Momentum Spillover from Stocks to Corporate Bonds[a]

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Abstract

We investigate and improve momentum spillover from stocks to corporate bonds, i.e. the phenomenon that past winners in the equity market are future winners in the corporate bond market. We find that a momentum spillover strategy exhibits strong structural and time-varying default risk exposures that cause a drag on the profitability of the strategy and lead to large drawdowns if the market cycle turns from a bear to a bull market. By ranking companies on their firm-specific equity return, instead of their total equity return, the default risk exposures halve, the Sharpe ratio doubles and the drawdowns are substantially reduced.

JEL classification: G11; G12; G14

Keywords: corporate bond; spillover; momentum; time-varying risk; residual return

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1. Introduction

We investigate and improve momentum spillover from stocks to corporate bonds. Momentum spillover is the phenomenon that companies that recently outperformed in the equity market tend to subsequently outperform in the corporate bond market. This spillover effect was first documented by Gebhardt, Hvidkjaer and Swaminathan (2005) for investment grade bonds. Our study contributes to the existing literature in four ways. First, we show that the spillover effect is also present for high yield bonds, whereas Gebhardt et al. (2005) only investigated investment grade. Second, we find that a momentum spillover strategy tends to select companies with low (high) default risk in the winner (loser) portfolio, as indicated by a variety of risk measures: credit volatility, credit market beta, credit rating, credit spread, distance-to-default and leverage. Therefore, the profitability of momentum spillover depends on the realized credit market return during the holding period, because companies with low (high) default risk tend to outperform in bear (bull) markets. This causes a drag on the profitability of the strategy, amounting to one third of the alpha, because the credit market has generated a positive premium on average.

Third, we document that the default risk exposure of momentum spillover strongly depends on the equity market return during the formation period: if the equity market has positive (negative) returns in the formation period, the default risk of the winner-minus-loser portfolio is smaller (larger). We show that this dependency is highly statistically significant in a conditional regression framework, in which we model the default risk exposure as a function of the equity market return in the formation period. The time-varying default risk exposure makes the momentum spillover strategy vulnerable to a scenario in which an equity bear market is followed by a credit bull market: a negative equity market return lowers the default risk exposure of the portfolio, which hurts performance in a subsequent credit bull market. For instance, in 2009 the momentum spillover winner-minus-loser portfolio suffered a drawdown of -80%. We find that the structural and time-varying default risk exposures together explain 44% of the variation in the profitability of momentum spillover.

Our final contribution to the literature is that we show that the time-varying default risk exposure of momentum spillover can be substantially reduced by ranking companies on their residual equity return. Moreover, residual momentum spillover achieves a larger risk reduction than hedging the default risk after formation of a total momentum spillover portfolio. Since the residual return of a stock is calculated by subtracting the expected return that can be attributed to its equity market exposure, it does not depend on the equity market return in the formation period, which is the primary driver of the structural and time-varying default risk exposure. We find that the volatility of residual momentum spillover is halved compared to total momentum spillover, from 8.85% to 4.80%, the Sharpe ratio is more than doubled, from 0.35 to 0.77, and the worst drawdown is reduced substantially, from -80% to -25%. We also find that a total momentum spillover portfolio in combination with a hedge after the portfolio has been constructed is in fact less effective in reducing the risk of the strategy, since volatility is reduced from 8.85% to at most 6.17%, depending on the chosen hedging method. The improvements offered by residual momentum spillover over total momentum spillover are robust to changes in the formation period and holding period lengths, the estimation method of residual equity returns, the specification of the factor model, correcting for equity momentum and bond momentum, liquidity effects and credit rating effects.

The structure of this paper is as follows. In Section 2 we provide an overview of the literature. In Section 3 we describe our data and in Section 4 we present our methodology and empirical results. In Section 5 we perform various robustness checks. Section 6 concludes.

2. Literature review

The profitability of momentum strategies in equity markets is well documented in the academic literature. In their seminal paper, Jegadeesh and Titman (1993) demonstrate that momentum returns are large and significant. Different explanations have been put forward for the momentum effect. Jegadeesh and Titman (2001) provide an overview and conclude that a risk-based explanation is unlikely. They argue that the evidence points towards behavioral explanations, of which underreaction to news seems to be the most prominent. For instance, the *gradual diffusion of information* hypothesis of Hong and Stein (1999) argues that when information travels slowly across investors, it can generate price underreaction and momentum effects. Moreover, they show that underreaction is more pronounced for firm-specific events than for common events.

Even though momentum profits cannot be explained by higher risk, various studies show that equity momentum portfolios exhibit time-varying exposures to the Fama and French (1993) common risk factors; see e.g. Grundy and Martin (2001) and Blitz, Huij and Martens (2011). Gutierrez and Pirinsky (2007), Blitz et al. (2011) and Chaves (2016) demonstrate that measuring momentum in idiosyncratic, or 'residual', equity returns, improves upon traditional total return momentum. Specifically, Blitz et al. (2011) show that residual momentum is effective in strongly reducing the time-varying factor exposures without harming the profitability of the momentum strategy. Residual momentum also fits well with Hong and Stein's (1999) gradual diffusion hypothesis on firm-specific news, because of its focus on firm-specific returns.

The literature on corporate bonds shows that investment grade bonds do not exhibit momentum; see e.g. Khang and King (2004), Gebhardt et al. (2005), Pospisil and Zhang (2010) and Jostova, Nikolova, Philipov and Stahel (2013). The latter study does document that momentum is a profitable strategy for high yield corporate bonds. Gebhardt et al. (2005) are the first to provide evidence on the momentum spillover phenomenon. They show that even though bond prices do not underreact to firm information, they do underreact to past stock returns: past winners (losers) in the equity market are future winners (losers) in the corporate bond market. Foster and Galindo (2007), using a relatively short data set from 2002 to 2006, also document a momentum spillover effect from stocks to bonds, and the other way around. Kwan (1996) and Gurun, Johnston and Markov (2015) obtain a similar finding, i.e. that corporate bond yield changes can be predicted with the company's lagged stock return. Looking for possible explanations for the momentum spillover effect, Gebhardt et al. (2005) demonstrate that high (low) past stock returns predict better (worse) bond ratings in the future, so that equity winners (losers) see their credit worthiness improve (deteriorate) and their bonds outperform (underperform) as time progresses. An alternative explanation for momentum spillover is offered by Hong, Torous and Valkanov (2007), who show, building on Hong and Stein (1997), that gradual information diffusion can lead to cross-asset return predictability if many, though not necessarily all, investors in one market (here: the credit market) do not pay close attention to information in other markets (here: the equity market).

Our paper contributes to the existing literature on stock-bond momentum spillover by providing new insights in the risk profile of the traditional momentum spillover strategy and by documenting superior performance of residual momentum spillover. Moreover, we are the first to document the momentum spillover effect for high yield bonds. Even though Gebhardt et al. (2005) show that equity winners (losers) become less (more) default-risky *in the future*, they do not investigate differences in default risk *at the moment* of forming momentum spillover portfolios. We find that equity winners are already less default-risky than equity losers at the time of creating the momentum spillover portfolios, and that these default risk differences affect the profitability of the momentum winner-minus-loser spillover strategy. Moreover, we document that this default risk difference is strongly time-varying and depends on the equity market return in the formation period. This insight motivates us to evaluate residual momentum spillover. We not only find that it is effective in reducing the time-variation in default risk, but also that it generates superior investment results. Finally, we compare the residual momentum technique with various hedging methods to reduce the default risk exposure of the constructed momentum spillover portfolio, amongst which the method used by Gebhardt et al. (2005). We find that residual momentum achieves a larger risk reduction than any of the investigated hedging methods.

3. Data

Our corporate bond data consist of all constituents of the Barclays U.S. Corporate Investment Grade Index and the Barclays U.S. High Yield Index. The data have a monthly frequency, start in January 1994 and end in December 2013. These two indexes represent the largest corporate bond market in the world: the Investment Grade (High Yield) bonds in our data set constitute 60% (62%) of the market value of the Barclays Global Investment Grade (High Yield) index.[1]

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[1] Source: Barclays (live.barcap.com). As of 31 December 2013.

For each bond, Barclays provides static characteristics, such as its issue date, maturity date and notional, as well as monthly data, such as total return, credit spread, and credit rating. In addition to a bond's total return, Barclays also provides its excess return over duration-neutral Treasuries, which properly cleans the total return from interest rate influences. Therefore, these excess returns are only affected by changes in credit spreads. We purposely use excess returns, because equity returns are positively related to the credit spread component of corporate bond returns, but negatively related to their interest rate component; see Ilmanen (2010, chapter 10) and Haesen and Houweling (2013). Our key results hold for both excess and total returns, results for total returns are available upon request.

If a company has more than one bond outstanding in a particular month, we compute the market value weighted return over all its outstanding bonds to represent the bond return for that company. Other characteristics, like credit spread, are also computed as market value weighted average over all outstanding bonds. If a company defaults, Barclays calculates the last return of its bonds from their last traded prices, reflecting the market's perception of the company's recovery rate. Hence, there is no survivorship bias in our data.

Because we are investigating stock-bond momentum spillover, we restrict our sample to companies that have publicly listed equity on a U.S. stock exchange with a history of at least three years. For each company, we obtain monthly equity returns from FactSet. We also download its equity market capitalization, the 1-year volatility of daily equity returns, the book value of total liabilities, and the book value of total assets on monthly frequency. These items are used to calculate the distance-to-default for each company (using the Byström (2006) method, see Appendix A) and the leverage (as the ratio of book value total liabilities and book value total assets). This results in a data set comprising 2,439 unique companies.

Table 1 shows various descriptive statistics for our total universe (ALL), as well as for the Investment Grade (IG) and High Yield (HY) universes separately. The entire corporate bond universe had an annualized excess return of 1.76%, with a volatility of 6.22% and a corresponding Sharpe ratio of 0.28. We observe that the HY universe had a higher average corporate bond return (2.70%), volatility (9.27%) and Sharpe ratio (0.29), while the IG universe had a higher average equity return (8.38%) and Sharpe ratio (0.54). Naturally, default risk is higher in the HY universe than in the IG universe, as measured by credit spread (528 bps vs. 159 bps), distance-to-default (3.26 vs. 5.81) and leverage (0.60 vs. 0.49).

