($\boldsymbol{\Sigma}_y(s_t=1)$) and diag($\boldsymbol{\Sigma}_y(s_t=2)$) pertaining to the 6-variate vector $\boldsymbol{y}_t$ as specified in section 3.2. They are computed using the regime-specific ML estimates of the matrices $\boldsymbol{A}_i(s_t)$ and $\sum_\varepsilon(s_t)$, the main diagonal elements of the latter being collected in the column vectors $diag(\boldsymbol{\Sigma}_\varepsilon(s_t=1))$ and $diag(\boldsymbol{\Sigma}_\varepsilon(s_t=2))$, while resorting to the appropriate formulas for the respective moments of VAR processes given in Lütkepohl (2005).

Regime-specific differences in moments of the two yield curve measures reveal interesting features: after a switch to Regime 2, mean values of both measures do not change dramatically. As indicated by the differing values of their respective error term variances, both YC_LEVEL and YC_SLOPE are affected by more volatile shocks during Regime 2 as compared to Regime 1. However, the autoregressive dynamics of the vector process as defined by the matrices $\boldsymbol{A}_i(s_t)$ can differ between the regimes and they determine the propagation of all shocks within the VAR system, i.e. the intensity and persistence of the impact of the shocks on the variable itself as well as on all other parameters while a particular regime prevails. Here, the relatively more volatile shocks which directly hit the two yield curve variables during the crisis regime eventually seem to be outweighed by shocks in the other variables that exert a weaker influence on the yield curve than during the normal

[23] The estimates for the error term variances lie on the principal diagonal of each regime's estimated error term covariance matrix $\hat{\sum}_\varepsilon(s_t)$. The within-state unconditional means and variances are computed using the regime-specific ML estimates of the matrices $\boldsymbol{A}_i(s_t)$ and $\sum_\varepsilon(s_t)$ while resorting to the appropriate formulas for the respective moments of VAR processes given in Lütkepohl (2005).

regime. Thus, the overall fluctuations in YC_LEVEL and YC_SLOPE are less pronounced in crisis times, as revealed by their regime-specific variance estimates. Arguably, these results may at least partly be attributed to the unconventional monetary policy interventions during the global financial crisis. Specifically, short-term and long-term Treasury rates marked all-time lows after cuts in the federal funds target rate which let effective short-term rates range just slightly above the zero lower bound from December 2008 until December 2015.

For the other four variables in $\boldsymbol{y}_t$, the differences across regimes are more straightforward. The stock market is characterized by a slightly positive (negative) mean return during normal times (periods of financial market stress). By contrast, Figure 1 documents that the means of VIX and SPREAD almost double during high-volatility regimes. Moreover, consistent with evidence of a liquidity squeeze in the corporate bond market (Bao et al., 2011; Dick-Nielsen et al., 2012), the average level of ILLIQUID nearly triples as compared to the normal state. Turning to the fluctuations, we find that, whenever a regime switch is accompanied by an increase in the variance of the innovations to a particular variable's equation, this directly translates into an increase in the variance of the respective variable. Apparently, the regimes exhibit substantially different stock return variances, which is consistent with the increase in stock market volatility as commonly observed in crisis periods.[24] Finally, the variances of VIX and SPREAD jump to almost the ninefold average of their pre-crisis values, while variation of the illiquidity measure even soars by more than 2,500 %.

4.4. Impulse response functions

4.4.1. General considerations

After having analyzed the time-varying means and variances of all six variables, we are now interested in the extent to which the dynamics of the VAR system differ between the two regimes. Regime-specific differences in both the simultaneous and the lagged interdependencies between all six variables are collectively determined by the within-regime estimates of the matrices $\boldsymbol{A}_i(s_t)$ and the off-diagonal elements in $\sum_\varepsilon(s_t)$. In order to provide an overall picture of the combined effect of these estimated VAR parameters on the behavior of each variable in a certain regime, we follow the standard practice in the VAR literature and conduct impulse-response analyses allowing us to visualize the simultaneous and lagged impact of shocks hitting the variables in the system on corporate bond index spreads.

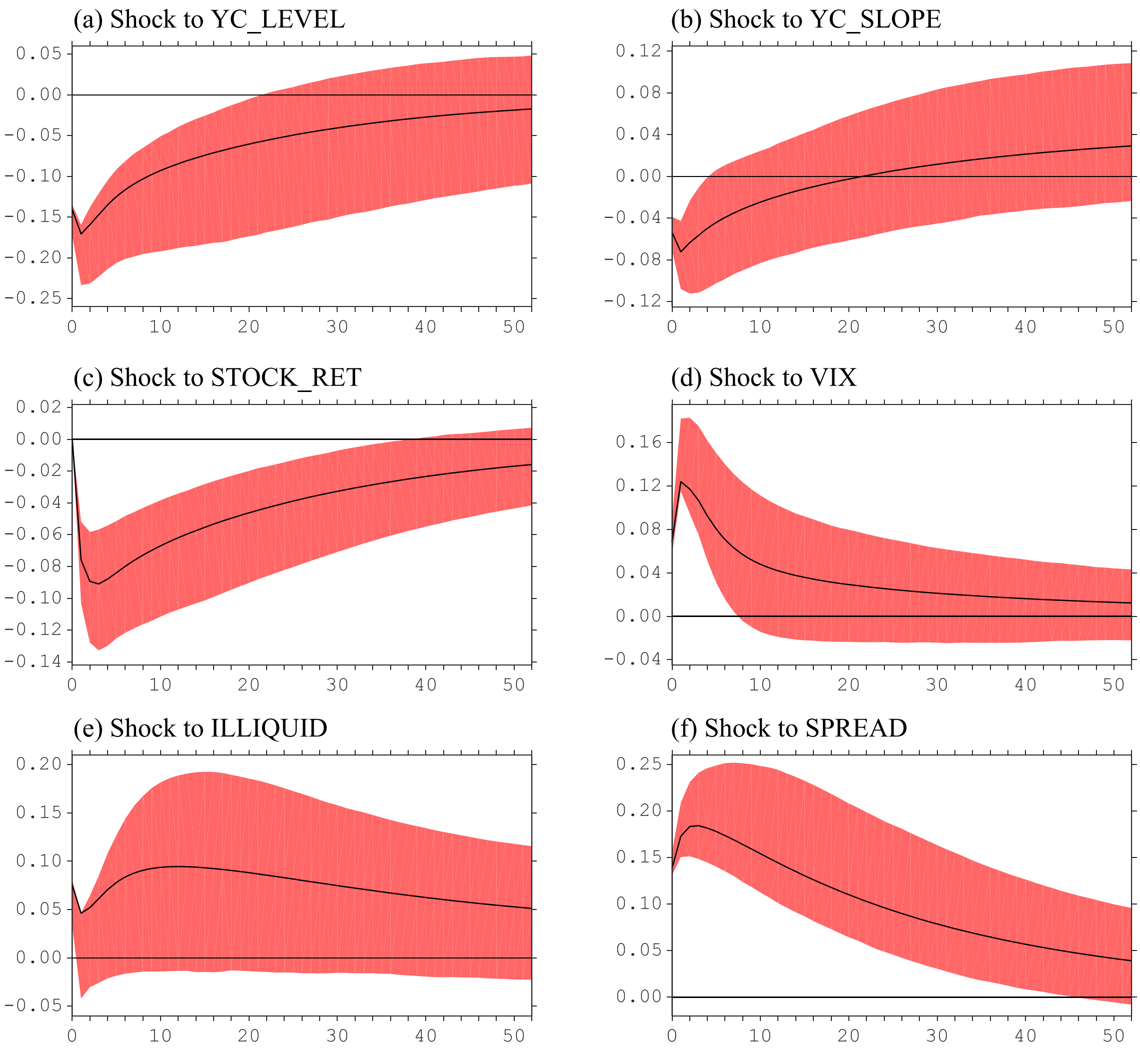
In the vein of Tillmann (2004), Kanas and Kouretas (2007) and Mittnik and Semmler (2013), we calculate regime-dependent impulse response functions (IRFs) employing the methodology suggested in

[24] The regime-specific variances identified here correspond to an annualized volatility of 13.63 % (29.55 %) for the broad U.S. stock market return during the low-volatility (high-volatility) regime.

Krolzig et al. (2002) and Ehrmann et al. (2003). In fact, regime-dependent IRFs permit a straightforward analysis of potential asymmetries in the responses between different regimes. To show how fundamental shocks impact the model's variables conditional on a given regime, traditional linear responses are calculated separately for each distinct regime based on the parameter estimates for the respective regime-specific linear VAR. Since these types of responses are based on the assumption that the process remains within a given regime during the horizon of the response, the responses in the low-volatility regime, for instance, are representative for normal market phases so long as the shocks are small enough not to trigger a transition to the high-volatility regime. That is why these within-regime IRFs can be considered *"a study of the local dynamic behavior"* of the MS-VAR system (Mittnik and Semmler, 2013; p. 1488). Provided that the expected duration of a certain regime does not differ markedly from the response horizon, this regime conditioning is not only valid for presenting the short-term effects, but also gives a meaningful picture of the differing VAR dynamics and correlations over time.[25]

[25] Alternatively, one could calculate generalized impulse response functions (GIRFs), in which the responses are history-dependent, i.e. conditional on past realizations of the states and the shocks, as well as dependent on the sign and the size of the shock considered; see Koop et al. (1996) for details. However, GIRFs are less helpful in understanding the differences between the regimes regarding the variables' dynamic interactions.

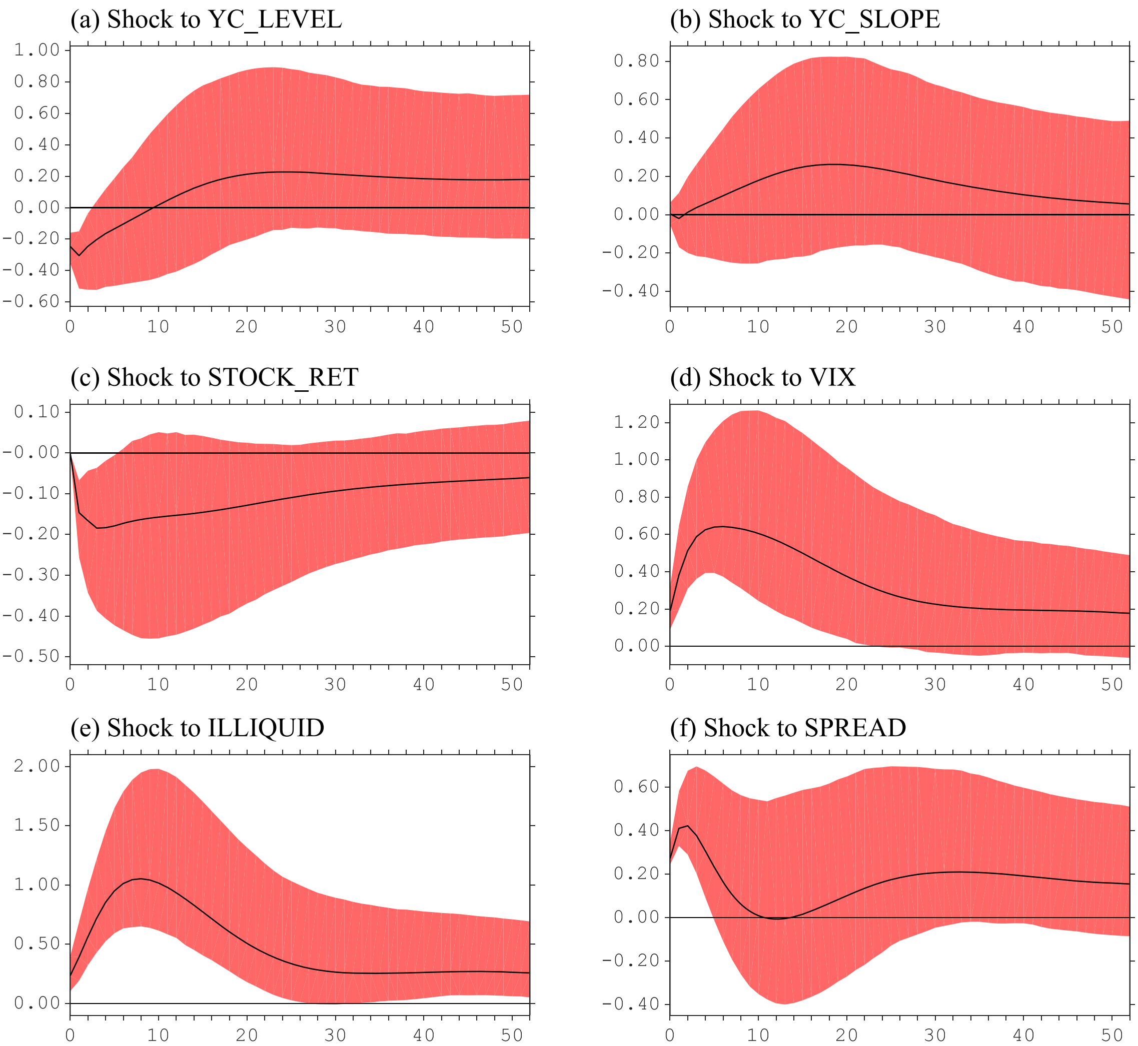
Figure 3a
Impulse of corporate bond spread to shocks during (low-volatility) Regime 1



Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 1, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET is imposed. The shaded areas indicate the respective 99% bootstrap confidence interval calculated following Hall (1992).

