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Acknowledgements

This dissertation marks the end of my PhD track at Tilburg University. Officially, this project started two years ago, but looking back it really has been the result of the support of many and my passion for economics and mathematics ever since my childhood. As a 12-year old, I was already intrigued by financial markets. After cycling back from school to my parents' home, I turned on the tv at 16.00, just in time for a new market update on RTL Z, a Dutch financial tv channel. The U.S. stock exchanges had just opened, and that usually meant markets were moving. I did not fully understand why markets were moving, but somehow this routine continued throughout secondary school. At the sixth grade, I had to pick a bachelor study. However, I could not find a study I liked until I found out about econometrics, a study combining mathematics with economics. I was immediately sold, and during the years at Tilburg University I only got more excited about econometrics.

During the master's phase a course called "Empirical Finance" was taught. I remember I was not too excited about this course, as all this research on the efficiency of markets seemed very abstract to me. However, during that course, there was a guest lecture from amongst others Laurens Swinkels, telling about the work he did at Robeco, and, of course, advertising the Robeco Super Quant internship program. That lecture had stuck in my mind, as in my final year I decided to apply at Robeco to write my master thesis. The interview was with Daniel Haesen and Patrick Houweling, and although it felt I would not be hired as I didn't knew anything about these instruments called "corporate bonds" (I even failed to mention interest rate risk as being important for corporate bonds...), they still decided to hire me, for which I am very grateful. Thanks to their dedication throughout the internship, I could quickly get my (corporate bonds) knowledge up to speed and write my thesis about the spillover of momentum effects from stocks to bonds. In the years after, we were able to turn this research into a publication in the Journal of Banking & Finance, and this also forms the basis of Chapter 5.

Although my name is on this dissertation, I could not have written it without all the support and feedback others have given me over the years.

First of all, I would like to thank my promotor Joost Driessen. We have had many lively discussions, either via Skype or in person, and they all had in common that they usually took much longer than the planned hour. My personal goal with the PhD track was to get better at putting results in an academic context, and I have definitely learned a lot while working on the various papers together. I couldn't have wished a better promotor, and I look forward to get the articles published. I would also like to thank Frank de Jong, my co-promotor, and the committee members Lieve Baele, Esther Eiling, Frans de Roon and Ton Vorst, for taking the time to review my work and providing me with feedback. You gave me the biggest compliment possible by saying you had enjoyed reading my work. To me, that is at least as important as the concise feedback on the contents.

Second, I like to thank all colleagues and interns at Robeco with whom I have worked with over the years. Not only because of all the time we shared at the office, but also for all the fun activities like running, cycling, after-work drinks, table soccer or the combination of the latter two. I want to thank a few in particular as there are too many to mention all. First, David for giving me the opportunity to combine my job with this PhD track and for regularly challenging my work. I want to thank Martin and Johan for all their fixed income expertise offered to me in the first years of my career and to thank Winfried, who seems to be an expert at everything. Whenever I needed a reference, Winfried would dig up exactly the (typically 1970/1980's) paper I needed. A big thank you to Weili and Wilma for their valuable advice when I needed it. Last but not least, a big thank you to Patrick for being my mentor throughout my career at Robeco. We both share the passion for corporate bonds and quant and I hope we can make the whole world as enthusiastic about this combination as we are. Our paper on corporate bond factor investing, Chapter 6 of this dissertation, is one attempt in achieving that goal.

Finally, I like to thank my friends and family. In particular, I want to thank my brother Jurgen for his help with the layout of this dissertation, and my parents for their support throughout my studies and career. Most importantly, I want to thank my girlfriend Janneke for her continuous support. It has not always been easy to combine the PhD track with other activities. When people asked me how I combined a full-time job with a PhD track, I usually replied, half-joking, "I get one day a week from Robeco and one day a week from Janneke". This dissertation marks the end of that period.

Jeroen van Zundert
Rotterdam, November 5, 2017

Contents

Chapter 1

Introduction

Global capital markets play a key role in today's world economy by connecting savers who do not need their wealth right away to those who can utilize the wealth productively, such as companies (for example to build factories, or acquire another company) and governments (to improve public infrastructure, invest in health care, etc.). Savers supply capital via their savings and investments accounts, but also via their pension savings.

In the academic world, a large debate is ongoing since the 1960's on whether capital markets are efficient (Malkiel and Fama, 1970). If markets are efficient, prices of assets should reflect all available information. In this dissertation, I study the efficiency of stock and corporate bond markets, i.e. the two primary means of financing for companies. There are five chapters, each taking a different angle at whether stock and/or corporate bond markets are efficient.

First, in Chapter 2 individual and aggregate stock returns are decomposed in three components, namely cash flow news, interest rate news and risk premium news. Previous studies, most notably the "good beta, bad beta" paper by Campbell and Vuolteenaho (2004), do not include an interest rate component. I find that unexpected interest rate changes account for more than $1/3^{\text{rd}}$ of all variation in stock market returns. Using various stock portfolio sorts, I find that exposure to interest rate news, called interest rate beta or "ugly" beta, has a higher price of risk than both nominal cash flow beta and risk premium beta.

Second, in Chapter 3 I study the link between the prices of stocks and corporate bonds of the same firm. In theory, as both securities are claims on the same firm assets, the prices should be integrated, a notion formalized by Merton (1974). I compare corporate bond implied stock returns, inferred from credit spreads and expected losses due to default, to realized stock returns to determine the level of integration. Surprisingly, there is a strong negative correlation between expected and realized stock returns over the period 1994-2015: stocks of which the corporate bond implies high returns realize low returns and vice versa. This effect is stronger for firms with higher default risk, as measured by probability of default, leverage or credit rating, and cannot be explained by differences in the pricing of risk factors in stock and bond markets, limits to arbitrage or liquidity premiums.

Third, in Chapter 4 I study a refined version of the standard cross-sectional momentum strategy, called volatility-adjusted momentum. In particular, while the standard methodology to create a momentum portfolio, originating from the work of Jegadeesh and Titman (1993), ignores differences in volatility amongst the individual assets, a rational investor would adjust for differences in volatility. Volatility-adjusted momentum differs from standard momentum in three ways: (1) assets are sorted on return-to-volatility, not on raw returns, (2) assets are weighted inverse to their volatility within the portfolio and (3) the portfolios target a constant volatility through time. Empirically, I find that volatility-adjusted momentum has much higher Sharpe ratios (from 0.34 to 1.14) and alphas than standard momentum in the CRSP U.S. stock sample spanning the 1927-2015 period. Moreover, for corporate bonds I find a similar Sharpe ratio of 1.04 when applying volatility-adjusted momentum, while standard momentum does not even reveal a significant momentum premium in corporate bonds.

Fourth, in Chapter 5 I focus on the effect of momentum spilling over from one asset class, equities (stocks), to another asset class, corporate bonds. As in Chapter 3, the pricing of stocks and bonds of the same firm should be related, and thus also momentum effects might be related. Like previous studies (Gebhardt, Hvidkjaer, and Swaminathan, 2005), I find that past winners in the equity market are future winners in the corporate bond market. However, I also 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.

Finally, in Chapter 6 I study the presence of the size, value, momentum and low-risk anomalies, well-known in the equity literature, in corporate bond markets. I find empirical evidence that these anomaly portfolios generate economically meaningful and statistically significant alphas in the corporate bond market. As the correlations between the single-factor portfolios are low, a combined multi-factor portfolio benefits from diversification between the factors: it has a lower tracking error and a higher information ratio than the individual factors. The results are robust to transaction costs, alternative factor definitions, alternative portfolio construction settings and the evaluation on a subsample of liquid bonds. Finally, allocating to corporate bond factors has added value beyond allocating to equity factors in a multi-asset context.

In summary, each of the chapters covers both stock and corporate bond markets, either by explicitly studying the relationship between the two (Chapters 3 and 5), studying the same anomaly in both markets (Chapter 4) or by porting concepts well-known in one market, i.e. interest rate risk in bond markets and factors in equity markets, to the other market (Chapters 2 and 6).

Chapter 2

Beta: The Good, the Bad and the Ugly

2.1 Introduction

The relation between stock prices and interest rates is a key theme in finance, which has been approached from various angles by existing work. Some studies focus on understanding the correlation between (aggregate) stock returns and interest rates (for example Baele, Bekaert, and Inghelbrecht, 2010 and Baker and Wurgler, 2012). Other studies investigate whether interest rates contain predictive information for stock returns (Fama and Bliss, 1987; Cochrane and Piazzesi, 2005). Yet another stream of articles investigates whether interest rate factors are priced in the cross-section of stock returns (for example Fama and French, 1993). Finally, recent work has introduced the concept of equity duration and how this affects the cross-section of stock returns (Dechow, Sloan, and Soliman, 2004; Weber, 2016).

In this paper we aim to deepen our understanding of the relation between stock prices and interest rates by using the present value approach of Campbell and Shiller (1988). This approach splits stock returns into cash flow news and discount rate news, and many researchers have applied this framework to understand stock returns. The starting point of our analysis is to decompose the total discount rate into the (nominal) risk-free interest rate and the equity risk premium. Aggregate stock returns are then decomposed into cash flow news, risk premium news, and interest rate news.

Our main focus is to extend the "good beta, bad beta" approach of Campbell and Vuolteenaho (2004), who posit a two-factor model with stocks having a beta for cash flow news and a beta for discount rate news instead of a single (CAPM) beta. By decomposing discount rate news into risk-free rate news and risk premium news, we obtain a three-factor model. Using various portfolio sorts, we show that splitting up the CAPM beta into a cash flow beta, risk premium beta and interest rate beta generates an improved fit of the cross-section of stock returns. In particular, we find that the interest rate beta carries the highest price of risk, which is why we refer to this beta as the ugly beta.

Our approach is as follows. Following existing work (for example Campbell and Vuolteenaho, 2004; Campbell, Polk, and Vuolteenaho, 2010), we use vector autoregressive (VAR) models for stock returns, interest rates and predicting variables (price-to-earnings ratio, term spread, small stock value spread, and default spread for the aggregate stock market; book-to-market and return-on-equity for the stock-specific model) to identify these components. We estimate these VAR models both for market returns and for individual stock returns, which allows us to make statements about both the time series and cross-section of stock returns. We focus on the U.S. stock market for the period 1927-2015. We use a quarterly frequency for these VAR models, and thus use the 3-month T-bill rate as the risk-free rate.

This framework generates a range of new insights on the relation between stock returns and interest rates. As mentioned above, our main analysis is that we decompose the CAPM beta into a cash flow beta, risk premium beta and interest rate beta and study the pricing of these betas. Campbell and Vuolteenaho (2004) call the cash flow beta a "bad" beta and the risk premium beta a "good" beta, because an Intertemporal CAPM predicts that the transitory risk premium variation should carry a lower price of risk. We call the interest rate beta an "ugly" beta because it turns out to have a price of risk that is even higher than the price of cash flow risk, while the price of risk premium risk is small and insignificant. We obtain this result using a standard Fama-MacBeth approach, applied to portfolio sorts on value, size, volatility, and various risk exposures. We can statistically reject the two-factor "good beta, bad beta" model in favor of our three-factor model with a separate "ugly" interest rate beta. While the "good beta, bad beta" model can explain up to 26.5% of the variation in portfolio returns, the addition of the "ugly" beta raises this to 31.8%.

Our analysis also delivers other insights. First of all, when decomposing the stock market return into cash flow, equity risk premium and interest rate news, we find that interest rate news accounts for more than $1/3^{\text{rd}}$ of the total variation in market returns. The impact of interest rate movements is large because of the persistence of interest rates. We also estimate the relevance of interest rate shocks at the individual stock level, and find it is small: most of the individual stock price movements are due to cash flows news, in line with Campbell, Polk, and Vuolteenaho (2010).

Second, we find that interest rates and risk premiums exhibit a negative relation. In fact, an orthogonal positive shock to interest rates drives down the total discount rate: while a 1% increase in the interest rate has a direct discounting effect of about -7% on stock prices, this is more than compensated by an indirect effect of interest rates on risk premiums, which corresponds to a stock return effect of 9% when interest rates increase by 1%. This indirect effect occurs because interest rates negatively predict risk premiums according to our estimates. Hence, the popular idea that the total discount rate varies one-to-one with the interest rate is not supported by our results. This also suggests that interest rate exposure cannot properly be estimated by accounting-based measures such as equity duration (Dechow, Sloan, and Soliman, 2004; Weber, 2016), as those measures directly measure the duration of the cash flows of the firm, ignoring indirect risk premium effects.

Third, we find that nominal interest rate news comoves somewhat negatively with nominal cash flow news and with equity risk premium news. Given that movements in nominal interest rates are to a substantial degree driven by changes in expected inflation (Brennan and Xia, 2002), this suggests that stocks might provide a hedge for expected inflation risk, though the size of these hedging effects is limited. This limited inflation hedging capability is in line with most existing work on the inflation hedging aspects of stock investments (see for example Bekaert and Wang, 2010).

Our paper relates to various existing streams in the literature. First, it builds on the stream of literature using the present-value framework of Campbell and Shiller (1988). Campbell (1991) finds that monthly U.S. unexpected aggregate stock market returns are driven by real cash flow news and discount rate news in similar proportions, while Campbell and Ammer (1993) find that discount rate news is the dominant driver. Campbell and Vuolteenaho (2004) find that exposure to the cash flow news, "bad beta", is significantly higher priced than exposure to discount rate news, called "good beta". Using this beta decomposition, they are able to explain the size and value anomalies. Vuolteenaho (2002) is the first paper to decompose individual stock returns, and finds that cash flow news is the main driver of firm-level stock returns. Campbell, Polk, and Vuolteenaho (2010) combine the market and firm-level decompositions to examine the sources of the good and bad betas. They find the firm-level cash flows to be the main driver of the different exposures of value and growth stocks to aggregate discount rate and cash flow news.

Second, our paper is linked to papers estimating interest rate sensitivity of stocks more directly. Baker and Wurgler (2012) add the excess return of long-term government bonds to the CAPM model to find that "bond-like stocks", which are stocks of large, mature, low-volatile, profitable and dividend paying firms, comove more strongly with government bonds than other stocks. Maio and Santa-Clara (2017) employ a similar model to explain the dispersion in average returns of CAPM anomalies (value, return reversal, equity duration, asset growth, inventory growth), and find short-term interest rates relevant for pricing cross-sectional equity risk premia. Weber (2016) uses balance sheet data to construct a measure of duration of the firms cash flows, similar to a Macaulay duration for bonds. He finds that the stocks with a high duration earn lower returns than short-duration stocks in the cross-section.

The remainder of this paper is organized as follows: Section 2.2 describes the three-way stock return decomposition employed as well as the VAR model to estimate the individual return components. Section 2.3 discusses the main results, while Section 2.4 contains robustness checks. Section 2.5 concludes.

2.2 Theoretical framework

2.2.1 Decomposing stock returns into shocks

The methodology of this paper builds on the log-linearization of asset returns introduced by Campbell and Shiller (1988) and Campbell (1991). Let r_{t+1} denote the log return of a stock from time t to time $t+1$. In general, this can be written as:

$$r_{t+1} = \log\left(\frac{P_{t+1} + D_{t+1}}{P_t}\right) \tag{2.1}$$

where P_t and P_{t+1} are the prices of the stock at time t and $t+1$ respectively, and D_{t+1} any dividend paid out to the investor at time $t+1$. Denote with lowercase letters log variables, i.e. $\log D_t = d_t$ and $\log P_t = p_t$. Taking a first-order Taylor expansion around the mean of the log dividend-price ratio $\overline{d-p}$ leads to the following equation

$$r_{t+1} \approx \rho\left(p_{t+1} - d_{t+1}\right) + \Delta d_{t+1} - \left(p_t - d_t\right) \tag{2.2}$$

where $\rho \equiv \frac{1}{1+e^{\overline{d-p}}}$ is the linearization constant. Iterating forward, taking expectations and ruling out rational bubbles, i.e. $\lim_{T\to\infty} \rho^T p_{t+T} \to 0$, results in

$$p_t \approx \frac{\kappa}{1-\rho} + \mathbb{E}_t\left[\sum_{j=0}^{\infty} \rho^j\left((1-\rho)d_{t+j+1} - r_{t+j+1}\right)\right] \tag{2.3}$$

where $\kappa \equiv -\log(\rho) - (1-\rho)\log\left(\frac{1}{\rho} - 1\right)$ and $\mathbb{E}_t$ the investors expectation at time t. Equation 2.3 shows that the price of an asset is high when future cash flows, i.e. dividends, are high and future returns are low.

Substituting Equation 2.3 into Equation 2.2 leads to a two-way decomposition of unexpected asset returns into cash flow (CF) news and discount rate (DR) news:[1]

$$
\begin{aligned}
r_{t+1} - \mathbb{E}_t\left[r_{t+1}\right] &= \left(\mathbb{E}_{t+1} - \mathbb{E}_t\right)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - \left(\mathbb{E}_{t+1} - \mathbb{E}_t\right)\sum_{j=1}^{\infty}\rho^j r_{t+1+j} \\
N_{t+1} &= N_{CF,t+1} - N_{DR,t+1}
\end{aligned}
\tag{2.4}
$$

This equation shows that unexpected high stock returns can be generated in two ways: either future cash flows are expected to be higher at $t+1$ than the expectation at time t, or expectations of future discount rates are lowered. Thus, if the expectations on future cash flows do not change, any gain today must be offset by losses in the future and vice versa.

In the literature various decompositions of stock returns are used. Campbell and Ammer (1993) and Campbell and Mei (1993), for instance, split stock returns into real dividends, real interest rates and excess stock returns. Campbell and Vuolteenaho (2004), Campbell, Polk, and Vuolteenaho (2010) and Campbell, Giglio, and Polk (2013) split stock returns into real dividends and excess stock returns, while assuming real interest rates remain constant. In Appendix 2.A we provide a detailed literature overview of the various return decomposition models, including details on the estimation inputs.

Before we turn to the specification used in this paper, we first discuss a more general decomposition of stock returns which captures the various two-way and three-way specifications in use. We rewrite Equation 2.4 into a four-way decomposition by decomposing the log discount rate r_{t+1} into the expected log rate of inflation π_t, a log inflation premium θ [2], the ex-ante expected log real-interest rate y_t^{real} and the log excess stock return e_{t+1}:

$$
r_{t+1} = y_t^{\text{nom}} + e_{t+1} = \pi_t + \theta + y_t^{\text{real}} + e_{t+1} \tag{2.5}
$$

where y_t^{nom} is the log of the nominal short-term risk-free rate. By definition the return of the nominal risk-free asset is known at the moment of investing. As a result, the risk-free component in the total discount rate r_{t+1} which spans the period from t to $t+1$, is given by the risk-free rate observed at time t.

[1] From here on, we assume the approximate equalities in Equations 2.2 and 2.3 hold exactly.

[2] Brennan and Xia (2002) show that the nominal risk-free rate may also contain a risk premium for unexpected inflation shocks, which we denote by θ. We assume this term is constant over time from here on, which it also is in the Brennan-Xia model. Thus this does not affect the decomposition of unexpected returns.

Hence we denote the nominal risk-free rate as y_t^{nom}, not as y_{t+1}^{nom}. Equation 2.4 becomes:

$$\begin{aligned}N_{t+1} &= r_{t+1} - \mathbb{E}_t\left[r_{t+1}\right]\\ &= e_{t+1} - \mathbb{E}_t\left[e_{t+1}\right]\\ &= \left(\mathbb{E}_{t+1} - \mathbb{E}_t\right)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j}^{\text{nom}} - \left(\mathbb{E}_{t+1} - \mathbb{E}_t\right)\sum_{j=1}^{\infty}\rho^j \pi_{t+j}\\ &\quad - \left(\mathbb{E}_{t+1} - \mathbb{E}_t\right)\sum_{j=1}^{\infty}\rho^j y_{t+j}^{\text{real}} - \left(\mathbb{E}_{t+1} - \mathbb{E}_t\right)\sum_{j=1}^{\infty}\rho^j e_{t+1+j}\\ &= N_{CF^{\text{nom}},t+1} - N_{\Pi,t+1} - N_{y^{\text{real}},t+1} - N_{e,t+1}\end{aligned} \tag{2.6}$$

where the second equality follows from $\mathbb{E}_t\left[y_t^{\text{nom}}\right] = y_t^{\text{nom}}$, and the third equality from substituting Equation 2.5 into Equation 2.4. Note that d_{t+1+j} has been written as d_{t+1+j}^{nom} to emphasize the difference with real dividends. If it is assumed that real interest rates remain constant as is commonly assumed (Campbell and Vuolteenaho, 2004; Campbell, Polk, and Vuolteenaho, 2010; Campbell, Giglio, and Polk, 2013), i.e. $N_{y^{\text{real}},t+1} = 0$, then the shock not due to excess returns $N_{e,t+1}$ represents a shock to real dividends $N_{CF^{\text{real}},t+1} = N_{CF^{\text{nom}},t+1} - N_{\Pi,t+1}$.

Equation 2.6 is of theoretical interest, but difficult to implement. This is because real rates and expected inflation are not directly observable.[3] In this study we therefore focus on measuring the total nominal interest rate component of stock returns, and focus on the term $N_{CF^{\text{nom}},t+1} = N_{CF^{\text{real}},t+1} + N_{\Pi,t+1}$. The decomposition that we use in our empirical analysis is given by

$$\begin{aligned}N_{t+1} &= r_{t+1} - \mathbb{E}_t\left[r_{t+1}\right]\\ &= e_{t+1} - \mathbb{E}_t\left[e_{t+1}\right]\\ &= \left(\mathbb{E}_{t+1} - \mathbb{E}_t\right)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j}^{\text{nom}} - \left(\mathbb{E}_{t+1} - \mathbb{E}_t\right)\sum_{j=1}^{\infty}\rho^j y_{t+j}^{\text{nom}}\\ &\quad - \left(\mathbb{E}_{t+1} - \mathbb{E}_t\right)\sum_{j=1}^{\infty}\rho^j e_{t+1+j}\\ &= N_{CF^{\text{nom}},t+1} - N_{y^{\text{nom}},t+1} - N_{e,t+1}\end{aligned} \tag{2.7}$$

From Equation 2.7 it follows that we obtain three components: interest rate risk $N_{y^{\text{nom}},t+1}$, equity premium risk $N_{e,t+1}$ and nominal cash flow risk $N_{CF^{\text{nom}},t+1}$.

[3] Only for our small part of our sample period inflation-indexed bonds and inflation swap data are available.

Thus our results for cash flow cannot be directly compared to those of Campbell and Vuolteenaho (2004), Campbell, Polk, and Vuolteenaho (2010) and Campbell, Giglio, and Polk (2013), since in these articles it is assumed that real interest rates are constant in order to determine a real cash flow component. In contrast, we allow interest rates to vary and decompose stock returns into nominal cash flows, nominal interest rates, and risk premiums. In Section 2.3.4, we do, however, use Equation 2.6 to interpret our results for nominal interest rates and to relate our results to existing work.

2.2.2 VAR methodology

To implement the three-way decomposition in Equation 2.7, we follow Campbell (1991) by using a vector autoregressive (VAR) model. In this method, first the terms $\mathbb{E}_t[e_{t+1}]$, $(\mathbb{E}_{t+1} - \mathbb{E}_t)\sum_{j=1}^{\infty}\rho^j y_{t+j}^{\text{nom}}$ and $(\mathbb{E}_{t+1} - \mathbb{E}_t)\sum_{j=1}^{\infty}\rho^j e_{t+1+j}$ are estimated. Next, given the realization e_{t+1}, we can compute the total shock N_{t+1} and back out the nominal cash flow shock $N_{CF^{\text{nom}},t+1}$ as a residual by Equation 2.7. This process has the advantage of only having to estimate expected stock excess returns and nominal interest rates, not the dynamics of the dividend process. Engsted, Pedersen, and Tanggaard (2012) show that if the VAR model is properly specified, it makes no difference whether cash flow news is computed directly or backed out as a residual. In the robustness checks, we estimate a VAR model with less state variables and find that the results are very similar; they are thus not driven by the inclusion of a particular state variable.

We assume the data originates from a first-order VAR model given by

$$X_{t+1} = AX_t + u_{t+1} \tag{2.8}$$

where X_{t+1} is a $m \times 1$ vector of state variables with e_{t+1} as the first element and y_{t+1}^{nom} as the second element, and $m-2$ remaining variables which are included to predict the first two components. A, also called the companion matrix, is a $m \times m$ matrix of the parameters of the model to be estimated and u_{t+1} an $m \times 1$ vector containing the VAR innovations corresponding to X_{t+1}. We do not include a constant but instead we demean the state variables prior to estimation. The VAR model is used to decompose the stock market return into cash flow, interest rate, and risk premium components. As discussed below, we also estimate a VAR model at the firm level to obtain these components for individual stocks.

From the process in Equation 2.8, the total, cash flow, interest rate and equity risk shocks can be computed as follows:

$$\begin{aligned} N_{t+1} &= e1' u_{t+1} \\ N_{e,t+1} &= e1' \rho A \left(I - \rho A\right)^{-1} u_{t+1} \\ N_{y^{\text{nom}},t+1} &= e2' \rho \left(I - \rho A\right)^{-1} u_{t+1} \\ N_{CF^{\text{nom}},t+1} &= \left(e1' + e1' \rho A \left(I - \rho A\right)^{-1} + e2' \rho \left(I - \rho A\right)^{-1}\right) u_{t+1} \end{aligned} \tag{2.9}$$

where $e1$ is an $m \times 1$ vector with the first element set to 1 and the remaining elements to zero, $e2$ an $m \times 1$ vector with the second element set to 1 and the remaining elements to zero, I the $m \times m$ identity matrix and A the estimated companion matrix. The term $(I - \rho A)^{-1}$ captures the persistence of a shock in a particular state variable. Variables which have a small direct impact but are very persistent can thus have high impact as stocks are long-term assets (i.e., ρ is typically close to one as dividends are usually 10% or less). Note that there is a difference between the excess return shock term $N_{e,t+1}$ and the interest rate shock term $N_{y^{\text{nom}},t+1}$: the former has an additional multiplication with A due to the risk-free rate being known at the moment of investing.

2.2.3 Beta decomposition

As in Campbell and Vuolteenaho (2004), we define the market beta of stock i as the covariance of total firm-specific shocks with contemporaneous total market shocks, scaled with the variance of total market shocks:

$$\begin{aligned} \beta_{i,M} &= \frac{\text{Cov}_t\left(e_{i,t+1} - \mathbb{E}\left[e_{i,t+1}\right], e_{M,t+1} - \mathbb{E}\left[e_{M,t+1}\right]\right)}{\text{Var}_t\left(e_{M,t+1} - \mathbb{E}\left[e_{M,t+1}\right]\right)} \\ &= \frac{\text{Cov}_t\left(N_{i,t+1}, N_{M,t+1}\right)}{\text{Var}_t\left(N_{M,t+1}\right)} \end{aligned} \tag{2.10}$$

where $e_{i,t+1}$ is the log excess return of stock i and $e_{M,t+1}$ is the log excess return of the market. Following our decomposition of firm-specific and market-wide total shocks in equity risk premium news $-N_e$, interest rate news $-N_y$, and cash flow news $N_{CF^{\text{nom}}}$, we can split this single beta into three betas by splitting the market total shock into excess return, interest rate and nominal cash flow shocks:[4]

$$\beta_{i,M} = \beta_{i,eM} + \beta_{i,yM} + \beta_{i,CFM} \tag{2.11}$$

where the subscripts denote the firm-specific (suffix i) and market (suffix M) shock components used to compute the covariance. Note that the signs of

[4] One could also split the firm-specific shocks into three components using the firm VAR model, yielding a total of 9 betas. In this study we focus on the betas involving total firm-specific shock to a particular market shock.

the risk premium and interest rate news terms have been flipped following Equation 2.7. A positive innovation of the shock means that current stock prices rise. The interest rate news component thus depends negatively on interest rate shocks, and can be interpreted in a similar way as a bond return.

2.3 Main empirical results

We first present results for an aggregate VAR model, to decompose market returns into risk premium, interest rate and cash flow news. We then turn to a firm-level VAR model to estimate the stock-specific shocks, which allows us to study the cross-section of the news components and study the various betas defined in Equation 2.11. In particular, we study whether these betas carry different prices of risk.

Our dataset draws from several databases. First, for the stock data, we use data from the Center of Research in Security Prices (CRSP) monthly stock files. We limit ourselves to common equity (share codes 10 and 11) and to stocks traded on the NYSE, AMEX or NASDAQ. This dataset contains stock prices, stock returns (including dividends) and shares outstanding. Second, we merge the Compustat Annual database, which contains accounting data for most publicly traded U.S. stocks, into our dataset. As the Compustat database does not contain book values of equity prior to 1952, we use hand-collected book equity values as used in Davis, Fama and French (2000). This data is provided on the website of Kenneth French.[5] Third, we source the CRSP US Treasury and Inflation files for the 3-month, 1-year and 10-year (nominal) US Treasury yields. The 10-year yield is provided from 1941 onwards. To cover the 1927-1940 period, we prepend this series with the Long-Term U.S. Government Securities series provided by the Federal Reserve Bank of St. Louis.[6] The sample data is on a quarterly frequency and runs from February 1927 to October 2015, spanning 355 quarters.

2.3.1 Aggregate VAR

We estimate our aggregate VAR on a quarterly frequency, following Campbell, Giglio, and Polk (2013) and Campbell et al. (2017). The quarterly frequency of the data is a compromise of statistical strength and ability to do more granular analyses (i.e., rolling model estimation; sub period analyses) on the one hand, for which a high data frequency is needed, and the focus on longer term relationships between variables on the other hand, as stocks are typically

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[6] https://fred.stlouisfed.org/series/LTGOVTBD

thought of as long-term assets, making the estimation of month-to-month dynamics less relevant.

We use six state variables in our VAR model, covering the models used in earlier studies since Campbell and Vuolteenaho (2004). See Appendix 2.A for details.

First, the excess log return of the market $e_{M,t}$ is the difference between annual log return on the CRSP value-weighted stock index and the annual log risk-free rate. When computing the return of the individual stocks, delisting returns are taken into account when available to prevent survivorship bias.

Second, the log risk-free rate y_t^{nom} is the log yield of the 3-month US Treasury bond in fractions. We pick the 3-month rate as the data is on a quarterly frequency, and transform it from an annual rate to a quarterly rate in order to match the investment horizon.

Third, we compute the term yield spread TY_t as the difference between the ten-year fixed maturity rate on US Treasuries and the 3-month rate. The term yield spread is quoted in percentages. This variable is included because the term yield spread is known to predict long-term bond excess returns (Fama and Bliss, 1987). Keim and Stambaugh (1986) and Campbell (1987) point out that stocks are also long-term assets, hence TY might also forecast stock excess returns. Moreover, the yield curve tracks the business cycle, and expected stock market returns are likely to vary along the business cycle.

Fourth, we include the log smoothed Shiller price-to-earnings ratio PE_t as the ratio of the current stock price to the trailing 10-year earnings of the S&P500 index (Campbell and Shiller, 1988). This ratio captures fluctuations in market valuations, with high (low) ratios indicating the stock market to be expensive (cheap), and thus implying lower (higher) long-run returns in the future. We source this ratio from the website of Robert Shiller.[7]

Fifth, we include the small-stock value spread VS_t. To compute the value spread, we use the 2x3 size and book-to-market portfolios provided by Kenneth French. These portfolios are constructed by rebalancing the portfolios at the end of June of year t by taking the intersection of two size groups and three book-to-market groups. The size breakpoint is the median NYSE size; for book-to-market, the 30% and 70% percentiles of NYSE book-to-market values are used, where the book and market values are from December of year $t-1$. Within the small cap stocks, we take the difference of the logs of the book-to-market ratio of the high and the low book-to-market portfolio as our measure.

Sixth, we include the default spread DEF_t, computed as the difference between the log yield on Moody's BAA and AAA bonds. The series are ob-

[7] http://www.econ.yale.edu/~shiller/data/ie_data.xls

tained from the Federal Reserve Bank of St. Louis.[8] This variable is included because the default spread reflects both aggregate default probabilities, which should be related to future cash flows, as well as a credit risk premium, which should be related to the equity market risk premium.

Table 2.1, panel A, presents the coefficient estimates of the aggregate VAR model.[9] The first row shows that the predictability of quarterly market excess returns is limited, as the adjusted R-squared is only 6.6%. However, this is still higher than other studies on quarterly frequency, with Campbell, Giglio, and Polk (2013, Table 3) obtaining a R-squared of 4.0% and Campbell et al. (2017, Table 2) obtaining a R-squared of 3.4% in slightly shorter data samples. As noted by Cochrane (2007), even such a low R-squared might generate substantial variation in risk premiums, because the predicting variables are persistent. The low R-squares do indicate that most deviations of the long-run mean are unexpected. Still, we find statistically significant predictive power for most variables. Past excess returns have a positive and significant (t-statistic of 2.98) impact similar to Campbell, Giglio, and Polk (2013). Nominal interest rates have a negative sign (t-statistic of -2.43), which conflicts with the popular idea that expected total stock returns can be decomposed in the risk-free rate and a constant risk premium (Sharpe, 1964). The negative coefficient suggests that interest rate changes are partly mitigated by risk premium changes in the opposite direction. For the other three variables, we find that the term-yield spread has a positive sign as expected but is statistically insignificant. The value spread has a significant negative (t-statistic of -1.82) impact on future stock returns, while the default spread coefficient is close to zero and statistically insignificant. These results are similar to Campbell, Giglio, and Polk (2013).

In the second row, the dynamics of nominal interest rates are given. We find that last quarter's interest rate is by far the dominant driver with a coefficient of 0.9866 (t-statistic of 46.40). This shows that interest rates are persistent and only slowly mean-revert. Lagged values of the excess market return also have a positive and significant impact on the risk-free rate, while other variables have limited statistical power. In the remaining rows, the dynamics of the term yield spread, the price-to-earnings ratio, the value spread and the default spread are given. We find that the own-lags have a large and highly significant impact; the cross-variable terms have a more limited impact.

In panel B, the variance-covariance matrix of the news terms is given on the left. These are derived by computing the shock vector u_{t+1} each period fol-

[8] https://fred.stlouisfed.org/categories/32348

[9] We find the modulus. i.e. the maximum absolute eigenvalue, of the VAR to be 0.9834, below 1. Thus the VAR is stationary.

lowing from the VAR model coefficients, and subsequently applying Equation 2.9 to split the excess return shocks into equity risk premium, interest rate and cash flow news. We set ρ to 0.95 at an annual level for this computation. The results are insensitive to modest variations in ρ. As mentioned above, we flip the signs of the risk premium and interest rate news terms for ease of interpretation: an increase in $-N_{e,t+1}$, $-N_{y^{\text{nom}},t+1}$ or $N_{CF^{\text{nom}},t+1}$ raises the current stock price, and a positive covariance means that the impact on the current stock price is in the same direction. We find that the largest component is risk premium news with a variance of 0.0060 out of a total of 0.0066, thus representing 90.8% of the total variation. Campbell, Giglio, and Polk (2013) find a similar figure.[10] Of the remaining variation interest rate news and nominal cash flow news are approximately equally important, with 36% and 40% respectively. Together, these contributions add up to 167%, which can be attributed to the negative covariance terms.

Interestingly, we find modest evidence for stocks being real assets. If we assume that real interest rates are constant, shocks in the nominal interest rate are driven by shocks in the expected inflation. If stocks are real assets, then an increase in inflation expectations should be offset by an increase in nominal cash flow expectations, by a decrease of future excess returns or a mix of the two. We find that the two covariance terms with interest rate news are indeed negative (Table 2.1, Panel B), but these offsetting effects are not very large. The correlations, listed on the right, equal -0.18 and -0.38 for risk premium news and cash flows news, respectively. These results can be compared to the literature on the limited inflation hedging capacity of stock market investments. For example, Bekaert and Wang (2010) document low correlations between stock market returns and inflation rates for many countries. Bekaert and Engstrom (2010) show that increases in expected inflation coincide with increases in equity risk premiums, while our results suggest a negative relation. The correlation between news on future nominal cash flows and future excess returns is small with -0.15. This suggests that, on a quarterly frequency, stock returns are driven almost independently by updated future excess returns and changes in future cash flow expectations.

One should be careful interpreting the finding that interest rate news drives as much of the variation in stock returns as nominal cash flow news, as the variance-covariance matrix does not show what the initial shock, i.e. "trigger", is for shocks in stock returns, only where these triggers accumulate: changes in expected future excess returns, future interest rates or future cash flows. The finding that interest rate "news" is a large component of stock returns should

[10] They report only the correlations and standard deviations. From these, it can be inferred that the ratio of variances of risk premium news to total news is 88.9%.

thus not be interpreted as stocks being very sensitive to contemporaneous interest rate changes. Indeed, the VAR coefficients suggest that future excess returns partly offset the future interest rate changes. Instead, it shows that updated expectations on future interest rates, irrespective of the "trigger", have contributed substantially to the total variation in stock returns.

Panel C of Table 2.1 provides more insight in which shocks are driving the news terms. On the left, the correlations between the residuals of the VAR state variables and the news terms are given. Unsurprisingly, shocks in the excess return correlate positively with risk premium news, interest rate news as well as cash flow news. A shock in the interest rate correlates negatively with risk premium news, implying that a positive interest rate shock causes future excess returns to be lower, raising current stock prices. As interest rates are persistent, future interest rates will also be higher, leading to lower current stock prices and hence we observe a strong negative correlation of -0.76 between interest rate shocks and future interest rate news. The correlation with cash flow news is relatively small, with a value of just -0.06. Shocks in the term yield spread TY correlate mainly with interest rate news: an increase in the term yield spread can be caused by higher 10-year rates, lower 3-month rates or a positive combined effect of the two. If the 3-month rate is lower, it means lower future interest rates, leading to positive interest rate news. For the price-to-earnings ratio, most of the shock comes from changing prices, as the 10-year earnings only slowly updates. The correlation with the excess return residual is 0.85 (not reported). Thus, it mainly correlates with risk premium news. The correlations for the value spread are relatively small, while an unexpected increase in the default spread, which typically happens at the start of a recession, leads to higher future risk premia, lower expected interest rates and lower future expected cash flows, in line with economic intuition.

The right part of panel C shows the analytical mapping functions as defined in Equation 2.9. These functions should be interpreted as marginal effects: given a one-unit shock in the respective state variable, and no shocks in any of the other state variables, it shows the distribution over the three news terms. Thus by construction, the terms either add up to 1 for excess return (as the three news terms add up to the excess return shock), or to 0 for all other state variables (as we force the excess return shock to be zero). Still, these functions provide insight in where shocks in particular state variables accumulate. For excess returns, we find that the majority of an orthogonal positive shock would be taken as positive news on future cash flows, with a relatively small positive effect on future excess returns, and a small negative effect on future interest rates. For interest rate shocks, we find a strong negative effect of -29.14 (t-statistic of -1.41): a higher interest rate means future interest rates will also be higher, lowering current stock prices. This is a direct discounting effect, and one can thus interpret the coefficient of -29.14, or -29.14/4 = -7.3 annually, as a duration effect. This direct discounting effect is, however, more than offset by lowered future excess returns (coefficient of 36.59), due to the fact that the interest rate negatively predicts risk premiums in the VAR model.

It should be noted that the coefficients for interest rate shocks are not all statistically significant though. For the term yield spread, value spread and default spread the absolute t-statistics do not exceed 1.20, meaning they do capture one of the news terms specifically. For the PE ratio, we find that an increase leads to a strongly negative cash flow. This is an intuitive result, as we impose that the excess return residual has to be zero, and thus by definition the price will change very little. The PE ratio can thus only increase due to lowered earnings. The lower the earnings of companies, the lower the expected future dividends will be.

In Figure 2.1, the news terms are plotted through time. For the sake of readability, the series have been smoothed by taking a exponentially weighted trailing average. In line with the covariances in the table, we observe little co-movement between the three news terms. The causes for up and downturns of the stock market are thus diverse. During the Great Depression (end 1920s), the cash flow shock was extremely negative, contributing substantially to this crisis. However, also equity risk was discounted more heavily. The only other period where both cash flow and risk premium news were very negative together was during the Great Financial Crisis (2008). Campbell, Giglio, and Polk (2013) find similar patterns for this "hard time". In the other "hard time" they document, namely the early 2000s, it was mainly due to investors increasing future equity premia leading to current stock prices dropping, after a long period of compressing equity risk premia in the second half of the 90s. For interest rate news, the largest losses occurred in the early 80s. This is mainly driven by strong upward shocks in interest rates at the time. We conclude that there is sufficient variation in the news terms through time to separately estimate the price of each.

2.3.2 Firm-level VAR

Besides the aggregate VAR, we also estimate a firm-level VAR to be able to derive shocks on the firm and portfolio level. These shocks can then be used to estimate betas of portfolios using Equation 2.11.

To estimate the firm-level VAR, we include the same state variables as for the market-level VAR, except that we add the firm-specific log excess stock return $e_{i,t}$, log book-to-market ratio $bm_{i,t}$ and log return-on-equity $roe_{i,t}$.[11]

[11] We do not remove the aggregate versions of the state variables, as we want these to drive

The choice for these variables follows Vuolteenaho (2002) and Campbell, Polk, and Vuolteenaho (2010).

The log book-to-market ratio is included to capture cross-sectional differences in valuations between stocks, where high (low) ratios indicate higher (lower) future long-run excess returns (Graham and Dodd, 1934). We compute the ratio by applying shrinkage prior to taking the log following Campbell, Polk, and Vuolteenaho (2010).[12] This is necessary, as taking the log of values (close to) zero leads to extreme observations. Therefore, we shrink the book-to-market ratio to 1, with a weight of 10% on the prior and 90% on the observation, resulting in

$$bm_{i,t} = \log\left(\frac{0.9BE_{i,t} + 0.1ME_{i,t}}{ME_{i,t}}\right) \tag{2.12}$$

where $BE_{i,t}$ ($ME_{i,t}$) is the book (market) value of equity of firm i at quarter t respectively. We assume the book value at the close of December of a particular year is available from April the next year onwards. The market value of equity is always the most recently observed value, ensuring the book-to-market ratio changes from quarter to quarter.

The log return-on-equity ratio is included to capture the evidence that firms with higher profitability, controlling for their book-to-market ratio, earn higher average stock returns (Haugen and Baker, 1996). We construct the measure as in Vuolteenaho (2002). First, to compute return on equity, we divide last year's US GAAP earnings to the beginning of last years book value of equity. The earnings and book value of equity are sourced from Compustat. When earnings are missing, the clean surplus formula is computed using the hand-collected book value of equity data from Kenneth French. See Vuolteenaho (2002) for details on the computation. We ensure that potential losses are not larger than the beginning-of-period book value of equity by winsorization of the earnings. Otherwise, the return-on-equity might be below -100%. The log return-on-equity ratio is then computed as:

$$roe_{i,t} = \log\left(1 + 0.9\frac{NI_{i,t-4:t}}{BE_{i,t-4}} + 0.1y_t\right) \tag{2.13}$$

where $NI_{i,t-4:t}$ is the net income over the last four quarters, $BE_{i,t-4}$ the beginning-of-period book value of equity and y_t the 3-month T-bill rate. We

the interest rate process in the same way as in the aggregate VAR model. Coefficients of aggregate variables (time $t+1$) on firm-specific variables (time t) are restricted to zero.

[12] For the firm-specific returns, we winsorize negative returns at -99.9% to prevent taking logs of zero.

shrink the return-on-equity to the risk-free rate to prevent the log transformation from returning extreme values in case the non-transformed return-on-equity is close to -100%.

As most firms do not exist throughout the sample, we assume that the companion matrix A is the same for all firms and time periods. In Section 2.4, we relax this assumption and find that our results are not altered in any significant way. We estimate the firm-level VAR model with pooled-panel OLS regressions. To ensure our results are not biased towards the end of the sample due to the strong growth in number of stocks over time, we weight each stock-quarter observation with the inverse of the number of stocks in that particular quarter. This adjustment also ensures that the coefficients for the aggregate variables are independent from the number of observations per time period, and are therefore the same as in the aggregate VAR.

Table 2.2 reports the results.[13] Panel A reports the dynamics of the firm-specific variables; the rows with the aggregate variables have been omitted for space reasons, as these are the same as in Table 2.1. We find that firm-specific returns are harder to predict than aggregate returns, as the R-squared is only 3.1%, versus 6.1% for the aggregate return. This is not surprising given that individual stock returns exhibit substantial idiosyncratic risk. Of the variables predicting the firm-specific returns well are the log book-to-market ratio, albeit with a t-statistic of only 1.50, and log return-on-equity with a t-statistic of 5.87, confirming the profitability effect. As with aggregate stock returns, past quarter stock market returns have significant positive effect, which is in line with the standard momentum effect of Jegadeesh and Titman (1993), while interest rates and the price-to-earnings ratio have a significant negative impact. Interest rate shocks now have a more negative effect than in the aggregate VAR model. The book-to-market ratio and return-on-equity load strongly on their own lags with coefficients of 0.97 and 0.89 respectively.

