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Does Credit Risk Impact Liquidity Risk? Evidence from Credit Default Swap Markets

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Abstract: During the recent financial crisis that erupted in mid-2007, credit default swap spreads increased by several hundred basis points, accompanied by a liquidity shortage in the U.S. financial sector. This period has both evidenced the importance that liquidity has for investors and underlined the need to understand the linkages between credit markets and liquidity. This paper sheds light on the dynamic interactions between credit and liquidity risk in the credit default swap market. Contrary to the common belief that illiquidity leads to a credit risk deterioration in financial markets, it is found that in a sample of German and Swiss companies, credit risk is more likely to be weakly endogenous for liquidity risk than vice versa. The results suggest that a negative credit shock typically leads to a subsequent liquidity shortage in the credit default swap market, in the spirit of, for instance, the liquidity spiral posited by Brunnermaier (2009), and extends our knowledge about how credit markets work, as it helps to explain the amplification mechanisms that severely aggravated the recent crisis and also indicates which macro-prudential policies would be suitable for preventing a similar financial crisis in the future.

Keywords: financial crisis, credit default swap, credit risk, liquidity risk, endogeneity, macro-prudential policy

JEL classifications: E37, E61, G14, G32, G38

1. Introduction

The recent financial crisis that erupted in mid-2007, less than a decade after the LTCM hedge fund collapsed in the aftermath of the Russian crisis in 1998 owing to highly illiquid financial markets, has again evidenced the importance that liquidity has for investors. In this period, credit default swap (CDS) spreads increased by several hundred basis points (bps), accompanied by a liquidity shortage in the U.S. financial sector. As a by-product of illiquidity, investors incurred increasing and accelerating losses: Some investors were forced to close trading positions in a period when prices of risky assets were falling sharply. These "fire sales" exemplify how fire sales trigger contagion effects by endogenously generating sales of assets (see, e.g., Cifuentes et al. (2005) or Cont and Wagalath (2012)) and therefore emphasizes the importance of giving ample consideration to liquidity in credit markets and credit risk models, especially in periods of financial turmoil.

Given the importance that the size of the CDS market and the value of CDS spreads have for gauging the health and the stability of the financial sector, it is crucial to understand the dynamic interactions between liquidity and credit risk in CDS markets.[1] For policy-makers, investors, and the field of financial market research, this is an important question as endogenous risk factors may reinforce each other, especially in periods of financial turmoil. The recent crisis is an example where we observed both illiquid financial markets and rising CDS spreads and where a small shock (i.e., relatively small losses on subprime assets) triggered a severe financial crisis. To better understand the amplification mechanisms that played a significant role during this period, it is important to understand how these two risk factors are related to each other. It remains, however, an open question whether liquidity shortage causes credit risk to increase[2] or whether the reverse causality holds.[3] Also when managing fixed-income portfolios, monitoring and modeling liquidity risk and how it interacts with credit risk is essential when it comes to meeting regulatory capital requirements. If risks reinforce each other in periods of adverse market conditions, portfolio managers risk being underfunded. To date, most risk models either do not include liquidity as a risk factor or treat it as an exogenous variable. However, the inclusion of liquidity as an exogenous variable in credit risk models is still controversial.

This study contributes to the existing literature on the dynamic relationship between liquidity and credit risk in several ways. First, it is the first study to analyze the dynamic interactions between both risk factors in the CDS market at the company level. In the present paper it is analyzed whether it is reasonable to treat liquidity as (weakly) exogenous in the time series sense (Hamilton, 1994) with respect to credit risk or vice versa. The findings indicate that for 38.6% of the German and Swiss companies analyzed in this study, credit risk is (weakly) endogenous for liquidity, while the reverse causality only holds in 4.5% of the cases. The results therefore suggest that a negative credit shock typically leads to a subsequent liquidity shortage in the CDS market, in the spirit of the liquidity spiral posited by Brunnermaier (2009), the amplification mechanism related to model uncertainty in Krishnamurthy (2010), or the banking model developed by Bolton et al. (2011), where asymmetric information about asset quality triggers early asset sales, but contrary to the model in He and Xiong (2012), where companies having to roll over maturing debt face rising credit spreads when liquidity in the bond market deteriorates, or the model in Easley and O'Hara (2010), where a negative liquidity shock arises from investors with incomplete preferences over portfolios. The findings of this paper thus extend our knowledge about how credit markets work, as they help to explain the amplification mechanisms that severely aggravated the recent crisis and also indicate which macro-prudential policies might be suitable for preventing a similar financial crisis in the future.

Second, this study is one of the few studies that analyzes non-U.S. company CDS data on a daily basis, instead of CDS indices and which includes the most recent period since the financial crisis. Despite intensive research in the field of CDSs, most studies concentrate on the U.S. market using lower frequency data and analyze a period before the recent financial crisis erupted in 2007 (Díaz et al., 2013). Hence, the insights into micro-level effects complement previous studies and include a period of special interest.

Third, before analyzing the relation between credit and liquidity risk in a multivariate context, this study first empirically establishes in a systematic way what univariate time series properties the proxies for these risk factors exhibit; i.e., the CDS bid-ask spread and the CDS mid-rate,

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[1] In the following, the focus is on the credit derivative market and CDS contracts, as these instruments are considered a good and readily available indicator of credit risk (Hull et al., 2004).
[2] See, e.g., Szegö (2008) for an illustration of a vicious circle that having been triggered by a liquidity shortage, causes financial institutions to go bankrupt.
[3] See, e.g., Brunnermaier (2009) for a liquidity spiral where an increase in a company's leverage ratio induces fire sales, which then cause liquidity to dry up.

which is a commonly used proxy variable for the CDS spread. As CDSs have only recently gained popularity, few stylized facts exist for CDS data. This contrasts with the variety of stylized facts that exist for equity data. The present study contributes towards filling this gap. The need to identify the univariate properties of the risk-factor proxies is important for, e.g., investors wanting to construct liquidity-adjusted investment portfolios or policy-makers seeking to design adequate macro-prudential policies.

Fourth, as a by-product of assessing the robustness of the results by including exogenous explanatory variables suggested by finance theory and variables that have been proven to be important in explaining the variation in CDS spreads in empirical studies, further insights into the factors that determine both changes in CDS spreads and in CDS bid-ask spreads are gained. Here the contribution of this paper is manifold. Previously, only Gündüz et al. (2007) and Meng and ap Gwilym (2008) have analyzed the determinants of the CDS bid-ask level. This paper is therefore the first study to analyze which factors explain the changes in the CDS bid-ask spread and contributes to the existing literature on liquidity in financial markets in general and CDS markets in particular. At the same time, it is analyzed which factors determine CDS spread changes, which accords with the work of Collin-Dufresne et al. (2001), Ericsson et al. (2009) and Corò et al. (2013), among others, and complements these studies.

The present study is structured as follows. In Section 2.1, both liquidity and liquidity risk are defined, the distinction between endogenous and exogenous liquidity risk is assessed and an overview of recent papers that deal with the relation between credit and liquidity risk is presented. In Section 2.2, the used liquidity risk proxy, the absolute bid-ask spread, is introduced. That section concludes with the definition of the used credit risk proxy, the CDS mid-rate. In Section 3, the methodology that is used to analyze the dynamic relationship between credit and liquidity risk is described; i.e., the Granger causality test and an extension of it, a vector autoregression (VAR) model with exogenous variables. After this section, the data sample is described and a subsample of it is presented in Section 4. In the empirical Section 5, first, the order of integration and the degree of autocorrelation of the used data sample is analyzed; and second, the Granger causality test is motivated by analyzing the cross-correlation between the used credit risk and liquidity risk proxy. Third, the dynamic relationship between both risk factors is analyzed; i.e., it is analyzed whether credit risk and/or liquidity risk can be treated as exogenous by applying the Granger causality test methodology. The robustness of the reported results is assessed in Section 5.4. Finally, Section 6 summarizes the findings of this paper and concludes.

2. Credit Risk and Liquidity Risk

2.1 Theoretical Background and Literature Review

2.1.1 Liquidity and Liquidity Risk

In line with the general definition of liquidity in the economic literature, liquidity is defined as the ease with which an asset can be traded. Therefore, assuming that investors have a preference for liquidity, more liquid assets are priced higher and exhibit lower trading costs. The costs associated with liquidity include direct trading costs (e.g., commissions, fees and taxes), the bid-ask spread, i.e., the direct costs of a round trip, the price impact when trading a large amount of assets, and the costs incurred when a deal cannot be executed immediately and has to be split up into smaller transactions.

Liquidity is linked to liquidity risk following the reasoning of Nikolaou (2009) and the assumption that investors have a preference for liquidity. Assuming that liquidity is stochastic (in line with, e.g., Amihud et al., 2005), liquidity risk then relates to the probability of not being able to trade an asset (Williamson, 2008).[4] Liquidity risk will therefore be higher, the higher the probability is that an asset cannot be traded. This probability includes the probability of incurred trading costs different than previously expected and the effect of systematic liquidity risk (de Jong and Driessen, 2013), i.e., the degree of commonality between an asset's liquidity and market-wide liquidity, among others. If this probability approaches one, liquidity risk is at its maximum and the market becomes illiquid. Hence, liquidity is negatively related to liquidity risk. Indeed, in the liquidity-adjusted capital asset pricing model (CAPM) of Acharya and Pedersen (2005), illiquid assets both demand a higher return and also have higher liquidity risk.[5] Their empirical results document that assets, whose liquidity is positively correlated with market liquidity, require a premium, consistent with the notion of a "flight-to-liquidity" in periods of illiquid markets. In addition, Lin et al. (2012) analyze the relationship between the bid-ask spread and liquidity risk for U.S. stocks from 2001 to 2005. They find a strong positive relationship between both variables. Their findings are rationalized with the market maker's optimal inventory level that becomes riskier, the larger the liquidity risk is. As a consequence, the market maker will demand a liquidity premium and therefore a higher bid-ask spread.[6] The high negative correlation between liquidity and liquidity risk is also supported by the findings in Bongaerts et al. (2012) for U.S. corporate bonds in the period from 2005 to 2008.

In sum, this means that the proposed liquidity proxy, the bid-ask spread, is in general small and stable, whenever both markets are highly liquid and liquidity risk is low. Therefore, liquidity risk is proxied by the bid-ask spread, which is in line with Düllmann and Sosinka (2007), van Landschoot (2008), Berndt and Obreja (2010) or de Jong and Driessen (2012), among others.

2.1.2 Exogenous vs. Endogenous Liquidity Risk

Following the definition in Bangia et al. (2002), exogenous liquidity risk is defined as that liquidity risk component that is common to all market makers and that only depends on the market structure. Consequently, any individual's transaction has no impact on liquidity. Endogenous liquidity risk, in contrast, refers to the component that is under the control of the market maker and therefore varies with the size of the trading position (see Figure 3 in Bangia et al. (2002) for a graphical explanation). The bid-ask spread essentially represents exogenous liquidity. In the following, therefore, it is analyzed whether exogenous liquidity risk is (weakly) exogenous with respect to credit risk.

2.1.3 Relationship between Credit Risk and Liquidity Risk

Before reviewing the literature about the relationship between credit risk and liquidity risk, credit risk is defined as the probability of a loss triggered by the default of a debtor. Following the reasoning in Section 2.1.1, notice that exposure to credit risk is maximum when the probability

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[4] Other studies, however, define liquidity risk simply as the change in liquidity (see Beber et al. (2009), among others).

[5] Chordia et al. (2000), Huberman and Halka (2001), Brockman and Chung (2002) and Lee et al. (2006), among others, document a negative relationship between the bid-ask spread and market liquidity in stock markets. Hence, an increase in illiquidity, and therefore liquidity risk, is associated with higher bid-ask spreads.

[6] See, e.g., Amihud and Mendelson (1991) for empirical evidence from the U.S. government bond market or Collin-Dufresne (2001) and Chen et al. (2007) for empirical evidence from the U.S. corporate bond market.

of a loss due to a debtor's default converges to one. In this case, the proxy for credit risk (see Section 2.2.2), the CDS mid-rate, is maximum.

Despite the substantial research which investigates the factors that determine changes in credit risk and liquidity (and therefore indirectly changes in liquidity risk), there are only a few studies which empirically analyze how both risk factors are related to each other over time.[7] It therefore remains an open question how these risk factors dynamically interact. No theoretical model is unanimously accepted as answering how these variables should interact in sign, magnitude and causality over time (Imbierowicz and Rauch, 2014). Cherubini and Della Lunga (2001), for instance, use the fuzzy measure method to introduce liquidity risk in the Merton model (Merton, 1974). Using a corporate bond as the underlying, they show that whenever liquidity risk increases, so does credit risk. According to their example, as bonds and CDSs are closely related, the correlation between the CDS bid-ask spread and the CDS mid-rate should be positive. This result is in line with Boss and Scheicher (2002), who find a positive relationship between credit risk and liquidity risk in the European corporate bond market. Moreover, Ericsson and Renault (2006) develop a structural bond valuation model that predicts a positive relationship between illiquidity and credit risk. As a consequence, any increase in illiquidity should be accompanied by an increase in credit risk proxies. Analyzing the U.S. corporate bond market, they find that the level of (market) liquidity spreads are positively correlated with credit risk.

To summarize the previous paragraph, given that during the recent financial crisis rising CDS spreads were accompanied by a liquidity shortage in the U.S. financial sector and due to the similarity between bonds and CDSs, a similar linkage is expected for CDSs, whereby credit spreads should be positively related to illiquidity and liquidity risk. At this point, however, the following observation becomes relevant: Traditional asset classes, such as bonds and equities, are assets which in partial equilibrium, as with the conventional CAPM or the liquidity-adjusted CAPM of Acharya and Pedersen (2005), are in positive net supply, in which case illiquidity depresses asset prices and increases expected returns. In a recent study, Bongaerts et al. (2011) analyze liquidity risk in derivatives, which are assets that in equilibrium are in zero net supply, and identify factors that determine the sign and the magnitude of the liquidity premium, which is the ex-ante return of an asset in excess of the ex-ante return of a more liquid benchmark asset (Ilmanen, 2011). Their equilibrium asset pricing model implies that the expected liquidity premium is earned by the credit protection seller and that liquidity risk is economically small, but significant. In their model, allowing for short sales, illiquid assets may exhibit higher prices than liquid assets, depending on the short-seller's risk aversion, his amount of wealth, or his investment horizon. Hence, the relationship between both risk factors may well contradict the aforementioned hypothesis, in line with Acharya and Johnson (2007), among others, who find a negative relationship between CDS bid-ask spreads and CDS spreads, or the aforementioned study by Beber et al. (2009), who find a negative relationship between credit quality and liquidity for Euro-area central government bonds from April 2003 to December 2004.

