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S. Bethke • M. Gehde-Trapp • A. Kempf

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Investor Sentiment, Flight-to-Quality, and Corporate Bond Comovement

Sebastian Bethke Monika Gehde-Trapp* Alexander Kempf

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Abstract

We examine the dynamics of bond correlation using a broad sample of US corporate bonds, and document that bond correlation varies heavily over time. We attribute this variation in bond correlation to variation in risk factor correlation reflecting time-varying flight-to-quality behavior of investors. We show that risk factor correlation increases when investor sentiment decreases, i.e., corporate bond investors exhibit stronger flight-to-quality when their sentiment is low. Thus, low investor sentiment leads to flight-to-quality behavior and, ultimately, high bond correlation.

JEL classification: G11; G12

Keywords: bond correlation; risk factor correlation; flight-to-quality; investor sentiment

* Corresponding author, email trapp@wiso.uni-koeln.de, phone +49 221 470 6966. All authors are from the Department of Finance, University of Cologne, Germany and are members of the Centre for Financial Research (CFR), Cologne.

1. Introduction

Correlations are crucial when setting up efficient portfolios, taking appropriate hedging decisions, and managing risks. Thus, it is not surprising that correlations are widely studied in the financial literature (e.g., Ang and Chen, 2002; Connolly et al., 2007; Baele et al., 2010; Abad et al., 2014; Nieto and Rodriguez, 2015). This evidence is based on correlations between equity markets, government bond markets, individual stocks and bonds, and common factors in asset prices and returns. Our paper contributes to this literature by identifying an economic mechanism of correlated risk factors driving corporate bond correlations.

Using a sample of US corporate bonds, we document that bond correlation varies heavily over time. Correlation between high-yield and investment-grade bonds is, for example, about three times higher in the financial crisis beginning in July 2007 than it was before.

Why does bond correlation display this time-series behavior? One possible explanation, typically adopted to explain correlations in equity markets, is investors' herding. Kumar and Lee (2006) show that trading is correlated across retail investors and influences stock comovements. However, it is unlikely that retail investor herding is as important in bond markets as in equity markets since bond markets are dominated by institutional investors less prone to herding in market downturns (Borensztein and Gelos, 2003).

We propose an alternative explanation. In a nutshell, our theoretical model is based on the idea that investor sentiment has two main effects on investor behavior: Investors with low sentiment avoid risky assets (Baker and Wurgler, 2006) and react more to negative information (e.g., Mian and Sankaraguruswamy, 2012; Kaplanski and Levy, 2014). Thus, when sentiment is low, investors are less prone to invest in bonds with high credit risk and these bonds are less liquid than when sentiment is high. Consequently, liquidity premiums increase more with credit risk premiums when sentiment is low, i.e., correlation between these two main risk factors in corporate bonds is higher. High risk factor correlation translates into high correlation between corporate bonds. Thus, low investor sentiment ultimately goes along with high bond correlation.

In the empirical part of our paper, we use TRACE (Trade Reporting and Compliance Engine) data from October 2004 to September 2010. We document how bond correlation evolves over time and test our model that links bond correlation to risk factor correlation and risk factor correlation to investor sentiment. We find strong support for the predictions of our model. Correlation between risk factors in the corporate bond market is high when investor sentiment is low and high risk factor correlation translates into high bond correlation. Investor sentiment has a significant indirect impact on bond correlation via risk factor correlation even after controlling for a possible direct impact of sentiment, herding behavior, and state of the economy. Our results are stable over time and remain stable when we dig deeper into the cross-section by analyzing correlations between more detailed credit rating buckets.

After establishing our main results, we run several tests to determine robustness of our findings. We show that our main findings depend neither on how we measure credit risk and liquidity premiums nor on how we proxy investor sentiment. They remain robust when we adjust correlations for interest rate risk and unexpected inflation, use the swap rate as proxy for the risk-free rate, or split the sample into a pre-crisis and crisis interval.

Our study is related to several strands of the literature. First, we contribute to the large body of literature measuring asset correlations across countries and asset classes. Inter-market studies for sovereign bonds (for Europe, e.g., Kim et al., 2006; Abad et al., 2010; Abad et al., 2014; for Europe and the US, e.g., Skintzi and Refenes, 2006; Christiansen, 2007; for developed countries, Driessen et al., 2003; for emerging and frontier countries, Nowak et al., 2011; and Piljak, 2013) and equities (Connolly et al., 2007; Christiansen and Ranaldo, 2009) focus on increasing financial integration at the international level. Studies that span asset classes such as sovereign bond and equity markets (e.g., Connolly et al., 2005; Yang et al., 2009; Baele et al., 2010; Baker and Wurgler, 2012; and Bansal et al., 2014) or sovereign bond, corporate bond and equity markets at the aggregate level (e.g., Baur and Lucey, 2009; Brière et al., 2012) document the evolution of financial integration and flight to low-risk sovereign bonds in market downturns. At the individual security level, Acharya et al. (2013) find higher inter-market correlation between distressed stocks and corporate bonds in times of market downturns; Nieto and Rodriguez (2015) document common factors driving correlation between US stocks and corporate bonds of the same issuer. Correlations within asset classes are assessed either directly (e.g., Steeley, 2006 for different maturity segments of the UK sovereign bond market) or via common risk factors (e.g., Steeley, 1990; Litterman and Scheinkman, 1991 for UK and US sovereign bonds; Fama and French, 1993; Collin-Dufresne et al., 2001; Elton et al., 2001; Gebhardt et al., 2005; and Lin et al., 2011 for US corporate bonds; Klein and Stellner, 2014 and Aussenegg et al., 2015 for European corporate bonds). We add to this literature by analyzing correlations within the US corporate bond market, determining and analyzing the correlation of systematic credit risk and liquidity, and interpreting this correlation as a flight-to-quality phenomenon.

Second, our paper is related to the literature that analyzes the economic mechanisms leading to higher correlation between asset returns. King and Wadhwani (1990) suggest that investors infer asset values in one market from values in another market to a larger degree when the information environment becomes more complex, which leads to higher correlations. Connolly et al. (2007) trace high correlation back to high market uncertainty. In Brunnermeier and Pedersen (2009), a sudden drying up of investors' funding ability leads to low market liquidity and high correlation. Barberis et al. (2005) argue that groups of investors are prone to "investment habitats". Investors within one habitat trade more similarly. Kumar and Lee (2006) show that such herding is caused by investor sentiment. Chordia et al. (2011) find that market downturns lead to retail investors' herding and to higher stock correlations. We add to this literature by showing that low investor sentiment increases risk factor correlation, and high risk factor correlation leads to high bond correlation.

Third, we contribute to the literature analyzing the relation between liquidity and credit risk. Vayanos (2004) argues that investors attach a higher value to liquidity when markets are volatile. Ericsson and Renault (2006) motivate and document a positive correlation between credit risk and liquidity premiums for corporate bonds. Dick-Nielsen et al. (2012) and Friewald et al. (2012) show that – consistent with flight-to-quality behavior – liquidity premiums increase more for low-rated than for high-rated corporate bonds during the recent financial crisis. In contrast, Longstaff et al. (2005) find a negative correlation between credit risk and liquidity premiums for corporate bonds. Our paper reconciles this contradictory evidence by showing that risk factor correlation varies over time and depends on investor sentiment. In addition, we show that stronger flight-to-quality increases the comovement within corporate bond markets.

Finally, our results extend the growing literature on the influence of investor sentiment in the US corporate bond market. Nayak (2010) finds that corporate bond spreads are affected by investor sentiment. Tang and Yan (2010) show that market-wide credit spreads negatively depend on investor sentiment. We add to this literature by showing that low investor sentiment leads to high risk factor correlation and, ultimately, high bond correlation.

The remainder of the paper is organized as follows. In Section 2, we document how bond correlation evolves over time. In Section 3, we develop our model to explain varying bond correlation and state our main hypotheses linking bond correlation to risk factor correlation and risk factor correlation to investor sentiment. Our hypotheses are tested in Section 4. In Section 5, we provide various robustness tests and Section 6 concludes.

2. Bond correlation over time

2.1. Bond sample

We calculate bond correlations based on bond transaction data (actual trade price, yield resulting from this price, trade size, trade time, and trade date) from TRACE (Trade Reporting and Compliance Engine). We filter out erroneous trades with the algorithm described in Dick-Nielsen (2009) and use only plain vanilla bonds with fixed coupons. We exclude bonds without S&P rating (obtained from Thomson Reuters Datastream) and initial time to maturity of more than 30 years. Additionally, we exclude bonds for which Thomson Reuters Datastream does not provide 5-year credit default swap (CDS) mid quotes, since we use these to calculate credit risk premiums.

As TRACE does not cover BBB-rated and high yield bonds before October 2004 (Goldstein and Hotchkiss, 2012), our sample starts on October 1, 2004. It ends on

September 30, 2010, since Thomson Reuters Datastream provides CDS data only until that date. We exclude federal holidays as only sparse trading occurs on these days. The final sample consists of 4,266 corporate bonds of 426 companies. Table 1 displays summary statistics.

Insert Table 1 about here.

Table 1 shows that the mean number of companies with actively traded bonds per month is 302, the majority with an investment grade (IG) rating (245 companies). The mean number of actively traded bonds per month (1,531) indicates that five bonds per issuing company are traded. Again, most bonds are in the IG segment, but even the high yield (HY) segment contains a broad bond portfolio (170 bonds). Mean outstanding volume is 453.64 m USD. It is significantly higher in the IG segment than in the HY segment (IG: 463.64 m USD; HY: 368.79 m USD). Mean time to maturity roughly equals 5 years and is significantly higher in the HY segment (IG: 5.24 years; HY: 5.87 years). The mean S&P rating for IG bonds is 6 (=A), the mean HY rating is almost 14 (=B+). Regarding trading activity, IG bonds trade significantly more frequently: 82 trades per bond per month, on average, compared to 54 trades of HY bonds. Mean trade size is 14% larger for IG bonds than for HY bonds. Despite the higher trading frequency and trading size, mean turnover is not larger for IG bonds than for HY bonds due to higher issuance volume in the IG segment.

An analysis of the specific credit rating buckets shows most bonds are rated A or BBB, but average bond volumes and number of trades (but not trade size) are larger in the AAA&AA bucket.[1] Time to maturity equals roughly five years in all buckets, and

[1] Like Wang and Wu (2015), we split the IG segment into three credit rating buckets and do not split the HY segment due to its much lower number of bonds and trading frequency. The first IG bucket

turnover is also similar in all buckets. As expected, coupon rates are larger for lower credit rating buckets.

2.2. Bond correlation

To calculate bond correlation, we first aggregate corporate bonds into two portfolios: an investment grade and a high yield corporate bond portfolio. Like Longstaff et al. (2005), we focus on bond spreads as the difference between the yield and the maturity-matched risk-free rate (obtained by interpolating US Treasury yields).[2] For each trading day, we compute one IG and one HY portfolio yield spread as the average yield spread across all traded bonds in the respective segment. We then calculate bond correlation as the 22-day rolling Pearson's correlation between the two portfolios' daily yield spread changes.[3] We focus on changes instead of levels to ensure stationarity. Figure 1 shows how bond correlation evolves over time.

(AAA&AA) consists of all bonds rated AAA or AA. The second and third IG buckets consist of bonds rated A and BBB, respectively.

2 More specifically, on each trading day we collect constant maturity US Treasury yields from Thomson Reuters Datastream of maturities between one month and 30 years. We then fit a cubic function with maturity as the independent variable to the observed yields, and use the interpolated yield as a proxy for the maturity-matched risk-free rate at this date.

3 As an alternative, we could measure time-varying correlation via a dynamic conditional correlation (DCC)-GARCH model, as Nieto and Rodriguez (2015) and Bartram and Wang (2015), or a smooth transition Markov-switching model, as Yang et al. (2009). We choose the conventional rolling window estimation as in Connolly et al. (2007); Panchenko and Wu (2009); Chordia et al. (2011); and Bansal et al. (2014) because it is more parsimonious with respect to the number of parameters that need to be estimated, does not depend on a specific distribution assumption or a specific functional form for the transition function, and is less likely to be dominated by past dynamics, and thus overstate persistence, if the data contains structural breaks.

Insert Figure 1 about here.

Figure 1 clearly shows that bond correlation varies strongly over time. It exhibits spikes around the acquisition of Bear Stearns by JPMorgan (March 16, 2008) and the September 2008 turmoil (federal takeover of Fannie Mae and Freddie Mac on September 7, the acquisition of Merrill Lynch by Bank of America on September 14, and the Lehman default on September 15). It is easy to see that bond correlation is much higher at the start of the financial crisis (July 2007). A numerical analysis shows that it is about three times as large, with 21.3% after July 2007 but only 6.3% before, and the difference is statistically significant at the 1% level. This increase in correlation mirrors the higher correlation between equities in crises widely documented in the empirical literature (King and Wadhwani, 1990; Longin and Solnik, 1995; De Santis and Gerard, 1997; Longin and Solnik, 2001; Connolly et al., 2007; Chordia et al., 2011).

Next we analyze bond correlations in the ratings cross-section. We use the same buckets as before, and compute correlation between two credit rating buckets using the same portfolio approach as for Figure 1 and Table 1. Table 2 reports summary statistics.

Insert Table 2 about here.

Table 2 shows that correlations between the different buckets are positive on average. However, average correlation is much lower (around 0.15) and only significant at the 5% level when the HY segment is involved, compared to correlations between the IG buckets (0.70 at least, always significant at the 1% level). This difference is consistent with empirical evidence in Brière et al. (2012) that cross-country correlations across the IG and HY segment are lower than correlations within the IG and the HY segment.

The standard deviation and the 5th and 95th percentile indicate high variation over time in all correlations, in line with the visual impression obtained from Figure 1.

3. Explaining bond and risk factor correlation

In this section, we propose a model to explain the evolution of bond correlation. The model uses the fact that the main risk factors priced in bond yield spreads are credit risk and liquidity. Therefore, higher correlation between these risk factors translates into higher bond correlation. This raises the question: What drives risk factor correlation? We show that low sentiment translates into high risk factor correlation and, thus, high bond correlation.

Our model consists of two basic ingredients: First, correlation between risk factors (credit risk premiums, liquidity premiums) depends crucially on investor sentiment. Second, bond correlation is determined by this correlation between credit risk premiums and liquidity premiums. We focus on the economic intuition in this section. In the appendix, we formally derive our hypotheses in a reduced-form model based on a discrete two-factor Hull and White (1994) term structure model.

3.1. Risk factor correlation and investor sentiment

We first derive the impact of investor sentiment on risk factor correlation. Consider a corporate bond whose credit risk and liquidity vary over time. For simplicity, consider a zero bond maturing at date *t=2* with notional value 1 and assume that the risk-free interest rate is r=0 and the recovery rate is R=0 as well. We can express the bond's risk-neutral price at time *t=1* as

$$B(1,2) = \exp(-\lambda_1 - \gamma_1), \tag{1}$$

where λ_1 is the bond's risk-neutral default intensity and γ_1 is the bond's risk-neutral illiquidity intensity, both known at *t=1*. From the perspective of time *t=0*, the default and illiquidity intensities at *t=1* are unknown, and the price at time *t=0* is

$$\mathrm{B}(0,2) = \exp(-\lambda_0 - \gamma_0) \cdot E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1\right)\right], \tag{2}$$

where expectations are computed under the risk-neutral measure. The corresponding per-period log yields at time *t=0* and time *t=1* are $ys_0 = \frac{1}{2}\left\{(\lambda_0 + \gamma_0) - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1\right)\right]\right)\right\}$ and $ys_1 = \lambda_1 + \gamma_1$, and the corresponding credit risk and liquidity premiums[4] are

$$\begin{aligned} cr_0 &= \frac{1}{2}\left\{\lambda_0 - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\right\}, \\ cr_1 &= \lambda_1, \end{aligned} \tag{3}$$

$$\begin{aligned} liq_0 &= ys_0 - cr_0 = \frac{1}{2}\left\{\gamma_0 - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1\right)\right]\right) + \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\right\}, \\ liq_1 &= ys_1 - cr_1 = \gamma_1. \end{aligned} \tag{4}$$

Equations (3) and (4) show that in this model, the covariance between credit risk and liquidity premium changes $Covar_0\left(\Delta\widetilde{cr}, \Delta\widetilde{liq}\right)$ equals the covariance between the intensities $Covar_0\left(\tilde{\lambda}_1, \tilde{\gamma}_1\right)$.