The variance-covariance matrix of the news terms is listed in Panel B of Table 2.2. The variance of interest rate news is, as it is an aggregate variable, similar to that in the aggregate model.[14] However, as the variance of returns on the firm-level is much larger, this represents just 3.9% of the total variance of firm-specific stock returns. The cash flow news variance is 91.0% of the total variance, and the equity risk premium news variance 32.0%. Thus nominal cash flow news is on the firm-level relatively much more important than it is on market level, where it accounted for just 40.2% of the total variation. This

[13] As with the aggregate VAR model, we find the maximum modulus of the eigenvalues to be 0.9834.

[14] We equal weight all firm-quarter observations, rather than equal weighting the cross-sections. Hence the variance deviates slightly from the aggregate VAR model, as it emphasizes recent quarters due to the growth in number of stocks over time.

finding has also been documented by Vuolteenaho (2002). The correlations, listed on the right of Panel B, are modest, ranging from -0.35 to +0.05.

Panel C reports the impact of shocks in VAR variables on the news terms. The table on the left shows the empirical correlations between the residuals of the VAR model and the news terms. We find similar effects as in the aggregate model for the firm-specific variables. For the market state variables, we find the correlation with (firm-specific) cash flow news to be approximately zero.

2.3.3 Betas of anomaly portfolios

Since its introduction in the 1960s, the Capital Asset Pricing Model (CAPM) has been challenged by numerous "anomalies", notably the size (Banz, 1981), value (Basu, 1977) and low volatility (Haugen and Heins, 1972) effects. One way to deal with these findings has been to simply add these anomalies as new factors to the model, arguing these anomalies are compensations for some unknown risks to investors. For instance, Fama and French (1992) developed a three-factor model containing the market, size and value factors. However, this approach does not provide a deeper understanding on why these anomalies exist.

The beta decomposition derived in Equation 2.11 can provide this deeper understanding. This study is not the first to employ beta decompositions to study CAPM anomalies. Based on an Intertemporal CAPM, Campbell and Vuolteenaho (2004) argue that market cash flow news should carry a higher risk premium than market discount rate news. This is because discount rate shocks are transitory: low returns due to an increase in discount rates today are partially compensated by higher future expected returns. They find that value and small cap portfolios have outperformed growth and large cap portfolios as they have a relatively high exposure to market cash flow shocks ("bad beta"), relative to exposure to market discount rate shocks ("good beta"). Campbell, Polk, and Vuolteenaho (2010) extend this work by documenting that for value portfolios this is mainly driven by a high sensitivity of the portfolio's cash flows to the market shocks, not the portfolio's discount rate shocks. Campbell et al. (2017) extend the two-way decomposition to include a premium for volatility. They find that growth not only better hedges declines in future discount rates, but also increases in volatility, hence demanding a lower risk premium. However, none of these studies have analyzed potential differences in interest rate beta as an explanation for differences in risk premiums.

To determine the pricing of the three betas we use portfolios as test assets. As in Campbell and Vuolteenaho (2004), our primary set of test assets are the 5x5 size-by-value portfolios. We construct these portfolios by sorting at the end of July[15] of each year all stocks in five market cap groups and independently in five book-to-market groups where the quintiles are based on the NYSE stocks only. Subsequently, we form 25 market-value weighted portfolios based on the intersection of these groups. For the book-to-market ratio, we take the book and market values as of December of the year before. For the three quarters following the rebalance, we maintain the positions unless there are delistings; in that case, the proceeds are reinvested proportionally in the remaining positions.

Besides these 25 portfolios, we add five market value weighted portfolios based on past 12-month stock return volatility. These are rebalanced each quarter, and are included to explicitly address the question whether low volatility stocks indeed have a higher interest rate exposure.

Finally, we add a third set of portfolios. This set is specifically designed to address the concern of Daniel and Titman (1997) that using only portfolios sorted on characteristics known to influence average returns like value and size might lead an asset pricing model to fit the high variation in mean returns to only small deviations in the betas, as the betas might be close to each other. To ensure there is sufficient spread in the betas, we construct 40 risk-sorted portfolios in the spirit of Campbell and Vuolteenaho (2004). First, per stock and per quarter, we estimate the following OLS regression over the past 20 quarters:

$$\begin{aligned} r_{i,t} = \beta_0 + &\beta_M r_{M,t} + \beta_y \Delta y_t^{\text{nom}} + \beta_{TY} \Delta TY_t \\ &+ \beta_{VS} \Delta VS_t + \beta_{DEF} \Delta DEF_t + \epsilon_{i,t} \end{aligned} \tag{2.14}$$

where $r_{i,t}$ is the log excess return of the stock over the quarter, the betas are the coefficients to be estimated, and the independent variables are changes in the aggregate state variables used in the VAR model. We exclude the Shiller price-to-earnings ratio PE_t from this regression as quarter-on-quarter changes in the PE ratio are almost entirely driven by stock returns, leading to a very high correlation with $r_{M,t}$. The delta operator indicates the change from the start of the quarter to the end of the quarter, i.e. the same period as over which the stock return is measured. Stocks are first sorted in five groups based on their estimated β_M, and then within each of the five groups sorted in two groups for each of the other state variable coefficients estimated in the regression. This yields a total of 40 risk-sorted portfolios, which are market-value weighted and rebalanced quarterly. The total number of portfolios is thus 70. The portfolio

[15] These portfolios are similar to the ones provided by Kenneth French, but are rebalanced at the end of July instead of June, as we do not have a quarter ending at the end of June. We need to rebalance at the end of a quarter to be able to determine the news terms of the portfolios, hence we rebalance one month later.

shocks are obtained by taking the market-value weighted average firm-specific shocks generated by the firm VAR model.

As we require 20 quarters of VAR shocks to compute the risk-sorted portfolios, the first quarter we can compute a return and shock runs from May to July 1932. For comparability, we use for all portfolios the betas from May 1932 to October 2015. As Campbell and Vuolteenaho (2004) find substantial differences in betas in the pre- and post-1963 periods (labeled "early" and "modern" sample), we also report results separately for these periods, where the early sample runs from May 1932 to January 1963 (123 quarters) and the modern sample from February 1963 to October 2015 (211 quarters).

Table 2.3, panel A, reports the betas for the size x value portfolios. In the full sample we find that small caps tend to have higher risk premium betas, higher interest rate betas but lower cash flow betas than large caps. For the early sample, a similar pattern emerges, but in the modern sample the relation between size and the interest rate beta is flat while the cash flow betas are actually higher. For value stocks, we find that they have lower interest rate betas then growth stocks in the early sample, but that this relation is flat in the modern sample. The risk premium beta results are mixed in the early sample, while in the modern sample value stocks have clearly lower risk premium betas than growth stocks. For the nominal cash flow betas, the results are very consistent: value stocks have higher cash flow betas than growth stocks. Campbell, Giglio, and Polk (2013) find a similar pattern for the real cash flow betas of value stocks in their model. In general, we find clear differences in betas between the early and modern sample for the size x value portfolios, consistent with prior studies.

Panel B reports the results for the five volatility portfolios. Not surprisingly, due to the close relationship between volatility and beta, the risk premium and cash flow betas tend to increase from low volatility to high volatility, which is consistent across the samples. The exception is the interest rate beta. Measured over the full sample as well as in the two sub samples, low volatility stocks tend to have a higher interest rate beta than high volatility stocks, consistent with other studies (Baker and Wurgler, 2012; Maio and Santa-Clara, 2017). However, we also note that this is mainly due to high volatility stocks having a lower interest rate beta, Q1 to Q4 are relatively close to each other.

Panel C reports the full sample results for the risk-sorted portfolios. Of particular interest are the portfolios double-sorted on market beta and the interest rate change, as the coefficient on the interest rate change corresponds closely with the interest rate beta. Within the high market beta portfolios, we find that stocks which had, in the past, a high sensitivity to interest rate changes (i.e., high β_Y in Equation 2.14), indeed also a higher interest rate beta going forward. However, it seems that this effect only exists in market beta

Q1 and Q2 portfolios, not in the lower market beta portfolios.

2.3.4 Pricing of the betas

In this section, we analyse the cross-sectional pricing of the betas using the 70 portfolios constructed in the previous section. Campbell (1993) derives a discrete time version of the Merton (1973) intertemporal capital asset pricing model (ICAPM) model to show that the expected return of an asset is a linear function of the betas under certain assumption. This pricing model has been employed by for instance Campbell and Vuolteenaho (2004) and Campbell et al. (2017) to estimate the premium on each of the betas.

To understand how nominal interest rate risk should be priced in an Intertemporal CAPM, we consider two extreme cases. First, if real interest rates are constant, all variation in nominal interest rates is due to changes in expected inflation. Then, nominal interest rate news and nominal cash flow news sum up to real cash flow news. Assuming that the ICAPM investor cares about real returns, the ICAPM of Campbell and Vuolteenaho (2004) implies a single price of risk for real cash flow news, and in this case nominal cash flow risk and nominal interest rate risk should thus carry the same price of risk, while risk premium news has a lower price of risk. Campbell and Vuolteenaho (2004) assume that real rates are constant, hence this case corresponds to the way they interpret their results.

The alternative extreme case is that inflation is constant. In this case, all variation in nominal interest rates is due to changes in real rates. These real rates directly enter the total discount rate, and hence in this case the price of interest rate risk should equal the price of risk premium risk.

In reality, both real rates and inflation vary over time and the pricing of nominal interest rate risk will differ from both cash flow risk and risk premium risk. This is why we mainly focus on a model where all three components have separate risk prices. As discussed below, we do however also include a specification that follows Campbell and Vuolteenaho (2004).

In addition, it is important to note that the Intertemporal CAPM is just one justification for why the different components carry different prices of risk. In particular, there are several reasons why investors might care about interest rate risk beyond its effect on stock prices. First, interest rates may affect risk premiums in bond markets, and investors who invest both in bonds and stocks will care about this. Second, pension funds and insurance companies have liabilities that depend on interest rates. Third, interest rate risk may be related to systemic liquidity risk which could in turn affect financial markets beyond stock markets.

To estimate the prices of risk, we employ a Fama and MacBeth (1973) procedure using the full-sample equity risk premium, interest rate and cash flow betas by estimating per year the following equation using Ordinary Least Squares:

$$R_{i,t} = \lambda_{e,t}\beta_{i,eM} + \lambda_y\beta_{i,yM} + \lambda_{CF}\beta_{i,CFM} + \epsilon_{i,t} \tag{2.15}$$

where $R_{i,t}$ is the simple excess return of portfolio i over the 3-month T-bill rate, and $\beta_{i,eM}$ ($\beta_{i,yM}$, $\beta_{i,CFM}$) the full-sample estimated risk premium (interest rate, cash flow) beta of portfolio i. The subscript t denotes the quarter; the lambda coefficients, which represent the return per unit of beta, are averaged over time. Standard errors are computed in two ways: first, we report heteroskedasticity and autocorrelation corrected standard errors (Newey and West, 1987).[16] Second, we report bootstrapped standard errors in square brackets where we resample quarters with replacement.[17]

We compute the price of the betas under three assumptions:

1. **CAPM** all betas are equally priced. This means we are pricing the total (CAPM) beta.

2. **GBBB** the interest rate and cash flows betas are equally priced ($\lambda_y = \lambda_{CF}$), the risk premium beta might differ. This is the same setup as in the "Good Beta, Bad Beta" study (Campbell and Vuolteenaho, 2004).

3. **unrestricted** all three betas priced separately.

For each of the three assumptions, we also re-estimate Equation 2.15 including a constant. There are two interpretations to the results with constant versus those without the constant. First, including a constant can be viewed as a model misspecification test. The betas should capture all risks, and thus no significant positive or negative excess return, captured by the constant, should remain. Alternatively, it can also be viewed as a lighter test on the model, as we no longer force the model to price both the equity premium as well as the cross-sectional differences between the 70 portfolios, but only the cross-section.

A priori, we would expect a small and probably insignificant premium for the risk premium beta, as it represents transitory risk, while for the sum of the interest rate and nominal cash flow betas (i.e. GBBB model) we would expect a highly positive premium if inflation risk is an important component

[16] We ignore the uncertainty in the estimation of the betas and news terms themselves. A common way to incorporate uncertainty in the beta estimates is to use the Shanken (1992) correction. However, we do not derive the betas from a multivariate regression as is common (Cochrane, 2001), but instead compute covariances directly as implied by the Campbell-Shiller return decomposition. When we use multivariate regressions to estimate the betas, we find similar values, and the Shanken correction factor amounts to 1.84.

[17] We thus maintain the cross-sectional correlation structure between the portfolios and the factors.

of interest rate risk, as it adds up to the real cash flow beta representing permanent risk (Campbell and Vuolteenaho, 2004). For the interest rate beta alone we would also expect a positive risk premium, as interest rate changes pose a risk to bond investors. Government bonds are assumed to carry a positive risk premium to compensate for this risk (Fama and Bliss, 1987), and thus one would also expect this premium to appear in stock returns. As discussed above, whether the nominal cash flow beta has a premium similar, lower or higher than the interest rate beta is undetermined.

Table 2.4, panel A, reports the full sample results. We first focus on the results without constant. Under the CAPM assumption, we find a positive and significant price of risk of 2.14% per quarter per unit of beta. The R-squared of 11.4%[18] indicates that the CAPM beta is not really able to price the portfolio returns. The GBBB model is much better at explaining the returns, increasing the R2 to 26.5%, while the mean absolute pricing error of the portfolios drops from 0.45% to 0.30%. To test whether the constraint $\lambda_e = \lambda_{y+CF}$ that the CAPM implicitly imposes versus the GBBB model can be rejected, we employ an F-test. The F-test statistic of 40.54 indicates that the GBBB model is also statistically significantly better at explaining the returns than the CAPM model. It achieves this by setting a low and insignificant price on the risk premium beta and a high premium on the real cash flow beta ($\beta_{i,yM} + \beta_{i,CFM}$) of 6.63% per quarter. Campbell and Vuolteenaho (2004) have found similar differences in the pricing of the two betas. The unrestricted model reveals, however, significant differences in the pricing of the interest rate beta versus the nominal cash flow beta. Although both are positive and significant, the interest rate beta has a much higher price of risk than the nominal cash flow beta. The F-statistic of 12.63 indicates that the unrestricted model is a statistically significant improvement over the GBBB model. Also, the R2 increases, and the mean absolute error declines slightly. We also find the unrestricted model to be significantly better than the CAPM model (F-statistic of 30.05). As mentioned above, there are several reasons why interest rate risk may carry a higher price of risk than cash flow risk.

The three right-most columns of Table 2.4, panel A, show the same analyses but then with a constant included. Clearly, the CAPM model without

[18]The adjusted R-squared is computed as follows per quarter:

$$R2 = 1 - \frac{n-1}{n-k} \frac{\sum_i \epsilon_i^2}{\sum_i (R_i - \bar{R})^2}$$

where n is the number of portfolios, k the number of regressors, ϵ_i the residuals, R_i the return of portfolio i and $\bar{R}$ the average over the portfolios returns. This allows negative R-squares as we force the constant to be zero. Subsequently, the quarterly R-squares are averaged over time.

constant only loads on the CAPM beta to explain the equity risk premium; the CAPM beta does not explain cross-sectional dispersion in returns, in line with literature on the relation between beta and return to be relatively flat (Haugen and Heins, 1972). Also with a constant, we find the GBBB and unrestricted models to be significant improvements over the CAPM model (F-statistics of 3.58 and 6.24 respectively), although the gain in R2 is less strong than without constant. For the GBBB model, we find that part of the loading on the real cash flow beta is shifted to the constant, which is positive and just significant (t-statistic of 1.70), implying misspecification of the model without constant. For the unrestricted model, the loadings on the three betas hardly change when the constant is included; the constant itself is close to zero and insignificant. We can thus not reject the hypothesis that the model without constant is correctly specified. Moreover, also with a constant included we find the unrestricted model to be statistically stronger than the GBBB model in pricing the portfolios (F-statistic of 6.24).

Panel B reports the results for the pre-1963 period. In general, we find that the GBBB and unrestricted models substantially improve upon the CAPM model when no constant is included. However, once a constant is included, we find hardly any statistical evidence of improved pricing of the GBBB and unrestricted models over the CAPM model. Campbell and Vuolteenaho (2004) come to a similar result, and point out that their real cash flow betas are during this period approximately a fixed proportion of the total beta across the test assets, making it hard for the asset pricing test to assign prices. We find that in our early sample this proportion ranges from 5% to 26%, whereas in the full sample it ranges from 15% to 43%. Thus there indeed seems to be less variation relative to the full sample, but variation in the relative betas certainly exists.

Panel C reports the results for the post-1963 period. For the CAPM model, the results are very similar: the constant subsumes the total beta coefficient. Both the GBBB and unrestricted models prove significant improvements over the CAPM model (F-statistics of 6.83 and higher), although the improvement of the unrestricted model over the GBBB model is now smaller and not always significant. The premium on the interest rate beta is a much smaller 3.24% (1.09%) versus the full sample estimate of 10.32% (10.07%) and the early sample estimate of 15.04% (4.09%) for the model without (with) constant.

Still, in the model with constant the interest beta is statistically significant and positive with a t-statistic of 1.79. Figure 2.2 plots the prices of risk through time for the final specification. For the sake of readability, the prices are smoothed using an exponentially weighted average with half-time of 12 quarters. It is immediately clear from the figure that the prices vary through time, but are also relatively smooth. While the risk premium (excess return) beta is usually close to zero or slightly negative, both cash flow and especially interest rate premiums vary strongly and are mostly positive. For the interest rate beta, 1999-2000, i.e. the dot-com bubble, is an exceptional period with a very negative price of risk.

The interest beta premium tends to comove with the cash flow premium (correlation of 33%), and to a lesser extent with the risk premium (correlation of 15%). Still, there are also periods where the correlation breaks down between interest rate and cash flow prices, such as the early 1950s and late 1960s.

So far, the assessment of the various asset pricing models has focused on statistical evidence: are the betas priced differently? Another way to compare the models is to check whether a model is better able to price the anomaly portfolios. As a measure, we compute per portfolio the pricing error, that is, the difference between the quarterly realized return and the fitted return of the pricing model, and subsequently take the average over the absolute values of errors. The smaller this mean absolute error (MAE), the better the pricing model is able to explain the returns of the anomaly portfolios.

Table 2.4 reports in the bottom two rows of each panel the MAE. The first row ("MAE1") is computed over all 70 portfolios, i.e. the exact same set as on which the prices are calibrated; the second row ("MAE2") reports the MAE over the 25 size x value portfolios plus the 5 volatility portfolios. Full sample, the improvement over all 70 portfolios is small for the three-beta model over the GBBB model. However, for the anomaly portfolios we find clear evidence the pricing improves when the interest beta is included, especially in the cross-section: the MAE drops from 0.4620% to 0.4178%. It also shows that still a relatively large portion of the errors remains. Over the early sample, the MAE is close to unchanged, and for the modern sample we observe a modest decrease in the pricing error.

In Table 2.5 the pricing errors for selected anomaly portfolios[19] are displayed per model specification. Although we observe that in general the errors indeed tend to shrink to zero when the interest beta is added, this is typically by a small magnitude. This holds for the size, value as well as the low volatility effect.

To conclude, there is clear statistical evidence that the interest rate beta is priced differently from the cash flow and risk premium beta, but we find the economic significance to be limited when it comes to pricing anomaly portfolios.

[19] Of the 25 size x value portfolios, only the Q1/Q3/Q5 combinations are shown to save space. The other portfolio results are available upon request.

2.4 Robustness checks

2.4.1 Reduced VAR model

In Section 2.3 we based all results on the aggregate VAR model with six state variables. Although the selection of state variables follows the literature well (see Appendix 2.A for a discussion), the inclusion of particular variables might drive our findings. Therefore we redo the analyses with a reduced VAR model. For the absolute minimum number of variables, we need to have the market excess return and the risk-free rate to estimate the two respective news components, as well as a variable which includes the current stock price, otherwise the decomposition no longer holds (Engsted, Pedersen, and Tanggaard, 2012). Amongst the six state variables, the Shiller PE ratio fulfills this role. The Shiller PE also happens to be the strongest of the four remaining state variables in predicting future market returns in the full VAR model (Table 2.1). Hence we re-estimate the VAR model with the market excess return, the risk-free rate and the price-to-earnings ratio.

Panel A of Table 2.6 contains the results of the estimation. We find that the adjusted R2 for the market return decreases slightly versus the full model, from 6.57% to 5.88%. For the risk-free rate and the price-to-earnings ratio it is virtually the same. The estimated transition matrix coefficients are also very similar. This indicates that there are no major changes compared to the full model.

In panel B, the covariance matrix of the news terms is shown. Compared to the full model, the covariances between the news terms change only modestly. Of the variance of the three terms, only the nominal cash flow changes from 0.0026 to 0.0018. In panel C, the correlations between the full model and reduced model news terms are listed. The correlation between the excess return components is very high at 0.97. The correlations for the other two news terms amount to 0.75. They are thus highly correlated, but not perfect.

To assess whether this has a meaningful impact on the pricing of the betas, the analysis in Table 2.4 is repeated with the reduced VAR model news terms in panel A of Table 2.7. We find that the results are similar or even stronger: the interest beta has a very high and significant premium, and is statistically different from the nominal cash flow premium.

Interestingly, we also find that the inclusion of the interest rate beta improves the pricing performance compared to the GBBB model: not only is the statistical evidence stronger (higher F-statistics), but also the mean absolute error decreases by about 25%, whether a constant is included (specification 6 vs. 5), or not (specification 3 vs. 2). This is large compared to the reductions found for the full model.

2.4.2 Out-of-sample estimation of the news terms

Underlying our main results is the assumption that the VAR model properly captures investors' expectations. In the previous robustness check, we checked the sensitivity of the results for the inclusion of particular state variables, but this still assumes that the relationships between the state variables are constant over the sample and known in advance to investors.

To incorporate a dynamic relationship between the state variables, stock returns and interest rates in particular, as well as to prevent foresight we re-estimate the VAR model in a rolling fashion. At each quarter, we use the previous 40 quarters, i.e. 10 years, to estimate the transition matrix and apply this to the next quarter to compute the news terms. If we would do this without any constraints, the transition matrix becomes non-stationary during some periods, as indicated by a modulus being greater than 1. To prevent this situation, we apply the following restrictions:

- We use the reduced VAR model to prevent too many coefficients to be estimated over relatively few data points.[20]
- We explicitly restrain the interest rate dynamics by requiring the same long-term average as in the full model as well as the same own-lag coefficient of 0.9834. If we would not do this, the own-lag coefficient can be greater than 1 at times, as interest rates are only stationary in the very long run, not per se on a 10-year horizon.
- To prevent non-stationarity, we explicitly restrain the modulus of the transition matrix to be 0.99 or smaller.

To incorporate the restrictions, we estimate the rolling VAR with the Generalized Method of Moments (GMM). Like Campbell, Giglio, and Polk (2013), we use Hansen, Heaton, and Yaron (1996) continuously updated (CUE) GMM as it has finite-sample advantages over standard GMM. For comparability with the full sample estimations, we include the first 10 years (February 1927 to January 1937) by using the coefficients estimated over this period.

Each quarter, we re-estimate the VAR coefficients and apply these out-of-sample to compute the news terms. We find that the total shock variance increases from 0.0067 for the full sample estimated VAR model to 0.0073 for the rolling VAR. The increase is relatively modest, given that the fit is no longer in-sample. If we analyze the decomposition in more detail, we find

[20]The full VAR model has 42 coefficients, as it has 6 state variables and per state variable 7 coefficients (a constant and 6 coefficients on the lagged state variables). The reduced VAR model has only 12 coefficients, of which we effectively fixate 2 (see second point), leaving 10 free coefficients to be estimated.

that the risk premium variance decreases from 0.0060 to 0.0044, while the other two variances increase. This suggests that the lack of foresight makes the changes in expected excess returns more muted, attributing more of the total shock variance to interest rates (from 0.0023 to 0.0037) and nominal cash flows (from 0.0026 to 0.0060) instead. Comparing the shock terms head-to-head, the total shocks have a correlation of 94%, while the individual news terms correlations range from 75% to 84%. This suggests that the in-sample estimation procedure does not lead to overfitting.

Panel B of Table 2.7 reports the asset pricing results for the full sample. In contrast to the full-sample VAR model results, we observe that nominal cash flow premium is no longer statistically larger than zero in the unrestricted model, while the price attached to the interest rate beta becomes even larger. Therefore, the evidence of the added value of splitting the real cash flow beta into an interest rate beta and a nominal cash flow beta is even stronger, with the F-statistics being 85.50 and 12.82 for the models without and with a constant respectively. Also economically, the gain of including the interest rate beta is large: the mean absolute pricing error decreases dramatically, with the strongest decrease for the anomaly portfolio under the specification without constant: from 0.5748% to 0.3017%. Thus by allowing one additional free parameter, the pricing error is almost halved.

2.4.3 Characteristic-dependent firm VAR model

In the main results we have assumed that the companion matrix A is the same for all firms. As we are employing characteristics-sorted portfolios in our asset pricing test, we are making the strong assumption that the dynamics of the individual stocks are the same across these portfolios. To alleviate this concern, we modify the firm VAR model by adding interaction dummies based on the characteristics. Specifically, each period we divide the universe in three equal sized groups based on the book-to-market ratio (market capitalization or 12-month historic volatility) to create the dummies $\mathbb{1}_{i,t}^{bmQ1}$ and $\mathbb{1}_{i,t+1}^{bmQ1}$, where the superscript indicates the characteristic on which the sort is based (i.e., bm for book-to-market, me for market capitalization equity and vol for volatility) and whether the stock is on this characteristic in the top (Q1) or bottom (Q3) tertile, where the ordering is such that high values of the characteristic are assigned to Q1 and low values to Q3. We take the middle group Q2 as the base group and hence do not include a dummy for this group. To ensure the groups are equal sized, we compute the dummies for t and $t+1$ every quarter again. Thus entrants and leavers in the universe do not bias the sizes of the groups. To prevent the number of parameters to become very large, we only interact the dummies with the interest rate state variable y_t^{nom}, and interaction terms are only driven by the interest rate variable y_t^{nom} and the interaction terms based on the same characteristic.

Table 2.8 reports the results. For space reasons, the rows and columns with the aggregate state variables have been removed, with the exception of the interest rate column, which is the only aggregate variable to drive the interacted variables. As we have three characteristics and two additional terms per characteristic, there are six new state variables in total. These state variables, being firm-specific, are constrained to only explain firm-specific variables, as are the other firm-specific variables. We first discuss the bottom 6 rows of the matrix, which describe the dynamics of the interaction terms, and then the impact on other state variables.

From the coefficients, we observe that the interaction terms are positively autocorrelated. For instance, $y_{t+1}^{\text{nom}}\mathbb{1}_{i,t+1}^{bmQ1}$ has a coefficient of 0.11 on y_t^{nom}, 0.75 on its own lag and -0.11 on $y_t^{\text{nom}}\mathbb{1}_{i,t}^{bmQ3}$. Thus if a stock belongs to the top book-to-market tertile Q1, next quarters value for the state variable $y_{t+1}^{\text{nom}}\mathbb{1}_{i,t+1}^{bmQ1}$ is expected to be $0.11 + 0.75 = 0.86y_t^{\text{nom}}$, which is positive. In words: if a stock is this quarter in the top book-to-market group, it likely is next quarter as well. The coefficient of 0.75 indicates how persistent this likeliness is.[21] On the other hand, if the stock currently belongs to the bottom group, next quarters expected value is 0.11-0.11, which is close to zero. Thus, the data tells us that it is unlikely a stock moves from the bottom to the top group from one quarter to the next. The opposite is also true: the coefficient for a stock currently being in the top group ending up in the bottom group $y_{t+1}^{\text{nom}}\mathbb{1}_{i,t+1}^{bmQ3}$ equals 0.09-0.09, which is zero as well. This persistence is also visible for the market cap groups, which have higher own-lag coefficients than the book-to-market interaction terms. This indicates that the market capitalization dummies are more persistent than the book-to-market dummies. For volatility, we also find persistence, but the own-lag coefficients are the lowest of the three characteristics, indicating that stocks transition groups fastest along the volatility dimension.

With these interaction terms, we can assess the impact on the other state variables. For the news decomposition the stock-specific log excess return $e_{i,t+1}$ and the interest rate dynamics y_{t+1}^{nom} are of particular importance. As the interest rate is an aggregate variable, it is not affected by the inclusion of firm-specific interaction terms. For the log excess return, we find that the effects are relatively modest and statistically insignificant for the book-to-market, but not for market cap and volatility: $t+1$ excess returns of low

[21] These coefficients also pick up the persistence in interest rates. As the coefficient for interest rates on its own lag is 0.87 is less than one, the coefficients of the interaction terms cannot directly be interpreted as probabilities of switching from one group to another.

market cap (volatility) stocks are more (less) negatively exposed to an interest rate shock in year t than middle market cap (volatility) stocks. For volatility, stocks in the Q1 group are also more negatively exposed.

This has implications for the news terms: if market participants expect a difference in the reaction of high volatility stocks to interest rate shocks versus low volatility, an interest rate shock will lead to different expected excess returns versus the firm-VAR model employed in the previous section. Results of the beta decomposition of the portfolio as well as the pricing of the betas show, however, very small differences (results are available upon request). The reason is that although the expected excess returns can now be estimated slightly more precisely, firm-specific excess returns remain very hard to predict.[22] For comparison, the standard deviation of interest rate residuals is 0.16%, whereas the standard deviations of the firm-specific excess return residuals in the base case firm VAR model is 24.99%. Thus the difference in coefficients between high and low volatility of 2.18 (0.70 + 1.48) is relatively small in comparison to the difference in the volatilities of the two state variables.

2.5 Conclusions

Since the introduction of the present-value decomposition of asset returns by Campbell and Shiller (1988), a number of studies have exploited this breakdown of stock returns into several components to better understand stock return dynamics, both in aggregate as well as in the cross-section. Although there has been active debate on the interest rate exposure of stock returns, and given the important role interest rates play in financial markets in general, to the best of our knowledge no other studies have separately estimated a nominal interest rate component of stock returns. Instead, most studies opt for estimating real cash flow and total discount rate shocks.

In this study, we disentangle interest rate shocks and nominal cash flow shocks, and find that unexpected interest rate shocks, i.e. "interest rate news", explains as much of the variation in stock returns as nominal cash flow news. Although interest rates have much lower variation than stock excess returns, we find that the high persistence of interest rates leads to sizeable effects. On the firm level, interest rates explain only 3.3% of the total variation, as interest rates, in contrast to firm-specific excess returns and cash flows, are

[22]By construction, adding explanatory variables in an OLS framework can only reduce the unexplained variation in the excess returns, not increase. The adjusted R-square, which corrects for the number of regressors included, shows a small increase from 3.05% (Table 2.2) to 3.30% (Table 2.8), indicating limited additional explanatory power of the six interaction terms.

identical for all firms in a given period, and are thus unable to explain any cross-sectional variation by construction.

We also analyze the sensitivity of anomaly portfolios to interest rate news. We find that growth stocks, large stocks and low volatility stocks have higher interest betas than value, small and high volatility stocks, but these relationships can vary through time. Allowing the prices of the three betas (equity risk premium beta, interest rate beta and nominal cash flow beta), to vary leads to a considerable improvement in explaining the returns of the anomaly portfolios. The price of interest rate beta is estimated to be positive, and is in most tests significantly different from the nominal cash flow beta price. Thus treating the two betas separately reveals important distinctions in interest rate exposures and pricing previously not observed.

2.A Literature overview VAR models and decompositions

In the academic literature, multiple VAR models are in use. Table 2.9 summarizes the main features of those models.

The model in this study draws primarily on the model of Campbell, Giglio, and Polk (2013). For the sample period, we are limited by the CRSP and COMPUTSTAT datasets, hence we start in February 1927. The quarterly frequency of the data is a compromise of statistical strength and ability to do more granular analyses (i.e., rolling VAR model estimation and rolling betas) on the one hand for which monthly or quarterly data is needed and the focus on longer term relationships between variables on the other hand, as stocks are typically thought of as long-term assets, making the estimation of month-to-month dynamics less relevant. We include all state variables used in the four most recent papers except stock return variance as we are not interested in a volatility beta. Campbell et al. (2017, Table 1, panel B) find that this variable has very limited and statistically insignificant forecasting power for the other state variables, thus excluding it is unlikely to affect our results. Campbell et al. (2017) is the only study of the four to use real returns; in this study we opt for excess stock returns rather than real returns for reasons explained in the beta decomposition section.

For the firm-VAR model, there are less studies to draw on; see Table 2.10. Both Vuolteenaho (2002) and Campbell, Polk, and Vuolteenaho (2010) use annual data with excess stock returns, book-to-market ratio (for the cross-sectional value effect) and a profitability measure.

Table 2.1: Aggregate VAR model

Panel A reports the OLS estimated coefficients, t-statistics (in brackets) and adjusted R2's. The state variables are constructed as described in Section 2.2 and demeaned prior to estimation. Panel B reports the empirical covariance matrix (left) and the correlations, off-diagonal terms, and standard deviations, diagonal (right) of the news terms. Panel C reports the mapping of a shock in a state variable to the news terms: left the empirical correlations, on the right the marginal effects of a state variable shock as implied by the VAR model. To compute the standard errors of these derived quantities, the delta-method (Cramér, 1946) is used. Significance at the 90%, 95% and 99% levels are indicated with *, ** and *** respectively. A ρ of 0.95 is assumed in the computation of the news terms. Sample period from February 1927 to October 2015.

Panel A: VAR coefficients

	$e_{M,t}$	y_t^{nom}	TY_t	PE_t	VS_t	DEF_t	Adj R2
$e_{M,t+1}$	0.1805***	-1.7159**	0.0017	-0.0385***	-0.0350*	0.0008	0.0657
(excess market return)	(2.9840)	(-2.4291)	(0.3817)	(-2.9441)	(-1.8299)	(0.0485)	
y_{t+1}^{nom}	0.0025**	0.9866***	0.0002	-0.0002	-0.0002	-0.0004*	0.9592
(risk-free rate)	(2.0108)	(46.3992)	(1.4542)	(-0.7391)	(-0.6614)	(-1.7818)	
TY_{t+1}	-0.1534	-2.6343	0.8526***	0.0489	0.0149	0.1739***	0.8150
(term yield spread)	(-0.3984)	(-0.4715)	(25.7095)	(0.6449)	(0.1380)	(2.7688)	
PE_{t+1}	0.3635***	-0.3705	0.0051	0.9726***	-0.0261	0.0049	0.9563
(price-to-earnings ratio)	(5.8013)	(-0.5445)	(1.0823)	(73.2478)	(-1.2581)	(0.2969)	
VS_{t+1}	0.0781	-1.8002***	-0.0116***	0.0250*	0.8934***	0.0687***	0.9451
(value spread)	(1.3961)	(-2.7611)	(-2.6449)	(1.8294)	(41.2596)	(6.1499)	
DEF_{t+1}	-0.4952**	5.2462**	0.0044	0.0005	0.2168***	0.8284***	0.8347
(default spread)	(-2.2153)	(2.3751)	(0.4068)	(0.0122)	(2.6595)	(14.5067)	

Panel B: News

Var/covar	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$
$-N_{M,e}$	0.0060	-0.0007	-0.0006
$-N_{M,y^{\text{nom}}}$	-0.0007	0.0023	-0.0009
$N_{M,CF^{\text{nom}}}$	-0.0006	-0.0009	0.0026

Corr/std	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$
$-N_{M,e}$	0.0773	-0.1812	-0.1454
$-N_{M,y^{\text{nom}}}$	-0.1812	0.0484	-0.3761
$N_{M,CF^{\text{nom}}}$	-0.1454	-0.3761	0.0514

Panel C: Shocks and news

Corr. shocks and news	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$
$e_{M,t+1}$	0.7527	0.1856	0.2711
y_{t+1}^{nom}	0.4649	-0.7579	-0.0558
TY_{t+1}	-0.2985	0.4353	-0.0543
PE_{t+1}	0.8276	0.3031	-0.1948
VS_{t+1}	0.2224	0.2489	-0.2359
DEF_{t+1}	-0.4166	0.4136	-0.5170

Functions	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$
$e_{M,t+1}$	0.1821	-0.0194	0.8373***
	(1.5050)	(-0.2731)	(7.2464)
y_{t+1}^{nom}	36.5884	-29.1380	-7.4504
	(1.2192)	(-1.4091)	(-0.3496)
TY_{t+1}	0.0457	-0.0314	-0.0144
	(0.7438)	(-0.8652)	(-0.2567)
PE_{t+1}	0.6678	0.2456	-0.9133**
	(1.5347)	(0.9012)	(-2.3928)
VS_{t+1}	0.0303	0.1858	-0.2161
	(0.1052)	(1.1972)	(-0.6781)
DEF_{t+1}	-0.0036	0.1036	-0.1000
	(-0.0230)	(1.3694)	(-0.5871)

Table 2.2: Firm VAR model

Panel A reports the OLS estimated coefficients, t-statistics (in brackets; clustered by firm-quarter as suggested by Petersen (2009)) and adjusted R2's of a pooled-panel regression. For space reasons only the results for the firm-specific state variables are shown; the other lines are identical to those in the aggregate VAR model (Table 2.1). Panel B reports the empirical covariance matrix (left) and the correlations, off-diagonal terms, and standard deviations, diagonal (right) of the news terms. Panel C reports the mapping of a shock in a state variable to the news terms: left the empirical correlations, on the right the marginal effects of a state variable shock as implied by the VAR model. To compute the t-statistics of these derived quantities, the delta-method (Cramér, 1946) is used. Significance at the 90%, 95% and 99% levels are indicated with *, ** and *** respectively. A ρ of 0.95 is assumed in the computation of the news terms. Sample period from February 1927 to October 2015.

Panel A: VAR coefficients

	$e_{i,t}$	$bm_{i,t}$	$roe_{i,t}$	$e_{M,t}$	y_t^{nom}	TY_t	PE_t	VS_t	DEF_t	Adj R2
$e_{i,t+1}$	-0.0082	0.0055	0.0326***	0.2968***	-2.9006***	-0.0008	-0.0648***	-0.0406	0.0023	0.0305
(excess return)	(-0.6280)	(1.4995)	(5.8730)	(3.4916)	(-3.2505)	(-0.1379)	(-4.2080)	(-1.4825)	(0.1258)	
$bm_{i,t+1}$	0.0103	0.9666***	0.0076	-0.2694***	0.7733	-0.0066	0.0272*	0.0434*	-0.0057	0.9192
(book-to-market ratio)	(0.8173)	(225.9875)	(1.6249)	(-3.4163)	(0.9400)	(-1.2154)	(1.9002)	(1.6827)	(-0.3176)	
$roe_{i,t+1}$	0.0284***	-0.0104***	0.8943***	-0.0419***	-0.7415***	-0.0062***	-0.0252***	0.0144***	-0.0098***	0.7872
(return-on-equity)	(7.7799)	(-7.5487)	(94.5513)	(-3.5549)	(-5.9849)	(-7.9441)	(-8.6599)	(3.1787)	(-3.8935)	

Panel B: News

Var/covar	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$	Corr/std	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$
$-N_{M,e}$	0.0202	-0.0025	-0.0066	$-N_{M,e}$	0.1420	-0.3491	-0.1937
$-N_{M,y^{\text{nom}}}$	-0.0025	0.0024	0.0006	$-N_{M,y^{\text{nom}}}$	-0.3491	0.0494	-0.0469
$N_{M,CF^{\text{nom}}}$	-0.0066	0.0006	0.0573	$N_{M,CF^{\text{nom}}}$	-0.1937	0.0469	0.2395

Panel C: Shocks and news

Corr. shocks and news	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$	Functions	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$
$e_{i,t+1}$	0.3123	0.0442	0.8538	$e_{i,t+1}$	-0.0003		1.0003***
					(-0.0248)		(75.2215)
$bm_{i,t+1}$	-0.3739	-0.0411	-0.5607	$bm_{i,t+1}$	-0.0561		0.0561
					(-0.6895)		(0.6895)
$roe_{i,t+1}$	-0.3795	-0.0078	0.2691	$roe_{i,t+1}$	-0.2784***		0.2784***
					(-5.4423)		(5.4423)
$e_{M,t+1}$	0.6265	0.2091	-0.0329	$e_{M,t+1}$	0.3409	-0.0194	-0.3215
					(1.5265)	(-0.2884)	(-1.5476)
y_{t+1}^{nom}	0.4173	-0.8056	-0.0780	y_{t+1}^{nom}	69.5739	-29.1380	-40.4360
					(1.2496)	(-1.5294)	(-0.8969)
TY_{t+1}	-0.0971	0.3899	-0.0264	TY_{t+1}	0.1418	-0.0314	-0.1104
					(1.3663)	(-1.0068)	(-1.1795)
PE_{t+1}	0.6848	0.2630	-0.1220	PE_{t+1}	1.0596	0.2456	-1.3051**
					(1.3738)	(0.9482)	(-2.0142)
VS_{t+1}	0.0380	0.2278	0.0216	VS_{t+1}	-0.2830	0.1858	0.0972
					(-0.4797)	(1.1042)	(0.1643)
DEF_{t+1}	-0.4449	0.3715	-0.0088	DEF_{t+1}	-0.0751	0.1036	-0.0285
					(-0.2640)	(1.0720)	(-0.1035)

Table 2.3: Beta decomposition portfolios

Portfolios are constructed as described in Section 2.3.3. The table reports per portfolio the beta to the three market news terms generated by the VAR model of Table 2.1. Betas are reported over the full sample period ("Full") which runs from May 1932 to October 2015, as well as for the early sample ("Early"; May 1932 - January 1963) and the modern sample ("Modern"; February 1963 - October 2015). To save space, we only report Q1, Q3 and Q5 for the 5x5 size x value portfolios; for the risk-sorted portfolio we only report the full sample results.