Figure 3a (Figure 3b) plots IRFs of the corporate bond spreads to shocks in all their determinants occurring while Regime 1 (Regime 2) prevails. All regime-dependent IRFs are calculated assuming a shock to the variable under review in the amount of one regime-specific standard deviation of the corresponding residual. The shaded areas indicate the 99 % bootstrap confidence intervals which were calculated following Hall (1992) percentile interval method using 10,000 replications.

Figure 3b
Impulse of corporate bond spread to shocks during (high-volatility) Regime 2



Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 2, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET is imposed. The shaded areas indicate the respective 99% bootstrap confidence interval calculated following Hall (1992).

The structural innovations are identified using a triangular Cholesky factorization of the regime-specific covariance matrix of the residuals, for which we impose the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET. The ordering can be justified by the notion that the equity market and the actively traded part of the corporate bond market incorporate new information comparably fast, while market liquidity only responds to shocks as well as fund flows between the various asset markets with a lag. Note, however, that our results obtained from the IRFs are qualitatively robust to alternative orderings.[26] To preview the detailed results below, the regime-dependent IRFs confirm our expectations that the five economic and financial determinants have significantly different impacts on corporate bond spreads in high- versus low-volatility regimes.

4.4.2. Impact of shocks to level and slope of the yield curve

Regarding the influence of the yield curve, we observe a negative relation between the level of the risk-free rate and the spread during low volatile markets, which is consistent with the theoretical predictions of Merton (1974) and the empirical evidence in Longstaff and Schwartz (1995) and Duffee (1998). A shock to the risk-free rate of about 8 bps leads to an instantaneous drop in the spread by about 14 bps, with the maximum impact (in absolute terms) of about 17 bps attained after one week. Moreover, the effect is remarkably persistent and only becomes insignificant after roughly five months.

On the contrary, the impact of an initial interest rate shock turns out higher in magnitude (albeit short-lived) during phases of high volatility. When a tense corporate bond market is hit by a sudden jump in the long-term Treasury yield of about 13 bps, the spread decreases by about 25 bps within the same week and reaches its low in the subsequent week at a level 31 bps below its pre-shock value. However, the influence of the shock has vanished after two weeks already. This points to a short-term market overreaction, while there is no significant long-run impact of unexpected interest rate movements on spreads during tense market phases – most likely because of other factors that come to the fore.[27]

Moreover, we find a significant spread response for shocks to the slope of the yield curve during the low-volatility regime. Specifically, following an unexpected 8 bps increase in the yield curve slope, the spread decreases by about 5 bps and reaches its low at around 7 bps within the first week subsequent to the shock. By contrast, we do not observe a significant spread reaction to a shock to YC_SLOPE during Regime 2. Note, however, that the Fed's zero-nominal-rate policy resulted in short-term Treasury rates being virtually zero from end-2008 to end-2015. Hence, the short end of the yield curve (which typically accounts for most of the variation in its slope) features virtually no variation for more than half of our sample period.

4.4.3. Impact of shocks to the stock market

[26] Following the suggestion of an anonymous referee, we investigate whether our results are robust to the exact position of the illiquidity factor within the causal ordering. Figures A1a and A1b in the appendix plot IRFs resulting from an alternative causal ordering in which the illiquidity factor is the most endogenous of all six variables. The evidence obtained from this specification is largely similar to the main results presented in Figures 3a and 3b, i.e. corroborating the robustness of our results with respect to the specific causal ordering employed.

[27] In their analysis of European CDS indices, Alexander and Kaeck (2008) find CDS spreads to be significantly affected by interest rate movements only during low-volatility regimes, too.

When an increase in the aggregate stock market return takes corporate bond investors by surprise, their aggregate reaction also depends on the regime the market is in. When spreads are low (and daily stock market returns are little volatile and on average positive), a better-than-expected stock index level is not heavily traded upon. Specifically, an increase in the daily mean index return – calculated over one business week – of about 34 bps leads to only a modest reduction of the spread by about 9 bps. When excitement and nervousness dominate markets, on the other hand, a sudden stock market upswing of about 81 bps decreases market tension, which may be interpreted as an increase in the attractiveness of corporate bonds relative to Treasuries such that the spread level drops by as much as 18 bps. This effect also appears to be somewhat less transient, since the convergence of the IRF to zero not so much resembles an exponential decay as it does in the normal regime. While qualitatively unchanged, reactions carry reversed signs once we compare the two state-dependent spread responses triggered by innovations in the option-implied expected equity market volatility. In line with expectations, an unanticipated increase in the VIX by an annualized 1.5 percentage points lets corporate bond investors demand a higher premium during calm market phases. As a result, the spread shows a simultaneous increase of roughly 7 bps, with a peak in the IRF of about 12 bps one week after the shock. The subsequent decline in the spread response indicates that the bad news has been entirely processed by the market after roughly eight weeks already, when the increase in the spread is no longer significant. In times of economic and financial stress, a shock to the VIX exerts a relatively higher influence on the corporate bond market. Specifically, a jump in the VIX by 3.9 percentage points causes the spread to increase by as much as 64 bps. This maximum impact is reached after about five to seven weeks past the shock and subsequently washes out. Thus, the disproportionately high and persistent spread expansion during bearish as opposed to bullish markets provides additional evidence of nonlinearities in the spread behavior over time.

4.4.4. Impact of market-wide liquidity shocks

Regarding the exposure of corporate bonds to illiquidity shocks, our results suggest that a substantial fraction of the observed increase in spreads during crisis times can be ascribed to a liquidity premium. Graph (e) of Figure 3b shows that the spread exhibits a substantial increase which peaks at more than 100 bps in response to a decline of liquidity. Even one year after the shock, the spread is still roughly 25 bps above its pre-shock level. By contrast, graph (e) of Figure 3a shows that illiquidity shocks do not appear to have any significant impact on spreads under normal market conditions. These interesting regime-specific differences provide further evidence for an asymmetric spread reaction conditional on the extent of market anxiety.

With respect to both magnitude and persistence, the spread response to an aggregate illiquidity shock displayed in Figure 3b turns out to be the most pronounced of all responses and thus suggests that shocks to liquidity provision accounted in large part for the unprecedented spread levels observed during the global financial crisis, i.e. that the global financial crisis can be classified a liquidity crisis to a large extent, which corroborates the findings of Bao et al. (2011). Moreover, following Wang and Wu (2015), the marked spread reaction may be interpreted as evidence of a flight-to-liquidity effect, i.e., investors divest corporate bonds in exchange for comparatively more liquid U.S. Treasuries.

Our findings are consistent with the results of Acharya et al. (2013) who document mostly insignificant effects of liquidity shocks on corporate bond prices during low-volatile markets as identified by their MS model over the 1973–2007 period. At the same time, however, the authors show that, in stress regimes, prices of speculative-grade bonds are strongly negatively affected by deteriorating liquidity. Specifically, their static model predicts that the magnitude of the impact of liquidity risk on bond returns roughly doubles in crisis periods. Based on a more recent sample including the global financial crisis, we extend this evidence and find a much more pronounced difference in the regime-dependent relevance of liquidity risk. For a given shock to the illiquidity measure, our MS-VAR model exhibits a rise in the spread level during high-volatility periods which amounts to more than eightfold the increase predicted for low-volatility periods. Moreover, our dynamic modeling approach for the first time allows for an investigation of the spread response as time elapses. Interestingly, we find that it gradually intensifies and reaches its maximum about two months after the shock. At this, our findings partly corroborate the evidence in Kalimipalli et al. (2013), who also find that (i) illiquidity matters predominantly in high-volatility regimes and (ii) that it has about fourfold the impact on spreads when their sample includes the global financial crisis. However, the linear VAR models of Kalimipalli et al. (2013) indicate that the (non-regime-specific) effect of illiquidity shocks on spreads is only very short-lived. According to their results, the market quickly recovers from an unexpected liquidity squeeze, typically within one month, and this short-term effect is independent of whether or not the sample includes the global financial crisis. By contrast, we document that a shock to market liquidity has a distinct long-term impact on spreads if it hits the market during a high-volatility regime.

4.4.5. Regime-specific persistence in aggregate corporate bond spread levels

Finally, the spread response to shocks hitting its own equation also reveals regime-specific differences. The reaction during Regime 1 exhibits a spread increase of about 18 bps, which gradually declines until it is no longer significant after roughly eleven months. Compared to that, the spread jump during Regime 2 is larger in magnitude, though less persistent. The spread's recovery from the shock follows a rather unsteady, somewhat oscillating downward trend towards the pre-shock level. Even after one year, the shock seems to disarrange the system it is still stuck in, yet the repercussions do not appear statistically significant. This asymmetric spread behavior across regimes indicates different degrees of mean reversion, i.e., the spreads appear highly serially correlated in the stress regime – potentially close to containing a unit root – while much less so in the normal regime.[28] Together with level jumps and changing volatility at regime switches, the regime-specific persistence hence represents yet another cause for the nonlinear spread behavior.

5. Robustness analysis

5.1. Sample extension

As a first check with respect to the robustness of our main findings, we extend our sample period to investigate if the relations between the credit spreads and their determinants, as estimated in the MS-VAR model over the 2004-2016 period, are robust to the inclusion of more than one business cycle during the period under review, or – alternatively – if they are specific to the global financial crisis.[29]

Figure A2 in the appendix reports the corresponding results for the regime classification using the extended sample covering the 1997-2016 period. The resulting regimes in the latter years of the sample clearly resemble those identified in the baseline specification using the 2004-2016 sample as exhibited in Figure 2. The model estimation based on the extended sample now also assigns several phases during the 1997-2003 period to Regime 2. The regime classification, however, is less clear-cut, as is evident from a RCM of 9.57.[30] Moreover, the early realizations of both regimes turn out to be relatively short-lived, which yields an expected duration of Regime 2 (Regime 1) of about 4.2 weeks (13.6 weeks) for the full 1997-2016 sample. The somewhat inconclusive results obtained for the early years might be attributed to several crises coinciding with the 2001 recession, e.g. the 1997 Asian Financial Crisis, the 1998 Russian Financial Crisis, and the September 11 attacks.[31] Alternatively, they could very likely owe to the inferior quality of data on the US corporate bond market prior to the launch of the TRACE system.

Figures A3a and A3b in the appendix report the IRFs regarding the regime-specific spread responses to shocks in all variables modelled in the MS-VAR system. While qualitatively unchanged, the negative spread reaction following a shock the level of the risk-free rate now turns out slightly smaller in magnitude during low volatile markets when extending the period under review. Likewise, in periods of high volatility, the effect of an interest rate shock is again higher in magnitude and appears rather short-lived.