4 Since we consider a risk-neutral investor, we use the term "risk premium" for the compensation this investor requires for expected losses. As Equations (2) to (4) show, the investor does not demand additional compensation for possible variations in the credit quality or liquidity of the bond.

In the empirical literature (e.g., Ericsson and Renault, 2006 or Dick-Nielsen et al., 2012), credit risk and liquidity premiums are usually assumed to be positively correlated, which corresponds to positively correlated intensities in our model (as in Schönbucher, 2002). Economically, this positive correlation reflects the pricing effect of the well-known flight-to-quality behavior of investors: bonds become less liquid when their credit quality deteriorates (e.g., Dick-Nielsen et al., 2012; Friewald et al., 2012; and Acharya et al., 2013) as investors shift their portfolios towards risk-free bonds or cash.

The novel mechanism we suggest is that the extent of flight-to-quality depends on investor sentiment. The economic rationale is twofold. First, low investor sentiment reduces an investor's propensity to invest in risky assets (Baker and Wurgler, 2006). Hence, the overall bond liquidity premium level is high when investor sentiment is low. We therefore link sentiment to liquidity premium levels. Second, the extent to which liquidity premiums change as a reaction to shocks in credit quality depends on sentiment. Investors perceive risks more severely when their sentiment is low (e.g., Kaplanski and Levy, 2014), and low sentiment affects an investor's reaction to negative information about firm fundamentals more than her reaction to positive information (e.g., Mian and Sankaraguruswamy, 2012). Therefore, we make the impact of credit risk shocks on liquidity premiums dependent on the sentiment level.

We model both effects in our setting by introducing a general investor sentiment parameter x and an impact variable $\tilde{a}_t$ which depends on the default intensity $\tilde{\lambda}_t$. Both x and $\tilde{a}_t$ jointly determine the magnitude of the flight-to-quality effect that investors exhibit as a reaction to a credit risk shock.[5] Larger values of x ($-1<x<1$, where $x=0$ corresponds to neutral sentiment) indicate lower investor sentiment; $\tilde{a}_t$ depends on whether the fundamental information is negative (then, $\tilde{a}_t = a_t^u$), neutral ($\tilde{a}_t = a_t^m$), or positive ($\tilde{a}_t = a_t^d$ with $a_1^d < a_1^m < a_1^u$). To illustrate the sentiment impact, consider a negative fundamental information ($\tilde{a}_t = a_t^u$) about the firm implying a credit risk shock at $t=1$ ($\lambda_1 > \lambda_0$). If investor sentiment is low, i.e., x is positive, investors react more strongly to this information, which leads to a higher flight-to-quality effect compared to the case of neutral sentiment ($x=0$). Conversely, positive sentiment ($x<0$) reduces the flight-to-quality effect compared to the case of neutral sentiment. We model this sentiment-dependent flight-to-quality effect by multiplying the liquidity intensity $\tilde{\gamma}_1$ with $\left(1 + a_1^u \cdot x\right)$.[6] Therefore, the liquidity premium depends on sentiment:

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[5] Conceivably, causality could also run in the opposite direction: a liquidity shock could be the fundamental information, and this could affect credit risk. In our model, we choose credit risk as the fundamental information for two reasons: First, only this direction of the effect is consistent with the economic intuition of Baker and Wurgler (2006), Kaplanski and Levy (2014), and Mian and Sankaraguruswamy (2012). Second, this is consistent with empirical evidence of Kalimipalli and Nayak (2012) and Kalimipalli et al. (2013) that liquidity shocks have a second-order effect on corporate bond spreads compared to credit risk shocks.

[6] Positive sentiment ($x<0$) can generate negative risk factor correlation in our model, leading to a flight-from-quality effect. Longstaff et al. (2005) and Ericsson and Renault (2006) have empirically documented that negative and positive correlations alternate in corporate bond markets. However, models that can explain both positive and negative risk factor correlations are scarce: for example, Ericsson and Renault (2006) can only generate consistently positive risk factor correlations. Beber et al. (2009), on the other hand, document average negative correlations between credit risk and liquidity premiums, and Chan et al. (2011) find flight-from-quality episodes in equity and commodity markets.

$$liq_0 = \frac{1}{2}\left\{\gamma_0\left(1+a_0 \cdot x\right) - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1 \cdot \left(1+\tilde{a}_1 \cdot x\right)\right)\right]\right) + \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\right\},$$
$$liq_1 = \gamma_1 \cdot \left(1+a_1 \cdot x\right), \tag{5}$$

and the covariance between credit risk and liquidity premium changes $Covar_0\left(\Delta\widetilde{cr}, \Delta\widetilde{liq}\right)$ equals the covariance between the credit risk intensity and the sentiment-adjusted liquidity intensities $Covar_0\left(\tilde{\lambda}_1, \tilde{\gamma}_1 \cdot \left(1+\tilde{a}_1 \cdot x\right)\right)$.[7] This covariance as well as the corresponding correlation both increase in the sentiment parameter x as shown in the appendix. This leads to our first hypothesis: risk factor correlation increases when investor sentiment decreases.

3.2. Bond correlation and risk factor correlation

Second, we link risk factor correlation and bond correlation. Consider two corporate bonds, for example, one investment grade bond *i* and one high yield bond *h* with positive default and liquidity intensities $\tilde{\lambda}_{i/h,t}$ and $\tilde{\gamma}_{i/h,t} \cdot \left(1+\tilde{a}_t \cdot x\right)$. Without loss of generality, the default (liquidity) intensity of a bond can be split into a systematic part $\tilde{\lambda}_{m,t} \cdot \beta_{i/h,\lambda}$ ($\tilde{\gamma}_{m,t} \cdot \left(1+\tilde{a}_t \cdot x\right) \cdot \beta_{i/h,\gamma}$) and an idiosyncratic part, $\tilde{\varepsilon}_{i/h}$ ($\tilde{\eta}_{i/h}$). Under the standard assumption that idiosyncratic factors are uncorrelated with systematic risk factors and across bonds, the covariance between yield spread changes of the two

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7 Alternatively, one could interpret $\tilde{a}_t$ x as the time-varying market price of liquidity risk, which could be caused by variations in the risk-free interest rate or in unexpected inflation. Since our model is derived from the perspective of a risk-neutral investor, we only account for these effects in our empirical analysis. In Section 5.2, we show that sentiment remains significant as a determinant of risk factor correlation even after adjusting credit risk and liquidity premiums for interest rate risk and unexpected inflation.

bonds results solely from covariance between systematic credit risk and systematic liquidity:[8]

$$\begin{aligned} Covar_0\left(\Delta\widetilde{ys}_i,\Delta\widetilde{ys}_h\right) = {} & \beta_{i,\lambda}\beta_{h,\lambda}\cdot Var\left(\tilde{\lambda}_{m,1}\right) + \beta_{i,\gamma}\beta_{h,\gamma}\cdot Var\left(\tilde{\gamma}_{m,1}\cdot\left(1+\tilde{a}_1\cdot x\right)\right) \\ & +\left(\beta_{i,\lambda}\beta_{h,\gamma}+\beta_{i,\gamma}\beta_{h,\lambda}\right)\cdot Covar\left(\tilde{\lambda}_{m,1},\tilde{\gamma}_{m,1}\cdot\left(1+\tilde{a}_1\cdot x\right)\right) \end{aligned} \quad (6)$$

In the appendix, we formally show that this relation also holds for correlations.[9] Thus, higher risk factor correlation (resulting from correlation between the systematic credit risk and liquidity) translates into higher bond correlation. This leads to our second hypothesis: bond correlation increases when risk factor correlation increases.

4. Hypotheses tests

4.1. Measuring investor sentiment and risk factor correlation

We use the Chicago Board Options Exchange (CBOE) daily market volatility index (VIX) to capture investor sentiment.[10] It measures the implied volatility of options on the S&P 500 and, thus, reflects investors' expectation about future market volatility. VIX is said to measure investor fear (e.g., Whaley, 2000, Baker and Wurgler, 2007)

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8 There is a large body of literature on correlated defaults and systematic credit risk: see, e.g., Das et al. (2007) or Duffie et al. (2009). Among others, Chacko (2006) and Lin et al. (2011) show that systematic liquidity is priced for corporate bonds. Bao et al. (2011) document a positive relation between systematic credit risk and systematic illiquidity in corporate bond markets.

9 Note that our model can generate negative bond correlation. The intuition is that if the systematic credit risk and liquidity intensity are sufficiently negatively correlated, bond covariance and thus bond correlation is also negative.

10 In the robustness section, we use alternative measures of investor sentiment and show that the qualitative results of this paper do not depend on the investor sentiment proxy.

and is widely used as investor sentiment proxy (e.g., Kurov, 2010; Kaplanski and Levy, 2010; Da et al., 2015; and Smales, 2015). A high value of VIX corresponds to low investor sentiment. In our sample, VIX has an average value of 21.42 and a standard deviation of 11.61. A possible concern is that VIX will not reflect pure investor sentiment, but mainly the state of the economy. To ensure that we do not capture this effect, we orthogonalize VIX to macroeconomic factors as in Baker and Wurgler (2006) and use the residual of this orthogonalization as our measure of sentiment in the remainder of the paper.[11] The residual has mean zero and its standard deviation is 6.40.

To determine risk factor correlation, we first calculate credit risk premiums and liquidity premiums at the bond level. We use daily 5-year CDS mid quotes from Thomson Reuters Datastream as a proxy for the bond's credit risk premium. As a proxy for the liquidity premium, we use the non-credit risk portion of the bond yield spread (see, e.g., Longstaff et al., 2005; Chen et al., 2007). To compute this, we subtract the CDS mid quote from the yield spread to obtain the bond's liquidity premium.[12] On average, the credit risk premium equals 0.85% for IG bonds and 3.59% for HY bonds. The difference in the liquidity premiums is less pronounced: The mean liquidity premium is 1.44% in

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[11] The factors used in the orthogonalization are the growth rate of the 12-month moving averages of growth in durable, nondurable, and services consumption, growth in employment, growth in industrial production, and a dummy for NBER recessions We obtain the time series from the Federal Reserve Economic Database: http://research.stlouisfed.org/fred2/

[12] Arguably, the CDS mid premium and the non-credit risk portion on the bond yield spread may also reflect factors other than credit risk and liquidity. In Section 5.1, we show that our empirical results are robust against the use of alternative credit risk and liquidity premium specifications. Section 5.2 adjusts correlations for additional risk factors.

the IG and 2.21% in the HY segment. Both differences are statistically significant at the 1% level.

To calculate risk factor correlation, we aggregate corporate bonds into an IG and a HY portfolio as in Section 2.2. For each portfolio, we determine daily credit risk premiums and liquidity premiums as the average across all traded bonds in the respective segment. We then compute 22-day rolling Pearson's correlation between credit risk and liquidity premium changes. The average of the IG and the HY correlation is our measure of risk factor correlation. To obtain an unbounded variable, we transform Pearson's correlation using the Fisher z-transformation from Section 4.2 onwards. We proceed in the same way when we calculate risk factor correlation for bonds belonging to specific credit rating buckets (e.g., A and BBB): We first form two portfolios (consisting of A and BBB bonds, respectively), then calculate the correlation between credit risk and liquidity premium changes in each portfolio, and finally average the two correlation estimates to come up with risk factor correlation. Table 3 reports summary statistics on risk factor correlations.

Insert Table 3 about here.

Table 3 documents that the average risk factor correlation is small in economic terms. The positive values, though not significant, indicate a moderate flight-to-quality effect in all credit ratings buckets. This finding is in line with evidence by Dick-Nielsen et al. (2012) that flight-to-quality affects both investment grade and speculative corporate bonds. Interestingly, the maximum value of 0.07 is attained for the highest credit rating buckets (AAA&AA with A), suggesting that even highly rated corporate bonds suffered from the flight-to-quality effect during our observation interval. However, differences between the average risk factor correlations are not statistically significant as indicated by the high standard deviations (≥ 0.20) and the values of the 5^{th} and 95^{th} percentile.

We conclude the descriptive analysis of risk factor correlation by comparing the cross-sectional results of Table 2 and Table 3. Consistent with the lower risk factor correlation when the HY segment is involved, Table 2 indicates lower bond correlation in these cases. Economically, this implies that diversification across the IG and HY segments decreases portfolio risk because risk factor correlation is low. However, if risk factor correlation increases, this diversification benefit is reduced. In the next section, we therefore turn to our analysis of sentiment as a driver of risk factor correlation.

4.2. The link between sentiment and risk factor correlation

In this section, we test our first main hypothesis: Risk factor correlation increases when sentiment decreases. To do so, we run the following time-series regression:

$$\text{Corr}_t^{Risk} = \alpha + \beta \cdot \text{Sentiment}_t + \Gamma \cdot \text{Controls}_t + \varepsilon_t . \tag{7}$$

Risk factor correlation Corr_t^{Risk} and sentiment are measured as described in Section 4.1. We use the Fisher z-transformations of risk factor correlations to obtain an unbounded variable. Controls_t is the vector of variables controlling for market-wide risk and for market downturns. We include these variables since equity market correlation is higher when market risk is high (e.g., King and Wadhwani, 1990; Longin and Solnik, 1995) and during market downturns (e.g., Longin and Solnik, 2001). To measure market-wide risk, we determine the market-wide yield spread as the sum of the credit risk premium and liquidity premium. We then compute its 22-day rolling standard deviation as a proxy for market-wide risk. The average value of this standard deviation is 0.33 with a standard deviation of 0.30. To indicate market downturns, we define a dummy variable that takes on a value of one if the yield spread at time *t* is above a one-sigma band compared to the previous month.

Table 4 shows the regression results. In the first column, we present results for the overall risk factor correlation calculated using all IG and HY bonds. Columns 2 to 7 present results for the more detailed credit rating buckets used above.

Insert Table 4 about here.

Table 4 provides strong support for our first hypothesis: Irrespective of whether we consider the overall (IG&HY) or the bucket-specific risk factor correlations, risk factor correlation is significantly (at least at the 5% level) related to sentiment with the hypothesized positive coefficient sign. Thus, risk factor correlation, and hence flight-to-quality, increases when investor sentiment decreases. With respect to the different credit rating buckets, the lower intercept when the HY segment is involved is consistent with the lower average values in Table 3. In contrast, the control variables have no consistent impact on risk factor correlation across the buckets.