Panel A: size (ME) x value (BE/ME) portfolios

	ME	Low			Q3			High		
	BE/ME	Low	Q3	High	Low	Q3	High	Low	Q3	High
Full	$\beta_{i,eM}$	1.38	1.07	1.17	1.02	0.86	0.96	0.73	0.64	0.86
	$\beta_{i,yM}$	0.24	0.21	0.16	0.18	0.16	0.17	0.14	0.11	0.12
	$\beta_{i,CFM}$	0.00	0.09	0.13	0.12	0.17	0.21	0.10	0.17	0.23
Early	$\beta_{i,eM}$	1.55	1.31	1.47	1.07	1.03	1.24	0.79	0.73	1.23
	$\beta_{i,yM}$	0.35	0.26	0.20	0.17	0.12	0.13	0.10	0.05	0.02
	$\beta_{i,CFM}$	-0.26	-0.07	0.02	-0.01	0.10	0.14	0.05	0.15	0.24
Modern	$\beta_{i,eM}$	1.22	0.85	0.90	0.97	0.70	0.71	0.66	0.55	0.53
	$\beta_{i,yM}$	0.15	0.16	0.13	0.18	0.20	0.21	0.18	0.17	0.20
	$\beta_{i,CFM}$	0.22	0.24	0.24	0.24	0.23	0.27	0.15	0.20	0.23

Panel B: volatility portfolios

	Vol	Low	Q2	Q3	Q4	High
Full	$\beta_{i,eM}$	0.52	0.78	1.00	1.15	1.37
	$\beta_{i,yM}$	0.16	0.11	0.14	0.14	0.10
	$\beta_{i,CFM}$	0.09	0.18	0.20	0.25	0.28
Early	$\beta_{i,eM}$	0.63	0.86	1.05	1.16	1.28
	$\beta_{i,yM}$	0.11	0.06	0.10	0.10	0.06
	$\beta_{i,CFM}$	0.01	0.15	0.13	0.19	0.27
Modern	$\beta_{i,eM}$	0.42	0.71	0.95	1.14	1.44
	$\beta_{i,yM}$	0.20	0.17	0.18	0.18	0.14
	$\beta_{i,CFM}$	0.17	0.21	0.26	0.29	0.28

Panel C: risk-sorted portfolios (full sample only)

	β_M	High		Q2		Q3		Q4		Low	
	β_Y	High	Low	High	Low	High	Low	High	Low	High	Low
Full	$\beta_{i,eM}$	1.26	1.11	0.96	0.89	0.82	0.75	0.64	0.55	0.55	0.41
	$\beta_{i,yM}$	0.18	0.13	0.17	0.14	0.10	0.13	0.14	0.16	0.16	0.14
	$\beta_{i,CFM}$	0.15	0.24	0.13	0.20	0.17	0.17	0.11	0.14	0.11	0.16

	β_M	High		Q2		Q3		Q4		Low	
	β_{TY}	High	Low	High	Low	High	Low	High	Low	High	Low
Full	$\beta_{i,eM}$	1.23	1.13	0.92	0.94	0.80	0.78	0.63	0.58	0.56	0.42
	$\beta_{i,yM}$	0.18	0.13	0.16	0.14	0.11	0.12	0.15	0.16	0.14	0.15
	$\beta_{i,CFM}$	0.15	0.25	0.15	0.17	0.16	0.18	0.10	0.16	0.12	0.17

	β_M	High		Q2		Q3		Q4		Low	
	β_{VS}	High	Low	High	Low	High	Low	High	Low	High	Low
Full	$\beta_{i,eM}$	1.21	1.16	0.95	0.93	0.80	0.80	0.60	0.60	0.53	0.46
	$\beta_{i,yM}$	0.13	0.17	0.15	0.17	0.11	0.12	0.14	0.17	0.16	0.14
	$\beta_{i,CFM}$	0.23	0.19	0.19	0.13	0.19	0.17	0.19	0.09	0.14	0.16

	β_M	High		Q2		Q3		Q4		Low	
	β_{DEF}	High	Low	High	Low	High	Low	High	Low	High	Low
Full	$\beta_{i,eM}$	1.16	1.19	0.90	1.00	0.73	0.88	0.53	0.72	0.43	0.60
	$\beta_{i,yM}$	0.16	0.15	0.16	0.16	0.12	0.11	0.15	0.18	0.17	0.13
	$\beta_{i,CFM}$	0.16	0.24	0.13	0.19	0.15	0.21	0.11	0.15	0.09	0.22

Table 2.4: Pricing of betas

We employ Fama and MacBeth (1973) regressions by regressing each quarter the simple returns of the 70 portfolios (25 size x value, 5 volatility, 40 risk-sorted) in excess of the risk-free rate on the full sample betas to market risk premium shock, market cash flow shock and market interest rate as reported in Table 2.3. In round brackets are the Fama-MacBeth standard errors, corrected for autocorrelation and heteroscedasticity (Newey and West, 1987); in square brackets bootstrapped standard errors. In the first column we restrict all beta coefficients to be equal to each other ("CAPM"), and in the second column we restrict the cash flow and interest rate betas to be equal to each other ("GBBB") and in the final column we leave all coefficients free ("unrestricted"). The adjusted R2 is the average adjusted R2 of the cross-sectional regressions. The F-tests below the columns show the test-statistic whether the model in that column (i.e. no longer imposing the equality of particular coefficients) is significantly better either the CAPM model ("F-test vs CAPM") or the "Good Beta, Bad Beta" model ("F-test vs GBBB"). The mean absolute error (MAE) is the mean of the absolute values of the difference of the actual and fitted quarterly mean return of the 70 portfolios ("MAE1") or only the 30 anomaly portfolios ("MAE2"). Stars denote the significance at the 10% (*), 5% (**) and 1% (***) level. Results are reported for the full sample period which runs from May 1932 to October 2015 (Panel A), as well as for the early sample May 1932 - January 1963 (Panel B) and the modern sample February 1963 - October 2015 (Panel C) separately.

	no constant			constant		
model	CAPM	GBBB	unrestricted	CAPM	GBBB	unrestricted
specification	1	2	3	4	5	6
Panel A: full sample (May 1932 - October 2015)						
constant				0.0168***	0.0103*	0.0005
				(2.9390)	(1.6974)	(0.0671)
				[3.3810]	[1.2919]	[0.0534]
λ_e (price $\beta_{i,eM}$)	0.0214***	0.0057	0.0026	0.0077	0.0053	0.0026
	(4.6029)	(0.7920)	(0.3464)	(1.1303)	(0.7292)	(0.3721)
	[4.7885]	[0.5608]	[0.2807]	[1.1690]	[0.6148]	[0.3019]
λ_y (price $\beta_{i,yM}$)	0.0214***	0.0663***	0.1032***	0.0077	0.0350**	0.1007***
	(4.6029)	(4.4299)	(4.1507)	(1.1303)	(2.1209)	(2.6487)
	[4.7885]	[3.2998]	[3.8297]	[1.1690]	[1.0768]	[1.9732]
λ_{CF} (price $\beta_{i,CFM}$)	0.0214***	0.0663***	0.0491***	0.0077	0.0350**	0.0479***
	(4.6029)	(4.4299)	(3.2349)	(1.1303)	(2.1209)	(2.9874)
	[4.7885]	[3.2998]	[1.7823]	[1.1690]	[1.0768]	[1.5030]
Adj. R2	11.4%	26.5%	31.8%	28.3%	32.0%	36.6%
F-test vs CAPM		40.54***	30.05***		3.58**	4.36**
F-test vs GBBB			12.63***			6.24**
MAE1	0.4567%	0.3011%	0.2940%	0.3081%	0.2961%	0.2938%
MAE2	0.5515%	0.4343%	0.4161%	0.4941%	0.4620%	0.4178%
Panel B: early sample (May 1932 - January 1963)						
constant				0.0151*	0.0128*	0.0126*
				(1.9163)	(1.6832)	(1.6550)
				[1.7299]	[1.5297]	[1.4453]
λ_e (price $\beta_{i,eM}$)	0.0331***	0.0250**	0.0136	0.0209	0.0189	0.0181
	(3.6336)	(1.9880)	(0.9042)	(1.6212)	(1.3319)	(1.3799)
	[3.8483]	[1.8073]	[0.7706]	[1.6275]	[1.1796]	[1.0489]
λ_y (price $\beta_{i,yM}$)	0.0331***	0.0740**	0.1504**	0.0209	0.0422	0.0490
	(3.6336)	(2.4857)	(2.3089)	(1.6212)	(1.3029)	(0.9655)
	[3.8483]	[2.1152]	[1.8799]	[1.6275]	[1.1003]	[0.6990]
λ_{CF} (price $\beta_{i,CFM}$)	0.0331***	0.0740**	0.1047***	0.0209	0.0422	0.0454*
	(3.6336)	(2.4857)	(3.1902)	(1.6212)	(1.3029)	(1.9353)
	[3.8483]	[2.1152]	[2.4594]	[1.6275]	[1.1003]	[1.1054]
Adj. R2	9.9%	18.9%	23.8%	25.3%	30.6%	32.7%
F-test vs CAPM		12.29***	8.50***		2.82*	1.33
F-test vs GBBB			4.14**			0.02
MAE1	0.4504%	0.4000%	0.3800%	0.3400%	0.3266%	0.3258%
MAE2	0.4882%	0.4647%	0.4555%	0.4544%	0.4303%	0.4304%

(Table 2.4 continued)

	no constant			constant		
model	CAPM	GBBB	unrestricted	CAPM	GBBB	unrestricted
specification	1	2	3	4	5	6
Panel C: modern sample (February 1963 - October 2015)						
constant				0.0181**	0.0022	0.0066
				(2.3889)	(0.2882)	(0.8120)
				[2.9504]	[0.2337]	[0.6327]
λ_e (price $\beta_{i,eM}$)	0.0143***	-0.0030	-0.0056	-0.0004	-0.0030	-0.0066
	(2.8922)	(-0.3563)	(-0.6265)	(-0.0548)	(-0.3571)	(-0.6967)
	[2.8684]	[-0.3171]	[-0.5170]	[-0.0591]	[-0.3443]	[-0.6329]
λ_y (price $\beta_{i,yM}$)	0.0143***	0.0478***	0.0324*	-0.0004	0.0426***	0.0109
	(2.8922)	(3.5171)	(1.7925)	(-0.0548)	(2.6014)	(0.5235)
	[2.8684]	[3.5449]	[1.3941]	[-0.0591]	[1.7712]	[0.2901]
λ_{CF} (price $\beta_{i,CFM}$)	0.0143***	0.0478***	0.0689***	-0.0004	0.0426***	0.0612***
	(2.8922)	(3.5171)	(3.3217)	(-0.0548)	(2.6014)	(2.8580)
	[2.8684]	[3.5449]	[2.0905]	[-0.0591]	[1.7712]	[1.9030]
Adj. R2	12.0%	31.7%	33.7%	32.0%	35.4%	36.9%
F-test vs CAPM		94.10***	49.25***		13.10***	6.83***
F-test vs GBBB			2.42			3.79*
MAE1	0.4846%	0.2804%	0.2712%	0.3333%	0.2829%	0.2764%
MAE2	0.6086%	0.4054%	0.3926%	0.4908%	0.4118%	0.3992%

Table 2.5: Pricing errors anomaly portfolios under various asset pricing models
Pricing errors full sample under the six specifications in Table 2.4. Errors represent quarterly returns, and are defined as realized return minus fitted return. The sample runs from May 1932 to October 2015.

Panel A: size (ME) x value (BE/ME) portfolios

ME	Low			Q3			High		
BE/ME	Low	Q3	High	Low	Q3	High	Low	Q3	High
1	-1.45%	0.36%	1.43%	-0.31%	0.41%	0.81%	-0.09%	0.35%	0.43%
2	-0.36%	0.68%	1.93%	-0.06%	0.28%	0.62%	-0.05%	0.06%	0.20%
3	-0.82%	0.42%	1.93%	-0.20%	0.25%	0.66%	-0.18%	0.15%	0.45%
4	-0.93%	0.55%	1.75%	-0.18%	0.36%	0.96%	-0.45%	-0.06%	0.40%
5	-0.60%	0.63%	1.87%	-0.11%	0.31%	0.81%	-0.29%	-0.04%	0.30%
6	-0.82%	0.42%	1.93%	-0.20%	0.25%	0.67%	-0.19%	0.15%	0.45%

Panel B: volatility portfolios

Vol	Low	Q2	Q3	Q4	High
1	0.39%	0.28%	-0.52%	-0.67%	-1.48%
2	0.07%	0.19%	-0.48%	-0.62%	-1.06%
3	-0.19%	0.33%	-0.35%	-0.35%	-0.54%
4	-0.24%	0.07%	-0.38%	-0.26%	-0.78%
5	-0.15%	0.11%	-0.41%	-0.39%	-0.84%
6	-0.19%	0.32%	-0.35%	-0.34%	-0.54%

Table 2.6: Reduced aggregate VAR model

Panel A reports the OLS estimated coefficients of the aggregate VAR model as well as the t-statistics in brackets. The final column reports the adjusted R2. The state variables are constructed as described in Section 2.3.1 and demeaned prior to estimation. Panel B reports descriptive statistics on the implied news terms. On the left, the empirical covariance matrix; on the right, the correlations (off-diagonal terms) and the standard deviations (diagonal). Panel C reports the correlations with the news terms of the full VAR model. Significance at the 90%, 95% and 99% levels are indicated with *, ** and *** respectively. A ρ of 0.95 is assumed in the computation of the news terms. The sample period runs from February 1927 to October 2015.

Panel A: VAR coefficients

	$e_{M,t}$	y_t^{nom}	PE_t	Adj R2
$e_{M,t+1}$	0.1825**	-1.1146*	-0.0343***	0.0588
(log excess market return)	(2.3275)	(-1.9380)	(-3.1410)	
y_{t+1}^{nom}	0.0031***	0.9834***	0.0000	0.9586
(risk-free rate)	(2.5925)	(66.8369)	(0.0124)	
PE_{t+1}	0.3575***	-0.3371	0.9709***	0.9562
(price-to-earnings ratio)	(4.9145)	(-0.5747)	(82.3894)	

Panel B: News

Var/covar	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$	Corr/std	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$
$-N_{M,e}$	0.0058	-0.0018	0.0009	$-N_{M,e}$	0.0763	-0.4632	0.2646
$-N_{M,y^{\text{nom}}}$	-0.0018	0.0025	-0.0008	$-N_{M,y^{\text{nom}}}$	-0.4632	0.0502	-0.3822
$N_{M,CF^{\text{nom}}}$	0.0009	-0.0008	0.0018	$N_{M,CF^{\text{nom}}}$	0.2646	-0.3822	0.0424

Panel C: Correlation full VAR model news with reduced VAR model news

reduced/full	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$
$-N_{M,e}$	0.9688	-0.1160	-0.1235
$-N_{M,y^{\text{nom}}}$	-0.4706	0.7536	-0.0056
$N_{M,CF^{\text{nom}}}$	0.2529	-0.3281	0.7462

Table 2.7: Pricing of betas under the reduced VAR model & under the rolling reduced VAR model

We employ Fama and MacBeth (1973) regressions by regressing each quarter the simple returns of the 70 portfolios (25 size x value, 5 volatility, 40 risk-sorted) in excess of the risk-free rate on the full sample betas to market risk premium shock, market cash flow shock and market interest rate. In round brackets are the Fama-MacBeth standard errors, corrected for autocorrelation and heteroscedasticity (Newey and West, 1987; Newey and West, 1994); in square brackets bootstrapped standard errors. In the first column we restrict all beta coefficients to be equal to each other ("CAPM"), and in the second column we restrict the cash flow and interest rate betas to be equal to each other ("GBBB") and in the final column we leave all coefficients free ("unrestricted"). The adjusted R2 is the average adjusted R2 of the cross-sectional regressions. The F-tests below the columns show the test-statistic whether the model in that column is significantly better either the CAPM model ("F-test vs CAPM") or the Good Beta, Bad Beta model ("F-test vs GBBB"). The mean absolute error (MAE) is the mean of the absolute values of the difference of the actual and fitted quarterly mean return of the 70 portfolios ("MAE1") or only the 30 anomaly portfolios ("MAE2"). Stars denote the significance at the 10% (*), 5% (**) and 1% (***) level. Results are reported for the full sample period which runs from May 1932 to October 2015. Panel A reports the results for the full-sample reduced VAR model (see Table 2.6) and Panel B reports the results for the out-of-sample rolling reduced VAR model.

	no constant			constant		
model specification	CAPM 1	GBBB 2	unrestricted 3	CAPM 4	GBBB 5	unrestricted 6
Panel A: full sample reduced VAR model						
constant				0.0172***	0.0109*	-0.0001
				(3.0228)	(1.9371)	(-0.0118)
				[3.4741]	[1.6917]	[-0.0111]
λ_e (price $\beta_{i,eM}$)	0.0213***	0.0005	0.0185*	0.0074	0.0013	0.0186
	(4.5997)	(0.0609)	(1.9351)	(1.0944)	(0.1665)	(1.6112)
	[4.7825]	[0.0396]	[1.3974]	[1.1365]	[0.1208]	[1.2268]
λ_y (price $\beta_{i,yM}$)	0.0213***	0.0829***	0.1608***	0.0074	0.0455***	0.1613***
	(4.5997)	(4.4450)	(4.4300)	(1.0944)	(2.6612)	(3.1742)
	[4.7825]	[2.9585]	[4.0963]	[1.1365]	[1.2934]	[3.2159]
λ_{CF} (price $\beta_{i,CFM}$)	0.0213***	0.0829***	0.0342	0.0074	0.0455***	0.0344*
	(4.5997)	(4.4450)	(1.6104)	(1.0944)	(2.6612)	(1.9050)
	[4.7825]	[2.9585]	[1.0369]	[1.1365]	[1.2934]	[1.0268]
Adj. R2	11.3%	24.3%	30.7%	28.3%	32.0%	38.7%
F-test vs CAPM		41.08***	47.26***		6.80**	31.87**
F-test vs GBBB			58.14***			12.77**
MAE1	0.4638%	0.3103%	0.2484%	0.3109%	0.2908%	0.2484%
MAE2	0.5619%	0.4254%	0.3187%	0.4977%	0.4462%	0.3183%
Panel B: rolling reduced VAR model						
constant				0.0178***	0.0171***	0.0078
				(3.1620)	(2.9394)	(1.2120)
				[3.4741]	[1.6917]	[-0.0111]
λ_e (price $\beta_{i,eM}$)	0.0246***	0.0466***	0.0341***	0.0079	0.0183	0.0239
	(4.5960)	(3.2997)	(2.5792)	(1.0229)	(1.0907)	(1.3505)
	[4.7825]	[0.0396]	[1.3974]	[1.1365]	[0.1208]	[1.2268]
λ_y (price $\beta_{i,yM}$)	0.0246***	-0.0188	0.2146***	0.0079	-0.0107	0.1668***
	(4.5960)	(-0.8122)	(4.6215)	(1.0229)	(-0.4640)	(3.7358)
	[4.7825]	[2.9585]	[4.0963]	[1.1365]	[1.2934]	[3.2159]
λ_{CF} (price $\beta_{i,CFM}$)	0.0246***	-0.0188	0.0302	0.0079	-0.0107	0.0231
	(4.5960)	(-0.8122)	(1.4654)	(1.0229)	(-0.4640)	(1.1952)
	[4.7825]	[2.9585]	[1.0369]	[1.1365]	[1.2934]	[1.0268]
Adj. R2	11.2%	15.3%	24.3%	28.0%	32.8%	37.8%
F-test vs CAPM		4.96***	48.85***		1.52	39.55***
F-test vs GBBB			85.50***			12.82***
MAE1	0.4749%	0.4504%	0.2728%	0.3167%	0.3154%	0.2592%
MAE2	0.5752%	0.5748%	0.3017%	0.5042%	0.5062%	0.3079%

Table 2.8: Firm VAR model with interaction terms

Panel A reports the OLS estimated coefficients, t-statistics (in brackets) and adjusted R2's of a pooled-panel regression. The standard errors to compute the t-statistics are clustered by firm-quarter (Petersen, 2009). The rows with the aggregate variables have been removed to save space. The dynamics of the aggregate variables are the same as in Table 2.1. Panel B reports descriptive statistics on the implied news terms. On the left, the empirical covariance matrix. On the right, the correlations (off-diagonal terms) and the standard deviations (diagonal). Significance at the 90%, 95% and 99% levels are indicated with *, ** and *** respectively. A ρ of 0.95 is assumed in the computation of the news terms. The sample period runs from February 1927 to October 2015. The columns with aggregate state variables, except for interest rate risk have also been removed to save space.

Panel A: VAR coefficients

	$e_{i,t}$	$bm_{i,t}$	$roe_{i,t}$	y_t^{nom}	$y_t^{\text{nom}}\mathbb{1}_{i,t}^{meQ1}$	$y_t^{\text{nom}}\mathbb{1}_{i,t}^{meQ3}$	$y_t^{\text{nom}}\mathbb{1}_{i,t}^{bmQq}$	$y_t^{\text{nom}}\mathbb{1}_{i,t}^{bmQ3}$	$y_t^{\text{nom}}\mathbb{1}_{i,t}^{volQ1}$	$y_t^{\text{nom}}\mathbb{1}_{i,t}^{volQ3}$	Adj R2
$e_{i,t+1}$	-0.0081	0.0044	0.0263***	-2.5812***	0.1673	-0.3844**	0.1205	-0.2355	-1.4836***	0.7026***	0.0330
(log excess return)	(-0.6326)	(0.8913)	(4.7177)	(-2.7604)	(1.1695)	(-2.1939)	(0.5792)	(-0.9378)	(-8.1774)	(3.9332)	
$bm_{i,t}$	0.0086	0.9678***	0.0100**	1.1659	-0.3574***	-0.3749**	-0.2779	0.0379	0.3669**	-0.4177***	0.9189
(book-to-market)	(0.6870)	(170.6688)	(2.0682)	(1.3641)	(-2.6627)	(-2.2308)	(-1.1232)	(0.1435)	(2.3494)	(-2.7007)	
$roe_{i,t}$	0.0265***	-0.0104***	0.8897***	-0.1874	0.2027***	-0.6543***	-0.1741**	-0.3214***	-0.9806***	0.2512***	0.7885
(return-on-equity)	(7.4453)	(-5.5851)	(89.3682)	(-1.4739)	(4.3727)	(-8.4610)	(-2.1843)	(-2.9151)	(-8.0636)	(6.4250)	
$y_{t+1}^{\text{nom}}\mathbb{1}_{i,t+1}^{meQ1}$				0.0296***	0.9242***	-0.0327***					0.8993
				(11.3013)	(81.6711)	(-35.3563)					
$y_{t+1}^{\text{nom}}\mathbb{1}_{i,t+1}^{meQ3}$				0.0434***	-0.0465***	0.8966***					0.8682
				(15.0337)	(-36.3080)	(81.5298)					
$y_{t+1}^{\text{nom}}\mathbb{1}_{i,t+1}^{bmQ1}$				0.1134***			0.7527***	-0.1127***			0.7170
				(30.1700)			(73.4231)	(-47.9399)			
$y_{t+1}^{\text{nom}}\mathbb{1}_{i,t+1}^{bmQ3}$				0.0957***			-0.0931***	0.7865***			0.7469
				(26.4699)			(-44.8889)	(75.7148)			
$y_{t+1}^{\text{nom}}\mathbb{1}_{i,t+1}^{volQ1}$				0.1466***					0.6751***	-0.1348***	0.6353
				(34.5499)					(62.0846)	(-46.5421)	
$y_{t+1}^{\text{nom}}\mathbb{1}_{i,t+1}^{volQ3}$				0.1486***					-0.1405***	0.6749***	0.6396
				(34.9431)					(-48.4664)	(61.6906)	

Panel B: News terms

Var/covar	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$	Corr/std	$-N_{M,e}$	$-N_{M,y^{\text{nom}}}$	$N_{M,CF^{\text{nom}}}$
$-N_{M,e}$	0.0211	-0.0024	-0.0077	$-N_{M,e}$	0.1451	-0.3353	-0.2204
$-N_{M,y^{\text{nom}}}$	-0.0024	0.0024	0.0005	$-N_{M,y^{\text{nom}}}$	-0.3353	0.0493	0.0435
$N_{M,CF^{\text{nom}}}$	-0.0077	0.0005	0.0582	$N_{M,CF^{\text{nom}}}$	-0.2204	0.0435	0.2412

Table 2.9: Literature overview aggregate VAR models

Studies marked with a * in the return components section assume that real interest rates are constant.

Study	Data sample	Frequency	State variables	Return components
Campbell (1991)	1927-1988	monthly	Real stock return Dividend-to-price 1M T-bill rate (12m demeaned)	Real stock return Real dividends
Campbell and Ammer (1993)	1952-1987	monthly	Excess stock return Dividend-to-price Real interest rate Change 1M T-bill rate 10Y-2M term yield 1M T-bill rate (12m demeaned)	Excess stock return Real interest rate Real dividends
Campbell and Mei (1993)	1952-1987	monthly	Excess stock return Real interest rate Dividend yield Inflation rate Growth rate industrial production	Excess stock return Real interest rate Real dividends
Vuolteenaho (2002)	1954-1996	annual	Excess stock return Book-to-market Profitability	Excess stock return Real dividends*
Campbell and Vuolteenaho (2004)	1929-2001	monthly	Excess stock return 10Y-3M term yield Shiller PE Value Spread	Excess stock return Real dividends*
Campbell, Polk, and Vuolteenaho (2010)	1928-2001	annual	Excess stock return 10Y-3M term yield Shiller PE Value Spread	Excess stock return Real dividends*
Campbell, Giglio, and Polk (2013)	1929-2010	quarterly	Excess stock return 10Y-3M term yield Shiller PE Value Spread Default Spread	Excess stock return Real dividends*
Campbell et al. (2017)	1926-2011	quarterly	Real stock return Stock return variance Shiller PE 3M T-bill rate Value Spread Default Spread	Real stock return Real dividends Volatility

Table 2.10: Literature overview firm VAR models
Studies marked with a * in the return components section assume that real interest rates are constant.

Study	Data sample	Frequency	State variables	Return components
Vuolteenaho (2002)	1954-1996	annual	Excess stock return Book-to-market Return-on-equity	Excess stock return Real dividends*
Campbell, Polk and Vuolteenaho (2010)	1928-2001	annual	Excess stock return Book-to-market Return-on-equity	Excess stock return Real dividends*

Figure 2.1: News terms through time

This figure plots the trailing exponentially weighted average quarterly news term in fractions. The smoothing parameter is set to $0.5^{1/12} = 0.9439$. The news terms are based on the aggregate VAR model displayed in Table 2.1.

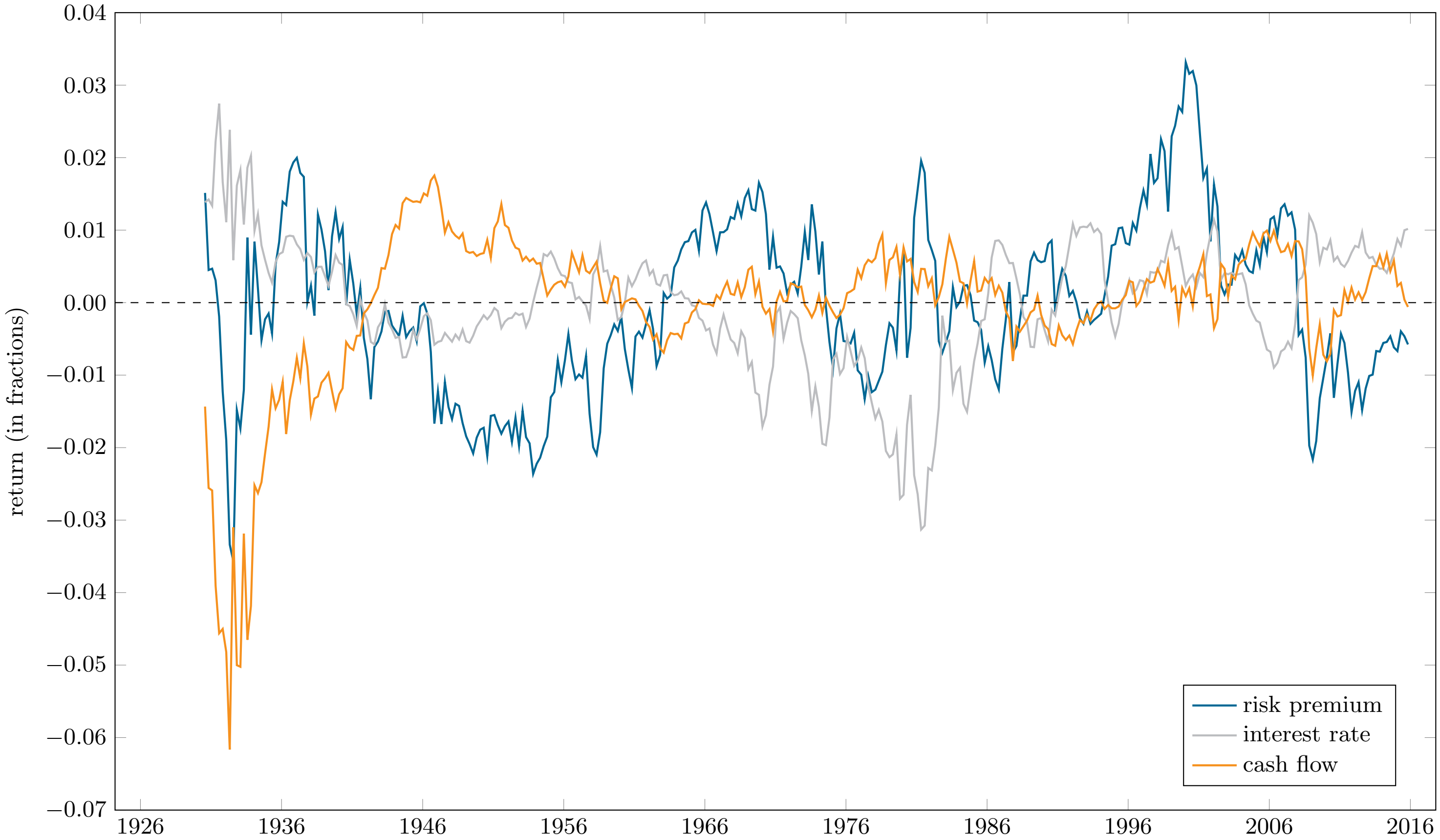
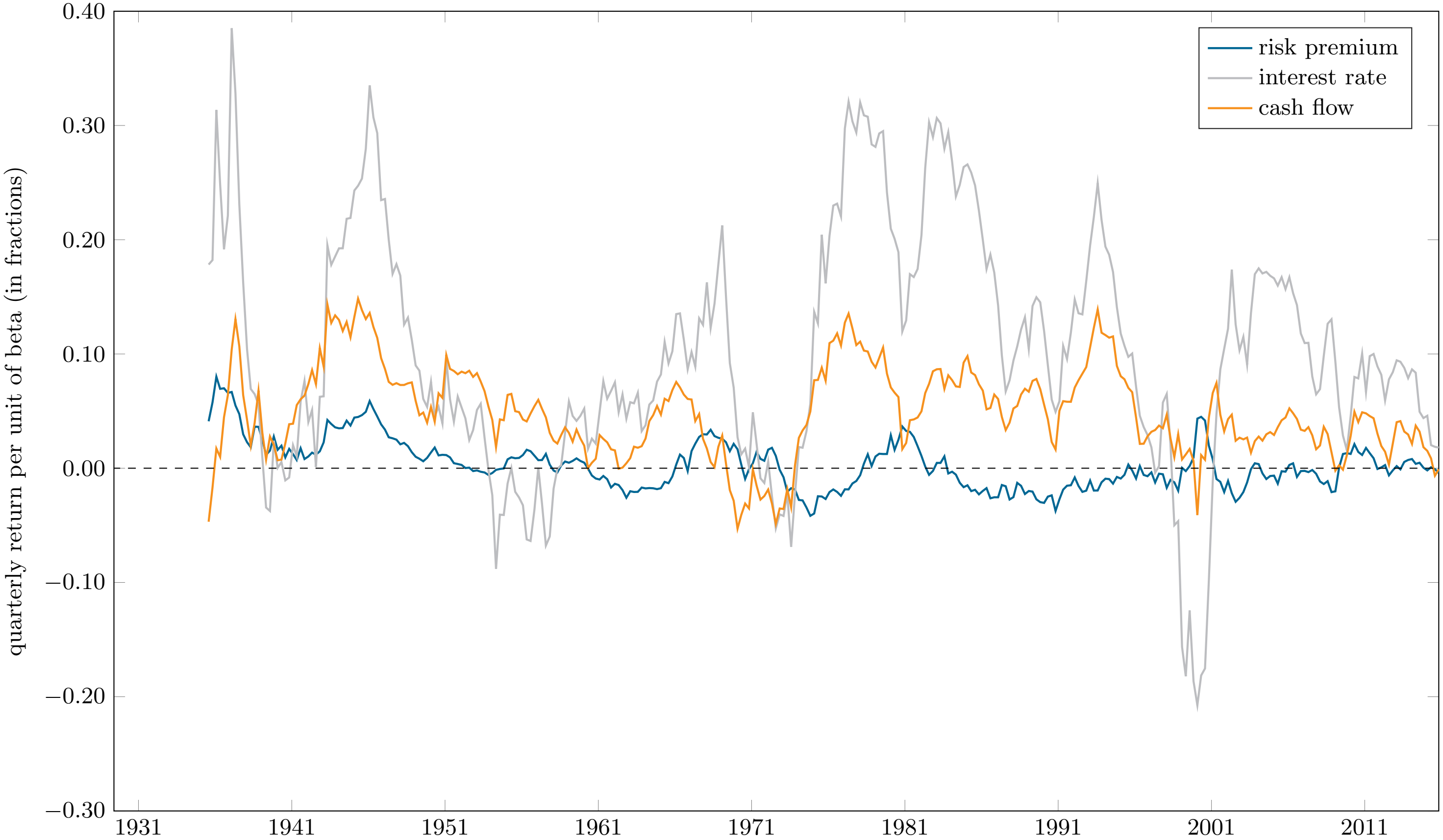


Figure 2.2: Prices through time

This figure plots the trailing exponentially weighted average quarterly prices of risk in fractions. The smoothing parameter is set to $0.5^{1/12} = 0.9439$. The prices are from specification 6 in Table 2.4.



Chapter 3

Are Stock and Corporate Bond Markets Integrated? Evidence from Expected Returns

3.1 Introduction

Firms can finance themselves on public capital markets in two ways: first, by issuing equity, i.e. stocks, and second by issuing debt, i.e. corporate bonds. Since both instruments are claims on the same assets, their prices and expected returns should be linked to each other. As discussed below, several studies have therefore studied the integration of stock and corporate bond markets using various empirical methods.

In this paper we add to this integration literature by directly comparing bond-implied expected equity returns to realized equity returns. For each firm, we construct the expected equity return that is implied by the credit spread on corporate bonds of this firm, following the approach of Campello, Chen, and Zhang (2008). We then analyze the cross-sectional relation between these bond-implied expected equity returns and average realized equity returns for the U.S. market. Surprisingly, we find a strong negative relation. Firms with high bond-implied expected equity returns have low average equity returns and vice versa. This suggests that corporate bonds and stocks are not priced consistently. The economic significance of this result is large. When sorting firms on the bond-implied expected equity return, we find a predicted equity return gap of 1.27% per month for the highest versus lowest decile portfolio, while the realized equity return gap equals -1.79% per month.

It is important to note that our analysis of expected and realized returns provides evidence for relative mispricing of corporate bonds versus stocks. We do not aim to explain the level of bond-implied expected returns, nor the level of realized average equity returns. For such an analysis, one would need to assume a specific asset pricing model and see if these levels are in line with the model predictions. In contrast, for our main result, the negative relation between expected bond and stock returns, we do not need to assume a specific asset pricing model.

We do need to make a few other modeling assumptions. This concerns first of all the default probability, which is required to transform the credit spread to a corporate bond expected return. Second, our approach requires an estimate of the sensitivity of equity returns to corporate bond returns, which is needed to transform the corporate bond expected return to an expected equity return. Our benchmark approach uses a Merton (1974) model to estimate default probabilities, following Feldhütter and Schaefer (2016). We find the Merton model to be more adaptive than the hazard rate model of Campbell, Hilscher, and Szilagyi (2008) and better able to capture the strongly increasing probability of default for low-rated debt. To estimate equity-bond sensitivities, we employ a regression approach following Campello, Chen, and Zhang (2008). We perform a wide range of robustness checks on these two methods. We also perform robustness checks on the benchmark cross-sectional analysis, to check that results are stable over time and not concentrated in small, hard-to-arbitrage stocks. In addition, we correct for liquidity effects. We find that our key result survives all these robustness checks.

We then proceed by trying to understand this lack of integration in more detail. First, we document that the anomalous realized equity returns to some extent reflect temporary mispricing in the equity market, but substantial mispricing remains even at longer horizons. Specifically, when we focus on the realized equity returns over a period of 5 years after sorting on the expected return, the realized return gap is -0.50% per month instead of -1.79%. Second, we analyze whether market risk or characteristics like size, book-to-market, momentum, profitability, and investments are priced differently in corporate bonds versus equities. We find some evidence that the market betas have a negative slope for average realized returns (in line with existing work on the "beta anomaly"; Frazzini and Pedersen, 2014), while the slope is positive for bond-implied returns. However, we find that these differences in pricing do not explain the negative relation between bond-implied and realized returns. In line with these results, the alpha of a portfolio that shorts stocks of firms with high bond-implied returns and buys stocks with low bond-implied returns is significantly positive, even when we control for the five factors in the Fama and French (2015) model, the Carhart (1997) momentum factor and the Quality-

Minus-Junk factor of Asness, Frazzini, and Pedersen (2017).

Our paper relates to various streams in the literature. Most importantly, two recent studies also focus on the cross-sectional relation between expected returns in credit markets (corporate bonds and credit default swaps) and realized equity returns: Friewald, Wagner, and Zechner (2014) and Anginer and Yildizhan (2017). Both studies conclude that there is a positive relation between the cross-section of credit risk premiums and average realized equity returns. Our results thus conflict with these studies. We now discuss both studies in more detail.

Friewald, Wagner, and Zechner (2014) and our study differ in several aspects. First, Friewald, Wagner, and Zechner (2014) use a different approach to construct credit risk premiums. Following Cochrane and Piazzesi (2005) they run predictive regressions of credit spread changes on forward credit spreads to obtain time series of the credit risk premium for each firm. Second, most of their analysis is in-sample, since they run the predictive regressions over the same period that is used to calculate realized equity returns. This is particularly important in this case. Consider a firm that has had excellent performance over the sample period with declining credit spreads and increasing equity prices. The in-sample estimation will then lead to high estimates for the credit risk premium as the credit spreads have compressed, while the average realized equity return will be high as well. Hence, the in-sample estimation biases towards finding a positive relation between credit risk premiums and equity returns.[1] In contrast, our credit risk premiums are only based on information available at the given point in time and sorting stocks on these credit risk premiums thus delivers a tradable investment strategy. Third, our sample is much more extensive, covering on average 685 firms per month for a period of more than 20 years. Friewald, Wagner, and Zechner (2014) use credit default swaps to obtain credit spreads, and as a result their sample period is less than 10 years and includes just 491 unique firms.

Anginer and Yildizhan (2017) use conceptually the same approach as we do to obtain the credit risk premium from credit spreads.[2] However, they do not transform the credit risk premium to an expected, corporate bond-implied, equity return. Hence, they cannot perform the quantitative comparison of expected corporate bond-implied equity returns and realized equity returns. Moreover, the focus of their paper is to analyze how systematic default risk

[1] In their out-of-sample robustness check Friewald, Wagner, and Zechner (2014) find much weaker evidence for a positive relation between credit premiums and stock returns.

[2] Anginer and Yildizhan (2017) employ a hazard rate model to estimate the probability of default rather than the probability of default implied by the Merton (1974) model. In the robustness section we employ the hazard rate model of Campbell, Hilscher, and Szilagyi (2008) and obtain results that are qualitatively similar to our benchmark results.

betas relate to these expected and realized returns, while our main focus is to perform an extensive and quantitative analysis of the bond-implied equity returns and realized equity returns. Finally, Anginer and Yildizhan (2017) use a longer sample period (1980 to 2010) but have a smaller cross-section of firms: about 338 firms each month[3], compared to 685 for our sample.

Our work also relates to other studies on the integration of stock and corporate bond markets. In particular, a number of studies study integration by looking at the time-series relation between stock and corporate bond returns. Hence, these studies do not focus on pricing and expected returns, and our work thus complements this stream in the literature. Examples of studies in this literature are Collin-Dufresne, Goldstein, and Martin (2001) and Demirovic, Guermat, and Tucker (2017), who focus on the contemporaneous relation between stock and bond returns, and conclude that stock and bond markets are not perfectly integrated.[4] In addition, there is a large body of literature on lead-lag effects, concluding either that stock returns lead bond returns (Kwan, 1996; Gebhardt, Hvidkjaer, and Swaminathan, 2005; Downing, Underwood, and Xing, 2009; Haesen, Houweling, and Van Zundert, 2017) or vice versa (Bittlingmayer and Moser, 2014; Ben Dor and Xu, 2015), which is also indirect evidence of disintegration between the two markets as it suggests new information is not priced in in both assets at the same time.[5] Note that, even if there is an imperfect time-series relation between stock and corporate bond returns, this does not necessarily imply that long-term expected returns are different, because this imperfect time-series relation might be caused by temporary illiquidity or price pressure effects, or by exposure to factors that are not priced.

In addition, our work is related to several studies that focus on the pricing of equity market anomalies in bond markets (Chordia et al., 2017; Choi and Kim, 2017). If bond and stock markets are integrated, then well-known anomalies should be present in both stock and bond markets. Concretely, Choi and Kim (2017) study the cross-sectional pricing of known equity anomalies in the cross-section of corporate bond returns, and find that some anomalies are similarly priced (net issuance, gross profitability, idiosyncratic volatility, beta and accruals), but others are not (asset growth and momentum). Related

[3] Anginer and Yildizhan (2017) report 121,714 firm-month observations over the period January 1981 to December 2010, which means on average there are 338 firms in a month.

[4] Schaefer and Strebulaev (2008) find that, despite this imperfect time-series relation, the size of the exposure of corporate bonds to equity returns is similar to predictions of a Merton (1974) model.

[5] Relatedly, there are also studies focusing on the link between credit default swaps and stocks at the firm level, such as Duarte, Longstaff, and Yu (2007), Kapadia and Pu (2012), Hilscher, Pollet, and Wilson (2015), and Kiesel, Kolaric, and Schiereck (2016).

to Choi and Kim (2017) is the work of Chordia et al. (2017), who study the predictive power of profitability, asset growth, equity market capitalization, accruals and earnings surprises. They find that, after transaction costs, bonds are efficiently priced. In our analysis, we examine whether our results can be explained by a different effect of anomalies on stock and bond markets. We control for anomalies related to beta, size, book-to-market, momentum, profitability, investment, and quality-minus-junk, and find that our main result cannot be explained by a different presence of these anomalies in stock versus corporate bond markets.

Finally, our paper is related to the literature that documents a relation between the default probability and average equity returns. They mostly document a negative relation: firms with a high default probability have low average returns. This result is often referred to as the "distress risk puzzle". We show that our main result is not simply a restatement of this distress risk puzzle. First of all, we show that the relation between our bond-implied equity return and default probabilities is not monotonic. Second, we double-sort on default probabilities and the bond-implied equity return and continue to find evidence for a negative relation between bond-implied and realized returns.

The remainder of this paper is organized as follows. In Section 3.2 we describe the data. Section 3.3 describes how we obtain expected equity returns from corporate bond credit spreads. Section 3.4 presents the benchmark empirical results: we analyze the relation between the bond-implied expected equity returns and realized equity returns. Section 3.5 provides robustness checks and Section 3.6 concludes.

3.2 Data

For our empirical analyses, we use stock data from the Center of Research in Security Prices (CRSP) at a monthly frequency over the period January 1994 to December 2015. We only include common equity (share codes 10 or 11) and exclude financials (SIC codes 6000-6999) as their financial structure is very different from corporates (see also Campbell, Hilscher, and Szilagyi, 2008).

To compute probabilities of default, we use accounting data from COMPUSTAT Quarterly. The COMPUSTAT data is linked to CRSP using the CRSP/Compustat Merged database, and all accounting data is lagged for two months to account for the reporting lag.

For the bond data we use monthly constituent data of the Bloomberg Barclays U.S. Corporate Investment Grade and Bloomberg Barclays U.S. Corporate High Yield indices, formerly known as the Lehman Brothers Fixed

Income database. This dataset includes per bond the *(option adjusted) spread duration*, which is adjusted for embedded options by Bloomberg. This is necessary in case bonds are likely to be called ahead of their maturity date, as the standard modified duration would overstate the interest rate sensitivity. Using the option-adjusted spread duration, the bond is matched with the appropriate U.S. Treasury bond. The *credit spread* (*excess return*) is computed as the difference between the yield (return) on the corporate bond and the yield (return) on the duration-matched Treasury bond. As the embedded option-adjustment for the spread duration and the credit spread fields are not available prior to January 1994, we start at this date. Furthermore, the credit rating is computed as the middle rating of S&P, Moody's and Fitch if all three are available, or the worst rating if only two are available, in line with the Bloomberg-Barclays index methodology.

We link the bond data to the stock/accounting data using CUSIP's and if not possible, hand-match the data, while taking M&A activity into account. See Appendix 3.A for details. A single stock can have multiple bonds associated. To make the selected bonds as comparable as possible between stocks, we always pick a senior unsecured bond. If multiple senior unsecured bonds exist, we pick the one with the spread duration closest to 5 years in order to reduce the dispersion across maturities.

Finally, we obtain the 1-month T-bill rate, the five Fama and French (2015) factors and the Carhart (1997) Momentum factor return series from the website of Kenneth French.[6] The Quality-Minus-Junk factor is from the website of AQR.[7]

3.3 Methodology

Our empirical framework is based on the idea that the equity and bond risk premium of a firm are linked to each other as both are contingent claims on the same firm assets (Merton, 1974). In the Merton (1974) model, the bond and equity value are dependent on the firm value, the interest rate and the asset volatility. To arrive at a parsimonious model, we assume, following Campello, Chen, and Zhang (2008)[8], the interest rate term structure to be flat and deterministic, and the asset volatility to be at most a function of asset value. This leaves the firm value as the sole driver of expected bond and equity returns.

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

[7] https://www.aqr.com/library/data-sets/

[8] Campello, Chen, and Zhang (2008) also include a convexity effect. As we estimate the expected return to maturity, convexity effects are not relevant in our setting.

3.3.1 Obtaining expected equity returns

In this framework, the expected return of the equity of firm j can be written as a function of the expected return on the bond:

$$\mathbb{E}_t\left(r_j^E\right) = y_{g,t} + \frac{\delta E/E}{\delta B/B}\left(\mathbb{E}_t(r_j^B) - y_{g,t}\right) \tag{3.1}$$

where $y_{g,t}$ is the yield of the duration-matched Treasury[9], $\frac{\delta E/E}{\delta B/B}$ the elasticity of equity returns to bond returns and $\mathbb{E}_t(r_j^B) - y_{g,t}$ the expected return of the bond of firm j over the duration matched Treasury bond. To implement this equation, we need to have estimates for the elasticity and the expected bond return.