But how important is liquidity risk and the liquidity premium for CDS contracts? Tang and Yan (2007) analyze CDS data for non-sovereign U.S. bond issuers from June 1997 to March 2006 and document an average liquidity premium of 13.2 bps or 11% of the CDS spread, which, accords, grosso modo, with the estimated 13% (5.6 bps) in Lin et al. (2011), among others, who analyze CDS data from around the world in the period from July 2002 to February 2005. Bühler and Trapp (2009), who analyze CDS data from June 2001 to June 2007 before the financial crisis erupted, find that 4% of the CDS spread was due to illiquidity. If this result is combined with the

[7] See, e.g., Imbierowicz and Rauch (2014) for a detailed literature review of the relevant articles that address this topic.

evidence in Mayordomo et al. (2014), who report that from January 1, 2004 to before August 9, 2007, the average CDS mid-rate for a sample of highly liquid CDS contracts of European blue chip companies was 31 bps and increased to 105 bps in the period after August 9, 2007 until March 2010, ceteris paribus, a liquidity premium of 4.2 bps in the second period results. Compared to other asset classes, this liquidity premium is small (see, e.g., Hibbert et al. (2009), Chen et al. (2010), Ilmanen (2011) or Ang (2014)). However, it is still controversial whether illiquid assets should in general trade at a discount, which contradicts the predictions of Amihud and Mendelson's model (1986). Ang et al. (2010), for instance, document that there is no conclusive evidence that average returns increase, when different asset classes become less liquid.[8]

2.2 Risk Measures

2.2.1 Liquidity Risk Proxy: The CDS Bid-Ask Spread

As liquidity is not directly observable and a multi-dimensional concept, it is proxied by a variable that describes this measure to a large degree in terms of the costs associated with a round trip, the absolute bid-ask spread, following Düllmann and Sosinka (2007), Chen et al. (2010), and Annaert et al. (2013), among others. This is the cost incurred when executing a trade in addition to fees and taxes and is a good approximation of the associated costs, such as adverse selection costs, inventory costs and processing costs.[9] Given the reasons mentioned in Subsection 2.1.1, the absolute bid-ask spread also proxies for liquidity risk and is defined for each company in the sample as follows:

$$BAS_t = A_t - B_t \tag{1}$$

where A_t and B_t are the corresponding (lowest) CDS ask and (highest) CDS bid prices of the respective company at time t.

The selection of this proxy is motivated as follows: As many studies use CDS spreads as the price of credit risk, using this spread as a proxy for the price of liquidity and liquidity risk is a consistent approach. But compared to other liquidity measures, it has additional desirable properties. Fleming (2003), for instance, compares different commonly-used liquidity measures for U.S. Treasury securities and finds that the bid-ask spread is the best performing proxy for liquidity risk in terms of consistency with the market participants' view about liquidity. In addition, different studies show that the bid-ask spread is highly correlated with alternative liquidity measures such as the trading volume and the effective spread, which include additional information on traded prices and volume. This has been documented for the stock market by Chordia et al. (2000) and Lee et al. (2006), among others. Hence, by assuming that equity and CDS markets are similar with respect to this feature (in line with, e.g., Das and Hanouna (2009)) the proposed liquidity measure also proxies other metrics. Huberman and Halka (2001) also conclude that alternative liquidity proxies should be correlated with each other, whenever there is a systematic liquidity component or if the liquidity measures are close substitutes. Therefore, the final decision of which proxy to use is less important.

2.2.2 Credit Risk Proxy: The CDS Mid-Rate

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[8] See also the aforementioned study by Bongaerts et al. (2011).

[9] A detailed overview of why bid-ask spreads are observed in financial markets at all and its three cost components can be found in Gourieroux and Jasiak (2001), Minguet (2003), Stoll (2003) or Hasbrouck (2007), among others.

Credit risk is measured by the price of credit risk, namely the CDS mid-rate, defined as the mean value of the bid and the ask price for each company in the sample:

$$MID_t = \frac{A_t + B_t}{2} \tag{2}$$

where A_t and B_t are the corresponding (lowest) CDS ask and (highest) CDS bid prices of the respective company at time t.

This study uses CDS data instead of the credit spread, as compared to corporate bond spreads, CDS spreads have two advantages. First, CDS spreads provide a relatively pure pricing of the default risk of the underlying entity and are typically traded on standardized terms. In contrast to this, bond spreads are more likely to be affected by differences in contractual arrangements and crucially depend on the chosen risk-free benchmark (see, for example, Hull et al. (2004), Houweling and Vorst (2005) or Ericsson et al. (2009)). Second, as shown by Blanco et al. (2005), CDS spreads are a useful indicator for assessing credit risk and tend to respond more quickly to changes in credit conditions in the short run than credit spreads, partly due to the absence of funding and short-sale restrictions in the derivatives market and the important non-default component in bond yields (see, e.g., Chen et al. (2007), Chen et al. (2010) and Huang and Huang (2012)). Even for the recent episode of sharply rising credit spreads, the study by Chiaramonte and Casu (2011), for example, provides empirical support for the suitability of this measure as a proxy for credit risk.

3. Methodology

In the empirical Section 5, this paper analyzes whether liquidity risk changes are (weakly) exogenous in the time series sense (Hamilton, 1994) with respect to credit risk changes, i.e., whether lagged changes in liquidity do not Granger-cause credit risk changes in a bivariate VAR model. As the conventional Granger causality test is restricted to stationary time series, using the stationarity test of Kwiatkowski et al. (1992), abbreviated by KPSS, this paper first tests in Section 5.1 whether the bid-ask spread and the mid-rate are stationary. This is important when testing for causality: Toda and Phillips (1993), for instance, show that testing for causality among stochastically trending, non-cointegrated variables using the standard critical values overestimates the likelihood of causality.

After determining the order of integration of the data, this paper proceeds with the Granger causality analysis in a bivariate VAR. In the following, it is assumed that both the changes in the bid-ask spread (ΔBAS_t) and the mid-rate (ΔMID_t) are (weakly) stationary. To ensure that any serial correlation in the residuals has been removed, the VAR allows for a maximum of seven lags. The optimal number of lags p is determined by minimizing the value of the Akaike information criterion.[10] After choosing p, the following unrestricted reduced form of the VAR(p) is estimated by ordinary least squares (OLS) for each company in the sample, equation by equation:

$$Y_t = \mu + \sum_{i=1}^{p} \Phi_i \cdot Y_{t-i} + \varepsilon_t, \text{ for } t = -p+1, -p+2, \ldots, T, \tag{3}$$

[10] To check for the sensitivity of the optimal lag length p, the Schwarz (BIC) and the Hannan-Quinn (HQC) information criterion are used as well. The results are, however, similar.

with $Y_t = \binom{\Delta BAS_t}{\Delta MID_t}$, $\mu = \binom{\mu_1}{\mu_2}$, where $\Phi_i = \begin{pmatrix} \varphi_{11,i} & \varphi_{12,i} \\ \varphi_{21,i} & \varphi_{22,i} \end{pmatrix}$ is a 2x2 coefficient matrix, where $\varepsilon_t = \binom{\varepsilon_{1t}}{\varepsilon_{2t}} \sim WN(0, \Sigma_\varepsilon)$ is a bivariate white noise process with the disturbance variance-covariance matrix Σ_ε and T is the number of observations. Before proceeding with the Granger causality test, the model assumptions and properties are checked, i.e., the residuals are tested for autocorrelation, conditional heteroskedasticity and non-normality using the corresponding multivariate test statistics, i.e., the multivariate Portmanteau test for serial correlation, the multivariate ARCH-LM test and the multivariate Jarque-Bera test, respectively. The exact formulas of the multivariate tests can be found in Lütkepohl and Krätzig (2004), among others.

In Equation 3, ΔMID does not Granger-cause ΔBAS ($\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$) iff the coefficient matrices Φ_i are lower triangular for all is. This implies that the 1-period-ahead forecast of ΔBAS only depends on lagged values of itself. Analogously, ΔBAS does not Granger-cause ΔMID ($\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$) iff the coefficient matrices Φ_i are upper triangular for all is, implying that the 1-period-ahead forecast of ΔMID only depends on lagged values of itself. To test for Granger causality, an F-test with the following null hypothesis for $\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$ is conducted:

$$H_0: \varphi_{12,1} = \varphi_{12,2} = \cdots = \varphi_{12,p} = 0$$

and the corresponding null hypothesis for $\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$:

$$H_0: \varphi_{21,1} = \varphi_{21,2} = \cdots = \varphi_{21,p} = 0$$

The significance level is set to 5%. As the CDS time series exhibit heteroskedasticity, the standard errors are corrected by the Newey-West heteroskedasticity-consistent (HC) estimator (Newey and West, 1987).

The test statistic asymptotically equals

$$S = \frac{T \cdot (RSS_r - RSS_u)}{RSS_u} \sim X_p^2 \qquad (4)$$

where RSS_r and RSS_u denote the residual sum of squares of the corresponding restricted and unrestricted VAR equation, respectively.

The VAR(p) is interpreted using the orthogonalized impulse response functions. For this purpose, the process in Equation 3 is written as a multivariate moving average process of infinite order (see, e.g., Lütkepohl (2007)):

$$Y_t = c + \Psi(L) \cdot \varepsilon_t \qquad (5)$$

with $\Psi(L) \coloneqq \sum_{i=0}^{\infty} \Psi_i \cdot L^i = [\Phi(\mathrm{L})]^{-1}$ and $c = \binom{c_1}{c_2}$, where L denotes the lag operator.

In a next step, the Cholesky decomposition is applied to the disturbance variance-covariance matrix Σ_ε and a lower triangular matrix P is defined, such that $\Sigma_\varepsilon = P \cdot P^T$. The following bivariate white noise residuals are obtained, which have unit variance:

$$\vartheta_t = P^{-1} \cdot \varepsilon_t \qquad (6)$$

The orthogonalized impulse response functions are obtained by combining Equation 5 with Equation 6:

$$Y_t = c + \Theta(L) \cdot \omega_t \tag{7}$$

with $\Theta(L) := \sum_{i=0}^{\infty} \Theta_i \cdot L^i = \Psi(L) \cdot P$ and $\omega_t = P^{-1} \cdot \varepsilon_t$. The element $\theta_{12,i}$ ($\theta_{21,i}$) of the 2x2 coefficient matrix $\Theta_i = \begin{pmatrix} \theta_{11,i} & \theta_{12,i} \\ \theta_{21,i} & \theta_{22,i} \end{pmatrix}$ represents the effect of a unit innovation in the second (first) variable that occurred i periods ago on the first (second) variable in Y_t.

To analyze the "long-run" effects, the cumulated responses over n periods are estimated as well:

$$\Gamma_n = \sum_{i=0}^{\infty} \Theta_i \tag{8}$$

with $\Gamma_i = \begin{pmatrix} \gamma_{11,i} & \gamma_{12,i} \\ \gamma_{21,i} & \gamma_{22,i} \end{pmatrix}$ a 2x2 coefficient matrix.

To check for the sensitivity of the results with respect to the inclusion of exogenous explanatory variables, the VAR(p) is subsequently extended with k exogenous explanatory variables which according to theoretical models and empirical studies determine changes in the CDS bid-ask spread and/or CDS mid-rate:

$$Y_t = \mu + \sum_{i=1}^{p} \Phi_i \cdot Y_{t-i} + B^T \cdot X_t + \varepsilon_{t,} \text{ for } t = -p+1, -p+2, \ldots, T, \tag{9}$$

where X_t denotes the $k\ x$ 1 vector of exogenous variables at time t and B the $k\ x$ 2 coefficient matrix. This VAR(p) model then is known as the VARX(p) model. To see whether omitted variables may have biased the initial parameter estimates and how robust these estimates are, the Granger causality test statistic of the VARX(p) model is calculated as well.

4. Data

The sample consists of daily senior single-name 5-year CDS bid and ask prices denominated in euros and quoted in basis points per year of the contract's notional amount, from August 24, 2007 to June 1, 2010, for 14 Swiss and 34 German companies. The period under consideration starts shortly before Lehman Brothers collapsed which spurred the subsequent financial crisis, and ends during the recent financial crisis. As the initial sample included CDS time series that were not available at the beginning of the sampling period (namely, the data of Swiss Life and Rheinmetall) and as some data included a lot of zero changes (namely, the data of IKB and MAN), they are excluded from the final data sample. Therefore, the final number of Swiss and German companies is reduced to 13 and 31, respectively (see Tables A.1 and A.2 in Appendix A for a list of the companies in this study). These tables also include the respective industry sector to which these companies belong, according to the global industry classification standard published by MSCI Barra.

This paper uses CDSs with a maturity of five years, as the 5-year CDS contracts are the most liquid contracts (Blanco et al., 2005). This paper uses daily data, as the focus of this study is on the short-run relationship between credit risk and liquidity risk, where imbalances between demand and supply impact liquidity and liquidity risk. In addition, using a relatively higher frequency than previous studies reduces the risk of aliasing (Popescu, 2011), which may arise when investors react to news faster than the sampling interval and can lead to spurious correlations in the innovations (Phillips, 1973). The data source is the Credit Market Analytics (CMA) database obtained from the data provider Thomson Reuters Datastream.[11] CMA collects data from the largest and most active buy-side investors; i.e., global investment banks, hedge funds and asset managers. Although the CDS market is an OTC market and therefore lacks transparency, using data from a large number of investors and with blue chip companies as the reference entity should mitigate this problem and should be sufficiently representative for the CDS market in general.