Other than for the baseline sample period, the spread now shows a significant positive reaction following a shock to the slope of the yield curve, i.e. consistent with the empirical findings of Morris

[28] The nonlinearities induced by the regime-dependency of the mean reversion as well as the change in means and variances through regime switching may lead to traditional unit root tests – which do not account for nonlinearities and are thus misspecified in this setting – not rejecting the null of nonstationarity even though the overall data-generating process underlying the spreads is globally stationary.

[29] We thank an anonymous referee for raising this relevant question.

[30] Note that the RCM decreases to 2.64 when computed for the 2004-2016 subperiod instead of the full 1997-2016 sample.

[31] See the recession periods as identified by the NBER available at http://www.nber.org/cycles.html.

et al. (1998).[32] Yet, note that the positive spread response is only small in magnitude. At the same time, the spread reaction to a shock to YC_SLOPE during Regime 2 now turns out significant during the three months after the shock but otherwise proves largely similar for the extended sample period.

Moreover, spread responses to shocks to both the aggregate stock market return and the VIX are virtually unchanged when including the years 1997 to 2004 in the sample period. Corroborating our evidence of nonlinearities in the spread behaviour obtained from the main specification, reactions are even more persistent for the extended period under review.

Similarly, we observe regime-specific differences regarding the exposure of corporate bond returns to liquidity shocks for the extended period under review, too. Specifically, spreads increase substantially in response to a decline of liquidity in times of crisis, while they are not significantly influenced by liquidity shocks during low-volatility markets.

Finally, we also document regime-specific persistence in aggregate corporate bond spread levels, with the spread reactions for the different regimes being largely similar to the baseline specification.

5.2. Alternative illiquidity measures

Recall that we use the noise measure introduced by Hu et al. (2013) to proxy for the liquidity factor. However, the Hu et al. (2013) metric might be affected by the measurement error in the function smoothing the zero-coupon yield curve.[33] Thus, as a second robustness check, we apply the MS-VAR model using alternative measures of illiquidity.

To this end, we first use the TED spread, i.e. the 3-month LIBOR less the 3-month CMT rate, as an alternative illiquidity proxy. Second, we substitute the noise measure by the 3-month USD LIBOR-OIS spread. Figure A4 in the appendix plots the noise measure as well as the two alternative illiquidity measures.[34] While sharing a common trend in levels, the three measures still exhibit distinct differences. For instance, the TED spread (LIBOR-OIS spread) shows pronounced spikes in 2005/2006 (2004) already, when the noise measure does not feature any significant peaks. The noise measure, in turn, shows the relatively strongest persistence during the global financial crisis, while the other two proxies rebound to pre-crisis levels rather quickly by the end of 2008.

Figure A5 (Figure A6) in the appendix exhibits the regime classification resulting from estimating the MS-VAR model with the TED spread (LIBOR-OIS spread) as illiquidity proxy. The results obtained for the two alternative illiquidity proxies are qualitatively similar to the original

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[32] At this, the observed positive relationship can be attributed to the role of the long-term interest rate in discounting future cash flows. The underlying rationale is that a rise in the long-term interest rate reduces the universe of investments with a positive net present value available to a company. This restricts the company's growth perspectives, curbs its valuation and thereby ultimately reduces its creditworthiness.

[33] We thank an anonymous referee for drawing our attention to this issue.

[34] Time series of the TED spread and the LIBOR-OIS spread were obtained from Thomson Reuters Datastream.

regime classification provided in Figure 2. While using the noise measure yields a slightly less ambiguous identification of Regime 2 during the global financial crisis and in the second half of 2011, the two alternative measures indicate a few more high-volatility regimes in 2004 and 2006 already. Note that RCM values decrease to 2.04 and 2.18 when applying the TED spread and the LIBOR-OIS spread, respectively.

Figure A7a and Figure A7b (Figure A8a and Figure A8b) in the appendix plot the regime-specific IRFs observed when using the TED spread (LIBOR-OIS spread) as a measure of illiquidity. As can be inferred from the graphs, the respective spread reactions to shocks in the MS-VAR system's equations are qualitatively very similar to the ones obtained in the baseline specification plotted in Figure 3a and Figure 3b. The lack of significance in spread responses to a shock to the VIX and the impact of shocks to the slope of the yield curve during the low-volatility regime, which now turns out positive again, mark the only notable exceptions to this pattern. Moreover, regardless of the alternative illiquidity proxy under review, regime-specific spread reactions to shocks to aggregate liquidity are largely comparable to the default setting, albeit slightly less pronounced in magnitude and characterized by a somewhat faster rebound to pre-shock levels if we use the LIBOR-OIS spread as a substitute for the noise measure.

5.3. Alternative measure of default risk

Finally, while the literature supports our choice of VIX and stock market development as proxies for aggregate default risk (e.g. Giesecke et al., 2011), we investigate if our main findings are robust to the choice of the default risk measure. In particular, we substitute the VIX by Fitch Ratings' 1-Year-Ahead Probability of Default (PD) Index for North America.[35] Pooling individual PDs of corporate debt issuers, this index generates an aggregate forecast of credit quality, i.e., it reflects systematic rather than firm-specific credit risk.[36] Figure A9 in the appendix plots the PD index against the corporate bond index spread.

As shown in Figure A10 in the appendix, the regime classification obtained when employing the PD index is very similar to the baseline specification reported in Figure 2. The global financial crisis still stands out prominently. Moreover, while the crisis regime at the end of 2011 is now somewhat less pronounced, we observe stronger support of a high-volatility regime in 2015/2016. Note that, at 2.92, the RCM is close to the one for the baseline model reported in section 4.2, too.

A comparison of the regime-specific IRFs given in Figures A11a and A11b in the appendix with those of the main specification reported in Figures 3a and 3b yields a very similar spread reaction to shocks in all variables regardless of the default risk proxy employed in the MS-VAR model. A minor difference in the low-volatility regime is that the spread reaction to shocks in

[35] We thank an anonymous referee for suggesting the potential need for an aggregate PD proxy.

[36] For further details on the PD index, the reader is referred to Fitch Solutions (2008, 2007).

YC_SLOPE vanishes entirely once VIX is substituted by PD. Moreover, spread reactions to shocks in STOCK_RET and shocks in ILLIQUID now feature a larger magnitude in the high-volatility regime. However, the spread does not show a significant reaction to shocks in PD in either regime. Given this evidence, we conclude that the variables used in our model setup adequately capture information about market-wide default risk relevant for pricing corporate bonds.

6. Conclusion

We study the dynamic interdependencies between corporate bond spreads and their key determinants over time. In particular, we investigate to what extent these relationships are affected by the respective market regime prevailing, which can essentially be characterized as a phase of either relatively low or exceptionally high volatility on corporate bond and equity markets. At this, we are the first to choose a MS-VAR approach to model the spread dynamics, which does a decent job in mapping the nonlinear spread behavior, predominantly level jumps and persistence.

Using weekly data covering the 2004–2016 period, we detect significant differences in how default- and non-default-related factors impact aggregate corporate bond spreads conditional on the prevailing market regime. Specifically, a shock to market-wide liquidity proves to have the relatively largest impact on spreads during the high-volatility regime in terms of magnitude and persistence. Moreover, aggregate liquidity also exhibits the most pronounced regime-specific differences in its effect on corporate bond spreads. Extending prior research, most prominently the studies by Acharya et al. (2013) and Kalimipalli et al. (2013), we document a highly significant and persistent impact of illiquidity on spreads during high-volatile market regimes. Thus, our results suggest that, during highly unstable times like the global financial crisis, investors demand a premium for taking on liquidity risk which constitutes a substantially higher fraction of the corporate bond spread than previously assumed – a piece of evidence which might contribute to explaining the *corporate bond spread puzzle*.

Moreover, the relative impact of credit risk is larger during tense markets, when spreads exhibit a disproportionately large and much longer-lasting increase following unexpected jumps (drops) in the VIX (stock market return). Finally, shocks to the risk-free interest rate also result in asymmetric spread behavior. While interest rate risk plays a fundamental role in normal times, it appears to have less of an impact relative to other risk factors when a bearish or generally anxious market sentiment prevails.

Our results suggest several avenues for further research. We show that the aggregate illiquidity proxy proposed by Hu et al. (2013) provides valuable information for high-yield corporate bond spreads when used in a regime-switching context. It would be interesting to investigate if liquidity measures generated directly from the corporate bond market are equally informative about the time-varying liquidity exposure of corporate bonds. Moreover, investors as well as bond issuers might be interested in whether the regimes identified by the MS-VAR model ex post can also be predicted ex ante, such that the nonlinear dynamics in the spread process can be exploited in a profitable issuance or trading strategy. If the asymmetric spread behavior was predictable, this would, e.g., be of material value for hedging strategies related to corporate bond portfolios. We leave investigations along these lines to future contributions in the field.