We follow Campello, Chen, and Zhang (2008), Bongaerts, De Jong, and Driessen (2017), and others for computing the expected bond return over Treasuries. Specifically, we assume defaults occur at maturity only and approximate the coupon-paying bonds by zero-coupon bonds with maturity equal to the duration of the original bonds. Then, an investment of \$1 in the zero-coupon corporate bond pays off $(1 + y_{g,t} + s_{j,t})^{T_{j,t}}(1 - L\pi_{j,t})$ by expectation at maturity $T_{j,t}$. Here, $s_{j,t}$ is the credit spread, $\pi_{j,t}$ the cumulative probability of default to maturity, L is the loss rate in case of default, and $T_{j,t}$ the time to maturity, which we set equal to the duration of the bond. It then follows that the annualized expected bond return in excess of a maturity-matched Treasury bond is given by

$$\mathbb{E}_t\left(r_j^B\right) - y_{g,t} = \left(1 + y_{g,t} + s_{j,t}\right)\left(1 - L\pi_{j,t}\right)^{1/T_{j,t}} - \left(1 + y_{g,t}\right) \tag{3.2}$$

Given the observed credit spread and Treasury bond yield, only an estimate of the loss rate and default probability are needed to obtain a forward-looking expected return. The loss rate L is set to 60% following Bongaerts, De Jong, and Driessen (2017).[10] In the next section we discuss the estimation of default probabilities.

[9]Under our assumption of a flat interest rate term structure, we can pick any maturity for the risk-free rate. Empirically, the term structure is not flat. We accommodate this by picking the duration-matched Treasury bond yield, which is the relevant rate for the chosen corporate bond. This also allows us to use the (option-adjusted) credit spreads as supplied by Bloomberg-Barclays to compute the expected bond return.

[10]A loss rate of 60% (recovery rate of 40%) is a reasonable assumption, as the recovery rates for senior unsecured bonds with credit ratings between AA and C vary between 37.2% and 44.5% for the period 1985-2014 (Moody's Investors Services, 2015, exhibit 21; assuming default occurs within two to five years). Setting it to 50% or 70% does not alter our conclusions. Results are available upon request.

3.3.2 Estimating default probabilities

There are several existing approaches to estimate default probabilities. A first popular approach is to use structural models such as the Merton (1974) model, calibrated to equity data, to obtain default probabilities. Besides academic work (Vassalou and Xing, 2004; Duffie, Saita, and Wang, 2007), this is also a common approach in practice. For example, Moody's-KMV use this approach. Second, several articles model default events as a function of various financial and accounting measures and estimate logit or hazard rate models to explain default occurrences (Campbell, Hilscher, and Szilagyi, 2008; Bharath and Shumway, 2008). Third, one can simply focus on credit ratings to measure default risk, using the historical default rates per credit rating (see for example Elton et al., 2001 and Campello, Chen, and Zhang, 2008).

Since the default probability is a key input variable for the expected equity return, we use all three approaches in this paper and find that our empirical results are largely similar across these three methods. For our benchmark analysis we choose to use the structural Merton model to estimate default probabilities. This approach is able to generate substantial cross-sectional and time-series variation in default probabilities, whereas the other two approaches generate much less variation. This is directly clear for the ratings-based approach, since credit ratings are quite stable over time while default rates spike around crisis periods. In Appendix 3.B we provide more details on the accuracy of hazard rate models. We find that the hazard rate model is unable to model the strong increase in default probabilities when credit ratings deteriorate, in contrast to the Merton model. For instance, the historically observed average 5-year cumulative default rate for B-rated bonds equals 20.5%. The Merton model predicts an average probability of 19.6% for all B-rated bonds in our sample, while the hazard-rate model predicts a mere 5.4%.

We now discuss the implementation of the Merton model in more detail. In the Merton model, the probability of default is given by (subscripts j and t have been removed for brevity):

$$\pi = N\left(-\frac{\log(V/D) + (\mu - \delta - 0.5\sigma^2)T}{\sigma\sqrt{T}}\right) \tag{3.3}$$

where $N(.)$ is the normal cumulative distribution function, V the value of the firm's assets and D the default barrier at maturity. The value of the firm is set to the market value of equity plus the book value of total liabilities, where book value of liabilities approximates the market value of liabilities. The default barrier is set to the book value of total liabilities. The term $\mu - \delta$ represents the net growth rate of the firm's assets over time, where the drift rate μ represents the earnings generated by the firm's assets and the payout rate δ represents the amount distributed to all stakeholders of the firm. This growth rate holds over the specific horizon T, and is unobservable ex-ante. Therefore, we set the drift rate μ equal to the risk-free rate over this horizon, the duration-matched Treasury yield $y_{g,t}$, plus a term to reflect the risk of the firm's assets. We set the risk premium equal to a constant price of risk (θ) times the volatility of the firm's assets σ, using $\theta = 0.22$ for all firm-month observations following Feldhütter and Schaefer (2016) and Chen, Collin-Dufresne, and Goldstein (2008). The procedure to compute the volatility of the firm's assets is described below. The payout rate δ consists of all cash distributed to or collected from debt (interest) and equity holders (dividends and stock issuance/repurchase). We compute the past years payout ratio and assume it remains at this level over the horizon T.

To compute the firm's assets volatility σ over the coming T years, we need to predict the volatility of equity and debt over T years. In most implementations of the Merton (1974) model, the asset volatility is derived from the equity volatility, which is assumed to be constant and equal to historically observed volatility levels. Empirically, however, equity volatility mean reverts to a long-run mean to a large extent within five years, which is the typical maturity of corporate bonds in our sample. For instance, the VIX, a measure of implied equity index volatility for the S&P500 index, reached in November 2008 a high of 80.86, whereafter it quickly fell to a level lower than the long run average of approximately 20 in January 2010. In the fall of 2008, we would overstate the expected volatility over the coming five years substantially by using the equity volatility level at that time. Therefore we estimate the expected average equity return variance over the horizon by incorporating the mean-reversion, and then transform it into an asset variance. The expected average variance can replace the constant variance in an option pricing model (like the Merton model) under some assumptions (Hull and White, 1987). In Appendix 3.C we discuss in detail how we obtain, for each firm and at each point in time, an estimate of the expected average equity return variance over the maturity of the given bond.

To transform the resulting equity volatility σ_E estimate into an asset volatility σ_A, we follow Feldhütter and Schaefer (2016). Their starting point is that, given that the assets of the firm (V) are the sum of equity (E) and debt (B) values, asset volatility is a weighted average of equity and debt volatility: $\sigma_A^2 = \left(\frac{E}{V}\right)^2 \sigma_E^2 + \left(\frac{B}{V}\right)^2 \sigma_B^2 + 2\frac{E}{V}\frac{B}{V}\sigma_{BE}$. To avoid estimation of the debt return variance σ_B and equity-debt covariance σ_{BE}, they propose an approximation. Specifically, their asset volatility is given by $\left(\frac{E}{V}\right)\sigma_E c$, where c is a factor depending on the leverage ratio $B/V (= 1 - E/V)$ to account for Treasury bond volatility. The factor c is 1 if $B/V < 0.25$, 1.05 if $0.25 < B/V \leq 0.35$, 1.10 if

$0.35 < B/V \leq 0.45$, 1.20 if $0.45 < B/V \leq 0.55$, 1.40 if $0.55 < B/V \leq 0.75$, and 1.80 if $B/V > 0.75$.

Table 3.1 shows the average value for each of the inputs of the probability of default estimation, both on average as well as per credit rating. The results show that as the credit rating deteriorates, the asset volatility, leverage and payout ratio increase, which all three lead (ceteris paribus) to a higher probability of default in Equation 3.3. The time-to-maturity is shorter when the credit rating is lower, reflecting shorter-dated issuance by high yield firms.

3.3.3 Estimating the elasticity

We then turn to estimation of the equity-bond elasticity $\frac{\delta E/E}{\delta B/B}$. We follow Campello, Chen, and Zhang (2008) and use the fitted values of a regression model for the realized elasticities. We now describe this approach in detail. For each firm and each month, we determine the change in market value of equity (E) and market value of debt (B) over the month. The market value of debt is estimated by the book value of total liabilities multiplied by the ratio of the corporate bond price and its nominal value ($100 usually). In this way, the monthly change in the market value of debt reflects the change in corporate bond market prices, which is important to capture the elasticity properly. If we would take book values, there would be many months with zero debt return as book values are not updated on a monthly basis.

We calculate the realized elasticity, $\frac{\delta E/E}{\delta B/B}$, for each month and each firm. Then we perform a panel regression of these realized elasticities on the variables of which the elasticity is a function in the Merton (1974) model: leverage, volatility, the (duration-matched) risk-free rate and the time-to-maturity. This results in the following panel regression for the elasticity for each month and each firm:

$$\frac{\delta E/E}{\delta B/B} = c + \beta_{LEV} LEV + \beta_{VOL} VOL + \beta_{y_g} y_g + \beta_T T + \epsilon \tag{3.4}$$

where all right hand variables are known as of the beginning of the month, and the elasticity is measured over the month. LEV is the leverage ratio B/V, VOL is the past 1-month annualized daily stock return volatility in fractions, y_g the duration matched Treasury yield in fractions and T the time-to-maturity in years. When estimating Equation 3.4, we remove the top and bottom 5% of elasticity observations, since bond returns close to zero can deliver extreme elasticities, and the top 5% of equity volatility observations. See Appendix 3.D for more discussion and robustness checks on this winsorization.

The results are reported in Table 3.2. We find that the coefficients for leverage (significantly positive), volatility (significantly positive) and the risk-free rate (negative but insignificant) have the signs as predicted by the Merton (1974) model (Schaefer and Strebulaev, 2008, p. 7). The effect for time-to-maturity is ambiguous in theory; we find a significantly negative coefficient of -0.09 for this sample.

Figure 3.1 reports the distribution of the fitted elasticities, which shows there is substantial variation between firm-month observations. The average value is 0.98, but values as low as 0.25 or as high as 2 are not uncommon. This shows that we cannot simply assume the elasticity to be identical across firms and time.

We use the fitted values of the regression model in Equation 3.4 to construct, for each firm and each month, the expected elasticity given the values of the explanatory variables. These fitted elasticities are then used to construct expected equity returns based on Equation 3.1. In Section 3.5 we find that our empirical results are robust to the exact specification of elasticity. In particular, using a 12-month historical elasticity or no elasticity at all (i.e., sort directly on expected bond returns) leads to similar results.

3.3.4 Aggregate expected returns over time

Before we turn to our main focus, the cross-sectional patterns in expected returns, we report in Figure 3.2 the market value weighted average of the expected bond and equity returns per month as estimated following the approach discussed in the previous sections. We find that there is substantial variation over time. Whereas in spring 2007 expected monthly equity returns (over 1-month T-bill) are close to zero, they are equal about 60 basis points at the beginning of November 2008. The average level is 18 basis points per month, or 2.19% per annum. Expected corporate bond returns (over duration-matched Treasury) tend to show lower variation through time compared to equities, with an average annualized level of 0.83%.

3.4 Benchmark results

In this section we compare our corporate bond-implied expected equity return with realized equity returns. Section 3.4.1 contains the results of portfolio sorts on expected returns. Section 3.4.2 tests whether the results can be explained by mispricing.

3.4.1 Cross-sectional results

If corporate bond and equity markets are integrated, the expected equity returns inferred from the corporate bond spreads should equal the realized equity return on average. At a minimum, stocks with high expected returns as implied from corporate bonds should have high realized returns as well and vice versa. We test this by creating each month equal-weighted decile portfolios based on the expected equity returns as implied from corporate bond spreads. The monthly rebalancing means that we implicitly test whether the bond-implied expected returns, which have an average horizon of 5 years, are consistent with realized 1-month returns. Hence we implicitly assume that the term-structure of expected returns is flat. In the next subsection, we evaluate this assumption. In the robustness checks, we verify that our results are robust to the sampling period, to value weighting of the portfolios and various methods to construct expected equity returns from corporate bond spreads.

Table 3.3 reports the full-sample results. The first row shows the expected return we sort on, sorting from high to low expected returns. It declines from 1.14% per month for the first decile (D1) to -0.14% per month for D10. However, for the realized stock returns, we observe a generally increasing pattern, with D1 (high expected return) having a strong negative average return of -0.87% per month, and then it increases until around D5. From D6 to D10 the returns are relatively similar, at a level of 0.8% to 1.0% per month. The last column reports the D1-D10 long-short portfolio, which has a realized return of -1.79% per month, with a corresponding robust t-statistic of -3.35, while the bond-implied expected return for the long-short portfolio is 1.27% per month.

These striking results show that the hypothesis that higher bond-implied expected returns imply higher equity returns is clearly rejected. The evidence points towards the opposite conclusion: the higher the expected return implied by the corporate bond, the lower the realized equity return is. A stricter test focuses on whether realized returns are (on average) equal to expected returns. We test this for each portfolio in lines 4 and 5 of Table 3.3. For 8 out of the 11 portfolios this hypothesis is rejected. In particular, for the long-short portfolio D1-D10, the difference between realized and expected returns amounts to -3.07% per month (-36.8% per annum), which is highly economically and statistically significant (t-statistic of -5.57). We thus conclude from this empirical evidence that there is major mispricing in the cross-section of equity versus corporate bond markets. This is the key finding of our paper. In Section 5 we therefore conduct a wide range of robustness checks on this result.

Rows 6 to 10 of Table 3 show the volatility of the realized returns, the average corporate bond spread, the expected bond return, the elasticity and the estimated probability of default. From all measures, it is clear that the high (default) risk firms are concentrated in D1, D2 and D10. This is important, as it shows that the puzzle we document is not simply a restatement of the low-volatility anomaly (Haugen and Heins, 1972), which states that low-volatility stocks have high risk-adjusted returns, or the distress risk anomaly (Dichev, 1998; Griffin and Lemmon, 2002; Campbell, Hilscher, and Szilagyi, 2008), which states that stocks with high default probabilities have low returns. We formally control for these anomalies in Section 3.5.

3.4.2 Understanding the mispricing

In this subsection, we aim to better understand the negative relation between bond-implied expected and realized equity returns. We first analyze realized bond and equity returns over various horizons. Second, we test whether the negative relationship between expected and realized equity returns can be related to well-known proxies of mispricing, and third, we link the expected and realized equity returns to standard asset pricing models. Before we discuss these analyses in detail, it is important to note that our analysis of expected and realized returns provides evidence for relative mispricing of corporate bonds versus stocks. We do not aim to explain the level of bond-implied expected returns, nor the level of realized average equity returns. For such an analysis, one would need to assume a specific asset pricing model and see if these levels are in line with the model predictions. As mentioned earlier, our analysis of relative mispricing does not require assumptions on an asset pricing model.

Horizon effects for bonds To understand our key finding better, we first study the horizon effects in more detail. In the previous section we assumed that the term structure of expected returns is flat in order to compare 5-year ahead expected returns with 1-month realized returns. It could however be that this term structure of expected returns is not flat. In the extreme case that bonds with a high (low) 5-year expected return have a low (high) expected return for the coming month, which is more than reversed in the remainder of the 5-year period, the realized 1-month equity returns would not be anomalous at all.

We thus start by analyzing the 1-month realized returns on the corporate bonds. We create each month ten portfolios based on the expected bond return. For each portfolio, we compute the 1-month realized return. Table 3.4, Panel A, reports the results. We find a monotonically increasing pattern in realized returns from the low expected return portfolio (-0.09%) to the high expected return portfolio (0.29%). Moreover, we observe that the 1-month realized returns, except for D1, match the 5-year expected returns in magnitude quite well. Hence we do not find evidence against a flat term structure of expected returns for bonds. Importantly, we can thus conclude that the mismatch in horizon between the expected and realized returns is not driving the empirical negative relation between expected and realized equity returns.

Panel A of Table 3.4 also presents realized bond returns over a 5-year horizon. We pick 5 years, as the bonds used to calculate expected returns tend to have an average maturity of about 5 years. If our estimate of the probability of default is unbiased, these 5-year realized bond returns should by construction be equal to the bond-implied expected returns (on average). This is because, corrected for expected default losses, the corporate bond yield exactly equals the return of holding the bond to maturity. Hence, analyzing 5-year bond returns provides an important check on the validity of our default probability estimates. Table 3.4 shows that, for these 5-year returns, expected and realized returns line up quite well. Realized returns depend positively on expected returns except for D9 and D10, but D9 and D10 (which have low expected returns) still have realized returns well below D1 and D2. Although the cross-sectional spread in 5-year realized returns is smaller in magnitude compared to the 1-month realized returns, implying that the effect is stronger on the short horizon, there is no evidence of a reversal after 1 month. This gives us confidence that we predict the probability of default reasonably well. If we would have strongly over (under) estimated the probabilities of default, the expected bond returns would be too low (high) compared to realized returns.

In sum, the main findings of this horizon analysis for bonds are: 1) both on a 1-month as well as a 5-year horizon, we find a positive relationship between expected and realized corporate bond returns, 2) this relation is strongest for the 1-month horizon, in the longer run it remains, though somewhat diminished and 3) the 1-month realized returns match the (5-year) expected returns well in magnitude.

Horizon effects for stocks We then turn to horizon effects for equities. Our main goal is to analyze how persistent the effects for 1-month realized returns are. If bond-implied expected returns and realized equity returns are more in line with each other on a longer horizon, this would suggest that equities are temporarily mispriced relative to bonds. Panel B of Table 3.4 reports the results for equities. The expected and 1-month realized returns are identical to the numbers in Table 3.3, Panel A, and are only included for reference purposes. The 5-year returns, like for bonds, differ less across the portfolios, but still reveal a negative relationship. In particular, D1-D10 has an economically sizeable negative return of -0.50% per month, which does not differ significantly from zero (t-statistic of -1.47). However, it does differ significantly from the bond-implied expected return of 1.27% for D1-D10 (t-statistic of -5.20). Given that the average return on D1-D10 equals -1.79% in the first month, these results indeed provide evidence for temporary mispricing of equities, which is partially but not fully resolved over a longer horizon.

Which stocks are mispriced most? A common concern for research that documents anomalies is that these anomalies might only be present in small, hard-to-arbitrage stocks. In such a case, the economic relevance of the anomaly might be limited. We analyze whether this issue applies to our setting using Fama and MacBeth (1973) regressions at the firm level. As proxies for the economic relevance and arbitrage costs we use the number of analysts following the stock (obtained from I/B/E/S; see for instance Hong, Torous, and Valkanov, 2007), the turnover of the stock over the past month (Amihud and Mendelson, 1986) and the market capitalization of the equity (Merton, 1987; Grossman and Miller, 1988).

Table 3.5 reports the results. In the first specification, the 1-month realized return is only regressed on the bond-implied expected return. If the expected and realized returns would match, we should find a slope equal to one and a R-squared of 100%. However, we find a strongly negative coefficient of -2.64 with a t-statistic of -5.30 and a R-squared of only 2.7%, confirming the results of the portfolio sorts in Table 3.3. If the mispricing is concentrated in small, hard-to-arbitrage stocks, we would expect this coefficient to be more negative for such stocks. For all three proxies, we therefore split the stock universe each month in three equal-sized groups and create dummies per group, which we interact with the bond-implied expected return. The base level is the group for which the number of analysts is high, the stock turnover high and the market capitalization large, i.e. the group of large stocks with low arbitrage costs. If mispricing is concentrated in small, hard-to-arbitrage stocks, the interaction terms should be significantly negative. However, columns 2 to 5 in Table 3.5 show that this is not the case. In specification 3, we even find a statistically positive coefficient (at the 10% level) for the middle stock turnover group. The coefficient for the base group in the specification with all three proxies included is -2.31 (t-statistic of -2.74), not far from the unconditional coefficient of -2.64 found in the first regression specification. The group with the least negative slope (high number of analysts following the stock, low turnover, large market capitalization) has a slope of -2.31+0.81=-1.50, still far below the a priori expected level of +1. In sum, even for the stocks which are least likely to be mispriced we find a strong negative relationship between the expected and realized equity returns.

Pricing of risk factors across markets A large number of studies in the asset pricing literature focuses on explaining differences in expected returns using factors, the prime example being the Fama and French (1992) three-factor model. In this paper we compute expected equity returns and compare those directly with realized equity returns. As mentioned earlier, this analysis does not require any assumptions on a specific asset pricing model. In other words, it does not matter which factors or characteristics drive the returns and whether they can fully explain the variation in returns. Any factor or characteristic that drives expected returns should affect both the bond-implied expected equity return and the realized equity return equally. But if equities are mispriced relative to bonds, it might be because, for some reason, some risk factor exposure or characteristic is priced differently in stock versus bond markets. Choi and Kim (2017) provide evidence this might be the case for asset growth and momentum.

To investigate this, we perform the usual Fama-MacBeth regressions where we regress the cross-section of realized (or expected) equity returns on the equity market beta and various characteristics. We focus on characteristics like size rather than exposure to the *SMB* factor to avoid estimating many risk factor exposures. We use the standard Fama and French (1992) characteristics (size and value, specification 1) and an extended version including the momentum, operating profitability and investments characteristics (specification 2). The construction of these variables follows standard practice, see Appendix 3.A for details.

Table 3.6 reports the results. When we use the realized return as left-hand-side variable, we find that the equity risk premium is not priced (specification 1) or even negatively priced (specification 2). This result is in line with an extensive literature on the slope of the Capital Asset Pricing Model being too flat or even negative (Jensen, Black, and Scholes, 1972). For size and value we also find effects contrary to expectations. This could be driven by the large cap bias in our universe as we require companies to have bonds outstanding meeting the minimum amount outstanding criteria of the Bloomberg-Barclays indices. However, for the expected equity returns, we find effects as expected: market beta, size (specification 1 only) and book-to-market are priced. For momentum, we find it to be strongly negatively priced.

When we use the expected return as left-hand-side variable, our results are similar to Campello, Chen, and Zhang (2008).[11] For operating profitability we do not find significant results. For the investments variable, we find that companies with high investments have actually higher expected returns than

[11] An important distinction between the approach of Campello, Chen, and Zhang (2008) and ours is that we do not use historical default rates per credit rating but rather use the Merton model directly to estimate the probability of default, leading to more adaptive probabilities of default through time. Appendix 3.B provides more details on the accuracy of our method.

companies with low investments in our sample. The final two columns of Table 3.6 show the statistics for regressions where the left-hand-side variable is the difference between the realized and expected return. Only in the full model (specification 2) do we find statistically significant pricing differences between realized and expected returns: especially the pricing of the market beta, size and momentum differ substantially between the equity and corporate bond market (t-statistics of -2.20, 1.91 and 1.60 respectively), suggesting that these are not well integrated.

It could thus be that we find a negative relationship between the expected and realized returns due to different pricing of risk factors or characteristics. Therefore, we remove the risk exposures and effects of characteristics from both the expected and realized returns by using the 6-factor coefficients in Table 3.6 (columns 2 and 4; *FF6*) to compute "excess" expected and realized returns. Subsequently, we regress these excess realized returns on excess expected returns in the same way as in Table 3.5, specification 1. The slope coefficient of -2.64 for the total return (Table 3.5) becomes -4.15 (t-statistic of -4.68) when using these "excess" returns, implying that the different pricing of risk factors and characteristics across equity and bond markets does not drive our findings. In fact, the relation between expected and realized returns becomes even more negative.

3.5 Robustness

This section describes the results of our robustness checks. We find that the results are robust through time, not dependent on implementation details of the portfolios and expected return calculations, and are not driven by default risk or liquidity.

3.5.1 Results are robust through time

In Table 3.7, panels A and B, the results are shown per sub period, where the first period covers January 1994 to December 2004 and the latter period January 2005 to December 2015. We find that the results are comparable to the full-sample results. Most importantly, for D1-D10, the hypothesis that realized returns are equal to expected returns is rejected. For the period January 1994 - December 2004 we reject the hypothesis that the return is equal to zero as well, as it is strongly negative; in the recent period the D1-D10 return is -128bps a month on average, but not statistically significant different from zero.

To provide more insight into the results in Table 3.3 through time, Figure 3.3 shows the cumulative (log) bond-implied expected equity return as well as the realized equity return. As the portfolio is constructed by going long high expected return and short low expected return, the bond-implied expected return is steadily trending upwards by construction. During crisis periods, such as the Dot-Com bubble and the Great Financial Crisis, the dispersion in expected equity returns is larger and as a result the line trends upwards at a higher rate during those periods. The realized equity return, on the other hand, is steadily declining. There is some variation through time, but except for the calendar years 2003 and 2009 the realized return is always negative. Thus the results are robust through time.

3.5.2 Results are robust to choices in portfolio construction and expected return calculation

We first conduct robustness checks on the construction of the decile portfolios. We test market-value weighted portfolios instead of equal-weighted portfolios. The results for the long-short portfolio are in Table 3.8, column 2. We find that the realized D1-D10 equity returns are still negative, but the effect is statistically weaker with a t-statistic of -1.68. Compared to the expected returns, the realized returns are significantly lower (t-statistic of -2.89).

For the robustness to the estimation of the elasticity we test two alternatives: 1) using the past 12-month observed elasticity and 2) exclude the elasticity altogether (i.e. assume it is one for every stock). The results are in Table 3.8, columns 3 and 4. We find that the results for both choices are very similar to the base case results, with all four tests (versus zero and versus expected return) having t-statistics of -2.17 and lower.

For the probability of default, we test two alternatives, namely using the hazard rate model of Campbell, Hilscher, and Szilagyi (2008), and using average default rates per credit rating. The hazard rate model of Campbell, Hilscher, and Szilagyi (2008) includes the following accounting and market-related explanatory variables: past 12-month net income to total assets (NIMTAAVG), total liabilities to total assets (TLMTA), past 12-month stock excess return over the S&P500 (EXRET), past 3-month daily stock return volatility (SIGMA), relative size of the stock in comparison the S&P500 total market capitalization (RSIZE), cash and cash equivalents to total assets (CASHMTA), market to book ratio (MB) and the log of the stock price winsorized at $15 (PRICE). We transform these variables to a probability of default using the estimated parameters for the 12-month horizon Campbell, Hilscher, and Szilagyi (2008, Table IV). For details on the construction of these variables, see Appendix 3.A.

In Appendix 3.B we analyze the differences with the probabilities of default as estimated by the Merton model. In particular, we find that the Merton model is better able to match the high probabilities of default for lower credit ratings. The portfolio return results when using the hazard rate model are in Table 3.8, column 5. We find that the realized returns D1-D10 are again negative at -0.24% per month, but no longer statistically different from zero. However, compared to the expected return, the returns are substantially lower with a t-statistic of -2.60.

The second alternative to estimate the probabilities of default is to use credit ratings. We obtain long-run average cumulative default rates provided by Moody's Investors Services (2015, exhibit 34) for the period 1920 to 2014. For each bond and each month, we use the credit rating and maturity to infer the cumulative default rate.[12] We find that the results, reported in column 6, are very similar to those of specification 1. In particular, the realized returns are still significantly different from the expected returns with a t-statistic of -4.72.

Finally, if we assume that 1) the expected credit return of a bond is a fixed proportion of the total credit spread, 2) the credit spread, and thus the expected return, is constant over maturities (flat term structure) and 3) firms do not differ in their elasticity, then expected equity returns are proportional to the credit spread. The assumption that expected equity returns are proportional to credit spreads is very strong. For instance, the expected return measure used in our benchmark analysis is not increasing in the credit spread. Rather, in the group with the 10% lowest expected returns, some of highest credit spreads can be found (see Table 3.3; D10 has a credit spread of 24bps per month, which is only exceeded by D1, D2 and D3). Still, we find that the results for sorting directly on the credit spread (column 7) are quite similar to those for the base case (column 1), with strongly negative t-statistics of -2.16 and -3.24 for the tests versus zero and the expected equity return respectively.

3.5.3 Interaction with default risk

In the portfolio sorts reported in Section 3.4.1 an interaction of expected equity returns with physical default risk is visible, but the relationship is not monotonic, as D1, D2 and D10 have higher risk than other groups. This suggests that our results are not simply a mirror image of the traditional distress risk puzzle. To further analyze this, we construct a double sort based on five (default) risk measures, namely 1) the credit spread of the bond, 2) the probability of default as measured with the Merton (1974) model implementation,

[12] As the maturity is usually not equal to a round number, we use linear interpolation between the two maturities nearest by. For example, a BB-rated bond with 4.5 years' time-to-maturity will have a default probability of 9.35% (average of 8.24% for 4-year horizon and 10.46% for 5-year horizon).

3) the credit rating of the bond, 4) past 1-month equity return volatility and 5) past 36-month equity market beta. First we split the universe each month in five equal sized groups based on the risk measure. Second, within each risk group, we sort on the bond-implied expected return and create a top 20% minus bottom 20% long-short portfolio. The mean realized returns and associated t-statistics of the top-bottom portfolios are reported in Table 3.9. We see that the negative returns on the top-bottom expected return portfolios are concentrated in the 40% highest risk groups, with highly significant negative returns for the 20% highest risk group for all default risk measures. For the 20% lowest risk group, we observe positive returns on the top-bottom expected return portfolios for all risk measures (except for the equity beta), but not significantly positive. Thus we conclude that also after correcting for the interaction with default risk, no evidence exists for a positive relation between expected and realized equity returns.

3.5.4 Bond liquidity

So far we assumed that the part of the credit spread that cannot be attributed to physical default risk probability is a risk premium for the credit risk. In various other studies part of the credit spread is attributed to an illiquidity premium (Bao, Pan, and Wang, 2011; Dick-Nielsen, Feldhütter, and Lando, 2012; Bongaerts, De Jong, and Driessen, 2017). Hence our expected return measure might be biased due to these liquidity effects. We therefore use data from the TRACE database to construct an estimate of the illiquidity premium. TRACE is a transaction report database covering almost all trading in USD-denominated corporate bonds. We use Enhanced TRACE from 2005 to Q3 2014, and standard TRACE afterwards, as Enhanced TRACE is only available after 18 months. To filter the data for cancellations, reversals and errors, we follow Dick-Nielsen (2009) and Dick-Nielsen (2014) for the non-enhanced and enhanced version respectively. The TRACE data is linked to the bond data using the CUSIPs.

We first compute the monthly turnover of all bonds per expected return portfolio, which is equal to the total dollar amount traded in a given month divided by the total dollar notional amount outstanding at the beginning of the month. Second, we follow the procedure of Feldhütter (2012) and compute realized bid-ask spreads by identifying pairs of transactions on a given day for the same bond and transaction size. The absolute value of the price difference of the two transactions, divided by the average of the two prices, is a good measure of the percentage bid-ask spread as the two transactions likely involve a dealer intermediating a bond transfer from a seller (or buyer) to a buyer (or seller). See Feldhütter (2012) for more details.[13] Finally, we compute the product of turnover and the realized bid-ask spread as a proxy for the illiquidity premium, which is what the Amihud and Mendelson (1986) model with homogeneous investors predicts. Bongaerts, De Jong, and Driessen (2017) estimate liquidity premiums for corporate bonds and find that their estimates are close to those of Amihud and Mendelson (1986).

Table 3.10 reports the results. We observe that the bonds of companies with the highest expected returns, D1, experience the highest turnover on average (14.3% per month, or 172% per annum), but also have the highest round-trip costs. This results in an average bond liquidity premium of 5.2 basis points per month (or 62 basis points per annum), substantially larger than the average liquidity premium of 2.3 basis point per month across all portfolios. Thus, our expected return measure is indeed tilted to companies with less liquid bonds. To correct the expected equity return for this liquidity premium, we multiply the bond liquidity premium with the average bond-equity elasticity; the results are reported in the third row of Table 3.10. We find that the expected equity returns are biased upwards by 8.2 basis points for D1, and somewhat less for other deciles. Still, the magnitude of this bias is small compared to the total expected return differences between portfolios. Specifically, Table 3.10 reports all liquidity-corrected expected returns and we see that the effect of liquidity is minor. For instance, D1 has an expected equity return of 114 basis points (row 4). Deducting 8.2 basis points monthly liquidity premium results in 106 basis points expected equity return after correction (row 5), which is still much higher than 38 basis points for D2. It is thus unlikely that the presence of a liquidity premium is substantially affecting our sorting, and therefore our results.

3.5.5 Risk factors

In Section 3.4.2 we show that the difference between expected and realized returns cannot be explained by different pricing of risk factors in bond versus equity markets. Although we construct expected returns independent of a particular asset pricing model, a comparison with leading asset pricing models is still of interest. In particular, we find a statistically and economically sizeable monthly return of -179bps for our D1-D10 portfolio sorted on expected returns (Table 3.3).

Before we turn to the asset pricing models, we show in Figure 3.4 the relation between the monthly D1-D10 portfolio returns and the monthly market returns. We find that there is a clear positive relationship, with a correlation

[13] In our data set, buy and sell indicators are available, allowing us to more precisely define roundtrips compared to Feldhütter (2012).

of 0.42. Thus the high expected return stocks outperform the low expected return stocks during positive states of the world. Given the higher volatility, credit spreads and probability of default of D1 in comparison to D10, this is not a surprising result. Next we show that this market beta cannot explain the negative return of D1-D10. In Table 3.11 we regress these D1-D10 realized equity portfolio returns on the five Fama and French (2015) equity risk-factors, the Carhart (1997) momentum factor and the Asness, Frazzini, and Pedersen (2017) Quality-Minus-Junk factor for various factor model specifications. Regardless of the specification, we find large and statistically significant negative alphas, ranging from -130bps a month to -236bps a month (t-statistics of -3.66 to -5.85). The coefficients reveal sizeable positive loadings on the market premium ($RMRF$) and size (SMB), and negative loadings on momentum (MOM) and profitability (RMW). Hence, our sort on expected returns implies an equity trading strategy with a considerable alpha, and this trading strategy does not simply mirror existing risk factors or anomalies.

3.6 Conclusions

We perform a direct test of the cross-sectional integration of corporate bond and stock market pricing. The test does not rely on a specific asset pricing model. As the stock and bond of a firm are contingent claims on the same assets, we can use the risk premium on the bond to infer a risk premium on the stock. We find empirically that bond-implied expected stock returns relate negatively to realized stock returns, suggesting stock and corporate bond markets are not integrated and that relative mispricing between stocks and corporate bonds exists.

This negative relation cannot be explained by methodological choices. First, to transform corporate bond spreads to expected bond returns, we deduct the expected loss from the corporate bond credit spread using an estimate of the probability of default. We model the probability of default using an implementation of the Merton (1974) model, but find similar results when employing a hazard rate model or using historical default rates as a function of credit rating instead. Second, to transform expected bond returns to equity returns, we measure the bond-equity sensitivity using a regression approach as in Campello, Chen, and Zhang (2008). Even when the sensitivity is set to one for all stocks, the results remain similar. Third, our main analyses compare 5-year ahead bond-implied stock returns with one-month realized stock returns. Also when using 5-year realized stock returns, we find a negative relationship.

We find differences in the pricing of systematic risk factors, especially momentum, between bond-implied stock returns and realized stock returns.

These differences cannot, however, explain our key result. Our findings can also not be attributed to the portfolio weighting scheme, specific time periods, limits to arbitrage nor a potential illiquidity premium in the corporate bond spread. Finally, our results point towards temporary mispricing in equity markets, which is only partially corrected over longer horizons.

3.A Data

3.A.1 Linking bond to stock data

In principle, linking bonds to stocks is straightforward. At bond issuance, the first six digits of the bond CUSIP should match the first six digits of issuers historical CUSIP. The seventh and eight digit of the CUSIP identify the specific security of the issuer; the last digit is a check digit. Hence one could match on the first six digits of the CUSIP. However, due to mergers, acquisitions, bankruptcies and other delisting reasons this might not work. Therefore, we match a bond to a company at issuance, and then follow it through time. Example:

Feb 16, 1993, MOBIL CORP issues MOBIL CORP 02/23/2033 (CUSIP: 607059AZ). Matching on the first six digits with CRSP's NCUSIP field leads to a match with PERMCO 21211 (CUSIP: 6075910), company name MOBIL CORP in CRSP. For this bond, from issuance we assign this PERMCO until it does not exist anymore. This happens in November 1999, when EXXON and MOBIL merge into EXXON MOBIL. CRSP has an ACPERM field which indicates that the stock has been taken over by PERMNO 11850, which belongs to the combined EXXON MOBIL entity (PERMCO 11850). From December 1999 onwards, the bond is assigned to PERMCO 11850, and the process is repeated until the bond expires.

Note that a single company (PERMCO) might have multiple stock listings (PERMNO). We always assign a bond to a PERMCO, hence a bond can be assigned to multiple stock listings (PERMNO) at the same time.

Our procedure thus consists of two steps:

1. For each bond, identify the issuing company in CRSP. If no match is found using the first six digits of the CUSIP, try to hand-match data using the company names in the bond and stock data sets. If still no match is found, the bond is not linked to any stock in CRSP.

2. If a PERMCO has been found at issuance, follow it in CRSP from the moment of bond issuance until either

   (a) the bond matures, or

   (b) the stock is delisted. In this case verify why it is delisted. If an acquiring company is known (ACPERM), continue by following this company and repeat. Otherwise the link stops.

3.A.2 Inputs for the Merton (1974) probability of default

In this section the exact definitions of the variables using CRSP and COMPUSTAT fields are given. All fields are from COMPUSTAT except *SHROUT*, *PRC* and *RET*. All COMPUSTAT data is lagged two months to account for the reporting lag and reported in millions USD.

- Value of the firm (V) = market value equity + book value total liabilities
  - Market value equity: $SHROUT \times |PRC| \ / \ 1000$ (in millions USD)
  - Book value total liabilities: *LTQ*
- Default barrier (D): *LTQ*. Feldhütter and Schaefer (2016) find that this choice for the default barrier fits historical probabilities of default well
- Drift rate (μ) = $y_{g,t} + \theta\sigma$
  - $y_{g,t}$: duration-matched Treasury yield from Barclays
  - $\theta = 0.22$ following Feldhütter and Schaefer (2016) and Chen, Collin-Dufresne, and Goldstein (2008)
  - σ: asset volatility; see below
- Payout ratio (δ) = (Interest payments - Net stock repurchases + Dividends) / V
  - The ratio is capped at 0.13 following Feldhütter and Schaefer (2016)
  - Interest payments: previous fiscal year's fourth quarter *INTPNY*
  - Dividends: $DVPSXQ \times SHROUT \ / \ 1000$ (in millions USD)
  - Net stock repurchases: previous fiscal year's fourth quarter *PRSTKCY*
- Time-to-maturity (T) = option-adjusted duration of the corporate bond
- Asset volatility (σ) = $(1 - D/V)\sigma_E c$
  - D and V as given above
  - σ_E: past 1-month daily stock return (RET) volatility; extrapolated using the method as described in Appendix 3.C.
  - c: coefficient to adjust for bond volatility following Feldhütter and Schaefer (2016), ranging from 1 to 1.8.

3.A.3 Inputs for the hazard rate model

In this section the exact definitions of the variables using CRSP and COMPUSTAT fields are given. All fields are from COMPUSTAT except *SHROUT*, *PRC* and *RET*. All COMPUSTAT data is lagged two months to account for the reporting lag and reported in millions USD.

- market value total assets: book value total liabilities (*LTQ*) plus market cap equity ($SHROUT \times |PRC| / 1000$)
- NIMTAAVG: weighted average over the past four fiscal quarters of NIMTA, where a weight of 1 is assigned the most recent quarter, 0.5 to the quarter before, 0.25 to the third most recent quarter and 0.125 for the first quarter.
- NIMTA: net income (*NIQ*) to market value of total assets
- TLMTA: total liabilities (*LTQ*) to market value of total assets
- EXRET: past 12-month stock return (*RET*) over the S&P500 (obtained from Bloomberg)
- SIGMA: past 3-month daily stock return (*RET*) volatility
- RSIZE: log of the ratio of the market cap of the stock ($SHROUT \times |PRC| / 1000$) to the market cap of the S&P500 (obtained from Bloomberg)
- CASHMTA: cash and cash equivalents (*CHEQ*) to market value of total assets
- MB: ratio of market value of total assets to book value of assets (*ATQ*), where for the latter 10% of the difference between the market value of equity and book value of common equity (*CEQQ*) is added. In case book value of equity is negative, we divide by $1+book value liabilities (*LTQ*) instead (i.e., the book value of equity cannot be below $1).
- PRICE: log of the stock price, where the price is winsorized at $15.

3.A.4 Construction risk characteristics

In this section the exact definitions of the variables using CRSP and COMPUSTAT fields are given. All fields are from COMPUSTAT except *SHROUT*, *PRC* and *RET*. All COMPUSTAT data is lagged two months to account for the reporting lag and reported in millions USD.

- Beta Mkt_Rf: the beta is obtained by regressing the past 36-month equity returns from CRSP on the *RMRF* factor provided by Kenneth French. If less than 18 out of the 36 months are available, no beta is estimated.

- Log(Mcap): log of total market capitalization of all common stocks outstanding ($SHROUT \times |PRC| / 1000$).

- Log(Book-to-Market): log of the ratio of book value equity (including deferred taxes; $CEQQ + TXDBQ$) to market value equity ($SHROUT \times |PRC| / 1000$). If book and/or market value are zero, no value is computed.

- Mom12_1M: the stock return (RET) over the past 12 months, skipping the most recent month to account for short-term reversals.

- Oper. Prof: revenues ($SALEQ$) minus cost of goods sold ($COGSQ$) minus selling, general and administrative expenses ($XSGAQ$) minus interest expense ($INTPNY$) over the quarter, divided by the book value of equity.

- Investments: book value of assets (ATQ) as of now minus the book value of assets 12 months ago divided by the book value of assets 12 months ago.

3.B Estimating the probability of default

To assess the accuracy of our estimated probabilities of default, we compare the 5-year probabilities from the Merton (1974) and Campbell, Hilscher, and Szilagyi (2008) hazard rate model (hereafter: CHS) through time and in the cross section with realized default data from Moody's Investors Services (2015). We use a 5-year horizon, as this is the average time-to-maturity of the bonds in our sample. As noted by Feldhütter and Schaefer (2016), default models should be calibrated to long-run averages of default rates, not to realizations over a short period of time. For instance, if we would compare the 5-year expectations of the models with 5-year realized default rates at January 2005, we would find a severe underestimation, because the realized rates will include the Great Financial Crisis in 2008/2009. It is unlikely market participants anticipated this event at the start of 2005.

Figure 3.6 reports the average 5-year cumulative probabilities of default through time, and compared with the long-run average based on 1920-2014

Moody's Investors Services (2015) data ("rating"). Both models show substantial variation in probability of default levels through time, with clear increases visible for the Dot-Com bubble (1999-2003) and the Great Financial Crisis (2008-2009). We find that the average level is higher for the Merton model, and better matches the historical average. In contrast, the CHS model is consistently below the historic average.

Table 3.12 reports the average levels through time per credit rating for the 5-year horizon. We find that the Merton model (10.03%) matches the long-run average of 9.44% probability of default well. Moreover, the model is able to capture the strong increase in default rates when credit ratings deteriorate, although estimated probabilities are a bit too high for AAA to BBB rated firms. The CHS model, on the other hand, underestimates default rates considerably for BB and lower rated bonds, leading to an overall substantial underestimation (3.61% versus 9.44%).

3.C Estimating volatility over long horizons

To estimate the degree of mean reversion of stock return variance, we estimate per firm an AR(1) time series model:

$$\sigma_{E,t}{}^2 - \gamma = \theta \left(\sigma_{E,t-12}{}^2 - \gamma \right) + \epsilon_t \tag{3.5}$$

where $\sigma_{E,t}{}^2$ is the squared stock return volatility over month t using daily stock returns from CRSP, γ the long run average parameter and θ the mean reversion parameter. We estimate this equation using standard Ordinary Least Squares. We use as explanatory variable the volatility 12 months ago, not the most recent month, to capture the long-run dynamics of volatility, as our typical horizon is five years due to choosing bonds closest to the 5-year point.

Per firm, we estimate Equation 3.5 for each of the 12 calendar months, with the restriction that at least 10 observations are required. As this effectively requires at least 10 years of stock return data, not all firms have an estimate for theta. Therefore, we average all thetas across all twelve calendar months per firm, and then over all firms. This results in an average $\hat{\theta}$ of 0.8735. Figure 3.1 shows the distribution of the thetas across the firms, showing that most firms have thetas in the 0.80 to 0.95 range. Thus, the average of 0.8735 is a close approximation for most firms in our data set. For the long run mean γ, we take into account that some firms are riskier than others by using the average stock return variance of all observations with the same credit rating.[14] Per credit rating, we compute per month the median variance (not mean, to

[14]The credit rating is of the selected (senior unsecured) bond.

prevent outliers affecting our results) of all stocks with this rating, and then average over time to obtain the long-run mean. The table below shows the long-run mean parameter per credit rating:

credit rating	AAA/AA	A	BBB	BB	B	CCC-C
gamma ($\hat{\gamma}$)	0.1078	0.1162	0.1349	0.2113	0.3938	1.0214

The average variance increases from 0.1078 to 1.0214 when moving from rating AAA/AA to CCC-C. The expected equity volatility over the horizon T is then given by:

$$\widehat{\sigma_{E,t,t+T}} = \frac{1}{12T}\sqrt{\sum_{k=1}^{12T}\widehat{\sigma_{E,t+k}}} = \frac{1}{12T}\sqrt{\sum_{k=1}^{12T}\hat{\gamma} + \hat{\theta}^k(\sigma^2_{E,t} - \hat{\gamma})} \qquad (3.6)$$

where $\sigma^2_{E,t}$ is the past 1-month daily equity return variance and $\hat{\gamma}$ and $\hat{\theta}$ the parameter estimates.