4.3. The link between risk factor correlation and bond correlation

We now test our second hypothesis: Bond correlation increases with risk factor correlation. We run the following time-series regression:

$$\text{Corr}_t^{Bond} = \alpha + \beta \cdot \text{Corr}_t^{Risk} + \gamma \cdot \text{Sentiment}_t + \delta \cdot \text{Herding}_t + \Gamma \cdot \text{Controls}_t + \varepsilon_t. \qquad (8)$$

The main variables are bond correlation Corr_t^{Bond} and risk factor correlation Corr_t^{Risk}. We use Fisher z-transformations of both correlations to obtain unbounded variables. We add the same vector of controls, Controls_t, as in Table 4 to capture possible effects of the state of the economy on bond correlation. Furthermore, we add sentiment (captured by VIX) to control for the direct impact of investor sentiment on bond correlation. Since empirical studies (e.g., Kumar and Lee, 2006) have documented a link between investors' herding behavior and equity market correlations and a similar link might exist in the bond market, we also control for herding in the bond market.[13] We calculate the herding measure of Lakonishok et al. (1992) for each traded bond *i* on each day *t* as:

$$\mathrm{LSV}_{i,t} = \left|\mathrm{br}_{i,t} - \overline{\mathrm{br}}_t\right| - E_t\left(\left|\mathrm{br}_{i,t} - \overline{\mathrm{br}}_t\right|\right). \tag{9}$$

The buyer ratio $\mathrm{br}_{i,t}$ denotes the fraction of buys relative to the total number of trades of bond *i* on day *t*. $\overline{\mathrm{br}}_t$ is the buyer ratio on day *t* averaged across bonds, and $E_t\left(\left|\mathrm{br}_{i,t} - \overline{\mathrm{br}}_t\right|\right)$ is the bias correction suggested by Bellando (2012). The resulting LSV measure has a mean of 0.09 and a standard deviation of 0.02. Table 5 reports the regression results.

Insert Table 5 about here.

Table 5 provides strong support for our second hypothesis. We find a positive and significant impact of risk factor correlation on bond correlation, no matter whether we consider the overall market or specific credit rating buckets. The A and HY credit rating bucket exhibits the highest sensitivity, but all coefficient estimates are of a similar order of magnitude. We also find a significant direct impact of sentiment on bond correlation, except for the highest credit rating buckets (AAA&AA and A). The herding variable and the remaining control variables have no consistent impact on bond correlation.

A possible concern with our empirical analysis in Equation (8) is that we cannot formally test whether sentiment affects bond correlation only directly, or also indirectly via the risk factor correlation channel we propose. To address this concern, we test for significance of this indirect impact using a causal mediation analysis as in Imai et al.

[13] Cai et al. (2012) document herding behavior among bond mutual fund managers.

(2010b). The mediation model is based on Equations (7) and (8), and allows us to quantify the indirect impact of sentiment on bond correlation via risk factor correlation.[14] We report the indirect impact of sentiment on bond correlation, measured via the average causal mediation effect, in the last row of Table 5. Significance is computed using bootstrapped standard errors from 10,000 simulation runs. The last row of Table 5 shows that investor sentiment has a statistically significant indirect impact on bond correlation via risk factor correlation, which amounts to up to 18% of the total impact of investor sentiment (for the A and HY credit rating buckets). Hence, sentiment affects bond correlation not only directly, but also indirectly via risk factor correlation.

Overall, the results of Section 4 clearly support the economic rationale developed in Section 3: When investor sentiment decreases, risk factor correlation increases, translating into increasing bond correlation.

5. Robustness

In this section, we perform various robustness tests. In Section 5.1, we check for the robustness of our results when we use alternative proxies for credit risk and liquidity premium. The motivation for this robustness analysis is that CDS mid quotes may not

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[14] Specifically, Equation (7) represents the mediator model and specifies the conditional distribution of the mediator risk factor correlation given the treatment sentiment, and the control variables. Equation (8) represents the outcome model and specifies the conditional distribution of the outcome bond correlation given the mediator risk factor correlation, the treatment sentiment, and the control variables. We fit both models sequentially, using standard errors with a Newey-West correction. We then estimate the average causal mediation effect (the indirect impact) using the algorithm in Imai et al. (2010a) for parametric inference, and determine its significance using bootstrapped standard errors.

be pure measures of credit risk, but may also reflect CDS illiquidity (e.g., Tang and Yan, 2008; Bongaerts et al., 2011), and bond yield spreads may reflect other time-varying factors than credit risk and liquidity (e.g., Collin-Dufresne et al., 2001). In Section 5.2, we adjust correlations for interest rate risk and unexpected inflation. The reason is that both may affect both credit risk premiums and liquidity premiums, and we might erroneously identify this impact as risk factor correlation. In Section 5.3 we, use alternative proxies for investor sentiment and in Section 5.4 we use the swap-rate as an alternative proxy for the risk-free rate. Finally, we test the temporal stability of our results in Section 5.5. For the sake of brevity, we report only results for the overall market (HY and IG) in the robustness tests.

5.1. Alternative credit risk and liquidity premium

We first control for the impact of CDS illiquidity on CDS mid premiums: correlation between CDS mid quotes and bond yield spreads minus CDS mid quotes (which we use as a proxy for liquidity premiums) may also reflect CDS illiquidity. Like Tang and Yan (2008), we use the CDS bid-ask spread as the independent variable to identify the liquidity component in the CDS mid quote. We run a time-series regression of CDS mid quotes on CDS bid-ask spreads for each CDS contract, and then compute risk factor correlation and bond correlation as in Section 3.2, this time using the unexplained part instead of the original CDS mid quotes. The first two columns of Table 6 present the results we obtain when repeating our analyses from Section 4 for these adjusted correlation measures.

Insert Table 6 about here.

All our main results remain valid when we use the alternative credit risk premium: sentiment explains risk factor correlation, and risk factor correlation explains bond correlation. We can therefore exclude CDS illiquidity as an alternative explanation for our effect.

In Columns 3 and 4 of Table 6 we use an alternative measure for the liquidity premium. Arguably, part of the non-credit yield spread may be due to factors other than illiquidity. Empirically, taxes (Elton et al., 2001), equity volatility and accounting variables (Campbell and Taksler, 2003), and an unexplained systematic factor (Collin-Dufresne et al., 2001) have been shown to affect bond yield spreads. Directly adjusting for these effects, however, is difficult since they differ across bonds but are basically constant over time (taxes, accounting variables), unavailable for some bonds (equity volatility), or impossible to proxy for (unexplained systematic factors).

We therefore compute an alternative liquidity measure not derived from yield spreads. Jankowitsch et al. (2011) introduce a price dispersion measure that reflects transaction costs as well as dealers' inventory risk and investors' search costs. Friewald et al. (2012) show that this measure is a major liquidity proxy in the corporate bond market. Hence, we focus on price dispersion as an alternative measure of bond illiquidity using the modified version of Schestag et al. (2014) and compute for each bond i on each trading day t the average price dispersion as

$$\text{PriceDispersion}_{\text{i,t}} = 2\sqrt{\frac{1}{\sum_{n=1}^{N} Q_n} \sum_{n=1}^{N} Q_n \left(\frac{P_n - \bar{P}}{\bar{P}}\right)^2} \tag{10}$$

where N denotes the number of trades on day t, Q_n is the trading volume of trade n on day t, P_n is the transaction price of trade n on day t, and $\bar{P}$ is the average across all transaction prices on day t. This relative dispersion measure gives us an estimate of the effective relative spread.

We then compute risk factor correlation and bond correlation, using price dispersion as the liquidity premium measure. Columns 3 and 4 of Table 6 present the results when we repeat the analyses from Section 4, using the new risk factor correlation and bond correlation. The results clearly show that the main results still hold. Investor sentiment drives risk factor correlation and risk factor correlation determines bond correlation. Thus, we can reject the hypothesis that our results are driven by our use of the non-credit risk component of the yield spread as the liquidity premium.

5.2. Correlations adjusted for interest rate risk and unexpected inflation

In this section, we control for the impact of interest rate risk and unexpected inflation by adjusting our correlation measures. The reason is that interest rate risk might affect both credit risk premiums (due to the link between a firm's default risk and the risk-free rate (see, e.g., Duffee, 1999) and liquidity premiums (because of the flight-to-quality effect). Hence, we might erroneously identify interest rate risk as risk factor correlation, leading to spurious results in the estimation of Equations (7) and (8). Similarly, unexpected inflation has been proposed as an explanation for time-varying risk aversion (Brandt and Wang, 2003), leading to higher market prices of risk for all risk sources, and thus also an increased comovement of credit risk and liquidity premiums.

To control for interest rate risk, we first regress yield spread, credit risk premium, and liquidity premium changes on changes in the 5-year constant-maturity Treasury yield. Then, we compute risk factor correlation and bond correlation as before, but now use the residuals of the first-step regression instead of the original observations. We then repeat the analyses from Section 4. The results are presented in the first two columns of Table 7.

Insert Table 7 about here.

The first two columns of Table 7 show that our main results remain valid when we use interest rate risk-adjusted correlations: sentiment explains risk factor correlation, and risk factor correlation explains bond correlation. Thus, interest rate risk does not drive our results.

We next control for the impact of unexpected inflation. We compute unexpected inflation as the difference between the realized inflation rate and its forecast using the following regression:

$$\text{Inflation}_t = \alpha + \beta_1 \cdot \text{Inflation}_{t-1} + \beta_2 \cdot \text{Inflation}_{t-2} + \varepsilon_t \,. \tag{11}$$

Inflation_t denotes the monthly inflation rate based on the Consumer Price Index (CPI) provided by the Federal Reserve Economic Database. We use the residuals from the above regression as the monthly unexpected inflation, and interpolate between monthly estimates to obtain a daily estimate.

To adjust our correlation measures for unexpected inflation, we use the same approach as before. We first regress yield spread, credit risk premium, and liquidity premium changes on changes in unexpected inflation. Then, we use the residuals from this regression to compute correlations and test our two hypotheses. The results, presented in Columns 3 and 4 of Table 7, document that our results still hold when we use inflation-adjusted correlations: When investor sentiment decreases, risk factor correlation increases, translating into increasing bond correlation. Thus, our proposed mechanism remains valid when using inflation-adjusted correlations, ruling out the possibility that unexpected inflation drives our results.

5.3. Alternative proxies for investor sentiment

In this section, we use five alternative proxies for investor sentiment: Individual Investor Sentiment Index (AAII) from Thomson Reuters Datastream (weekly) as in Brown and Cliff (2004); Economic Cycle Research Institute United States Leading Index (ECRI) (weekly); Daily Economic Policy Uncertainty Index (EPU) (daily) suggested by Baker et al. (2015)[15]; St. Louis Fed Financial Stress Index (FSI) from the St. Louis Fed (weekly) which is similar to the Kansas City Financial Stress Index described in Hakkio and Keeton (2009); and the SENTIX World Economic Sentiment Index (SENTIX) (monthly). If necessary, we interpolate the indices to a daily frequency.

The indices offer different ways of capturing sentiment: They are based on surveys of investors' expectations in the US (AAII) and worldwide (SENTIX), screen US newspaper articles for positive and negative terms (EPU), are constructed from market variables capturing financial stress (FSI), or anticipate turns in the economic cycle (ECRI). Given the index construction, high sentiment is associated with high values for AAII, ECRI, and SENTIX and low values for EPU and FSI. To assure that all proxies have the same expected sign as our main sentiment proxy (VIX), we redefine AAII, ECRI, and SENTIX by multiplying them with -1. We again orthogonalize each sentiment index to the macroeconomic factors as in Baker and Wurgler (2006) to ensure that they do not capture the state of the economy.

Insert Table 8 about here.

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15 http://www.policyuncertainty.com/us_daily.html

Table 8 shows that our main results also hold when we use alternative proxies for investor sentiment. Sentiment drives risk factor correlation, and risk factor correlation drives bond correlation, no matter which proxy we use for investor sentiment.

5.4. Alternative proxy for risk-free rate

In Section 4 we use maturity-matched constant maturity US-Treasury bonds to approximate risk-free rates. We now show that our results are robust when we use swap rates as a proxy for the risk-free rates, as in, e.g., Friewald et al. (2012).[16,17] The results are presented in Table 9.

Insert Table 9 about here.

Table 9 shows that our results do not change when we use the swap rate to proxy the risk-free rate. The impact of sentiment on risk factor correlation remains significant as does the impact of risk factor correlation on bond correlation.

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16 More specifically, on each trading day we collect US swap rates from Thomson Reuters Datastream of maturities between one week and 30 years. We then fit a cubic function with maturity as the independent variable to the observed yields, and use the interpolated yield as a proxy for the maturity-matched risk-free rate at this date.

17 Alternatively, one could use Overnight Index Swap rates (Michaud and Upper, 2008), the general collateral rate (Longstaff, 2000) or risk-free rates implied by derivatives prices (Brenner and Galai, 1986; Brenner et al., 1990). However, these rates are either not available for longer maturities, or empirically lie between Treasury rates and swap rates (Naranjo, 2009). We therefore focus on plain-vanilla interest rate swap rates.

5.5. Stability over time

In this section, we test the stability of our main results over time. We use two time splits. First, we split our sample period into two subperiods of equal size. Second, we spilt our sample at the beginning of the financial crisis (July 1, 2007 as in Friewald et al., 2012). For each subperiod we repeat the analyses from Section 4. The results are presented in Table 10.

Insert Table 10 about here.

Table 10 shows that our results are stable when splitting our sample in the middle or at the beginning at the financial crisis. In both subperiods, we find a significant impact of sentiment on risk factor correlation and of risk factor correlation on bond correlation. Since the effects seem to be so stable over time, we expect our findings to remain valid in the years following our sample period.

6. Conclusion

In this paper, we theoretically and empirically explore the link between investor sentiment, risk factor correlation, and bond correlation. We set up a simple theoretical model that shows that investors exhibit a stronger flight-to-quality when sentiment is low. This in turn leads to higher risk factor correlation between the two main risk factors in corporate bond markets: credit risk and liquidity. As a consequence of this higher risk factor correlation when sentiment is low, bonds exhibit a higher comovement. Thus, sentiment-induced flight-to-quality effectively reduces diversification benefits across corporate bonds.

We test our model predictions using data on US corporate bonds and find strong and robust empirical support for our hypotheses: (i) When investor sentiment decreases, risk factor correlation increases. (ii) This increasing risk factor correlation translates into increasing bond correlation. We rule out several alternative explanations for our findings and show that they are stable over time and in the cross-section.

Appendix

In Section 3, we outline the economic intuition of how risk factor correlation is linked to investor sentiment and how bond correlation is linked to risk factor correlation. We formalize this intuition in a discrete two-factor model in this appendix. We first provide a detailed model description and then derive our hypotheses.

Model setup

Our model is based on a discrete two-factor Hull and White (1994) term structure model. We consider a single default-risky zero bond with two periods to maturity. The bond can default after one period (*t*=1) or after two periods (*t*=2). Default occurs at the end of a period, and in default the bond holder is paid a fraction *R* (recovery rate) of the bond's notional value. For simplicity, we set the default-free interest rate *r* and the bond's recovery rate to zero (*r*=0, *R*=0). The credit risk of this bond is described by the risk-neutral survival probability $\tilde{P}$:

$$\tilde{P}(t_1, t_2) = \exp\left(-\sum_{t=t_1}^{t_2} \tilde{\lambda}_t\right), \tag{A.1}$$

where $\tilde{\lambda}_t$ is the discrete stochastic default intensity at time *t*. We model the default intensity evolution from λ_0 (which is known at t=0) to $\tilde{\lambda}_1$ (conditional on no default in *t*=1, which occurs with probability $1 - PD = \exp(-\lambda_0)$). The default intensity can increase or decrease by a constant factor $\Delta\lambda$ or remain the same $\left(\tilde{\lambda}_1 \in \left\{\lambda_1^u, \lambda_1^m, \lambda_1^d\right\} = \left\{\lambda_0 + \Delta\lambda, \lambda_0, \lambda_0 - \Delta\lambda\right\}\right)$ and the unconditional probability of the states are $(1-PD)\cdot p_u^\lambda$, $(1-PD)\cdot p_m^\lambda$, and $(1-PD)\cdot p_d^\lambda$, respectively. The conditional probabilities for each state are derived via the following moment conditions of Schönbucher (2002):

$$p_u^{\lambda} + p_m^{\lambda} + p_d^{\lambda} = 1$$

$$E_0\left[\tilde{\lambda}_1 - \lambda_0\right] = p_u^{\lambda} \cdot \Delta\lambda + p_m^{\lambda} \cdot 0 - p_d^{\lambda} \cdot \Delta\lambda = 0 \tag{A.2}$$

$$E_0\left[\left(\tilde{\lambda}_1 - \lambda_0\right)^2\right] = p_u^{\lambda} \cdot \Delta\lambda^2 + p_m^{\lambda} \cdot 0^2 + p_d^{\lambda} \cdot \Delta\lambda^2.$$

The first condition implies that there are no other states for the default intensity in t=1. The second condition ensures that there is no drift in the default intensity. The third condition links the conditional probabilities to the conditional variance.