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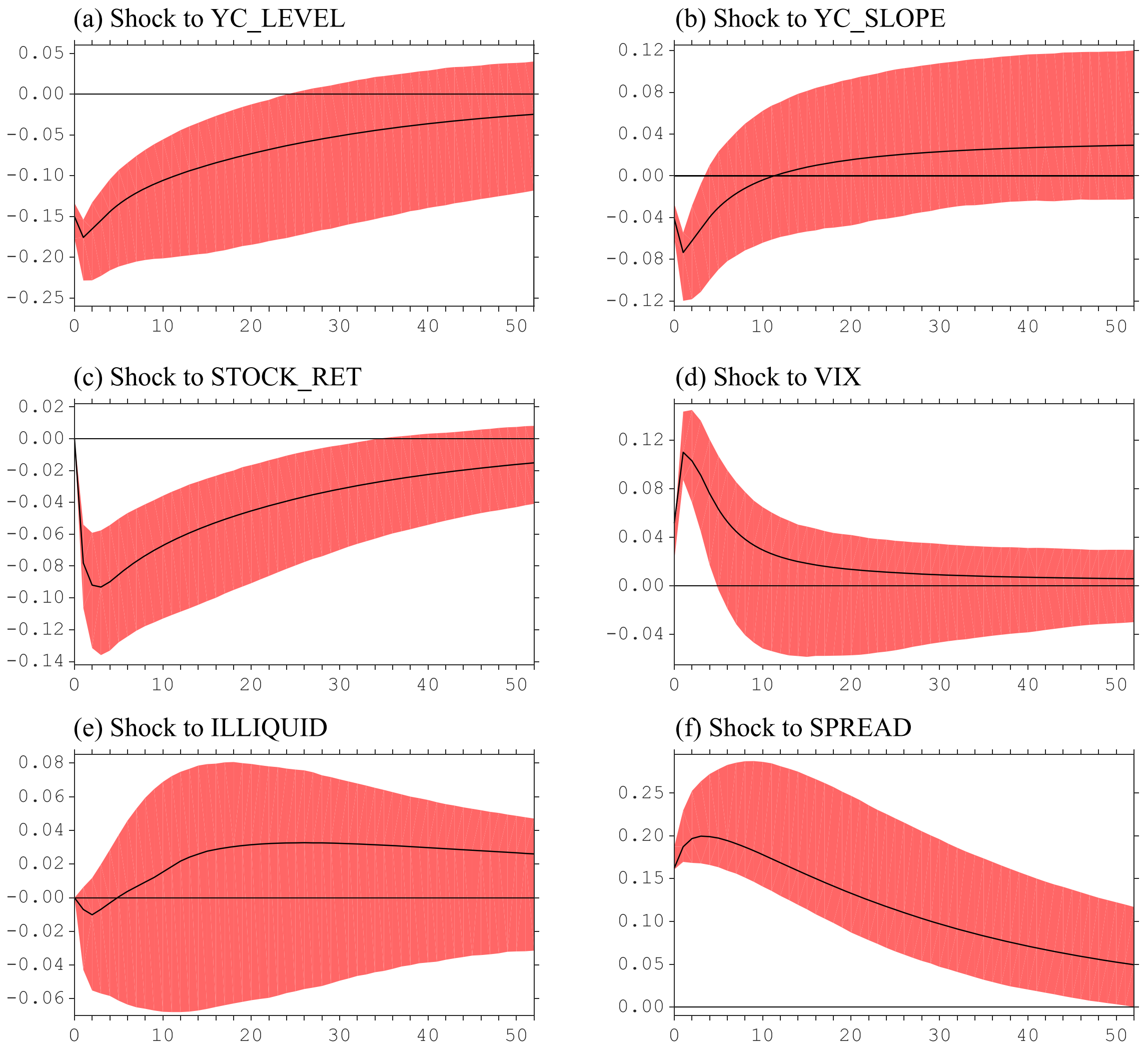
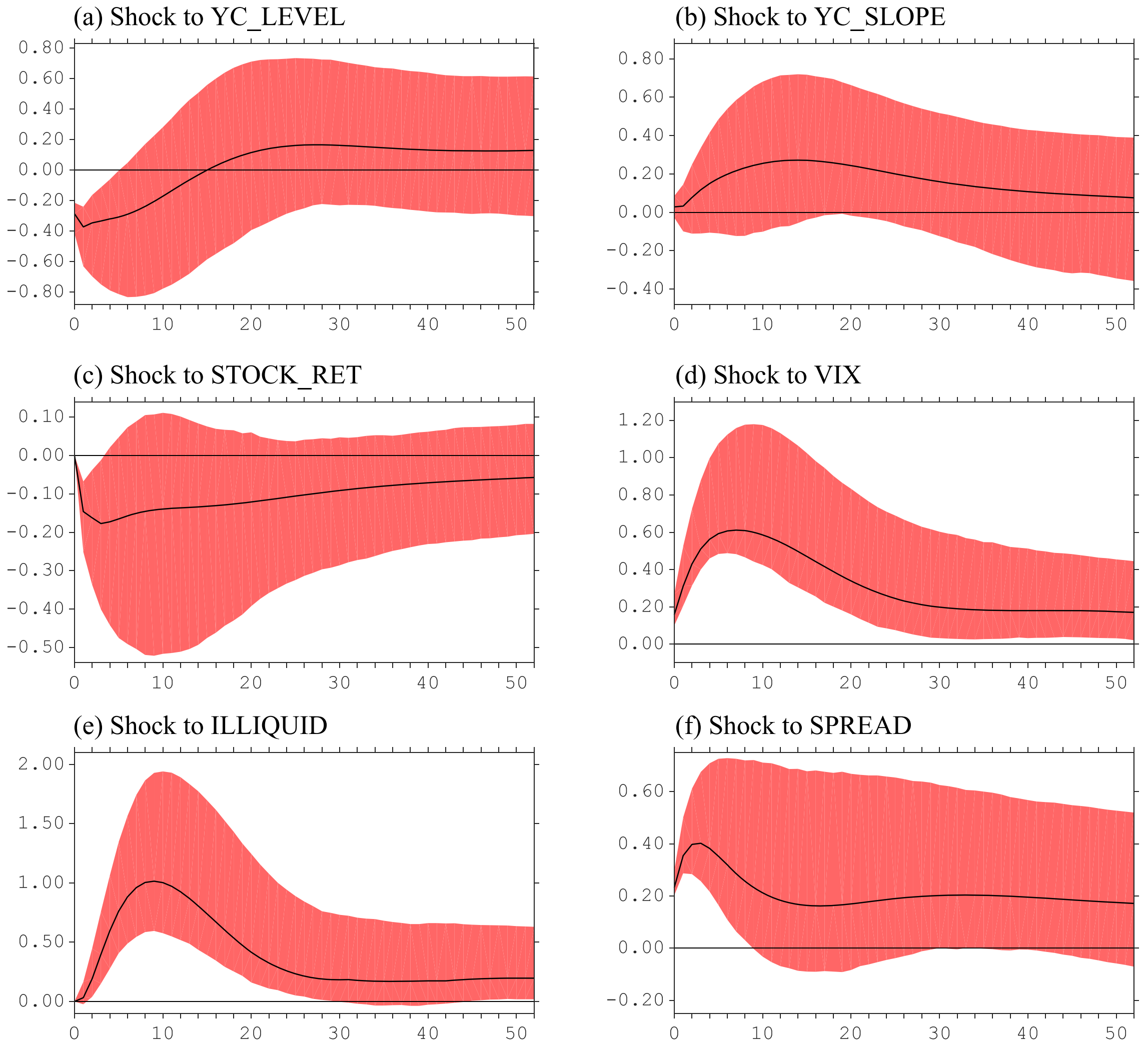
Appendix

Figure A1a
Impulse of corporate bond spread to shocks during (low-volatility) Regime 1
– Alternative causal ordering –



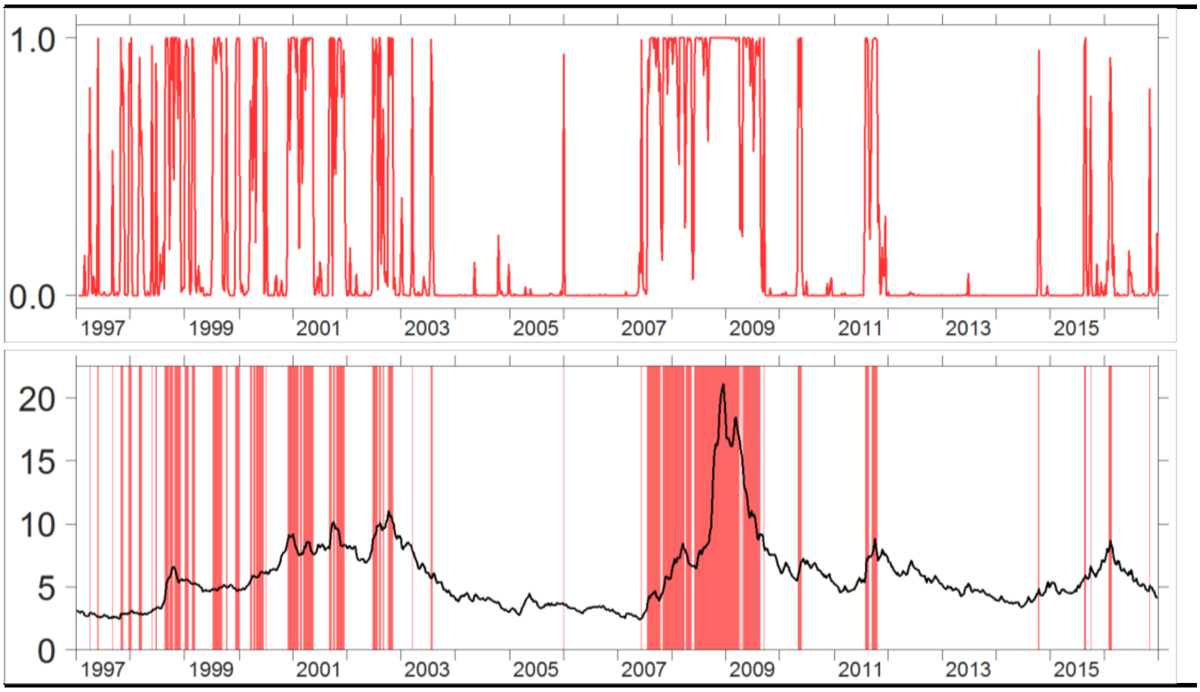
Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 1, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET → ILLIQUID is imposed. The shaded areas indicate the respective 99% bootstrap confidence interval calculated following Hall (1992).

Figure A1b
Impulse of corporate bond spread to shocks during (high-volatility) Regime 2
– Alternative causal ordering –



Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 2, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET → ILLIQUID is imposed. The shaded areas indicate the respective 99% bootstrap confidence interval calculated following Hall (1992).

Figure A2
Underlying regimes in corporate bond index spreads
– Extended sample –

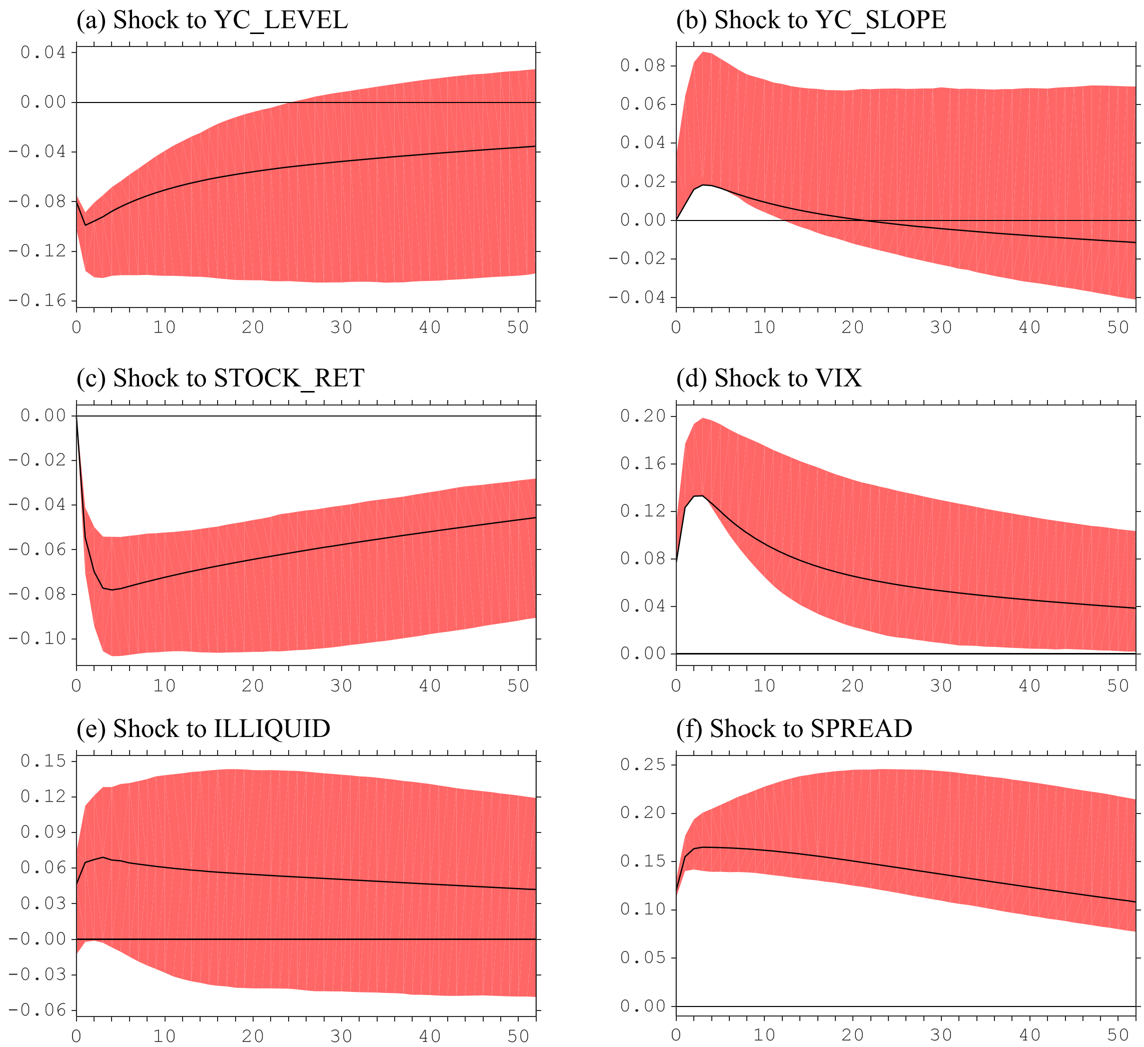


Notes: The upper graph plots the smoothed probability of being in Regime 2, $\Pr(s_t=2|\boldsymbol{Y}_T)$, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) and using the variables introduced in section 3.2 for the extended sample period 1997-2016. The bottom graph presents the time series of the corporate bond index spread, with the shaded areas indicating periods when Regime 2 prevails, i.e. the smoothed probability of being in Regime 2 is 0.5 or greater.