To see whether the data exhibit some peculiarities and/or large outliers, the daily bid-ask spread and the mid-rate are plotted in Figures 1 and 2, respectively.[12] Since the plots of the other companies in the sample are qualitatively similar, in Figures 1 and 2, the liquidity risk proxy (the CDS bid-ask spread) is plotted for only four Swiss and four German representative companies. The figures of the other companies in the sample are available from the author upon request.

In general, the daily CDS bid-ask spread is relatively stable and low over the sample period (Figures 1 and 2). There are, however, periods where the bid-ask spread suddenly exhibits large spikes and becomes more volatile, as in spring 2008, after the investment bank Bear Stearns had to be rescued and signed a merger agreement with JP Morgan Chase on March 16, 2008 or even more pronounced around the end of 2008, after the investment bank Lehman Brothers filed for Chapter 11 bankruptcy protection on September 15, 2008.

A closer look at the bid-ask spread changes (the first differences) in Figures 3 and 4 reveals that the data exhibit volatility clustering, especially in the aforementioned periods.

In Figures 5 and 6, the credit risk proxy (the CDS mid-rate) is plotted for the Swiss and the German companies, respectively. In general, the mid-rate is less volatile than the bid-ask spread (compare Figures 1 or 2 with Figures 5 or 6) and larger in absolute value, as it is the mean of two positive prices, as opposed to the absolute value of the difference between the two. In the case of UBS (panel 4 in Figure 5), Merck and VW (panels 2 and 4 in Figure 6), the CDS mid-rate even rises above 300 bps in some periods. In addition, there are periods where the time series seem to be non-stationary (for example, in spring 2008 or around the end of 2008 in Figures 5 or 6, where soaring mid-rates are observed, which also become more volatile) and periods where this is not the case. The stationarity test results in Section 5.1 supports this conjecture.

Assuming conservatively that approximately 4% of the CDS spread compensates for liquidity risk (Bühler and Trapp, 2009), there are periods where the liquidity risk premium was between 10-16 bps (Figures 5 and 6), but could well be as large as 33-52 bps, for example, by applying the estimates in Lin et al. (2011).

This section concludes with the plot of the daily changes (first differences) of the mid-rate of the corresponding four Swiss and German companies in Figures 7 and 8, respectively. As it is the case with the changes in the bid-ask spread, the changes in the mid-rate exhibit volatility clusters. Compared to the changes in the bid-ask spread, however, the changes in the mid-rate are more pronounced (compare Figures 3 and 4 with Figures 7 and 8, respectively).

[11] For a detailed description of this database and a comparison of this database with five alternative major sources, please refer to the study of Mayordomo et al. (2014).
[12] The computations in this paper were performed using the software package R (version 3.0.0).

5. Empirical Results

5.1 Univariate Time Series Properties: Order of Integration and Autocorrelation

Bid-Ask Spread Stationarity: As the correct critical values of the KPSS test depend on the deterministic component and in accordance with Figures 1, 2, 5 and 6, first it is checked whether a time trend is present in both the bid-ask spread and the mid-rate (these figures are not included in this paper).[13] Based on these figures, an intercept is included under the null hypothesis of level stationarity. Table B.1 in Appendix B reveals that the levels of the bid-ask spread are non-stationary according to the KPSS test, whereas the changes are stationary (Table B.2 in Appendix B). This finding accords with, for example, Chordia et al. (2000), Blanco et al. (2005) and Corò et al. (2013), among others, but contrasts with Hasbrouck and Seppi (2001), Tang and Yan (2007), Acharya and Johnson (2007) or Pires et al. (2010). The results for the other companies in the sample (results not included) are similar to the presented results.

To date, there is no consensus as to whether the CDS bid-ask spread should be stationary or not. In view of this, and in accordance with the test results and in order to exclude the possibility of spurious results (see, e.g., the aforementioned study by Toda and Phillips (1993)), in the following it is assumed that the bid-ask spread is integrated of order 1. Also the fact that both the bid-ask spread and the mid-rate are time series that are bounded from zero supports this decision, as in this case conventional unit root tests reject the null hypothesis of a unit root too often, even asymptotically, and more adequate unit root tests in the spirit of Cavaliere and Xu (2014) are required. Accordingly, the asymptotic power of conventional stationarity tests should also be lower than when dealing with unbounded time series.

As is evident, the bid-ask spread exhibits a large number of zero changes and may better be described by a discrete time series with more frequent zero changes (see Figures 1, 2, 3, 4 and Table B.3 in Appendix B) than what is generally assumed in conventional time series tests, which may bias the results. For instance, the simulation study by Annaert et al. (2004), who analyze how commonly used normality tests detect deviations from normality, indicates that if a given time series, which under the null hypothesis follows a geometric Brownian motion, is rounded to the nearest cent (this corresponds to a tick size of 1 cent for equities), the Jarque-Bera test, for instance, will be biased if the discreteness of the data is ignored.[14] There are, however, only a few studies that emphasize this potential problem; see Huberman and Halka (2001), among others.

Mid-Rate Stationarity: The KPSS test for the mid-rate in levels and for the first differences in Tables B.1 and B.2 in Appendix B indicates that the mid-rate is integrated of order 1. In both cases, an intercept is included under the null hypothesis. The KPSS test results accords with the test results in the rest of the sample (test results not included). As a robustness check, other unit root tests are applied that support this result (test results not included).

These results accord with the time series properties of the CDS spreads data in Blanco et al. (2005), Greatrex (2009) or Norden and Weber (2009), among others. Mayordomo et al. (2014) analyze a similar period than in the present study, namely the period after August 9, 2007 until

[13] To save space, some figures and test results have been omitted in the text, but most of them are part of a separate supplement.

[14] In addition, the discreteness of the data may require alternative central limit theorems, see, e.g., Chapter 5 in Judge et al. (1985).

March 29, 2010,[15] and use a sample that includes one Swiss and 13 German companies which are also contained in this study. They also conclude that the CDS mid-rates in their sample are best described by a unit-root process, except for Commerzbank.[16] Hence, in the following, this study assumes that the mid-rate has a unit root.

Concluding this section, in the following, it is assumed that the time series in the used data sample are all integrated of order 1. To complement the univariate time series properties, this study also applies the unit root test developed by Zivot and Andrews (1992) that allows for a single break in the intercept, the trend or both. The test results do support the null hypothesis of a unit root in the original time series (the test statistics of both the cointegration test and the unit root test allowing for a single break are part of a separate supplement). In addition, also a cointegration analysis is performed to analyze whether the bid-ask spread and the mid-rate are cointegrated. The test results, however, reject this hypothesis.[17]

Bid-Ask Spread and Mid-Rate Autocorrelation: Using the Ljung-Box test, it is further analyzed whether the changes in the bid-ask spread (ΔBAS) and the mid-rate (ΔMID) are serially correlated. As the sample is sufficiently large (there are in total 723 observations), 20 lags are used. The test results in Table B.4 in Appendix B clearly reject the null hypothesis of serially uncorrelated time series. Therefore, when performing the causality tests in Sections 5.3 and 5.4, more than one lag of the variables ΔBAS and ΔMID are included.

5.2 Cross-Correlation between Credit Risk and Liquidity Risk

In this section, the Granger causality analysis in Sections 5.3 and 5.4 is motivated by analyzing the correlation between the bid-ask spread changes and the mid-rate changes for up to 25 leads and lags by means of the cross-correlation function (CCF):

$$\rho_{\Delta BAS,\Delta MID}(i) = \frac{\gamma_{\Delta BAS,\Delta MID}(i)}{\sigma_{\Delta BAS} \cdot \sigma_{\Delta MID}} \tag{10}$$

for $i = 0, \pm 1, \pm 2, \ldots \pm 25$. $\gamma_{\Delta BAS,\Delta MID}(i)$ denotes the cross-covariance function between ΔBAS and ΔMID at lead or lag $\pm i$ and $\sigma_{\Delta BAS}$ and $\sigma_{\Delta MID}$ denote the corresponding standard deviations. The CCF measures the strength and the direction of the correlation between both time series. It is shown that there are significant leads and lags of the bid-ask spread changes and/or the mid-rate changes to help predict the next periods' realizations.

As seen in Section 5.1, the data are both difference-stationary and exhibit a large degree of persistence. In addition, it is assumed that the cross-covariance $\gamma_{\Delta BAS,\Delta MID}(i)$ between the bid-ask spread changes and the mid-rate changes only depends on the time difference, such that the CCFs can be calculated. At lag 0, the CCF displays the contemporaneous correlation between the changes in the bid-ask spread and the mid-rate. At a negative lag $i < 0$, the CCF measures the correlation between the bid-ask spread changes at time t, ΔBAS_t, and the mid-rate changes at a date before time t (ΔMID_{t+i} [= $\Delta MID_{t-|i|}$]). Analogously, at a positive lag $i > 0$, the CCF

[15] They do not explicitly state the exact start and end date. Given their information and the number of observations, it is assumed that they analyze the period from September 14, 2007 to March 29, 2010.
[16] For the Commerzbank mid-rate, however, the KPSS test and several unit root tests in R indicate that the data are non-stationary.
[17] Also in this case, the conventional cointegration tests suffer from size distortions (Cavaliere, 2006). However, as the distance to the lower bound is large, the standard methods are still appropriate.

measures the correlation between the bid-ask spread changes at time t (ΔBAS_t) and the mid-rate changes at a date after time t (ΔMID_{t+i}).

In Figures 9 and 10, the CCFs for ΔBAS and ΔMID for the four Swiss and four German companies in the sample are plotted. In each figure, the corresponding 95% confidence interval is included. For the Swiss companies (Figure 9), there are significant correlation coefficients between both measures at lag 1 or 2 with alternating and varying signs, except for ABB (panel 1 in Figure 9). In the case of ABB, only a contemporaneous correlation between ΔBAS and ΔMID can be detected. For Nestlé (panel 2 in Figure 9), the second lag coefficient ($i = 2$) is negative and significantly different from zero, indicating that the changes in the bid-ask spread two periods ago help to predict the changes in the mid-rate in period zero. For Roche (panel 3 in Figure 9), the changes in the mid-rate in the previous periods ($i < 0$) help to predict the change in the bid-ask spread in the following period, although with alternating and varying signs. For UBS, predictability is detected for both variables (panel 4 in Figure 9), but again with varying and alternating signs.

The results for the German companies (Figure 10) reveal a different picture. Ignoring significant coefficients at higher leads and lags, these data only exhibit a contemporaneous correlation among both measures, except for VW. For VW (panel 4 in Figure 10), the first lag coefficient ($i = -1$) is positive and significant, indicating that the changes in the mid-rate one period ago help to predict the changes in the bid-ask spread in period zero. For the other three German companies, the correlation at lag 0 is shown to be both significantly different from zero and positive. Only the magnitude of the contemporaneous cross-correlation differs across companies. For Deutsche Bank, Merck, Siemens and VW, the cross-correlation coefficient approximately equals 0.22, 0.4, 0.3 and 0.16, respectively.

Concluding this section, notice that the results in this section suggest that analyzing the lead-lag relationship between the changes in the bid-ask spread and the changes in the mid-rate in order to identify whether liquidity risk changes are endogenous with respect to credit risk changes or not, and vice versa, is a worthwhile exercise.

5.3 Granger Causality Test: Testing Credit Risk and Liquidity Risk for Exogeneity

In this section, it is finally tested whether liquidity changes are weakly exogenous in the time series sense (Hamilton, 1994) with respect to credit risk changes. This is done following the methodology described in Section 3. Section 5.1 showed that in the present data sample both the bid-ask spread and the mid-rate are integrated of order 1 and that they are both not cointegrated. As a consequence, first differences are used to perform the Granger causality test. The causality test results for the null hypothesis that changes in the bid-ask spread do not Granger-cause changes in the mid-rate ($\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$) and vice versa ($\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$) are given in Tables 1 and 2 for the Swiss and German companies, respectively.

The Granger causality test shows that the changes in the CDS mid-rate (ΔMID) Granger-cause the changes in the CDS bid-ask spread (ΔBAS) for approximately 46% of the Swiss companies (Table 1) and 35% of the German companies (Table 2) at the 5% significance level (or 39% in total). The number increases to approximately 54% and 52%, respectively, if a significance level of 10% (or 52% in total) is chosen. In contrast, the changes in the bid-ask spread are significant at the 5% significance level only for Kabel Deutschland (Table 2) and at the 10% significance level for Swiss Re (Table 1), Bayer and Munich Re (Table 2). For Swiss Re, Kabel Deutschland and Munich Re, even a feedback relationship is detected. It is interesting that in this sample a feedback relationship for two of the three most important reinsurance companies in the world is found.[18] This may deserve further investigation, as Jarrow (2011) argues that counterparty risk in the CDS market may be mitigated by introducing the requirement of 100% of the notional amount as collateral, which is the standard practice in reinsurance contracts, meaning that this industry exhibits special features that may in part explain this phenomenon. These results also extend previous findings in Breitenfellner and Wagner (2012), among others, who find that liquidity proxies are only relevant for CDS spread changes for financial companies. First, a reverse Granger causality is detected in this sample, second, it is found that also for financial companies the used liquidity proxy does not Granger-cause CDS spread changes (see Tables 1 and 2 below for the relevant companies, and Tables A.1 and A.2 in Appendix A for the assigned industry classification of these companies).

It is interesting to observe that UBS, the bank that had to be rescued by the Swiss National Bank in October 2008, is the sole bank in this sample, where credit risk changes are not (weakly) endogenous with respect to liquidity risk changes. However, also Commerzbank has been bailed out by the German government in January 2009, where the reported results imply that credit risk changes are (weakly) endogenous with respect to liquidity risk changes.

In sum, these results indicate that credit risk shocks are followed by a subsequent liquidity shortage in the CDS market. However, liquidity shocks in general do not Granger-cause credit risk changes. Hence, in this sample liquidity or liquidity risk seems to be rather (weakly) exogenous than endogenous for credit risk changes. Consequently, these findings support previous ad hoc assumptions that liquidity is (weakly) exogenous with respect to credit risk changes, but also show that in credit markets, credit risk might be endogenous with respect to liquidity risk, in the spirit of, e.g., the liquidity spiral posited by Brunnermaier (2009).