Now consider a bond affected by illiquidity. The price impact of illiquidity is described by a liquidity discount factor $\tilde{L}$:

$$\tilde{L}(t_1, t_2) = \exp\left(-\sum_{t=t_1}^{t_2} \tilde{\gamma}_t\right), \tag{A.3}$$

where $\tilde{\gamma}_t$ is a non-negative, discrete stochastic liquidity intensity process. We model the evolution of $\tilde{\gamma}_t$ in a similar trinomial tree model as the evolution of $\tilde{\lambda}_t$. In Figure A.1, we describe the common dynamics of the credit risk and liquidity intensity.

Insert Figure A.1 about here.

Panel A of Figure A.1 shows the base case where the credit risk and liquidity intensity are independent.

In Panel B of Figure A.1, we introduce the well-known flight-to-quality by allowing for a positive correlation between both intensities without taking investor sentiment into account. We model this as Schönbucher (2002) and introduce a parameter ε that ranges from zero to one. This parameter affects the joint probabilities of the credit risk and liquidity intensity. For $\varepsilon > 0$, it increases the joint probabilities for states where both intensities move in the same direction: higher ε indicates higher correlation between the two intensities. Hence, positive values of ε model the price effect of investors' flight-to-quality behavior not due to investor sentiment.

Panel C of Figure A.1 displays our full model, which also takes investor sentiment and its impact on flight-to-quality into account. We capture investor sentiment in the parameter x. Larger values of x $(-1 \leq x \leq 1)$ indicate lower investor sentiment. The non-negative random variable $\tilde{a}_t$ captures fundamental news about the firm. Thus, our full model extends the model in Panel B of Figure A.1 by allowing an additional sentiment-driven flight-to-quality. We assume (consistent with the empirical evidence of Mian and Sankaraguruswamy, 2012) that investors react more to negative information than to neutral or positive information when investor sentiment is low. Thus, $\tilde{a}_t$ takes on a value of a_1^u for λ_1^u, a_1^m for λ_1^m, and a_1^d for λ_1^d with $0 \leq a_1^d < a_1^m < a_1^u$. Consistent with the assumption that $\lambda_0 = \lambda_1^m$, we choose $a_0 = a_1^m$.

Impact of investor sentiment on risk factor correlation

Based on the model described above, we now derive the correlation between changes in a corporate bond's credit risk premium and liquidity premium, and show that this correlation increases when investor sentiment decreases.

We start by considering a zero bond with maturity in *t*=2 which is only subject to credit risk. From the perspective of time *t*=1 and conditional on no default at *t*=1, the risk-neutral price of such a zero bond is $\exp(-\lambda_1)$ and the log yield a risk-neutral investor requires for investing in this bond equals:

$$cr_1 = \log\left(\frac{1}{\exp(-\lambda_1)}\right) = \lambda_1. \tag{A.4}$$

At time t=0, the bond price is $\exp(-\lambda_0)\cdot E_0\left[\exp(-\tilde{\lambda}_1)\right]$, and the per-period log yield required by a risk-neutral investor is:

$$\begin{aligned} cr_0 &= \log\left(\left(\frac{1}{\exp(-\lambda_0)\cdot E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]}\right)^{\frac{1}{2}}\right) \\ &= \frac{1}{2}\left\{\lambda_0 - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\right\} \end{aligned} \tag{A.5}$$

with $E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right] = \mathrm{p}_u^{\lambda}\cdot\exp\left(-\lambda_1^{u}\right) + \mathrm{p}_m^{\lambda}\cdot\exp\left(-\lambda_1^{m}\right) + \mathrm{p}_d^{\lambda}\cdot\exp\left(-\lambda_1^{d}\right)$. Since the bond price is determined solely by credit risk, the change in its log yield equals the change in the credit risk premium:

$$\Delta\widetilde{cr} = \widetilde{cr_1} - cr_0 = \tilde{\lambda}_1 - \frac{1}{2}\cdot\left\{\lambda_0 - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\right\}. \tag{A.6}$$

Now consider a bond that is subject to both credit risk and illiquidity. From the perspective of time t=1 and conditional on no default in t=1, this bond has a risk-neutral price of $\exp\left(-\lambda_1 - \gamma_1\cdot\left(1+a_1\cdot x\right)\right)$ and a log yield of $ys_1 = \lambda_1 + \gamma_1\cdot\left(1+a_1\cdot x\right)$. At time t=0, the price is $\exp\left(-\lambda_0 - \gamma_0\cdot\left(1+a_0\cdot x\right)\right)\cdot E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right)\right]$, and the corresponding per-period log yield is

$$ys_0 = \frac{1}{2}\left\{\left(\lambda_0 + \gamma_0\cdot\left(1+a_0\cdot x\right)\right) - \log\left(E_0\left[\exp\left(-\tilde{\lambda}_1 - \tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right)\right]\right)\right\} \tag{A.7}$$

with:

$$
\begin{aligned}
E_0\left[\exp\left(-\tilde{\lambda}_1-\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right)\right] = & \left(\mathrm{p}_u^{\lambda}\mathrm{p}_u^{\gamma}+\tfrac{5}{36}\varepsilon\right)\cdot\exp\left(-\lambda_1^u-\gamma_1^u\cdot\left(1+a_1^u\cdot x\right)\right) \\
& +\left(\mathrm{p}_u^{\lambda}\mathrm{p}_m^{\gamma}-\tfrac{4}{36}\varepsilon\right)\cdot\exp\left(-\lambda_1^u-\gamma_1^m\cdot\left(1+a_1^u\cdot x\right)\right) \\
& +\left(\mathrm{p}_u^{\lambda}\mathrm{p}_d^{\gamma}-\tfrac{1}{36}\varepsilon\right)\cdot\exp\left(-\lambda_1^u-\gamma_1^d\cdot\left(1+a_1^u\cdot x\right)\right) \\
& +\left(\mathrm{p}_m^{\lambda}\mathrm{p}_u^{\gamma}-\tfrac{4}{36}\varepsilon\right)\cdot\exp\left(-\lambda_1^m-\gamma_1^u\cdot\left(1+a_1^m\cdot x\right)\right) \\
& +\left(\mathrm{p}_m^{\lambda}\mathrm{p}_m^{\gamma}+\tfrac{8}{36}\varepsilon\right)\cdot\exp\left(-\lambda_1^m-\gamma_1^m\cdot\left(1+a_1^m\cdot x\right)\right) \\
& +\left(\mathrm{p}_m^{\lambda}\mathrm{p}_d^{\gamma}-\tfrac{4}{36}\varepsilon\right)\cdot\exp\left(-\lambda_1^m-\gamma_1^d\cdot\left(1+a_1^m\cdot x\right)\right) \\
& +\left(\mathrm{p}_d^{\lambda}\mathrm{p}_u^{\gamma}-\tfrac{1}{36}\varepsilon\right)\cdot\exp\left(-\lambda_1^d-\gamma_1^u\cdot\left(1+a_1^d\cdot x\right)\right) \\
& +\left(\mathrm{p}_d^{\lambda}\mathrm{p}_m^{\gamma}-\tfrac{4}{36}\varepsilon\right)\cdot\exp\left(-\lambda_1^d-\gamma_1^m\cdot\left(1+a_1^d\cdot x\right)\right) \\
& +\left(\mathrm{p}_d^{\lambda}\mathrm{p}_d^{\gamma}+\tfrac{5}{36}\varepsilon\right)\cdot\exp\left(-\lambda_1^d-\gamma_1^d\cdot\left(1+a_1^d\cdot x\right)\right).
\end{aligned}
\tag{A.8}
$$

Since the yield of this zero bond consists of the credit risk premium (which is known from (A.4) and (A.5)) and the liquidity premium, the latter equals:

$$
liq_1 = ys_1 - cr_1 = \gamma_1\cdot\left(1+a_1\cdot x\right),
\tag{A.9}
$$

$$
\begin{aligned}
liq_0 &= ys_0 - cr_0 \\
&= \frac{1}{2}\left\{\begin{array}{l}\gamma_0\left(1+a_0\cdot x\right)-\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1-\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right)\right]\right) \\ +\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\end{array}\right\}.
\end{aligned}
\tag{A.10}
$$

The liquidity premium change is:

$$
\begin{aligned}
\Delta\widetilde{liq} &= \widetilde{liq}_1 - liq_0 \\
&= \tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)-\frac{1}{2}\left\{\begin{array}{l}\gamma_0\left(1+a_0\cdot x\right) \\ -\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1-\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right)\right]\right) \\ +\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\end{array}\right\}.
\end{aligned}
\tag{A.11}
$$

The correlation between credit risk and liquidity premium changes can now be easily derived. Since the terms in brackets are constants in (A.6) and (A.11), the covariance between credit risk and liquidity premium changes is given by:

$$Covar_0\left(\Delta\widetilde{cr},\Delta\widetilde{liq}\right)=Covar_0\left(\tilde{\lambda}_1,\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right)$$
$$=E_0\left[\tilde{\lambda}_1\cdot\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right]-E_0\left[\tilde{\lambda}_1\right]\cdot E_0\left[\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right]. \tag{A.12}$$

The expected values are

$$E_0\left[\tilde{\lambda}_1\right]=p_u^{\lambda}\cdot\lambda_1^u+p_m^{\lambda}\cdot\lambda_1^m+p_d^{\lambda}\cdot\lambda_1^d, \tag{A.13}$$

$$E_0\left[\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right]=(p_u^{\lambda}\cdot p_u^{\gamma}+\frac{5}{36}\varepsilon)\cdot\gamma_1^u\cdot\left(1+a_1^u\cdot x\right)$$
$$+\ldots+(p_d^{\lambda}\cdot p_d^{\gamma}+\frac{5}{36}\varepsilon)\cdot\gamma_1^d\cdot\left(1+a_1^d\cdot x\right), \tag{A.14}$$

$$E_0\left[\tilde{\lambda}_1\cdot\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right]=(p_u^{\lambda}\cdot p_u^{\gamma}+\frac{5}{36}\varepsilon)\cdot\lambda_1^u\cdot\gamma_1^u\cdot\left(1+a_1^u\cdot x\right)$$
$$+\ldots+(p_d^{\lambda}\cdot p_d^{\gamma}+\frac{5}{36}\varepsilon)\cdot\lambda_1^d\cdot\gamma_1^d\cdot\left(1+a_1^d\cdot x\right). \tag{A.15}$$

The correlation between credit risk and liquidity premium changes directly follows from these expressions. Note that the correlation depends on investor sentiment x. Figure A.2 illustrates the impact of investor sentiment on risk factor correlation. More specifically, it shows that risk factor correlation increases when investor sentiment decreases, the first hypothesis stated in Section 3.

Insert Figure A.2 about here.

To prove this relation formally, we show that the first derivative of the correlation with respect to x is larger than zero. We assume that the usual regularity conditions apply for all random variables, i.e., the first and second moment exist and are finite, and the variance is positive. For ease of exposition, we consider the case $\varepsilon=0$, i.e., the flight-to-quality effect is purely driven by sentiment. However, the relation also holds in the more general case $\varepsilon>0$.

We start by showing how the numerator of the correlation, the covariance between credit risk and liquidity premium changes, depends on investor sentiment. For $\varepsilon = 0$, $\tilde{\lambda}_1$ and $\tilde{\gamma}_1$ are independent. Therefore, the covariance summands given in Equation (A.12) can be written as

$$\begin{aligned} E_0\left[\tilde{\lambda}_1 \cdot \tilde{\gamma}_1 \cdot (1+\tilde{a}_1 \cdot x)\right] &= E_0\left[\tilde{\gamma}_1\right] \cdot E_0\left[\tilde{\lambda}_1 + x \cdot \tilde{\lambda}_1 \cdot \tilde{a}_1\right] \\ &= E_0\left[\tilde{\gamma}_1\right] \cdot \left\{E_0\left[\tilde{\lambda}_1\right] + x \cdot E_0\left[\tilde{\lambda}_1 \cdot \tilde{a}_1\right]\right\}, \end{aligned} \tag{A.16}$$

$$E_0\left[\tilde{\lambda}_1\right] \cdot E_0\left[\tilde{\gamma}_1 \cdot (1+\tilde{a}_1 \cdot x)\right] = E_0\left[\tilde{\lambda}_1\right] \cdot E_0\left[\tilde{\gamma}_1\right] \cdot \left(1 + x \cdot E_0\left[\tilde{a}_1\right]\right). \tag{A.17}$$

Consequently, the covariance between the premium changes becomes

$$\begin{aligned} Covar_0\left(\Delta\widetilde{cr}, \Delta\widetilde{liq}\right) &= E_0\left[\tilde{\gamma}_1\right] \cdot E_0\left[\tilde{\lambda}_1\right] + x \cdot E_0\left[\tilde{\gamma}_1\right] \cdot E_0\left[\tilde{\lambda}_1 \cdot \tilde{a}_1\right] \\ &\quad - E_0\left[\tilde{\gamma}_1\right] \cdot E_0\left[\tilde{\lambda}_1\right] - x \cdot E_0\left[\tilde{\gamma}_1\right] \cdot E_0\left[\tilde{\lambda}_1\right] \cdot E_0\left[\tilde{a}_1\right] \\ &= x \cdot E_0\left[\tilde{\gamma}_1\right] \cdot \left(E_0\left[\tilde{\lambda}_1 \cdot \tilde{a}_1\right] - E_0\left[\tilde{\lambda}_1\right] \cdot E_0\left[\tilde{a}_1\right]\right) \\ &= x \cdot E_0\left[\tilde{\gamma}_1\right] \cdot Covar_0\left(\tilde{\lambda}_1, \tilde{a}_1\right). \end{aligned} \tag{A.18}$$

Equation (A.18) shows two properties of our model. First, the covariance between the premium changes increases when investor sentiment decreases, since

$$\begin{aligned} Covar_0\left(\tilde{\lambda}_1, \tilde{a}_1\right) &= E_0\left[(\tilde{\lambda}_1 - E_0\left[\tilde{\lambda}_1\right]) \cdot (\tilde{a}_1 - E_0\left[\tilde{a}_1\right])\right] \\ &= p_u^{\lambda} \cdot (\lambda_1^u - E_0\left[\tilde{\lambda}_1\right]) \cdot (a_1^u - E_0\left[\tilde{a}_1\right]) \\ &\quad + p_m^{\lambda} \cdot (\lambda_1^m - E_0\left[\tilde{\lambda}_1\right]) \cdot (a_1^m - E_0\left[\tilde{a}_1\right]) \\ &\quad + p_d^{\lambda} \cdot (\lambda_1^d - E_0\left[\tilde{\lambda}_1\right]) \cdot (a_1^d - E_0\left[\tilde{a}_1\right]) \end{aligned} \tag{A.19}$$

is always positive. This follows from the fact that by construction (i) $\tilde{\lambda}_1$ has no drift $\left(\lambda_1^m - E\left[\tilde{\lambda}_1\right] = 0\right)$, and (ii) the following inequalities hold:

$$
\begin{aligned}
&a_1^u - E_0\left[\tilde{a}_1\right] > 0,\\
&a_1^d - E_0\left[\tilde{a}_1\right] < 0,\\
&\lambda_1^u - E_0\left[\tilde{\lambda}_1\right] > 0,\\
&\lambda_1^d - E_0\left[\tilde{\lambda}_1\right] < 0.
\end{aligned}
\tag{A.20}
$$

Second, since the second and third factor in (A.18) are positive, the covariance between the premium changes is positive if x>0 (bad sentiment) and negative if x<0 (good sentiment). Thus, our model can generate both positive and negative risk factor correlations.