Figure A3a

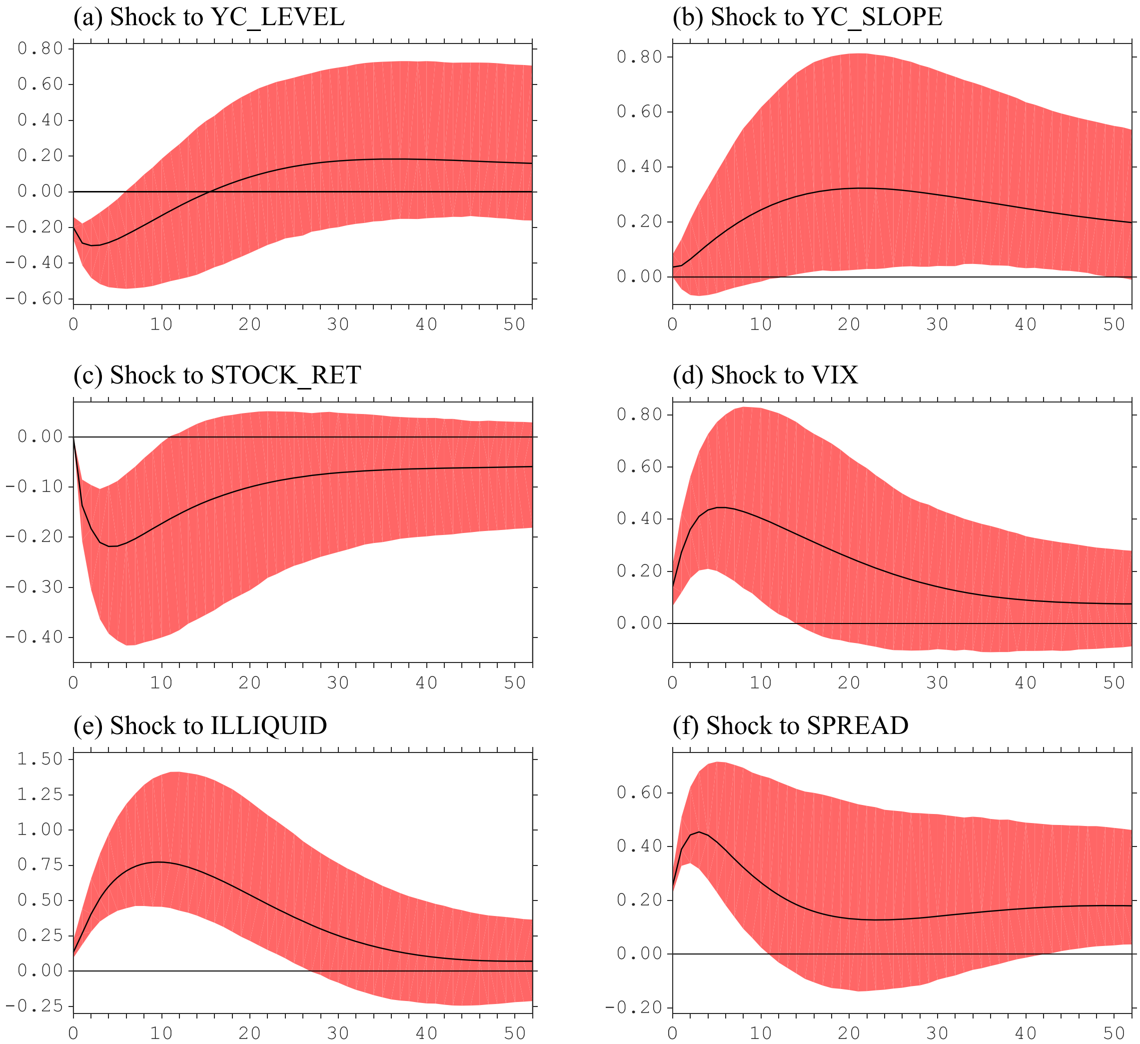
Impulse of corporate bond spread to shocks during (low-volatility) Regime 1

– Extended sample –



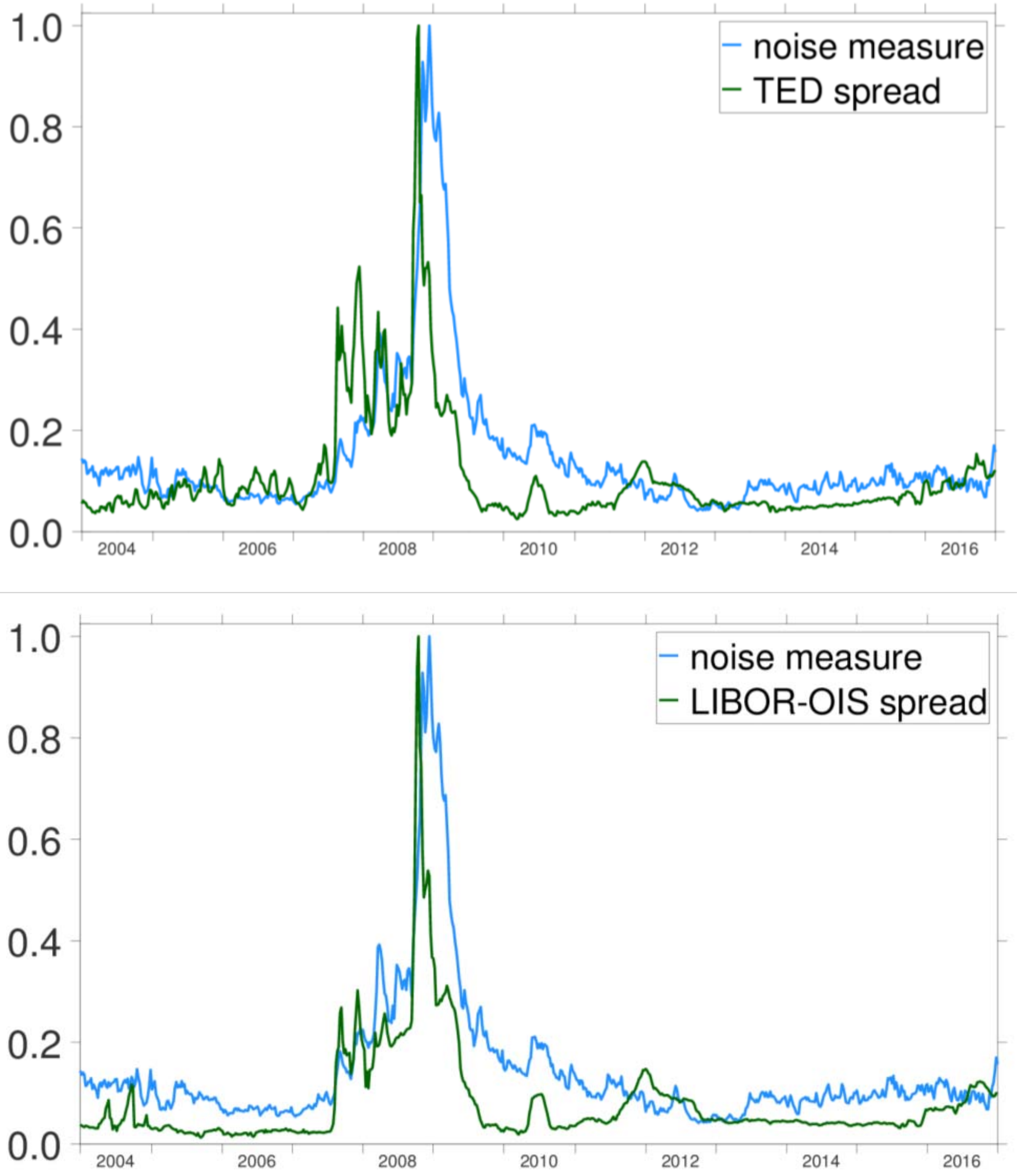
Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 1, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2 for the extended sample period 1997-2016. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET is imposed. The shaded areas indicate the respective 99% bootstrap confidence interval calculated following Hall (1992).

Figure A3b
Impulse of corporate bond spread to shocks during (high-volatility) Regime 2
– Extended sample –



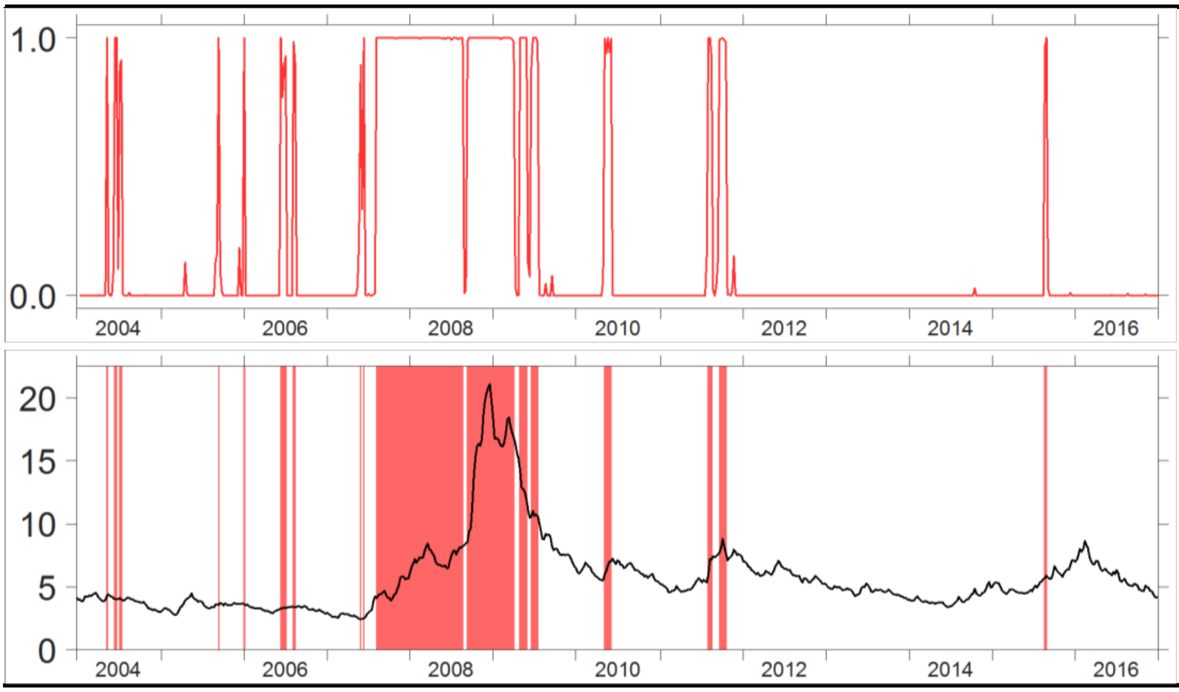
Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 2, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2 for the extended sample period 1997-2016. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET is imposed. The shaded areas indicate the respective 99% bootstrap confidence interval calculated following Hall (1992).