3.D Equity-bond elasticity

For each firm and each month, we determine the change in market value of equity (E) and market value of debt (B) over the month. The market value of debt is estimated by the book value of total liabilities multiplied by the ratio of the corporate bond price and its nominal value (100 usually). In this way, the monthly change in the market value of debt reflects the change in corporate bond market prices, which is important to capture the elasticity properly. If we would take book values, there would be many months with zero debt return.

We can calculate the realized elasticity, $\frac{\delta E/E}{\delta B/B}$, for each month and each firm. We find that this is very noisy, and as bond returns can be zero (which happens for 3.68% of all observations) or close to zero, there can be extreme values as the distribution shows:

Percentile	< 1.5	2.5	3	5	95	97	97.5	> 98.5
Elasticity	-inf	-137.52	-85.84	-35.62	42.12	105.83	192.42	+inf

Instead of directly plugging in the most recently observed, potentially extreme, elasticity, we follow Campello, Chen, and Zhang (2008) by regressing these realized elasticities on variables suggested by the Merton (1974) model using Ordinary Least Squares (OLS). To prevent the outliers from distorting the fit, we exclude those observations which have an elasticity in the top or bottom 5% (i.e., bond return is close to zero, hence hard to infer the elasticity between the bond and the equity), or an equity volatility in the top 5% (which corresponds with a volatility of 90.63% per annum). Together, this removes 14.41% of all observations from the estimation of the coefficients. To check for the robustness of the estimation, we run four separate estimations, using either 2.5%, 5% (the base case), 7.5% or 10% as the threshold; see Table D.2. We find that the coefficients differ not much from one estimation to another.

We have also considered various alternative regression specifications. In particular, Kronmal (1993) suggests for regressions involving ratios on the left-hand side to move the denominator to the right hand side, and use a Weighted Least Squares approach where the weight is the inverse of the denominator to correct for the change in definition of the error term. However, in our setting the bond return is the denominator, and negative and zero values are perfectly valid. Hence this is not an option, as it would result in observations with infinite weight.

Taking all considerations into account, the OLS fit seems the best option available. To ensure our conclusions are not driven by this particular choice, we have also included results for two alternative equity-bond elasticity estimation methods:

- use the past 12-month observed bond-equity elasticity, or
- assume the elasticity to be one for all firms.

Neither these alternatives changes our conclusion that there is a distress risk puzzle (Table 3.8).

Table 3.1: Parameter estimates equity volatility and average characteristics
For each column (rating group), per month, the asset volatility, leverage, payout ratio and time to maturity are averaged, and subsequently averaged over time. The column *All* denotes the average across all credit ratings. The data sample runs from January 1994 to December 2015.

Rating	All	AAA/AA	A	BBB	BB	B	CCC-C
Avg. number of observations per month	685	31	150	207	103	155	39
Asset volatility (σ)	24.31%	20.16%	19.79%	21.11%	25.04%	30.43%	37.44%
Leverage (B/V)	0.54	0.43	0.48	0.51	0.55	0.61	0.71
Payout ratio (δ)	2.76%	2.17%	2.31%	2.59%	2.83%	3.27%	3.77%
Time-to-maturity (T, in years)	4.88	5.19	5.24	5.26	4.70	4.29	4.07
Equity market capitalization (bln USD)	12.34	96.47	24.29	9.20	3.61	1.58	0.99
Book-to-market ratio	0.75	0.50	0.55	0.68	0.83	0.84	1.63

Table 3.2: Determinants of bond-equity return elasticity

This table shows the results of the full sample pooled panel regression estimated using Ordinary Least Squares: $\frac{\delta E/E}{\delta B/B} = c + \beta_{LEV} LEV + \beta_{VOL} VOL + \beta_{y_g} y_g + \beta_T T + \epsilon$ where LEV is defined as the ratio of the book value of total liabilities to book value total liabilities + market value equity, VOL is the past 1-month annualized equity volatility, y_g is the duration matched Treasury yield, and T is the time-to-maturity of the bond. The table shows the coefficients and associated t-statistics. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Standard errors are calculated using two-way firm-month clustered standard errors (Petersen, 2009). The data sample runs from January 1994 to December 2015.

	constant	LEV	VOL	y_g	T	Adj R2	# obs
coefficient	0.63**	1.00***	1.09***	-3.54	-0.09***	0.15%	153527
t-statistic	(2.08)	(4.85)	(2.44)	(-0.71)	(-3.24)		

Table 3.3: Decile portfolios based on expected equity return

This table shows the returns and other characteristics of decile portfolios based on expected equity returns, where D1 contains the 10% highest expected equity returns and D10 the lowest 10% expected equity returns. D1-D10 is long the D1 portfolio and short the D10 portfolio. Expected equity returns are constructed as described in Section 3.3. The portfolios are monthly rebalanced and equal weighted. For each portfolio, the expected return, the realized return, realized minus expected return, the volatility of realized returns, the spread, expected bond return, elasticity and probability of default are shown. All returns and the credit spread are monthly and in percentages. The t-statistics use Newey and West (1987) and Newey and West (1994) robust standard errors. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Data sample is from January 1994 to December 2015.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Expected return	1.14	0.41	0.32	0.27	0.24	0.21	0.19	0.17	0.14	-0.14	1.27
Realized return	-0.87	0.66	0.83*	0.84**	0.90***	0.99***	0.88***	0.87***	0.78***	0.92**	-1.79***
	(-1.06)	(1.22)	(1.86)	(2.18)	(2.76)	(3.21)	(2.99)	(3.25)	(2.87)	(2.29)	(-3.35)
Realized minus expected return	-2.01**	0.25	0.52	0.57	0.66**	0.78**	0.69**	0.70***	0.64**	1.06***	-3.07***
	(-2.37)	(0.46)	(1.15)	(1.47)	(2.02)	(2.50)	(2.33)	(2.60)	(2.35)	(2.65)	(-5.57)
Volatility realized returns	11.33	8.07	6.39	5.61	4.88	4.71	4.40	4.08	4.00	5.78	7.52
Credit spread	0.70	0.36	0.26	0.21	0.18	0.15	0.13	0.12	0.12	0.24	0.46
Expected return bond	0.50	0.22	0.17	0.14	0.11	0.09	0.08	0.06	0.04	-0.12	0.62
Elasticity	1.57	1.11	0.96	0.89	0.84	0.79	0.77	0.77	0.83	1.28	0.29
Probability of default (in %)	17.90	11.34	8.59	7.16	6.20	5.40	4.84	4.64	5.96	20.87	-2.97

Table 3.4: Expected versus realized returns over short and long horizon

In panel A (B) the expected and realized returns for bonds (equities) are shown of decile portfolios sorted on the expected return of the bond (equity). All figures are monthly and in percentages. The *t*-statistics use Newey and West (1987) and Newey and West (1994) robust standard errors. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Data sample is from January 1994 to December 2015.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Panel A: Bonds											
Expected bond return	0.52	0.23	0.17	0.14	0.11	0.09	0.08	0.06	0.03	-0.13	0.65
Realized return 1-month	0.29	0.33	0.23	0.13	0.13	0.09	0.04	0.03	-0.01	-0.09	0.38
	(0.70)	(1.51)	(1.52)	(0.98)	(1.25)	(0.93)	(0.51)	(0.40)	(-0.16)	(-0.76)	(1.16)
Realized 1-month minus expected	-0.23	0.10	0.06	-0.01	0.02	-0.00	-0.03	-0.03	-0.04	0.04	-0.27
	(-0.56)	(0.45)	(0.40)	(-0.07)	(0.19)	(-0.02)	(-0.37)	(-0.43)	(-0.58)	(0.32)	(-0.84)
Realized return 5-years	0.23	0.21	0.16	0.15	0.13	0.12	0.10	0.09	0.10	0.14	0.09
	(0.79)	(1.03)	(1.01)	(1.11)	(1.14)	(1.17)	(1.17)	(1.15)	(1.03)	(1.03)	(0.53)
Realized 5-year minus expected	-0.29	-0.02	-0.01	0.01	0.02	0.03	0.02	0.03	0.07	0.27**	-0.56***
	(-1.00)	(-0.10)	(-0.06)	(0.07)	(0.18)	(0.29)	(0.23)	(0.38)	(0.72)	(1.99)	(-3.30)
Panel B: Equities											
Expected equity return	1.14	0.41	0.32	0.27	0.24	0.21	0.19	0.17	0.14	-0.14	1.27
Realized return 1-month	-0.87	0.66	0.83*	0.84**	0.90***	0.99***	0.88***	0.87***	0.78***	0.92**	-1.79***
	(-1.06)	(1.22)	(1.86)	(2.18)	(2.76)	(3.21)	(2.99)	(3.25)	(2.87)	(2.29)	(-3.35)
realized 1-month minus expected	-2.01**	0.25	0.52	0.57	0.66**	0.78**	0.69**	0.70***	0.64**	1.06***	-3.07***
	(-2.37)	(0.46)	(1.15)	(1.47)	(2.02)	(2.50)	(2.33)	(2.60)	(2.35)	(2.65)	(-5.57)
Realized return 5-years	0.30	0.60	0.73*	0.83**	0.88***	0.84***	0.83***	0.78***	0.80***	0.80**	-0.50
	(0.46)	(1.19)	(1.72)	(2.25)	(2.69)	(2.71)	(2.71)	(2.58)	(2.80)	(2.13)	(-1.47)
Realized 5-year minus expected	-0.84	0.19	0.41	0.56	0.64**	0.63**	0.64**	0.61**	0.66**	0.94***	-1.77***
	(-1.29)	(0.38)	(0.97)	(1.52)	(1.96)	(2.03)	(2.09)	(2.02)	(2.31)	(2.50)	(-5.20)

Table 3.5: Fama-MacBeth
Each month, a cross-sectional regression of realized equity return on the corporate bond implied equity return (*EXP*) and one or more interaction terms is conducted. Equity return and expected equity return are monthly and in percentages. Specifications 2 to 5 include interaction terms of *EXP* with dummies proxying the likelihood of mispricing. The dummies are constructed by each month splitting the universe in three equal sized buckets based on the number of analysts following the stock, the turnover of the stock and the equity market cap. The base case is a stock with high number of analysts, high stock turnover and large equity market cap (i.e. least likely mispriced). The t-statistics use Newey and West (1987) and Newey and West (1994) robust standard errors. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Sample period January 1994 to December 2015.

	1	2	3	4	5
constant	1.21***	1.22	1.21	1.23	1.23***
	(3.91)	(4.02)	(4.15)	(3.68)	(3.68)
EXP	-2.64***	-2.09***	-3.23***	-1.97***	-2.31***
	(-5.30)	(-3.13)	(-4.23)	(-2.37)	(-2.74)
EXP × [#analysts mid]		-0.70			-0.57
		(-1.22)			(-1.15)
EXP × [#analysts low]		-0.77			-0.58
		(-1.23)			(-1.03)
EXP × [#turnover mid]			0.98*		0.80
			(1.83)		(1.63)
EXP × [#turnover low]			0.93		0.81
			(1.44)		(1.30)
EXP × [#equity mcap mid]				-0.44	-0.01
				(-0.55)	(-0.02)
EXP × [#equity mcap low]				-0.90	-0.40
				(-0.89)	(-0.40)
Adj R2	2.7%	3.5%	3.7%	3.7%	5.2%
#observations per month	685	685	685	685	685

Table 3.6: Fama-MacBeth regressions on factor characteristics
Each month, a cross-sectional regression of the monthly realized equity return (monthly bond-implied expected equity return) on various characteristics (winsorized at 1 and 99% percentile each month) is conducted: 1. FF3: 36-month beta to RMRF, log of equity market cap in millions USD, log of book-to-market ratio 2. FF6: FF3 + 12 minus 1-month momentum, operating profitability, and investments. Equity return and expected equity return are monthly, in excess of the risk-free rate and in percentages. The t-statistics use Newey and West (1987) and Newey and West (1994) robust standard errors. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Sample period January 1994 to December 2015.

Dependent variable	Realized equity returns		Expected equity returns		Realized minus expected returns	
Factor model	FF3	FF6	FF3	FF6	FF3	FF6
constant	0.52	-1.79	0.64***	0.15	-0.12	-1.94
	(0.61)	(-1.06)	(7.72)	(1.40)	(-0.14)	(-1.10)
Beta Mkt_RF	0.03	-0.60**	0.04***	0.05***	-0.01	-0.65**
	(0.25)	(-2.01)	(4.83)	(2.59)	(-0.07)	(-2.20)
Log(Mcap)	0.01	0.30**	-0.05***	0.00	0.05	0.30*
	(0.08)	(2.01)	(-5.82)	(0.27)	(0.69)	(1.91)
Log(Book-to-Market)	-0.14	-0.34	0.05***	0.04**	-0.19	-0.37
	(-1.20)	(-1.12)	(5.25)	(2.20)	(-1.62)	(-1.21)
Mom12_1M		1.56		-0.21***		1.77
		(1.45)		(-3.27)		(1.60)
Oper. Prof.		-0.79		0.20		-1.00
		(-0.68)		(1.19)		(-0.76)
Investments		0.06		0.03***		0.03
		(0.13)		(2.52)		(0.07)
Adj. R2	0.05	0.12	0.09	0.11	0.05	0.12
Nobs	627	530	627	530	627	530

Table 3.7: Decile portfolios based on expected equity return for sub periods
This table shows the returns and other characteristics of decile portfolios based on expected equity returns, where D1 contains the 10% highest expected equity returns and D10 the lowest 10% expected equity returns. D1-D10 is long the D1 portfolio and short the D10 portfolio. Expected equity returns are constructed as described in Section 3.3. The portfolios are monthly rebalanced and equal weighted. For each portfolio, the expected return, the realized return, realized minus expected return, the volatility of realized returns, the spread, expected bond return, elasticity and probability of default are shown. All returns and the credit spread are monthly and in percentages. The t-statistics use Newey and West (1987) and Newey and West (1994) robust standard errors. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Panel A reports the first 11 years and Panel C the final 11 years of the sample

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
Panel A: Jan 1994 - Dec 2004											
Expected return	1.37	0.40	0.30	0.26	0.23	0.21	0.19	0.18	0.15	-0.07	1.43
Realized return	-1.25	0.69	0.93**	0.87**	0.88**	0.99***	0.91**	0.92***	0.78**	1.06**	-2.31***
t-statistic vs 0	(-1.24)	(1.15)	(2.07)	(2.20)	(2.19)	(2.90)	(2.47)	(2.71)	(2.18)	(2.34)	(-3.32)
Realized minus expected return	-2.61**	0.29	0.63	0.61	0.65	0.78**	0.71*	0.75**	0.63*	1.13**	-3.74***
t-statistic vs expected return equity	(-2.45)	(0.48)	(1.39)	(1.53)	(1.60)	(2.25)	(1.92)	(2.18)	(1.75)	(2.47)	(-4.90)
Panel B: Jan 2005 - Dec 2015											
Expected return	0.90	0.42	0.33	0.28	0.24	0.21	0.19	0.16	0.12	-0.21	1.11
Realized return	-0.50	0.63	0.73	0.80	0.92*	0.99*	0.86*	0.82**	0.78*	0.78	-1.28
t-statistic vs 0	(-0.38)	(0.70)	(0.94)	(1.22)	(1.78)	(1.92)	(1.85)	(1.97)	(1.91)	(1.17)	(-1.60)
Realized minus expected return	-1.41	0.21	0.40	0.52	0.67	0.77	0.67	0.66	0.66	0.98	-2.39***
t-statistic vs expected return equity	(-1.08)	(0.23)	(0.51)	(0.79)	(1.30)	(1.50)	(1.44)	(1.57)	(1.59)	(1.50)	(-3.11)

Table 3.8: Robustness top-bottom decile portfolio results

This table shows the returns of top-bottom decile portfolios based on expected equity returns. There are six specifications:

1. Base case (as in Table 3.3)
2. Market value weighted stock positions (instead of equal weighted)
3. Sort on expected bond returns
4. Elasticity is based on past 12-month OLS of realized equity returns on realized credit returns (instead of pooled panel regression)
5. Probability of default estimated using the CHS model rather than implementation of the Merton (1974) model
6. Probability of default using long-term cumulative default rates per credit rating over the period 1920-2014 (Moody's Investors Services, 2015, Exhibit. 32)
7. Sort on credit spread

For each portfolio, the expected return, the realized return, and realized minus expected return are shown. The expected returns are computed as described in Section 3.3, except for specifications 4, 5, 6, where the expected equity return follows the modification. All returns are monthly and in percentages. The *t*-statistics use Newey and West (1987) and Newey and West (1994) robust standard errors. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Sample runs from January 1994 to December 2015.

Specification	1	2	3	4	5	6	7
Expected return	1.27	0.76	0.98	1.87	1.61	1.35	0.80
Realized return	-1.79***	-1.10*	-1.03**	-0.85**	-0.24	-1.87***	-1.48**
t-stat vs 0	(-3.35)	(-1.68)	(-2.21)	(-2.17)	(-0.34)	(-2.81)	(-2.16)
Realized minus expected return	-3.07***	-1.86***	-2.01***	-2.72***	-1.84***	-3.22***	-2.29***
t-stat vs expected return equity	(-5.57)	(-2.89)	(-4.10)	(-6.50)	(-2.60)	(-4.72)	(-3.24)

Table 3.9: Expected equity return top-bottom portfolios within risk groups
Each month, the universe is split in five groups according to a risk measure. The risk measures are (1) the credit spread of the bond, (2) the probability of default as described in Section 3.3.2, (3) the credit rating, (4) the past 1-month daily equity return volatility and (5) the equity market beta which is computed by regressing the past 36 month stock returns on the *RMRF* factor provided by Kenneth French. Within each group, an equal weighted long-short portfolio is constructed by going long (short) the 20% highest (lowest) expected equity returns stocks. The table reports the mean monthly realized return in percentages and the associated t-statistic which uses Newey and West (1987) and Newey and West (1994) robust standard errors. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Sample runs from January 1994 to December 2015.

	1 (high risk)	2	3	4	5 (low risk)
Credit spread	-2.79***	-0.67***	-0.21	0.11	0.06
	(-4.91)	(-3.01)	(-1.02)	(0.63)	(0.44)
Probability of default	-2.89***	-1.35***	-0.07	-0.29	0.47
	(-4.56)	(-3.05)	(-0.23)	(-1.27)	(1.40)
Credit rating	-3.50***	-0.49	-0.07	0.15	0.15
	(-5.05)	(-1.54)	(-0.22)	(0.66)	(0.84)
Equity volatility	-2.93***	-0.35	-0.53**	-0.23	0.14
	(-5.16)	(-0.87)	(-2.16)	(-1.40)	(0.88)
Equity *RMRF* beta	-1.59***	-0.63*	-0.84***	-0.46	-1.55***
	(-2.99)	(-1.88)	(-2.62)	(-1.30)	(-2.90)

Table 3.10: Liquidity of the expected return portfolios

This table shows liquidity characteristics for the ten decile portfolios sorted on expected equity returns as in Table 3.3, where D1 contains the 10% highest expected equity returns and D10 the lowest 10% expected equity returns. The monthly turnover is computed per month and per portfolio as the total trading volume in TRACE divided by the total notional amount outstanding of the bonds, and subsequently averaged over time. The round-trip cost is computed per bond per month as the average bid-ask spread of all customer-to-customer round trips that occur within 24 hours, and then averaged over all bonds in the portfolio and subsequently over time. The bond liquidity premium per month is the product of the monthly turnover and the average round-trip cost. The last row shows the implied liquidity premium in the expected bond return by multiplying the bond liquidity premium with the average elasticity. The data runs from January 2005 to December 2015.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Monthly turnover	14.3%	9.9%	8.7%	7.9%	7.4%	7.3%	7.3%	8.7%	8.4%	9.6%
Round-trip cost	0.37%	0.28%	0.24%	0.24%	0.23%	0.22%	0.21%	0.20%	0.23%	0.24%
Bond liquidity premium per month	0.052%	0.028%	0.021%	0.019%	0.017%	0.016%	0.016%	0.017%	0.020%	0.023%
Liquidity premium in exp. equity return	0.082%	0.031%	0.020%	0.017%	0.014%	0.013%	0.012%	0.013%	0.016%	0.029%
Exp. equity return before liquidity premium	1.14	0.41	0.32	0.27	0.24	0.21	0.19	0.17	0.14	-0.14
Exp. equity return after liquidity premium	1.06	0.38	0.30	0.25	0.23	0.20	0.18	0.16	0.12	-0.17

Table 3.11: Expected equity return top-bottom portfolio factor regressions
The D1-D10 expected equity return portfolio is constructed as described in Table 3.3. The realized returns of this portfolio (R) are regressed on one or more factors denoted by $\mathbf{F}$: $R = \alpha + \beta\mathbf{F} + \epsilon$. The factor series are obtained from the website of Kenneth French. The table reports the monthly alpha in percentages, the coefficients β and all associated robust t-statistics following Newey and West (1987) and Newey and West (1994). Sample period is January 1994 to December 2015.

	1 (CAPM)	2 (FF3)	3 (FF3-Carhart)	4 (FF5)	5 (FF5-Carhart)
alpha	-2.30***	-2.36***	-1.78***	-1.65***	-1.30***
	(-5.49)	(-5.87)	(-5.06)	(-3.70)	(-3.66)
RMRF	0.83***	0.74***	0.44***	0.45***	0.26**
	(6.07)	(5.62)	(4.90)	(3.84)	(2.57)
SMB		0.63***	0.72***	0.33**	0.45***
		(5.26)	(4.78)	(2.18)	(3.33)
HML		0.04	-0.24	0.69***	0.21
		(0.17)	(-1.16)	(2.58)	(1.23)
MOM			-0.74***		-0.69***
			(-6.26)		(-6.36)
RMW				-1.12***	-0.91***
				(-4.79)	(-4.14)
CMA				-0.72	-0.38
				(-1.42)	(-1.19)
Adj. R2	0.23	0.30	0.52	0.38	0.57

Table 3.12: Cumulative 5-year probability of default per credit rating
Long-run average: based on data per credit rating of Moody's Investors Services (2015, Exhibit 32), spanning the 1920-2014 period.

model	Avg.	AAA/AA	A	BBB	BB	B	CCC/CC/C
Merton	10.03%	2.14%	2.83%	4.69%	9.39%	19.61%	35.81%
CHS	3.61%	1.86%	2.09%	2.45%	3.36%	5.38%	10.38%
Long-run average	9.44%	0.70%	1.37%	2.87%	9.34%	20.54%	39.77%

Table 3.13: Coefficients panel OLS regression for various thresholds
This table shows the results of the full sample pooled panel regression estimated using Ordinary Least Squares: $\frac{\delta E/E}{\delta B/B} = c + \beta_{LEV} LEV + \beta_{VOL} VOL + \beta_{y_g} y_g + \beta_T T + \epsilon$, where LEV is defined as the ratio of the book value of total liabilities to book value total liabilities + market value equity, VOL is the past 1-month annualized equity volatility, y_g is the duration matched Treasury yield, and T is the time-to-maturity of the bond. The table shows the coefficients and associated t-statistics for various winsorization thresholds. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. Standard errors are calculated using two-way firm-month clustered standard errors (Petersen, 2009). The data sample runs from January 1994 to December 2015.

threshold	constant	LEV	VOL	y_g	T	Adj R2	# obs
2.5%	1.20***	0.79**	0.76	-2.61	-0.10*	0.02%	166311
	(2.59)	(2.00)	(1.27)	(-0.35)	(-1.88)		
5%	0.63**	1.00***	1.09***	-3.54	-0.09***	0.15%	153527
	(2.08)	(4.85)	(2.44)	(-0.71)	(-3.24)		
7.5%	0.48*	0.85***	1.10***	-2.79	-0.07***	0.22%	141173
	(1.92)	(5.40)	(2.77)	(-0.67)	(-3.47)		
10%	0.35*	0.80***	1.01***	-1.83	-0.05***	0.26%	129216
	(1.68)	(6.16)	(2.85)	(-0.55)	(-3.24)		

Figure 3.1: Distribution of fitted elasticities
The following pooled panel OLS regression is estimated: $\frac{\delta E/E}{\delta B/B} = c + \beta_{LEV} LEV + \beta_{VOL} VOL + \beta_{y_g} y_g + \beta_T T + \epsilon$ where $\frac{\delta E/E}{\delta B/B}$ is the observed elasticity measured over the month (winsorized top and bottom 5%); all right hand variables are known as of the beginning of the month: LEV is the leverage ratio B/V, VOL is the past 1-month annualized stock return volatility (winsorized top 5%), y_g the duration matched Treasury yield and T the time-to-maturity. The figure reports the distribution of the fitted elasticities, winsorized at the 0.5% and 0.995% quantiles.

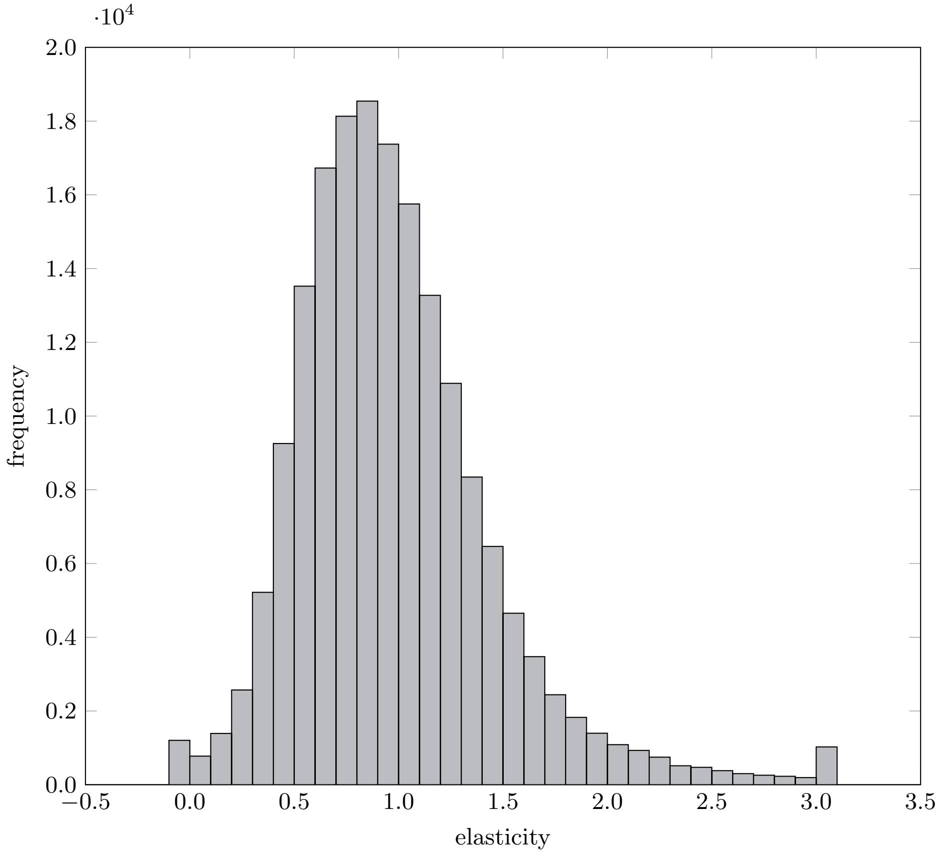


Figure 3.2: Average expected bond and equity returns through time
This figure reports the market value weighted average of the monthly expected bond return over duration matched Treasuries and the expected equity return over the 1-month T-bill following the methodology in Section 3.3. Sample from January 1994 to December 2015.

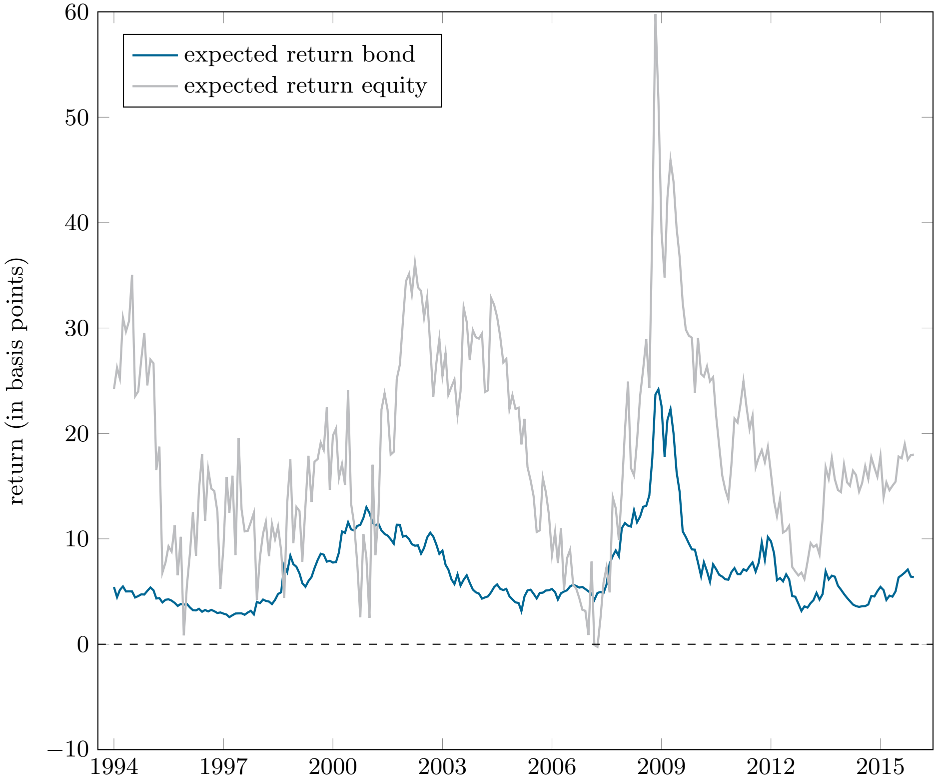


Figure 3.3: Bond-implied expected and realized returns D1-D10
This figure plots the cumulative bond-implied and realized equity returns of the bond-implied expected return sorted D1-D10 portfolio following the methodology in Section 3.3. Sample from January 1994 to December 2015.

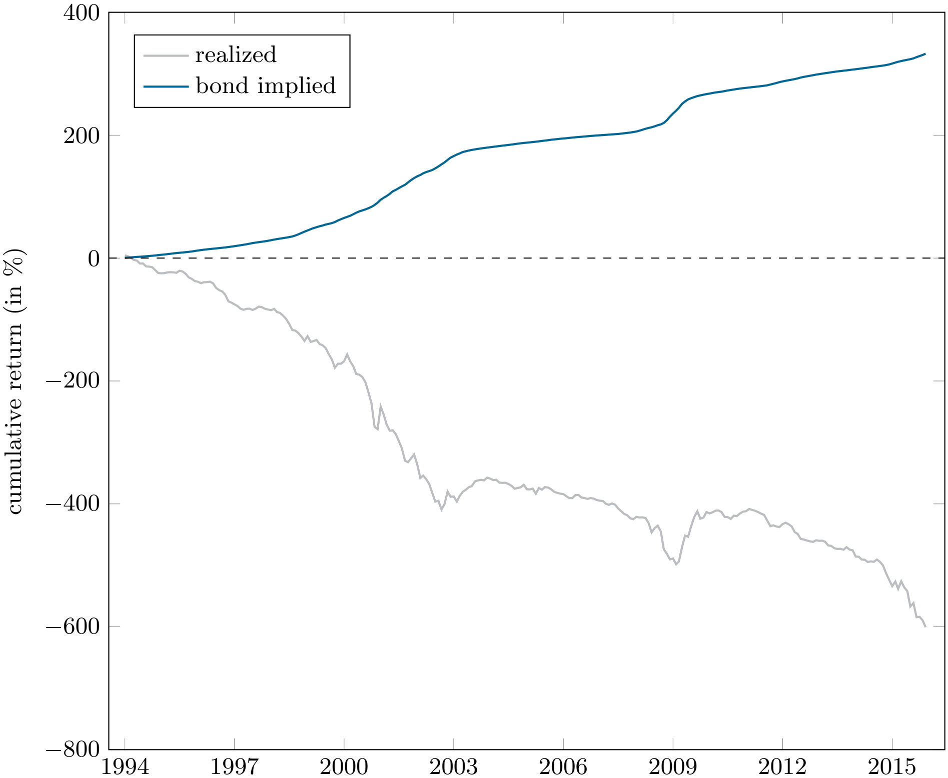


Figure 3.4: Relation D1-D10 expected equity return portfolio with stock market return

This figure plots the monthly realized equity return of the market over the 1-month T-bill to the D1-D10 expected equity return portfolio monthly realized returns following the methodology in Section 3.3. Sample from January 1994 to December 2015.

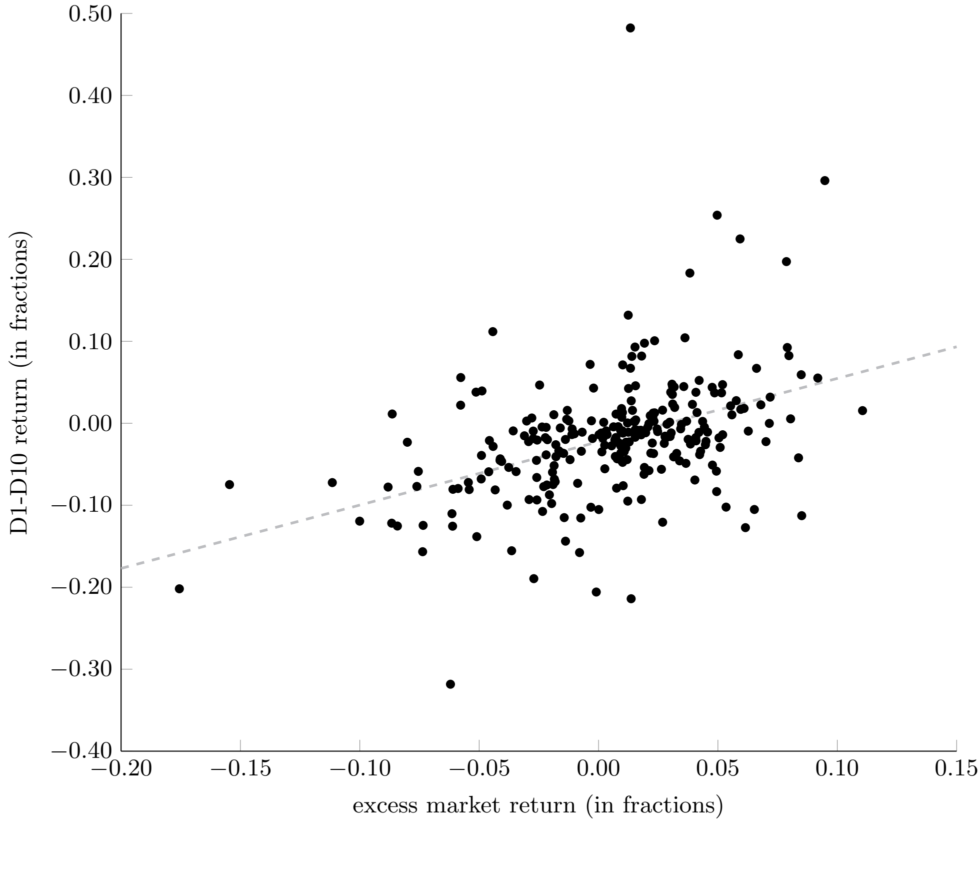


Figure 3.5: Distribution mean-reversion parameter equity return variance
Per stock, we estimate for each calendar month the following regression using OLS: $\sigma^2_{Et} - \gamma = \theta\left(\sigma^2_{Et-12} - \gamma\right) + \epsilon_t$, where σ^2_{Et} is the squared stock volatility over month t using daily stock returns from CRSP, γ the long run average parameter and θ the mean reversion parameter. For each stock, we take the average over the 12 θ's. The figure shows the distribution of thetas, where thetas below zero or above 1 are excluded.

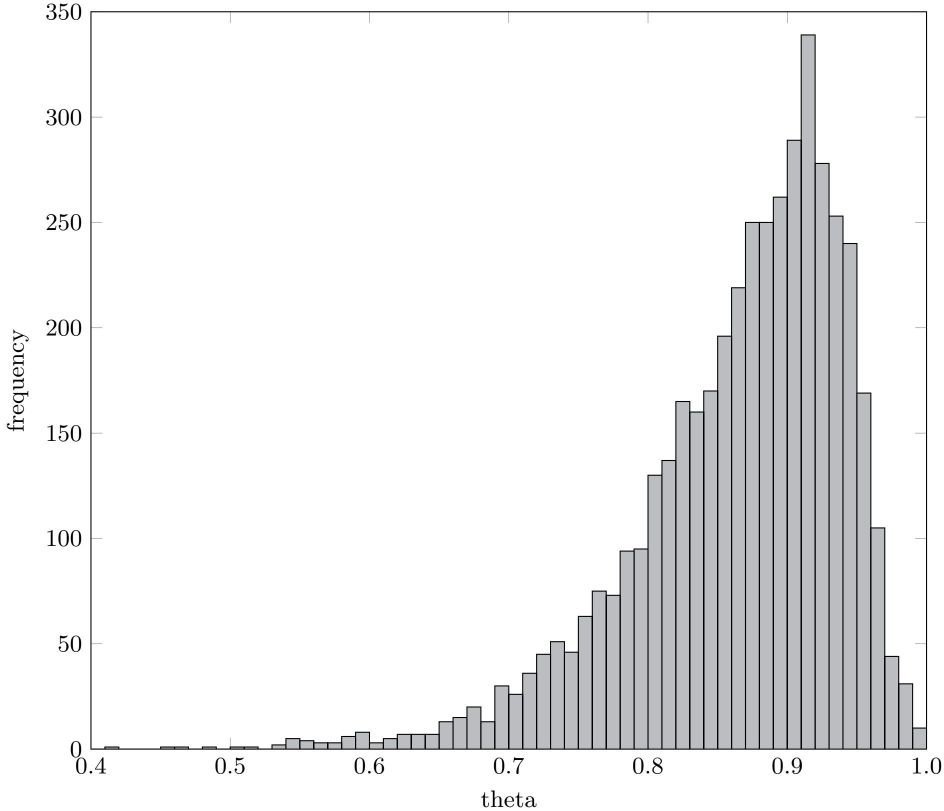
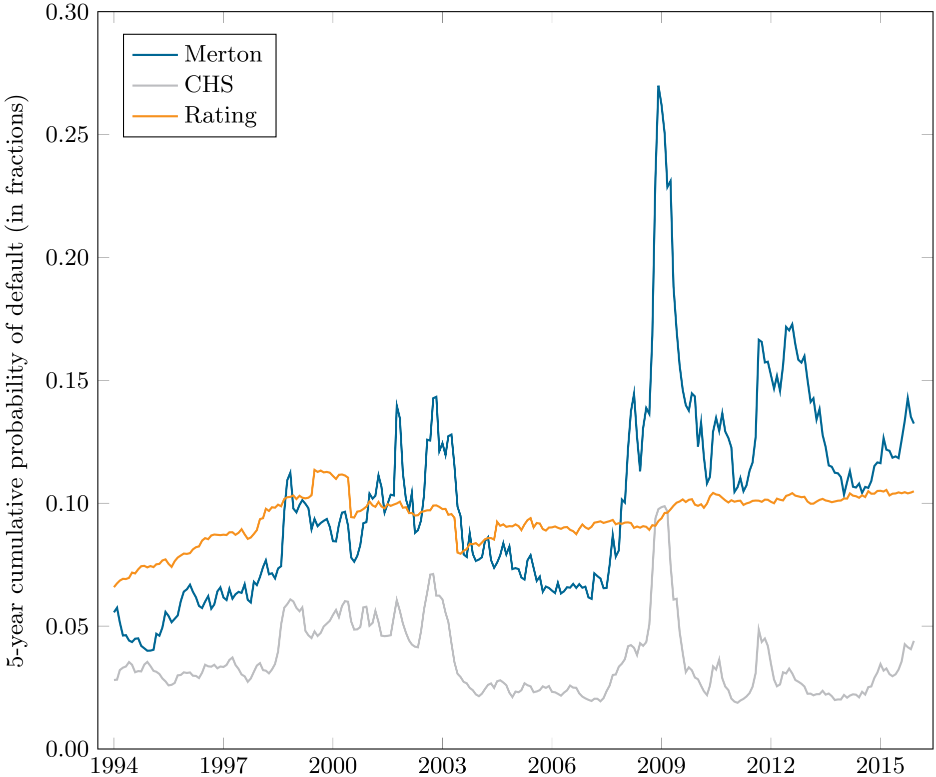


Figure 3.6: Average 5-year cumulative probability of default through time
Average 5-year cumulative probability of default for the Merton (1974) model implementation and the Campbell, Hilscher, and Szilagyi (2008, CHS) hazard rate model; equal weighted. "Rating" is the average cumulative 5-year default rate for a bond given its credit rating using data from Moody's Investors Services (2015). Fluctuations in this series are caused by a changing credit rating composition of the universe. Sample period January 1994 to December 2015.



Chapter 4

Volatility-Adjusted Momentum

4.1 Introduction

Cross-sectional momentum premia have been thoroughly documented in the academic literature for many asset classes over the past two decades, first for US equities by Jegadeesh and Titman (1993), and subsequently in other asset classes such as international equities (Rouwenhorst, 1998), commodities (Miffre and Rallis, 2007), currencies (Okunev and White, 2003; Menkhoff et al., 2012), high-yield corporate bonds (Jostova et al., 2013), sovereign bonds (Asness, Moskowitz, and Pedersen, 2013) and real estate (Derwall et al., 2009; Beracha and Skiba, 2011). Ever since the first study in 1993, the de-facto standard methodology is to construct a non-levered long-short quantile portfolio based on past returns. This “winner-minus-loser” (*WML*) momentum portfolio is long assets with the highest past returns, and finances these long positions with short positions in assets with the lowest past returns.

There are a number of details in the exact construction of the momentum portfolio that vary across studies, such as the percentage of assets in the long and short leg (e.g., decile, quintile or tertile portfolios), the horizon over which past returns are measured (the formation period length), whether to skip the most recent week/month or not to account for bid-ask bounces (Jegadeesh and Titman, 1993), the rebalancing frequency and the weighting scheme within the portfolio (equal or market value weighted). Despite these differences, sorting assets based on past returns seems to be taken as a given.

The main contribution of this paper, motivated by portfolio theory going back to Markowitz (1952), is to make assets with different volatilities comparable to each other, such that there is a “level playing field”. I achieve this by incorporating ex-ante volatility estimates in both the sorting stage and the weighting scheme when constructing the momentum portfolio. The resulting *volatility-adjusted momentum* portfolio differs in three ways from the standard momentum portfolio, namely (1) assets should not be sorted into quantile portfolios based on their past returns, but rather on their past returns-to-volatility ratio, (2) the weight of an asset within the quantile portfolio should be inverse proportional to its volatility and (3) each quantile portfolio should target a constant volatility through time.

The empirical contribution of this paper is to compare volatility-adjusted momentum, and each of the individual steps from standard momentum to volatility-adjusted momentum, to standard momentum on CRSP U.S. stock data from January 1927 to December 2015. I find that the Sharpe ratio increases from 0.34 for standard momentum to 1.14 for volatility-adjusted momentum, the alpha more than doubles and that volatility-adjusted momentum has much less crash risk as evidenced by the reduction in skewness (from -3.91 to -1.02). This improvement is visible in both large caps and small caps.

The stronger performance is primarily driven by two effects. First, volatility-adjusted momentum avoids selling the highest volatility losers. Although high volatility stocks do not tend to have higher returns than low volatility stocks in general (Haugen and Heins, 1972), this is not the case amongst the losers, where the high volatility stocks do not continue their decline, but rather have an alpha close to zero. Avoiding the short-selling of high volatility losers raises the Sharpe ratio from 0.34 to 0.85.

Second, volatility-adjusted momentum (de-)levers the winner and loser portfolios when past 12-1 month daily return volatility of the stocks selected has been low (high), targeting a constant volatility instead. As future Sharpe ratios of the winner and loser portfolios are almost uncorrelated to their ex-ante volatility estimates, de-levering high volatility months and levering low volatility months boosts the Sharpe ratio. In particular, the winner portfolio is improved as a negative relation exists between ex-ante volatility and the realized 1-month Sharpe ratio. For the loser portfolio, the relation is flat, leading to a smaller increase in Sharpe ratio. Also, the constant volatility targeting reduces the natural imbalance in volatilities between winners and losers: losers tend to be more risky, as also documented by Haesen, Houweling, and Van Zundert (2017). The reduced volatility imbalance increases the winner-minus-loser Sharpe ratio by 0.12. In total, the Sharpe ratio rises from 0.85 to 1.14 due to the constant volatility targeting.

Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), instead of levering the individual winner and loser portfolios, lever the standard *WML* portfolio as a whole. In particular, Barroso and Santa-Clara (2015) target a constant volatility of *WML* by scaling with the volatility of the past 6 month of daily returns of the same portfolio. Adding this *WML*-specific leverage on top of the volatility-adjusted momentum portfolio increases the Sharpe ratio even further, to 1.31. Stand-alone, this timing element leads to a Sharpe ratio of only 0.74, well below the ratio of 1.14 for volatility-adjusted momentum.

As an out-of-sample test, I employ volatility-adjusted momentum on USD-denominated corporate bond data spanning the 1994-2015 period. Especially the application on investment-grade bonds, i.e., higher credit quality bonds, is of interest as it is one of the few asset classes for which no momentum effect has been found so far (Khang and King, 2004; Gebhardt, Hvidkjaer, and Swaminathan, 2005). In line with those earlier findings, no momentum effect is visible using traditional return-based sorts. I find the *WML* alpha to be only 1.80% per annum and statistically insignificant, and the Sharpe ratio with a value of 0.04 is close to zero as well. However, as the dispersion in volatility is very large within this dataset, the volatility-adjusted momentum portfolio generates a significant positive alpha of 3.26% per annum with a Sharpe ratio of 1.04.

This paper relates to several streams in the literature. First, it is closely connected to recent studies on understanding and improving stock momentum. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) find that timing the momentum factor for US stocks, using indicators like the past 6-month realized return volatility of the winner-minus-loser momentum portfolio itself, substantially improves the performance. In particular, the crashes associated with standard momentum are largely mitigated. I deviate from their work by not scaling the *WML* portfolio, but go one level deeper by first making the individual assets comparable in terms of ex-ante risk. This is an important difference as it also affects the selection of assets in the long and short portfolios, whereas scaling after the construction of the long and short portfolio completely ignores biases in the selection of individual assets, leading to suboptimal portfolios to start with. The Sharpe ratio of Barroso and Santa-Clara (2015) risk-managed momentum (0.74) is lower than the Sharpe ratio of volatility-adjusted momentum (1.14).

Second, it relates to the concurrent work of Ledoit, Wolf, and Zhao (2017) who test a large number of anomalies on U.S. stock data. Similar to this paper, they argue that the standard portfolio sort ignores the covariances of the asset returns. The key challenge with the mean-variance portfolio of Markowitz (1952) is exactly to estimate the covariance matrix of asset returns. Ledoit, Wolf, and Zhao (2017) solve this by using the *DCC-NL* estimator of Engle, Ledoit, and Wolf (2017). In contrast, the adjustment proposed in this paper assumes a uniform correlation structure and explicitly creates quantile portfolios rather than a single optimized portfolio. This simplifies the portfolio construction drastically and provides a clear interpretation of the differences versus the standard quantile portfolio sort.

Third, it relates to earlier work on momentum in corporate bond markets. Gebhardt, Hvidkjaer, and Swaminathan (2005) and Khang and King (2004) find evidence for reversals in the investment grade market. Jostova et al. (2013) and Houweling and Van Zundert (2017) do not find momentum in investment grade bonds, but do find momentum in high yield bonds. Barth, Hühn, and Scholz (2017) document similar findings for euro-denominated bonds. A concurrent paper by Lin, Wu, and Zhou (2017) identifies momentum effects in the US corporate bond market, but with a different methodology. First, Lin, Wu, and Zhou (2017) empirically determine the optimal combination of moving averages of bond yields over eight horizons, ranging from 1 month to 60 months, to form a signal. In contrast, in this paper a single horizon is used as is standard in the momentum literature. Second, this paper purposely uses excess returns over duration matched Treasuries, i.e. the credit component of returns, not total returns as used by Lin, Wu, and Zhou (2017). The reason is that, especially for investment grade bonds, a sizable part of the return is driven by the interest rate component. Any momentum effects documented could thus entirely be due to momentum in Treasuries, not by momentum in the firm-related credit return. By zooming in on the credit return, I ensure that the results are driven by the firm-related credit component.

The remainder of this paper is structured as follows: Section 4.2 discusses the theoretical framework in which volatility-adjusted momentum is optimal. Section 4.3 contains the main empirical analyses. Section 4.4 describes the results of the out-of-sample check on corporate bonds. Section 4.5 concludes.

4.2 Methodology

In this section I explain and motivate the volatility adjustments to the standard momentum portfolio. First, I explain the adjustment to the standard top 10% winner minus bottom 10% loser momentum portfolio. Then, I use a reduced-form model to motivate the inclusion of volatility in the momentum portfolio construction process. This model is not meant as an explanation to momentum, rather, it shows why the incorporation of volatility in the construction process is optimal from the point of view of a rational momentum trader. Finally, I break down the adjustment from standard momentum to volatility-adjusted momentum in three steps. The empirical section shows results for each of the steps as to better understand the source of the improvement versus standard momentum.

4.2.1 Adjusting for volatility

The volatility adjustment aims to make assets with different levels of volatility comparable by scaling their returns $R_{i,t}$ with an ex-ante volatility estimate $\widehat{\sigma_{i,t}}$, where the subscript i (t) denotes the asset (time). This adjustment is common in studies involving multiple asset classes, such as Moskowitz, Ooi, and Pedersen (2012) who study time series momentum over numerous asset classes.

Denote the money weight as $w_{i,t}$, the past k-period return per unit of ex-ante volatility as $R^*_{i,t-k:t} \quad \left(= \frac{R_{i,t-k:t}}{\widehat{\sigma_{i,t}}}\right)$, and the weight in units of volatility as $w^*_{i,t} \quad (= w_{i,t} \times \widehat{\sigma_{i,t}})$.

The concept of volatility-adjusted momentum, as introduced in this paper, works a follows. I construct the top (bottom) decile momentum portfolio as an equal $w^*_{i,t}$ weighted portfolio of the 10% assets with the highest (lowest) $R^*_{i,t-k:t}$, with the total weight of the top (bottom) portfolio $\sum_i w^*_{i,t}$ constant through time. I.e., after scaling the returns of the assets with their ex-ante volatility and adjusting positions correspondingly, the methodology of volatility-adjusted momentum is exactly the same as the standard momentum portfolio sorts.

4.2.2 A single optimal portfolio

I now present a simple model to motivate the concept for volatility-adjusted momentum. In this model an agent has information on past price innovations to construct an optimal portfolio at time t. The agent has a constant relative risk aversion utility with risk aversion parameter γ and can invest in N risky assets which have normally distributed returns with mean μ_t and a variance-covariance matrix Σ_t. For simplicity, the problem is assumed to be single-period. I assume a riskless asset exists, and without loss of generality set it's return to zero. Under these assumptions, the optimal portfolio is the mean-variance portfolio, with weights given by (Markowitz, 1952):

$$w_t = \frac{1}{\gamma} {\Sigma_t}^{-1} \mu_t \tag{4.1}$$

The disadvantage of this solution is that the full variance-covariance matrix Σ_t has to be estimated, and that the optimal weights w_t are very sensitive to the estimated covariance terms. Therefore, I make the assumption that the pairwise correlations are uniform, which has been shown to produce better out-of-sample forecasts than many more sophisticated methods (Elton and Gruber, 1973). This simplifies Equation 4.1. Setting the correlation to a specific value $\rho \in (0,1)$[1], the *relative* weight[2] of asset i in the portfolio at time t, $z_{i,t}$, is given by (Elton, Gruber, and Padberg, 1976, Equation 12):

$$z_{i,t} = \frac{1}{1-\rho}\frac{1}{\sigma_{i,t}}\left[\frac{\mu_{i,t}}{\sigma_{i,t}} - \frac{\rho}{1-\rho+N\rho}\sum_{j=1}^{N}\frac{\mu_{i,t}}{\sigma_{i,t}}\right] \tag{4.2}$$

where $\sigma_{i,t}$ is the volatility of asset i at time t. Note that this is a relative weight, not an absolute weight. The absolute weight depends on the exact level of risk aversion of the investor.

4.2.3 Translation of single optimal portfolio to quantile portfolios

In the momentum literature, the usage of non-levered long-only quantile portfolios is standard. For comparability, I convert the single optimal portfolio into quantile portfolios. Although this reduces the optimality of the portfolio, it provides a clear interpretation of the differences between the standard and the volatility-adjusted momentum quantile portfolios. The differences can be broken down in three steps, and for better understanding of the differences I test each step separately in the empirical section.

Step 1 selecting assets To translate the portfolio in Equation 4.2, I use the insight that if a limited number of assets may be selected for the optimal portfolio, those assets included should be the ones with the highest Sharpe ratio $\frac{\mu_{i,t}}{\sigma_{i,t}}$ (Elton, Gruber, and Padberg, 1976, p. 1354). Thus, these assets do not have to be the ones with the highest weight in the single optimal portfolio! For instance, an asset with a just above-average Sharpe ratio and very low volatility will receive a high weight, but would not be selected in the top portfolio as the Sharpe ratio does not belong to the highest values. Intuitively, given that leverage is possible in the Markowitz (1952) framework, the optimal risky-asset portfolio will be the one that produces the highest Sharpe ratio. As all assets are equal in terms of diversification benefits due to the assumption of uniform correlations, the assets with the highest Sharpe ratio are most attractive to include. Leverage can be used to attain the desired risk given the risk aversion of the investor.

The assets in the top decile portfolio are therefore the 10% assets with the highest Sharpe ratios. The next decile portfolio, which cannot select assets

[1] Correlations could also be negative, but in the context of individual stocks they are positive in general. For example, Pollet and Wilson (2010) show that the average pairwise correlation between the 500 largest exchange-traded stocks in the U.S. is approximately 0.3.

[2] I.e., $w_{i,t} = \frac{z_{i,t}}{\sum_j z_{j,t}}$. Later the absolute weight will be derived.

already included in the top decile portfolio by construction, should thus include the next 10% assets sorted by Sharpe ratio. This process is repeated until the bottom decile contains the 10% assets with the lowest Sharpe ratio. The sorting of assets into quantile portfolios is thus straightforward: sort on the Sharpe ratio, rather than on raw returns.

Step 2 weighting assets within the (non-levered) portfolio The next question is how large the weight of an asset within its decile portfolio should be. Due to the sorting of the assets by their Sharpe ratio into decile portfolios, the k assets included in a specific decile portfolio will have approximately the same Sharpe ratio $\overline{SR^q}$. Under the simplifying assumption that all assets included in the quantile portfolio have exactly the same Sharpe ratio[3], the weight of each asset in a quantile portfolio is given by (Appendix 4.A provides the details for the derivation)

$$w_{i,t} = \frac{1}{\sigma_{i,t}} \frac{1}{\gamma} \left(\frac{1}{1 - \rho + k\rho} \right) \overline{SR^q} \tag{4.3}$$

In this step, I aim to construct portfolios that are not levered, since this is what standard momentum does. Thus the portfolio money weights $w_{i,t}$ have to add up to 1, implying

$$w_{i,t} = \frac{\sigma_{i,t}^{-1}}{\sum_{j=1}^{k_t} \sigma_{j,t}^{-1}} \tag{4.4}$$

as γ, ρ, k and $\overline{SR^q}$ cancel out. Thus within the quantile portfolio, assets should be weighted with the reciprocal of their volatility.

Step 3 levering portfolios After steps 1 and 2, there are 10 non-levered decile portfolios by sorting assets on their Sharpe ratio and within each portfolio weighting the assets by the inverse of their volatility. However, Equation 4.3 shows that the total portfolio weight, i.e. leverage, varies through time as the investors risk-aversion γ, the correlation parameter ρ, the number of assets k, the risk premium $\overline{SR^q}$ and the asset specific volatilities $\sigma_{i,t}$ can vary through time. Under the assumption that γ, ρ and $\overline{SR^q}$ are constant through

[3]Between the quantile portfolios, the Sharpe ratios will differ, as that is the goal of constructing anomaly portfolios. As the focus is on optimizing each individual quantile portfolio and show the difference in risk and return characteristics across the quantile portfolios, the same Sharpe ratio for each portfolio is implicitly assumed in step 3. As for the standard momentum methodology, which also creates $1 decile portfolios from D1 to D10, I make each decile portfolio the same. A momentum trader would invest more in D1 than in D2, and short-sell less in D9 than in D10.

time (i.e., the momentum trader does not update correlation nor risk premium estimates), Appendix 4.A shows that $w_{i,t}$ can be approximated by

$$w_{i,t} = c\sigma_{i,t}^{-1} k_t^{-1} \tag{4.5}$$

where the parameter c is a scaling parameter. This parameter depends on the assumed risk aversion γ, the correlation parameter ρ and the assumed risk premium $\overline{SR^q}$. In the empirical section I set c to 0.60. As I explicitly construct *WML* portfolios with equal full sample volatility to allow a meaningful comparison of mean returns and alphas between portfolios, the exact value is not important.

To conclude, the leverage of the portfolio is inverse proportional to the volatilities $\sigma_{i,t}$. If the volatilities double (halve), the weights $w_{i,t}$ halve (double). Due to this levering, the quantile portfolio volatility is (approximately) constant through time. See Appendix 4.A for the details. The parameter k_t is included to control for the number of assets. Otherwise, if the number of assets included in the portfolio would double, the leverage would also double, as the total weight invested, w^q, is the sum over all individual positions: $w^q = \sum_{j=1}^{k} w_{j,t}$.

4.2.4 Momentum trader inputs

In the concept of volatility-adjusted momentum, the momentum trader uses past returns to forecast future volatilities and Sharpe ratios. For the volatilities, the momentum trader estimates the volatility of asset i at time t, $\sigma_{i,t}$, by the past 12-1 month daily return volatility $S_{i,t-12:t-2}$. For the Sharpe ratio, the trader assumes that the returns over the past 12 months, skipping the most recent month, continue into the future:

$$\widehat{SR_{i,t}} = \frac{R_{i,t-12:t-2}}{S_{i,t-12:t-2}} \tag{4.6}$$

where $R_{i,t-12:t-2}$ is the realized return of asset i over the past 12-1 months. The decile volatility-adjusted momentum portfolios are thus constructed by sorting on $\frac{R_{i,t-12:t-2}}{S_{i,t-12:t-2}}$, and weighting with $S_{i,t-12:t-2}^{-1}$.

4.3 Empirical results

4.3.1 Data

For the stock data, I select all common equity (share codes 10 and 11) listed on the New York Stock Exchange, the American Stock Exchange and the Nasdaq

Stock Market (exchange codes 1, 2 and 3) in the Center of Research in Security Prices (CRSP) database from the daily files. The resulting dataset contains stock returns at a daily frequency over the period January 1926 to December 2015. All stocks are made long-short assets by subtracting the risk-free rate, which I proxy with the 1-month T-bill rate from the CRSP Treasury index files. As this is a monthly available rate, it is converted to a daily rate at the beginning of each month, and assumed to be constant throughout the month.

Momentum decile portfolios are constructed by ranking each month all stocks on their past 12-month returns, excluding the most recent month in line with previous studies on stock momentum to avoid the bid-ask bounce (Jegadeesh and Titman, 1993). Both the returns, as well as the volatilities for the volatility-adjusted momentum portfolios are based on these 11 calendar months of returns. The stocks with the 10% highest returns (or return-to-volatility) are incorporated in the first decile portfolio (D1), the next 10% in D2, etcetera, until the lowest 10% which are included in D10. The momentum portfolios are rebalanced every month-end. In between rebalancing moments the weights are updated with the daily stock returns. The constituents of the decile portfolios remain constant throughout the remainder of the month, except for delistings. If delisting returns are provided in the CRSP dataset, I include these in the return calculation. The proceeds from the divestment of the delisted stocks are reinvested proportionally in the remaining constituents of the momentum portfolios.

4.3.2 Momentum versus volatility-adjusted momentum

As the benchmark for volatility-adjusted momentum, I compute equal weighted standard momentum decile portfolios, as equal weighting is a natural benchmark in the context of portfolio choice. In Section 4.3.5, I discuss the robustness of the results to value-weighting, which is also commonly used in stock momentum studies. Moreover, the portfolios are recalculated on a large cap universe. The conclusions are unchanged. Due to the 12-month look back window, the portfolio returns start from the 2nd of January 1927.

Table 4.1 reports the results of the standard momentum portfolios (panel A), the volatility-adjusted momentum portfolios (panel D) as well as the in-between steps (panels B and C). In line with existing literature, the standard momentum deciles in Panel A show a near-monotonic declining pattern in mean return, Sharpe ratio, and alpha when moving the winners (D1) to the losers (D10). The winner portfolio excess return of 18.59% is much higher than the loser's portfolio returns of 8.64%. The long-short momentum portfolio WML, which is long D1 and short D10, achieves a return of 9.95% per annum, with a volatility of 29.40%, resulting in a Sharpe ratio of 0.34.

Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) find Sharpe ratios of 0.53 and 0.60 respectively for the standard momentum *WML* portfolio. The difference with those studies is caused by the usage of equal weights instead of market cap weights. If I apply value weighting, I find a Sharpe ratio of 0.61 over the 1927:01-2013:03 period studied in Daniel and Moskowitz (2016), close to their estimate of 0.60. Section 4.3.5 discusses the impact of value weighting and the interaction with inverse volatility weighting. In particular, the improvement of volatility-adjusted momentum over standard momentum is not driven by small caps.

The final two rows of panel A report the Fama and French (1993) 3-factor alpha. This alpha is computed by estimating a full-sample OLS regression on the *RMRF*, *SMB* and *HML* factors.[4] The alphas are monotonously declining across the momentum deciles. The *WML* 3-factor alpha amounts to 16.67% per annum, which is higher than the raw return due to negative loadings on *RMRF* (-0.25), *SMB* (-0.48) and *HML* (-0.75) while all three factors have a positive premium over this sample.

Panel B reports step 1, sorting stocks based on return to 12-1 month ex-ante volatility rather than on raw returns. Compared to standard momentum, the return of the loser portfolio (D10) is substantially lower, from 8.64% to 3.31%, while the return for the winner portfolio stays approximately the same. This increases the return of *WML* by 48%. Moreover, the volatility of *WML* declines from 29.40% to 18.78%, which is mainly driven by the decline in volatility of the loser portfolio from 41.03% to 28.09% per annum. The correlation between the winner and loser portfolio increases only slightly, from 0.70 to 0.75. In summary, step 1 improves the *WML* portfolio by lowering the loser portfolio return and volatility.

Panel C reports step 2, where stocks are not only sorted on return-to-volatility, but also weighted with the inverse of their ex-ante 12-1 month volatility following Equation 4.4. The improvement over step 1 is relatively small, with the *WML* Sharpe ratio increasing from 0.79 to 0.85. Adjusting the within-portfolio weighting scheme thus has very limited impact.[5]

The volatility-adjusted momentum results are shown in panel D. The Sharpe ratio increases from 0.85 for step 2 to 1.14. The returns and alphas in panel D are not directly comparable with those in the previous panels, as leverage is used. Therefore, the final column WML^C reports the results of *WML* scaled to an annualized volatility of 30% using the full sample *WML* portfolio

[4]These have been obtained from the website of Kenneth French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

[5]If the standard momentum portfolio is adjusted by only adjusting the weighting scheme (step 2), but not the sorting (step 1), the Sharpe ratio increases from 0.34 to 0.43, which is also a small improvement.

volatility for each of the steps. The raw returns (alphas) more than triple (double) when considering volatility-adjusted momentum (panel D) instead of standard momentum (panel A).

What is even more surprising is that the negative skewness, dubbed “crash risk” by Daniel and Moskowitz (2016), largely disappears. While standard momentum has a skewness of -3.91, this reduces to just -1.02 for volatility-adjusted momentum. This negative skewness is pronounced during and just after crisis periods. Figure 4.1 shows the cumulative log returns through time. The standard momentum portfolio (“MOM”) experiences substantial crashes in 1929, 1939, 2000 and 2009. It is exactly during these periods that volatility-adjusted momentum (“VA-MOM”) outperforms. The high *WML* alpha of 17% per annum could be explained by an aversion of investors to the crash risk. However, volatility-adjusted momentum has relatively small crash risk, but obtains an alpha of over 39% per annum. This suggests crash risk is an unlikely explanation of the momentum premium, in line with the conclusions of both Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016).

Table 4.2 shows the details of the Fama and French (1993) regression for the standard (panel A) and volatility-adjusted (panel B) momentum portfolios. I use the 30% volatility scaled versions to make the alphas comparable between the two portfolios. Volatility-adjusted momentum, due to the per-stock volatility target, is constructed to be close to market-neutral and this is confirmed by the zero coefficient on *RMRF*, while standard momentum has a significant negative exposure in line with previous literature (Barroso and Santa-Clara, 2015). Specification 2 in both panels shows that volatility-adjusted momentum can fully explain the alpha of standard momentum, but not the other way around. Still, volatility-adjusted momentum can only explain up to 63% of the total variant in standard momentum, which shows that the two also behave differently through time.

In specification 3, a levered *LOWVOL* factor is included. This factor is constructed like volatility-adjusted momentum, but instead of sorting stocks based on their past return-to-volatility ratio, stocks are sorted based on their volatility, selecting low volatility stocks in the top and high volatility stocks in the bottom. The reason for considering this factor is that volatility-adjusted momentum will overweight low volatility stocks in the winner portfolio (but also, as it is a short position, underweight low volatility stocks in the loser portfolio). It might be that part of the alpha is driven by the low volatility anomaly (Haugen and Heins, 1972). Table 4.2 shows that indeed part of the alpha disappears after including *LOWVOL*, as the alpha drops from 39.1% to 33.4% for volatility-adjusted momentum. Interestingly, also for standard momentum (panel A), the alpha declines, by more than 7%-point. Thus the low volatility exposure of volatility-adjusted momentum seems to be a feature of momentum in general, and not the construction procedure in particular. Haesen, Houweling, and Van Zundert (2017) provide evidence for this low volatility bias. Most importantly, low volatility cannot explain the high alpha of volatility-adjusted momentum.

4.3.3 The source of the improvement

The results from the previous section indicate that volatility-adjusted momentum has a substantial higher Sharpe ratio than standard momentum, mainly due to (1) the inclusion of different assets in the winner and loser portfolios, i.e. step 1, and (2) targeting a constant volatility for the winner and loser portfolios in step 3. These two steps present two dimensions of volatility: the first step improves the profitability of individual positions by relating momentum and volatility in the cross-section, and the second step (de)levers the winner and loser portfolios through time.[6] To better understand the source of the improvement, I analyze the relation between momentum and volatility both in the cross-section and through time.

To determine the impact of the cross-sectional adjustment, I employ a 5x5 doublesort.[7] First, five momentum portfolios are created based on past 12-1 month stock returns. Then, within each momentum portfolio, stocks are sorted into five 12-1 month daily return volatility portfolios, resulting in 25 portfolios in total. Table 4.3 shows the raw returns (panel A) as well as the 3-factor alphas (panel B). Within the momentum portfolios, high volatility has a higher return but lower alpha than low volatility in general, reflecting the empirical finding that the relation between risk and return is too flat (Haugen and Heins, 1972). Within each volatility portfolio, high momentum portfolios have higher returns and alphas than low momentum portfolios (i.e., the momentum effect). However, there is an exception for the high volatility loser portfolio: it has above average return, even higher than the high volatility winner portfolio, and by far the highest alpha across the losers. It thus seems that of the losers, for the ones with the highest volatility the downward trend does not continue but remains (risk-adjusted) flat, suggesting that the negative news has been priced in already. Volatility-adjusted momentum avoids short selling these stocks as it uses return-to-volatility rather than raw returns to construct quantile portfolios.

For the time series component, step 3, we note that both top and bottom portfolio Sharpe ratios improve with 0.19 and 0.06 respectively due to scaling

[6] Step 2 shows that weighting assets based on the reciprocal of their volatility within the portfolio, but not through time, is just a minor improvement.

[7] A 10x10 sort is not feasible in the earlier part of the sample, as there is an insufficient number of stocks to select from.

the portfolios through time versus step 2. The scaling adds value as the relation between the ex-ante volatility and the realized Sharpe ratio is negative. For the top (bottom) portfolio, an OLS regression of the realized annualized 1-month Sharpe ratio on the ex-ante volatility results in a coefficient of -0.076 (-0.0137) on the ex-ante volatility. Hence, the Sharpe ratios of both the loser, but especially the winner portfolio, improve, as more (less) weight is given to high (low) Sharpe ratio months.[8]

Figure 4.2 shows the leverage ratios of the winner and loser portfolios, where 1 means that the portfolio is fully invested in stocks, a value greater than 1 that part of the long stock position is financed by borrowing at the risk-free rate and a value below 1 that part of the portfolio is not invested in stocks but in the riskfree asset instead. The average level is above 1 due to the choice of 60% per stock volatility. This is merely a scaling constant. However, the average leverage of the winners is also higher than of the losers by 20%, as stocks with improving momentum tend to have lower volatility than losers. This effect has been documented before by Haesen, Houweling, and Van Zundert (2017), and by reducing this imbalance in portfolio volatilities the *WML* Sharpe ratio rises from 0.85 to 0.97 already.[9] The remainder of the improvement, from 0.97 to 1.14, is driven by the increase in the winner portfolio Sharpe ratio versus the loser portfolio Sharpe ratio.

4.3.4 How does volatility-adjusted momentum compare to *WML* timing?

Barroso and Santa-Clara (2015), taking the standard *WML* portfolio as given, show that this portfolio can be timed, as the volatility is relatively predictable while returns are unrelated to the volatility. Although this is similar to step 3 of this study, it is not the same as on the one hand their method does not separately consider winners and losers, but on the other hand there might also be information in the volatility of the *WML* portfolio itself that is not captured in the bottom-up stock volatility adjustment used in this study.

To verify which effect is stronger, I replicate the Barroso and Santa-Clara (2015) methodology. That is, given a *WML* portfolio, I scale the returns over month t with the annualized volatility estimated on the daily returns over the

[8] Even if the relation is positive, the smoothing of the volatility through time can potentially outweigh the loss in average monthly return per unit of risk.

[9] Simple algebra shows that the Sharpe ratio of the *WML* portfolio can be written as $SR_{WML} = \frac{\delta SR_W - SR_L}{\sqrt{1+\delta^2-2\delta\rho_{W,L}}}$, where SR_W and SR_L are the Sharpe ratios of the winner and loser portfolio respectively, $\delta = \frac{\sigma_W}{\sigma_L}$ is the ratio of the volatilities, and $\rho_{W,L}$ the correlation between the winner and loser portfolios. Plugging in all values of step 2, but with the ratio of volatilities (δ) of step 3, gives a Sharpe ratio of 0.97

past 6 calendar months:

$$S_{t-6:t-1} = \sqrt{\frac{250}{K}\sum_{j=1}^{K} {r_j}^2} \tag{4.7}$$

where r_j is the return on day j in the window and K the total number of days in the six-month window.

Table 4.4 reports the results for the standard momentum portfolio (columns 1 and 2), as well as for volatility-adjusted momentum (columns 3 and 4). All portfolios are scaled to a full-sample volatility of 30% for comparability of raw returns and alphas. I find that the Barroso and Santa-Clara (2015) method more than doubles the standard momentum portfolio Sharpe ratio, from 0.34 to 0.74. The Fama and French (1993) 3-factor alpha also increases by 9.9%-point to 26.9%, which is a relative increase of just over 50%. Still, this is lower than the Sharpe ratio (alpha) of volatility-adjusted momentum (1.14; 39.1%).

However, this does not mean that there is no value in the timing element. In the final column of Table 4.4, the Barroso and Santa-Clara (2015) methodology is applied on top of the volatility-adjusted momentum portfolio. The Sharpe ratio increases from 1.14 to 1.31, and the alpha from 39.1% to 42.5%.

To conclude, bottom-up adjusting for volatility in the construction of the momentum portfolio is superior to ex-post timing of the momentum portfolio as a whole, but it does not subsume this method.

4.3.5 Volatility and market cap

As noted in Section 4.3.2, many studies use value weighting rather than equal weighting to control for liquidity concerns. To ensure the results are not driven by the small caps in the dataset, I make a direct comparison between equal weighted momentum, value weighted momentum, and volatility-adjusted momentum on three size universes: all caps, large caps and small caps.

Table 4.5 reports the results on the winner-minus-loser portfolios. For the all cap universe, I indeed find that value weighted momentum has a much higher Sharpe ratio of 0.62, compared to 0.34 for equal weighted momentum. This difference in Sharpe ratios is driven by higher returns for the value weighted portfolios.

Zooming in on the large cap and small cap universe results, the main cause of the relative under performance of the equal weighted versus the market weighted portfolio is with the small caps, where the Sharpe ratio is a mere 0.24 (although the alpha is still highly significant). Within the large caps, the performance of the equal-weighted portfolio is actually slightly better than for the value weighted portfolio. Both the equal and value weighted portfolios

Sharpe ratios and alphas are, however, low compared to volatility-adjusted momentum. Within the large caps (small caps), the Sharpe ratio increases from 0.53 (0.71) for the value weighted portfolio to 1.06 (1.17) for volatility-adjusted momentum. Thus the finding that volatility-adjusted momentum substantially improves over both equal or value weighted momentum is robust to the exclusion of the small cap stocks.

4.4 Corporate bond results

Momentum effects have been documented in many different asset classes. However, investment grade corporate bonds seem to be a notable exception to this empirical finding. Previous studies have either found no momentum premium (Gebhardt, Hvidkjaer, and Swaminathan, 2005; Jostova et al., 2013; Houweling and Van Zundert, 2017), or even a reversal effect (Khang and King, 2004). On the other hand, within high yield bonds momentum premia exist (Jostova et al., 2013; Houweling and Van Zundert, 2017). Therefore corporate bonds provide a suitable out-of-sample test for volatility-adjusted momentum.

4.4.1 Data

For the corporate bond dataset, I use all constituents in the Barclays U.S. Corporate Investment Grade and Barclays US High Yield indices. The data is on a monthly frequency and spans the period January 1994 to December 2015, containing 1,350,229 bond-month observations. The indices consist of US dollar denominated corporate bonds with a time-to-maturity of at least one year and a minimum notional of 150 million, preventing the most illiquid bonds to enter the index.

The dataset contains a number of characteristics per observation. The *total return* is the return of the bond from the previous month-end to the current month-end, and assumes coupons are reinvested. In case of a default, the last available return of the bond is based on the last traded price, hence reflecting the market perception of the recovery rate. There is thus no survivorship bias. The *excess return* is the total return over the duration-matched Treasury return. I use duration-matched excess returns throughout this section to properly clean for interest rate risk differences. The momentum results are thus only driven by the firm-related credit part, not by momentum across the Treasury curve. This is an important difference from most earlier studies, which tend to focus on the total return. The usage of total returns has the disadvantage that any momentum effect found could be driven by momentum in Treasuries alone, not necessarily in the firm-specific component of corporate bond returns. The excess returns can be obtained in practice by hedging the interest rate exposure with interest rate swaps or bond futures. The duration used to match the corporate bond with the correct Treasury includes adjustments for embedded options and is provided by Barclays. The *credit rating* is the middle credit rating of the three rating agencies Standard and Poor's, Moody's and Fitch. If only two ratings are known, the lowest rating is assumed.

To control for systematic risks, I use the five Fama and French (1993) risk factors and the Carhart (1997) momentum factor. The equity market factor ($RMRF$), the equity size factor (SMB), the equity value factor (HML) and equity momentum factor (MOM) are from the website of Kenneth French. For the bond factors, I use the return-based term and default factors. Specifically, for the bond term factor ($TERM$), I use the return of the Barclays U.S. Treasury 7-10 year index over the 1-month T-bill return (from the website of Kenneth French). For the default risk factor (DEF), I use the excess return over duration-matched Treasuries of the Barclays U.S. Corporate Investment Grade index. This definition, in contrast to the Fama and French (1993) Ibbotson based factor, properly cleans for interest rate risk (Hallerbach and Houweling, 2013).

4.4.2 Empirical results

Volatility-adjusted momentum, which improves standard momentum by sorting on return relative to risk rather than return alone, is especially effective if the volatility differences between securities are large. As a proxy for the cross-sectional dispersion, I compute each month the ratio between the 90th and 10th percentile of the past 12-1 month return volatility per bond/stock, and subsequently take the average of the ratios over time. For the stock sample, the average ratio amounts to 3.1, which is small relative to the ratio of 14.2 for the corporate bonds data. The reason for this large dispersion is that bonds cannot only differ in terms of their credit rating (lower rated bonds tend to be more volatile), but also in their time-to-maturity. As a result, some bonds have a duration of 20, while others have a duration of just 1. Thus a parallel upward spread curve shift will mean the long bond suffers a 20 times larger loss than the short bond. Due to the large dispersion, it is expected that volatility-adjusted momentum can provide even larger improvements for corporate bond momentum.

To compute the momentum signal, a 7-minus-1 month window is used, following previous studies on corporate bond momentum (Gebhardt, Hvidkjaer, and Swaminathan, 2005; Jostova et al., 2013). Table 4.6 reports the full sample, i.e. investment grade and high yield together, decile portfolio results for standard momentum (panel A) and volatility-adjusted momentum (panel

B). As with stock momentum, the more volatile assets tend to be among the winner and loser portfolios, as indicated by the higher volatility of those portfolios. Intuitively, high volatility assets are more likely to show extreme returns, and thus to be selected in the extreme portfolios. Although the mean return of the winners is larger than that of the losers by 0.38% per annum, the *WML* column shows clearly that it has a very insignificant t-statistic of 0.12. Also after correcting for the five Fama and French (1993) bond risk factors, the alpha is not significantly positive (t-statistic of 0.81). However, for volatility-adjusted momentum there is a significant positive premium of 3.18% per annum (t-statistic of 4.58), and this remains after controlling for the bond risk factors. Thus while the standard momentum methodology does not pick up a premium, volatility-adjusted momentum does.

Table 4.7 shows the results for the winner-minus-loser portfolio for various credit qualities. Panel A makes a distinction between investment grade and high yield. Both raw returns and alphas show significant positive premia for volatility-adjusted momentum, while standard momentum has only a significantly positive alpha in high yield.

Panel B provides a more granular breakdown by credit quality. As the number of observations becomes smaller within a particular bucket, this analysis uses momentum quintiles rather than deciles. Except for AAA/AA rated bonds, which account for just 8.4% of the total dataset, volatility-adjusted momentum has significant positive returns. Risk-adjusted, the premium in A-rated bonds is not significant though. Interestingly, standard momentum, which has been found by previous studies to have a positive premium in high yield (Jostova et al., 2013), only shows a statistically significant premium for bonds rated CCC and lower. These bonds constitute just 20.2% of high yield, and 5.8% of the total dataset.

In conclusion, based on the standard methodology, momentum seems to be largely absent in corporate bond markets. This is, however, due to the large volatility dispersion. Volatility-adjusted momentum reveals significant momentum premia in both high yield as well as investment grade.

4.5 Conclusions

Sorting assets based on past returns into unlevered quantile portfolios is a natural way to test for cross-sectional momentum. Therefore, this method has become the de-facto standard method to test for the existence of momentum in many asset classes since the first momentum study of Jegadeesh and Titman (1993). However, standard portfolio theory suggests to scale assets, i.e. the past returns to sort on as well as the position size, with their ex-ante expected volatility to construct quantile momentum portfolios. I call this volatility-adjusted momentum.

For US stock data, 1927 to 2015, the annualized alpha increases from 17% for standard momentum to 39% for volatility-adjusted momentum, and this result is robust when the universe is restricted to large caps only. A detailed analysis shows that the benefit mainly comes from two sources.

First, it comes from not selecting high volatility stocks among the losers. Such stocks, which have experienced very negative and also very volatile returns over the past year, tend to have average returns going forward, in contrast to lower volatility losers which tend to keep under performing. Second, as the winner and loser portfolios differ in volatility, i.e. losers tend to have higher volatility than winners going forward, the constant volatility targeting through time of the quantile portfolios reduces the imbalance in volatility between winners and losers, benefiting the winner-minus-loser portfolio

As an out-of-sample check, the analysis is repeated for USD-denominated corporate bonds over the 1994-2015 period. Due to the high cross-sectional dispersion in volatility of the individual bonds, the standard momentum methodology does not even reveal momentum premia except for the 6% lowest-rated bonds. This has led previous studies to conclude momentum is largely absent from corporate bond markets. However, volatility-adjusted momentum has economically and statistically significant alphas for both high and low rated bonds, revealing a momentum premium previously masked by the large dispersion in volatility in the cross-section.

4.A Derivation optimal portfolio

This appendix provides more details on the derivation of the optimal portfolio weights. The optimal portfolio is a simplification of the mean-variance optimal portfolio, given by (Markowitz, 1952):

$$w_t = \frac{1}{\gamma} {\Sigma_t}^{-1} \mu_t \tag{4.8}$$

where t denotes the time, μ_t is the vector of mean returns and Σ_t the variance-covariance matrix.

Elton, Gruber, and Padberg (1976) show that the optimal *relative* portfolio weights $z_{i,t}$ under the assumption of uniform correlations (ρ)[10] and no short-sales is (Elton, Gruber, and Padberg, 1976, p. 1354):

$$z_{i,t} = \frac{1}{1-\rho} \frac{1}{\sigma_{i,t}} \left[\frac{\mu_{i,t}}{\sigma_{i,t}} - \frac{\rho}{1-\rho+k\rho} \sum_{j=1}^{k} \frac{\mu_{j,t}}{\sigma_{j,t}} \right] \tag{4.9}$$

for all non-zero weight assets, where k is the number of included assets in the portfolio and $\mu_{i,t}$ and $\sigma_{i,t}$ the mean and volatility of the return of asset i, respectively.

This formula provides a straightforward decision rule to determine whether a particular asset should be included (Elton, Gruber, and Padberg, 1976): asset i should be included as long as $z_{i,t}$ is positive. Clearly, $z_{i,t} > 0$ is only satisfied if the term in square brackets is positive. The last term in the square brackets is, given any k, a constant if a particular asset with Sharpe ratio $\frac{\mu_{i,t}}{\sigma_{i,t}}$ is included, any asset with a higher ratio should also be included in the portfolio. Thus, determining which assets should be included is based on the Sharpe ratio $\frac{\mu_{i,t}}{\sigma_{i,t}}$: order all assets from high to low, and continue adding until $z_{i,t}$ turns negative. To translate this to quantile portfolios: assets are sorted on $\frac{\mu_{i,t}}{\sigma_{i,t}}$, and the top 10% is put in the first decile portfolio, the next 10% in the second decile, etcetera, until the final 10% is put in the bottom decile.

The ordering on Sharpe ratio is an intuitive result, as the goal is to optimize the portfolio's Sharpe ratio. Leverage is used to attain the risk level that fits the investor's risk aversion γ. As all assets are, in terms of diversification, equal, i.e. the assumption of uniform correlations, the most attractive asset is the one with the highest Sharpe ratio.

Equation 4.9 is the solution for the relative weight $z_{i,t}$, not for the absolute weight $w_{i,t}$. To compute the absolute weight, I use the *separation theorem* of Tobin (1958). That is, the relative weights in the risky asset portfolio are

[10] I assume $\rho \in (0, 1)$.

independent of the allocation of the total portfolio to the (optimal) risky asset portfolio and the riskfree asset. The optimal portfolio can thus always be written as a linear combination of the riskfree asset and the (unscaled) optimal risky asset portfolio.

The optimal weight of the quantile portfolio in the total portfolio of the riskfree asset and the risky-asset portfolio w^q is again the mean-variance optimal portfolio (dropping subscripts t for notational convenience):

$$w^q = \frac{1}{\gamma} \frac{\mu^q}{{\sigma^q}^2} \tag{4.10}$$

where μ^q and σ^q are the (unscaled) risky asset quantile portfolio mean return and volatility respectively, with weight per asset given by z_i. If w^q is known, then it is straightforward to derive the absolute weight, as $w_i^q = w^q z_i$.

All that remains is to solve for w^q. For analytical tractability, and as a reasonable approximation, I assume that for a quantile portfolio q the following holds:

$$\frac{\mu_i}{\sigma_i} = \overline{SR^q} \quad \forall i \in q \tag{4.11}$$

Thus, the Sharpe ratios are assumed to be equal in the cross-section. This a reasonable assumption, as the quantile portfolios are created by sorting on the Sharpe ratio, and thus by definition the Sharpe ratios will be close to each other.

Given this assumption, the relative weight becomes

$$\begin{aligned} z_i &= \frac{1}{1-\rho} \frac{1}{\sigma_i} \left[\frac{\mu_i}{\sigma_i} - \frac{\rho}{1-\rho+k\rho} \sum_{j=1}^{k} \frac{\mu_j}{\sigma_j} \right] \\ &= \frac{1}{1-\rho} \frac{1}{\sigma_i} \left[\overline{SR^q} - \frac{\rho}{1-\rho+k\rho} k \overline{SR^q} \right] \\ &= \frac{1}{\sigma_i} \left(\frac{1}{1-\rho+k\rho} \right) \overline{SR^q} \end{aligned} \tag{4.12}$$

The portfolio mean return is then

$$\begin{aligned} \mu^q &= \sum_{i=1}^{k} z_i \mu_i \\ &= \sum_{i=1}^{k} \frac{\mu_i}{\sigma_i} \left(\frac{1}{1-\rho+k\rho} \right) \overline{SR^q} \\ &= \left(\frac{k}{1-\rho+k\rho} \right) \overline{SR^q}^2 \end{aligned} \tag{4.13}$$

and the variance is equal to

$$\begin{aligned}
{\sigma^q}^2 &= \sum_{i=1}^{k}\sum_{j=1}^{k} z_i z_j \sigma_i \sigma_j \rho_{i,j} \\
&= \sum_{i=1}^{k}\sum_{j=1}^{k} \frac{1}{\sigma_i}\left(\frac{1}{1-\rho+k\rho}\right)\overline{SR^q}\frac{1}{\sigma_j}\left(\frac{1}{1-\rho+k\rho}\right)\overline{SR^q}\sigma_i\sigma_j\rho_{i,j} \\
&= \left(\frac{1}{1-\rho+k\rho}\right)^2 \overline{SR^q}^2 \sum_{i=1}^{k}\sum_{j=1}^{k}\rho_{i,j} \\
&= \left(\frac{1}{1-\rho+k\rho}\right)^2 \overline{SR^q}^2 \left(k + k(k-1)\rho\right) \\
&= \left(\frac{k}{1-\rho+k\rho}\right)\overline{SR^q}^2
\end{aligned} \tag{4.14}$$

where $\rho_{i,j}$ is equal to ρ if $i \neq j$, and 1 otherwise. The optimal weight in the risky asset portfolio is then given by

$$\begin{aligned}
w^q &= \frac{1}{\gamma}\frac{\left(\frac{k}{1-\rho+k\rho}\right)\overline{SR^q}^2}{\left(\frac{k}{1-\rho+k\rho}\right)\overline{SR^q}^2} \\
&= \frac{1}{\gamma}
\end{aligned} \tag{4.15}$$

This implies that the absolute weight of an asset is given by

$$w_i = \frac{1}{\sigma_i}\frac{1}{\gamma}\left(\frac{1}{1-\rho+k\rho}\right)\overline{SR^q} \tag{4.16}$$

Instead of estimating the parameters γ and ρ and forecasting $\overline{SR^q}$, I assume that each of these are equal through time.[11,12] Approximating the term $\frac{1}{1-\rho+k\rho}$ by $\frac{1}{\rho k}$[13], an intuitive formula for the proportional weight appears:

$$w_{i,t} \propto \sigma_{i,t}^{-1} k_t^{-1} \tag{4.17}$$

where the subscript t has been added back to emphasize that both volatilities and the number of assets can change through time. Thus, under the assumption of a constant premium per unit of risk (Sharpe ratio), constant pairwise

[11] This is more restrictive than necessary. As long as the combination in which they appear in the equation is constant, the individual parts are allowed to be dynamic.

[12] Empirically, I find that the Sharpe ratio of the winner and loser portfolios is negatively related to the ex-ante volatility estimate, but only mildly.

[13] This is a slight overestimation. Given $\rho = 0.3$ and $k = 50$, the overestimation is 4.7%. If $k = 100$, the estimation error is 2.3%. The larger k, the smaller the error is.

correlations, constant risk aversion and the number of assets not too small, the weight per asset is inverse proportional to (1) the number of assets k in the quantile portfolio and (2) its own volatility σ_i. Thus if from one period to the next all volatilities double, all money weights w_i will halve, resembling a constant volatility strategy. Indeed, simple algebra shows that the portfolio volatility, under the solution in Equation 4.16, is given by $\frac{1}{\gamma}\overline{SR^q}\sqrt{\frac{k}{1-\rho+k\rho}}$, which is constant given the assumptions.