The denominator of the bond correlation equals the square root of the product of the variances of premium changes. The credit risk premium, and hence its change, is independent of investor sentiment x. Hence, its variance is also independent of x. The variance of the liquidity premium, however, depends on x:

$$
\begin{aligned}
Var\left(\Delta\widetilde{liq}\right) &= Var\left(\tilde{\gamma}_1\left(1+\tilde{a}_1\cdot x\right) - \underbrace{\frac{1}{2}\left\{\begin{array}{l}\gamma_0\left(1+a_0\cdot x\right)\\ -\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1-\tilde{\gamma}_1\left(1+\tilde{a}_1\cdot x\right)\right)\right]\right)\\ +\log\left(E_0\left[\exp\left(-\tilde{\lambda}_1\right)\right]\right)\end{array}\right\}}_{=:const}\right)\\
&= Var\left(\tilde{\gamma}_1\left(1+\tilde{a}_1\cdot x\right)\right)\\
&= Var\left(\tilde{\gamma}_1\right) + x^2\cdot Var\left(\tilde{a}_1\cdot\tilde{\gamma}_1\right) + 2\cdot Covar_0\left(\tilde{\gamma}_1, x\cdot\tilde{a}_1\cdot\tilde{\gamma}_1\right)\\
&= Var\left(\tilde{\gamma}_1\right) + x^2\cdot\left\{E_0\left[\tilde{a}_1^{\,2}\tilde{\gamma}_1^{\,2}\right] - E_0\left[\tilde{a}_1\tilde{\gamma}_1\right]^2\right\}\\
&\quad +2\cdot\left\{E_0\left[x\tilde{a}_1\tilde{\gamma}_1^{\,2}\right] - E_0\left[\tilde{\gamma}_1\right]E_0\left[x\tilde{a}_1\tilde{\gamma}_1\right]\right\}\\
&= Var\left(\tilde{\gamma}_1\right) + x^2\cdot E_0\left[\tilde{a}_1^{\,2}\right]E_0\left[\tilde{\gamma}_1^{\,2}\right] - x^2\cdot E_0\left[\tilde{a}_1\right]^2 E_0\left[\tilde{\gamma}_1\right]^2\\
&\quad +2\cdot x\cdot E_0\left[\tilde{a}_1\right]\cdot E_0\left[\tilde{\gamma}_1^{\,2}\right] - 2\cdot x\cdot E_0\left[\tilde{a}_1\right]\cdot E_0\left[\tilde{\gamma}_1\right]^2\\
&= Var\left(\tilde{\gamma}_1\right) + 2\cdot x\cdot E_0\left[\tilde{a}_1\right]\cdot Var\left(\tilde{\gamma}_1\right)\\
&\quad + x^2\cdot\left\{E_0\left[\tilde{a}_1^{\,2}\right]E_0\left[\tilde{\gamma}_1^{\,2}\right] - E_0\left[\tilde{a}_1\right]^2 E_0\left[\tilde{\gamma}_1\right]^2\right\}.
\end{aligned}
\tag{A.21}
$$

Using Equations (A.18) and (A.21) and taking the first derivative of the correlation with respect to x yields:

$$\frac{\partial Corr_0\left(\Delta\widetilde{cr},\Delta\widetilde{liq}\right)}{\partial x}=\frac{Var(\Delta\widetilde{cr})^{\frac{1}{2}}}{Var(\Delta\widetilde{cr})\cdot Var(\Delta\widetilde{liq})}$$

$$\cdot\left\{\frac{\partial Covar_0\left(\Delta\widetilde{cr},\Delta\widetilde{liq}\right)}{\partial x}Var(\Delta\widetilde{liq})^{\frac{1}{2}}-Covar_0\left(\Delta\widetilde{cr},\Delta\widetilde{liq}\right)\cdot\frac{\partial Var(\Delta\widetilde{liq})^{\frac{1}{2}}}{\partial x}\right\}$$

$$=\underbrace{\frac{Var(\Delta\widetilde{cr})^{\frac{1}{2}}}{2\cdot Var(\Delta\widetilde{cr})\cdot Var(\Delta\widetilde{liq})^{3/2}}}_{>0}\underbrace{Covar_0\left(\tilde{\lambda}_1,\tilde{a}_1\right)}_{>0}$$

$$\cdot E_0\left[\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right]\cdot\left\{2\cdot Var(\Delta\widetilde{liq})-x\cdot\frac{\partial Var(\Delta\widetilde{liq})}{\partial x}\right\}. \tag{A.22}$$

The usual regularity conditions for random variables and the fact that $Covar_0\left(\tilde{\lambda}_1,\tilde{a}_1\right)>0$ ensure that the first two terms after the second equal sign in Equation (A.22) are positive.

To show that the product of the last two terms in Equation (A.22) is also positive, we re-write the third term in Equation (A.22) using the independence of $\tilde{\gamma}_1$ and $\tilde{a}_1$:

$$E_0\left[\tilde{\gamma}_1\cdot\left(1+\tilde{a}_1\cdot x\right)\right]=E_0\left[\tilde{\gamma}_1\right]\cdot\left(1+x\cdot E_0\left[\tilde{a}_1\right]\right). \tag{A.23}$$

We further use (A.21) and re-write the last term in brackets in Equation (A.22) as

$$\begin{aligned}\left\{2\cdot Var(\Delta\widetilde{liq})-x\cdot\frac{\partial Var(\Delta\widetilde{liq})}{\partial x}\right\}&=2\cdot Var(\tilde{\gamma}_1)+2\cdot x\cdot E_0\left[\tilde{a}_1\right]Var(\tilde{\gamma}_1),\\&=2\cdot Var(\tilde{\gamma}_1)\cdot\left(1+x\cdot E_0\left[\tilde{a}_1\right]\right).\end{aligned} \tag{A.24}$$

Multiplying Equation (A.24) with Equation (A.23) results in:

$$E_0\left[\tilde{\gamma}_1\right]\cdot\left(1+x\cdot E_0\left[\tilde{a}_1\right]\right)\cdot 2\cdot Var(\tilde{\gamma}_1)\cdot\left(1+x\cdot E_0\left[\tilde{a}_1\right]\right)=2\cdot E_0\left[\tilde{\gamma}_1\right]\cdot Var(\tilde{\gamma}_1)\cdot\left(1+x\cdot E_0\left[\tilde{a}_1\right]\right)^2. \qquad \text{(A.25)}$$

Consequently, the product of the last two terms in Equation (A.22) is always positive. This proves that risk factor correlation increases when investor sentiment decreases – the first hypothesis tested in the empirical part of our paper.

Bond correlation and risk factor correlation

In this section, we provide a formal proof that higher risk factor correlation translates into higher bond correlation. We consider two bonds, e.g., one investment grade bond *i* and one high yield bond *h* with positive default and liquidity intensities $\tilde{\lambda}_{i/h,t}$ and $\tilde{\gamma}_{i/h,t}$. Both intensities contain a systematic credit risk and a systematic liquidity intensity, $\tilde{\lambda}_{m,t}$ and $\tilde{\gamma}_{m,t}$, as well as idiosyncratic credit risk and liquidity intensities, $\tilde{\varepsilon}_{i/h}$ and $\tilde{\eta}_{i/h}$. For ease of exposition, we use the notation $\tilde{\gamma}^x_{i/h/m,t} := \tilde{\gamma}_{i/h/m,t}\cdot\left(1+\tilde{a}_t\cdot x\right)$ in the following. We define the default and liquidity intensities for bonds i and h as follows:

$$\begin{aligned}
\tilde{\lambda}_{i,t} &= \tilde{\lambda}_{m,t}\cdot\beta_{i,\lambda}+\tilde{\varepsilon}_i,\\
\tilde{\lambda}_{h,t} &= \tilde{\lambda}_{m,t}\cdot\beta_{h,\lambda}+\tilde{\varepsilon}_h,\\
\tilde{\gamma}^x_{i,t} &= \tilde{\gamma}^x_{m,t}\cdot\beta_{i,\gamma}+\tilde{\eta}_i,\\
\tilde{\gamma}^x_{h,t} &= \tilde{\gamma}^x_{m,t}\cdot\beta_{h,\gamma}+\tilde{\eta}_h.
\end{aligned} \qquad \text{(A.26)}$$

We assume that the systematic factors are positively correlated, the idiosyncratic risk factors are uncorrelated with the systematic risk factors and across bonds, and that both bonds have positive loadings on the systematic factors ($\beta_{i,\gamma}>0$, $\beta_{i,\lambda}>0$, $\beta_{h,\gamma}>0$, $\beta_{h,\lambda}>0$).

The covariance between the yield spread changes of bond *i* and *h* is given by

$$
\begin{aligned}
Covar_0\left(\Delta\widetilde{ys}_i, \Delta\widetilde{ys}_h\right) &= Covar_0\left(\tilde{\lambda}_{i,1} + \tilde{\gamma}^x_{i,1}, \tilde{\lambda}_{h,1} + \tilde{\gamma}^x_{h,1}\right) \\
&= \beta_{i,\lambda}\beta_{h,\lambda} \cdot Var\left(\tilde{\lambda}_{m,1}\right) + \beta_{i,\gamma}\beta_{h,\gamma} \cdot Var\left(\tilde{\gamma}^x_{m,1}\right) \\
&\quad + \left(\beta_{i,\lambda}\beta_{h,\gamma} + \beta_{i,\gamma}\beta_{h,\lambda}\right) \cdot Var\left(\tilde{\lambda}_{m,1}\right)^{1/2} Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2} Corr_0\left(\tilde{\lambda}_{m,1}, \tilde{\gamma}^x_{m,1}\right)
\end{aligned}
\tag{A.27}
$$

since the constants in brackets in (A.6) and (A.11) drop out of the covariance. Equation (A.27) shows three properties of our model: first, the covariance between the two bonds increases when the correlation between the systematic intensities $\tilde{\lambda}_{m,1}$ and $\tilde{\gamma}^x_{m,1}$ increases. Second, bond correlation is strictly positive if risk factor correlation is positive. Third, for sufficiently negative correlation between $\tilde{\lambda}_{m,1}$ and $\tilde{\gamma}^x_{m,1}$, the covariance between the two bonds (and thus bond correlation) can become negative. Whether bond correlation is negative depends on the standard deviation ratios of $\tilde{\lambda}_{m,1}$ and $\tilde{\gamma}^x_{m,1}$ and on the systematic risk factor loadings $\beta_{i,\gamma}$, $\beta_{i,\lambda}$, $\beta_{h,\gamma}$, and $\beta_{h,\lambda}$:

$$
\begin{aligned}
& Covar_0\left(\Delta\widetilde{ys}_i, \Delta\widetilde{ys}_h\right) < 0 \\
\Leftrightarrow\ & Corr_0\left(\tilde{\lambda}_{m,1}, \tilde{\gamma}^x_{m,1}\right) < -\frac{Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}}{Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}} \frac{\beta_{i,\lambda}\beta_{h,\lambda}}{\beta_{i,\lambda}\beta_{h,\gamma} + \beta_{i,\gamma}\beta_{h,\lambda}} - \frac{Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}}{Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}} \frac{\beta_{i,\gamma}\beta_{h,\gamma}}{\beta_{i,\lambda}\beta_{h,\gamma} + \beta_{i,\gamma}\beta_{h,\lambda}}
\end{aligned}
\tag{A.28}
$$

Equation (A.28) shows that bond correlation can become negative for sufficiently negative risk factor correlation. This is the case whenever either $\frac{\beta_{i,\lambda}}{\beta_{i,\gamma}}$ or $\frac{\beta_{\mathrm{h},\lambda}}{\beta_{\mathrm{h},\gamma}}$ (but not both) are smaller than $\frac{Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}}{Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}}$. We illustrate this relation in Figure A.3.

Insert Figure A.3 about here.

Figure A.3 shows that bond correlation monotonously increases in risk factor correlation and becomes positive for risk factor correlations higher than -0.24.

We now turn to the formal analysis of the relation between bond correlation and risk factor correlation. The denominator of the correlation between the yield spread changes equals the square root of the product of the variances of the yield spread change of bonds *i* and *h*. The variance of $\Delta\widetilde{ys}_{i/h}$ can be expressed as follows:

$$\begin{aligned} Var\left(\Delta\widetilde{ys}_{i/h}\right) &= Var\left(\tilde{\lambda}_{i/h,1} + \tilde{\gamma}^{x}_{i/h,1}\right) \\ &= Var\left(\tilde{\lambda}_{m,1}\cdot\beta_{i/h,\lambda} + \tilde{\varepsilon}_{i/h} + \tilde{\gamma}^{x}_{m,1}\cdot\beta_{i/h,\gamma} + \tilde{\eta}_{i/h}\right) \\ &= Var\left(\tilde{\varepsilon}_{i/h}\right) + Var\left(\tilde{\eta}_{i/h}\right) + \beta^{2}_{i/h,\lambda}Var\left(\tilde{\lambda}_{m,1}\right) \\ &\quad + \beta^{2}_{i/h,\gamma}Var\left(\tilde{\gamma}^{x}_{m,1}\right) + 2\beta_{i/h,\lambda}\beta_{i/h,\gamma}Covar_{0}\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^{x}_{m,1}\right). \end{aligned} \tag{A.29}$$

We now use (A.27) and (A.29) to calculate the first derivative of the correlation between $\Delta\widetilde{ys}_{i}$ and $\Delta\widetilde{ys}_{h}$:

$$Corr_{0}\left(\Delta\widetilde{ys}_{i},\Delta\widetilde{ys}_{h}\right) = \frac{Covar_{0}\left(\Delta\widetilde{ys}_{i},\Delta\widetilde{ys}_{h}\right)}{\mathrm{Var}\left(\Delta\widetilde{ys}_{i}\right)^{1/2}\mathrm{Var}\left(\Delta\widetilde{ys}_{h}\right)^{1/2}} \tag{A.30}$$

with respect to risk factor correlation $Corr_{0}\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^{x}_{m,1}\right)$:

$$\begin{aligned} \frac{\partial Corr_{0}\left(\Delta\widetilde{\mathrm{ys}}_{i},\Delta\widetilde{\mathrm{ys}}_{h}\right)}{\partial Corr_{0}\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^{x}_{m,1}\right)} = &\underbrace{\frac{Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}Var\left(\tilde{\gamma}^{x}_{m,1}\right)^{1/2}}{\mathrm{Var}\left(\Delta\widetilde{ys}_{h}\right)^{3/2}\mathrm{Var}\left(\Delta\widetilde{ys}_{i}\right)^{3/2}}}_{>0} \\ &\cdot\begin{pmatrix} \left(\beta_{i,\lambda}\beta_{h,\gamma} + \beta_{i,\gamma}\beta_{h,\lambda}\right)\cdot\mathrm{Var}\left(\Delta\widetilde{ys}_{h}\right)\mathrm{Var}\left(\Delta\widetilde{ys}_{i}\right) \\ -Covar_{0}\left(\Delta\widetilde{\mathrm{ys}}_{i},\Delta\widetilde{\mathrm{ys}}_{h}\right)\cdot\left(\beta_{i,\lambda}\beta_{i,\gamma}\mathrm{Var}\left(\Delta\widetilde{ys}_{h}\right) + \beta_{h,\lambda}\beta_{h,\gamma}\mathrm{Var}\left(\Delta\widetilde{ys}_{i}\right)\right) \end{pmatrix}. \end{aligned} \tag{A.31}$$

The first factor is a function of the variances of the yield spread changes, systematic credit risk, and liquidity intensities. Due to the regularity conditions, all variances are larger than zero. Hence, we consider the second factor and show that it is larger than zero. We first show this for $0 \le Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right) \le 1$ and address negative risk factor correlation below.