For the companies that experienced no change in credit rating,[19] the results show that credit risk is endogenous with respect to liquidity risk in 58% (or 67% at the 10% significance level) of the cases, compared to 31% (or 47% at the 10% significance level) in the case of the companies that suffered a credit rating change. This is consistent with the findings in Beber et al. (2009), who disentangle the effect of a flight-to-quality from the effect of a flight-to-liquidity for Euro-area government bonds in periods of heightened uncertainty. They document that in these periods investors' demand for liquid assets dominates the demand for credit quality. Although their sample analyzes a different environment than in the present study, the empirical results in this analysis indicate that a credit shock widens the bid-ask spread substantially in the subsequent days, consistent with the market microstructure literature view that in times of heightened uncertainty bid-ask spreads rise. This effect is more pronounced among the companies with a stable credit rating, whereas there's no difference between high- and low-rated companies, meaning that the credit rating per se is of secondary relevance in determining changes in liquidity, which may deserve additional research.

To provide further information about the relationship between credit risk and liquidity risk, the orthogonalized impulse response functions (IRFs) are displayed in Figures 11-18 for $i = 0, 1, \ldots, 10$ steps ahead. Focusing on the corresponding panels 2 and 3 in each figure, the graphical results in panel 2 in all the figures show that positive innovations in credit risk on the previous day ($\Delta MID > 0$) are followed by a deterioration of liquidity ($\Delta BAS > 0$) on the following day.

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[18] According to the gross premiums written in 2011, Munich Re is the largest reinsurance company in the world, followed by Swiss Re and Hannover Rück.

[19] These are Credit Suisse, Swisscom, Allianz, Bayer, E.ON, EnBW, Fresenius, Hannover Rück, Lanxess, Munich Re, Siemens and Südzucker.

As a consequence, the coefficient at lag 1 is positive and in most cases significantly different from zero, but numerically small. As expected, the credit risk innovations do not have a sustainable effect on the equation system, as in most cases the effect fades away after the second or third day. The response of credit risk to a liquidity risk innovation, however, is different. In most cases, the response is not significantly different from zero (panel 3 in all the figures).

Resuming this section, the presented results imply that credit risk and illiquidity are positively correlated. This result is in line with the findings of Cherubini and DellaLunga (2001), Boss and Scheicher (2002), and Ericsson and Renault (2006), among others (see Section 2.1.3 for more details). To be more specific, it seems that in the short run credit risk changes are more likely to induce CDS market liquidity to dry-up than vice versa. This is interesting, as this observation indicates that a liquidity shortage may be preceded by credit risk shocks, in the spirit of the liquidity spiral in Brunnermaier (2009). Hence, a deterioration in credit risk, as was observed during the beginning of the current financial crisis, may trigger a liquidity crisis in the CDS market. This linkage may be one of the amplifying mechanisms that aggravated and propagated the initial credit shocks in the subprime market. Brunnermaier (2009), for instance, describes an economic balance sheet mechanism that shows how unexpected and initially small losses (implying higher credit risk) can initiate a loss spiral, as highly levered companies may be forced to sell assets to hold constant, e.g., a target leverage ratio, which may cause margins to rise, as asymmetric-information frictions emerge. Hence, according to the microstructure literature, bid-ask spreads rise. This loss spiral is expected to be more pronounced in relatively illiquid markets and in periods of heightened uncertainty. This spiral then may cause the CDS market to become illiquid. The breakdown of the CDS market may also have real effects on the economy, as CDS contracts may enhance financial market efficiency by offering insurance against the default of fixed-income instruments. Jaccard (2013), among others, develops a macroeconomic model that shows how credit shocks can lead to a liquidity shortage with real effects on the macroeconomy.

Alternatively, the information amplification mechanism in Caballero and Krishnamurthy (2008) and Krishnamurthy (2010), among others, may well describe the observed increase in the CDS bid-ask spreads during the recent financial crisis, as it is well documented that in this period investors started to put into question the standard CDS pricing models, after investors had suffered unexpectedly large losses on CDS contracts and therefore closed investment positions in the CDS market and sought more liquid assets, with the consequence that CDS bid-ask spreads widened, consistent with the microstructure literature view that bid-ask spreads widen when the risk of adverse selection increases. The banking model developed by Bolton et al. (2011), where asymmetric information about asset quality (a real shock in the form of a lower quality of the risky assets) triggers early asset sales, thereby deteriorating liquidity, also accords with the findings of this paper.

For the other companies in the sample, where no significant lead-lag relationship between credit risk shocks and liquidity is detected, alternative explanations, such as the model in Easley and O'Hara (2010), where illiquidity arises from uncertainty (i.e., investors having incomplete preferences over portfolios) or the model in He and Xiong (2012), where companies that have to roll over maturing debt face rising credit spreads, in a market environment where liquidity in the bond market is deteriorating, may describe the observed increase in both the CDS bid-ask spreads and the CDS spreads during the recent financial crisis.

To sum up, the findings of this paper imply that credit risk might be (weakly) endogenous with respect to liquidity risk, which has important consequences for the asset pricing and the risk management literature. For example, a liquidity-enhanced CAPM or a value-at-risk model that includes illiquidity as an additional variable should treat liquidity as endogenous and control for the interaction between credit and liquidity risk, which contradicts the standard practice until now. Also for policy-makers, the indication that a negative credit shock may cause a liquidity shortage in the CDS market should be taken into account when setting capital requirements for financial institutions. In addition, when pricing derivatives that are related to assets with credit risk the results in this study imply that liquidity risk may be an important factor to include and to control for its interaction with credit risk.

5.4 Model Extension

If an important variable that is correlated with one of the dependent variables and one of the included regressors is omitted, a spurious Granger causality among the endogenous variables may be found, as the effect of omitted variables is contained in the innovations (see, e.g., Lütkepohl (2007)). Therefore, in the following, the robustness of the reported causality test results are analyzed, with a special focus on the changes in the CDS mid-rate. For the changes in the CDS bid-ask spread, most of the commonly used explanatory variables are not available from Bloomberg and Datastream. To gain additional insights, however, this study checks how the included financial and macroeconomic explanatory variables that determine the changes in the CDS mid-rate impact the CDS bid-ask spread. As previously commented, there are only two studies that analyze the determinants of the CDS bid-ask spreads. Hence, the results of this study add to the strand of literature that analyzes liquidity in CDS markets.

To control for potential omitted variables bias, the VAR(p) model is extended by introducing variables suggested by finance theory and variables that have been proven to be important in explaining the variation in CDS spreads in empirical studies. The data is obtained from Bloomberg and covers the same period as before. The extended VAR(p) model (denominated as VARX(p) model) includes some of the key variables that in the Merton-type structural models for default determine credit spreads. These are the risk-free interest rate, the degree of leverage and the volatility of the firm's assets' value. In more general models, additional state variables are included to capture the stochastic volatility of the firm's assets' value or the randomness of the risk-free interest rate.[20] Therefore, the VARX(p) model includes commonly used state variables, such as the slope of the yield curve, the TED spread, the default yield spread, an index of stock market option-implied volatility, and the returns of a broad stock market index as a proxy for the business climate. Moreover, the VARX(p) model also includes variables that are commonly associated with expected returns; i.e., the dividend yield, the price-to-book ratio and two momentum indicators (one short-term and one long-term indicator) of the companies in the sample, since Collin-Dufresne et al. (2001) and Campbell and Taksler (2003), among others, show that credit spreads are partly determined by equity-related variables. Since both the changes in the CDS bid-ask spread and the CDS mid-rate are analyzed, the first differences of these variables are taken in order to be consistent with this strand of literature. In the following, the exogenous variables are described and it is explained what their expected impact on the changes in the CDS bid-ask rate and in the CDS mid-rate is. Table C.1 in Appendix C summarizes the expected signs for all the included exogenous explanatory variables.

1.) Risk-Free Interest Rate r_t^f: A higher risk-free interest rate r_t^f raises the discount rate and therefore reduces the value of bonds. Hence, for a given firm value, if the interest rate rises, the distance to default increases. Given that in the Merton model the firm value process grows with

[20] In the original Merton model, no state variables are necessary, as the risk-free rate is assumed to be constant over time.

the risk-neutral interest rate, the expected growth rate of the firm's value will also adjust accordingly. Hence, for a given notional amount, the risk-neutral default probability will fall (Longstaff and Schwartz, 1995). Therefore, CDS spreads should in general fall with a higher risk-free interest rate r_t^f. This conjecture has been empirically proven in Skinner and Townend (2002) and Ericsson and Renault (2006), among others. The (short-term) risk-free interest rate is proxied by the 3-month EUR LIBOR interest rate,[21] following the practice of derivative traders, among others. For the CDS bid-ask spread, this paper conjectures that higher risk-free interest rates, as a proxy for the inventory costs associated with holding overnight positions, cause bid-ask spreads to widen, in line with Bessembinder (1994), among others.

2.) Leverage and Firm Value (Stock Returns r_t): In the structural framework, default is triggered whenever the leverage ratio equals or falls below one. Consequently, the larger the firm value is for a given debt level, the larger the distance to default, which is an inverse representation of the default probability. Hence, CDS spreads should rise, whenever the leverage ratio increases. As in the structural framework total firm value equals total debt plus equity, this implies that the return on equity should be negatively related to CDS spreads.[22] As accounting data are not available at a daily frequency, changes in the firm's financial health are proxied by the company's continuously compounded equity returns, following, e.g., Blanco et al. (2005):

$$r_t \equiv \ln\left(\frac{S_t}{S_{t-1}}\right) \tag{11}$$

where S_t stands for the stock price of the reference entity at time t. Some studies, however, linearly interpolate low-frequency data to obtain higher frequency data, see Collin-Dufresne (2001) or Greatrex (2009), among others. Given that this paper works with daily data, this approach makes little sense. The expected negative relationship between equity returns and credit spreads is supported by the empirical findings in Ericsson and Renault (2006), among others. With reference to the CDS bid-ask spread, a higher leverage ratio (or lower stock returns) is expected to cause CDS liquidity to worsen (see Section 2.1.3), consistent with the empirical evidence from U.S. bond markets provided by Hong and Warga (2000). Indeed, Brunnermaier and Pedersen (2009) report that positive stock returns increase the availability of capital that market makers use to fund their trading positions, thereby lowering the bid-ask spread.

3.)-5.) Asset Volatility (Stock Volatility σ_t): In the structural framework, the volatility σ of the firm's assets equals the volatility of the sum of debt and equity. This variable is proxied by the historical short-term and long-term equity return volatility σ_t^{30} and σ_t^{360}, i.e., the volatility of each company's stock returns for the most recent 30 and 360 trading days.[23] Cremers et al. (2008) show empirically that the individual stock option-implied volatility is an important determinant of credit spreads. Therefore also the implied volatility σ_t^{imp} of each company's stock options with a time to maturity of three months is included, following Pires et al. (2010) and Hibbert et al. (2011), among others. In the structural framework, since the value of debt equals risk-free debt plus a short position in a credit put option with an exercise price equal to the face value of debt, credit spreads should rise with volatility, because the short put price decreases when volatility

[21] It can be argued that for 5-year CDS contracts, the risk-free interest rate r_t^f should instead be a long-term interest rate, e.g., the expected return on a default-free 5-year zero coupon bond. The present study, however, follows the standard practice in this strand of literature.
[22] As changes in the debt value should be transmitted one to one to the equity value. In addition, lower stock returns suggest that a firm's future business is expected to worsen, whereby default risk would rise.
[23] This implies that it is assumed that the volatility of debt approximately equals minus two times the covariance between debt and equity.

rises. This is also intuitive, as the larger the volatility becomes, the more likely it is that the firm's asset value will fall below its debt value, meaning that the probability of default is positively related to volatility. For the CDS bid-ask spread, a positive relationship is expected as well, since Stoll (2000), among others, finds a positive relationship between bid-ask spreads and the level of stock market volatility. In the following, the state variables that are included in the VARX(p) model are motivated and described.

6.) Slope of the Yield Curve sl_t: It is commonly accepted that the level and the slope of the yield curve explain a large portion of the bond return variability. This conjecture has been analyzed and empirically proven for U.S. bonds by Litterman and Scheinman (1991). Although the slope does not enter the equation of the firm value process in the Merton model, the risk-free interest may well depend on the characteristics of the yield curve. If an increase in the slope causes the expected future risk-free rate to rise, CDS spreads may decrease (see the previous reasoning for the risk-free interest rate). Hence, a negative relationship between the slope of the yield curve sl_t and the CDS mid-rate may be expected. This conjecture is supported by the empirical findings in Ericsson and Renault (2006), among others. In addition, a steeper yield curve is commonly interpreted as the expectation of a booming economy. As a consequence, the recovery rate is expected to rise and the default probability to fall. Hence, CDS spreads should fall. Fama and French (1989), among others, find that default spreads widen when overall economic conditions worsen. For the CDS bid-ask spread, this paper conjectures that a better economic outlook is associated with lower funding costs, in the spirit of Brunnermaier and Pedersen (2009), among others. Hence, the CDS bid-ask spread should be negatively related to the slope of the yield curve. The slope of the yield curve sl_t is proxied by the yield difference between the 10-year constant maturity EMU government bond yield and the 1-year constant maturity EMU government bond yield.

7.) TED Spread ted_t: Due to its relevance in integrated global financial markets, the U.S. TED spread is used, i.e., the 3-month USD LIBOR interest rate minus the 3-month U.S. Treasury Bill rate, as a proxy for funding illiquidity (Brunnermaier, 2009). As already mentioned, this paper expects that an increase in funding illiquidity is accompanied by an increase in both the CDS mid-rate and the CDS bid-ask spread. Hence, a positive sign is expected for the impact of this variable on both aforementioned CDS variables.

8.) Default Yield Spread $dspread_t$: This paper also controls for the portion of credit risk that is related to aggregate (market) default risk. This risk factor is proxied by the spread between Moody's Baa Corporate Bond Yield Index and Moody's Aaa Corporate Bond Yield Index. In line with the reasoning in Section 2.1.3, a positive relationship between this variable and the level of CDS spreads is expected. Hence, changes in both of these variables should also be positively correlated. As mentioned in the theoretical part of this chapter (Section 2.1.3), the expected sign on the liquidity risk proxy is ambiguous. However, due to the argumentation in Section 2.1.3, this paper conjectures a positive sign, i.e., that an increase in systematic credit risk is related to a decrease in liquidity.