Table 4.1: Performance statistics of momentum portfolios

Each month-end, all stocks are sorted into 10 decile portfolios based on their past 12-1 month returns (panel A) or past 12-1 month return-to-volatility ratios (panels B, C & D), where D1 is the portfolio with the highest values (winners) and D10 with the lowest values (losers). The stocks are equal weighted (panels A & B) or inverse volatility weighted (panels C & D). The portfolios are either non-levered (panels A, B & C) or target a constant volatility per stock of 60% per annum (panel D). The column *WML* reports the results of the long D1 - short D10 portfolio. The final column WML^C is the same portfolio as *WML*, but scaled to a volatility level of 30% per annum using the full-sample volatility. For each portfolio the mean return (mean), volatility (vol), Sharpe ratio (SR), skewness (skew) and Fama and French (1993) 3-factor alpha are reported. All statistics are based on monthly returns and subsequently annualized. In brackets are the Newey and West (1987) and Newey and West (1994) t-statistics. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. The sample runs from January 2, 1927 to December 31, 2015.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	WML	WML^C
Panel A: Momentum												
mean	18.59	15.85	14.43	12.99	12.24	10.43	11.03	8.58	8.64	8.64	9.95	10.15
vol	26.34	22.83	22.18	22.68	22.98	24.21	26.74	28.13	32.70	41.03	29.40	30.00
SR	0.71	0.69	0.65	0.57	0.53	0.43	0.41	0.31	0.26	0.21	0.34	0.34
skew	0.14	0.13	0.98	1.22	1.35	1.81	2.45	1.88	2.85	2.73	-3.91	-3.91
alpha	8.93***	6.42***	4.78***	2.74***	1.70***	-0.78	-1.32*	-4.08***	-5.75***	-7.74***	16.67***	17.01***
	(7.88)	(9.00)	(8.58)	(5.31)	(3.40)	(-1.48)	(-1.84)	(-4.67)	(-4.58)	(-3.98)	(6.91)	(6.91)
Panel B: Momentum sorted on return-to-volatility (Step 1)												
mean	18.08	15.64	14.68	13.61	12.49	12.18	11.86	11.62	7.92	3.31	14.77	23.60
vol	23.75	24.58	23.69	25.05	26.19	26.68	29.37	30.78	29.64	28.09	18.78	30.00
SR	0.76	0.64	0.62	0.54	0.48	0.46	0.40	0.38	0.27	0.12	0.79	0.79
skew	1.36	3.71	1.76	1.76	1.74	1.58	2.28	2.22	1.37	0.99	-0.64	-0.64
alpha	8.92***	5.07***	4.06***	2.24***	0.50	0.22	-1.31	-1.90**	-4.52***	-8.40***	17.32***	27.67***
	(9.71)	(6.68)	(7.06)	(3.98)	(0.79)	(0.29)	(-1.48)	(-2.05)	(-4.15)	(-7.23)	(9.88)	(9.88)
Panel C: Momentum sorted on return-to-volatility and inverse volatility weighted (Step 2)												
mean	16.64	14.67	13.45	12.38	11.41	10.16	9.88	9.30	6.93	2.83	13.81	25.62
vol	19.66	21.06	20.62	21.67	22.46	22.84	24.85	25.96	25.64	24.70	16.17	30.00
SR	0.85	0.70	0.65	0.57	0.51	0.44	0.40	0.36	0.27	0.11	0.85	0.85
skew	-0.02	3.06	1.79	1.54	1.47	1.22	1.70	1.63	1.06	0.73	-1.17	-1.17
alpha	9.25***	5.61***	4.20***	2.47***	1.02**	-0.21	-1.47**	-2.38***	-4.10***	-7.63***	16.88***	31.33***
	(11.06)	(8.44)	(7.86)	(4.95)	(1.96)	(-0.35)	(-2.16)	(-3.29)	(-4.45)	(-7.12)	(10.80)	(10.80)
Panel D: Volatility-adjusted momentum (Step 3)												
mean	34.40	29.70	25.93	22.89	20.08	16.88	15.39	13.36	10.61	6.20	28.20	34.18
vol	33.17	31.75	30.81	30.61	30.10	29.71	30.96	31.79	32.61	36.54	24.75	30.00
SR	1.04	0.94	0.84	0.75	0.67	0.57	0.50	0.42	0.33	0.17	1.14	1.14
skew	-0.66	-0.55	-0.46	-0.29	-0.23	-0.15	0.21	0.27	0.31	0.40	-1.02	-1.02
alpha	23.99***	18.79***	14.86***	11.33***	8.29***	5.23***	2.86*	0.30	-2.45	-8.24***	32.23***	39.07***
	(10.66)	(9.16)	(7.55)	(6.28)	(5.18)	(3.36)	(1.83)	(0.20)	(-1.44)	(-4.22)	(12.88)	(12.88)

Table 4.2: Factor regressions momentum portfolios
Each month-end, all stocks are sorted into 10 decile portfolios based on their past 12-1 month returns (panel A) or past 12-1 month return-to-volatility ratio (panel B), where D1 is the portfolio with the highest values (winners) and D10 with the lowest values (losers). The stocks are equal weighted (panels A) or a volatility of 60% per stock is targeted (panel B). Both momentum portfolios are scaled to 30% volatility per annum to make the alphas comparable. The monthly returns of the portfolios are regressed on several factors. Factors included are the three Fama and French (1993) factors *RMRF*, *SMB* and *HML*, a levered low vol factor *LOWVOL* and the momentum portfolios themselves (*MOM* & *VA-MOM*). The alphas are annualized. In brackets are the Newey and West (1987) and Newey and West (1994) t-statistics. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. The sample runs from January 2, 1927 to December 31, 2015.

	alpha	RMRF	SMB	HML	VA-MOM	MOM	LOWVOL	Adj R2
Panel A: Momentum (MOM)								
(1)	17.01***	-0.26***	-0.49***	-0.77***				0.21
	(6.91)	(-2.92)	(-2.78)	(-3.38)				
(2)	-10.16***	-0.26***	-0.23***	-0.18	0.70***			0.63
	(-3.27)	(-4.79)	(-2.58)	(-1.08)	(11.86)			
(3)	9.63***	-0.64***	-0.24	-0.74***			0.35***	0.29
	(2.73)	(-4.56)	(-1.56)	(-3.63)			(4.23)	
Panel B: Volatility-adjusted momentum (VA-MOM)								
(1)	39.07***	0.00	-0.38**	-0.84***				0.15
	(12.88)	(0.02)	(-2.08)	(-5.85)				
(2)	26.23***	0.20***	-0.01	-0.26***		0.75***		0.59
	(11.27)	(3.23)	(-0.06)	(-2.68)		(13.35)		
(3)	33.43***	-0.29**	-0.18	-0.82***			0.27***	0.19
	(10.03)	(-2.48)	(-1.05)	(-5.97)			(4.11)	

Table 4.3: Doublesort momentum and volatility
Each month-end, all stocks are first sorted into 5 groups based on their past 12-1 month returns, and then within each group the stocks are sorted into 5 groups based on past 12-1 month daily return volatility, yielding a total of 25 portfolios. For each of the 25 portfolios the raw returns (panel A) and Fama and French (1993) 3-factor alphas (panel B) are reported. Returns and alphas are annualized. The sample runs from January 2, 1927 to December 31, 2015.

		volatility groups				
		Q1 (high)	Q2	Q3	Q4	Q5 (low)
Panel A: Raw returns						
	Q1 (high)	17.09	19.01	17.29	16.97	15.72
	Q2	16.50	14.39	13.53	13.20	10.98
momentum groups	Q3	14.27	12.00	11.34	9.80	9.35
	Q4	13.97	10.34	8.71	8.86	7.31
	Q5 (low)	18.30	7.82	6.02	5.00	6.26
Panel B: Alphas						
	Q1 (high)	3.77	7.62	8.07	9.17	9.60
	Q2	2.35	2.75	3.89	4.98	4.75
momentum groups	Q3	-0.70	-0.37	0.72	0.43	2.19
	Q4	-2.38	-3.83	-3.69	-2.34	-1.25
	Q5 (low)	-0.39	-8.80	-9.52	-9.36	-5.57

Table 4.4: Timing the winner-minus-loser portfolio
Portfolios are computed as described in Section 4.3.4. Every portfolio is scaled to a volatility level of 30% per annum using the full-sample volatility. For each portfolio the mean return (mean), volatility (vol), Sharpe ratio (SR), skewness (skew) and Fama and French (1993) 3-factor alpha are reported. All statistics are based on monthly returns and subsequently annualized. In brackets are the Newey and West (1987) and Newey and West (1994) *t*-statistics. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. The sample runs from January 2, 1927 to December 31, 2015.

Volatility-adjusted	no	no	yes	yes
Timing	no	yes	no	yes
mean	10.15	22.34	34.18	39.21
vol	30.00	30.00	30.00	30.00
SR	0.34	0.74	1.14	1.31
skew	-3.91	-1.38	-1.02	-0.46
alpha	17.01***	26.88***	39.07***	42.52***
	(6.91)	(9.60)	(12.88)	(12.46)

Table 4.5: Performance statistics of size x momentum portfolios
Each month-end, all stocks are sorted into 10 decile portfolios based on their past 12-1 month returns (MOM-VW & MOM-EW) or past 12-1 month return-to-volatility ratio (VA-MOM), where D1 is the portfolio with the highest values (winners) and D10 with the lowest values (losers). The stocks are market cap weighted (MOM-VW), equal weighted (MOM-EW) or inverse volatility weighted (VA-MOM). The portfolios are either non-levered (MOM-VW & MOM-EW) or target a constant volatility per stock such that the MOM portfolio has 30% volatility (VA-MOM). This procedure is applied on the full universe ("all caps"), the 50% largest stocks by market capitalization at the moment of sorting ("large caps") and the 50% smallest stocks ("small caps"). For each portfolio the mean return, volatility, Sharpe ratio, skewness and Fama and French (1993) 3-factor alpha are reported. All statistics are based on monthly returns and subsequently annualized. In brackets are the Newey and West (1987) and Newey and West (1994) t-statistics. Stars denote significance at the 10% (*), 5% (**) and 1% (***) level. The sample runs from January 2, 1927 to December 31, 2015.

	all caps			large caps			small caps		
	MOM-VW	*MOM-EW*	*VA-MOM*	*MOM-VW*	*MOM-EW*	*VA-MOM*	*MOM-VW*	*MOM-EW*	*VA-MOM*
mean	18.41	9.95	34.18	14.08	15.84	31.93	20.89	7.49	35.12
vol	29.93	29.40	30.00	26.77	25.27	30.00	29.31	31.58	30.00
SR	0.62	0.34	1.14	0.53	0.63	1.06	0.71	0.24	1.17
skew	-1.98	-3.91	-1.02	-2.42	-2.95	-0.73	-3.08	-3.95	-1.12
alpha	25.50***	16.67***	39.07***	19.88***	21.72***	37.03***	27.17***	13.23***	41.08***
	(9.64)	(6.91)	(12.88)	(8.13)	(9.32)	(11.96)	(10.48)	(5.21)	(14.13)

Table 4.6: Momentum portfolios corporate bonds
Each month t, bonds are ranked into equal-weighted decile portfolios D1 (highest returns/winners) to D10 (lowest returns/losers) based on their excess return over duration matched Treasuries over the months $t-6$ to $t-1$. In Panel B, all bonds are first scaled with $\frac{1.7\%}{\widehat{\sigma_{i,t-12:t-1}}}$, where $\widehat{\sigma_{i,t-12:t-1}}$ is the monthly standard deviation of the excess returns over the past 12 months, skipping the most recent month. Positions are held for 6 months. The return of a portfolio is the average of the portfolios formed at $t-6$ up to $t-1$. The table reports per portfolio and the difference between D1 and D10 (*WML*) average excess returns over duration matched Treasuries (mean), the volatility (vol), annualized Sharpe ratio (SR) and the alpha over the five Fama and French (1993) bond risk-factors. The mean return, volatility and alpha are annualized and in percentages. In brackets the Newey and West (1987) and Newey and West (1994) t-statistics. Stars denote the significance at the 10% (*), 5% (**) and 1% (***) level. The sample period is from January 1994 to December 2015.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	*WML*
Panel A: Momentum decile portfolios											
mean	2.48	1.40	1.18	1.04	1.11	1.07	1.13	1.18	1.24	2.10	0.38
	(1.18)	(1.05)	(1.01)	(0.94)	(0.96)	(0.82)	(0.76)	(0.68)	(0.53)	(0.47)	(0.12)
vol	7.54	5.06	4.33	4.02	4.11	4.56	5.10	5.92	7.82	14.37	10.49
SR	0.33	0.28	0.27	0.26	0.27	0.23	0.22	0.20	0.16	0.15	0.04
alpha	1.80*	0.90	0.70*	0.63*	0.73**	0.75*	0.79	0.87	0.58	0.00	1.80
	(1.83)	(1.56)	(1.70)	(1.75)	(2.03)	(1.70)	(1.52)	(1.32)	(0.67)	(0.00)	(0.81)
Panel B: Volatility-adjusted momentum decile portfolios											
mean	2.68*	1.60	1.25	1.07	0.95	0.73	0.43	0.30	-0.13	-0.50	3.18***
	(1.91)	(1.25)	(0.98)	(0.84)	(0.74)	(0.56)	(0.31)	(0.21)	(-0.09)	(-0.30)	(4.58)
vol	5.35	5.02	5.10	5.12	5.15	5.20	5.35	5.40	5.77	6.23	3.06
SR	0.50	0.32	0.24	0.21	0.18	0.14	0.08	0.05	-0.02	-0.08	1.04
alpha	2.02*	1.00	0.69	0.49	0.39	0.20	-0.17	-0.31	-0.80	-1.24	3.26***
	(1.94)	(1.16)	(0.82)	(0.61)	(0.48)	(0.25)	(-0.21)	(-0.40)	(-0.90)	(-1.31)	(4.82)

Table 4.7: Momentum portfolios corporate bonds by credit quality
Decile (Panel A)/quintile (Panel B) top-bottom momentum portfolios are within the respective credit quality group (investment grade/high yield in Panel A; AAA-AA/A/BBB/BB/B/CCC-C in panel B) constructed following Table 4.6. The table reports the average absolute number of observations per month, the percentage this constitutes of the total universe, the return and the alpha of the momentum portfolios, where *MOM* indicates the standard momentum portfolio and *VA-MOM* the volatility-adjusted momentum portfolio. The alpha is computed versus the five Fama and French (1993) bond risk-factors. The return and alpha are annualized and in percentages. In brackets are the Newey and West (1987) and Newey and West (1994) t-statistics. Stars denote the significance at the 10% (*), 5% (**) and 1% (***) level. The sample period is from January 1994 to December 2015.

credit rating	observations		mean return		5-factor alpha	
	absolute	percentage	*MOM*	*VA-MOM*	*MOM*	*VA-MOM*
Panel A: Momentum decile portfolios (D1-D10)						
investment grade	3185	71.3	-1.08	2.47***	-1.27	2.40***
			(-0.66)	(3.19)	(-0.98)	(3.06)
high yield	1284	28.7	2.56	4.02***	6.29**	4.52***
			(0.60)	(4.03)	(2.05)	(4.44)
Panel B: Momentum quintile portfolios (Q1-Q5)						
AAA/AA	377	8.4	-0.33	0.46	-0.20	0.74
			(-0.41)	(0.62)	(-0.26)	(0.99)
A	1410	31.6	-0.85	1.26**	-1.20	0.92
			(-0.74)	(2.11)	(-1.16)	(1.38)
BBB	1398	31.3	-0.64	2.75***	-0.74	2.77***
			(-0.41)	(3.66)	(-0.64)	(3.59)
BB	467	10.4	-0.99	1.78***	-0.54	1.82***
			(-0.44)	(2.79)	(-0.34)	(3.01)
B	559	12.5	2.09	2.71***	3.93	2.95***
			(0.62)	(3.91)	(1.36)	(4.57)
CCC-C	258	5.8	7.17	4.36***	10.44***	4.85***
			(1.64)	(4.98)	(2.99)	(5.98)

Figure 4.1: Cumulative log return of momentum portfolios

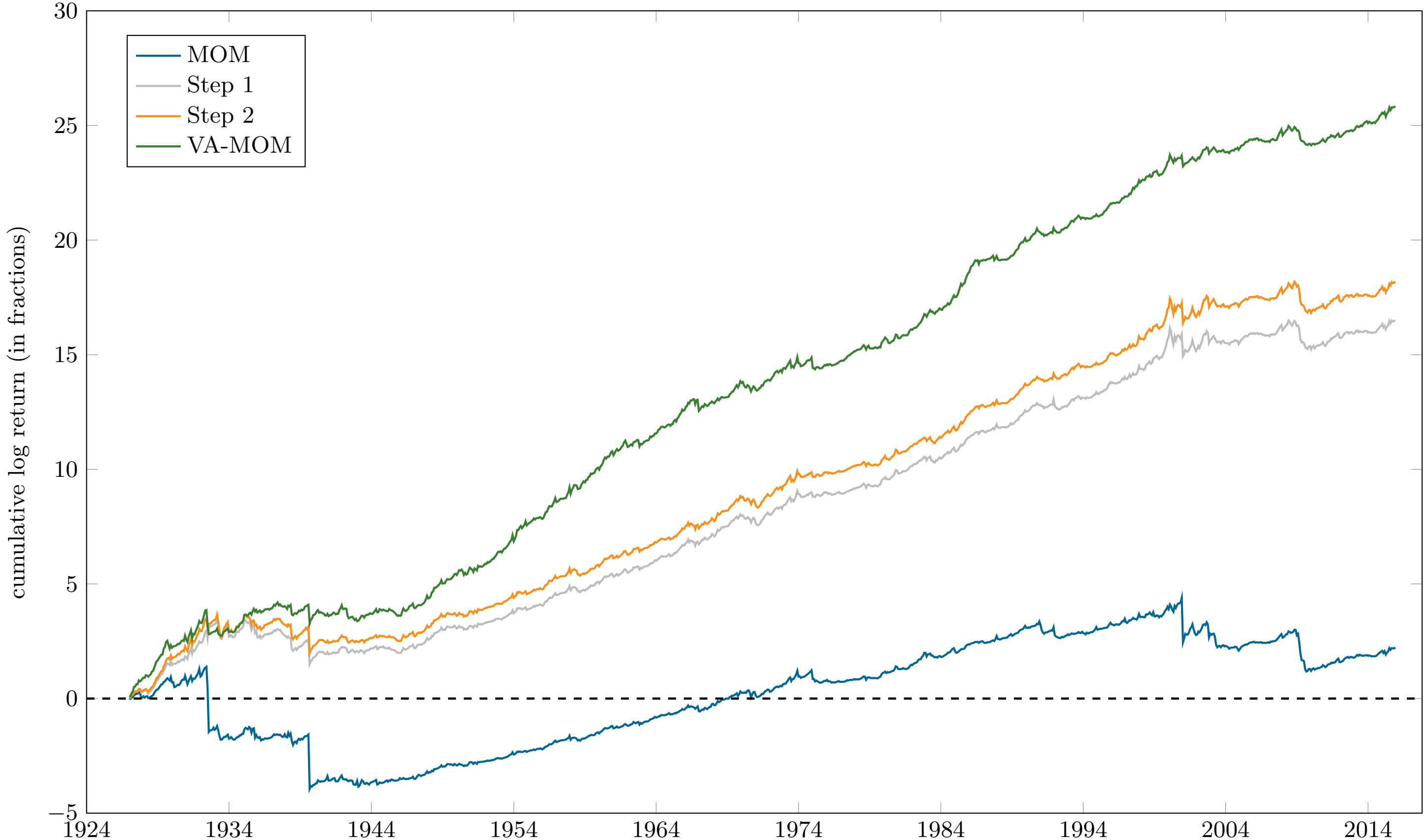
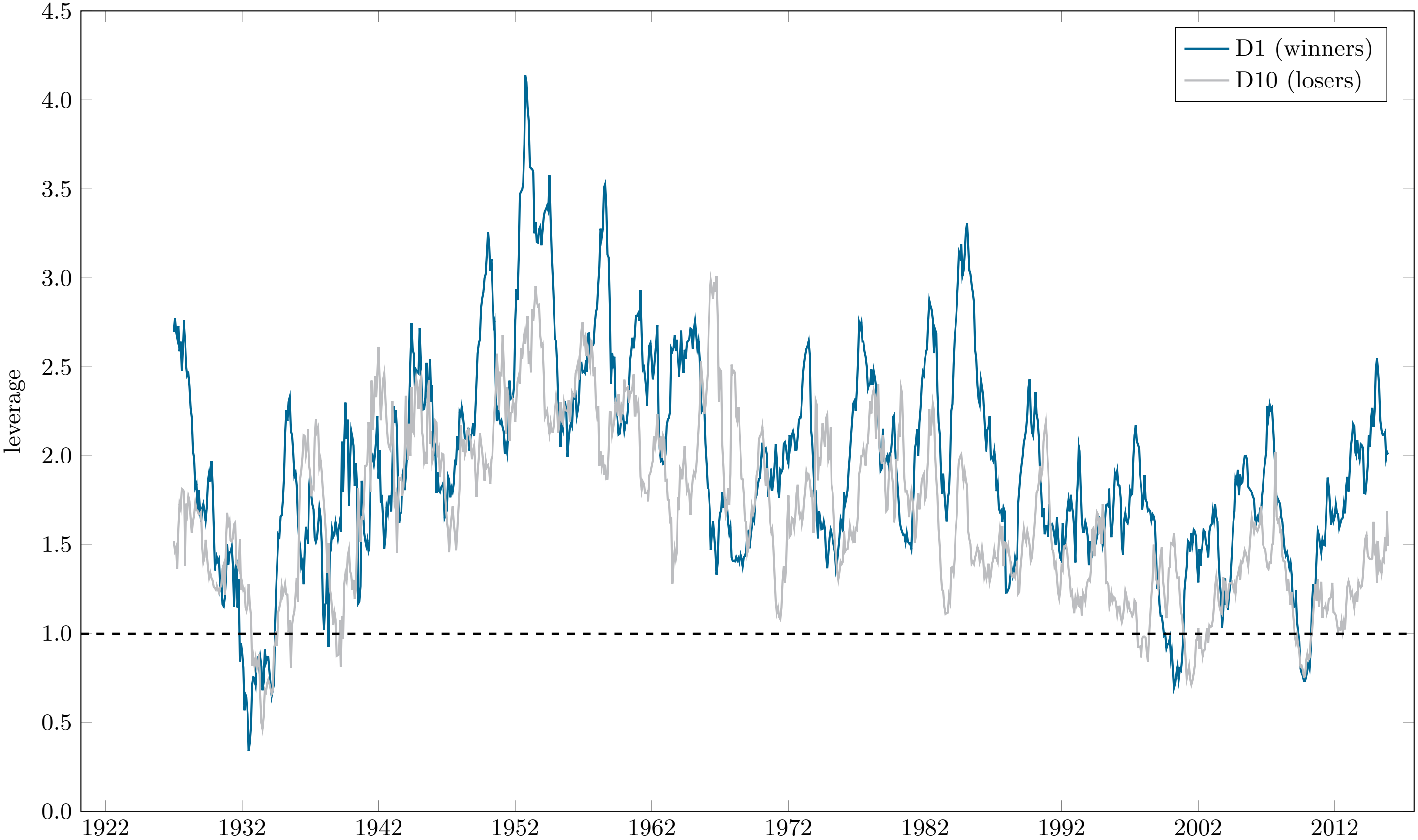


Figure 4.2: Leverage D1 & D10 volatility-adjusted momentum portfolios
This figure shows the leverage used in the winners (D1) and losers (D10) of volatility-adjusted momentum.



Chapter 5

Momentum Spillover from Stocks to Corporate Bonds

5.1 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, Hvidkjaer, and Swaminathan (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 over 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 5.2 we provide an overview of the literature. In Section 5.3 we describe our data and in Section 5.4 we present our methodology and empirical results. In Section 5.5 we perform various robustness checks. Section 5.6 concludes.

5.2 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 under reaction to news seems to be the most prominent candidate. 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 under reaction and momentum effects. Moreover, they show that under reaction 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, Huij, and Martens (2011) and Chaves (2016) demonstrate that measuring momentum in idiosyncratic, or residual, equity returns, improves upon traditional total return momentum. Specifically, Blitz, Huij, and Martens (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 gradual diffusion hypothesis on firm-specific news of Hong and Stein (1999), 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, Hvidkjaer, and Swaminathan (2005), Pospisil and Zhang (2010) and Jostova et al. (2013). The latter study does document that momentum is a profitable strategy for high yield corporate bonds.

Gebhardt, Hvidkjaer, and Swaminathan (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, Hvidkjaer, and Swaminathan (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 (1999), 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, Hvidkjaer, and Swaminathan (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, Hvidkjaer, and Swaminathan (2005). We find that residual momentum achieves a larger risk reduction than any of the investigated hedging methods.

5.3 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. 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 (2011, Chapter 10) and Haesen and Houweling (2012). 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 companys 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 a monthly frequency. These items are used to calculate the distance-to-default for each company (using the Byström (2006) method, see Appendix 5.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 5.1 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).

In our analyses, we also use the five Fama and French (1993) bond risk factors. We download the equity market factor ($RMRF$), the equity size factor (SMB) and the equity value factor (HML) from Kenneth French' website.[1] For the bond term factor ($TERM$) and corporate bond default factor (DEF), we purposely deviate from Fama and French (1993)'s use of the Ibbotson factors, because Hallerbach and Houweling (2013) show that the Ibbotson DEF factor

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

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* 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).

5.4 Results

5.4.1 Return characteristics of momentum spillover

Following Gebhardt, Hvidkjaer, and Swaminathan (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, Hvidkjaer, and Swaminathan (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.

Table 5.2 shows the return, volatility 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:

$$r_t = \alpha + \beta DEF_t + \epsilon_t \tag{5.1}$$

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, Hvidkjaer, and Swaminathan (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.

5.4.2 Risk characteristics of momentum spillover

Next, we analyze the risk of momentum spillover in more detail. Moving from D6 to D10 in Table 5.2, 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 calculate 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 and Goldstein (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, Hvidkjaer, and Swaminathan (2005) who relate momentum spillover to default risk in the period after formation.

Table 5.3 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 5.3, 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 5.1), 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 (Table 5.2).

5.4.3 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 5.2 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.

In Table 5.4 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.

The state-specific default risk estimates in Table 5.4 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 5.2 suggest that this relationship is approximately linear. Inspired by the conditional regression frameworks in Grundy and Martin (2001) and Blitz, Huij, and Martens (2011), we estimate the following equation to formally test the time-varying risk profile:

$$r_t = \alpha + (\beta_{DEF} + \beta_{DEF,RMRF} RMRF_{t-K:t-1})\, DEF_t + \epsilon_t \qquad (5.2)$$

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 5.1, 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 5.2. Equation 5.2 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 5.1, which thus only estimates the structural exposure β_{DEF} to the credit market.

For the time-varying framework, column two in Table 5.5 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 R2 in column three 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 5.2, 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, Hvidkjaer, and Swaminathan (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.

5.4.4 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 5.4. 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, Huij, and Martens (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:

$$E_{i,t} = \alpha_i + \beta_{RMRF,i} RMRF_t + \epsilon_{i,t} \tag{5.3}$$

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 $\epsilon_{i,t}$. 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 5.3. We observe that the relation is much weaker than in case of TM spillover in Figure 5.2. So, RM clearly reduces the dependency of the default risk exposure of momentum spillover on the equity market return.

Next, we formally test the significance of the structural and time-varying default risk exposure by estimating Equation 5.2, see the right-hand side of Table 5.5. 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 5.2. The lower adjusted R2 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.

5.4.5 Reducing drawdowns using residual momentum

To visualize the impact of the reduced time variation in default risk exposure, Figure 5.1 plots the cumulative returns through time of the winner-minus-loser portfolio, for both TM and RM spillover. 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%.

5.4.6 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. To test whether this yields similar results, we use three methods to calculate risk-adjusted strategy returns, which could be interpreted as hedging methods:

Static *DEF* method adjusting strategy returns for the structural DEF exposure by using the full-sample β_{DEF} estimate as shown in Table 5.5. 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.

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 5.5. 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.

Dynamic rating x maturity method adjusting strategy returns for the bottom-up rating and maturity biases. We follow the methodology of Gebhardt, Hvidkjaer, and Swaminathan (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 5.6 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, Huij, and Martens (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 5.6 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 5.6 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.

5.5 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.

5.5.1 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. 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.

5.5.2 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:

$$E_{i,t} = \alpha_i + \beta_{RMRF,i} RMRF_t + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \epsilon_{i,t} \quad (5.4)$$

The results are reported in Table 5.7, 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:

$$r_t = \alpha + \sum_{j \in FF5} \beta_j F_{j,t} + \sum_{j \in FF3} \beta_{DEF,j} F_{j,t-K:t-1} DEF_t + \epsilon_t \tag{5.5}$$

where $FF5 = \{RMRF, SMB, HML, TERM, DEF\}$, $FF3 = \{RMRF, SMB, HML\}$, $F_{j,t}$ is the return of factor j in month t and β_j and $\beta_{DEF,j}$ 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 5.7, 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 driver remains *RMRF*, reducing the adjusted R2 from 0.54 to 0.30. Including *SMB* and *HML* in the residualization reduces the R2 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*.

5.5.3 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 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 EW 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 bonds age (elapsed time since issuance) is a strong liquidity proxy; see e.g. Sarig and Warga (1989), and Houweling, Mentink, and Vorst (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 5.8 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 R2-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.

5.5.4 Credit Rating Effects

Avramov et al. (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 5.5: the alphas are also highly significant in the Investment Grade universe. In Table 5.9 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 alpha is 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.

5.5.5 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. 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.

5.6 Conclusions

This paper investigates stock-bond momentum spillover. We first confirm and extend the results of Gebhardt, Hvidkjaer, and Swaminathan (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.

5.A Distance-to-Default computation

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 firms assets, with the strike price being the value of the debt. The physical probability of default is given by

$$\pi^P = N(-DD^P) \tag{5.6}$$

where $N(.)$ denotes the cumulative distribution function of the standard normal distribution, and the distance-of-default is given by

$$DD_t^P = \frac{\log\left(V_t/X_t\right) + \left(\mu - 0.5\sigma^2\right)(T-t)}{\sigma\sqrt{T-t}} \tag{5.7}$$

where log is the natural logarithm, V_t the value of the firms 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 5.7 then simplifies to

$$DD_t^P = \frac{\log(V_t/X_t)}{\sigma_E\sqrt{T-t}} \tag{5.8}$$

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.

Table 5.1: Descriptive statistics
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. The *excess return* is the difference between a corporate bonds 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 5.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, Moodys 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. Mean returns and volatilities are annualized.

	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

Table 5.2: Performance statistics of momentum spillover

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). Newey and West (1987) and Newey and West (1994) 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.

	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	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	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	10.1	12.46	18.13	13.25
Sharpe	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)

Table 5.3: Default risk statistics of momentum spillover per decile portfolio
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, Moodys 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 5.A for the 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 portfolios 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.

	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

Table 5.4: Default risk statistics of momentum spillover per equity state
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 5.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 portfolios 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.

	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

Table 5.5: Structural and time-varying default exposures of total and residual momentum spillover

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 5.2. The structural exposure β_{DEF} to the corporate bond market factor DEF is estimated using Equation 5.1. 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 5.2. Newey and West (1987) and Newey and West (1994) 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.

Total momentum spillover			Residual momentum spillover		
β_{DEF}	$\beta_{DEF,RMRF}$	Adj. R2	β_{DEF}	$\beta_{DEF,RMRF}$	Adj. R2
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)	

Table 5.6: Risk-adjusted returns of total and residual momentum spillover
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 5.3. We test three risk-adjustments: 1. excess returns after hedging with the full sample exposure β_{DEF} (as reported in Table 5.5), 2. excess returns after hedging with the full sample β_{DEF} and $\beta_{DEF,RMRF}$ exposure (as reported in Table 5.5) 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. Newey and West (1987) and Newey and West (1994) 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.

Risk-adjustment	Non		β_{DEF}		β_{DEF} & $\beta_{DEF,RMRF}$		Rating & maturity	
Mom. 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

Table 5.7: Alphas and betas of total and residual momentum spillover for various factor model specifications
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 5.3 for *RMRF*-residual momentum spillover or Equation 5.3 for *FF*3-residual momentum spillover. We estimate the structural exposure β_{DEF} and time-varying exposures $\beta_{DEF,RMRF}$ to the corporate bond market factor *DEF* using Equation 5.2, for Panel A (*DEF* exposure depends on *RMRF* in the formation period) or using Equation 5.4 for Panel B (*DEF* exposure depends on *RMRF*, *SMBF* and *HML* in the formation period). Newey and West (1987) and Newey and West (1994) 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.

Momentum spillover	Alpha	β_{RMRF}	β_{SMB}	β_{HML}	β_{TERM}	β_{DEF}	$\beta_{DEF,RMRF}$	$\beta_{DEF,SML}$	$\beta_{DEF,HML}$	Adj. R2
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)	

Table 5.8: Statistics total and residual momentum spillover per liquidity segment
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 5.3. Alphas and betas are estimated according to Equation 5.2. 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. Newey and West (1987) and Newey and West (1994) 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.

	Momentum spillover	Mean	Volatility	Sharpe ratio	Alpha	β_{DEF}	$\beta_{DEF,RMRF}$	Adj. R2
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)	

Table 5.9: Statistics total and residual momentum spillover per rating sub-universe
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 5.3. Alphas and betas are estimated according to Equation 5.2. 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. Newey and West (1987) and Newey and West (1994) 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.

	Momentum spillover	Mean	Volatility	Sharpe ratio	Alpha	β_{DEF}	$\beta_{DEF,RMRF}$	Adj. R2
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)	

Figure 5.1: Cumulative returns total & residual momentum portfolios

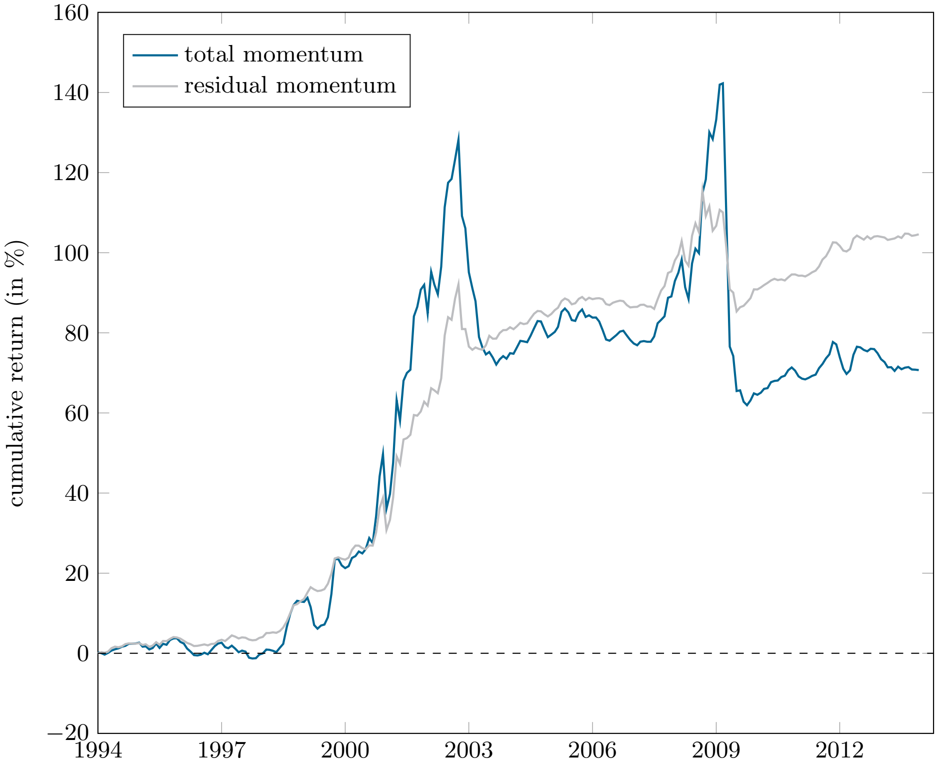


Figure 5.2: Exposures D1-D10 total momentum portfolio vs. stock market return formation period
D1-D10 total momentum portfolio risk exposures at formation versus *RMRF* realization over the formation period. Risk measures are credit spread (top-left), Distance-to-Default (top-right), credit rating (bottom-left) and leverage(bottom-right).

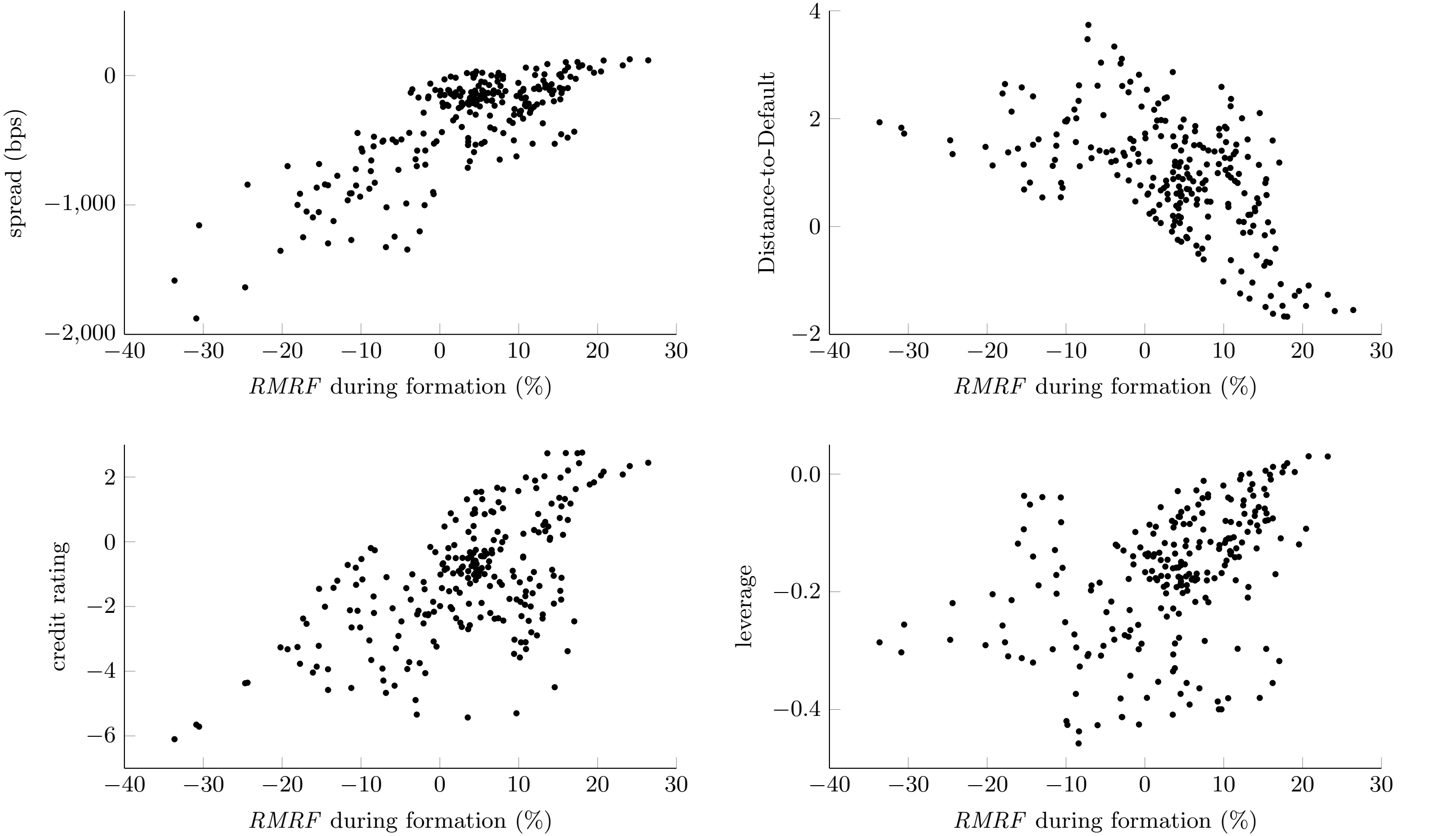
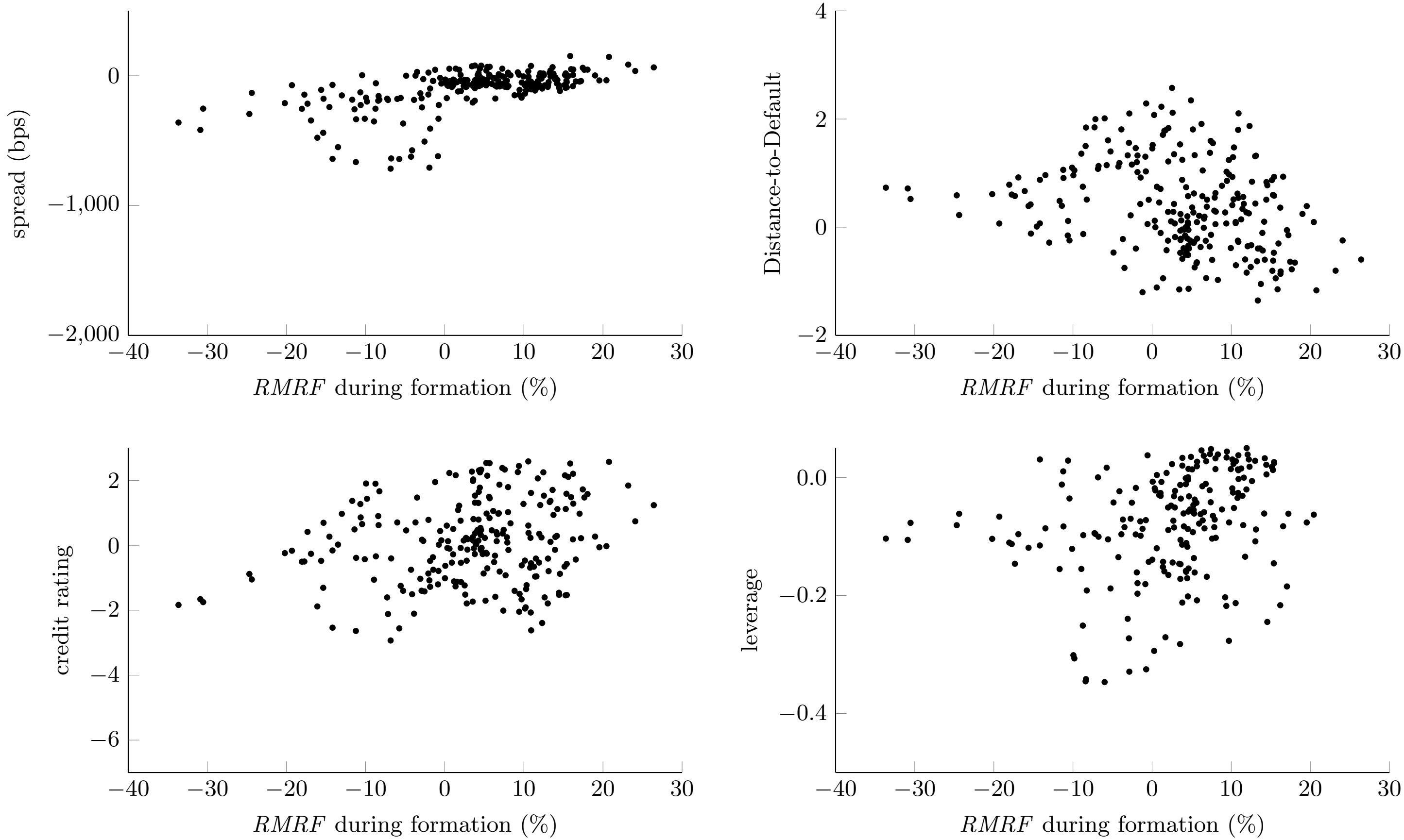


Figure 5.3: Exposures D1-D10 residual momentum portfolio vs. stock market return formation period
D1-D10 residual momentum portfolio risk exposures at formation versus *RMRF* realization over the formation period. Risk measures are credit spread (top-left), Distance-to-Default (top-right), credit rating (bottom-left) and leverage(bottom-right).



Chapter 6

Factor Investing in the Corporate Bond Market

6.1 Introduction

This paper examines the performance of Size, Low-Risk, Value and Momentum factor portfolios in the corporate bond market. A factor portfolio is constructed by sorting bonds on a specific characteristic: Size contains bonds of small companies, based on the market value of their outstanding bonds; Low-Risk contains short-maturity bonds with a high credit rating; Value selects bonds whose credit spread is high relative to a model-implied fair spread; Momentum consists of bonds with high past returns. In addition to these individual factors, we analyze a multi-factor portfolio that combines the four factors. We find that both single-factor and multi-factor portfolios generate economically meaningful and statistically significant alphas.