Expanding the second factor results in:

$$\begin{aligned}
&\left\{Var\left(\tilde{\varepsilon}_h\right)+Var\left(\tilde{\eta}_h\right)\right\} \\
&\quad \cdot \left\{\begin{array}{l}\left(\beta_{h,\lambda}\beta_{i,\gamma}+\beta_{i,\lambda}\beta_{h,\gamma}\right)\cdot\left(Var\left(\tilde{\varepsilon}_i\right)+Var\left(\tilde{\eta}_i\right)+\beta_{i,\lambda}\beta_{i,\gamma}Covar_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\right) \\ +\beta_{h,\lambda}\beta^3_{i,\gamma}+\beta_{h,\gamma}\beta^3_{i,\lambda}\end{array}\right\} \\
&\underbrace{\begin{aligned}&+\left\{Var\left(\tilde{\varepsilon}_i\right)+Var\left(\tilde{\eta}_i\right)\right\} \\ &\quad\cdot\left\{\beta^3_{h,\gamma}\beta_{i,\lambda}+\beta^3_{h,\lambda}\beta_{i,\gamma}+\left(\beta_{h,\gamma}\beta^2_{h,\lambda}\beta_{i,\gamma}+\beta^2_{h,\gamma}\beta_{h,\lambda}\beta_{i,\lambda}\right)Covar_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\right\}\end{aligned}}_{=:summand_1} \\
&\underbrace{+Var\left(\tilde{\lambda}_{m,1}\right)Var\left(\tilde{\gamma}^x_{m,1}\right)\cdot\left(\beta^3_{h,\lambda}\beta^3_{i,\gamma}-\beta_{h,\gamma}\beta^2_{h,\lambda}\beta^2_{i,\gamma}\beta_{i,\lambda}-\beta^2_{h,\gamma}\beta_{h,\lambda}\beta_{i,\gamma}\beta^2_{i,\lambda}+\beta^3_{h,\gamma}\beta^3_{i,\lambda}\right)}_{=:summand_2} \\
&\underbrace{\begin{aligned}&+Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right) \\ &\quad\cdot\left(\beta_{h,\gamma}\beta_{i,\gamma}Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{3/2}+\beta_{h,\lambda}\beta_{i,\lambda}Var\left(\tilde{\lambda}_{m,1}\right)^{3/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}\right). \\ &\quad\cdot\left(\beta^2_{h,\lambda}\beta^2_{i,\gamma}-2\beta_{h,\gamma}\beta_{h,\lambda}\beta_{i,\gamma}\beta_{i,\lambda}+\beta^2_{h,\gamma}\beta^2_{i,\lambda}\right)\end{aligned}}_{=:summand_3}
\end{aligned} \tag{A.32}$$

Due to our assumptions ($\beta_{i,\gamma} > 0$, $\beta_{i,\lambda} > 0$, $\beta_{h,\gamma} > 0$, $\beta_{h,\lambda} > 0$, $0 \le Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right) \le 1$) and the fact that all variances are larger than zero, $summand_1$ is larger than zero. Hence, it only remains to show that $summand_2$ and $summand_3$ are larger than or equal to zero. Rearranging $summand_2$ gives:

$$\begin{aligned}
&Var\left(\tilde{\lambda}_{m,1}\right)Var\left(\tilde{\gamma}^x_{m,1}\right)\cdot\left(\beta^3_{h,\lambda}\beta^3_{i,\gamma}-\beta_{h,\gamma}\beta^2_{h,\lambda}\beta^2_{i,\gamma}\beta_{i,\lambda}-\beta^2_{h,\gamma}\beta_{h,\lambda}\beta_{i,\gamma}\beta^2_{i,\lambda}+\beta^3_{h,\gamma}\beta^3_{i,\lambda}\right)\ge 0 \\
\Leftrightarrow\ &Var\left(\tilde{\lambda}_{m,1}\right)Var\left(\tilde{\gamma}^x_{m,1}\right)\cdot\left(\beta_{h,\lambda}\beta_{i,\gamma}-\beta_{h,\gamma}\beta_{i,\lambda}\right)\cdot\left(\beta^2_{h,\lambda}\beta^2_{i,\gamma}-\beta^2_{h,\gamma}\beta^2_{i,\lambda}\right)\ge 0.
\end{aligned} \tag{A.33}$$

Both terms in braces in Equation (A.33) always have the same sign. If $\beta_{h,\lambda}\beta_{i,\gamma} > \beta_{h,\gamma}\beta_{i,\lambda}$, it follows that $\beta^2_{h,\lambda}\beta^2_{i,\gamma} > \beta^2_{h,\gamma}\beta^2_{i,\lambda}$. Similarly this holds for $\beta_{h,\lambda}\beta_{i,\gamma} < \beta_{h,\gamma}\beta_{i,\lambda}$. If

$\beta_{h,\lambda}\beta_{i,\gamma} = \beta_{h,\gamma}\beta_{i,\lambda}$, then the product is zero. Consequently Equation (A.33) is always larger than or equal to zero. Rearranging $summand_3$ gives:

$$\begin{aligned}
&Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\cdot\left(\beta_{h,\gamma}\beta_{i,\gamma}Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{3/2}+\beta_{h,\lambda}\beta_{i,\lambda}Var\left(\tilde{\lambda}_{m,1}\right)^{3/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}\right)\\
&\quad\cdot\left(\beta^2_{h,\lambda}\beta^2_{i,\gamma}-2\beta_{h,\gamma}\beta_{h,\lambda}\beta_{i,\gamma}\beta_{i,\lambda}+\beta^2_{h,\gamma}\beta^2_{i,\lambda}\right)\geq 0\\
\Leftrightarrow\ &Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\cdot\left(\beta_{h,\gamma}\beta_{i,\gamma}Var\left(\tilde{\lambda}_{m,1}\right)^{1/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{3/2}+\beta_{h,\lambda}\beta_{i,\lambda}Var\left(\tilde{\lambda}_{m,1}\right)^{3/2}Var\left(\tilde{\gamma}^x_{m,1}\right)^{1/2}\right)\\
&\quad\cdot\left(\beta_{h,\lambda}\beta_{i,\gamma}-\beta_{h,\gamma}\beta_{i,\lambda}\right)^2\geq 0.
\end{aligned} \tag{A.34}$$

Due to our assumptions ($\beta_{i,\gamma}>0$, $\beta_{i,\lambda}>0$, $\beta_{h,\gamma}>0$, $\beta_{h,\lambda}>0$, $0\leq Corr_0\left(\tilde{\lambda}_{m,1},\tilde{\gamma}^x_{m,1}\right)\leq 1$) and the fact that all variances are larger than zero, all factors in Equation (A.34) are larger than or equal to zero. Hence, we have shown that (A.33) and (A.34) are larger than or equal to zero.

We now turn to negative risk factor correlation. As discussed above, negative risk factor correlation can result in negative bond correlation. Equation (A.31) directly shows that *negative* bond correlation always increases in risk factor correlation, since all terms in brackets are positive. It therefore remains to be shown whether bond correlation also increases in risk factor correlation when bond correlation is *positive* (and risk factor correlation is negative). This positive relation will not hold in general, and we therefore derive conditions under which it holds. From Equation (A.31), we know that bond correlation increases in risk factor correlation if and only if

$$\frac{\mathrm{Var}\left(\Delta\widetilde{ys}_h\right)\mathrm{Var}\left(\Delta\widetilde{ys}_i\right)}{Covar_0\left(\Delta\widetilde{ys}_i,\Delta\widetilde{ys}_h\right)}\left(\beta_{i,\lambda}\beta_{h,\gamma}+\beta_{i,\gamma}\beta_{h,\lambda}\right)>\beta_{i,\lambda}\beta_{i,\gamma}\mathrm{Var}\left(\Delta\widetilde{ys}_h\right)+\beta_{h,\lambda}\beta_{h,\gamma}\mathrm{Var}\left(\Delta\widetilde{ys}_i\right) \tag{A.35}$$

Without loss of generality, we set $\mathrm{Var}\left(\Delta\widetilde{ys}_i\right)=z_1 \cdot \mathrm{Var}\left(\Delta\widetilde{ys}_h\right)$, $\beta_{i,\lambda} = z_2 \cdot \beta_{h,\lambda}$, and $\beta_{i,\gamma} = z_3 \cdot \beta_{h,\gamma}$. It is economically plausible that $z_1 < 1$, $z_2 < 1$, and $z_3 < 1$ since we consider two bonds with different credit and liquidity risk, e.g., one investment grade bond *i* and one high yield bond *h.* The condition therefore becomes

$$\begin{aligned} &\frac{z_1 \mathrm{Var}\left(\Delta\widetilde{ys}_h\right)^2 \beta_{h,\lambda}\beta_{h,\gamma}\left(z_2 + z_3\right)}{Corr_0\left(\Delta\widetilde{ys}_i, \Delta\widetilde{ys}_h\right) z_1 \mathrm{Var}\left(\Delta\widetilde{ys}_h\right)} > \left(z_2 z_3 + z_1\right)\beta_{h,\lambda}\beta_{h,\gamma}\mathrm{Var}\left(\Delta\widetilde{ys}_h\right) \\ &\Leftrightarrow Corr_0\left(\Delta\widetilde{ys}_i, \Delta\widetilde{ys}_h\right) < \frac{z_2 + z_3}{z_1 + z_2 z_3}. \end{aligned} \tag{A.36}$$

For the special case that $z_1 = z_3$, it is immediately clear that (A.36) holds, since the correlation is positive but bounded from above by 1. Otherwise, (A.36) holds when either $z_1 < z_2$ or $z_1 < z_3$.

This completes our analysis of the relation between bond correlation and risk factor correlation. This substantiates the economic rationale of our second hypothesis to be tested in the empirical part of our paper.

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Figure 1 – Correlation time series

The figure displays bond correlation time series. The depicted time period lasts from November 2, 2004 to September 30, 2010. Bond correlation is computed as the 22-day rolling Pearson's correlation between the average investment grade and the average high yield bond yield spread changes.

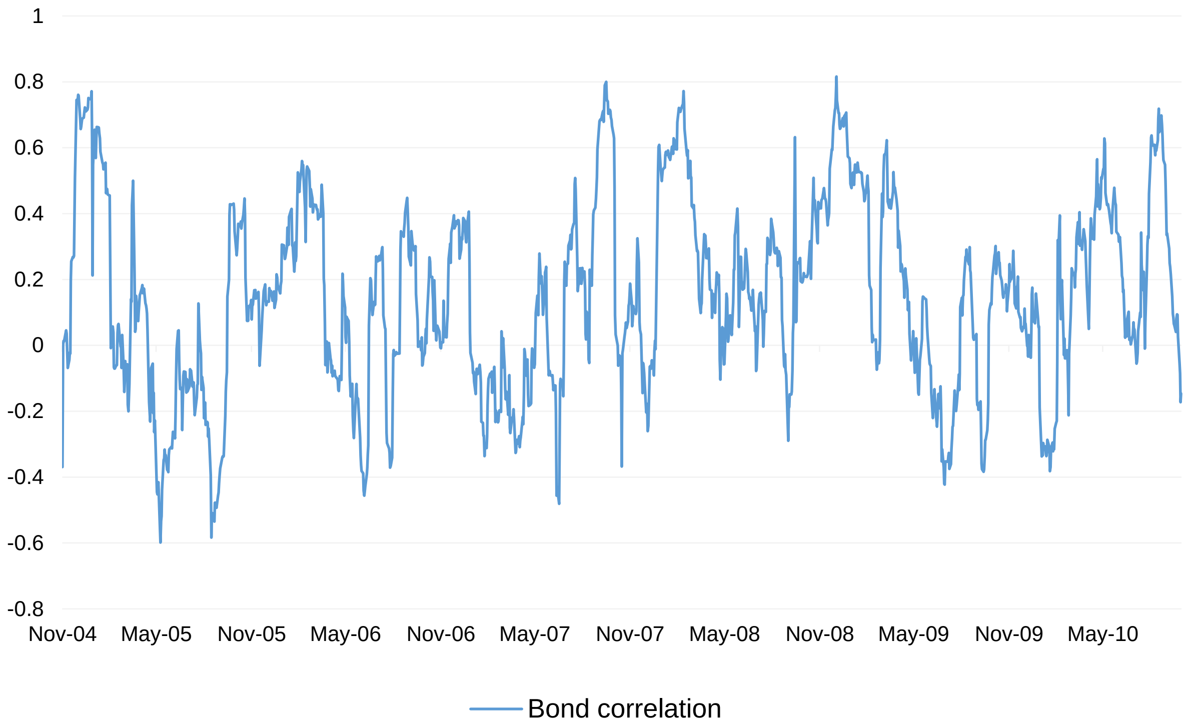


Table 1 – Summary statistics of the TRACE sample

The table reports characteristics of the TRACE corporate bond sample. We report the mean of these characteristics for the full sample, the investment grade (IG) sample and high yield (HY) sample. The IG sample is further split into three subsamples consisting of all bonds belonging to specific credit rating buckets. The buckets are AAA and AA, A, and BBB. #Firms is the average number of companies with actively traded bonds, #Bonds is the average number of actively traded bonds per month. Volume is the average outstanding volume per actively traded bond in million USD. Time to maturity is the average time to maturity in years. Coupon is the average per annum coupon rate in percentage points. S&P rating is the average S&P rating expressed as a number (AAA=1, …, C=21). #Trades is the average number of trades per bond per month. Trade size is the average trade size per bond in thousand USD. Turnover is the average monthly trading volume per bond as a percentage of issue volume. In the last column, we report the difference between the IG and HY sample ***, **, and * denote significance of a t-test for differences from zero at the 1%, 5%, and 10% significance level, respectively.

	All	IG	HY	AAA&AA	A	BBB	IG – HY	
#Firms	302.44	245.01	65.04	35.69	97.21	140.47	179.97	***
#Bonds	1,531.61	1,364.13	169.79	333.00	626.93	412.25	1,194.34	***
Volume	453.16	463.64	368.19	598.38	450.81	382.26	95.45	***
Time to maturity	5.32	5.24	5.87	5.24	4.92	5.81	-0.63	***
Coupon	6.10	5.92	7.54	5.05	5.87	6.66	-1.62	***
S&P rating	6.88	6.03	13.59	2.40	5.61	8.56	-7.56	***
#Trades	78.87	81.86	53.81	97.57	93.33	50.23	28.05	***
Trade Size	360.20	365.54	319.68	243.79	281.07	591.27	45.86	***
Turnover	0.04	0.04	0.04	0.05	0.04	0.04	0.00	

Table 2 – Summary statistics of bond correlations

This table reports the mean, standard deviation, 5^{th}, and 95^{th} percentile of bond correlations. Bond correlations are determined as described in Section 2.2. We report correlations between investment grade (IG) and high yield (HY) bonds. The IG sample is further split into three subsamples consisting of all bonds belonging to specific credit rating buckets. The buckets are AAA and AA, A, and BBB. ***, **, and * denote significance of a t-test for differences from zero at the 1%, 5%, and 10% significance level, respectively. Significance is determined using Newey-West standard errors.