[Insert Table 1 around here]

In our analyses, we also use the five Fama and French (1993) risk factors. We download the equity market factor (*RMRF*), the equity size factor (*SMB*) and the equity value factor (*HML*) from Kenneth French' website.[2] For the bond term factor (*TERM*) and corporate bond default factor (*DEF*), we purposely deviate from Fama and French' (1993) use of the Ibbotson factors, because Hallerbach and Houweling (2013) show that the Ibbotson *DEF* factor is seriously flawed. They find that the Ibbotson *DEF* factor has a statistically significant negative sensitivity to interest rate changes and a statistically insignificant sensitivity to credit spread changes and thus does not represent a default premium. Instead, we calculate *DEF* as the average excess return over duration-neutral Treasuries of the corporate bonds in our universe. By using duration-neutral excess returns, *DEF* does not contain a term premium, which is already captured by *TERM*. *DEF* is universe-specific, i.e. if we analyze momentum spillover in the IG universe, *DEF*

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[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

is the average return of all IG-rated bonds. Likewise for the HY and ALL universes. We calculate *TERM* as the return of the Barclays U.S. Treasury 7-10 year index minus the 1-month T-bill return (obtained from the website of Kenneth French).[3]

4. Results

4.1. Return characteristics of momentum spillover

Following Gebhardt et al. (2005), we use the overlapping portfolio approach of Jegadeesh and Titman (1993) as our methodological framework. Each month, all companies are divided into ten decile portfolios based on their past *J*-month equity return. For each decile portfolio (D1 to D10), we calculate the future *K*-month equally weighted excess return over Treasuries of the corporate bonds. We also construct a zero net-investment winner-minus-loser portfolio (D1-D10) by going long (short) the companies with the highest (lowest) past equity returns. We calculate the return of a portfolio in period *t* as the equally weighted average of the portfolios constructed in periods *t-K* to *t-1*. Following Gebhardt et al. (2005), our base case strategy uses a formation period of *J*=6 months, a holding period of *K*=6 months and an implementation lag of 1 month. We show results for other formation and holding periods in the robustness section.

[3] We use this index, because it best matches the average maturity of the corporate bonds. For Investment Grade, the average maturity over our sample period is about 10.7 years, while for High Yield the average is 7.2 years. We could have taken an index containing all maturities, such as the Barclays US Treasury index. However, our results do not materially change as the return correlation of the Barclays US Treasury 7-10 year index with the Barclays US Treasury index is very high: 98.6%.

Table 2 shows the return, volatility[4] and Sharpe ratio of the momentum spillover decile portfolios as constructed on our entire universe (Panel A), as well as on IG (Panel B) and HY (Panel C) separately. We also calculate a 1-factor alpha by regressing the strategy return r_t on the credit market return DEF_t

$$r_t = \alpha + \beta DEF_t + \varepsilon_t \tag{1}$$

We find strong evidence that momentum spills over from the equity market to the corporate bond market, as the Sharpe ratios and alphas are monotonically decreasing as we move from the winner portfolio D1 to the loser portfolio D10. For example, in Panel A (ALL universe) the Sharpe ratios decline from 0.59 for D1 to 0.06 for D10 and the alphas from 1.94% to -2.86% per annum. For all three universes, we find that the positive alphas of the D1, D2 and D3 portfolios and the negative alphas of the D9 and D10 portfolios are statistically significant. This also holds for the alphas of the winner-minus-loser portfolios, which are all significant at the 99% confidence level.

For IG (Panel B), the return of 1.73% per annum (14 bps per month) of the winner-minus-loser portfolio is of the same order of magnitude as the 11 bps per month that Gebhardt et al. (2005, Table 3) report. Since they use data from 1973 to 1996, our results on data from 1994 to 2013 provide a successful out-of-sample test of momentum spillover. Furthermore, our results in Panel C show that the strategy also works for HY, with a very similar Sharpe ratio for the winner-minus-loser portfolio as for IG: 0.44 vs. 0.42.

[Insert Table 2 around here]

[4] We correct standard errors for autocorrelation and heteroskedasticity using Newey and West (1987). We follow Newey and West (1994) for the calculation of the number of lags.

4.2. Risk characteristics of momentum spillover

Next, we analyze the risk of momentum spillover in more detail. Moving from D6 to D10 in Table 2, we observe a strictly monotonous pattern of increasing volatilities for all three universes. So, the lower a company's equity return in the formation period, the higher its credit volatility in the holding period. Especially the higher volatility of D10 stands out. For the ALL and HY universes, it is about twice as large as the volatility of D1, while for IG it is about 60% higher.

To better understand the differences in credit volatility between the decile portfolios, we calculate portfolio risks according to various measures of default risk. These risk measures are not meant as an exhaustive list, but rather serve to shed light on the risk differences from various angles, as assessed by the credit market, the equity market, the company's balance sheet and rating agencies:

- *credit spread*: the credit market's current assessment of the company's credit risk. The credit spread is provided by Barclays and is calculated as the yield difference between the corporate bond and a duration-matched government bond.
- *credit beta*: the realized sensitivity of the portfolio to the credit market, thus measuring the systematic risk component. We calculate the beta of each decile portfolio by regressing its return on the *DEF* factor.
- *credit rating:* the rating agencies' assessment of the company's credit worthiness. Barclays calculates the composite rating by using the middle rating in case of three available ratings (Moody's, S&P, Fitch) and the lowest in case of two ratings. We

convert this composite rating to a numerical scale (AAA=1, AA+=2, AA=3, etc.) to allow for aggregation of individual bond ratings to the portfolio level.

- *distance-to-default:* the equity market's assessment of the company's default risk in the structural framework of Merton (1974), measuring the proximity of the firm to the default barrier. We calculated distance-to-default using the Byström (2006) method, which combines the market value of equity, the 1-year equity volatility and the book value of the total liabilities into a single measure of default risk. Distance-to-default is used in various empirical studies on credit markets, e.g. by Schaefer and Strebulaev (2008) and Correia, Richardson and Tuna (2012).
- *leverage:* a measure of the company's riskiness as indicated by its balance sheet. We calculate leverage as the book value of a company's total liabilities divided by the book value of its total assets. Various empirical studies on corporate bond markets use leverage as a control variable, e.g. Collin-Dufresne et al. (2001) and Campbell and Taksler (2003).

Except for the credit beta, all portfolio risk measures are first calculated as cross-sectional averages over a portfolio's constituents at the time of formation, and then averaged over time. This is different from Gebhardt et al. (2005) who relate momentum spillover to default risk in the period *after* formation. Table 3 shows these average risk measures for all decile portfolios. As we move from D1 to D10, we find a smirk-like pattern for all risk measures: D1 and D2 generally have somewhat higher risk than the middle portfolios, but risk starts to increase as we move on from D6 and sharply increases for D9 and D10. This pattern indicates that the momentum winners tend to be a bit more risky than the average company in the universe, but that the momentum losers are much more risky. Especially the differences in credit beta and credit spread stand out, because according to these measures D10 is about twice as risky as D1 in the ALL and HY universes, and about 30-40% riskier in the IG universe.

The much higher risk of D10 is immediately visible from the last column of Table 3, which presents the differences in default risk between D1 and D10. For the ALL and HY universes, this column consistently shows that D10 is the more risky portfolio for all five risk measures. For IG, this is the case for four out of five risk measures. Because D1-D10 is negatively exposed to default risk, and in particular because it has a negative credit beta, its return is negatively affected by the credit market return in the holding period. This means that the profitability of momentum spillover not only depends on its ability to distinguish winners from losers, but also to a large extent on the credit market return. Since the credit market has a positive premium on average (see Table 1), the negative beta of momentum spillover eats into its long-term profits, as evidenced by the mean return being up to one third lower than the alpha.

[Insert Table 3 around here]

4.3. Time-varying risk of momentum spillover

In this section we investigate the time-varying risk profile of momentum spillover. Above we showed that at the time of creating the momentum spillover portfolios, equity losers are much more risky than equity winners, as indicated by a variety of default risk measures. Next we investigate whether these risk differences depend on the market environment in the formation period. Previous studies on time-varying risks of momentum in the equity market, like Grundy and Martin (2001), show that in equity bear markets the companies in the loser portfolio tend to be more risky than in equity bull markets. Therefore, one may hypothesize that the momentum losers exhibit higher default risk in bear markets than in bull markets.

To explore this hypothesis, we first conduct a graphical analysis, just like Grundy and Martin (2001, Figures 4 and 5). We plot the equity market return in the formation period against the default risk of the winner-minus-loser portfolio. Figure 1 shows scatter plots for the ALL universe for credit rating (Panel A), credit spread (Panel B), distance-to-default (Panel C) and leverage (Panel D). In each panel we observe the expected relation: the lower the equity market return in the formation period, the higher the default risk of the winner-minus-loser portfolio. For example, in times of higher (lower) equity returns, the momentum spillover strategy selects higher-rated (lower-rated) firms in the winner portfolio and lower-rated (higher-rated) firms in the loser portfolio. Hence, during equity bull (bear) markets, the momentum spillover winner-minus-loser portfolio has a bias towards companies with higher (lower) ratings. A similar reasoning applies to the other default risk proxies in Panels B, C and D.

[Insert Figure 1 around here]

In Table 4 we extend this analysis to the IG and HY universes by calculating the average default risk measure of the winner-minus-loser portfolios in five states as defined by the equity market return. State 1 (“Low *RMRF*”) contains all months in our data sample with the 20% lowest equity market returns, state 2 the next 20%, etc., until state 5 (“High *RMRF*”) with the 20% highest equity market returns. The reported credit beta in a particular state is estimated by regressing the strategy return on the *DEF* factor in a sample consisting of the months in that state. For the risk measures credit spread and leverage we observe a strictly monotonous relation between the equity market return and the default risk of the winner-minus-loser portfolio in all three universes. This confirms our earlier observation, that when the equity market return in the formation period was stronger (weaker), the difference in default risk between the momentum spillover winner and loser portfolio is smaller (larger). For distance-to-default this also holds in the IG and HY universes, and for credit rating in the HY universe. For the remaining cases, we observe a strong relation pointing in the same direction, but not strictly monotonous.

[Insert Table 4 around here]

The state-specific default risk estimates in Table 4 suggest a time-varying risk profile of momentum spillover: its default risk exposure strongly depends on the equity market return in the formation period. The default risk scatter plots in Figure 1 suggest that this relationship is approximately linear. Inspired by the conditional regression frameworks in Grundy and Martin (2001) and Blitz et al. (2011), we estimate the following equation to formally test the time-varying risk profile:

$$r_t = \alpha + \left(\beta_{DEF} + \beta_{DEF,RMRF} RMRF_{t-K:t-1}\right) DEF_t + \varepsilon_t \tag{2}$$

where r_t is the return of the momentum spillover winner-minus-loser portfolio in month t, $RMRF_{t-K:t-1}$ is the equity market return in the formation period, and DEF_t is the credit market return in month t. This equation, which is an extension of Equation (1), models the strategy's beta to the credit market as a linear function of the equity market return in the formation period, as suggested by Figure 1. Equation (2) stipulates that, if indeed $\beta_{DEF}<0$ and $\beta_{DEF,RMRF}>0$, a negative equity market return $RMRF_{t-K:t-1}$ in the formation period, results in a stronger negative exposure to the credit market return DEF_t in the evaluation period. As a reference, we also estimate a restricted version of this equation with $\beta_{DEF,RMRF} = 0$. This results in Equation (1), which thus only estimates the structural exposure β_{DEF} to the credit market.