9.) Stock Market Option-Implied Volatility $vdax_t$: In periods of financial turmoil, risk aversion rises and a "flight-to-quality" is expected, i.e., an increase in the demand for more liquid assets, which has been documented by Longstaff (2004) for U.S. Treasury bonds, among others. Option-implied volatility indices are commonly used as risk aversion measures. For the option-implied volatility of European stock markets, the DAX Volatility Index (VDAX index) is used, which measures the implied volatility of DAX index options. It is quoted in percentage points per annum and represents the expected movements in the stock market over the next 30-day period. If global risk aversion rises, this goes hand-in-hand with an increase in global default risk, which translates into larger CDS spreads at the individual company level. If the perception of risk increases, it is also expected that liquidity dries up and therefore CDS bid-ask spreads widen, as investors prefer to hold cash or liquid assets in periods of high uncertainty and as margin requirements tend to rise, increasing the investors' need for capital (Corò et al., 2013). Hence, the expected sign is positive for both variables.

10.) Business Climate (Stock Market Returns $r_{m,t}$): Altman and Kishore (1996) or Bruche and González-Aguado (2010), among others, show that recovery rates vary over time and are lower in a recession. Default probabilities are also negatively related to the business climate, i.e., default probabilities increase when economic conditions worsen. As a consequence, a negative relationship between CDS spreads and the business climate is expected. This state variable is proxied using the returns of a broad stock market index:

$$r_{m,t} \equiv \ln\left(\frac{S_{m,t}}{S_{m,t-1}}\right) \tag{12}$$

where $S_{m,t}$ stands for the level of the respective market index at time t , as it is well documented that equity markets are highly correlated with the economic environment, i.e., if economic expectations worsen and credit risk rises, stock market returns tend to fall. For the Swiss and German companies, the SPI and the DAX index are used as the market index, respectively. Both are total return indices. Liquidity is expected to be positively related to the business climate, as funding conditions improve in a booming economic environment, whereby inventory costs tend to fall.

11.)-14.) Dividend Yield dy_t, Price-to-Book Ratio pb_t, and both Momentum Indicators rsi_t and mom_t: Stocks with higher expected returns are often associated with higher dividend yields (for each company, the variable with the Bloomberg ticker symbol EQY_DVD_YLD_12M is used). Hence, it is expected that an increase in the dividend yield of a company's stocks is associated with lower default probabilities and therefore with lower CDS spreads. Analogously, stocks with a lower price-to-book ratio pb_t (with the Bloomberg ticker symbol PX_TO_BOOK_RATIO) tend to be related to higher expected returns, whereby an increase in pb_t is expected to be associated with an increase in the CDS spread. For the momentum indicators, the sign for the CDS mid-rate is ambiguous, as it depends on whether the stock exhibits positive or negative momentum. As a short-term momentum indicator, the relative strength indicator in the previous 14 days rsi_t (with the Bloomberg ticker symbol RSI) is used. As a long-term momentum indicator, $rmom_t$ (with the Bloomberg ticker symbol REL_SHR_PX_MOMENTUM) is used, which is defined as the percentage change over the last six months in the 1-month moving average of the share price relative to the corresponding market index, i.e., the SPI and the DAX index. The sign for the CDS bid-ask spread with respect to changes in these two indicators is again ambiguous.

In the following, only the most important results concerning the exogenous explanatory variables that are included in Equation 9 are presented and discussed. For the CDS bid-ask spread changes, the adjusted R^2 ranges from 8.7% (HeidelbergCement) to 33.5% (Commerzbank), with the median $\bar{R}^2$ equal to 23.6% (Zurich, TUI). These values are similar to those in Gündüz et al. (2007) and Meng and ap Gwilym (2008) for the CDS bid-ask spread in levels. For the CDS mid-rate changes, the adjusted R^2 ranges from 0.1% (Südzucker) to 30.1% (HeidelbergCement), with the median $\bar{R}^2$ equal to 8.4% (ThyssenKrupp). This is in line with other recent studies which analyze the determinants of CDS spread changes, see Ericsson et al. (2009) and Corò et al. (2013), among others.

When including the previously presented exogenous explanatory variables, the causal structure remains qualitatively unchanged (compare Tables 1 and 2 with Tables C.2 and C.3 in Appendix C). A plot of both the orthogonalized and the cumulative orthogonalized IRFs (this figures are available from the author upon request) reveals that the dynamic interaction between credit risk and liquidity risk and the VARX(p) coefficients remain essentially unchanged. This observation supports the main conclusions of this paper. In both the VAR model as well as in the VARX model the results indicate that new information is quickly reflected in the CDS bid-ask spreads and in the CDS mid-rates, as in most cases, only the respective first autoregressive lags are significant.

Apart from the corresponding lags of the CDS bid-ask spread changes and the CDS mid-rate changes, the most relevant explanatory variables are the changes in the stock returns (Δr_t), the changes in the long-term equity return volatility ($\Delta\sigma_t^{360}$), the changes in the slope of the yield curve (Δsl_t), the changes in the TED spread (Δted_t), the changes in the default yield spread ($\Delta dspread_t$) and the changes in the market stock returns ($\Delta r_{m,t}$). In general, the relevance of the other explanatory variables is negligible. Therefore, in the following, only the results for the most relevant exogenous explanatory variables are presented and also only for the relevant equation in the VARX model.

In general, the coefficient for the changes in the stock returns (Δr_t) of the reference entity is in line with the expected sign. Higher stock returns are accompanied by a decrease in both the CDS bid-ask spreads and the CDS mid-rates. This observation accords with the aforementioned hypothesis that a higher company value decreases the default probability and increases the availability of capital that market makers can use to fund their trading positions.

Changes in the long-term volatility ($\Delta\sigma_t^{360}$) are, in general, a relevant explanatory variable for the changes in the CDS mid-rate only. The coefficients are in line with the expected sign, i.e., higher asset volatility (proxied by the stock volatility) increases the probability of default and therefore CDS mid-rates tend to increase.

For the slope of the yield curve, the results indicate that a steeper yield curve ($\Delta sl_t > 0$) precedes a decrease in the CDS mid-rate. This finding is in line with the corresponding hypothesis in Table C.1 and the findings in Abid and Naifar (2006), among others, who analyze CDSs from different countries. It also accords with Ericsson et al. (2009) and in part with the results in Breitenfellner and Wagner (2012), but is contrary to the findings of, for example, Collin-Dufresne et al. (2001) and Oliveira et al. (2012) for Eurozone government credit spreads or Di Cesare and Guazzarotti (2010), who analyze CDS contracts for U.S. non-financial firms and find that an increase in the slope of the yield curve is followed by an increase in the CDS mid-rate.

Interestingly, the coefficients for the changes in the TED spread ($\Delta ted_t > 0$), an important proxy variable for the degree of funding illiquidity, contradicts the conjectured sign, as an increase in the TED spread is in general accompanied by a decrease in the CDS mid-rate.

The importance of the systematic credit risk component, proxied by the changes in the default yield spread ($\Delta dspread_t$), accords with the findings in Di Cesare and Guazzarotti (2010), among others, who document that subsequent to the financial crisis the relevance of a common credit risk factor has increased. In the sample of this study, this variable is significant for both the CDS bid-ask spread and the CDS mid-rate. While the predicted sign for the changes in the CDS mid-rate is in line with the conjecture in Table C.1, the results are ambiguous for the CDS bid-ask spread.

In the present analysis, the return on a broad stock market index ($\Delta r_{m,t}$), as a proxy for the overall state of the economy, is negatively related to the CDS mid-rate, whereas it is positively related to the CDS bid-ask spread. This observation accords with the expected signs in Table C.1 for the former variable, but not for the latter variable.

In the following, additional results that support the robustness of the documented empirical results are reported (these results are in part included in a separate supplement). To assess whether the sample of exogenous explanatory variables is subject to multicollinearity, the correlation between all possible pairs of exogenous explanatory variables is analyzed. The results indicate that in most cases multicollinearity only plays a minor role.

Despite the fact that the distribution of the changes in the sample exhibits fat tails and in part shows left-skewed tails (these results are also available in a separate supplement), the Granger causality test results are robust with respect to these features, as in this case the F-test remains robust (see, e.g., Levine and Dunlap (1982)).

To assess parameter constancy over time, the cumulative sum of OLS residuals (OLS-CUSUM) test developed by Ploberger and Krämer (1992) is employed. If the fluctuations of the OLS-CUSUM process cross some pre-specified boundaries, the null hypothesis of parameter stability is rejected. More details about how to perform this test can be found in Lütkepohl and Krätzig (2004). These analyses (these test results are available in a separate supplement) indicate that in the present sample the parameters remain statistically constant over time, which again is positive news for the reported empirical results.

If the zero changes in both the CDS bid-ask spread and the CDS mid-rate are interpreted as a day when no trades occurred, the parameter estimates would be downward biased. This would also most likely bias the test results towards accepting the false null hypothesis too often (a type-2 error). In this case, the impact on the reported findings of this study is inconclusive, as it would simultaneously impact both equations in the VAR and the VARX, so that the direction of causality between the CDS bid-ask spread and the CDS mid-rate might change for some companies in the used sample.

To summarize this section, it can be concluded that the documented results are robust to omitted variable bias, to the time series properties of the data set, i.e., the exhibited skewness and fat-tailedness, and to multicollinearity. In addition, the parameter estimates remain constant over time. All these robustness checks support the reported empirical results of this paper.

6. Conclusion

The recent financial crisis that started in mid-2007 has both evidenced the importance that liquidity has for investors and underlined the need to understand the linkages between credit and liquidity risk. In this period, credit default swap spreads soared by several hundred basis points, accompanied by a liquidity shortage in the U.S. financial sector. This episode stresses the importance of giving ample consideration to liquidity in risk models, especially in periods of financial turmoil. In this paper, applying the Granger causality test methodology it is found that contrary to the common belief that illiquidity leads to a credit risk deterioration in financial markets, for 39% of the German and Swiss companies in the used data sample, credit risk is weakly endogenous for liquidity risk. The results show that in the short run credit risk changes are more likely to induce CDS market liquidity to dry-up than vice versa. This finding implies that a deterioration in credit risk, as was observed during the beginning of the current financial crisis, may trigger a liquidity crisis in the CDS market, in the spirit of the liquidity spiral in Brunnermaier (2009) or the information amplification mechanism in Caballero and Krishnamurthy (2008) and Krishnamurthy (2010). These linkages may be one of the amplifying mechanisms that aggravated and propagated the initial credit shocks in the subprime market, with real effects on the macroeconomy. Alternatively, some companies in the used sample, where no significant lead-lag relationship between credit risk changes and liquidity changes is detected, the observed increase in both the CDS bid-ask spreads and the CDS spreads during the recent financial crisis might be the result of investors that have incomplete preferences over portfolios (Easley and O'Hara, 2010), or due to companies that have to roll over maturing debt and face rising credit spreads when liquidity in the market has previously deteriorated (He and Xiong, 2012).

The findings of this paper imply that, for instance, a liquidity-enhanced CAPM or a value-at-risk model that includes liquidity should treat liquidity as endogenous and control for the interaction between credit and liquidity risk, contrary to the standard practice until now. In addition, for policy-makers, the indication that a negative credit shock may cause a liquidity shortage in the CDS market should be taken into account when setting capital requirements for financial institutions. A better understanding of the market for credit risk is also crucial for policy-makers when it comes to designing new macro-prudential policies. The empirical evidence in this paper has the policy implication that policy-makers should cushion credit shocks during periods of heightened uncertainty to prevent a liquidity shortage in, e.g., credit markets. In view of the importance of CDS spreads as a strategic financial variable in the investment decision process, the capacity to control CDS spreads could therefore be used to prevent rapid surges in CDS market illiquidity and their consequent negative impact on financial markets in the future.

As the current crisis has shown that CDS contracts are also prone to the default of the CDS seller, which accords with the observation of Hibbert et al. (2009) that counterparty risk becomes especially relevant in periods of financial distress, in future research, the impact of counterparty credit risk on the CDS spread should be assessed and the former should be disentangled from the latter, applying the CDS valuation model proposed by Hull and White (2001), which explicitly takes into account this additional risk factor.

Furthermore, by applying the valuation approach in Walker (2012), the analysis in this paper could be extended to illiquid CDS contracts, whereby we could gain additional insights about the dynamic relationship between credit risk and liquidity. In this respect, using intraday CDS data may also extend our knowledge about how liquidity impacts credit markets and how credit markets work in general.

The fact that discreteness is more pronounced in the case of CDS data than it is in the case of, for example, equities necessitates the use of other testing procedures, as some studies demonstrate that the standard testing procedures in time series analysis are biased when plugging in discrete data (Annaert et al., 2004). Therefore, applying alternative causality tests for discrete time series (e.g., using the Granger causality test for high-frequency data developed by de Jong and Nijman (1997)) may be a natural extension of the present paper.

