Deutsche Bank

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Signal Processing

Do bonds know better?

Research Summary
In this report we show how quantitative equity investors can harness fixed income data. We find that stocks whose corporate bonds have outperformed - after controlling for stock momentum and interest rate effects - are good buy candidates for equity investors.

Harnessing fixed income data for equity investment strategies

Cross-asset class alpha
In this report, we show that fixed income data is useful for quantitative equity investors. We use a unique Deutsche Bank database of corporate bonds – the DBIQ database – to analyze whether fixed income metrics have predictive power for future stock returns. We find that certain signals from the bond market do lead the equity market and as such can offer a new alpha source, even for those who can only trade equities.

What do bonds know that stocks don't?
Specifically we find that corporate bond momentum – after we control for stock momentum and interest rate effects – has significant predictive power for future stock returns. This factor, which we call adjusted bond momentum (ABM), generates a consistently positive payoff over time, and has not seen the performance downgrade that many of the "traditional" quant factors have experienced in recent years.

Value without the trap
A compelling feature of the adjusted bond momentum factor is that it takes a long position in value stocks with lower operating performance, negative earnings momentum, and higher volatility. In other words, the factor favors what would often be called "value trap" stocks. In our analysis, we show that corporate bond information can be a useful way to pick when these stocks are becoming turnaround stories.

Source: Getty Images

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A letter to our readers

Fixed income data for equity investors

The financial crisis illustrated the significant linkages between different asset markets

Today's capital markets are more integrated than ever. Indeed, one of the eye opening lessons hammered home in the credit crisis was the symbiotic link between financial markets, not just across geographies but also across asset classes. The notion that problems in one isolated market – namely mortgage backed securities – could be easily contained within that market quickly evaporated in the onslaught of contagion that swept through the financial system. This realization has raised significant questions for quantitative equity investors. In a world where asset classes are so interlinked, can we continue to myopically focus on factors that play stock-level characteristics, or do we need to expand our horizon and start taking a more holistic view of the financial world?

In this paper we argue that information from the fixed income market can be useful even for those who only trade equities

In this paper, we argue in favor of the latter. We show the information from the fixed income market can be useful even for quantitative investors who trade equities exclusively. In particular, we show that stocks whose corporate debt has outperformed – after controlling for stock price momentum and interest rate effects – are good buy candidates for equity investors. In fact, we find that these buy ideas tend to be "value trap" stocks, which most quant models would ordinarily steer away from. Our analysis suggests that listening to what the bond market is telling us about the debt of a company is a good way to pick the turning point for these out-of-favor securities.

This research extends our recent work on cross-asset class alpha signals

The idea of looking across asset classes for new alpha ideas is one we have been researching extensively since we launched our research just over a year ago. Previously we examined how information from the options market can help stock investors select stocks (Cahan et al. [2010a]), and how data from the world of high frequency trading can improve even low frequency investing strategies (Cahan et al. [2010b]). Our view is that most of the traditional, bottom-up stock selection factors have largely been arbitraged away given the increased popularity of quant investing over the past decade. By looking across asset classes, we think there is a much greater chance of discovering new signals that are much less scrutinized than those from the standard pricing, volume, and accounting data sources.

This paper is just a starting point; the fixed income market is a rich source of data for equity quants

As with any new data source, this paper merely scratches the surface. The world of bonds is incredibly rich, and in this paper we only touch on one small area. In the future we want to expand our research to consider other parts of the fixed income market, like CDS spreads for example. In the meantime, we hope the ideas in this paper will stimulate more equity quants to consider how they might profit from non-equity information sources.

Regards,

Yin, Rocky, Miguel, Javed, and John
Deutsche Bank North American Quantitative Strategy

Stock screens

Below we screen the S&P 500 for our best buy and sell ideas, based on the adjusted bond momentum factor (ABM) described in this research. This factor is designed to indentify companies whose corporate bonds have been outperforming, after controlling for stock price momentum and interest rate effects. We show in our research that such stocks are good buy candidates, while stocks with poor adjusted bond momentum are good sell candidates.

For the complete details of the factor, please see the remainder of this report.

Buy ideas

Figure 1: Buy ideas from the S&P 500 universe

Ticker	Name	GICS Sector	Adjusted Bond Momentum Score (higher = better buy idea)
UNM	UNUM GROUP	Financials	2.7
LO	LORILLARD INC	Consumer Staples	2.4
WMB	WILLIAMS COS INC	Energy	2.3
HBAN	HUNTINGTON BANCSHARES	Financials	2.1
WY	WEYERHAEUSER CO	Financials	2.1
JNS	JANUS CAPITAL GROUP INC	Financials	1.9
CINF	CINCINNATI FINANCIAL CORP	Financials	1.8
SVU	SUPERVALU INC	Consumer Staples	1.7
DGX	QUEST DIAGNOSTICS INC	Health Care	1.7
EP	EL PASO CORP	Energy	1.6
ETFC	E TRADE FINANCIAL CORP	Financials	1.5
KSS	KOHL'S CORP	Consumer Discretionary	1.5
BSX	BOSTON SCIENTIFIC CORP	Health Care	1.5
RDC	ROWAN COS INC	Energy	1.4
RF	REGIONS FINANCIAL CORP	Financials	1.4
FHN	FIRST HORIZON NATIONAL CORP	Financials	1.4
LNC	LINCOLN NATIONAL CORP	Financials	1.4
AKS	AK STEEL HOLDING CORP	Materials	1.4
HRB	BLOCK H & R INC	Consumer Discretionary	1.3
CHK	CHESAPEAKE ENERGY CORP	Energy	1.3

Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Sell ideas

Figure 2: Sell ideas from the S&P 500 universe

Ticker	Name	GICS Sector	Adjusted Bond Momentum Score (lower = better sell idea)
DOV	DOVER CORP	Industrials	-2.4
IRM	IRON MOUNTAIN INC	Industrials	-2.3
NDAQ	NASDAQ OMX GROUP INC	Financials	-2.2
AGN	ALLERGAN INC	Health Care	-2.2
AMGN	AMGEN INC	Health Care	-2.1
DTV	DIRECTV	Consumer Discretionary	-2.0
DHR	DANAHER CORP	Industrials	-1.9
OXY	OCCIDENTAL PETROLEUM CORP	Energy	-1.9
CSCO	CISCO SYSTEMS INC	Information Technology	-1.8
HSP	HOSPIRA INC	Health Care	-1.8
TWX	TIME WARNER INC	Consumer Discretionary	-1.8
JNJ	JOHNSON & JOHNSON	Health Care	-1.8
HD	HOME DEPOT INC	Consumer Discretionary	-1.7
MRO	MARATHON OIL CORP	Energy	-1.6
PCG	PG&E CORP	Utilities	-1.6
ABT	ABBOTT LABORATORIES	Health Care	-1.6
UNH	UNITEDHEALTH GROUP INC	Health Care	-1.6
K	KELLOGG CO	Consumer Staples	-1.6
NEM	NEWMONT MINING CORP	Materials	-1.5
BAX	BAXTER INTERNATIONAL INC	Health Care	-1.5

Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Academic review

Does the academic literature offer any clues?