For the time-varying framework, column three in Table 5 shows that for all universes the estimated $\beta_{DEF,RMRF}$ coefficient is positive and statistically significant with t-values of 3.35 for the ALL universe, 2.49 for IG and 2.84 for HY. Also, the adjusted R^2 in column four has increased compared to the specification without the time-varying *DEF* exposure. The estimated $\beta_{DEF,RMRF}$ coefficient is around 1, implying that for every 10% lower return in the equity market over the formation period, the *DEF* beta of the winner-minus-loser portfolio is 0.1 lower. Since the equity market return in the formation period, $RMRF_{t-K:t-1}$ in equation (2), ranges from about -34% to +26%, the *DEF* beta difference between the worst state and the best state amounts to about 0.6. This is a large difference, given the structural *DEF* beta of -0.21 for IG and -0.76 for HY. These results suggest that the time-variation in default risk of momentum spillover is both statistically and economically meaningful, and distinguish our work clearly from Gebhardt et al. (2005). They do establish a structural link between momentum spillover and default risk, but they do not explore the time-varying nature of this risk profile.

[Insert Table 5 around here]

4.4. Reducing time-varying risk using residual momentum

The evidence presented in the previous section shows that the default risk exposure of momentum spillover strongly depends on the equity market return in the formation period. In order to reduce the dependency of momentum spillover to the equity market return in the formation period, we first need to understand its origin. For this, we look at the *RMRF*-beta of the stocks that are selected by the momentum strategy in each of the five equity market states, see the last column of Table 4. We find that in states with low (high) equity market returns, the equity beta is small (large). This finding is consistent with the equity momentum literature, e.g. Grundy and Martin (2001) who show that equity momentum exhibits a time-varying exposure to the equity market: in bull markets, the winner portfolio tends to contain high-beta stocks and the loser portfolio low-beta stocks, and vice versa in bear markets.

Hence, if we are able to reduce dependency of the equity momentum strategy on *RMRF*, we can also reduce the time-varying *DEF* exposure of momentum spillover. To accomplish this, we follow Gutierrez and Pirinsky (2007), Blitz et al. (2011) and Chaves (2016) by ranking companies on their firm-specific, or residual, equity return. To make the distinction clear, we call the momentum measure of the previous section *total momentum spillover* as it uses total equity returns. To estimate the residual return we regress the excess equity return on the equity market factor *RMRF* using a moving window regression over 36 months:

$$E_{i,t} = \alpha_i + \beta_{RMRF,i} RMRF_t + \varepsilon_{i,t} \tag{3}$$

where $E_{i,t}$ denotes the equity return of company i in excess of the 1-month T-bill return in month t. The residual equity return is equal to $\varepsilon_{i,t}$.

To construct the J-month residual equity momentum, we compound the last J residuals and divide it by the standard deviation of all 36 residuals over the estimation window, hence penalizing uncertain estimates. Gutierrez and Pirinsky (2007) argue that this improves the residual momentum measure, because a firm-specific return can either be real news or just noise. The resulting strategy is lagged by one month, in line with total momentum spillover. The top-minus-bottom portfolio construction method for residual momentum (RM) is identical to that for total momentum (TM), except for the momentum measure used to rank the companies. Note that by ranking companies on their residual equity return, the winner and loser portfolios are populated by different companies than in case of ranking on total equity returns. For example, higher-beta stocks do not necessarily enter the winner portfolio after a positive equity market return in the formation period, but only if they performed better than the beta-dependent expected return.

Below we investigate to which extent RM is able to reduce the time-varying default risk exposure of momentum spillover. First, we conduct a visual inspection of the dependency of the default risk exposure of the winner-minus-loser portfolio on the equity market return in the formation period. Again, we measure default risk using four risk measures, credit rating, credit spread, distance-to-default and leverage; see Figure 2. We observe that the relation is much weaker than in case of TM spillover in Figure 1. So, RM clearly reduces the dependency of the default risk exposure of momentum spillover on the equity market return.

[Insert Figure 2 around here]

Next, we formally test the significance of the structural and time-varying default risk exposure by estimating Equation (2), see the right-hand side of Table 5. We find that the $\beta_{DEF,RMRF}$ coefficient, which relates to the dependency on the equity market return, is strongly reduced compared to TM spillover: from 1.31 to 0.37 for the ALL universe (Panel A), from 0.90 to 0.01 for IG (Panel B) and from 1.02 to 0.41 for HY (Panel C). For IG it is no longer statistically significant. Moreover, for all three universes we see a strong reduction in the structural *DEF* exposure, as measured by the β_{DEF} coefficient of equation (2). The lower adjusted R^2 values for RM spillover also suggest that the *DEF* factor explains less of the return variation of RM spillover compared to TM spillover. We thus conclude that RM spillover exhibits much smaller structural and time-varying default risk exposures than traditional TM spillover. In other words, the use of residual equity returns instead of total equity returns proofs to be an effective way of reducing the structural and time-varying default risk exposures in momentum spillover.

4.5. Reducing drawdowns using residual momentum

To visualize the impact of the reduced time variation in default risk exposure, Figure 3 plots the cumulative returns through time of the winner-minus-loser portfolio, for both TM and RM spillover.

[Insert Figure 3 around here]

The chart shows that the time-variation in the *DEF* beta is especially hurting the performance of TM spillover when a strong equity bear market is followed by a strong credit bull market. For instance, the profits of TM spillover doubled during the 2008 sub-prime crisis, when the strategy correctly selected low-beta companies in the winner portfolio and high-beta companies in the loser portfolio. However, all gains were lost again in 2009, when the low beta was detrimental in months with strongly positive credit returns. This generated a drawdown of -80%. The same behavior occurred in the 2002 equity bear market following the collapse of the IT bubble, and the subsequent 2003 credit bull market. This time the drawdown was -51%. These episodes illustrate the sensitivity of TM spillover to strong changes in market sentiment from an equity bear market to a credit bull market. RM spillover is much less affected in such circumstances, because RM has a lower tendency to select companies with a low equity beta and low default risk during equity bear markets, so that it suffers less in the subsequent credit bull market. While TM spillover lost approximately -80% in 2009, RM spillover managed to limit the loss to -25%. Likewise, in 2003, RM spillover lost substantially less than TM spillover: -14% vs. -51%.

4.6. Risk-adjusted company selection or risk-adjusted strategy returns?

The residual equity return of a company can be interpreted as a risk-adjusted return: it corrects the equity return for the expected return that is driven by the company's exposure to the equity market. Therefore, the RM strategy tends to selects different companies than TM, which does not use this risk-adjustment. The results shown above demonstrate that the company selection based on residual equity returns substantially lowers the structural and time-varying risk of the momentum spillover strategy. However, one may wonder whether the risk reduction of RM could also be obtained by TM in combination with a hedge of the default risk of the strategy *after* the portfolio has been constructed.[5] To test whether this yields similar results, we use three methods to calculate risk-adjusted strategy returns, which could be interpreted as hedging methods:

1. *Static DEF method:* adjusting strategy returns for the structural *DEF* exposure by using the full-sample β_{DEF} estimate as shown in Table 5. For example, for TM spillover in the ALL universe, the beta equals -0.89, so that the risk-adjustment in month t is the credit market return DEF_t times -0.89.
2. *Dynamic DEF method:* adjusting strategy returns for both the structural and time-varying *DEF* exposures, by using the full sample β_{DEF} and $\beta_{DEF,RMRF}$ estimates as shown in Table 5. Extending the previous example, the risk-adjustment in month t equals the credit market return DEF_t times (-0.70 + 1.31$RMRF_{t-K:t-1}$), where $RMRF_{t-K:t-1}$ is the equity market return in the formation period.

[5] We thank an anonymous referee for this excellent suggestion.

3. *Dynamic rating x maturity method:* adjusting strategy returns for the bottom-up rating and maturity biases. We follow the methodology of Gebhardt et al. (2005) by first dividing the universe in six rating groups (AAA/AA, A, BBB, BB, B, CCC-C), and then, within each rating group, further dividing bonds in four maturity groups (0-10yr, 10-15yr, 15-20yr, 20+yr). For each bond, the risk-adjusted return is computed in excess of the average return of all bonds in the same rating x maturity peer group.

Table 6 reports the risk-adjusted return statistics for the momentum spillover strategies for the three methods, as well as the non-adjusted returns for comparison. Looking first at the non-adjusted returns, we observe that RM spillover has much lower volatility than TM spillover. For the ALL universe, the volatility is reduced by approximately 50%, which is in line with the reduction found by Blitz et al. (2011) and Chaves (2016) for equities. For the IG and HY universes, the reductions are smaller, but still substantial. Since the returns of RM spillover are a bit higher, the Sharpe ratios vastly improve, e.g. from 0.35 to 0.77 for the ALL universe.

Next, we consider the risk-adjusted return statistics. We find that all methods result in a reduction of the volatility of TM spillover. For example, for the ALL universe the static *DEF* hedge reduces volatility from 8.85% to 6.92%, the dynamic *DEF* hedge to 6.57% and the rating-maturity hedge to 6.17%. However, these risk reductions are not as large as obtained by RM spillover, which reduces volatility to 4.80%. We see the same patterns in the IG and HY universes. This implies that hedging the risk exposures *after* the construction of the TM spillover portfolio does not achieve the same level of risk reduction as directly constructing the portfolio based on residual equity returns.

Nonetheless, the Sharpe ratios of the hedged TM spillover portfolios are similar to the Sharpe ratio of the RM spillover portfolio. Does this suggest that the residualization of equity returns is redundant? Table 6 shows that combining RM spillover with a hedging method achieves the strongest results, regardless of the hedging method chosen, since the volatilities are the lowest and the Sharpe ratios the highest.

We conclude from Table 6 that by selecting companies on their residual momentum is effective in reducing the volatility from total momentum spillover and results in a superior Sharpe ratio, whether one uses risk-adjusted or non-adjusted returns to evaluate the strategies. This shows that there is added value in selecting companies on residual equity returns that cannot be realized by hedging the constructed portfolio.