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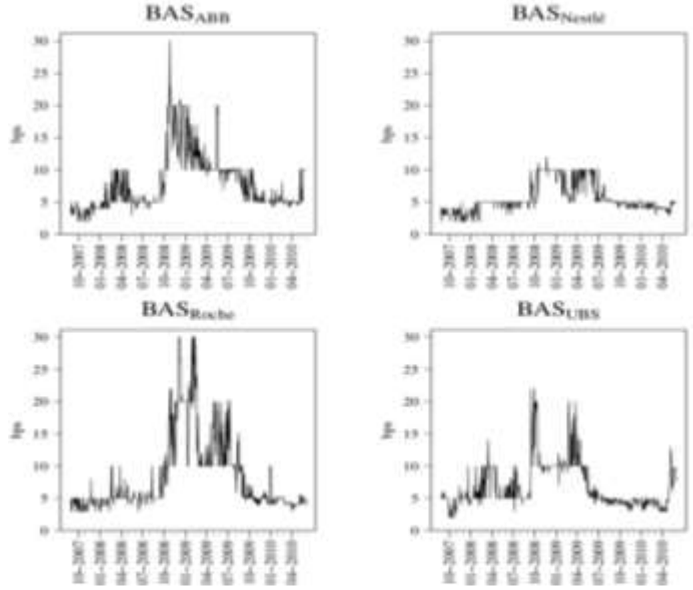
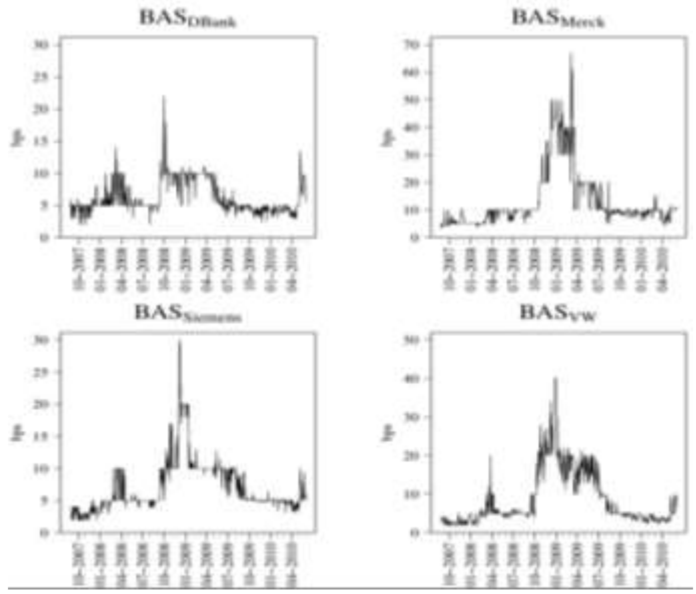
Figure 1: The Bid-Ask Spread for ABB, Nestlé, Roche and UBS



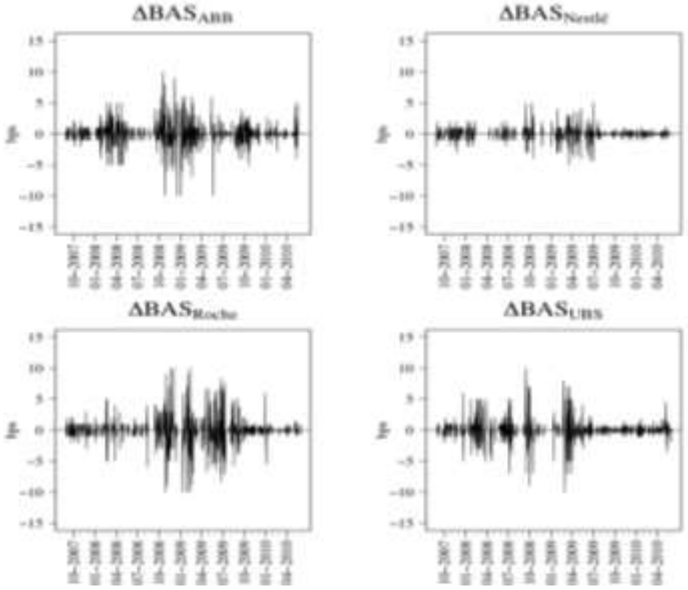
Notes: The figure shows the daily bid-ask spread (*BAS*) denominated in euros and quoted in basis points (bps) per year of the contract's notional amount for a representative subsample of four Swiss companies; i.e., ABB, Nestlé, Roche and UBS. The sample period is from August 24, 2007 to June 1, 2010. Data source: Datastream.

Figure 2: The Bid-Ask Spread for Deutsche Bank, Merck, Siemens and VW



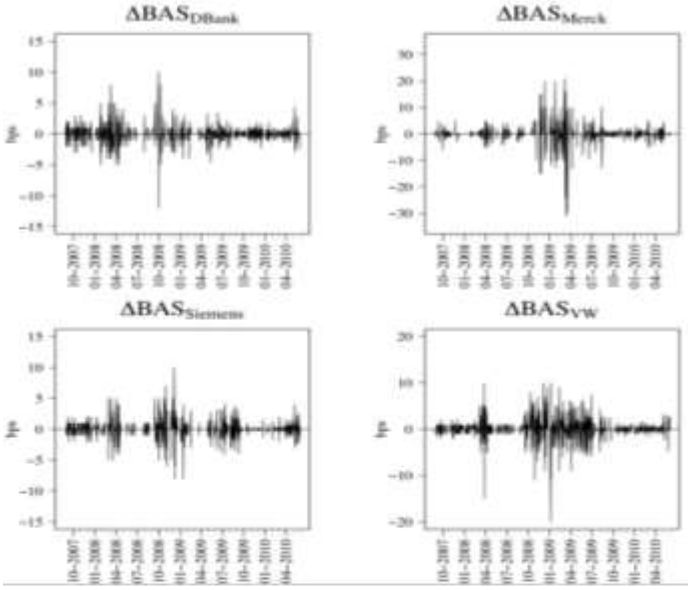
Notes: The figure shows the daily bid-ask spread (*BAS*) denominated in euros and quoted in basis points (bps) per year of the contract's notional amount for a representative subsample of four German companies; i.e., Deutsche Bank (DBank), Merck, Siemens and VW. The sample period is from August 24, 2007 to June 1, 2010. Notice that for graphical convenience, the y-axis for Merck and VW differs from the y-axis in the other two panels. Data source: Datastream.

Figure 3: Changes in the Bid-Ask Spread for ABB, Nestlé, Roche and UBS



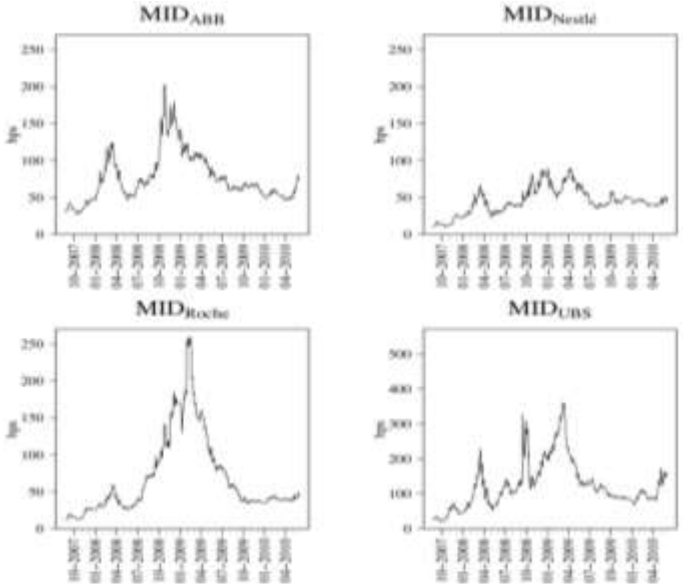
Notes: The figure shows the changes (first differences) in the daily bid-ask spread (ΔBAS) denominated in euros and quoted in basis points (bps) per year of the contract's notional amount, from August 24, 2007 to June 1, 2010, for a representative subsample of four Swiss companies; i.e., ABB, Nestlé, Roche and UBS. Data source: Datastream.

Figure 4: Changes in the Bid-Ask Spread for Deutsche Bank, Merck, Siemens and VW



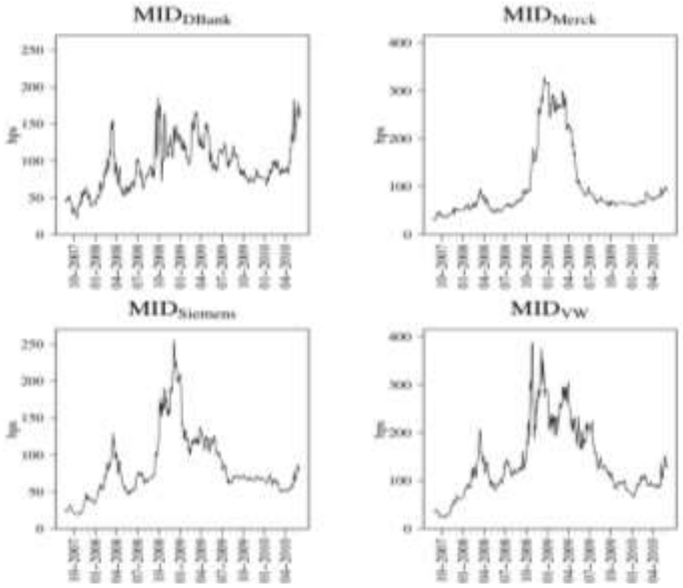
Notes: The figure shows the changes (first differences) in the daily bid-ask spread (ΔBAS) denominated in euros and quoted in basis points (bps) per year of the contract's notional amount, from August 24, 2007 to June 1, 2010, for a representative subsample of four German companies; i.e., Deutsche Bank (DBank), Merck, Siemens and VW. Notice that for graphical convenience, the y-axis for Merck and VW differs from the y-axis in the other two panels. Data source: Datastream.

Figure 5: The Mid-Rate for ABB, Nestlé, Roche and UBS



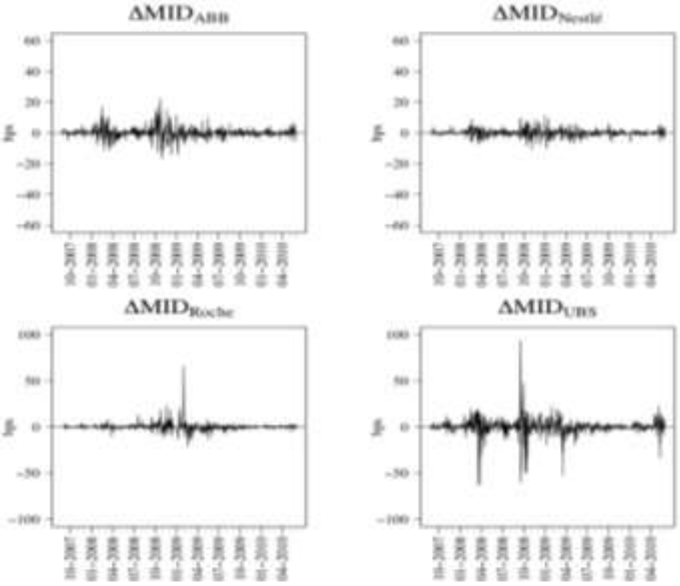
Notes: The figure shows the daily mid-rate (MID) denominated in euros and quoted in basis points (bps) per year of the contract's notional amount, from August 24, 2007 to June 1, 2010, for a representative subsample of four Swiss companies; i.e., ABB, Nestlé, Roche and UBS. Notice that for graphical convenience, the y-axis for UBS differs from the y-axis in the other three panels. Data source: Datastream.

Figure 6: The Mid-Rate for Deutsche Bank, Merck, Siemens and VW



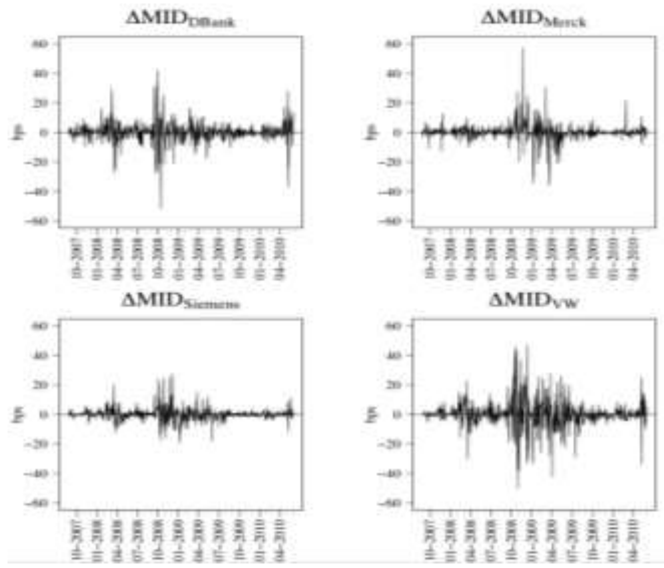
Notes: The figure shows the daily mid-rate (MID) denominated in euros and quoted in basis points (bps) per year of the contract's notional amount, from August 24, 2007 to June 1, 2010, for a representative subsample of four German companies; i.e., Deutsche Bank (DBank), Merck, Siemens and VW. Notice that for graphical convenience, the y-axis for Merck and VW differs from the y-axis in the other two panels. Data source: Datastream.

Figure 7: Changes in the Mid-Rate for ABB, Nestlé, Roche and UBS



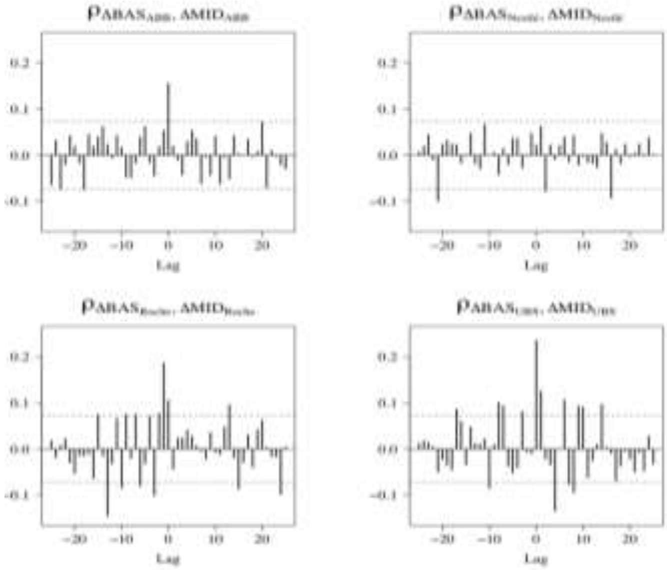
Notes: The figure shows the changes (first differences) of the daily mid-rate (ΔMID) denominated in euros and quoted in basis points (bps) per year of the contract's notional amount, from August 24, 2007 to June 1, 2010, for a representative subsample of four Swiss companies; i.e., ABB, Nestlé, Roche and UBS. Notice that for graphical convenience, the y-axis for Roche and UBS differs from the y-axis in the other two panels. Data source: Datastream.