There is a surprising lack of academic research on the link between the stocks and bonds of individual companies

The academic literature on stocks and bonds is vast, but the intersection between these two areas of the literature is surprisingly small. In fact, there are only a handful of recent papers that directly address the topic of this research, namely the lead-lag relationship between the tradable corporate debt and the listed equity of a given company. Of course, as practitioners we are in no position to criticize: most major financial institutions are similarly delineated into asset class silos. Indeed, for most equity professionals the fixed income trading floor is right next door, but it might as well be on Mars given how separate the business lines usual are. However, as we have argued before in our research, we think it is precisely this lack of overlap that may present a cross-asset class arbitrage opportunity.[1]

Most academic papers find that equities lead bonds

Of the papers that have been published on the lead-lag relationship between company-level debt and equity, the majority find that stock returns tend to lead bond returns. For example, Kwan [1996] uses a sample of 702 bonds representing 327 individual companies from 1986 to 1990, and finds that on average lagged stock returns predict week-ahead bond returns. Similarly, Hotchkiss and Ronen [2002] examine the intraday reaction of stocks and bonds to earnings announcements. They also find that stocks and bonds tend to react similarly to such events, and there is no real lead-lag relationship at the intraday level. At the other end of the frequency spectrum, Gebhardt, Hvidkjaer, and Swaminathan [2005] find that companies whose stocks outperform in one year tend to have bonds that outperform in the following year. So once again, the academic evidence suggests that stocks lead bonds rather than the other way around.

However, a more recent strand of the literature does seem to find predictive power going from bonds to stocks

So the evidence would seem to be stacking up against finding any useful alpha information in the bond market for equity trading strategies. However, two more recent papers offer a glimmer of hope. Downing, Underwood, and Xing [2009] study bonds for around 300 firms at an intraday frequency from 2004 to 2005 and find that the number of bonds which show some lead effect on stocks is slightly greater than what would be expected due to chance. Even more promising though is a new working paper by Bittlingmayer and Moser [2011]. We summarized this paper in the March 2011 edition of our monthly *Academic Insights* report, so we refer interested readers to page 7 of that publication for more details. In their research, the authors find that a 10% decline in the price of a firm's bonds leads to around a 3 to 6% subsequent decline in the firm's stock price. On the other hand, a bond price rise has no impact on future stock returns. The asymmetry in the results is interesting and perhaps intuitive – credit analysts and traders tend to focus more on downside risk, so it is plausible that they may lead equity investors when evaluating default risk. Another interesting hypothesis is that increased liquidity actually hampers efficiency because it leads to much greater short-term noise. Because the bond market is relatively illiquid, a bond investor may choose to trade only when there is a compelling reason to do so, which may act as a natural filter to ensure that only the most important information is reflected in bond trades.

Overall, the academic literature suggests the barriers to finding alpha signals in the bond market are high. Having said that, we are encouraged by the recent direction the literature has taken, and the Bittlingmayer and Moser [2011] paper in particular suggests a promising angle of attack, which we will expand on in this research.

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[1] For example, in Cahan et al. [2010b] we argue that the lack of cross-communication between those who trade in the high frequency domain and those who invest with a long-term horizon presents an alpha opportunity for investors willing to bridge this divide and borrow information from the other side. Similarly, in Cahan et al. [2010a] we show that equity investors who are willing to harness information from the options market can also gain an edge.

Introducing the DBIQ database

Leveraging Deutsche Bank's fixed income expertise

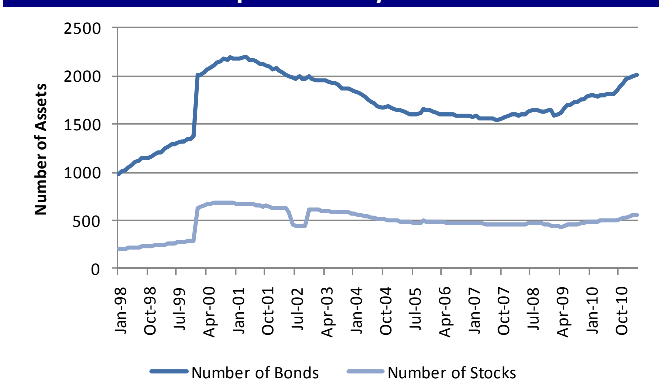
In this research we use the DBIQ database, a proprietary database used by Deutsche Bank to price and manage index products

One of the advantages of working at a major investment bank like Deutsche Bank is the rich suite of internal databases that we can leverage in our research. Deutsche Bank is a major player in global debt trading, and as a result collects a vast array of fixed income data points every day. One such database is the DBIQ database, which is the engine behind Deutsche Bank's wide range of index products.[2] In the fixed income space, our colleagues in the DBIQ team run indexes globally, covering everything from U.S. Domestic Investment Grade Debt to Global Sovereign Debt to Emerging Markets Debt and everything in between. To compute the returns and analytics for these indexes, the DBIQ team maintains a large database of bond data, including pricing information, maturities, coupons, yield calculations, duration and convexity estimates, information about call and put features, credit rating scores, etc.

The history starts in 1998 for investment grade debt, and 2000 for high yield debt

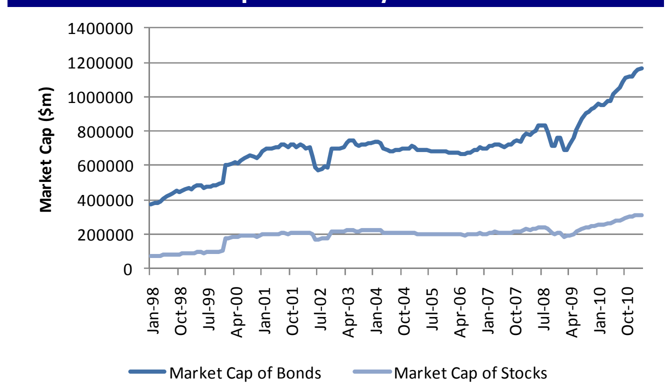
For U.S. investment grade bonds, the history goes back to 1998, while data for high yield bonds start in 2000. Figure 3 shows the number of individual corporate bonds for U.S. companies that exist in the database over time, along with the number of distinct companies that those bonds represent (of course, an individual company can, and usually does, have multiple bonds trading over it). Figure 4 shows the same chart, except using market value instead of a simple count.

Figure 3: Number of bonds in DBIQ universe and number of stocks represented by those bonds



Source: DBIQ, Deutsche Bank

Figure 4: Market cap of bonds in DBIQ universe and number of stocks represented by those bonds



Source: DBIQ, Deutsche Bank

The first important point to note is that breadth is unfortunately somewhat limited. On average the database has around 1,700 corporate bonds for the U.S. market, but those bonds only represent around 500 stocks at any point in time. Therefore, as we begin to explore potential alpha strategies one of the biggest questions will be whether we can find enough predictive power to offset the limited breadth.[3] We will return to this point in more detail later in this report.