[Insert Table 6 around here]

5. Robustness checks

In this section we show that our results are robust to different formation periods, holding periods, estimation window lengths and factor models for the residualization of equity returns and the evaluation of the portfolios. Besides we also document that the improvements of residual momentum spillover are robust across liquidity groups and credit ratings. Finally, we show that momentum spillover is not equity momentum or bond momentum in disguise.

5.1. Sensitivity to model parameters

So far, we have used a formation period and holding period of 6 months. The results are however robust for other combinations. We have verified the results for TM spillover and RM spillover for a formation period of 6 months with holding periods of 1, 3 and 12 months, and for a holding period of 6 months with formation periods of 1, 3 and 12 months.[6] For each combination of formation and holding period, RM spillover has much lower exposures (time-varying exposures ranging from 0.16 to 0.63) than TM spillover (time-varying exposures ranging from 0.64 to 1.52), resulting in a much lower volatility and higher Sharpe ratio for the residual strategy.

We have also investigated alternative regression windows for estimating residual equity returns, ranging from 24 to 60 months. For each estimation window the alphas and Sharpe ratios remain highly significant. Alphas range between 3.90% and 4.43%, while Sharpe ratios are between 0.68 and 0.81. Furthermore, all structural and time-varying default risk exposures of RM spillover remain substantially smaller than those of TM spillover.

5.2. Other factor models

In the construction of the residual equity returns, we have only residualized with respect to the equity market factor *RMRF*. However, as documented by Fama and French (1993), stock returns are not only driven by *RMRF*, but also by size (*SMB*) and value (*HML*). Therefore, we test an alternative residual momentum spillover strategy, denoted *FF3*-residual, that residualizes equity returns to all three Fama and French (1993) factors:

[6] A detailed overview of the results in this section are available upon request.

$$E_{i,t} = \alpha_i + \beta_{RMRF,i} RMRF_t + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \varepsilon_{i,t}\,. \tag{4}$$

The results are reported in Table 7, Panel A. The alpha is slightly lower compared to the 1-factor *RMRF*-only residual momentum spillover: 3.98% versus 4.43%, but still highly significant. However, the reduction in time-varying exposure ($\beta_{DEF,RMRF}$) is even stronger; while total momentum spillover has a coefficient of 1.31 and *RMRF*-only residual momentum spillover of 0.37, *FF3*-residual momentum spillover has a coefficient of just 0.25, which is not statistically significant.

So far, to evaluate momentum spillover we calculated a 1-factor alpha by regressing its returns on the credit market factor *DEF*. However, bond returns may also be driven by the equity factors *RMRF*, *SMB* and *HML*, as well by the *TERM* premium (Fama and French, 1993). Moreover, the *SMB* and *HML* exposures might spill over from the equity market to the bond market in a similar way as the *RMRF* exposure does, driving time-variation in the default risk exposure. Therefore we extend our evaluation framework to a more general form:[7]

$$r_t = \alpha + \sum_{i \in FF5} \beta_i F_{i,t} + \sum_{i \in FF3} \beta_{DEF,i} F_{i,t-K:t-1} DEF_t + \varepsilon_t \tag{5}$$

where *FF5*={*RMRF*, *SMB*, *HML*, *TERM*, *DEF*}, *FF3*={*RMRF*, *SMB*, *HML*}, $F_{i,t}$ is the return of factor *i* in month *t* and β_i and $\beta_{DEF,i}$ are the associated coefficients. Because we use excess returns over duration-matched Treasuries, we do not expect strong loadings on the *TERM* factor. The results are reported in Table 7, Panel B. This extended specification reveals that the time-variation in default risk exposure is not only driven by *RMRF*, but also by *SMB*. The strongest

[7] We also test an even more extended framework, which allows for time-varying exposures to not only *DEF*, but also to *RMRF*, *SMB*, *HML* and *TERM.* The results from this framework are very similar to those of equation (4): the R^2 increases from 0.54 to 0.56 and 11 of the additional 12 betas are insignificant.

driver remains *RMRF*, reducing the adjusted R^2 from 0.54 to 0.30. Including *SMB* and *HML* in the residualization reduces the R^2 further, from 0.30 to 0.25. Even though *RMRF*-residual momentum spillover does not explicitly residualize equity returns for *SMB* exposures, the time-variation due to *SMB* is nonetheless substantially reduced from 2.80 to 1.32. The time-variation is still statistically significant. By explicitly residualizing for *SMB* and *HML*, as is done in the *FF3*-residual momentum spillover, this time-variation coefficient $\beta_{DEF,SMB}$ is no longer significant.

We conclude that the profitability of momentum spillover cannot be explained by structural exposures to the five Fama and French (1993) factors, nor by the time-variation in default risk exposure spilling over from the equity market due to *RMRF*, *SMB* or *HML*. Moreover, the main channel driving time-variation in default risk exposure is via *RMRF*.

[Insert Table 7 around here]

5.3. Liquidity Effects

A concern when investing in corporate bonds is that they are less liquid than stocks. Some corporate bond strategies may unintentionally favor illiquid bonds, leading to less reliable results. Lin, Wang and Wu (2013) show that a substantial part of the momentum spillover return in corporate bond markets is a compensation for bearing liquidity risk. To examine the effect of liquidity on momentum spillover, we run two analyses.

In the first analysis, we create market value-weighted (VW) portfolios instead of equally-weighted (EW) portfolios. VW portfolios require lower turnover and therefore lower transaction costs to maintain than EW portfolios. Moreover, a VW portfolio is tilted towards larger bonds, which tend to be more liquid than smaller bonds; see Crabbe and Turner (1995) and Houweling, Mentink and Vorst (2005). When we compare the VW results[8] to the EW results, we observe lower, but still highly significant, alphas. Importantly, we find that RM spillover has substantially lower structural and time-varying *DEF* exposures than TM spillover, just like for EV portfolios. Also, the volatility of RM spillover is roughly half the volatility of TM spillover and the Sharpe ratio is more than doubled.

The second analysis in this section is more granular, as we run both the TM and RM spillover strategies on subsamples of bonds with different degrees of liquidity. In addition to bond size, previous literature shows that a bond's age (elapsed time since issuance) is a strong liquidity proxy; see e.g. Sarig and Warga (1989), and Houweling et al. (2005). For age we create groups of young, middle and old bonds, while for size we create groups of large, middle and small bonds. We construct momentum spillover portfolios within each of these equally-populated groups. Table 8 reports the results. In every liquidity group RM spillover has a lower volatility and a higher Sharpe ratio than TM spillover. Also, in line with earlier results, exposures and R^2-values are substantially smaller for RM spillover. The reduction in the time-varying exposure seems to be even stronger for young (and thus more liquid) bonds than for old bonds.

From these analyses, we conclude that momentum spillover returns and the enhancements obtained by using residual equity returns cannot be attributed to illiquidity.

[Insert Table 8 around here]

[8] The results for value-weighted portfolios are available upon request.

5.4. Credit Rating Effects

Avramov, Chordia, Jostova and Philipov (2007) find that equity momentum leads to disproportionally large investments in the lowest-rated companies. After excluding the lowest-rated issuers from their sample, they find that momentum disappears. One may wonder whether stock-bond momentum spillover also only works for lower-rated companies. A first indication that momentum spillover does work for higher-rated companies is provided in Table 5: the alphas are also highly significant in the Investment Grade universe. In Table 9 we make a more granular decomposition by splitting the universe in five equally populated sub-universes based on the credit rating. Within each rating group, quintile winner-minus-loser portfolios are constructed based on total or residual equity returns. The results clearly show that for lower ratings the alphas are higher, the structural default exposure is more negative and the spillover of default risk is also stronger. This is not surprising, given the more equity-like behavior of high-risk corporate bonds (Kwan, 1996). However, also within the 20% highest-rated bonds, there is still significant positive alpha and spillover of time-varying default risk. We conclude that the momentum spillover alpha cannot be attributed to the riskiest companies only.

[Insert Table 9 around here]

5.5. Is momentum spillover equity momentum or bond momentum in disguise?

The results so far show strong performance of momentum spillover. However, given that momentum spillover uses equity returns, just like a momentum strategy applied to equities, it could be that the alpha of momentum spillover is just the alpha of equity momentum, manifested in the corporate bond market. To test this hypothesis, we construct a decile equity momentum winner-minus-loser portfolio on the same data set and with the same formation and holding period as momentum spillover. Then we regress the return of the momentum spillover strategy in the corporate bond market on the return of the momentum strategy in the equity market, while controlling for structural and time-varying *DEF* exposures.[9] We find that (total) momentum spillover shows a highly significant positive loading on equity momentum, halving the alpha. However, the alpha remains highly significant, indicating that the momentum spillover effect is not subsumed by the equity momentum effect. We also observe that the $\beta_{DEF,RMRF}$ coefficient reduces from 1.31 to 0.75 (but still significant), because equity momentum has a similar time-varying risk profile as momentum spillover.

If we run the same regression for residual momentum spillover, we see similar patterns, though to a lesser extent. Both the coefficient and the *t*-statistic of equity momentum are smaller for RM spillover than for TM spillover. Also, the alpha reduction is smaller. Finally, we still observe the ability of residual momentum spillover to lower the structural and time-varying *DEF* exposures.

Next, we conduct the same regressions as above, but with bond momentum instead of equity momentum. We find that for both TM and RM spillover, the exposure to bond momentum is actually negative, not positive. We conclude that the alpha of momentum spillover is neither explained by equity momentum nor by bond momentum.

[9] The results of this regression are available upon request.

6. Conclusions

This paper investigates stock-bond momentum spillover. We first confirm and extend the results of Gebhardt et al. (2005) on the existence of a momentum spillover effect in investment grade bonds and continue by identifying, understanding and reducing the risks of the strategy. First, we show that the momentum spillover effect not only exists for investment grade bonds, but also for high yield bonds. Our second contribution is that we demonstrate that a traditional momentum spillover portfolio based on total equity returns exhibits a significantly negative default risk exposure at the moment of constructing the portfolio. We measure default risk by a variety of risk measures, including the beta to the credit market. This means that the strategy return is sensitive to the credit market return in the holding period. More specifically, this causes a drag on the profitability of momentum spillover, because the credit market has generated a positive return, on average.