Figure 8: Changes in the Mid-Rate for Deutsche Bank, Merck, Siemens and VW



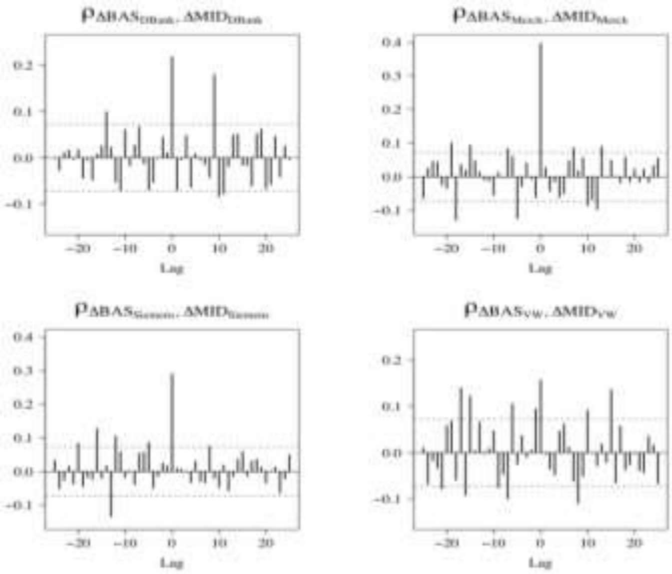
Notes: The figure shows the changes (first differences) in the daily mid-rate (ΔMID) denominated in euros and quoted in basis points (bps) per year of the contract's notional amount, from August 24, 2007 to June 1, 2010, for a representative subsample of four German companies; i.e., Deutsche Bank (DBank), Merck, Siemens and VW. Data source: Datastream.

Figure 9: Cross-Correlation between Changes in Credit Risk and Liquidity Risk for ABB, Nestlé, Roche and UBS



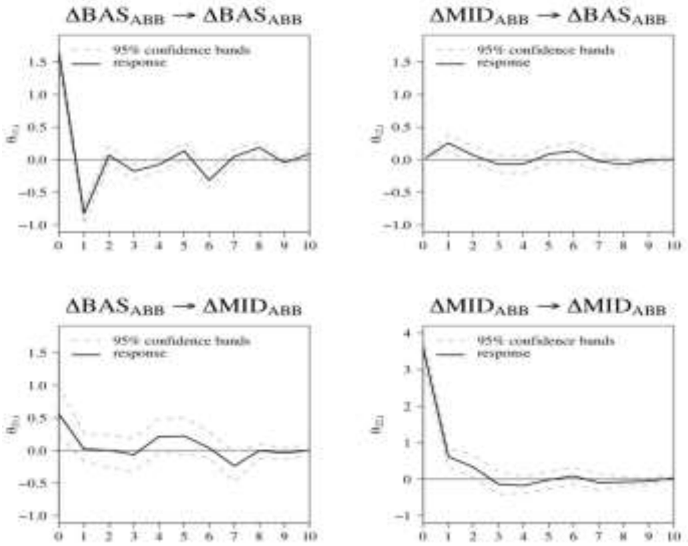
Notes: The figure shows the cross-correlation function (CCF) for the changes in the bid-ask spread ΔBAS and the changes in the mid-rate ΔMID for ABB, Nestlé, Roche and UBS with the corresponding 95% confidence interval. At lag 0, the CCF displays the contemporaneous correlation between changes in the bid-ask spread and the mid-rate. At a negative lag $i < 0$, the CCF measures the correlation between ΔBAS_t and ΔMID_{t+i} $(= \Delta MID_{t-|i|})$, at a positive lag $i > 0$, the CCF measures the correlation between ΔBAS_t and ΔMID_{t+i}. The sample period is from August 24, 2007 to June 1, 2010. Data source: Datastream.

Figure 10: Cross-Correlation between Changes in Credit Risk and Liquidity Risk for Deutsche Bank, Merck, Siemens and VW



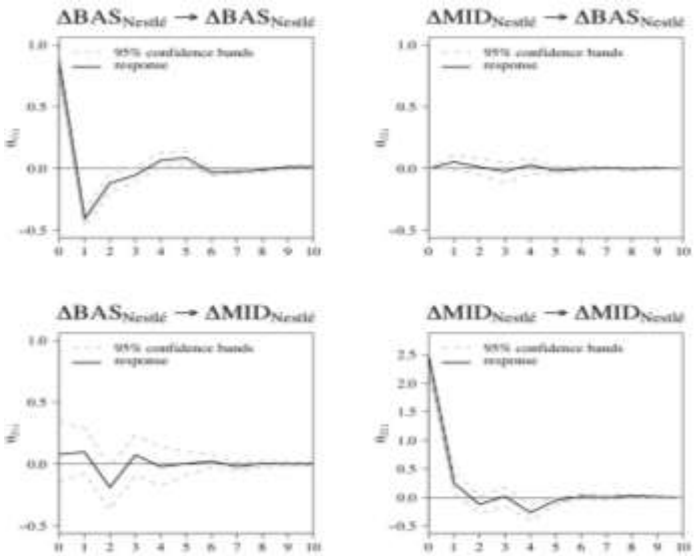
Notes: The figure shows the cross-correlation function (CCF) for the changes in the bid-ask spread ΔBAS and the changes in the mid-rate ΔMID for Deutsche Bank (DBank), Merck, Siemens and VW with the corresponding 95% confidence interval. At lag 0, the CCF displays the contemporaneous correlation between changes in the bid-ask spread and the mid-rate. At a negative lag $i < 0$, the CCF measures the correlation between ΔBAS_t and ΔMID_{t+i} $(= \Delta MID_{t-|i|})$, at a positive lag $i > 0$, the CCF measures the correlation between ΔBAS_t and ΔMID_{t+i}. Notice that for graphical convenience, the y-axis for Merck and Siemens differs from the y-axis in the other two panels. The sample period is from August 24, 2007 to June 1, 2010. Data source: Datastream.

Figure 11: Orthogonalized Impulse Response Functions for ABB



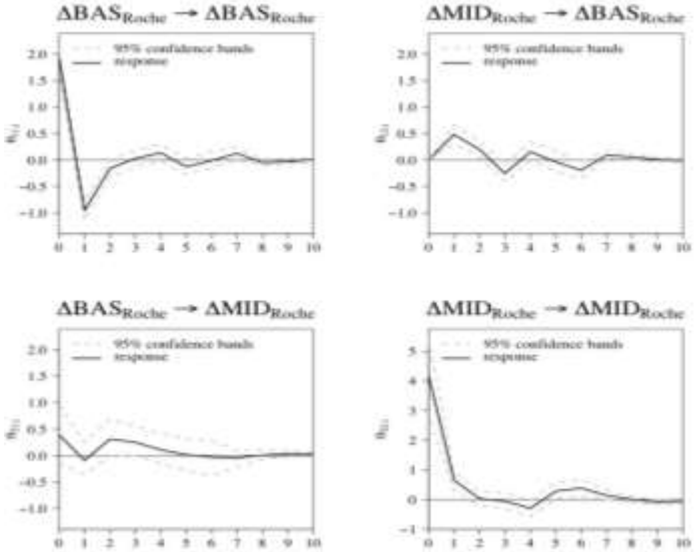
Notes: The figure shows the orthogonalized impulse response functions 10 steps ahead with the corresponding bootstrapped confidence bands of the daily bid-ask spread changes ΔBAS_{ABB} and the mid-rate changes ΔMID_{ABB} in response to a unit change in each of these (presumably) endogenous variables. Notice that for graphical convenience, the y-axis in panel 4 differs from the y-axis in the other three panels. Data source: Datastream.

Figure 12: Orthogonalized Impulse Response Functions for Nestlé



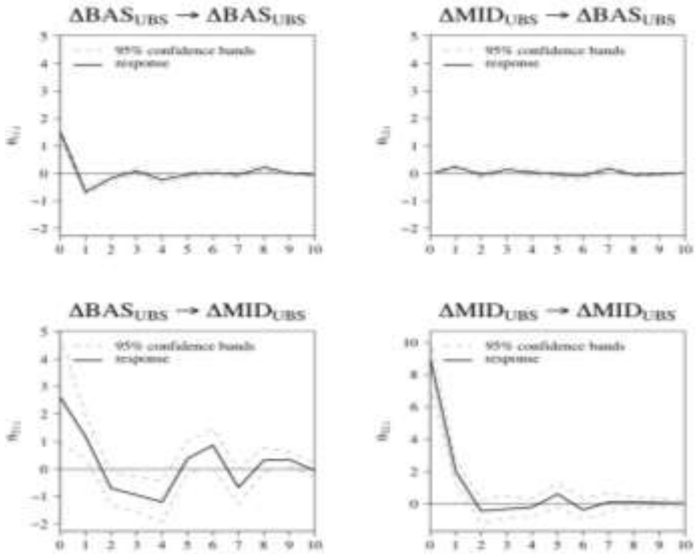
Notes: The figure shows the orthogonalized impulse response functions 10 steps ahead with the corresponding bootstrapped confidence bands of the daily bid-ask spread changes $\Delta BAS_{Nestlé}$ and the mid-rate changes $\Delta MID_{Nestlé}$ in response to a unit change in each of these (presumably) endogenous variables. Notice that for graphical convenience, the y-axis in panel 4 differs from the y-axis in the other three panels. Data source: Datastream.

Figure 13: Orthogonalized Impulse Response Functions for Roche



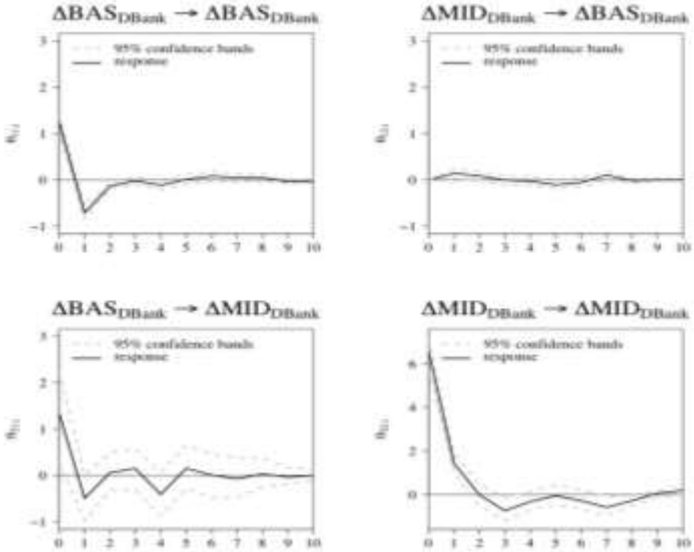
Notes: The figure shows the orthogonalized impulse response functions 10 steps ahead with the corresponding bootstrapped confidence bands of the daily bid-ask spread changes ΔBAS_{Roche} and the mid-rate changes ΔMID_{Roche} in response to a unit change in each of these (presumably) endogenous variables. Notice that for graphical convenience, the y-axis in panel 4 differs from the y-axis in the other three panels. Data source: Datastream.

Figure 14: Orthogonalized Impulse Response Functions for UBS



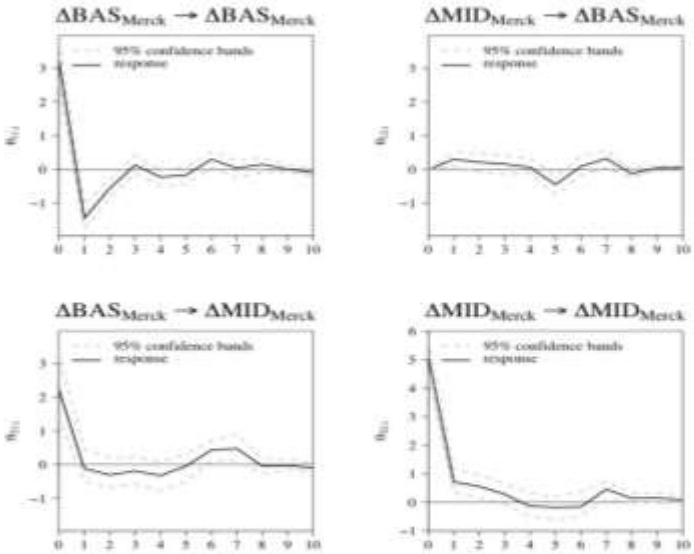
Notes: The figure shows the orthogonalized impulse response functions 10 steps ahead with the corresponding bootstrapped confidence bands of the daily bid-ask spread changes ΔBAS_{UBS} and the mid-rate changes ΔMID_{UBS} in response to a unit change in each of these (presumably) endogenous variables. Notice that for graphical convenience, the y-axis in panel 4 differs from the y-axis in the other three panels. Data source: Datastream.

Figure 15: Orthogonalized Impulse Response Functions for Deutsche Bank



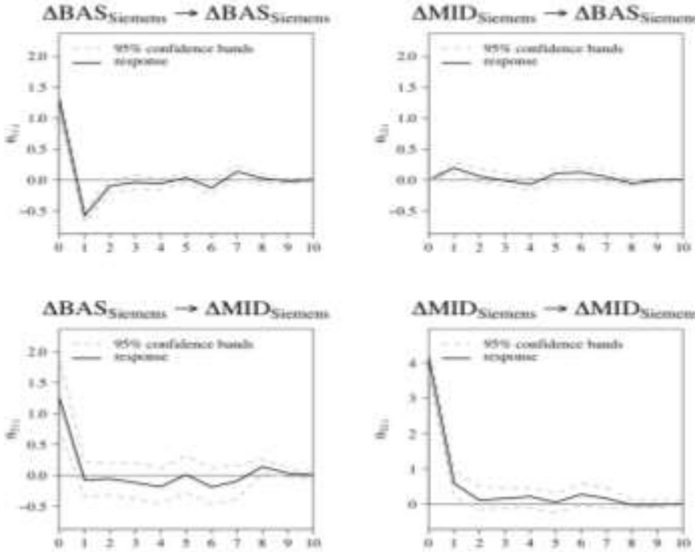
Notes: The figure shows the orthogonalized impulse response functions 10 steps ahead with the corresponding bootstrapped confidence bands of the daily bid-ask spread changes ΔBAS_{DBank} and the mid-rate changes ΔMID_{DBank} in response to a unit change in each of these (presumably) endogenous variables. Notice that for graphical convenience, the y-axis in panel 4 differs from the y-axis in the other three panels. Data source: Datastream.