Figure A4
Noise measure against alternative illiquidity measures



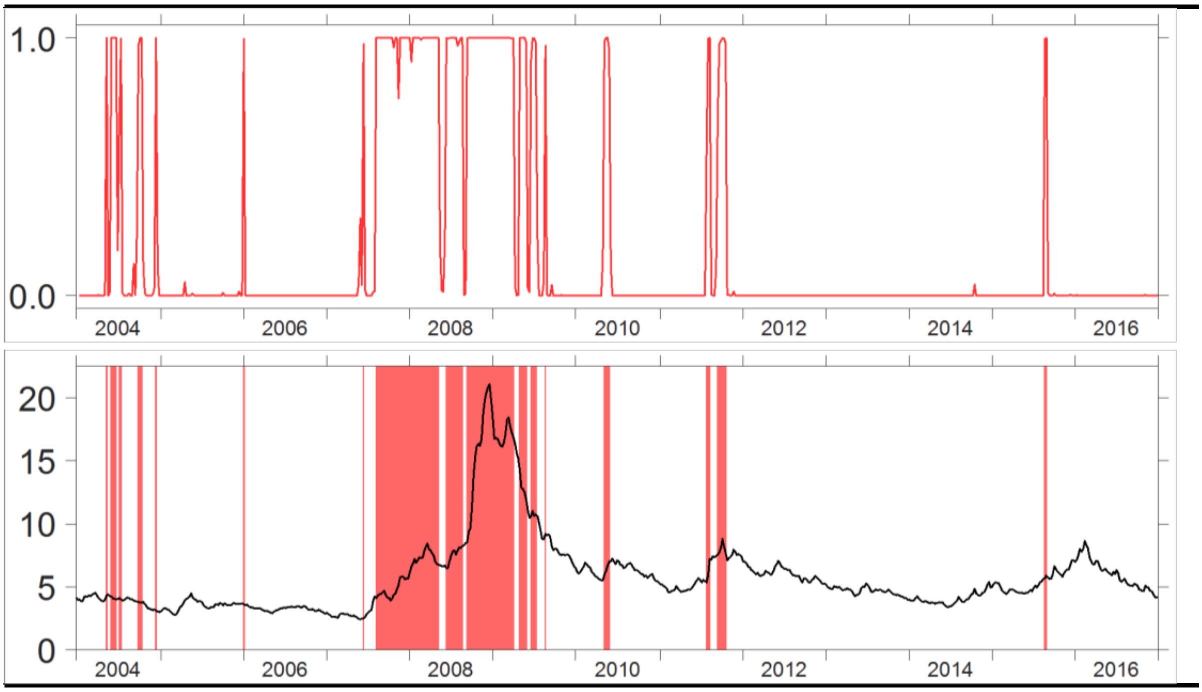
Notes: The upper (bottom) graph plots the noise measure together with the TED spread (LIBOR-OIS spread). In both graphs each time series is normalized such that the respective maximum value is unity.

Figure A5
Underlying regimes in corporate bond index spreads
– TED spread as illiquidity proxy –



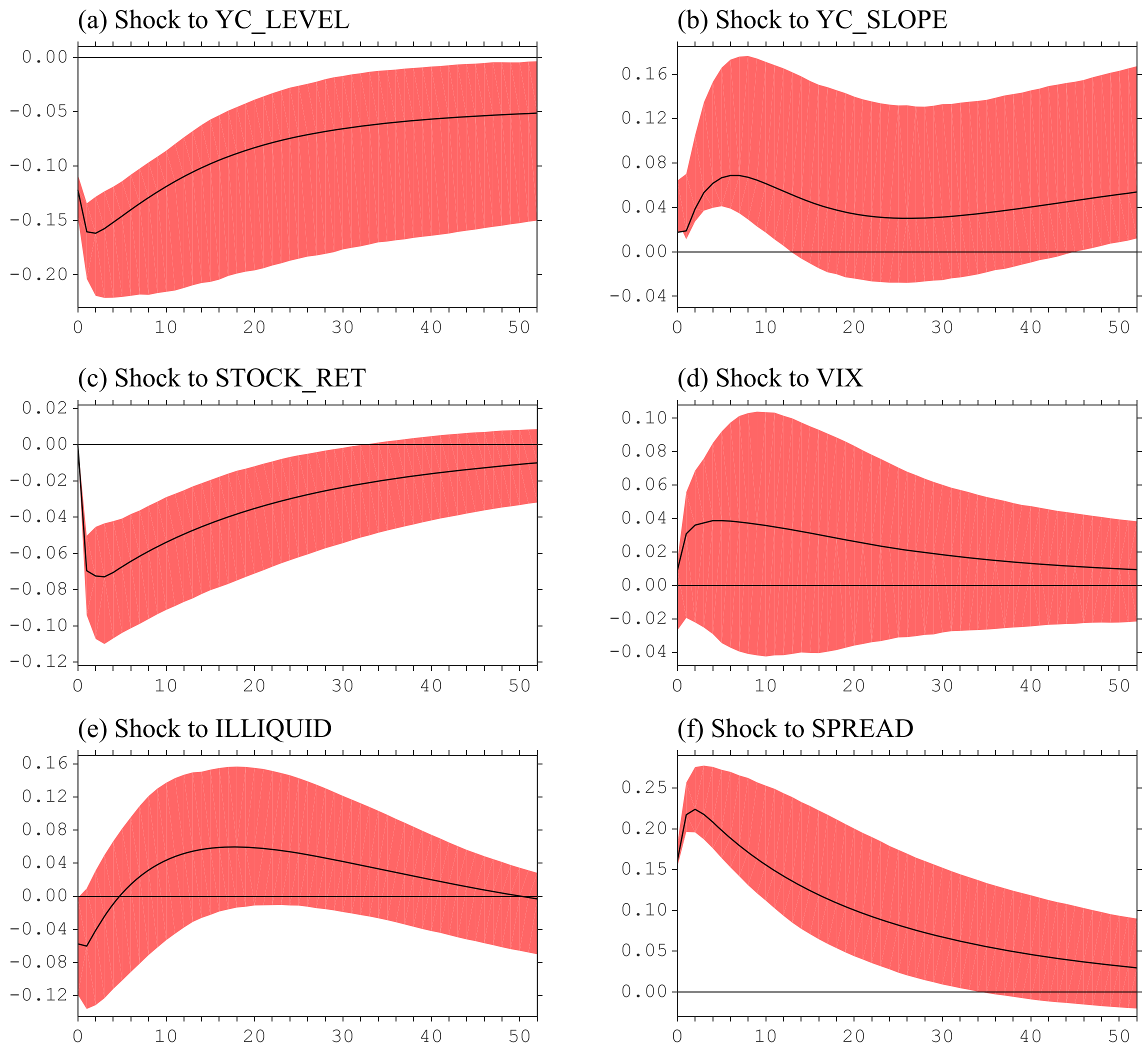
Notes: The upper graph plots the smoothed probability of being in Regime 2, $\Pr(s_t=2|\boldsymbol{Y}_T)$, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) and using the variables introduced in section 3.2. In this specification, the noise measure is replaced by the alternative illiquidity proxy TED spread. The bottom graph presents the time series of the corporate bond index spread, with the shaded areas indicating periods when Regime 2 prevails, i.e. the smoothed probability of being in Regime 2 is 0.5 or greater.

Figure A6
Underlying regimes in corporate bond index spreads
– LIBOR-OIS spread as illiquidity proxy –



Notes: The upper graph plots the smoothed probability of being in Regime 2, Pr(s_t=2|$\boldsymbol{Y}_T$), based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) and using the variables introduced in section 3.2. In this specification, the noise measure is replaced by the alternative illiquidity proxy LIBOR-OIS spread. The bottom graph presents the time series of the corporate bond index spread, with the shaded areas indicating periods when Regime 2 prevails, i.e. the smoothed probability of being in Regime 2 is 0.5 or greater.

Figure A7a
Impulse of corporate bond spread to shocks during (low-volatility) Regime 1
– TED spread as illiquidity proxy –

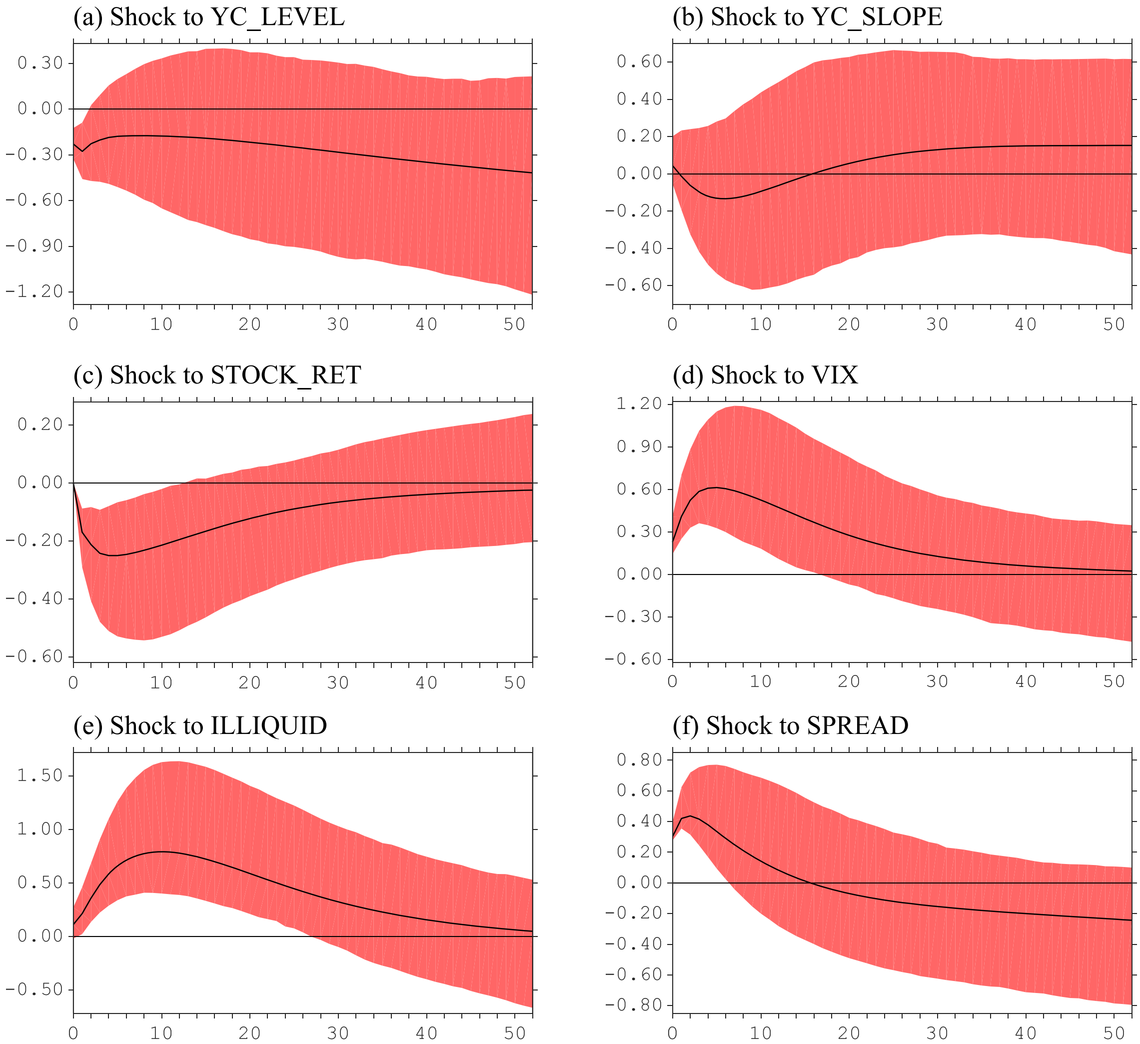


Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 1, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2. In this specification, the noise measure is replaced by the alternative illiquidity proxy TED spread. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET is imposed. The shaded areas show the respective 99% bootstrap confidence interval calculated following Hall (1992).