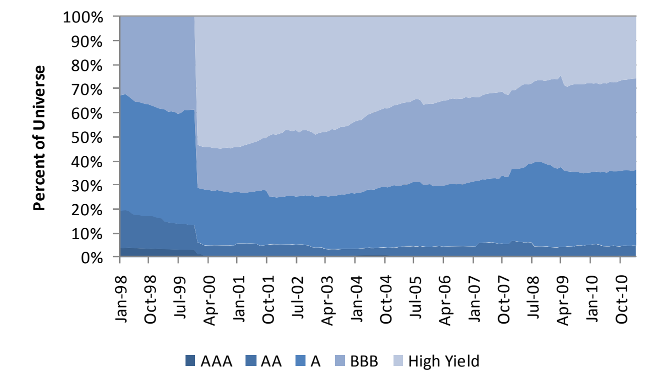
[2] See http://index.db.com for more information.

[3] This is a trade-off we have seen many times in our previous research. For example, in Luo [2010a] we examined industry-specific factors. In that dataset we had a similar limited breadth, but still found a favorable tradeoff.

The bonds come from a range of credit ratings, from triple A to junk

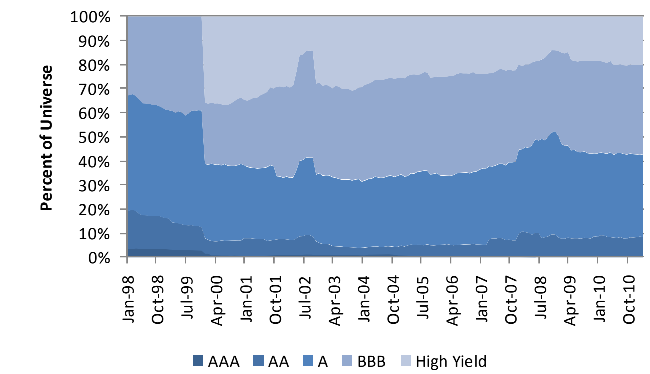
In Figure 5 and Figure 6 we show the percent of the DBIQ U.S. corporate bond universe at each credit rating, by number and market cap respectively. As mentioned, the high yield data became available in 2000, which is why there is a large step-change at the start of that year. Overall there is a good mix of bonds from the various rating categories, ranging from top investment grade through to junk status.

Figure 5: Percent of DBIQ bond universe at each rating, by number



Source: DBIQ, Deutsche Bank

Figure 6: Percent of DBIQ bond universe at each rating, by market cap

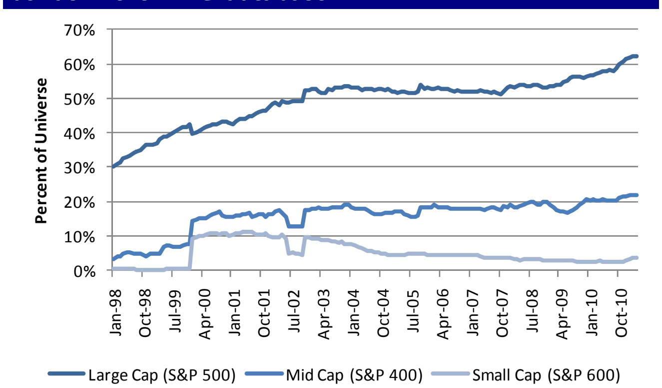


Source: DBIQ, Deutsche Bank

The majority of the bonds come from large cap stocks, e.g. S&P 500 constituents

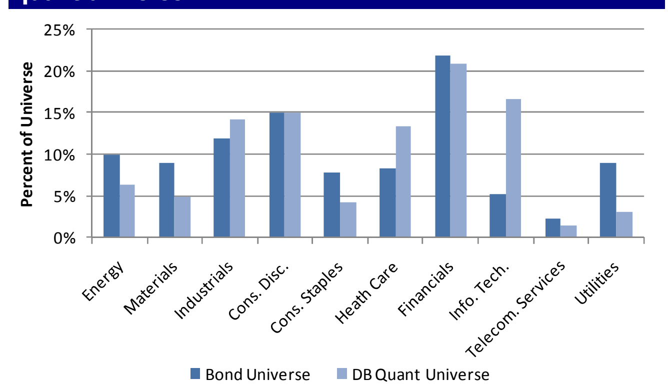
But what type of companies do these bonds represent? Figure 7 shows what percent of the S&P 500 (large caps), S&P 400 (mid caps), and S&P 600 (small caps) have bonds available. Currently just over 60% of S&P 500 companies have bonds available in our database, while for the S&P 400 and S&P 600 only 20% and 5% have bond information respectively. These numbers seem low at first, but keep in mind that many companies do not have debt to start with, particularly among small cap companies. This is particularly noticeable in the Technology and Health Care sectors, where many newly-listed, high-growth companies have no public debt on their balance sheet (Figure 8).

Figure 7: Percent of stocks from each index that have bonds in the DBIQ database



Source: DBIQ, Russell, Compustat, S&P, Deutsche Bank

Figure 8: Sector breakdown for bond universe and DB quant universe



Source: DBIQ, Russell, Compustat, S&P, Deutsche Bank

Backtesting bond factors

Starting with the basics

We test two types of bond factors: bond price momentum, and bond characteristics (e.g. maturity, coupon, yield, duration, etc.)

As a first pass, we start our analysis by backtesting some basic bond factors within the universe for which we have bond data. As mentioned in the previous section, this is about 500 stocks at each point in time from 1998 to present. The factors we pick to start with are straightforward, and fall into two categories:

- **Bond momentum:** The most basic factor we consider is trailing bond returns, measured as the total return (i.e. price appreciation plus coupon) over a trailing period. We consider 1, 3, and 12 month bond momentum.
- **Bond characteristics:** This category includes the yield-to-maturity (YTM) of the bond, estimates of the duration and convexity, and the spread over Treasuries. In addition we also consider changes to these variables.

Most stocks have multiple bonds, so we weight by market value to get one value for each stock

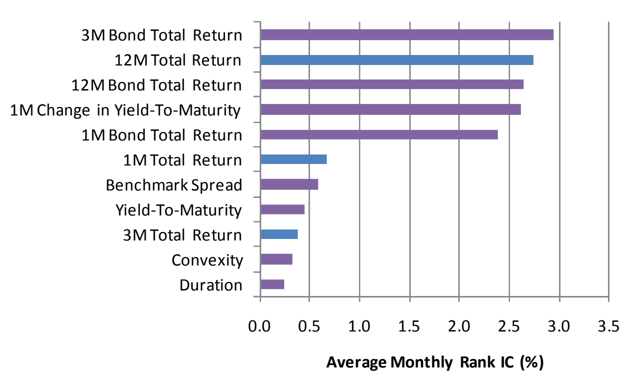
For each of these factors, one of the problems is how to handle the many-to-one mapping from bonds to stocks (i.e. the fact that a company will have only one stock, but potentially many different bonds with different yields, coupons, maturities, credit ratings, put/call features, and so on). We follow the academic literature and weight the bonds by their market value. For example, when computing bond momentum, we compute total returns for each bond and then weight by the market value of each bond to get the final momentum score.