Bond correlation	Mean		Std. Dev.	5^{th} Percentile	95^{th} Percentile
IG with HY	0.15	**	0.29	-0.33	0.66
AAA&AA with A	0.91	***	0.12	0.62	0.99
AAA&AA with BBB	0.70	***	0.18	0.35	0.92
AAA&AA with HY	0.14	**	0.28	-0.34	0.62
A with BBB	0.70	***	0.18	0.35	0.94
A with HY	0.15	**	0.30	-0.35	0.66
BBB with HY	0.15	**	0.31	-0.38	0.67

Table 3 – Summary statistics of risk factor correlations

This table reports the mean, standard deviation, 5th, and 95th percentile of risk factor correlations. Risk factor correlations are determined as described in Section 4.1. We report risk factor correlations calculated for the investment grade (IG) and high yield (HY) segment. The IG sample is further split into three subsamples consisting of all bonds belonging to specific credit rating buckets. The buckets are AAA and AA, A, and BBB. ***, **, and * denote significance of a t-test for differences from zero at the 1%, 5%, and 10% significance level, respectively. Significance is determined using Newey-West standard errors.

Risk factor correlation	Mean	Std. Dev.	5th Percentile	95th Percentile
IG and HY	0.03	0.20	-0.27	0.37
AAA&AA and A	0.07	0.23	-0.30	0.46
AAA&AA and BBB	0.05	0.22	-0.33	0.40
AAA&AA and HY	0.04	0.21	-0.30	0.39
A and BBB	0.04	0.20	-0.26	0.41
A and HY	0.03	0.24	-0.35	0.45
BBB and HY	0.01	0.24	-0.36	0.42

Table 4 – Risk factor correlation and investor sentiment

The table reports the results of the regression of risk factor correlation on sentiment and control variables. Risk factor correlation is the Fisher z-transformation of Pearson's correlation coefficients, determined as described in the main text in Section 4.1. Sentiment is measured as CBOE VIX index orthogonalized to macroeconomic factors. The control variables are market-wide risk and a market downturn dummy. Market-wide risk is measured as the 22-day rolling standard deviation of the sum of the credit risk premium and liquidity premium. The market downturn dummy takes on a value of one if the yield spread at time t is above a one-sigma band compared to the previous month. Columns (1) to (7) provide the results for the investment grade (IG) and high yield (HY) segment The IG sample is further split into three subsamples consisting of all bonds belonging to specific credit rating buckets. The buckets are AAA and AA, A, and BBB. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Significance is determined using Newey-West standard errors. Adjusted R² are in percentage points. The number of observations is 1,456 in all regressions.

	Dependent variable: Risk factor correlation						
Explanatory variables	IG and HY	AAA&AA and A	AAA&AA and BBB	AAA&AA and HY	A and BBB	A and HY	BBB and HY
Sentiment	0.0037 ***	0.0058 ***	0.0033 **	0.0024 **	0.0066 ***	0.0059 ***	0.0034 **
	(0.0001)	(0.0000)	(0.0321)	(0.0444)	(0.0000)	(0.0000)	(0.0171)
Market-wide risk	0.2967 ***	-0.0410 *	-0.0484	0.3044 ***	-0.0532 **	0.3007 ***	0.2915 ***
	(0.0000)	(0.0891)	(0.1021)	(0.0000)	(0.0171)	(0.0000)	(0.0000)
Market downturn	0.0070	0.1288 ***	-0.0741 **	-0.1214 ***	0.0734 **	0.0325	-0.1813 ***
	(0.8161)	(0.0019)	(0.0452)	(0.0004)	(0.0265)	(0.3879)	(0.0003)
Constant	-0.0713 ***	0.0866 ***	0.0705 ***	-0.0503 ***	0.0585 ***	-0.0634 ***	-0.0766 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Adj. R^2	21.86	4.36	1.20	14.27	4.62	18.58	10.39

Table 5 – Bond correlation and risk factor correlation

The table reports results of the regression of bond correlation on risk factor correlation, sentiment, herding, market-wide risk, and market downturn. Both bond correlation and risk factor correlation are the Fisher z-transformation of Pearson's correlation coefficients, determined as described in the main text in Section 2.2 and 4.1. Herding is measured using the approach of Lakonishok et al. (1992) as described in Section 4.3. Sentiment, market-wide risk, and market downturn are as in Table 4. We report correlations between investment grade (IG) and high yield (HY) bonds. The IG sample is further split into three subsamples consisting of all bonds belonging to specific credit rating buckets. The buckets are AAA and AA, A, and BBB. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors. Adjusted R^2 are in percentage points. In the last row, we report the indirect impact of sentiment on bond correlation, measured by the average causal mediation effect using the approach of Imai et al. (2010b) as described in Section 4.3. The corresponding standard errors are bootstrapped. The number of observations is 1,456 in all regressions.

	Dependent variable: Risk factor correlation						
Explanatory variables	IG and HY	AAA&AA and A	AAA&AA and BBB	AAA&AA and HY	A and BBB	A and HY	BBB and HY
Risk factor correlation	0.2461 ***	0.2753 ***	0.2738 ***	0.2500 ***	0.1277 *	0.3490 ***	0.2394 ***
	(0.0001)	(0.0000)	(0.0000)	(0.0006)	(0.0758)	(0.0000)	(0.0011)
Sentiment	0.0094 ***	-0.0050	0.0131 ***	0.0095 ***	0.0143 ***	0.0099 ***	0.0072 ***
	(0.0000)	(0.1096)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0012)
Herding	0.8971	-1.7728 **	1.8381 **	-0.2783	3.3710 ***	1.2131 *	0.2824
	(0.1276)	(0.0467)	(0.0182)	(0.6804)	(0.0001)	(0.0626)	(0.6928)
Market-wide risk	0.0279	-0.5279 ***	-0.3777 ***	0.0254	-0.4206 ***	-0.0291	-0.1364 **
	(0.4744)	(0.0000)	(0.0000)	(0.6693)	(0.0000)	(0.5675)	(0.0186)
Market downturn	0.1124 **	0.1542	-0.0170	0.2081 ***	-0.1259	0.1443 **	0.2310 ***
	(0.0406)	(0.1585)	(0.8058)	(0.0077)	(0.1073)	(0.0271)	(0.0023)
Constant	0.0610	2.0890 ***	0.9095 ***	0.1456 **	0.8114 ***	0.0501	0.1723 ***
	(0.2519)	(0.0000)	(0.0000)	(0.0268)	(0.0000)	(0.4028)	(0.0070)
Adj. R^2	11.22	11.31	14.38	13.16	14.61	16.67	6.78
Indirect impact	0.0009 ***	0.0016 ***	0.0009 ***	0.0006 **	0.0008 ***	0.0021 ***	0.0008 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0100)	(0.0000)	(0.0000)	(0.0000)

Table 6 – Alternative credit risk and liquidity premiums

The table replicates Table 4 and 5 using only the investment grade and high yield segment. In Columns 1 and 2, risk factor correlation (RFC) and bond correlation (BC) are computed using CDS mid quotes adjusted for CDS illiquidity as the credit risk measure as described in Section 5.1. In Columns 3 and 4, RFC and BC are computed using price dispersion as the liquidity measure as described in Section 5.1. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors for the regression analyses, and bootstrapped standard errors for the indirect impact. Adjusted R^2 are in percentage points. The number of observations is 1,456 in all regressions.

	Alternative credit risk premium				Alternative liquidity premium			
Explanatory variables	RFC		BC		RFC		BC	
Risk factor correlation			0.1920	***			0.1728	**
			(0.0076)				(0.0357)	
Sentiment	0.0028	**	0.0096	***	0.0068	***	0.0082	***
	(0.0354)		(0.0000)		(0.0000)		(0.0011)	
Herding			1.9002	**			1.8942	**
			(0.0139)				(0.0136)	
Market-wide risk	0.1716	***	-0.1693	***	0.0624	**	-0.0939	*
	(0.0000)		(0.0007)		(0.0228)		(0.0680)	
Market downturn	-0.0806	*	0.2564	***	0.1247	***	0.2369	***
	(0.0636)		(0.0001)		(0.0092)		(0.0006)	
Constant	-0.0418	***	0.1402	**	0.0363	***	0.0899	
	(0.0029)		(0.0418)		(0.0020)		(0.1735)	
Adj. R^2	4.80		9.27		11.90		8.49	
Indirect impact			0.0005	***			0.0012	***
			(0.0000)				(0.0000)	

Table 7 – Correlations adjusted for interest rate risk and unexpected inflation

The table replicates Table 4 and 5 using only the investment grade and high yield segment. In Columns 1 and 2, risk factor correlation (RFC) and bond correlation (BC) are adjusted for interest rate risk as described in Section 5.2. In Columns 3 and 4, both RFC and BC are adjusted for unexpected inflation as described in Section 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors for the regression analyses, and bootstrapped standard errors for the indirect impact. Adjusted R^2 are in percentage points. The number of observations is 1,456 in all regressions.

	Adjustment for interest rate risk		Adjustment for unexpected inflation	
Explanatory variables	RCF	BC	RFC	BC
Risk factor correlation		0.3172 ***		0.2787 ***
		(0.0000)		(0.0015)
Sentiment	0.0034 ***	0.0089 ***	0.0031 ***	0.0100 ***
	(0.0003)	(0.0000)	(0.0013)	(0.0000)
Herding		0.7771		0.8897
		(0.2241)		(0.2170)
Market-wide risk	0.2687 ***	0.0045	0.3049 ***	0.0512
	(0.0000)	(0.9213)	(0.0000)	(0.3712)
Market downturn	0.0034	0.0971	0.0372	0.0748
	(0.9006)	(0.1461)	(0.1947)	(0.3475)
Constant	-0.0628 ***	0.0722	-0.0810 ***	0.0562
	(0.0000)	(0.2109)	(0.0000)	(0.3942)
Adj. R^2	18.42	12.00	24.20	12.58
Indirect impact		0.0011 ***		0.0009 ***
		(0.0000)		(0.0000)

Table 8 – Alternative proxies for investor sentiment

The table replicates Table 4 (Panel A) and 5 (Panel B) for alternative proxies for investor sentiment using only the HY and IG segment. AAII is the Individual Investor Sentiment Index, ECRI the Economic Cycle Research Institute United States Leading Index, EPU the Daily Economic Policy Uncertainty Index, FSI the St. Louis Fed Financial Stress Index, and SENTIX the SENTIX World Economic Sentiment Index. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors for the regression analyses, and bootstrapped standard errors for the indirect impact. Adjusted R² are in percentage points. The number of observations is 1,456 in all regressions.

Panel A: Risk factor correlation as dependent variable

Explanatory variables	AAII	ECRI	EPU	FSI	SENTIX
Sentiment	0.0023 ***	0.0103 ***	0.0004 ***	0.0386 ***	0.0016 *
	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0989)
Market-wide risk	0.3046 ***	0.2639 ***	0.2961 ***	0.2911 ***	0.2990 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Market downturn	0.0535 **	0.0285	0.0239	0.0068	0.0369
	(0.0464)	(0.3674)	(0.3778)	(0.8313)	(0.1971)
Constant	-0.0770 ***	-0.0613 ***	-0.0718 ***	-0.0695 ***	-0.0736 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Adj. R^2	23.59	26.87	22.18	21.85	21.01

Panel B: Bond correlation as dependent variable

Explanatory variables	AAII	ECRI	EPU	FSI	SENTIX
Risk factor correlation	0.2933 ***	0.2249 ***	0.2758 ***	0.2361 ***	0.2720 ***
	(0.0008)	(0.0052)	(0.0003)	(0.0018)	(0.0016)
Sentiment	-0.0010	0.0075 ***	0.0001	0.1296 ***	0.0045 *
	(0.2952)	(0.0038)	(0.7378)	(0.0000)	(0.0758)
Herding	1.4351 **	0.7133	1.3624 **	0.8424	1.0865
	(0.0402)	(0.2485)	(0.0338)	(0.1814)	(0.1176)
Market-wide risk	0.0342	0.0274	0.0382	0.0056	0.0234
	(0.5664)	(0.5841)	(0.4535)	(0.9016)	(0.6743)
Market downturn	0.1922 **	0.1933 ***	0.1960 ***	0.0840	0.1852 **
	(0.0175)	(0.0032)	(0.0064)	(0.1237)	(0.0155)
Constant	0.0064	0.0742	0.0115	0.0749	0.0413
	(0.9206)	(0.1889)	(0.8450)	(0.1905)	(0.5205)
Adj. R^2	8.64	9.56	8.43	13.24	9.09
Indirect impact	0.0007 ***	0.0023 ***	0.0001 ***	0.0091 ***	0.0004 **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0200)

Table 9 – Swap rate as proxy for the risk-free rate

The table replicates Table 4 and 5 using only the investment grade and high yield segment. Instead of calculating the risk-free rate from US Treasuries, we now use swap rates. Risk factor correlation (RFC) and bond correlation (BC) are computed based on yield spreads computed from swap rates. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors for the regression analyses, and bootstrapped standard errors for the indirect impact. Adjusted R^2 are in percentage points. The number of observations is 1,456 in all regressions.

Explanatory variables	RCF		BC	
Risk factor correlation			0.1460	*
			(0.0667)	
Sentiment	0.0029	***	0.0078	***
	(0.0022)		(0.0002)	
Herding			0.4830	
			(0.4578)	
Market-wide risk	0.3429	***	0.0203	
	(0.0000)		(0.7134)	
Market downturn	-0.0433		0.1087	*
	(0.1589)		(0.0770)	
Constant	-0.0935	***	0.1141	*
	(0.0000)		(0.0590)	
Adj. R^2	8.63		6.01	
Indirect impact			0.0004	***
			(0.0000)	

Table 10 – Temporal stability

The table replicates Table 4 (Panel A) and 5 (Panel B) using only the investment grade and high yield segment. In Columns 1 and 2, we report results for the first and second half of the sample period. The number of observations is 728 in each subsample. In Columns 3 and 4, we cut the sample at July 1st, 2007 as in Friewald et al. (2012) to capture the beginning of the financial crisis. The number of observations is 644 in the first and 812 in the second subsample. ***, **, and * denote significance at the 1%, 5%, and 10% level. Significance is determined using Newey-West standard errors for the regression analyses, and bootstrapped standard errors for the indirect impact. Adjusted R^2 are in percentage points.