Our third contribution is that we find that the default risk exposure of momentum spillover is time-varying, and strongly depends on the equity market return in the formation period. We show that the credit market beta of momentum spillover is more negative after negative equity market returns. This makes the strategy vulnerable to a turn in the market cycle, in which an equity bear market is followed by a credit bull market. For instance, in 2009, when the credit market recovered from the sub-prime crisis, the winner-minus-loser momentum spillover portfolio suffered a drawdown of -80%.

Fourth, we show that the time-varying default risk exposure of momentum spillover can be substantially reduced by ranking companies on their residual equity return, instead of on their total equity return. Compared to traditional momentum spillover based on total equity returns, residual momentum spillover has much smaller structural and time-varying default risk exposures. Further, it has half the volatility, the same return and hence double the Sharpe ratio. Also, the drawdowns are substantially reduced, e.g. in 2009 from -80% to -25%. Using residual equity returns to construct a momentum spillover portfolio is more effective in reducing the risk of the strategy than adding a hedge on top of a total momentum spillover portfolio. The benefits of using residual momentum are robust to the model specification and the effects of liquidity and credit ratings.

Appendix A: Distance-to-Default

The distance-to-default measure originates from the Merton (1974) structural model. In this model, the equity is modeled as a call option on the firm's assets, with the strike price being the value of the debt. The physical probability of default is given by

$$\pi^{P} = N(-DD^{P}) \tag{A1}$$

where *N(.)* denotes the cumulative distribution function of the standard normal distribution, and DD^{P}, the distance-of-default is given by

$$DD_t^P = \frac{\log\left(\frac{V_t}{X_t}\right) + (\mu - 0.5\sigma^2)(T - t)}{\sigma\sqrt{T - t}} \tag{A2}$$

where *log* is the natural logarithm, V_t the value of the firm's assets at time *t*, X_t the strike price of the option, μ the drift rate of the firms assets, σ the volatility of the assets and *T* the time-to-maturity of the option. The drift rate μ and volatility σ are unobservable. In the literature several methods exist to estimate these. We follow the procedure by Byström (2006), as it is not computationally intensive while it provides a good proxy. Equation (A2) then simplifies to

$$DD_t^P = \frac{\log\left(\frac{V_t}{X_t}\right)}{\sigma_E\left(1 - \frac{V_t}{X_t}\right)} \tag{A3}$$

where σ_E is the volatility of the firm´s equity.

We proxy the value of the firm with the sum of book value of total liabilities and market value of equity. The strike is set equal to the book value of total liabilities and σ_E is taken to be the past 1-year daily equity return volatility.

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Table 1: Descriptive statistics

	ALL	IG	HY
Mean excess return	1.76%	0.80%	2.70%
Volatility excess return	6.22%	4.04%	9.27%
Sharpe ratio excess return	0.28	0.20	0.29
Mean equity return over risk-free	7.99%	8.38%	6.01%
Volatility equity return over risk-free	19.31%	15.50%	25.49%
Sharpe ratio equity return	0.41	0.54	0.24
Credit spread (bps)	289	159	528
DtD	4.70	5.81	3.26
Leverage	0.54	0.49	0.60
Rating	10.56	7.57	14.50
Age	3.07	3.33	2.70
Amount outstanding	1650	2386	773
Number of companies per month	760	425	335

Descriptive statistics over the period January 1994 to December 2013 of Barclays U.S. Investment Grade and High Yield index constituents that have at least three years of stock return history on a US stock exchange. If a company has more than one bond outstanding in a particular month, we compute the market value weighted return over all its outstanding bonds. *ALL* represents the total universe, *IG* is the Investment Grade universe and *HY* is the High Yield universe. *Excess return* is the difference between a corporate bond's total return and duration-neutral Treasuries; *equity return* is the return of the corresponding stock; *credit spread* is the difference between the option-adjusted yield on the corporate bond and the duration-neutral Treasury yield; *DtD* is the distance-to-default, see Appendix A; *leverage* is the company's book value of total liabilities divided by the book value of total assets; *rating* is the median credit rating of the ratings provided by Standard & Poors, Moody's and Fitch. If the credit rating from only two agencies is available, the minimum rating is selected. Ratings are converted to a numerical scale: AAA=1, AA+=2, AA=3, etc. *Age* is the time-since-issuance in years; *amount outstanding* is the notional amount outstanding in mln USD. All statistics, except for the last row, are first calculated as an equally-weighted cross-sectional average, and subsequently computed over time. *Number of companies per month* is computed as the average through time. Means and volatilities are annualized.

Table 2: Performance statistics of momentum spillover

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Panel A: ALL											
Mean	3.92	2.46	2.03	2.03	1.67	1.69	1.68	1.69	1.77	0.85	3.08
Volatility	6.63	5.17	4.89	4.86	4.95	5.18	5.69	6.39	7.95	13.15	8.85
Sharpe ratio	0.59	0.48	0.42	0.42	0.34	0.33	0.30	0.26	0.22	0.06	0.35
Alpha	1.94***	0.89***	0.54**	0.54**	0.15	0.10	-0.07	-0.28	-0.65*	-2.86**	4.80***
	(4.23)	(3.28)	(2.45)	(2.25)	(0.70)	(0.47)	(-0.33)	(-1.16)	(-1.75)	(-1.97)	(2.77)
Panel B: IG											
Mean	1.56	1.36	1.31	1.09	1.04	0.95	0.86	0.66	0.36	-0.17	1.73
Volatility	3.94	3.74	3.86	3.98	4.06	3.86	4.17	4.29	4.45	6.38	4.16
Sharpe ratio	0.40	0.36	0.34	0.27	0.26	0.25	0.21	0.15	0.08	-0.03	0.42
Alpha	0.72***	0.56***	0.49***	0.24	0.17	0.12	-0.04	-0.26***	-0.60***	-1.34**	2.06***
	(4.00)	(4.09)	(3.52)	(1.45)	(1.36)	(1.05)	(-0.41)	(-3.06)	(-3.37)	(-1.97)	(2.60)
Panel C: HY											
Mean	5.83	4.05	3.62	3.47	3.42	3.55	3.26	3.15	2.20	0.04	5.79
Volatility	8.20	7.50	7.57	7.48	8.11	8.54	9.27	10.10	12.46	18.13	13.25
Sharpe ratio	0.71	0.54	0.48	0.46	0.42	0.42	0.35	0.31	0.18	0.00	0.44
Alpha	3.12***	1.53***	1.04***	0.92***	0.65	0.62	0.06	-0.34	-2.01**	-5.63***	8.74***
	(4.51)	(3.18)	(2.68)	(2.70)	(1.48)	(1.35)	(0.14)	(-0.77)	(-2.33)	(-2.79)	(3.55)

Mean return, volatility, Sharpe ratio and 1-factor alpha of momentum spillover for decile portfolios D1, …, D10 and winner-minus-loser portfolio D1-D10. The return per decile portfolio in month *t* is calculated as the average return of the decile portfolios constructed from month *t-6* to *t*-1. Each month, the decile portfolios take equally-weighted positions in the bonds of the companies that according to their past 6-month equity returns belong in the decile portfolio. The 1-factor alpha is obtained by regressing the strategy return on the corporate bond default factor (*DEF*). *t*-statistics are reported in parentheses. Significance at the 90%, 95% and 99% levels are indicated with *, ** and *** respectively. Mean, volatility and alpha are annualized and expressed in percentages. Panel A shows results for the total universe (ALL), Panel B for Investment Grade (IG) and Panel C for High Yield (HY). Sample period from January 1994 to December 2013.

Table 3: Default risk statistics of momentum spillover per decile portfolio

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Panel A: ALL											
DEF beta	1.02	0.81	0.77	0.77	0.78	0.82	0.90	1.02	1.25	1.91	-0.89
Rating	12.51	10.48	9.79	9.46	9.36	9.40	9.56	10.04	10.94	13.66	-1.15
Credit spread	334	246	223	215	217	220	234	265	338	684	-350
DtD	3.71	4.78	5.22	5.37	5.44	5.38	5.24	4.87	4.30	2.77	0.94
Leverage	0.51	0.50	0.50	0.51	0.51	0.52	0.53	0.55	0.57	0.68	-0.17
Panel B: IG											
DEF beta	0.94	0.90	0.93	0.95	0.98	0.93	1.01	1.04	1.07	1.31	-0.37
Rating	7.96	7.61	7.48	7.41	7.42	7.42	7.42	7.49	7.56	7.87	0.09
Credit spread	161	152	150	150	152	152	155	161	168	207	-46
DtD	5.18	5.85	6.09	6.09	6.15	6.14	6.04	5.82	5.54	4.61	0.57
Leverage	0.45	0.47	0.48	0.49	0.50	0.50	0.51	0.52	0.52	0.54	-0.09
Panel C: HY											
DEF beta	0.83	0.77	0.79	0.78	0.85	0.90	0.98	1.07	1.29	1.73	-0.90
Rating	14.91	14.19	14.00	13.94	13.90	13.99	14.10	14.34	14.71	15.75	-0.84
Credit spread	470	415	411	415	422	451	483	541	654	1021	-550
DtD	2.86	3.57	3.79	3.91	3.91	3.82	3.63	3.31	2.84	1.99	0.87
Leverage	0.55	0.54	0.55	0.56	0.57	0.59	0.61	0.63	0.67	0.76	-0.21

Default risk statistics for decile portfolios D1, …, D10 and winner-minus-loser portfolio D1-D10 of momentum spillover.. Each month, the decile portfolios take equally-weighted positions in the bonds of the companies that according to their past 6-month equity returns belong in the decile portfolio. *DEF beta* is obtained from a time-series regression of the portfolio return on the *DEF* factor; *rating* is the median credit rating of the ratings provided by Standard & Poors, Moody's and Fitch. If the credit rating from only two agencies is available, the minimum rating is selected. Ratings are converted to a numerical scale: AAA=1, AA+=2, AA=3, etc.; *credit spread* is the difference between the option-adjusted yield on the corporate bond and the duration-neutral Treasury yield; *DtD* is the distance-to-default, see Appendix A for a definition; *leverage* is the company's book value of total liabilities divided by the book value of total assets. All risk measures, except for the *DEF beta*, are first calculated as cross-sectional averages over a portfolio's constituents at the time of formation, and then averaged over time. Panel A shows results for the total universe (ALL), Panel B for Investment Grade (IG) and Panel C for High Yield (HY). Sample period from January 1994 to December 2013.