A second important point to be aware of is the fact that many bond returns are not computed until well after the close of the equity market. This is because pricing for bonds is more complicated given the over-the-counter nature of the market, and hence takes longer to arrive in the database. To account for this, we always lag our bond data by one trading day to ensure that all data would have been available at each point in time.

We start with a simple backtest of each factor, rebalanced monthly

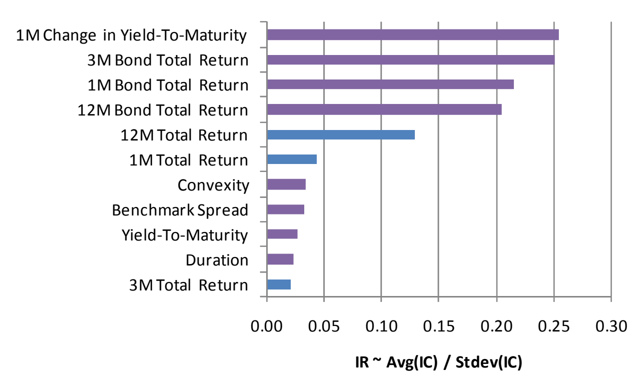
Figure 9 shows the average monthly rank information coefficient for our set of potential bond factors. The purple bars represent bond factors, while the blue bars represent 1, 3, 12 month stock price momentum (included for comparison with the corresponding bond price momentum factors). The risk-adjusted results are shown in Figure 10.

Figure 9: Average monthly rank IC, 1998-present



Note: Purple bars denote bond factors, blue bars denote "standard" factors
Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 10: Risk-adjusted rank IC, 1998-present



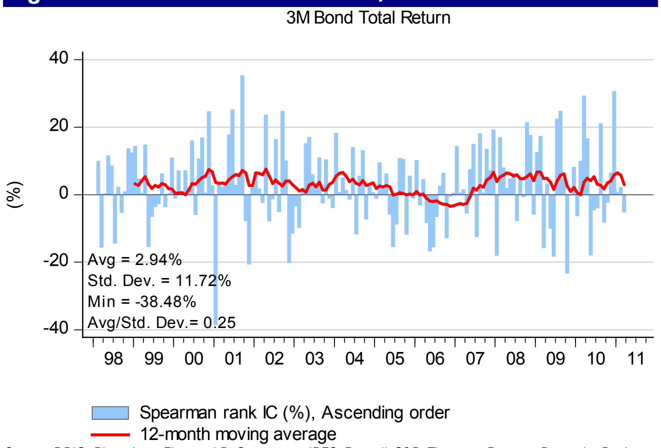
Note: Purple bars denote bond factors, blue bars denote "standard" factors
Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Even in this somewhat superficial first pass the results are quite interesting. Bond momentum in particular shows promising performance, particularly in risk-adjusted terms. In contrast, returns to factors based on bond characteristics (e.g. YTM, duration, convexity, etc.) are poor. This does not surprise us – the characteristics of bonds are typically more specific to each bond rather than the underlying company. For example, duration is just a measure of the sensitivity of a particular bond to changes in interest rates, and is driven by the time to maturity and coupon cashflow stream of the bond. As such, it is not surprising that duration has little predictive power for the cross-section of stock returns.

We find bond momentum factors show the most promise

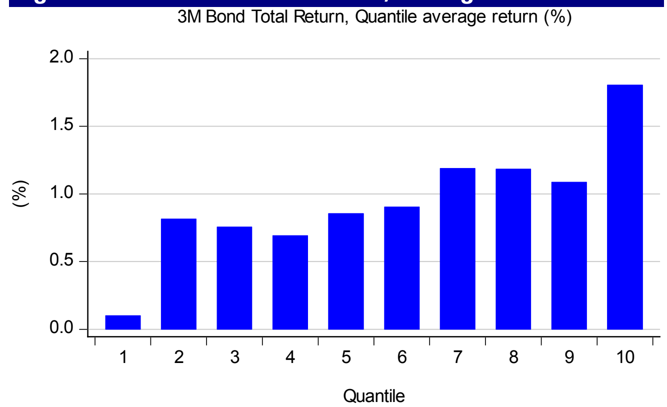
Returning to the more promising momentum factors, Figure 11 shows a time-series of the monthly rank IC for 3-month bond momentum, and Figure 12 shows the average monthly returns to simple decile portfolios. The results are not spectacular by any means, but they do show some consistency over time. As well, the pattern of decile returns is reasonably monotonic.

Figure 11: 3M Bond Total Return, rank IC



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

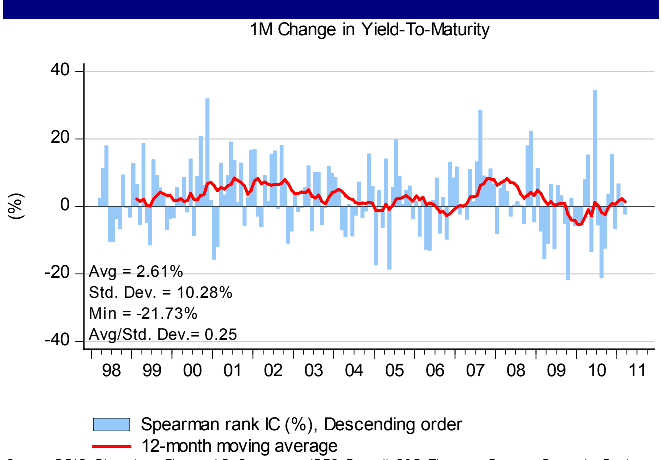
Figure 12: 3M Bond Total Return, average decile returns



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

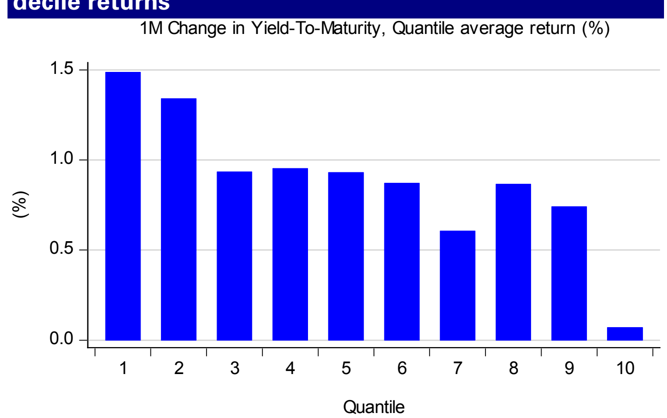
Figure 13 and Figure 14 show the same charts for another factor that worked reasonably well in preliminary backtesting: 1-month change in yield-to-maturity. Because yield and price are inversely linked in the bond world, this is effectively measuring 1-month momentum. Again we see moderately positive results, both in the time-series and the pattern of decile returns.