Panel A. Risk factor correlation as dependent variable

Explanatory variables	First half of sample period	Second half of sample period	Before July 2007	From July 2007
Sentiment	0.0059 **	0.0020 *	0.0094 ***	0.0023 **
	(0.0124)	(0.0625)	(0.0001)	(0.0251)
Market-wide risk	0.3372 ***	0.3203 ***	0.3009 ***	0.3351 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Market downturn	0.0145	0.0675 **	0.0422	0.0611 **
	(0.5872)	(0.0154)	(0.1161)	(0.0265)
Constant	-0.0352 **	-0.1359 ***	-0.0068	-0.1461 ***
	(0.0126)	(0.0000)	(0.6188)	(0.0000)
Adj. R^2	17.57	34.90	20.23	34.33

Panel B. Bond factor correlation as dependent variable

Explanatory variables	First half of sample period	Second half of sample period	Before July 2007	From July 2007
Risk factor correlation	0.3148 ***	0.4125 ***	0.4003 ***	0.5227 ***
	(0.0004)	(0.0001)	(0.0003)	(0.0000)
Sentiment	0.0227 ***	0.0101 ***	0.0116 **	0.0110 ***
	(0.0000)	(0.0000)	(0.0400)	(0.0000)
Herding	-0.7876	-0.5408	0.0053	-1.7016 **
	(0.3967)	(0.5720)	(0.9956)	(0.0255)
Market-wide risk	0.1489 **	-0.0100	0.1437 **	-0.0769
	(0.0198)	(0.8784)	(0.0201)	(0.1532)
Market downturn	-0.3764 ***	0.0236	-0.3952 ***	0.0065
	(0.0000)	(0.7332)	(0.0000)	(0.9116)
Constant	0.1823 **	0.2728 ***	0.0707	0.4254 ***
	(0.0232)	(0.0036)	(0.3818)	(0.0000)
Adj. R^2	18.28	20.68	20.82	21.69
Indirect impact	0.0019 ***	0.0008 **	0.0037 ***	0.0012 ***
	(0.0000)	(0.0100)	(0.0000)	(0.0000)

Figure A.1 – Reduced-form credit risk and liquidity model

The figure displays the joint dynamics of default and liquidity intensities, conditional on no default at time 1. At time 0, λ and γ equal λ_0 and γ_0. At time 1, the default intensity may increase ($\lambda_1^u = \lambda_0 + \Delta\lambda$) with probability p_u^λ, decrease ($\lambda_1^d = \lambda_0 - \Delta\lambda$) with probability p_d^λ, or remain the same ($\lambda_1^m = \lambda_0$) with probability p_m^λ. $\Delta\lambda$ is defined as $\Delta\lambda = \sigma_\lambda \cdot \sqrt{3} \cdot \sqrt{\Delta t}$. Also, the liquidity intensity may increase ($\gamma_1^u = \gamma_0 + \Delta\gamma$) with probability p_u^γ, decrease ($\gamma_1^d = \gamma_0 - \Delta\gamma$) with probability p_d^γ, or remain the same ($\gamma_1^m = \gamma_0$) with probability p_m^γ. $\Delta\gamma$ is defined as $\Delta\gamma = \sigma_\gamma \cdot \sqrt{3} \cdot \sqrt{\Delta t}$. Panel A displays the tree for uncorrelated intensities. Panel B shows the tree for correlated intensities. Panel C presents our final model. There, the liquidity intensity level depends on the default intensity level. This is modeled by the random variable $\tilde{a}_1 \in \left\{a_1^u, a_1^m, a_1^d\right\}$. Furthermore the influence of investor sentiment on liquidity intensities is modeled by the parameter x where high values of x indicate low investor sentiment.

Panel A:

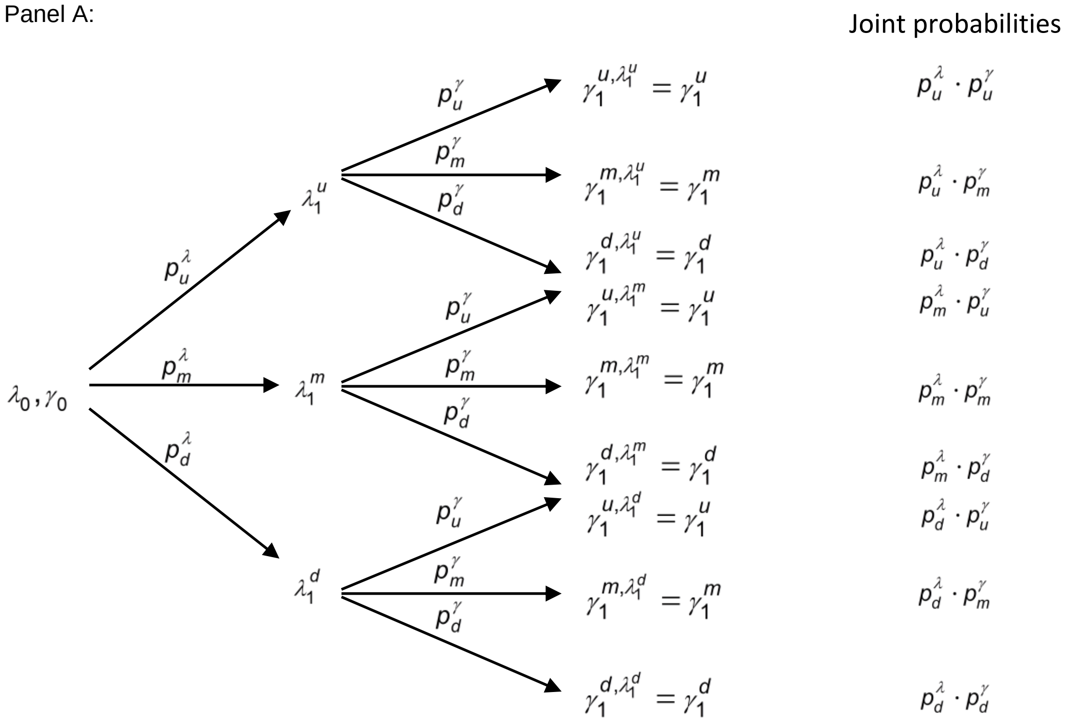
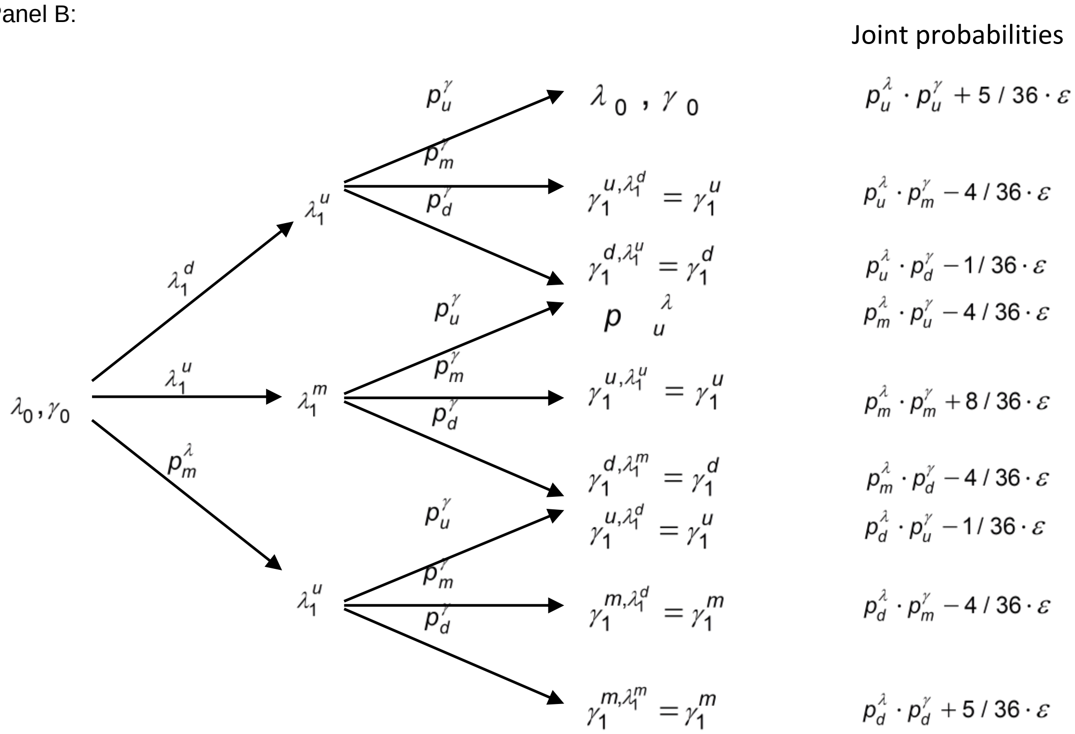


Figure A.1 (continued) – Reduced-form credit risk and liquidity model

Panel B:



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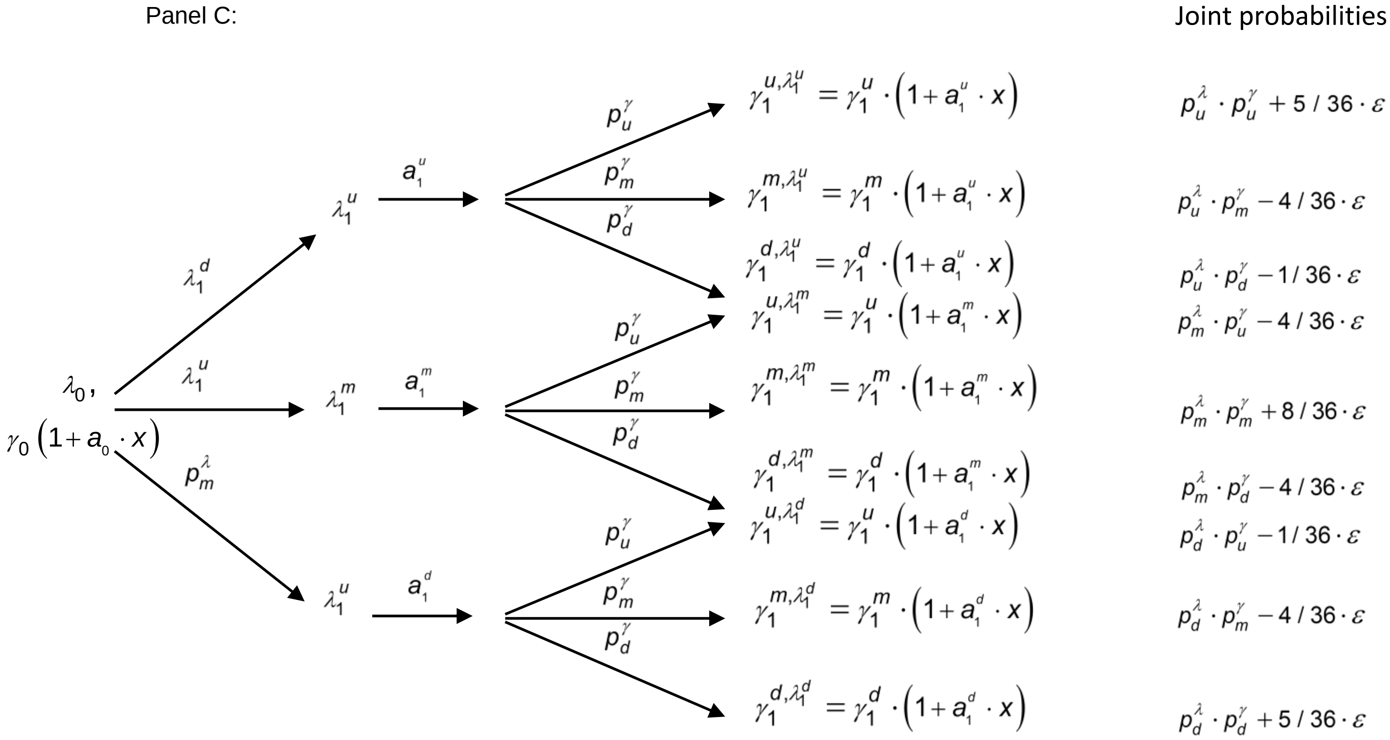


Figure A.2 – Risk factor correlation and sentiment

The figure displays correlation between credit risk and liquidity premium changes as a function of investor sentiment x. High values of x indicate low investor sentiment. The plot is based on the following parameter values: $\Delta t = 1$, $\lambda_0 = 3.00\%$, $\gamma_0 = 2.00\%$, $\Delta\lambda = 1.73\%$, $\Delta\gamma = 1.30\%$, $a_u = 1.00$, $a_m = 0.50$, $a_d = 0.00$.

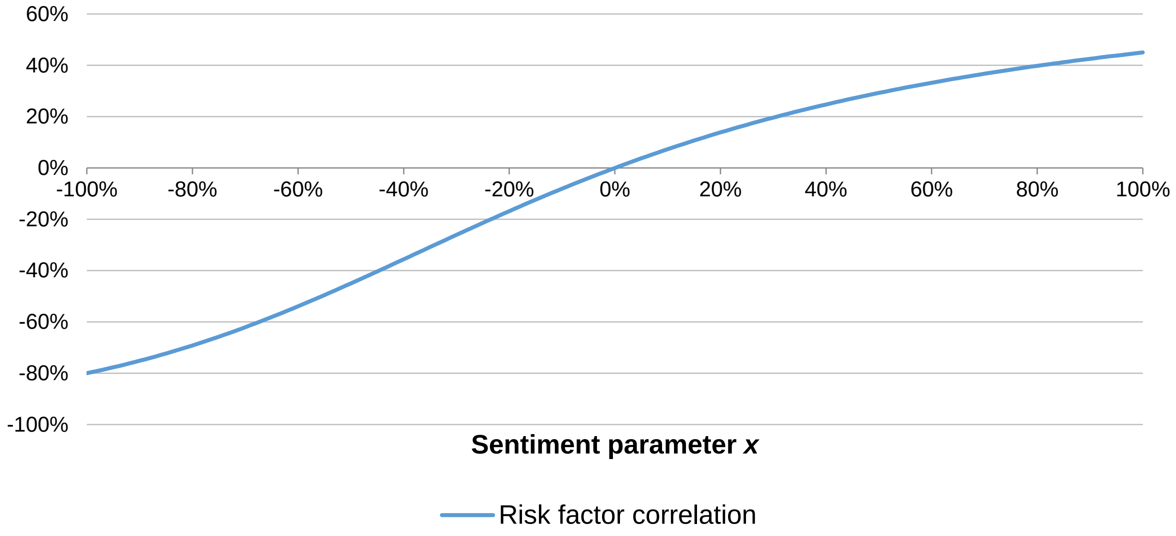
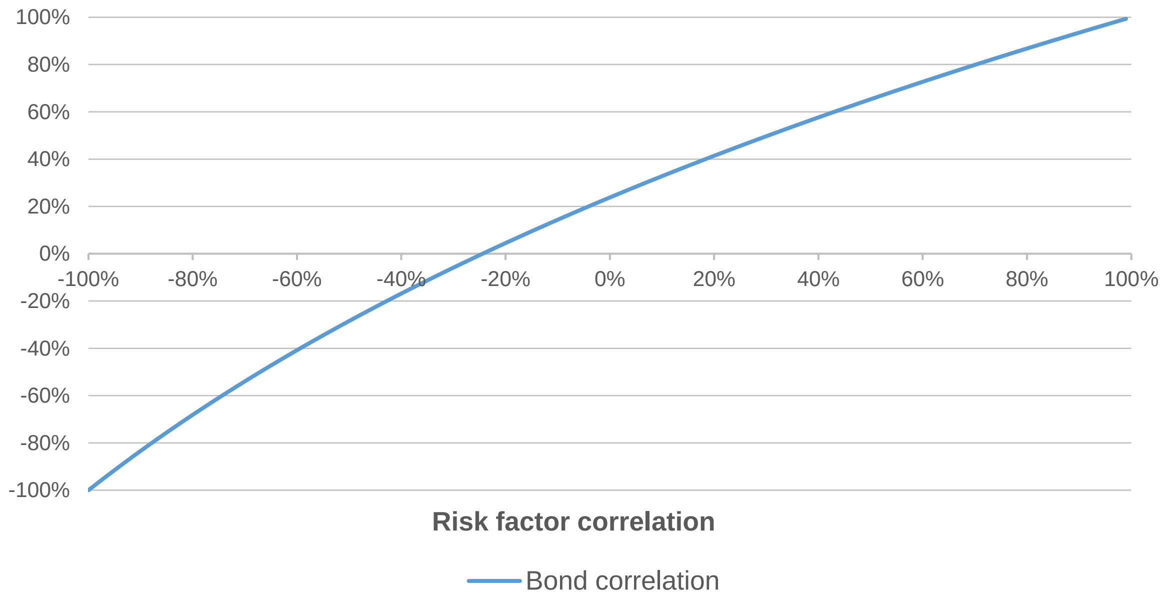


Figure A.3 – Bond correlation and risk factor correlation

The figure displays correlation between bond yield spread changes as a function of investor sentiment risk factor correlation. The plot is based on the following parameter values: $\beta_{i,\lambda} = 1.13$ $\beta_{h,\lambda} = 0.60$, $\beta_{i,\gamma} = 0.01$, $\beta_{h,\gamma} = 2.72$, $Var\left(\lambda_m\right) = 0.15$, $Var\left(\gamma_m\right) = 0.14$.



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centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de