Table 4: Default risk statistics of momentum spillover per equity state

	DEF beta	Rating	Credit spread	DtD	Leverage	*RMRF* beta
Panel A: ALL						
Average	-0.89	-1.15	-350	0.94	-0.17	-0.10
Low *RMRF*	-0.97	-2.88	-913	1.75	-0.25	-0.77
2	-1.21	-1.58	-314	1.42	-0.20	-0.33
3	-0.72	-0.61	-224	0.81	-0.18	-0.09
4	-0.59	-1.15	-221	0.93	-0.15	0.12
High *RMRF*	-0.25	0.49	-75	-0.24	-0.07	0.54
Panel B: IG						
Average	-0.37	0.09	-46	0.57	-0.09	-0.07
Low *RMRF*	-0.35	0.11	-153	1.73	-0.15	-0.63
2	-1.10	0.00	-45	1.10	-0.13	-0.20
3	-0.42	0.19	-20	0.39	-0.11	-0.01
4	-0.15	-0.06	-15	0.28	-0.06	0.09
High *RMRF*	0.11	0.22	3	-0.68	0.00	0.40
Panel C: HY						
Average	-0.90	-0.84	-550	0.87	-0.21	-0.10
Low *RMRF*	-1.02	-1.98	-1339	1.33	-0.28	-0.74
2	-0.98	-0.90	-456	1.15	-0.23	-0.39
3	-0.53	-0.69	-368	0.88	-0.22	-0.10
4	-0.63	-0.69	-376	0.88	-0.20	0.14
High *RMRF*	-0.49	0.05	-213	0.08	-0.12	0.59

Default risk statistics for winner-minus-loser portfolio of momentum spillover. The return in month *t* is calculated as the average of the winner-minus-loser portfolio constructed from month *t-6* to *t*-1. Each month, the winner (loser) portfolio takes equally-weighted positions in the bonds of the best (worst) companies according to their past 6-month equity returns. *DEF beta* is obtained from a time-series regression of the portfolio return on the *DEF* factor; *rating* is the median credit rating of the ratings provided by Standard & Poors, Moody's and Fitch. If the credit rating from only two agencies is available, the minimum rating is selected. Ratings are converted to a numerical scale: AAA=1, AA+=2, AA=3, etc.; *credit spread* is the difference between the option-adjusted yield on the corporate bond and the duration-neutral Treasury yield; *DtD* is the distance-to-default, see Appendix A; *leverage* is the company's total liabilities divided by the total assets*; RMRF beta* is obtained by calculating per stock the rolling 36-month beta to the *RMRF* factor. All risk measures, except for the *DEF beta*, are first calculated as cross-sectional averages over a portfolio's constituents at the time of formation, and then averaged over time. Panel A shows results for the total universe (ALL), Panel B for Investment Grade (IG) and Panel C for High Yield (HY). Sample period from January 1994 to December 2013.

Table 5: Structural and time-varying default exposures of total and residual momentum spillover

	Total momentum spillover			Residual momentum spillover		
	β_{DEF}	$\beta_{DEF,RMRF}$	Adj. R^2	β_{DEF}	$\beta_{DEF,RMRF}$	Adj. R^2
Panel A: ALL						
	-0.89***		0.39	-0.33**		0.18
	(-3.72)			(-2.33)		
	-0.70***	1.31***	0.44	-0.28**	0.37**	0.19
	(-3.49)	(3.35)		(-2.05)	(2.23)	
Panel B: IG						
	-0.37		0.13	-0.15		0.03
	(-1.55)			(-1.02)		
	-0.21	0.90**	0.18	-0.15	0.01	0.03
	(-1.03)	(2.49)		(-0.96)	(0.08)	
Panel C: HY						
	-0.90***		0.40	-0.52***		0.33
	(-5.47)			(-5.07)		
	-0.76***	1.02***	0.43	-0.47***	0.41**	0.34
	(-5.55)	(2.84)		(-4.65)	(2.08)	

Structural and time-varying default exposures for winner-minus-loser portfolio of total momentum spillover (left) and residual (right) momentum spillover. The return r_t in month t is calculated as the annualized average of the winner-minus-loser portfolio constructed from month t-6 to t-1. Each month, the winner (loser) portfolio takes equally-weighted positions in the bonds of the winner (loser) companies according to their past 6-month total or residual equity return. Residual equity returns are estimated using equation (3). The structural exposure β_{DEF} to the corporate bond market factor *DEF* is estimated using equation (1). The time-varying exposures $\beta_{DEF,RMRF}$, where the exposure to *DEF* is dependent on the equity market return *RMRF* in the formation period, is estimated according to equation (2). t-statistics are reported in parentheses. Significance at the 90%, 95% and 99% levels are indicated with *, ** and *** respectively. Mean, volatility and alpha are annualized and expressed in percentages. Panel A shows results for the total universe (ALL), Panel B for Investment Grade (IG) and Panel C for High Yield (HY). Sample period from January 1994 to December 2013.

Table 6: Risk-adjusted returns of total and residual momentum spillover

Risk-adjustment	Non-adjusted		β_{DEF} -adjusted		β_{DEF} & $\beta_{DEF,RMRF}$ - adjusted		Rating & maturity adjusted	
Momentum spillover	**total**	**residual**	**total**	**residual**	**total**	**residual**	**total**	**residual**
Panel A: ALL								
Mean	3.08%	3.70***	4.80***	4.34***	5.12***	4.43***	4.21%**	3.78%***
	(1.19)	(3.05)	(2.77)	(3.75)	(2.97)	(3.80)	(2.33)	(3.76)
Volatility	8.85%	4.80%	6.92%	4.33%	6.57%	4.29%	6.17%	3.98%
Sharpe ratio	0.35	0.77	0.69	1.00	0.78	1.03	0.68	0.95
Panel B: IG								
Mean	1.73%*	1.99***	2.06***	2.12***	2.28***	2.12***	1.68%*	1.98%***
	(1.85)	(3.13)	(2.60)	(3.03)	(2.92)	(3.08)	(1.95)	(3.63)
Volatility	4.16%	3.08%	3.87%	3.02%	3.75%	3.02%	3.82%	2.64%
Sharpe ratio	0.42	0.64	0.53	0.70	0.61	0.70	0.44	0.75
Panel C: HY								
Mean	5.79%	6.13***	8.74***	7.83***	8.96***	7.92***	6.69%**	5.96%***
	(1.59)	(2.88)	(3.55)	(4.58)	(3.61)	(4.63)	(2.32)	(3.21)
Volatility	13.25%	8.40%	10.26%	6.86%	9.96%	6.79%	10.48%	7.32%
Sharpe ratio	0.44	0.73	0.85	1.14	0.90	1.17	0.64	0.81

Risk-adjusted returns of winner-minus-loser portfolios of total momentum spillover ('total') and residual momentum spillover ('residual'). The return r_t in month t is calculated as the average of the winner-minus-loser portfolio constructed from month t-6 to t-1. Each month, the winner (loser) portfolio takes equally-weighted positions in the bonds of the best (worst) companies according to their past 6-month total (residual) equity returns. Residual equity returns are estimated using equation (2). We test three risk-adjustments: 1. excess returns after hedging with the full sample exposure β_{DEF} (as reported in Table 5), 2. excess returns after hedging with the full sample β_{DEF} and $\beta_{DEF,RMRF}$ exposure (as reported in Table 5) and 3. excess returns over rating (AAA/AA, A, BBB, BB, B, CCC-C) x maturity (0-10yr, 10-15yr, 15-20yr, 20+yr) peer groups. t-statistics are reported in parentheses. Significance at the 90%, 95% and 99% levels are indicated with *, ** and *** respectively. Mean and volatility are annualized and expressed in percentages. Panel A shows results for the total universe (ALL), Panel B for Investment Grade (IG) and Panel C for High Yield (HY). Sample period from January 1994 to December 2013.

Table 7: Alphas and betas of total and residual momentum spillover for various factor model specifications

Momentum spillover	Alpha	β_{RMRF}	β_{SMB}	β_{HML}	β_{TERM}	β_{DEF}	$\beta_{DEF,RMRF}$	$\beta_{DEF,SMB}$	$\beta_{DEF,HML}$	Adj. R^2
Panel A: time-varying *DEF* exposures depend on *RMRF*										
total	5.12***					-0.70***	1.31***			0.44
	(2.97)					(-3.49)	(3.35)			
RMRF-residual	4.43***					-0.28**	0.37**			0.19
	(3.80)					(-2.05)	(2.23)			
FF3-residual	3.98***					-0.24**	0.25			0.15
	(3.84)					(-1.99)	(1.60)			
Panel B: time-varying *DEF* exposures depend on *RMRF*, *SMB* and *HML*										
total	5.15***	-0.06	-0.09**	-0.11**	0.02	-0.49*	1.87***	2.80***	-0.46	0.54
	(2.60)	(-1.27)	(-1.97)	(-1.99)	(0.16)	(-1.91)	(4.64)	(3.21)	(-1.06)	
RMRF-residual	4.35***	-0.04	-0.04	-0.03	-0.01	-0.17	0.67***	1.32**	-0.50	0.30
	(3.15)	(-1.36)	(-1.29)	(-1.43)	(-0.19)	(-1.06)	(3.48)	(2.17)	(-1.58)	
FF3-residual	3.95***	-0.04	-0.04	-0.05*	0.00	-0.11	0.55***	1.07	-0.52	0.25
	(3.25)	(-1.39)	(-1.45)	(-1.66)	(0.02)	(-0.76)	(2.75)	(1.63)	(-1.49)	

Structural and time-varying factor exposures for winner-minus-loser portfolio of total momentum spillover, residual momentum spillover based on *RMRF* and residual momentum spillover based on *RMRF*, *SMB* and *HML* (FF3). The return r_t in month t is calculated as the average of the winner-minus-loser portfolio constructed from month t-*6* to t-1. Each month, the winner (loser) portfolio takes equally-weighted positions in the bonds of the companies that according to their past 6-months (residual) equity returns belong in the winner (loser) portfolio. Residual equity returns are estimated using equation (2) for *RMRF*-residual momentum spillover or equation (3) for *FF3*-residual momentum spillover. We estimate the structural exposure β_{DEF} and time-varying exposures $\beta_{DEF,i}$ to the corporate bond market factor *DEF* using equation (2),for Panel A (*DEF* exposure depends on *RMRF* in the formation period) or using equation (4) for Panel B (*DEF* exposure depends on *RMRF*, *SMB* and *HML* in the formation period). t-statistics are reported in parentheses. Significance at the 90%, 95% and 99% levels are indicated with *, ** and *** respectively. Mean, volatility and alpha are annualized and expressed in percentages. Results are on the total universe. Sample period from January 1994 to December 2013.