Figure A7b

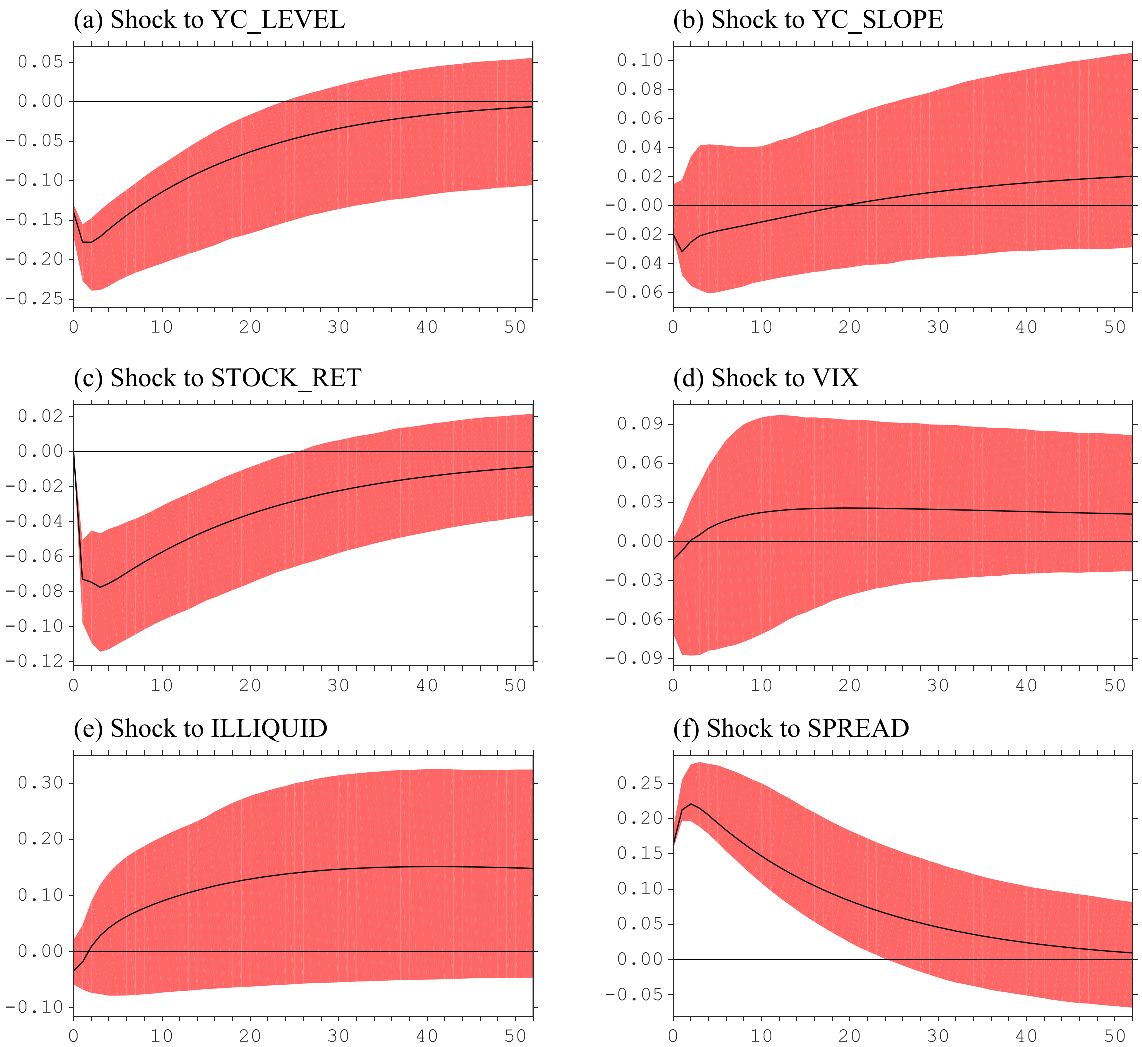
Impulse of corporate bond spread to shocks during (high-volatility) Regime 2

– TED spread as illiquidity proxy –



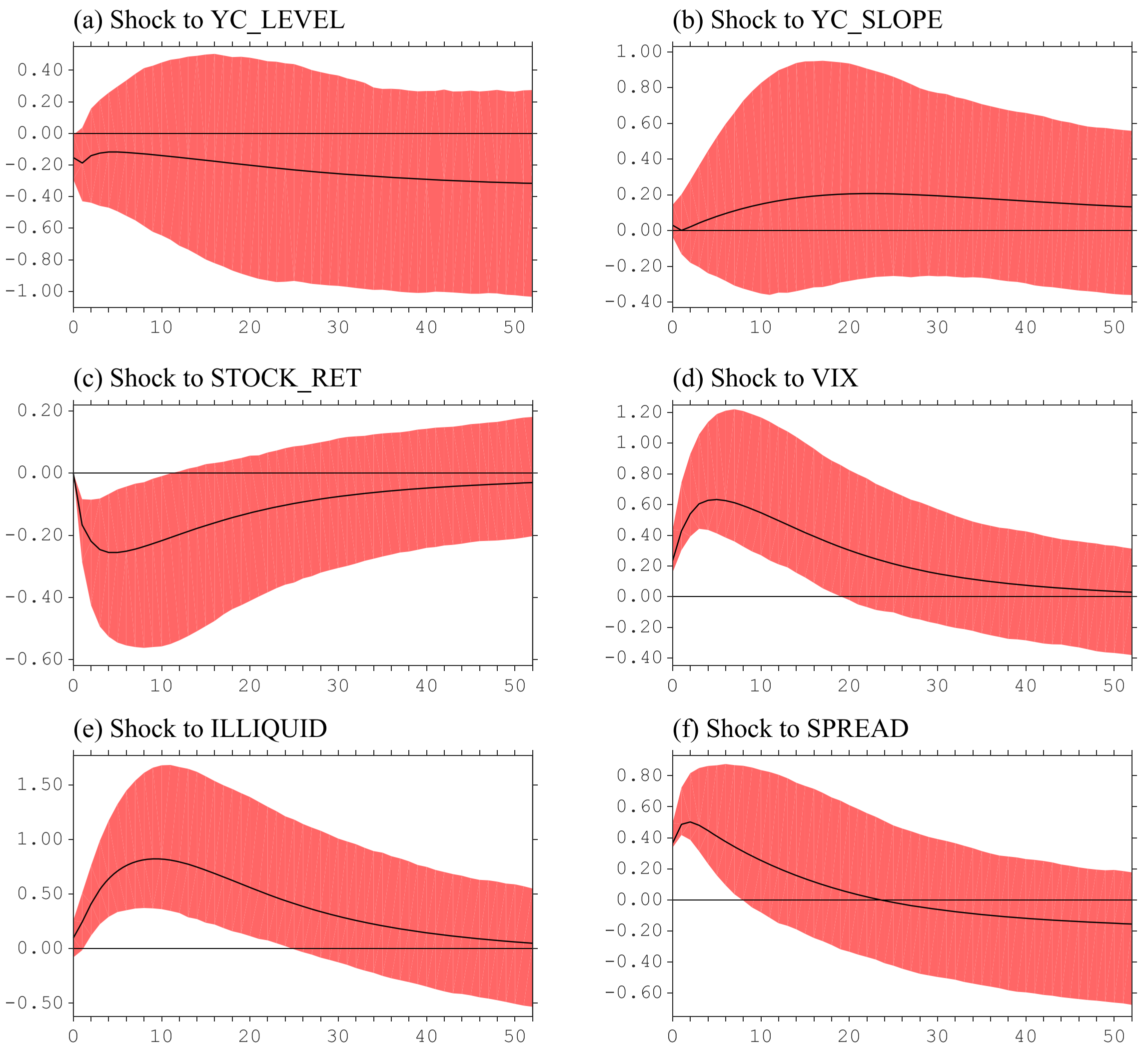
Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 2, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2. In this specification, the noise measure is replaced by the alternative illiquidity proxy TED spread. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET is imposed. The shaded areas show the respective 99% bootstrap confidence interval calculated following Hall (1992).

Figure A8a
Impulse of corporate bond spread to shocks during (low-volatility) Regime 1
– LIBOR-OIS spread as illiquidity proxy –



Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 1, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2. In this specification, the noise measure is replaced by the alternative illiquidity proxy LIBOR-OIS spread. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET is imposed. The shaded areas show the respective 99% bootstrap confidence interval calculated following Hall (1992).

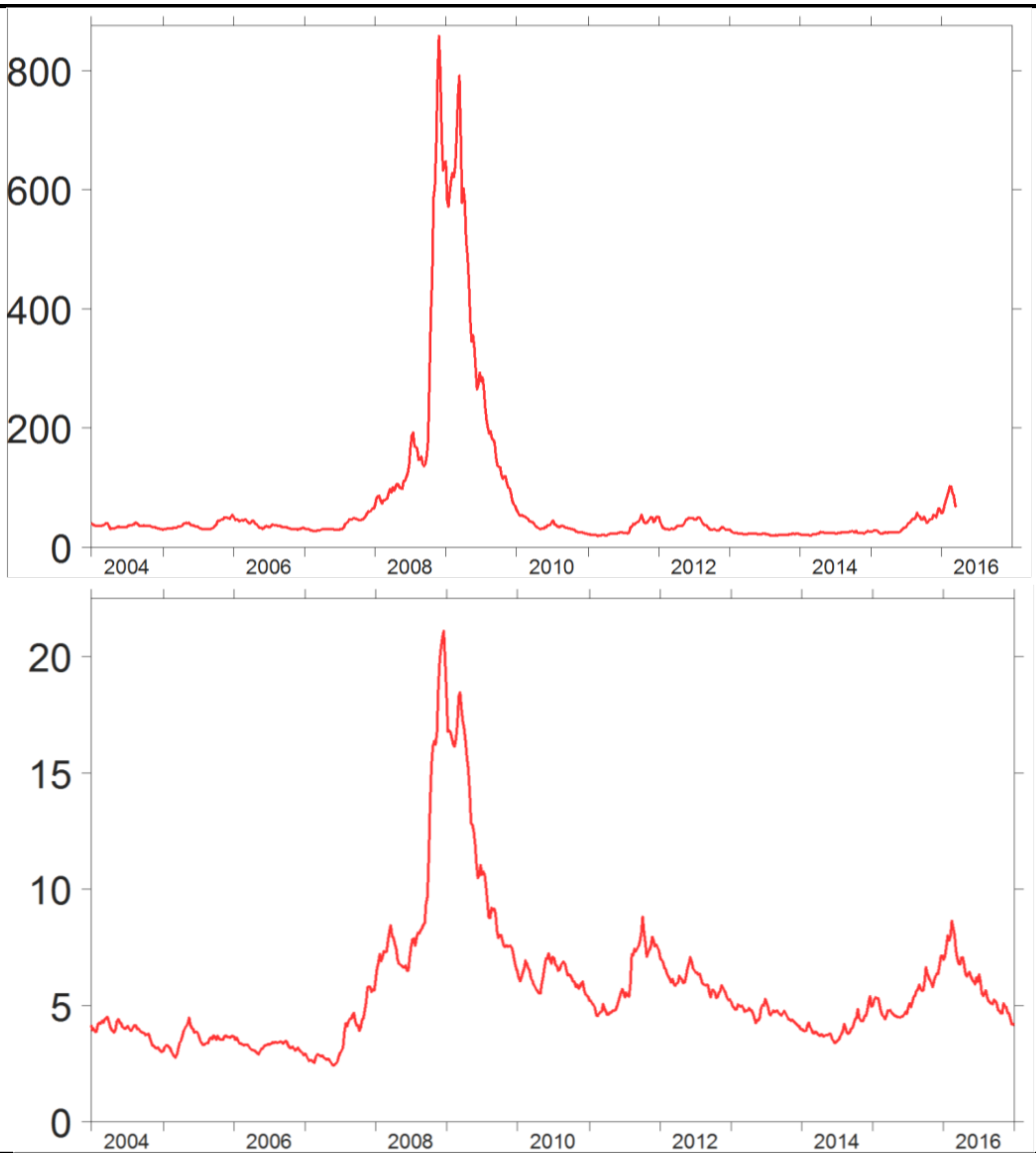
Figure A8b
Impulse of corporate bond spread to shocks during (high-volatility) Regime 2
– LIBOR-OIS spread as illiquidity proxy –



Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 2, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2. In this specification, the noise measure is replaced by the alternative illiquidity proxy LIBOR-OIS spread. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET is imposed. The shaded areas show the respective 99% bootstrap confidence interval calculated following Hall (1992).