Figure 16: Orthogonalized Impulse Response Functions for Merck



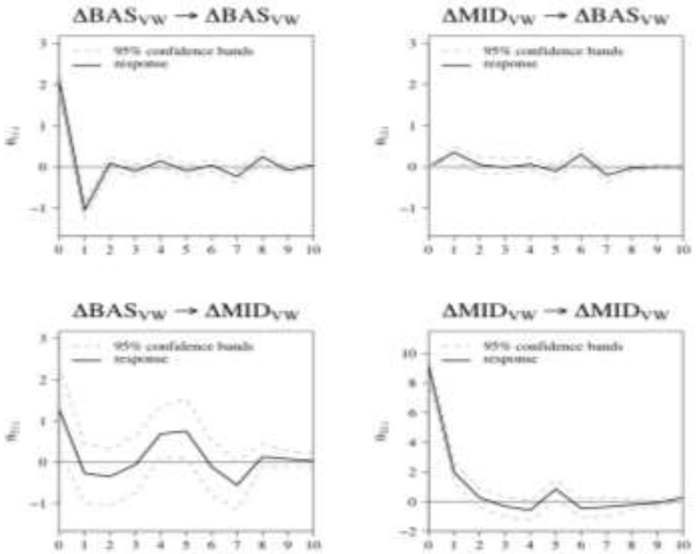
Notes: The figure shows the orthogonalized impulse response functions 10 steps ahead with the corresponding bootstrapped confidence bands of the daily bid-ask spread changes ΔBAS_{Merck} and the mid-rate changes ΔMID_{Merck} in response to a unit change in each of these (presumably) endogenous variables. Notice that for graphical convenience, the y-axis in panel 4 differs from the y-axis in the other three panels. Data source: Datastream.

Figure 17: Orthogonalized Impulse Response Functions for Siemens



Notes: The figure shows the orthogonalized impulse response functions 10 steps ahead with the corresponding bootstrapped confidence bands of the daily bid-ask spread changes $\Delta BAS_{Siemens}$ and the mid-rate changes $\Delta MID_{Siemens}$ in response to a unit change in each of these (presumably) endogenous variables. Notice that for graphical convenience, the y-axis in panel 4 differs from the y-axis in the other three panels. Data source: Datastream.

Figure 18: Orthogonalized Impulse Response Functions for VW



Notes: The figure shows the orthogonalized impulse response functions 10 steps ahead with the corresponding bootstrapped confidence bands of the daily bid-ask spread changes ΔBAS_{VW} and the mid-rate changes ΔMID_{VW} in response to a unit change in each of these (presumably) endogenous variables. Notice that for graphical convenience, the y-axis in panel 4 differs from the y-axis in the other three panels. Data source: Datastream..

Table 1: Granger Causality Test for the Swiss Companies

	$\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$	$\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$
ABB	0.330	1.006
Adecco	1.029	1.445
Clariant	1.053	2.346**
CS	1.192	2.228**
Holcim	1.159	3.061***
Nestlé	1.059	1.097
Novartis	1.128	0.987
Roche	0.208	6.154***
Swisscom	0.816	2.389**
SwissRe	2.022**	2.517**
Syngenta	0.955	0.667
UBS	1.410	1.187
Zurich	0.954	1.780*

Notes: The table displays the value of the F-test statistic of the Granger causality test in the bivariate $VAR(p)$ for the null hypothesis that changes in the bid-ask spread do not Granger-cause changes in the mid-rate ($\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$) and vice versa ($\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$) for the 13 Swiss companies in the sample. * / ** / *** denotes significance at the 10%, 5% and 1% significance level, respectively. Data source: Bloomberg, Datastream.

Table 2: Granger Causality Test for the German Companies

	$\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$	$\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$
Allianz	0.918	2.084*
BASF	0.615	0.345
Bayer	2.142*	1.338
BMW	0.427	0.834
Commerzbank	1.041	2.992***
Continental	1.316	3.539***
Daimler	0.330	1.379
DBank	0.500	1.814*
DPost	0.682	1.836*
DTelekom	0.450	1.273
EnBW	1.321	1.036
E.ON	0.758	2.456**
Fresenius	2.213**	4.254***
HannoverRück	1.465	2.658**
HeidelbergCement	0.793	0.536
Henkel	1.330	1.290
Lanxess	0.268	1.337
Linde	1.653	1.660
Lufthansa	1.065	1.802*
Merck	1.118	1.478
Metro	0.869	2.066*
Munich Re	2.130*	2.687**
Porsche	0.922	1.697
ProSiebenSat.1	1.624	1.287
RWE	1.716	2.067**
Siemens	0.502	2.238**
Südzucker	0.511	1.411
ThyssenKrupp	0.568	4.099***
TUI	0.591	2.272**
VW	0.449	2.143**

Notes: The table displays the value of the F-test statistic of the Granger causality test in the bivariate $VAR(p)$ for the null hypothesis that changes in the bid-ask spread do not Granger-cause changes in the mid-rate ($\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$) and vice versa ($\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$) for the 31 German companies in the sample. * / ** / *** denotes significance at the 10%, 5% and 1% significance level, respectively. Data source: Bloomberg, Datastream.

Appendix A. Data

Table A.1: Swiss Companies in the Sample

Company	Industry
ABB	Construction & Engineering
Adecco	Commercial Services
Clariant	Chemicals
Credit Suisse[1]	Banks
Holcim	Building Materials
Nestlé	Food
Novartis	Pharmaceuticals
Roche	Pharmaceuticals
Swiss Re	Insurance
Swisscom	Telecommunications
Syngenta	Chemicals
UBS	Banks
Zurich	Insurance

[1] Henceforth abbreviated by CS.

Notes: The table displays the 13 Swiss companies that constitute the final sample of Swiss companies with the corresponding industry classification according to the global industry classification standard published by MSCI Barra.

Table A.2: German Companies in the Sample

Company	Industry
Allianz	Insurance
BASF	Chemicals
Bayer	Chemicals
BMW	Auto Manufacturers
Commerzbank	Banks
Continental	Auto Parts & Equipment
Daimler	Auto Manufacturers
Deutsche Bank[1]	Banks
Deutsche Post	Transportation
Deutsche Telekom	Telecommunications
E.ON	Electric
Energie Baden-Württemberg[2]	Electric
Fresenius	Healthcare-Services
Hannover Rück	Insurance
HeidelbergCement	Building Materials
Henkel	Household Products/Wares
Kabel Deutschland	Telecommunications
Lanxess	Chemicals
Linde	Construction & Engineering
Lufthansa	Airlines
Merck	Pharmaceuticals
Metro	Food
Munich Re	Insurance
Porsche	Auto Manufacturers
ProSiebenSat.1	Media
RWE	Electric
Siemens	Miscellaneous Manufacturing
Südzucker	Food
ThyssenKrupp	Iron/Steel
TUI	Leisure Time
VW	Auto Manufacturers

[1] Henceforth abbreviated by DBank.
[2] Henceforth abbreviated by EnBW.

Notes: The table displays the 31 German companies that constitute the final sample of German companies with the corresponding industry classification according to the global industry classification standard published by MSCI Barra.

Appendix B. Univariate Time Series Properties

Table B.1: Stationarity Test for the Bid-Ask Spread and the Mid-Rate

	BAS	MID
ABB	1.84***	1.59***
Nestlé	2.10***	3.08***
Roche	1.75***	2.05***
UBS	1.38***	1.92***
DBank	1.36***	2.92***
Merck	1.70***	1.65***
Siemens	1.75***	1.81***
VW	1.76***	2.17***

Notes: The table displays the value of the KPSS test statistic under the null hypothesis that both the bid-ask spread (BAS) and the mid-rate (MID) are level stationary for the eight companies in the subsample. The Newey-West estimator is used to estimate σ^2 and the lag truncation parameter is set equal to $3 \cdot \sqrt{T}/13$, where T is the number of observations. * / ** / *** denotes significance at the 10%, 5% and 1% significance level, respectively. Data source: Datastream.

Table B.2: Stationarity Test for the Changes in the Bid-Ask Spread and the Mid-Rate

	BAS	MID
ABB	0.03	0.13
Nestlé	0.03	0.12
Roche	0.04	0.26
UBS	0.03	0.07
DBank	0.02	0.04
Merck	0.05	0.24
Siemens	0.04	0.16
VW	0.04	0.11

Notes: The table displays the value of the KPSS test statistic under the null hypothesis that both the changes in the bid-ask spread ($\Delta\ BAS$) and the mid-rate ($\Delta\ MID$) are level stationary for the eight companies in the subsample. The Newey-West estimator is used to estimate σ^2 and the lag truncation parameter is set equal to $3 \cdot \sqrt{T}/13$, where T is the number of observations. * / ** / *** denotes significance at the 10%, 5% and 1% significance level, respectively. Data source: Datastream.

Table B.3: Number of Zero Changes in the Bid-Ask Spread

	Total No. of Zeros	Rel. No. of Zeros (in %)
ABB	259	35.87
Nestlé	317	43.91
Roche	245	33.93
UBS	237	32.83
DBank	244	33.80
Merck	315	43.63
Siemens	308	42.66
VW	208	28.81

Notes: The table displays the total number (No.) of zero changes in the bid-ask spread (column 2) and the same number relative (Rel.) to the total number of observations (column 3) for the eight companies in the subsample. Data source: Datastream.

Table B.4: Autocorrelation Test for the Changes in the Bid-Ask Spread and the Mid-Rate

	ΔBAS	ΔMID
ABB	186.80***	52.88***
Nestlé	123.20***	32.17***
Roche	134.30***	61.12***
UBS	139.40***	86.16***
DBank	125.80***	62.35***
Merck	116.70***	82.75***
Siemens	113.60***	35.82***
VW	183.60***	78.03***

Notes: The table displays the value of the Ljung-Box test statistic under the null hypothesis that both the changes in the bid-ask spread (ΔBAS) and the mid-rate (ΔMID) are serially uncorrelated for the eight companies in the subsample. * / ** / *** denotes significance at the 10%, 5% and 1% significance level, respectively. Data source: Datastream.

Appendix C. Empirical Results with Exogenous Variables

Table C.1: Exogenous Explanatory Variables and Expected Sign

Variable	Description	Sign ΔBAS	Sign ΔMID
r_t^f	Risk-Free Rate	+	-
r_t	Stock Returns	-	-
σ_t^{30}	Historical Stock Volatility (30 Days)	+	+
σ_t^{360}	Historical Stock Volatility (360 Days)	+	+
σ_t^{imp}	Option-Implied Volatility (Stock)	+	+
sl_t	Slope of the Yield Curve	-	-
ted_t	TED Spread	+	+
$dspread_t$	Default Yield Spread	+	+
$r_{m,t}$	Stock Market Returns	-	-
$vdax_t$	Option-Implied Volatility (DAX)	+	+
dy_t	Dividend Yield	n.a.	-
pb_t	Price-to-Book Ratio	n.a.	-
rsi_t	Short-Term Momentum	n.a.	n.a.
$rmom_t$	Long-Term Momentum	n.a.	n.a.

Notes: The table displays the expected sign for the impact of the used exogenous explanatory variables (column 1, "Variable") on the changes of both the CDS bid-ask spread (column 3, "Sign ΔBAS") and the CDS mid-rate (column 4, "Sign ΔMID"), respectively, assuming that the corresponding exogenous variable rises. Rows with a "n.a." value denote the cases, where the expected sign is ambiguous. In the column 2 ("Description"), the exogenous variables are briefly explained.

Table C.2: Granger Causality Test for the Swiss Companies with Exogenous Variables

	$\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$	$\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$
ABB	0.391	0.768
Adecco	1.402	1.227
Clariant	0.904	2.137^{*}
CS	0.704	1.876^{*}
Holcim	1.492	2.926^{***}
Nestlé	1.101	0.826
Novartis	0.933	0.902
Roche	0.232	6.884^{***}
Swisscom	0.855	1.944^{*}
SwissRe	1.796^{*}	2.106^{**}
Syngenta	0.778	0.628
UBS	1.451	1.181
Zurich	1.210	1.694

Notes: The table displays the value of the F-test statistic of the Granger causality test in the bivariate $VARX(p)$ for the null hypothesis that changes in the bid-ask spread do not Granger-cause changes in the mid-rate ($\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$) and vice versa ($\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$) for the 13 Swiss companies in the sample. * / ** / *** denotes significance at the 10%, 5% and 1% significance level, respectively. Data source: Bloomberg, Datastream.

Table C.3: Granger Causality Test for the German Companies with Exogenous Variables

	$\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$	$\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$
Allianz	1.010	1.794*
BASF	0.670	0.171
Bayer	2.153*	1.509
BMW	1.065	1.123
Commerzbank	0.843	2.672**
Continental	2.092*	2.513**
Daimler	0.348	1.454
DBank	0.437	1.545
DPost	0.700	1.929*
DTelekom	0.507	1.287
EnBW	1.377	1.352
E.ON	0.792	2.475**
Fresenius	2.341**	4.037***
HannoverRück	1.379	2.416**
HeidelbergCement	0.726	0.508
Henkel	1.388	1.271
Lanxess	0.250	1.265
Linde	1.710	1.576
Lufthansa	0.936	1.678
Merck	1.166	1.489
Metro	0.991	1.871*
Munich Re	2.218*	2.645**
Porsche	1.049	1.597
ProSiebenSat.1	1.590	0.933
RWE	1.706	1.959*
Siemens	0.390	1.876*
Südzucker	0.563	1.192
ThyssenKrupp	0.599	3.842***
TUI	0.718	2.208**
VW	0.496	2.345**

Notes: The table displays the value of the F-test statistic of the Granger causality test in the bivariate $VARX(p)$ for the null hypothesis that changes in the bid-ask spread do not Granger-cause changes in the mid-rate ($\Delta BAS \overset{GrC}{\nRightarrow} \Delta MID$) and vice versa ($\Delta MID \overset{GrC}{\nRightarrow} \Delta BAS$) for the 31 German companies in the sample. * / ** / *** denotes significance at the 10%, 5% and 1% significance level, respectively. Data source: Bloomberg, Datastream.