Table 8: Statistics total and residual momentum spillover per liquidity segment

	Momentum spillover	Mean	Volatility	Sharpe ratio	Alpha	β_{DEF}	$\beta_{DEF,RMRF}$	Adj. R^2
Panel A: Age								
Age 1 (old)	total	1.53	5.04	0.30	2.78***	-0.40***	0.91***	0.52
		(0.99)			(3.20)	(-7.16)	(5.80)	
	residual	1.52**	2.82	0.54	1.96***	-0.13***	0.35***	0.20
		(2.38)			(4.02)	(-2.72)	(2.68)	
Age 2	total	1.70	7.11	0.24	3.37**	-0.53***	1.21***	0.46
		(0.84)			(2.55)	(-3.30)	(4.21)	
	residual	3.06***	4.28	0.71	3.60***	-0.25**	0.10	0.15
		(3.05)			(3.61)	(-2.27)	(0.67)	
Age 3 (young)	total	2.39	7.17	0.33	4.13***	-0.55***	1.31***	0.50
		(1.10)			(2.87)	(-3.27)	(3.55)	
	residual	3.15**	4.61	0.68	3.87***	-0.33***	0.17	0.22
		(2.48)			(3.33)	(-2.88)	(1.02)	
Panel B: Size								
Size 3 (small)	total	1.82	5.96	0.31	3.24***	-0.44***	1.07***	0.47
		(1.05)			(2.99)	(-3.03)	(2.76)	
	residual	2.56***	3.68	0.70	3.17***	-0.25***	0.23	0.24
		(2.75)			(3.86)	(-2.61)	(1.48)	
Size 2	total	0.87	7.02	0.12	2.68***	-0.54***	1.45***	0.56
		(0.43)			(2.81)	(-5.58)	(4.45)	
	residual	1.95**	3.85	0.51	2.52***	-0.25***	0.17	0.20
		(2.46)			(3.96)	(-4.59)	(1.25)	
Size 1 (large)	total	2.88	7.42	0.39	4.30***	-0.50***	0.86***	0.30
		(1.37)			(2.60)	(-3.21)	(3.54)	
	residual	3.34***	4.79	0.70	3.86***	-0.23*	0.11	0.10
		(2.58)			(3.00)	(-1.94)	(0.75)	

Total and residual momentum spillover performance statistics for three liquidity segments based on age (Panel A) and size (Panel B). We first split the universe in three equally populated sub-universes based on age or size. Subsequently we create 5 portfolios based on total or residual spillover momentum. The return r_t in month t is calculated as the average of the winner-minus-loser quintile portfolio constructed from month t-K to t-1. Each month, the winner (loser) portfolio takes equally-weighted positions in the bonds of the companies that according to their past J-months (residual) equity returns belong in the quintile winner (loser) portfolio. Residual equity returns are estimated using equation (2). Alphas and betas are estimated according to equation (2). β_{DEF} is the structural exposure to the corporate bond market DEF, and $\beta_{DEF,RMRF}$ is the time-varying exposure, where the exposure to DEF is dependent on the equity market return $RMRF$ in the formation period. t-statistics are reported in parentheses. Significance at the 90%, 95% and 99% levels are indicated with *, ** and *** respectively. Mean, volatility and alpha are annualized and expressed in percentages. Results are on the total universe. Sample period from January 1994 to December 2013.

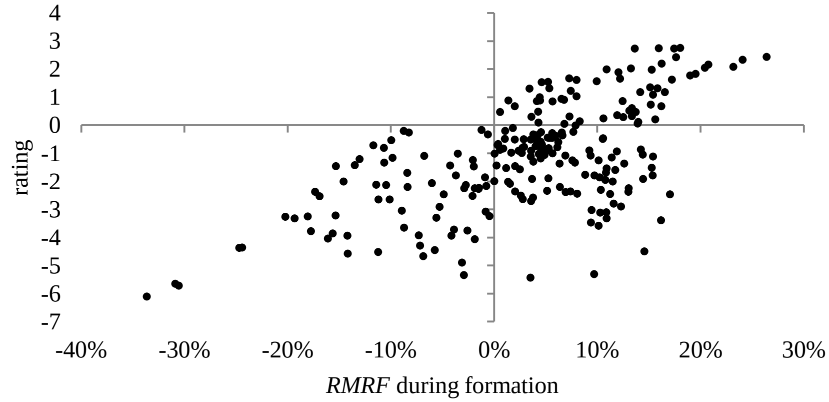
Table 9: Statistics total and residual momentum spillover per rating sub-universe

	Momentum spillover	Mean	Volatility	Sharpe ratio	Alpha	β_{DEF}	$\beta_{DEF,RMRF}$	Adj. R^2
Q1 (low rating)	total	7.87**	13.80	0.57	10.48***	-1.06***	1.03**	0.31
		(2.09)			(3.78)	(-8.19)	(2.50)	
	residual	7.71***	10.38	0.74	9.32***	-0.68***	0.56*	0.21
		(2.88)			(4.23)	(-5.71)	(1.65)	
Q2	total	1.79	6.14	0.29	3.24***	-0.56***	0.67**	0.48
		(1.02)			(2.87)	(-4.42)	(2.34)	
	residual	2.35**	4.06	0.58	3.07***	-0.37***	0.03	0.32
		(2.22)			(3.59)	(-3.88)	(0.19)	
Q3	total	1.14	3.79	0.30	1.95***	-0.26***	0.58***	0.38
		(1.10)			(2.75)	(-3.31)	(3.64)	
	residual	1.97***	2.67	0.73	2.17***	-0.17***	-0.25	0.12
		(3.30)			(3.89)	(-3.12)	(-1.54)	
Q4	total	1.25*	2.83	0.44	1.63***	-0.09	0.40	0.15
		(1.94)			(2.71)	(-0.87)	(1.63)	
	residual	1.44***	2.00	0.72	1.56***	-0.07	-0.02	0.03
		(3.39)			(3.43)	(-1.10)	(-0.22)	
Q5 (high rating)	total	1.20*	3.10	0.39	1.51**	-0.10	0.22**	0.07
		(1.93)			(2.36)	(-1.16)	(2.08)	
	residual	1.14**	2.57	0.44	1.13*	-0.04	-0.16**	0.00
		(2.28)			(1.95)	(-0.54)	(-2.51)	

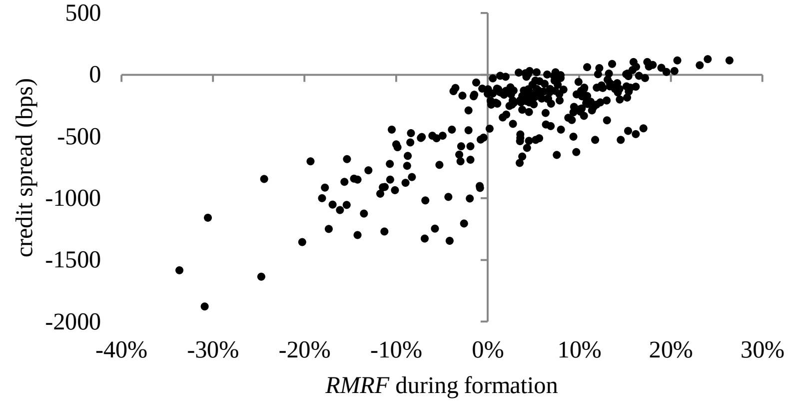
Total and residual momentum spillover performance statistics for five rating sub universes. We first split the universe in five equal sized sub universes based on rating. Subsequently we create 5 portfolios based on total/residual spillover momentum. The return r_t in month t is calculated as the average of the winner-minus-loser quintile portfolio constructed from month t-K to t-1. Each month, the winner (loser) portfolio takes equally-weighted positions in the bonds of the companies that according to their past J-months (residual) equity returns belong in the quintile winner (loser) portfolio. Residual equity returns are estimated using equation (2). Alphas and betas are estimated according to equation (2). β_{DEF} is the structural exposure to the corporate bond market DEF, and $\beta_{DEF,RMRF}$ is the time-varying exposure, where the exposure to DEF is dependent on the equity market return $RMRF$ in the formation period. t-statistics are reported in parentheses. Significance at the 90%, 95% and 99% levels are indicated with *, ** and *** respectively. Mean, volatility and alpha are annualized and expressed in percentages. Results are on the total universe. Sample period from January 1994 to December 2013.