Figure 13: 1M Change in Yield-to-Maturity, rank IC



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 14: 1M Change in Yield to Maturity, average decile returns



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

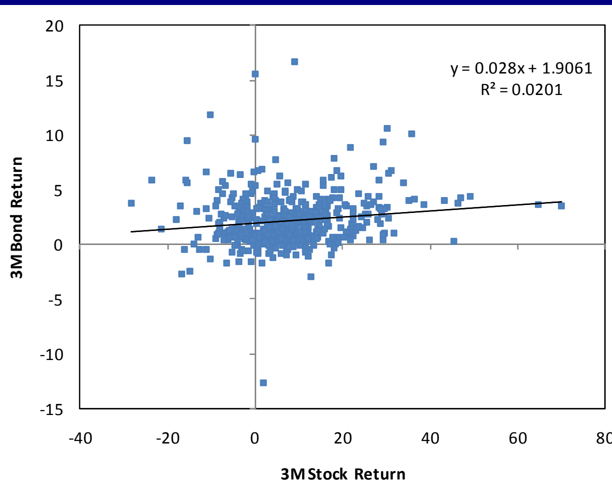
But we need to control for stock momentum

So far the results suggest bond momentum may have some predictive power for future stock returns. However, we have so far glossed over an important point: stock momentum also has predictive power for future stock returns. Even if bonds and stocks move contemporaneously, we would expect bond momentum to show some predictive power due to its positive correlation with stock momentum. What we really need to do is look at bond momentum, *after controlling for stock momentum*. This will tell us whether bond momentum is adding any incremental value on top of the well known stock momentum factors.

We need to control bond momentum for stock momentum

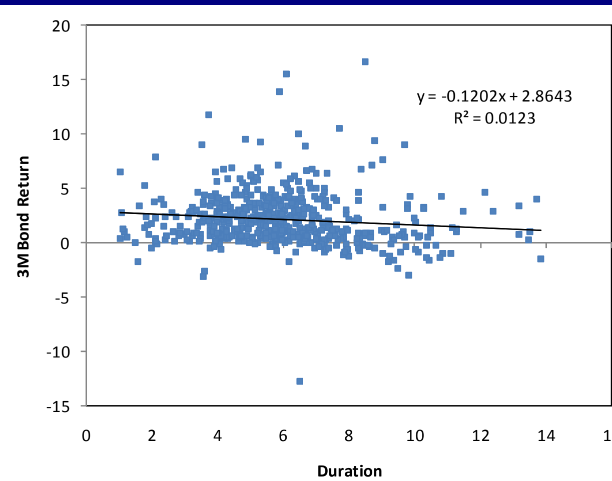
One way we can do this is to regress bond momentum cross-sectionally onto stock momentum. To illustrate this, Figure 15 shows a scatter plot of 3-month bond momentum onto 3-month stock momentum, as at 31 March 2011. Interestingly the R-squared from the cross-sectional regression is quite low, which suggests that companies with good bond returns in the past are not necessarily the same as those with good stock returns. However, the correlation is positive as we would expect given both bonds and stocks are a claim on the same underlying company.

Figure 15: 3M Bond Return versus 3M Stock Return, as at 31 March 2011



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 16: 3M Bond Return versus Duration, as at 31 March 2011



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

We also control for duration, otherwise our factor could be impacted by underlying interest rate changes

In addition to controlling for stock momentum, we also need to control our bond momentum for duration (Figure 16). Bond returns are driven to a great degree by changes in interest rates, and the degree of this co-movement can be measured by duration. This means the price of a company's bond, particularly a high duration bond, could change purely because of interest rate changes. Such a change would say nothing about the prospects for the underlying company. Therefore, by controlling for duration we can try to remove the difference in performance between the bonds of two companies that is due to interest rate changes; hopefully what is left over says more about the underlying companies than the raw bond momentum factor.[4]

With this in mind, we define what we call adjusted bond momentum (ABM), or $\widetilde{R}_{B,i,t}$, as the residual, $\varepsilon_{i,t}$, from the cross-sectional regression

$$R_{B,i,t} = c + \beta_1 R_{S,i,t} + \beta_2 Dur_{B,i,t} + \varepsilon_{i,t}$$

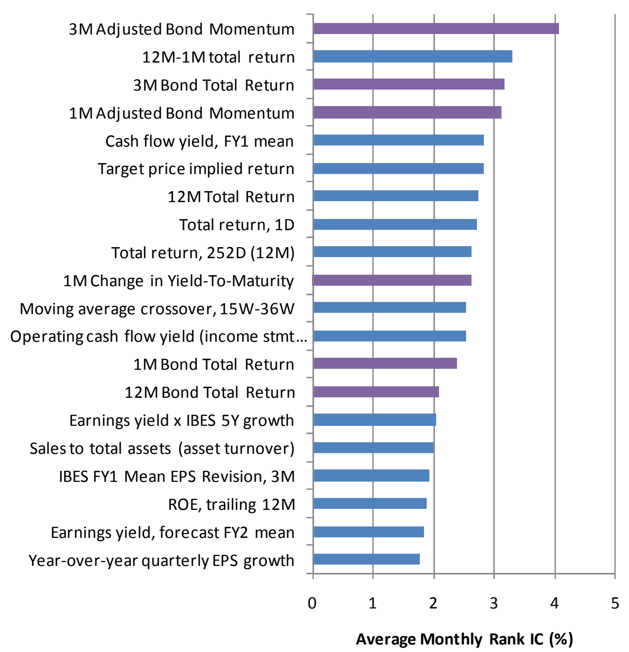
[4] Note that we could try to control for convexity as well. However, we find that the cross-sectional relationship between bond returns and duration is fairly weak to begin with, so adding in convexity adds little incremental value.

where $R_{B,i,t}$ is the trailing bond return for stock i at time t, $R_{S,i,t}$ is the trailing stock return over the same trailing window, and $Dur_{B,i,t}$ is the bond duration. As discussed, the bond return and duration are market value weighted averages for all bonds trading over company i at time t.