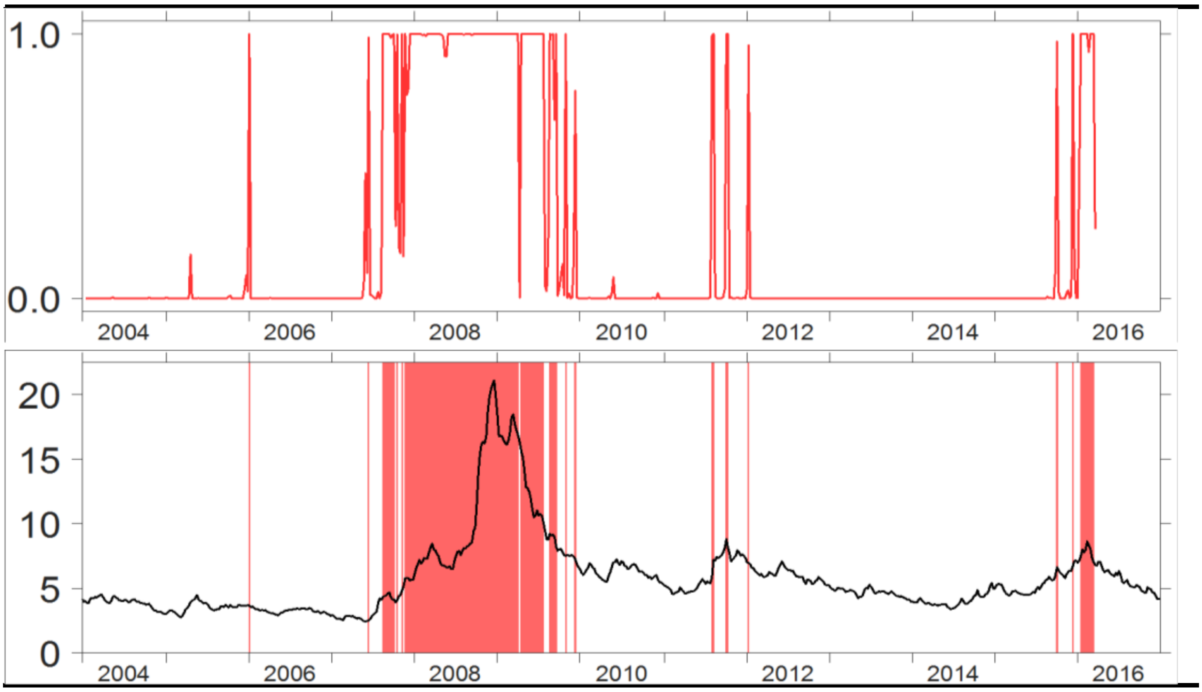
Figure A9

Fitch Ratings' 1-Year-Ahead PD index (North America) against corporate bond index spreads



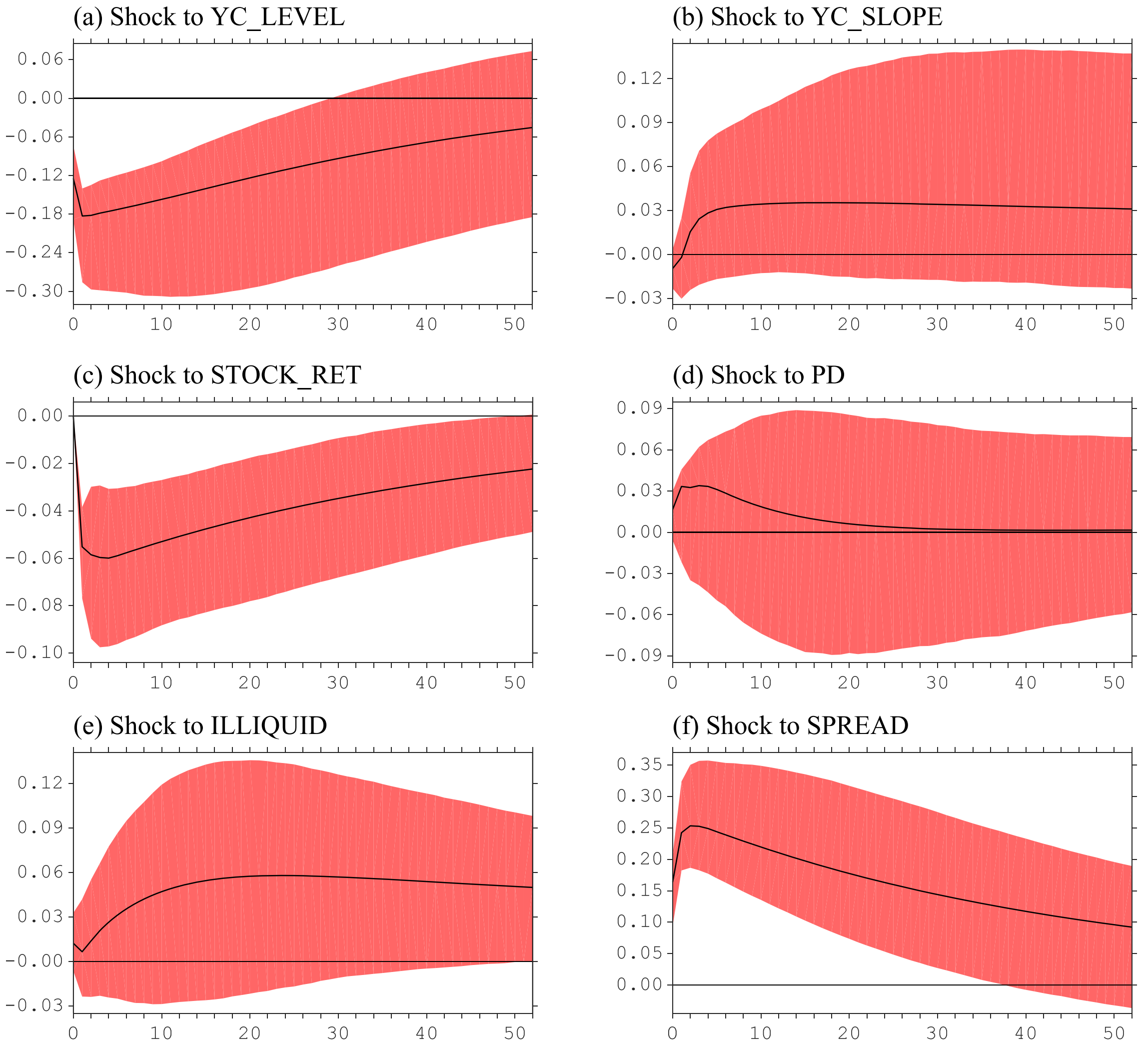
Notes: The upper graph plots Fitch Ratings' 1-Year-Ahead Probability of Default (PD) index for North America (in basis points); the bottom graph plots the corporate bond index spreads (SPREAD, in percentage points).

Figure A10
Underlying regimes in corporate bond index spreads
– Fitch Ratings' 1-Year-Ahead PD index (North America) as default risk proxy –



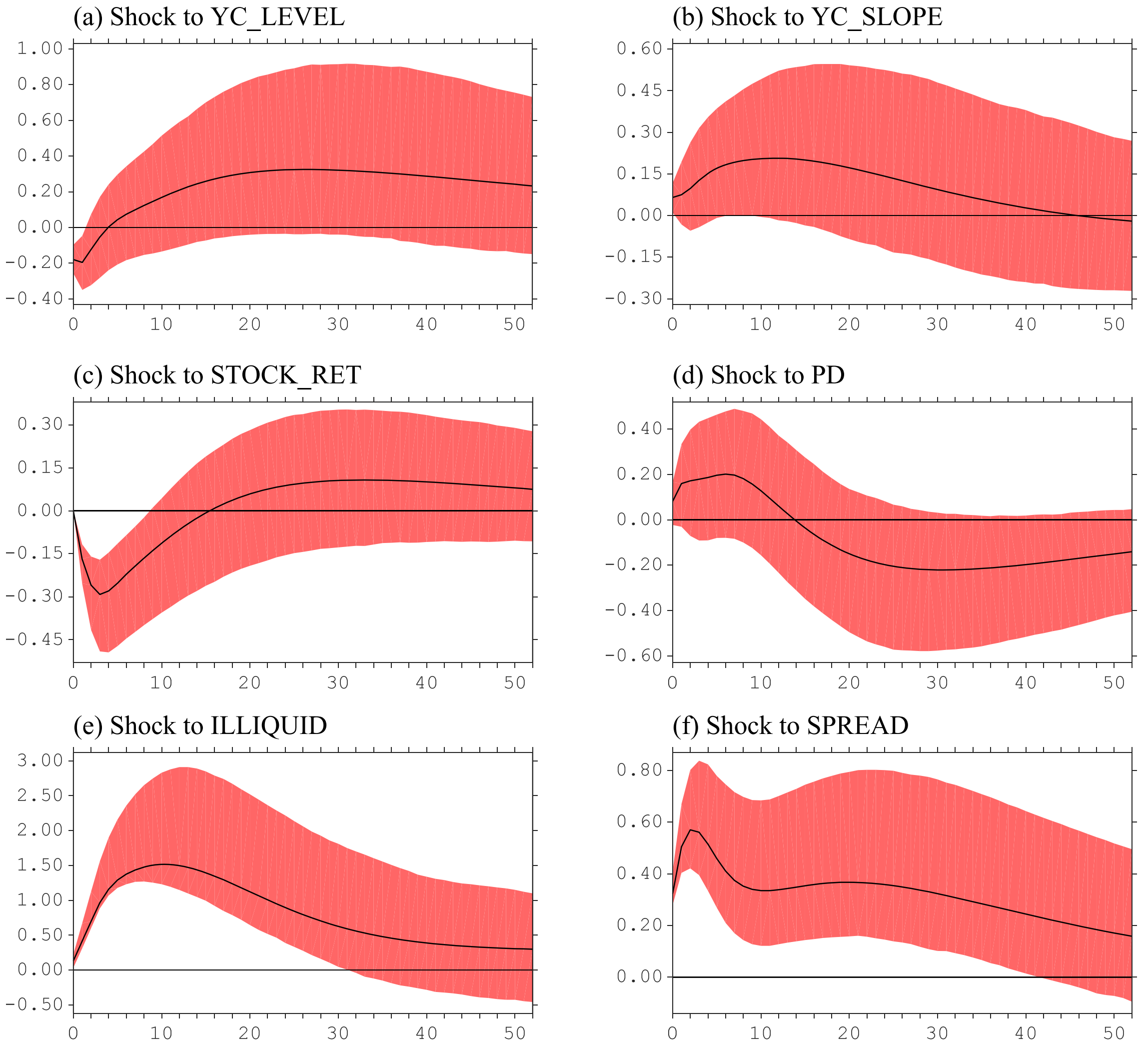
Notes: The upper graph plots the smoothed probability of being in Regime 2, $\Pr(s_t=2|Y_T)$, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) and using the variables introduced in section 3.2. In this specification, the VIX is replaced by Fitch Ratings' 1-Year-Ahead Probability of Default Index for North America (PD) as an alternative proxy for aggregate default risk. The bottom graph presents the time series of the corporate bond index spread, with the shaded areas indicating periods when Regime 2 prevails, i.e. the smoothed probability of being in Regime 2 is 0.5 or greater.

Figure A11a
Impulse of corporate bond spread to shocks during (low-volatility) Regime 1
– Fitch Ratings' 1-Year-Ahead PD index (North America) as default risk proxy –



Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 1, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2. In this specification, the VIX is replaced by Fitch Ratings' 1-Year-Ahead Probability of Default Index for North America (PD) as an alternative proxy for aggregate default risk. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET is imposed. The shaded areas show the respective 99% bootstrap confidence interval calculated following Hall (1992).

Figure A11b
Impulse of corporate bond spread to shocks during (high-volatility) Regime 2
– Fitch Ratings' 1-Year-Ahead PD index (North America) as default risk proxy –



Notes: This graph plots orthogonalized impulse response functions (IRF) of the corporate bond index spread SPREAD (in percentage points) to a one standard deviation shock to the respective variable of the regime-specific VAR system during Regime 2, based on the estimation of the two-state MS-VAR(2) model as specified in equation (1) using the variables introduced in section 3.2. In this specification, the VIX is replaced by Fitch Ratings' 1-Year-Ahead Probability of Default Index for North America (PD) as an alternative proxy for aggregate default risk. The structural innovations are identified using a triangular Cholesky factorization of the residuals' regime-specific covariance matrix, for which the causal ordering ILLIQUID → YC_LEVEL → YC_SLOPE → VIX → SPREAD → STOCK_RET is imposed. The shaded areas show the respective 99% bootstrap confidence interval calculated following Hall (1992).