Our paper belongs to the empirical asset pricing literature that documents that factor portfolios carry a premium beyond the traditional asset class premium, as postulated by the CAPM. Even though this literature has existed for decades, it has predominantly focused on equities. The best documented factors in the equity literature are Low-Risk (starting with Haugen and Heins, 1972), Value (Basu, 1977), Size (Banz, 1981), and Momentum (Jegadeesh and Titman, 1993). For corporate bonds, the evidence is more limited and more recent. Documented factors are Low-Risk (e.g. Ilmanen et al., 2004; Frazzini and Pedersen, 2014) and Momentum (Pospisil and Zhang, 2010; Jostova et al., 2013). Evidence on other factors is scarce. We are aware of only two papers on Value (L'Hoir and Boulhabel, 2010; Correia, Richardson, and Tuna, 2012) and none on Size. The existing studies on factors in the corporate bond market each focus on one particular factor, while we jointly analyze the Size, Low-Risk, Value and Momentum factors using a consistent methodology on a single data set. Our data set consists of all bonds in the Barclays U.S. Corporate Investment Grade and High Yield indexes over the period from January 1994 to June 2015.

Our paper contributes to the existing literature in three ways. First, we confirm previous work on Low-Risk and Momentum, we confirm and extend the relatively new evidence on Value, and we are the first to provide evidence on Size. We show that all factors have significant alphas, both in the CAPM, correcting factor returns for their beta to the corporate bond market, and in the Fama-French-Carhart framework, additionally correcting for betas to equity and bond common risk factors.

Our second contribution is that we go beyond previous work by combining factors in a multi-factor portfolio. We find that factors have relatively low pairwise correlations, so that the multi-factor portfolio substantially reduces the tracking error and improves the information ratio versus the corporate bond market index, compared to single-factor portfolios. The annualized Fama-French-Carhart alpha of a long-only multi-factor portfolio is 0.84% (3.65%) in Investment Grade (High Yield), which is sizable given the corporate bond market premium of 0.50% (2.33%). We find that break-even transaction costs are well above actual transaction costs of corporate bonds reported in various studies, so that after-cost alphas remain substantial. These findings are robust to a variety of sensitivity checks, including alternative factor definitions, alternative portfolio construction choices and the evaluation of factor portfolios on a subset of liquid bonds.

Our final contribution is the joint application of factor investing in the equity and the corporate bond markets. We show that the corporate bond factors have added value beyond their counterparts in the equity market: by not only applying factor investing in the equity market, but also in the corporate bond market investors can increase the alpha of their multi-asset portfolio by more than 1% per year.

Our results have strong implications for strategic asset allocation decisions. Most investors focus on traditional asset classes when determining their strategic investment portfolio. For example, by including stocks, government bonds and corporate bonds, they aim to earn the Equity, Term and Default premiums. Implementation of the actual investment portfolio is typically delegated to external managers. However, the results of our study, in line with results of similar studies on equity markets, suggest that investors should strategically and explicitly allocate to factors instead of relying on external managers to implement factor exposures. A seminal study on this topic is that of Ang, Goetzmann, and Schaefer (2009) who were asked by the Norwegian Government Pension Fund to analyze the funds performance. This study finds that a large part of the funds outperformance versus its strategic benchmark could be explained by factor exposures that were implicitly present in the investment portfolios. Therefore, the authors recommend making the funds exposure to factors a top-down decision rather than emerging as a byproduct of bottom-up active management (Ang, Goetzmann, and Schaefer, 2009, p. 20). Blitz (2012) argues that investing in factors should be a strategic decision, because of the long-term investment horizon required to harvest the premiums. Bender et al. (2010) and Ilmanen and Kizer (2012) also make the case for strategic allocations to factors, stressing the diversification benefits. Ang (2014) devotes an entire book to factor investing.

Two papers that are related to ours are Israel, Palhares, and Richardson (2017) and Bektic et al. (2017). Like our paper, these papers study single-factor and multi-factor portfolios in the corporate bond market.

Our paper differs from Israel, Palhares, and Richardson (2017) in three important aspects. First, we use more realistic assumptions, such as a holding period of 12 months (instead of 1 month), we study long-only portfolios (instead of long-short) and we do not use leverage. Secondly, in our paper we conduct a variety of sensitivity analyses, including alternative factor definitions, to verify the robustness of our results. Finally, we conduct a multi-asset analysis to investigate the added value of corporate bond factor investing beyond equity factor investing.

The key difference between Bektic et al. (2017) and our paper is that they use equity definitions for each factor, whereas we focus on bond-specific factor definitions. In one of our robustness checks we show that although factor portfolios constructed using the equity definitions do generate a premium in the corporate bond market, they do not work as well as the bond-specific definitions, with the exception of Momentum.

6.2 Data and Methodology

6.2.1 Data

We use monthly constituent data of the Barclays U.S. Corporate Investment Grade index and the Barclays U.S. Corporate High Yield index from January 1994 to June 2015. For each bond in each month, Barclays provides various characteristics, including its market value, time-to-maturity, credit rating, credit spread and return. The data set is survivorship-bias free: whenever a firm defaults, the returns of its bonds are based on their final traded price, reflecting the markets expected recovery rate.

To calculate the monthly return of the factor portfolios, we use the excess return of each corporate bond versus duration-matched Treasuries. These excess returns are provided by Barclays as well and accurately remove the Term premium. The Term premium is driven by changes in risk-free interest rates and can be efficiently harvested by investing in government bonds. The main purpose of investing in corporate bonds is to additionally earn the Default premium, which is driven by changes in credit spreads. By using excess returns versus Treasuries we can focus on the credit spread component.

Since we evaluate factor portfolios using excess returns versus Treasuries, we also obtain excess returns for the Investment Grade and High Yield market indexes from Barclays. Barclays calculates the index return each month as the market value-weighted average excess return over all index constituents in that month. We use the index returns to calculate outperformances and alphas of the factor portfolios. Note that this index return is basically the standard benchmark return for active portfolio managers, but calculated using excess returns instead of total returns. In practice, portfolio managers are benchmarked using total returns. Portfolio managers could come close to replicating the excess return outperformance by using Treasury bond futures to hedge the interest rate exposure of the portfolio to that of the benchmark.

Our data set contains over 1.3 million bond-month observations, of which about 900,000 are in Investment Grade and about 400,000 in High Yield. The average number of observations per month is 3,520 in Investment Grade and 1,473 in High Yield. Table 6.1 provides further summary statistics of our data set by showing the mean and various percentiles of the bond characteristics. All statistics are first calculated cross-sectionally per month, and then averaged over time. We observe that Investment Grade bonds tend to have lower excess returns over Treasuries, longer time-to-maturities, and are issued by larger companies, as compared to High Yield.

6.2.2 Methodology

For each factor in each month, we construct an equally-weighted top (bottom) portfolio of the 10% corporate bonds with the highest (lowest) exposure to that factor. Our key results are presented in two ways. First, we analyze long-short portfolios on a one-month investment horizon. This analysis serves to identify the potential of the factors to generate alpha in the corporate bond market by overweighting or underweighting bonds. However, shorting corporate bonds is hard and costly in practice, so including the short-side inflates potential benefits beyond those achievable in practice; see also Blitz et al. (2014) for a discussion on long-short factor portfolios in the equity market. In our second set of results, we therefore analyze long-only portfolios on a twelve-month horizon using the overlapping portfolio methodology of Jegadeesh and Titman (1993). This is a realistic holding period and prevents extreme turnover. Next to the single-factor portfolios, we also analyze a multi-factor portfolio, which invests 25% in each of the four single-factor portfolios. In the online appendix[1] we check the robustness of our results when the factor portfolios contain 20% of the bonds (instead of 10%) or when the bonds in the portfolio are market value weighted (instead of equal weighted).

We create the factor portfolios separately for Investment Grade and High Yield, because these market segments are basically treated as two separate asset classes by financial market participants, such as asset owners (making separate allocations to Investment Grade and High Yield), both passive and active asset managers (offering separate investment products for Investment Grade and High Yield), index providers (offering separate indices for Investment Grade and High Yield) and regulators (often prohibiting certain groups of institutional investors to hold High Yield-rated bonds). Evidence on the segmentation of the corporate bond market into Investment Grade and High Yield segments is provided by Ambastha et al. (2010) and Chen et al. (2014). Chen et al. (2014) mention that a large stream of theoretical literature exists that shows that labels (in this case: ratings of corporate bonds) can lead to market segmentation and asset class effects by affecting investors willingness to hold the security and thus can affect security prices. Chen et al. (2014) provide empirical evidence that credit ratings indeed segment the market in two parts: Investment Grade and High Yield. Therefore, it is crucial to create and evaluate the factor portfolios separately in the Investment Grade and High Yield market segments.

We calculate outperformances and alphas of factor portfolios versus their own market segment. To calculate the CAPM-alpha we run the following regression:

$$R_t = \alpha + \beta DEF_t + \epsilon_t \tag{6.1}$$

where R_t is the return on a factor portfolio and DEF_t the corporate bond market premium, which is the Investment Grade index excess return for Investment Grade factor portfolios and the High Yield index excess return for High Yield factor portfolios. The intercept of Equation 6.1 is the CAPM-alpha. We also evaluate the factor portfolios against the Fama and French (1993) five-factor model supplemented with the Carhart (1997) equity momentum factor:

$$\begin{aligned} R_t = \alpha + &\beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \\ &\beta_4 MOM_t + \beta_5 TERM_t + \beta_6 DEF_t + \epsilon_t \end{aligned} \tag{6.2}$$

where $RMRF_t$ is the equity market premium, SMB_t the equity Size premium,

[1] The appendix is available at http://www.cfapubs.org/doi/suppl/10.2469/faj.v73.n2.1/suppl_file/houweling_faj_appendix_2017.docx.

HML_t the equity Value premium, MOM_t the equity Momentum premium, and $TERM_t$ the default-free interest rate Term premium. We refer to the intercept of Equation 6.2 as the Fama-French-Carhart alpha. The four equity factors are downloaded from the website of Kenneth French. The Term factor is constructed as the total return of the Barclays US Treasury 7-10 year index minus the 1-month T-bill rate from Kenneth French.

6.3 Defining factors in the corporate bond market

Next, we describe the definitions of the Size, Low-Risk, Value and Momentum factors. For each factor definition, we purposely use only bond characteristics, such as rating, maturity and credit spread, and we do not use accounting data, e.g. leverage or profitability, or equity market information, e.g. equity returns or equity volatility. This choice makes sure that we can include all bonds in our analyses, and not only bonds issued by companies with publicly listed equity. Our definitions also facilitate the actual implementation of factors in investment portfolios. We acknowledge that accounting and equity market information, or the use of more sophisticated methods, could improve the results. However, by using bond-only definitions we demonstrate that factor investing already works using readily available data and methods. In the online appendix we investigate the sensitivity of our results to the specific choice for the factor definitions.

6.3.1 Size

To define the Size factor in the corporate bond market, we use the total index weight of each company, calculated as the sum of the market value weights of all its bonds in the index in that month. We thus look at a company's total public debt instead of the size of individual bonds, because most explanations for the Size effect in equity markets relate to the company size, e.g. incomplete information about small firms, or size being a proxy for (default) risk; see Van Dijk (2011) for a literature overview. Moreover, since smaller companies tend to issue smaller bonds, and smaller bonds are less liquid than larger bonds (Sarig and Warga, 1989), our Size definition picks up a potential illiquidity premium as well. To the best of our knowledge we are the first to document a Size effect at the company level in the corporate bond market.

To construct Size decile portfolios, we rank each month all bonds on their issuer's size. The top (bottom) portfolio contains the bonds of the 10% smallest (largest) companies.

6.3.2 Low-Risk

Previous studies show that bonds with lower risk earn higher risk-adjusted returns. Most papers use maturity and/or rating as risk measures. The short-maturity effect has been documented by Ilmanen et al. (2004) and Derwall et al. (2009); the high-rating effect has been documented by amongst others Kozhemiakin (2007) and Frazzini and Pedersen (2014). Blitz, Falkenstein, and Vliet (2014) provide an overview of possible explanations for the existence of a low-volatility effect in equity markets. Most explanations in their overview are related to human behavior, incentive structures or constraints, and are therefore equally applicable to corporate bond markets as they are to equity markets.

We follow Ilmanen (2011) by using both maturity and rating to construct our Low-Risk factor portfolios. For the Low-Risk top portfolio, we select high-rated, short-dated bonds, while the bottom portfolio consists of low-rated, long-dated bonds. For the Investment Grade top portfolio, we first select all bonds rated AAA to A-, hence excluding the most risky bonds rated BBB+, BBB or BBB-. From these bonds, we select each month all bonds shorter than M years such that the portfolio makes up 10% of the total number of bonds. This maturity threshold M thus fluctuates through time. We use this approach to allow a fair comparison with the other factor portfolios that also contain 10% of the bonds by definition. For High Yield, we follow the same procedure, selecting bonds rated BB+ to B- in the first step. On average, the maturity threshold equals 3.1 (3.6) years for Investment Grade (High Yield).

For the bottom portfolio, we select for Investment Grade (High Yield) the longest 10% of all bonds rated below AA- (BB-). On average, the maturity threshold for the bottom portfolio equals 26.4 (11.6) years for Investment Grade (High Yield).

6.3.3 Value

The Value effect in equity markets is well-documented since the 1970s, starting with Basu (1977). It can be summarized as mean-reversion in valuations: cheap stocks outperform, while expensive stocks underperform. To determine whether a stock is cheap or expensive, the market value of a company is compared to a fundamental measure, such as earnings or the equity book value. As far as we know, L'Hoir and Boulhabel (2010) and Correia, Richardson, and Tuna (2012) are the only papers that study Value investing in the corporate bond market. They translate the Value concept from equities to credits by comparing the markets required compensation for the bonds riskiness (i.e. the credit spread) to fundamental risk measures. In other words, a bond is cheap if it offers an ample reward for the risk investors bear by buying the bond.

Both studies consider a variety of risk measures, including leverage, profitability, equity volatility and the distance-to-default measure of Merton (1974). Our methodology is in the spirit of L'Hoir and Boulhabel (2010) and Correia, Richardson, and Tuna (2012), but we restrict ourselves to risk measures that can be derived from the bond market only. We choose maturity, rating, and the 3-month change in the bonds credit spread. The latter is motivated by Norden and Weber (2004) and Norden (2017), who show that, on average, credit spreads already increase three months prior to a rating downgrade. Therefore, the spread change is a useful risk indicator beyond rating or maturity.

Specifically, to construct Value factor portfolios each month, we first run a cross-sectional regression of credit spreads on rating dummies (AAA, $AA+$, AA, ..., C), time-to-maturity and 3-month spread change

$$S_i = \alpha + \sum_{r=1}^{21} \beta_r \mathbb{1}_{ir} + \gamma M_i + \delta \Delta S_i + \epsilon_i \tag{6.3}$$

where S_i is the credit spread of bond i, $\mathbb{1}_{ir}$ is equal to 1 if bond i has rating r, and 0 otherwise, M_i is the maturity and ΔS_i is the 3-month change in the credit spread. Then, following Correia, Richardson, and Tuna (2012), we calculate the percentage difference between the actual credit spread and the fitted (fair) credit spread for each bond. Finally, we rank all bonds on this percentage difference from high to low and select the first (last) 10% bonds for the top (bottom) Value portfolio.

6.3.4 Momentum

Research on Momentum started with the seminal study by Jegadeesh and Titman (1993) on equity markets. Results of studies on corporate bond Momentum are mixed. Investment Grade bond returns exhibit either reversal (Khang and King, 2004; Gebhardt, Hvidkjaer, and Swaminathan, 2005) or insignificant Momentum effects (Jostova et al., 2013). In the High Yield market, on the other hand, Momentum strategies have been shown to generate profits; see Pospisil and Zhang (2010) and Jostova et al. (2013).

We follow Jostova et al. (2013) by defining Momentum as the past 6-month return using a one-month implementation lag. We use the excess return versus duration-matched Treasuries, for consistency with our return measure for evaluating factor portfolios. The 10% bonds with the highest (lowest) past returns are selected for the Momentum top (bottom) portfolio.

6.4 The benefits of allocating to factors

In this section we present our main result that factor portfolios in the corporate bond market earn alpha beyond the corporate bond market premium and beyond common equity and bond risk premiums. We also highlight the tension between evaluating factors in an absolute or relative risk context and the importance of a long investment horizon. Further, we show the diversification benefits of combining the factors in a multi-factor portfolio, which substantially reduces the tracking error and improves the information ratio versus the corporate bond market, compared to single-factor portfolios. Finally, by calculating break-even transaction costs and comparing them to actual transaction costs, we show that single-factor and multi-factor portfolios deliver positive after-cost alphas.

6.4.1 Long-short factor portfolios

We start our empirical analysis by showing performance statistics for long-short factor portfolios, which go long in the top decile portfolio and short in the bottom decile portfolio; see Table 6.2.

Panels A and B show the annualized CAPM-alphas and Fama-French-Carhart alphas. A comparison of these panels shows that both alphas are actually very similar. For Investment Grade, alphas range from around 1.2% for Size and Low-Risk to 2.5 to 3% for Value. For Low-Risk and Value the alphas are statistically significant, with t-values well above 2 for Low-Risk and above 3 for Value. For Size the t-values are around 1.6. The absence of a Momentum effect in Investment Grade is consistent with previous literature; see e.g. Jostova et al. (2013).

For High Yield, the CAPM-alphas and Fama-French-Carhart-alphas of Value and Momentum are highly significant with t-values between 2 and 3. Alphas are around 5% for Value and around 8% for Momentum. For Low-Risk, the CAPM-alpha of 2.0% is statistically significant, while the Fama-French-Carhart-alpha of 1.2% is not. Just like for Investment Grade, the alphas for Size are strongly positive, but insignificant.

To investigate diversification opportunities between the factors, Panel C shows pairwise correlations between the CAPM-alphas. Most correlations tend to be below 20%, except between Value and Size. Correlations are lowest between Value and Momentum. The results imply that there are diversification benefits to be gained by combining multiple factors in one portfolio. We will investigate this below in a long-only context.

6.4.2 Long-only single-factor portfolios

Having discussed the more theoretical long-short portfolios evaluated on a 1-month investment horizon, we now turn our attention to the more realistic long-only portfolios on a 12-month horizon.

Table 6.3 contains the performance statistics for the long-only factor portfolios as well as for the corporate bond market. Panel A shows that for our sample period from January 1994 to June 2015 the Investment Grade (High Yield) corporate bond market generated 0.50% (2.33%) per annum in excess of duration-matched Treasury bonds. For both Investment Grade and High Yield we find substantial outperformances for Size (1.12% and 5.50%, respectively), Low-Risk (0.41% and 1.45%), Value (1.30% and 4.26%) and Momentum (0.30% and 2.04%) versus the corporate bond market; see Panel B. The magnitude of these factor premiums is substantial: investors could have tripled their long-term average excess returns by investing in factors as compared to passively investing in the corporate bond market index.

We calculate risk-adjusted returns in three ways. First, in Panel A we measure returns relative to total volatility using the Sharpe ratio measure. For Investment Grade (High Yield) the Sharpe ratios of the factor portfolios are all higher than the Sharpe ratio of 0.12 (0.23) of the market. Except for Investment Grade Momentum, these differences are statistically significant. Second, in Panel C, we calculate annualized CAPM-alphas, risk-adjusting factor returns for their systematic exposure to the corporate bond market. We find that all CAPM-alphas are positive, large and statistically significant, except for Momentum and Value in Investment Grade. For Investment Grade, alphas range from 0.35% to 1.24% and for High Yield from 2.15% to 5.68%. These alphas are sizeable compared to the average corporate bond market returns of 0.50% and 2.33% for Investment Grade and High Yield, respectively. Third, we calculate annualized Fama-French-Carhart alphas. These are actually very similar in magnitude to the CAPM-alphas. Again, most alphas are statistically significant, except for Size and Momentum in Investment Grade. We conclude that factor portfolios generate superior risk-adjusted returns, measuring risk either as volatility, beta to the corporate bond market, or betas to equity and bond common risk factors.

Nonetheless, investing in factor portfolios could be considered risky in a relative sense, as evidenced by the substantial tracking errors (volatility of the outperformance) in Panel B. For Investment Grade, the tracking errors range from 1.84% to 3.07%, which are fairly large compared to the markets excess return volatility of 4.32%. For High Yield, tracking errors range from 3.86% to 7.95%, which are again substantial compared to the High Yield markets excess return volatility of 10.04%. As a result, the information ratios of single-factor portfolios are not high. This is especially true for Low-Risk, with information ratios of only 0.14 and 0.29 in Investment Grade and High Yield, respectively. On the other hand, the Low-Risk portfolio does have high Sharpe ratios of 0.41 and 0.56, respectively. This highlights the importance of a long-term investment horizon for factor investing, because on shorter horizons factor portfolios may underperform the market index due to their large tracking errors. The relatively low information ratios also make clear that single-factor portfolios are unattractive from the point of view of portfolio managers of delegated investment portfolios that are benchmarked to the market index.

6.4.3 Long-only multi-factor portfolio

The correlations in Table 6.2 indicate that combining multiple factors in a single portfolio can generate substantial diversification benefits. We construct a multi-factor long-only portfolio that has equal allocations to each of the single-factor portfolios. Table 6.3 shows that both for Investment Grade and for High Yield, the multi-factor portfolio has a lower tracking error than each of the single-factor portfolios. Nonetheless, the alphas and Sharpe ratios are among the highest. Because of the lower tracking error, and the still substantial outperformance, the information ratio of the multi-factor portfolio is higher than of all single-factor portfolios. The Investment Grade (High Yield) multi-factor portfolio has a Sharpe ratio of 0.32 (0.56), which is more than twice as high as the Sharpe ratio of the corporate bond market of 0.12 (0.23), and an information ratio of 0.66 (0.85). The CAPM (Fama-French-Carhart) alphas are 0.84% (0.84%) and 3.49% (3.65%) per annum.

Note that one can easily improve the multi-factor portfolio, e.g. by allocating more to Size and Low-Risk, which have the highest stand-alone Sharpe ratios, or by allocating more to Size and Value, which have the highest returns and alphas, or by omitting Momentum from the Investment Grade multi-factor portfolio. However, one should be careful in cherry-picking the results. A multi-factor approach, which balances the individual factors, is a robust method to harvest the various premiums offered in the corporate bond market.

6.4.4 Break-even transaction costs

The results above show that allocating to factors leads to higher risk-adjusted returns. However, the analyses do not take transaction costs into account. Therefore, we calculate break-even transaction costs, both for single-factor and multi-factor portfolios. We define the break-even transaction costs of a portfolio as the costs that would lower its CAPM-alpha to 0.

In order to calculate the break-even transaction costs, we first calculate the turnover of each portfolio. Recall from Section 6.2.2 that we use the overlapping portfolio approach of Jegadeesh and Titman (1993) with a 12-month holding period. This implies that the weight of each bond in a factor portfolio is equal to the average weight across the 12 portfolios constructed from month $t-11$ to t. The single-counted turnover from month t to month $t+1$ is subsequently determined as the sum over all weight increments across the portfolio constituents.

Likewise, we calculate the turnover for the Investment Grade and High Yield market indexes. Panel D of Table 6.3 reports the results. Note that the 31% (55%) annualized turnover of the Investment Grade (High Yield) index indicates that tracking the market comes at a cost. The index turnover comes from new bonds entering the index (due to bond issuance or rating migrations from Investment Grade to High Yield or vice versa) and from bonds leaving the index (due to redemptions, calls, and migrations, or from no longer satisfying the index inclusion rules, e.g. a maturity shorter than one year). The four single-factor portfolios have higher turnover than the market, with Size being on the lower end (small companies tend to remain small), and Momentum on the high end, with more than 100% turnover. One may expect that the Low-Risk portfolio also has low turnover (because ratings tend be fairly sticky). However, as it contains only short-dated bonds, it has to regularly reinvest redemptions from maturing bonds. The turnover of the multi-factor portfolio is equal to the average turnover of the single-factor portfolios.

Next, we calculate the break-even transaction costs of each portfolio as its gross alpha divided by its turnover; see Panel D. For Investment Grade, we find that Low-Risk, Value and the multi-factor portfolio can sustain transaction costs of around 1% to generate positive after-cost alphas. For Size, the break-even transaction costs are the highest (around 2%), because it has the highest gross alpha and the lowest turnover. The opposite holds for Momentum, which has the lowest before-cost alpha and the highest turnover, resulting in break-even transaction costs of only 0.34%. We see similar patterns for High Yield, with Size having the highest break-even transaction costs of 6.60% and Momentum the lowest of 1.82%. The break-even transaction costs for Low-Risk, Value and the multi-factor portfolio are in between.

To put these figures into perspective, we compare them to actual bid-ask spreads and transaction costs of corporate bonds. Chen, Lesmond, and Wei (2007, Table I) report that the average bid-ask spread over the period from 1995 to 2003 are 41 (81) bps for Investment Grade (High Yield). Feldhütter (2012, Table I), using data from 2004 to 2009, estimates average transaction costs at 42 (25) [18] bps for trade sizes of at least USD 100,000 (500,000) [1,000,000], without distinguishing between Investment Grade and High Yield.

Harris (2015, Table 1) analyzes a 2014-2015 data set and estimates bid-ask spreads at 30 (51) bps for Investment Grade (High Yield). Finally, Mizrach (2015, Figure 13) analyses data from 2003 to 2015 and estimates a 30 bps average bid-ask spread across all ratings.

All these transaction cost and bid-ask spreads are well below the break-even transaction costs reported in Panel D, except for Momentum in Investment Grade. We thus conclude that also after transaction costs single-factor and multi-factor portfolios generate positive CAPM-alphas.

6.4.5 Robustness checks

For all results documented above, we have done extensive robustness checks. In particular, we have checked whether our findings are robust to the specific definition of the factors, the portfolio weighting, and the portfolio size. We have also verified that the performance is robust across sub periods, ratings, maturity segments and sectors. Finally, we checked that our results our robust to liquidity effects by creating factor portfolios on a liquid subset of our data sample. We refer the interested reader to the online appendix for more details.

6.5 Strategic allocation to factors in a multi-asset context

Asset owners do not only hold corporate bonds in their portfolios, but also other assets such as government bonds and equities. Below we show that allocating to corporate bond factors leads to better performance, also if investors already apply factor investing for their equity investments.

6.5.1 Data

For the equity factors Size, Value and Momentum we use the top decile portfolio returns from Kenneth French' website.[2] For Size, we take the equal-weighted portfolio consisting of the 10% stocks with lowest equity market value ("Lo 10"). For Value, we take the equal weighted portfolio containing the 10% stocks with the highest equity book-to-market ratio ("Hi 10"). For Momentum, we take the equally weighted portfolio containing the 10% stocks with the highest past 12-1 month returns ("High"). The construction of these portfolios is most similar to the methodology used in this paper. Unfortunately, Kenneth French does not provide a series for the equity Low-Risk factor. Therefore, we use the returns of the MSCI Minimum Volatility Index,

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

obtained via Bloomberg (code: $M00IMV\$T$). For all four equity factor series, we subtract the 1-month T-bill rate ("RF") of Kenneth French. The $RMRF$ factor is used to reflect the equity market premium. We construct the government bond market premium ($TERM$) as the total return of the Barclays US Treasury 7-10 year index minus the 1-month T-bill rate; see also Section 6.2.1.

So far, we have used excess returns over Treasuries to analyze the corporate bond market and factor premiums. To compare them with equity and government bond premiums, which are measured in excess of the risk-free rate, we add the $TERM$ premium to our corporate bond series. This implies that the corporate bond total returns thus constructed have the same interest rate return as the $TERM$ factor, so that interest duration differences do not affect our results.

6.5.2 Analyses

Table 6.4, Panel A, shows the performance statistics of the market portfolios for equities, government bonds, and Investment Grade and High Yield corporate bonds. As Treasury yields have declined substantially over this sample period, government bonds have generated a large 3.50% annualized excess return over the risk-free rate with a Sharpe ratio of 0.55. This also leads to high Sharpe ratios for the Investment Grade and High Yield market portfolios of 0.61 and 0.64. Note that these Sharpe ratios are higher than the 0.12 and 0.23 mentioned in Table 6.3, because the return series in Table 6.4 additionally benefit from the Term premium. The equity market Sharpe ratio of 0.49 is the lowest across the four asset classes.

Panel B shows the same statistics for the multi-factor portfolios in equities and Investment Grade and High Yield corporate bonds. All three multi-factor portfolios have higher returns and Sharpe ratios than their own market portfolios. The Sharpe ratios range from 0.72 (equities) to 1.00 (High Yield). Panel C shows that the multi-factor portfolios also did well in a relative sense, significantly outperforming their market indexes with information ratios between 0.58 and 0.85. In Panel D, we compute the correlation of the outperformance of the multi-factor portfolios between Investment Grade, High Yield and equities. We find modestly positive correlations, between 0.17 and 0.35. This shows that the outperformance of the corporate bond multi-factor portfolios diversify with the outperformance of the equity multi-factor portfolio. Hence, factor investing in the corporate bond market captures different, though partially similar, effects as factor investing in the equity market.

To further analyze the added value of factor investing in a multi-asset context, we construct four portfolios. The first portfolio, "Traditional", consists of an equal allocation of 25% to each asset class. The second portfolio, "Equity Factor Investing", allocates the 25% equities to the equity multi-factor portfolio instead of to the equity market. The third portfolio, "Corporate Bond Factor Investing", replaces the Investment Grade and High Yield allocations of the Traditional portfolio with their respective multi-factor portfolios. The fourth portfolio, "Equity + Corporate Bond Factor Investing", allocates both to the equity and corporate bond multi-factor portfolios.

Table 6.5, Panel A, shows the return statistics of the four portfolios. Clearly, both equity and corporate bond factor investing lead to higher Sharpe ratios: 0.91 and 0.96 versus 0.78 for the Traditional portfolio. However, investing in factors in both the equity and the corporate bond market leads to an even higher Sharpe ratio of 1.07. Panel B shows that not only investing in the equity multi-factor portfolio, but also in the corporate bond multi-factor portfolios improves the outperformance from 1.33% to 2.35% and the information ratio from 0.58 to 0.81. Panel C shows the 4-factor alpha relative to the four market portfolios. The alphas of the three portfolios that include at least one multi-factor portfolio are large and highly significant. The "Equity + Corporate Bond Factor Investing" portfolio has an alpha of 2.53%, versus 1.26% for "Equity Factor Investing". This shows that the corporate bond factors add over 1% alpha per annum for investors beyond their equity counterparts.

6.6 Conclusions and implications

We provide empirical evidence that explicitly allocating to the four well-known factors Size, Low-Risk, Value and Momentum, delivers economically meaningful and statistically significant risk-adjusted returns in the corporate bond market. We use monthly constituent data of the Barclays U.S. Corporate Investment Grade index and the Barclays U.S. Corporate High Yield index from January 1994 to June 2015 and measure corporate bond returns in excess of duration-matched Treasury bonds. Both single-factor and multi-factor portfolios show higher Sharpe ratios than the corporate bond market and significant alphas. The Investment Grade long-only multi-factor portfolio has a Sharpe ratio of 0.32, versus 0.12 for the market. In High Yield, the Sharpe ratio also more than doubles, from 0.23 to 0.56. The Fama-French-Carhart-alphas are 0.84% and 3.65% per annum, for Investment Grade and High Yield respectively. These alphas are statistically significant and are large compared to the Investment Grade (High Yield) market returns over this period of 0.50% (2.33%). We find that break-even transaction costs are well above actual transaction costs of corporate bonds reported in various studies, so that after cost-alphas remain substantial. These findings are robust to a variety of sensitivity checks, including alternative factor definitions, alternative portfolio construction choices and the evaluation of factor portfolios on a subset of liquid bonds. Finally, we find that the corporate bond factors have added value above equity factors. Investors that already apply factor investing in the equity market can add more than 1% alpha and 0.1 Sharpe ratio by allocating to factors in the corporate bond market too.

We see several advantages of investing in a multi-factor portfolio over selecting a single factor. Firstly, diversifying across factors protects against the possible underperformance of one or more factors for prolonged periods of time; see also Bender et al. (2010) and Ilmanen and Kizer (2012) for a more detailed exposition on the diversification benefits of allocating to factors. Secondly, the tracking errors of individual factors to the market are relatively large, but given the modest correlations between the factors' outperformances, the tracking error of the multi-factor portfolio is well below the average of the tracking errors of the individual factors. Thirdly, the magnitude of the premiums realized in the past may not be representative for the future. So, the best-performing factor in the past might not be the winning factor in the future.

What about the implementation of factors in actual investment portfolios? Traditionally, investors delegate the implementation of their investment portfolios to contracted external managers. However, these investment managers, being benchmarked to the market index, might not be willing to implement certain factors, because of the factors' large tracking errors or limited information ratios. The Low-Risk factor, for example, does not yield a high information ratio. Therefore, the traditional paradigm of delegated and benchmarked asset management, at best leads to implicit and time-varying exposures to factors, and at worst to no exposures at all.

In an absolute-risk framework, evaluated by the Sharpe ratio instead of the information ratio, allocating to factors does offer clear benefits. Factor investing is thus a strategic choice: in the short run, the tracking error versus the market may be large, but in the longer run higher risk-adjusted returns lure on the horizon. Investors should therefore seek managers that explicitly and consistently implement factor exposures in their investment strategy.

At the moment investors do not have many investment vehicles available to harvest factor premiums in the corporate bond market. In equity markets, value, small cap and low-vol funds are numerously available. Therefore, with the increasing popularity of the factor investing concept, we expect this to change in the near future in the corporate bond market too.

Table 6.1: Summary statistics dataset
This table shows summary statistics for U.S. Investment Grade and U.S. High Yield corporate bonds over the period January 1994 - June 2015. The *annualized excess return* is the monthly return of the bond over duration-matched Treasuries, multiplied by 12, and reported in percentages. The *time-to-maturity* is the number of years until the bond expires. *credit rating* is the middle credit rating of the three rating agencies S&P, Moodys and Fitch (worst rating in case of two ratings), where the credit ratings have been converted to a numeric scale as follows: $AAA = 1, AA+ = 2, AA = 3$, etc. The *credit spread* is the option-adjusted yield of the bond in excess of the yield of the duration-matched government bond, in basis points. The *market value of the company* is the sum of the market value of all bonds of the company in the corporate bond index, in billion USD. The *number of observations* is the average number of bonds per month. For every characteristic the mean and five percentiles (5%, 25%, 50%, 75%, 95%) are reported. Each statistic is first calculated cross-sectionally per month, and subsequently averaged over time.

	Investment Grade						High Yield					
	mean	5%	25%	50%	75%	95%	mean	5%	25%	50%	75%	95%
annualized excess return	0.58	-1.75	-0.40	0.08	0.56	1.86	2.46	-5.78	-1.02	0.33	1.68	5.92
time-to-maturity	10.89	1.63	3.92	7.21	16.13	28.93	7.74	2.45	4.98	6.76	8.44	18.61
credit rating	6.69	3.45	5.56	7.04	8.80	10.00	14.30	11.00	12.93	14.67	16.09	18.22
credit spread	148.16	58.95	93.55	127.15	172.65	293.77	481.11	213.76	322.48	440.70	677.44	1540.58
market value company	13.83	0.44	1.70	4.43	9.49	19.32	3.27	0.14	0.30	0.77	2.10	8.48
number of observations	3520						1473					

Table 6.2: Performance statistics and correlations of long-short factor portfolios

This table shows performance statistics of the Size, Low-Risk, Value and Momentum factors for U.S. Investment Grade and U.S. High Yield corporate bonds over the period January 1994 - June 2015. Each month, a factor portfolio takes equally-weighted long positions in the top 10% of the bonds and short positions in the bottom 10% of the bonds following the definitions in Section 6.3. Panel A shows the CAPM-alpha and -beta with respect to the corporate bond market (*DEF*). Panel B shows the Fama-French-Carhart-alpha (*RMRF*, *SMB*, *HML*, *MOM*, *TERM* and *DEF*). Panel C shows pairwise correlations between the CAPM-alphas of the factors. Alphas are annualized. Corporate bond returns are measured as excess returns versus duration-matched Treasuries. * and ** indicate statistical significance at the 95% and 99% confidence levels, respectively, of two-sided tests whether the mean returns and alphas are different from 0 (t-tests with Newey and West (1987) and Newey and West (1994) standard errors).

	Investment Grade				High Yield			
	Size	Low-Risk	Value	Momentum	Size	Low-Risk	Value	Momentum
Panel A: CAPM statistics								
alpha	1.15%	1.27%*	2.56%**	-1.38%	3.28%	2.02%*	5.14%**	8.49%**
t-value	(1.63)	(2.49)	(3.14)	(-0.77)	(1.21)	(2.04)	(2.70)	(2.80)
beta	-0.27	-1.28	0.98	-1.04	0.19	-0.76	0.60	-1.07
adjusted R2	0.17	0.81	0.65	0.29	0.03	0.66	0.40	0.38
Panel B: Fama-French-Carhart statistics								
alpha	1.22%	1.18%*	3.01%**	-3.46%	4.84%	1.19%	5.33%**	7.84%*
t-value	(1.56)	(2.39)	(3.24)	(-1.68)	(1.77)	(1.18)	(2.82)	(2.28)
adjusted R2	0.23	0.82	0.67	0.38	0.09	0.70	0.43	0.40
Panel C: CAPM-alpha correlations								
Size		-17%	41%	18%		-19%	51%	-19%
Low-Risk			10%	-17%			-18%	10%
Value				-14%				-36%
Momentum								

Table 6.3: Performance statistics of long-only factor portfolios

This table shows performance statistics of the corporate bond market and the Size, Low-Risk, Value and Momentum factors for U.S. Investment Grade and U.S. High Yield corporate bonds over the period January 1994 - June 2015. The return in month t is calculated as the average of the portfolios constructed from month $t-11$ to t. Each month, a factor portfolio takes equally-weighted long positions in 10% of the bonds following the definitions in Section 6.3. The multi-factor portfolio is an equally weighted combination of Size, Low-Risk, Value and Momentum. Panel A shows the return statistics. Panel B shows the outperformance statistics. Panel C shows the CAPM-alpha (*DEF*) and the Fama-French-Carhart alpha (*RMRF*, *SMB*, *HML*, *MOM*, *TERM* and *DEF*). Panel D shows the turnover and break-even transaction costs implied by the CAPM-alpha and turnover. Mean, volatility, outperformance, tracking error and alphas are annualized. Corporate bond returns are measured as excess returns vs. duration-matched Treasuries. * and ** indicate statistical significance at the 95% and 99% confidence levels, respectively, of two-sided tests whether the Sharpe ratio is different from the Sharpe ratio of the corporate bond market (Panel A, Jobson and Korkie (1981)-test), whether the outperformance is different from 0 (Panel B, t-test), and whether the alphas are different from 0 (Panel C, t-test). The t-tests are calculated with Newey and West (1987) and Newey and West (1994) standard errors.

	Investment Grade						High Yield					
	Market	Size	Low-Risk	Value	Momentum	Multi	Market	Size	Low-Risk	Value	Momentum	Multi
Panel A: Return statistics												
mean	0.50%	1.61%	0.91%	1.79%	0.80%	1.28%	2.33%	7.83%	3.78%	6.58%	4.37%	5.64%
volatility	4.32%	3.82%	2.24%	6.76%	4.32%	3.98%	10.04%	12.20%	6.69%	13.37%	10.29%	10.04%
Sharpe ratio	0.12	0.42*	0.41*	0.27*	0.19	0.32**	0.23	0.64**	0.56**	0.49**	0.42*	0.56**
t-value JK test		(2.57)	(2.14)	(2.02)	(0.76)	(3.44)		(2.72)	(3.32)	(3.02)	(2.33)	(3.88)
Panel B: Outperformance statistics												
outperformance		1.12%*	0.41%	1.30%	0.30%	0.78%**		5.50%*	1.45%	4.26%*	2.04%*	3.31%**
tracking error		2.29%	2.85%	3.07%	1.84%	1.18%		7.95%	5.02%	5.66%	3.86%	3.88%
information ratio		0.49	0.14	0.42	0.16	0.66		0.69	0.29	0.75	0.53	0.85
t-value		(2.15)	(0.60)	(1.35)	(0.72)	(2.79)		(2.24)	(1.16)	(2.28)	(2.20)	(3.04)
Panel C: Alpha statistics												
CAPM		1.24%*	0.70%**	1.06%	0.35%	0.84%**		5.68%*	2.39%**	3.72%*	2.15%*	3.49%**
t-value		(2.08)	(3.12)	(1.87)	(0.81)	(2.71)		(2.36)	(3.43)	(2.49)	(2.24)	(3.12)
Fama-French-Carhart		1.13%	0.78%**	1.32%*	0.15%	0.84%**		6.36%**	2.28%**	3.62%**	2.36%**	3.65%**
t-value		(1.76)	(3.68)	(2.01)	(0.35)	(2.64)		(2.78)	(3.61)	(2.64)	(2.88)	(3.61)
Panel D: Turnover and break-even transaction costs												
turnover	31%	63%	78%	80%	103%	81%	55%	86%	92%	96%	118%	98%
break-even costs		1.97%	0.90%	1.33%	0.34%	1.04%		6.60%	2.60%	3.88%	1.82%	3.56%

Table 6.4: Performance statistics government bond, corporate bond and equity market and factor portfolios
This table shows the performance statistics for equities, government bonds and U.S. Investment Grade and U.S. High Yield corporate bonds over the period from January 1994 to June 2015. The government bond index is the Barclays US Treasury 7-10 year index. Panel A shows the mean, volatility and Sharpe ratio of the excess return over the 1-month T-bill rate for the market portfolios. Panel B shows the same statistics for the multi-factor portfolios for equities and Investment Grade and High Yield corporate bonds. Panel C shows the outperformance statistics. Panel D shows the correlations between the outperformances. Mean, volatility, outperformance and tracking error are annualized. * and ** indicate statistical significance at the 95% and 99% confidence levels, respectively, of two-sided tests whether the Sharpe ratio is different from the Sharpe ratio of the market (Panel B, Jobson and Korkie (1981)-test), and whether the outperformance is different from 0 (Panel C, t-test with Newey and West (1987) and Newey and West (1994) standard errors).

		Corporate Bonds		
	Government bonds	Investment Grade	High Yield	Equities
Panel A: Market				
mean	3.50%	3.99%	5.82%	7.54%
volatility	6.34%	6.51%	9.10%	15.30%
Sharpe ratio	0.55	0.61	0.64	0.49
Panel B: Multi-factor portfolio				
mean		4.78%	9.14%	12.85%
volatility		6.21%	9.14%	17.87%
Sharpe ratio		0.77**	1.00**	0.72
t-value JK test		(3.84)	(3.77)	(1.93)
Panel C: Outperformance statistics				
outperformance		0.78%**	3.31%**	5.31%*
tracking error		1.18%	3.88%	9.21%
information ratio		0.66	0.85	0.58
t-value		(2.79)	(3.04)	(2.22)
Panel D: Outperformance correlations				
Investment Grade			0.23	0.17
High Yield				0.35
Equities				

Table 6.5: Performance statistics multi-asset portfolios
This table shows performance statistics of four multi-asset portfolios consisting of government bonds, corporate bonds and equities over the period from January 1994 to June 2015. All portfolios are constructed using the portfolios displayed in Table 6.4. The "Traditional" portfolio invests 25% in equities, 25% in government bonds, 25% in Investment Grade corporate bonds and 25% in High Yield corporate bonds. The "Factor Investing Equity" portfolio only applies factor investing in the equity market. The "Factor Investing Corporate Bond" only applies factor investing in the corporate bond market. The "Factor Investing Equity + Corporate Bond" portfolio applies factor investing in both the equity and corporate bond markets. Panel A shows the statistics of the excess return over the 1-month T-bill rate. Panel B shows the outperformance statistics. Panel C shows the alpha of a regression of the portfolio return on the four market returns (Table 6.4, Panel A). Mean, volatility, outperformance, tracking error and alpha are annualized. * and ** indicate statistical significance at the 95% and 99% confidence levels, respectively, of two-sided tests whether the Sharpe ratio is larger than the Sharpe ratio of the traditional portfolio (Panel A, Jobson and Korkie (1981)-test), whether the outperformance is different from 0 (Panel B, t-test), and whether the alpha is different from 0 (Panel C, t-test). The t-tests are calculated with Newey and West (1987) and Newey and West (1994) standard errors.

		Factor investing		
	Traditional	Equity	Corporate Bond	Equity + Corporate Bond
Panel A: Return statistics				
Mean	5.21%	6.54%	6.24%	7.57%
Volatility	6.69%	7.16%	6.48%	7.09%
Sharpe ratio	0.78	0.91	0.96**	1.07**
t-value JK test		(1.86)	(4.65)	(3.07)
Panel B: Outperformance statistics				
outperformance	0.00%	1.33%*	1.02%**	2.35%**
tracking error	0.00%	2.30%	1.17%	2.91%
information ratio		0.58	0.88	0.81
t-value		(2.22)	(3.13)	(2.91)
Panel C: Alpha statistics				
alpha		1.26%*	1.27%**	2.53%**
t-value		(2.09)	(4.10)	(3.18)

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