We find that our adjusted bond momentum factor outperforms all the factors in our library, for the universe of stocks with bond data

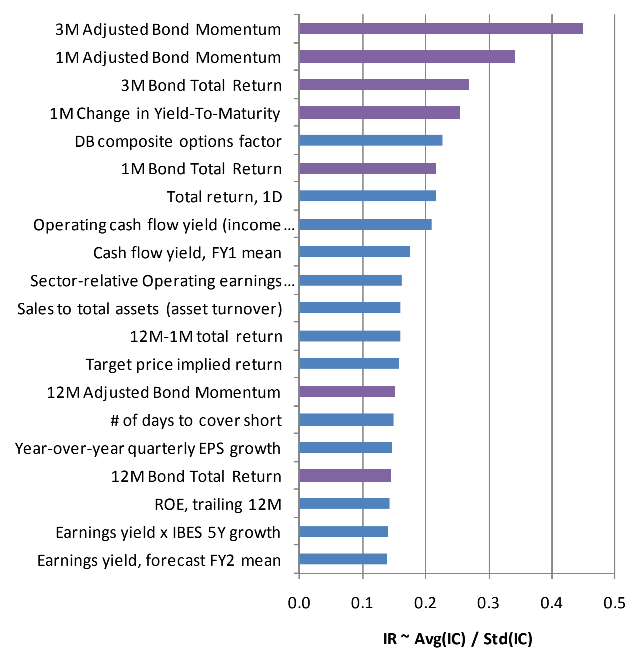
We then re-run our backtest with our new adjusted momentum factors. At the same time, we also include all factors from our standard factor library of around 80 quant factors. For these standard factors we restrict the universe to those stocks that have bond data for, so that that we are comparing the performance over the same set of stocks for each factor. Figure 17 shows the best 20 factors based on average monthly rank IC and Figure 18 shows the risk-adjusted rankings. Again, purple bars are bond factors and blue bars are "standard" quant factors.

Figure 17: Average rank IC, top 20 factors



Note: Purple bars denote bond factors, blue bars denote "standard" factors
Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 18: Risk-adjusted rank IC, top 20 factors



Note: Purple bars denote bond factors, blue bars denote "standard" factors
Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

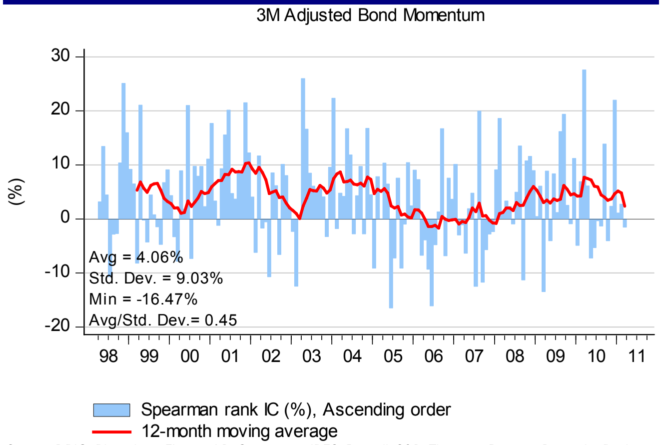
The expanded result set is intriguing. The best performing factor from 1998-present is 3-month adjusted bond momentum. We can think of this factor as measuring the performance of the bonds for each company in our universe, after controlling for stock price momentum and the sensitivity of each company's debt to interest rate movements. Keep in mind the charts only show the best 20 factors out of a library of over 80 factors. So the 3-month ABM factor outperforms our entire factor library over the backtest period.

Risk-adjusted performance for the ABM factor is attractive

Figure 19 shows the time-series performance of the factor. The 12-month average performance is consistently above zero, and the variability of that performance over time is quite contained. In fact, the risk-adjusted monthly IC of 0.45 is extremely attractive compared to other factors, and is particularly attractive given the universe we are using is heavily skewed towards large cap stocks, where most factors struggle.

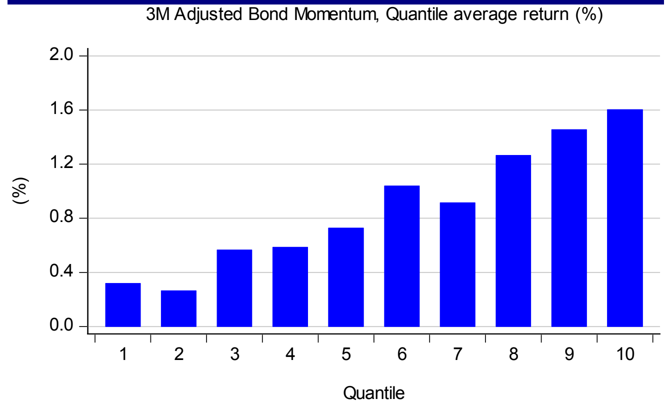
The return pattern of decile portfolios is also attractive because it shows a nicely monotonic pattern. In other words, the factor is good at differentiating stocks over the entire cross-section of the universe, not just the tails.

Figure 19: 3M Adjusted Bond Momentum, rank IC



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

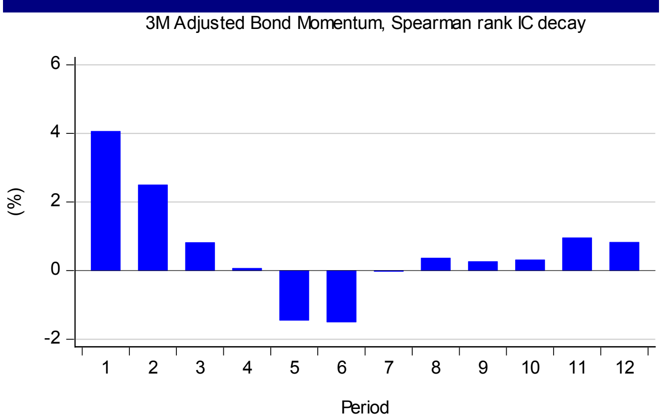
Figure 20: 3M Adjusted Bond Momentum, average decile returns



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

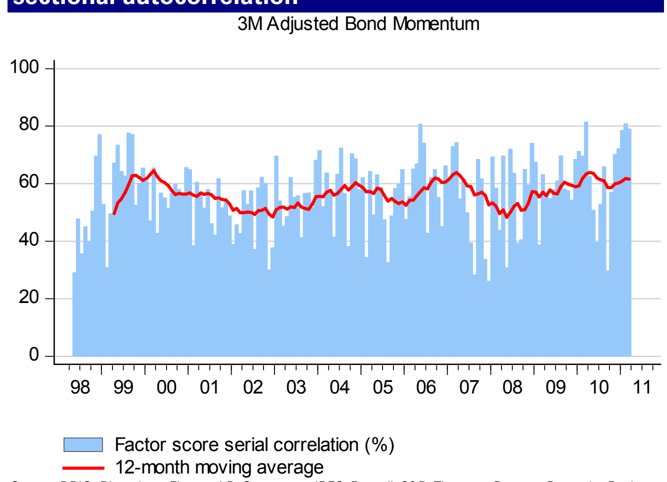
On the downside, the information decay in the factor is fairly quick at around three months (Figure 21). This means the factor will be at the higher end of the turnover spectrum; the autocorrelation of the factor over time is around 50%, as shown in Figure 22.

Figure 21: 3M Adjusted Bond Momentum, rank IC decay



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 22: 3M Adjusted Bond Momentum, cross-sectional autocorrelation



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

These results are very promising. However, questions remain. Perhaps the most important one is why the factor should work in the first place? Why should bond momentum, controlled for stock momentum, have predictive power for future stock returns? In the next section we scrutinize the characteristics of stocks that rate well on the factor, in the hope of better understanding the economic rationale behind the factor.