Figure 1: Time-varying risk characteristics of momentum spillover

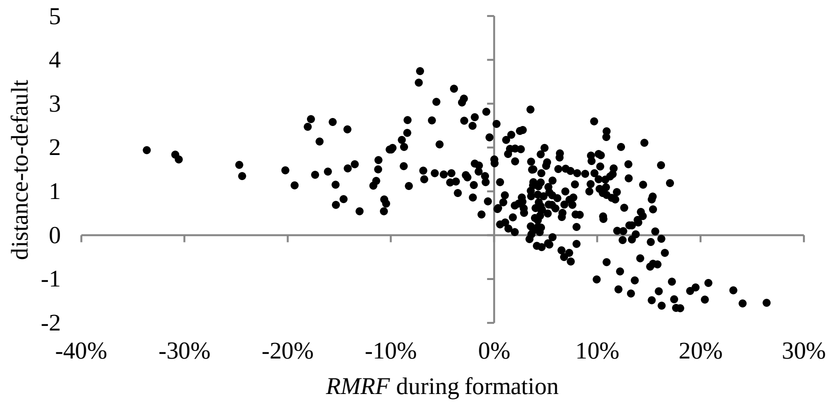
Panel A: rating



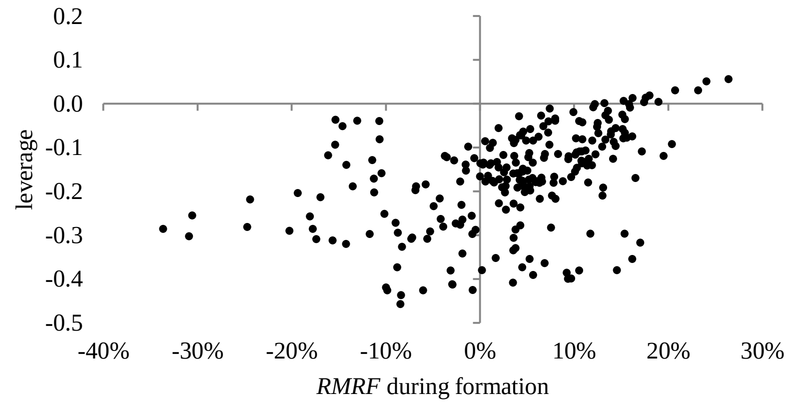
Panel B: credit spread



Panel C: DtD

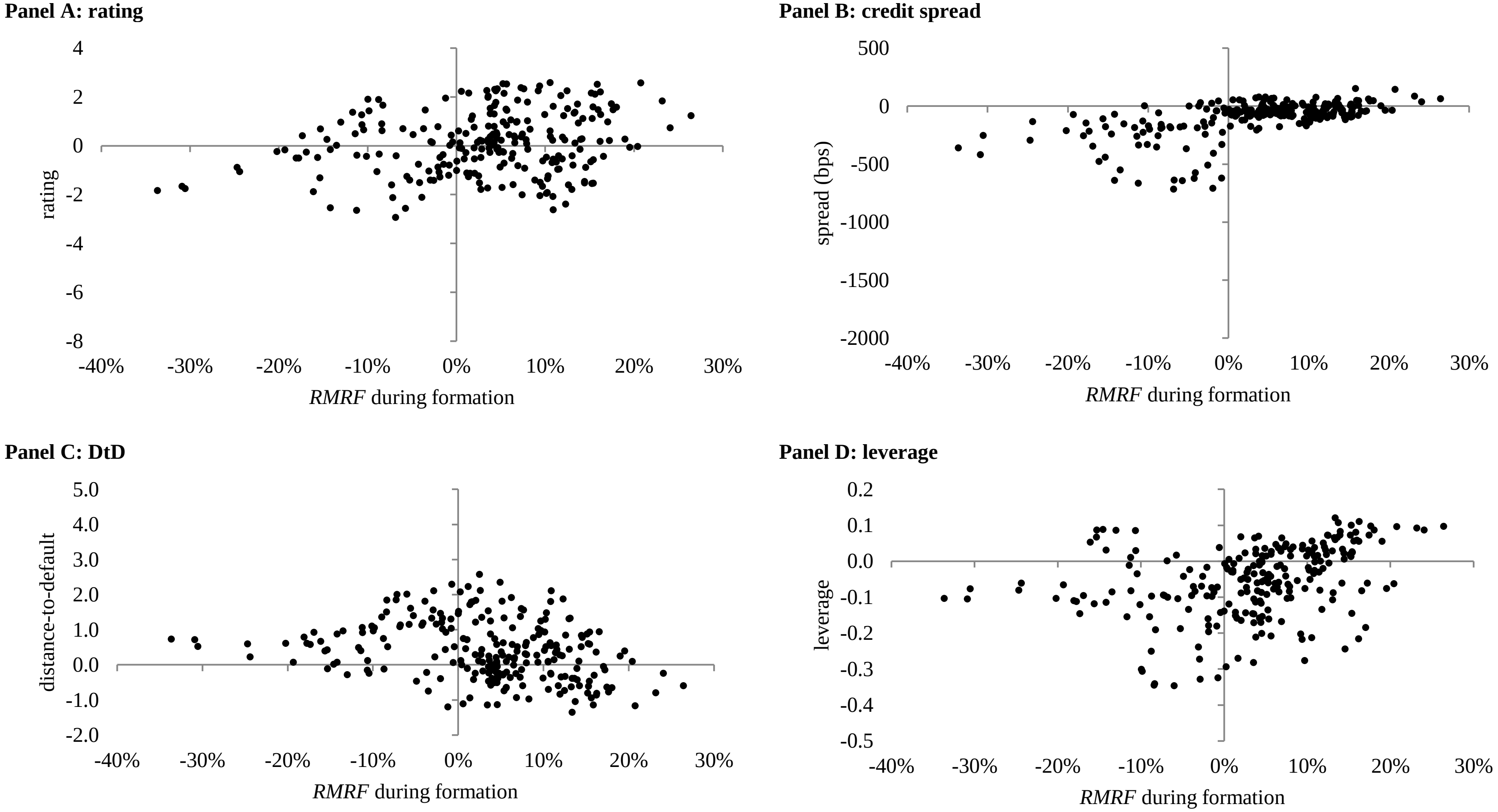


Panel D: leverage



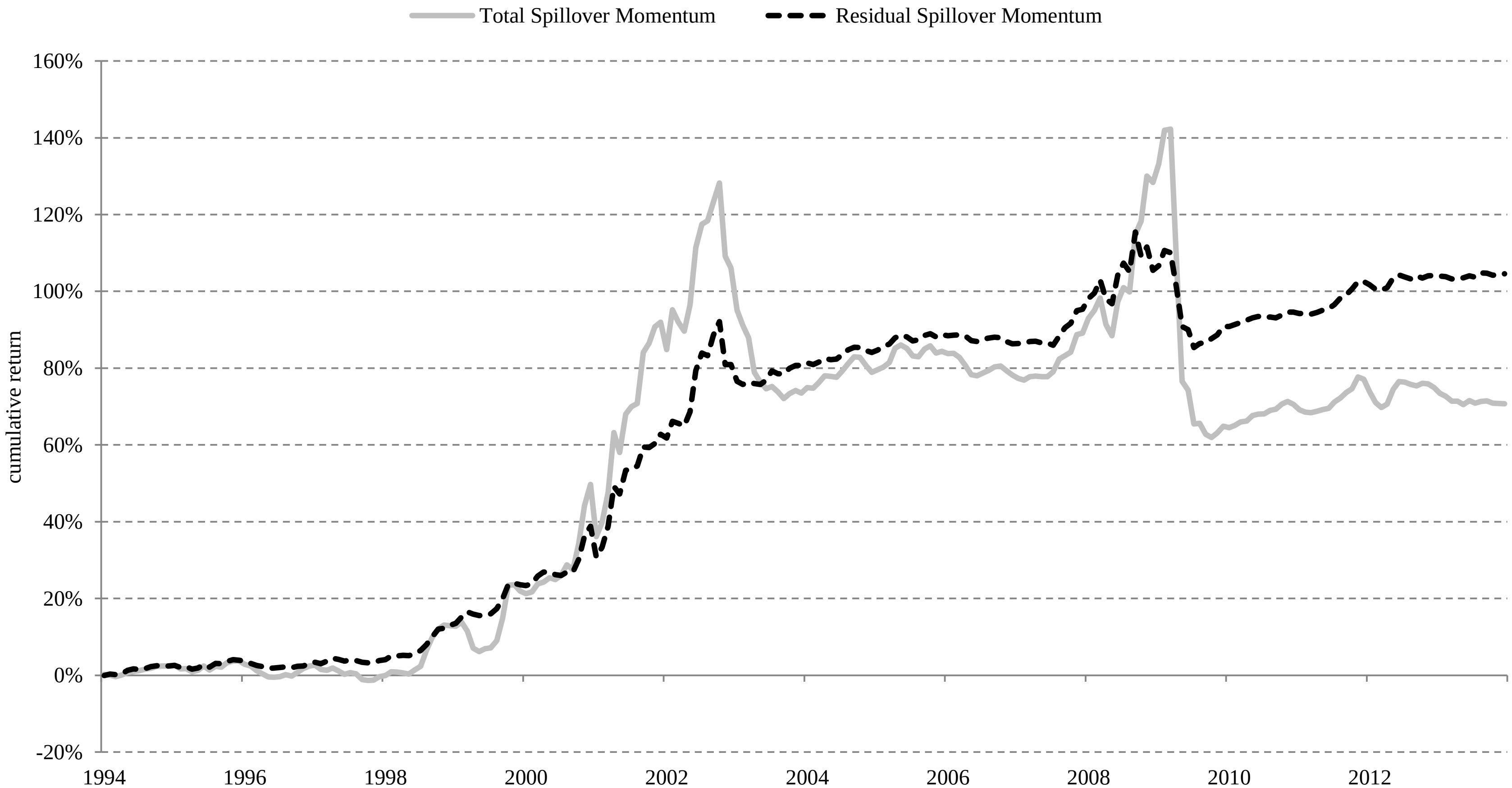
Graphical representation of the relationship between the equity market return in the formation period and average default risk characteristics of winner-minus-loser D1-D10 momentum spillover portfolio in holding period. The momentum spillover portfolio has a 6-month formation period and 6-month holding period. The equity market return is represented by the Fama and French (1993) *RMRF* factor and is measured over the 6-month formation period. The default risk characteristics are *rating* (Panel A), *spread* (Panel B), *DtD* (Panel C) and *leverage* (Panel D). *Rating* is the median credit rating of the ratings provided by Standard & Poors, Moody's and Fitch. If the credit rating from only two agencies is available, the minimum rating is selected. Ratings are converted to a numerical scale: AAA=1, AA+=2, AA=3, etc.; *credit spread* is the difference between the option-adjusted yield on the corporate bond and the duration-neutral Treasury yield; *DtD* is the distance-to-default, see Appendix A for details; *leverage* is the company's total liabilities divided by the total assets. All risk measure observations are calculated as cross-sectional averages over the constituents in the winner-minus-loser portfolio. Results are on the total universe, comprising Investment Grade and High Yield. Sample period from January 1994 to December 2013.

Figure 2: Time-varying risk characteristics of residual momentum spillover



Graphical representation of the relationship between the equity market return in the formation period and average default risk characteristics of winner-minus-loser residual momentum spillover portfolio in holding period. The residual momentum spillover portfolio has a 6-month formation period and 6-month holding period. The equity market return is represented by the Fama and French (1993) *RMRF* factor and is measured over the 6-month formation period. The default risk characteristics are *rating* (Panel A), *spread* (Panel B), *DtD* (Panel C) and *leverage* (Panel D). *Rating* is the median credit rating of the ratings provided by Standard & Poors, Moody's and Fitch. If the credit rating from only two agencies is available, the minimum rating is selected. Ratings are converted to a numerical scale: AAA=1, AA+=2, AA=3, etc.; *credit spread* is the difference between the option-adjusted yield on the corporate bond and the duration-neutral Treasury yield; *DtD* is the distance-to-default, see Appendix A for a definition; *leverage* is the company's total liabilities divided by the total assets. All risk measure observations are calculated as cross-sectional averages over the constituents in the winner-minus-loser portfolio. Results are on the total universe, comprising Investment Grade and High Yield. Sample period from January 1994 to December 2013.

Figure 3: Cumulative return total and residual momentum spillover top-minus-bottom portfolios



Cumulative return of the total and residual momentum spillover winner-minus-loser portfolio. The spillover portfolio return in month *t* is calculated as the average of the winner-minus-loser portfolio constructed from month *t-6* to *t*-1. Each month, the winner (loser) portfolio takes equally-weighted positions in the bonds of the companies that according to their past 6-months equity returns belong in the winner (loser) portfolio. Residual equity returns are estimated following equation (2). Results are on the total universe, comprising Investment Grade and High Yield. Sample period from January 1994 to December 2013.