Digging deeper

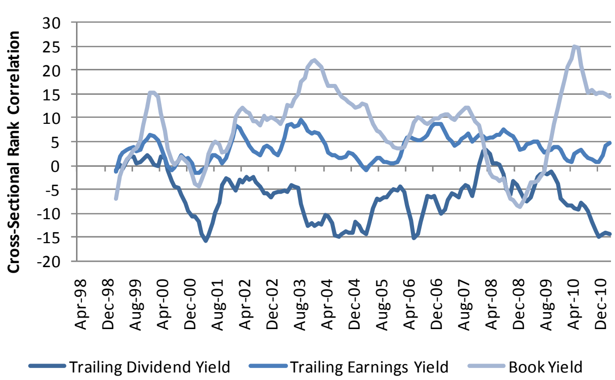
What type of stocks are we buying?

We need to understand what kind of stocks the ABM factor favors

What does a stock that has good adjusted bond momentum actually look like? We know such a stock has debt that has outperformed relative to what we would expect given its corresponding stock momentum. But what are the fundamental characteristics of these stocks? One way to visualize this is to plot the exposure of the factor to other factors. At each point in time, we can measure the cross-sectional rank correlation between our 3-month ABM factor and other common quant factors.

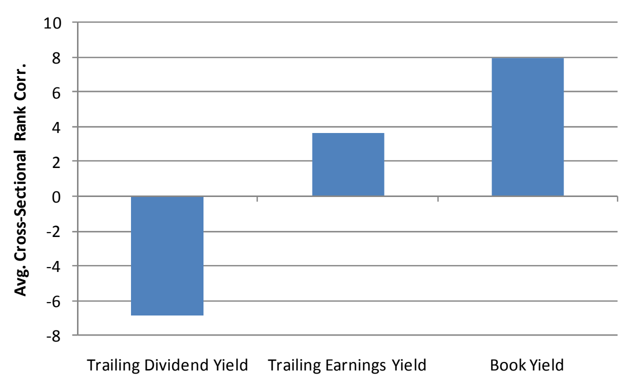
Figure 23 shows the results for a set of representative Value factors over time, while Figure 24 shows the average of these exposures in the long run. The interesting conclusion is that on average stocks with good ABM tend to be low dividend yield stocks that are cheap on common valuation ratios like earnings yield and book yield.

Figure 23: Value exposures, time-series



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

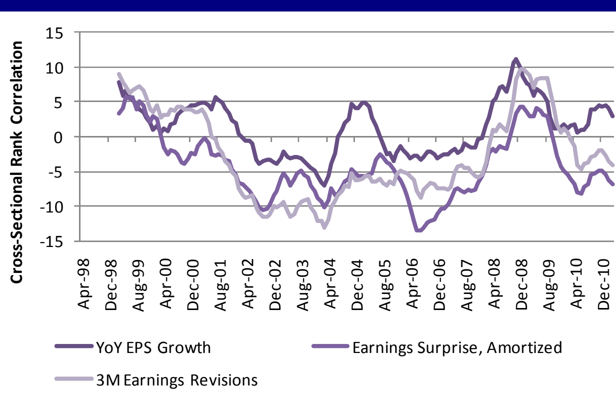
Figure 24: Value exposures, long-term average



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

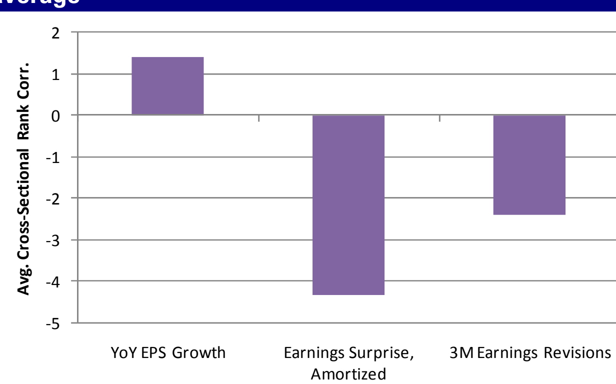
We can repeat the exercise for Growth and Sentiment factors (Figure 25 and Figure 26). It turns out that ABM loads up on stocks with negative earnings surprises and negative analyst earnings revisions.

Figure 25: Growth & Sentiment exposures, time-series



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

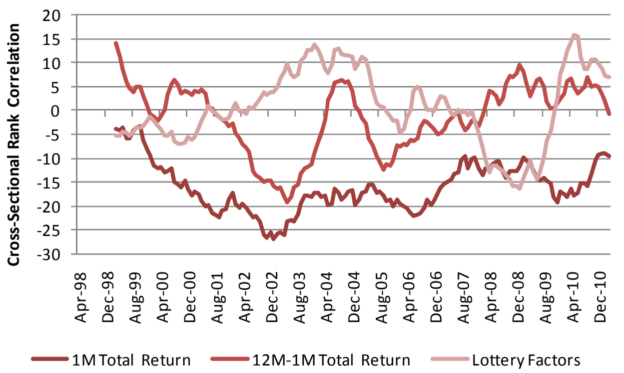
Figure 26: Growth & Sentiment exposures, long-term average



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

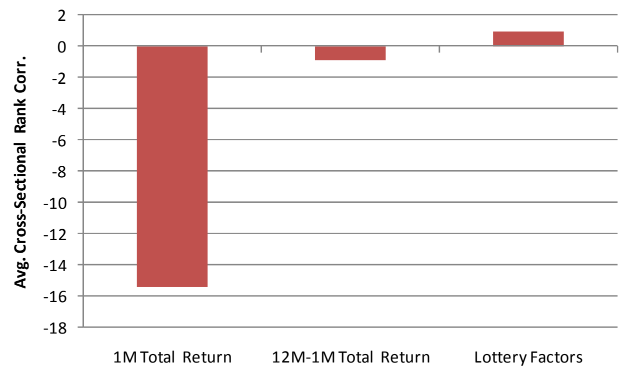
In terms of Momentum/Reversal, the biggest correlation is a negative exposure to past 1-month stock returns. In other words, buying stocks with good ABM on average means buying stocks that have underperformed in the last month, so the factor is picking up on something of a reversal effect.

Figure 27: Momentum/Reversal exposures, time-series



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

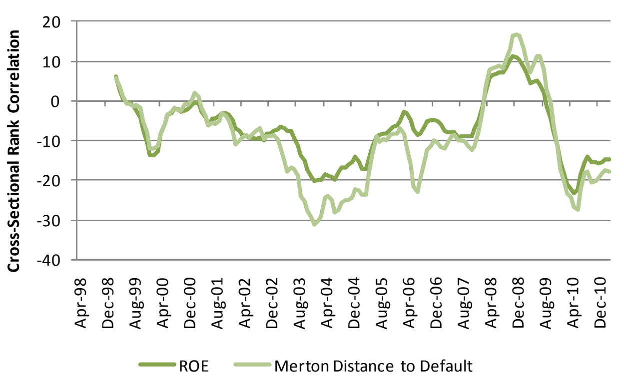
Figure 28: Momentum/Reversal exposures, long-term average



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

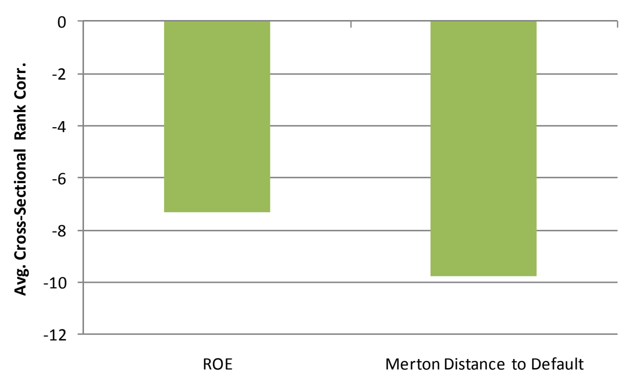
The ABM factor is also taking a strong negative exposure to Quality (Figure 30), both in terms of operating performance (measured as ROE) as well as risk of default (using the Merton model). The only exception was through the credit crisis, where the factor rotated towards a positive exposure to quality (Figure 29).

Figure 29: Quality exposures, time-series



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

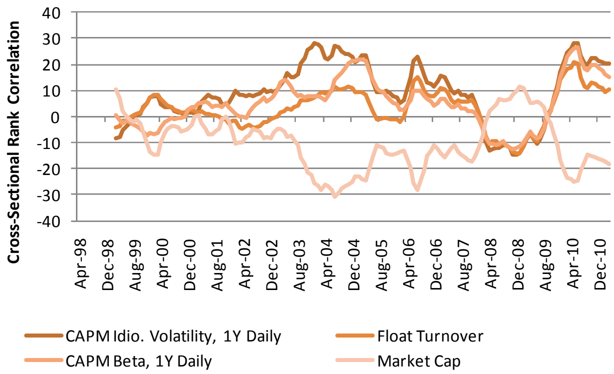
Figure 30: Quality exposures, long-term average



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

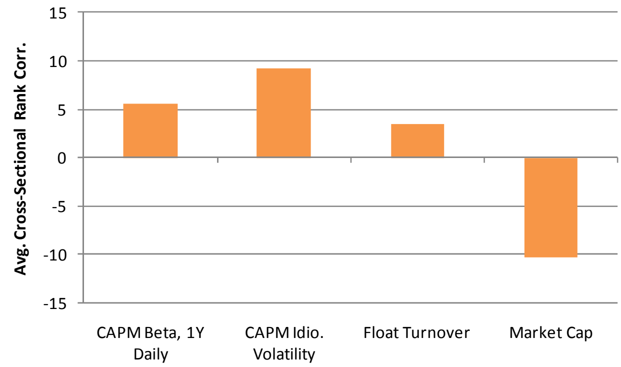
Figure 31 and Figure 32 show the time-series and long-term average exposure to Technical factors. On average the ABM factor is buying more volatile, higher beta stocks. It also tends to favor small cap stocks over large caps, on average.

Figure 31: Technicals exposures, time-series



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 32: Technicals exposures, long-term average



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

It turns out the factor takes a positive position on lower quality stocks, or what we might call "value trap" stocks

Overall the exposure analysis leads to a surprising conclusion: on average the adjusted bond momentum factor is buying small cap value stocks with low dividend yield, negative earnings revisions and surprises, short-term underperformance, weak operating performance, high risk of default, and high volatility. In fact, apart from the positive exposure to value, these would be the type of stocks that almost every quant model would be avoiding, not buying! Furthermore, the ABM factor is so contrarian that we might call it an "anti-quant" factor; it favors stocks that most quant models would do everything possible to avoid.

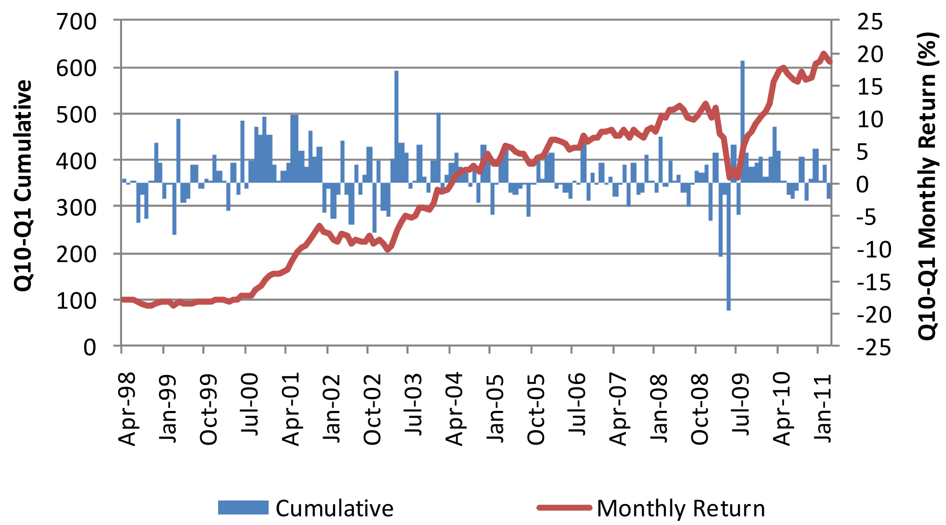
However, the intriguing result is that the factor actually generates positive performance, despite loading up on what most would term "value trap" stocks. This suggests a powerful idea: perhaps the bond market is giving us an early warning for when these types of stocks are starting to turn around. Intuitively this makes sense – bond investors are asymmetrically focused on downside risk (i.e. the risk of default), so it does make sense that they may anticipate a turnaround story and re-rate the company's debt before equity investors jump on board. The negative loading on short-term returns also supports this thesis. Stocks which the ABM factor likes have just underperformed in the most recent month, so the factor does becomes positive on stocks before the stock return momentum becomes positive, which is the time when more traditional quant models would get on board.

The paradox of the junk rally

Despite the "value trap" exposure the factor did poorly in the 2009 junk rally; we need to understand why

Unfortunately, there is one major flaw with the hypothesis that the adjusted bond momentum factor is a good turnaround signal: the junk rally in March – May 2009. If our factor is really working as we hope, then the factor should have performed very well over this period, since presumably it would have positioned us well for the rally. But as Figure 33 shows, the factor actually had a massive drawdown in the junk rally months; a simple portfolio that goes long decile 10 and short decile 1 would have lost over 30% of its value in the space of three months. This suggests that calling the ABM factor a turnaround indicator is a little too simplistic. We need to understand what really happened over the junk rally period, if we want to be confident we can use the factor going forward.

Figure 33: Performance of Q10-Q1 portfolio formed on 3M Adjusted Bond Momentum



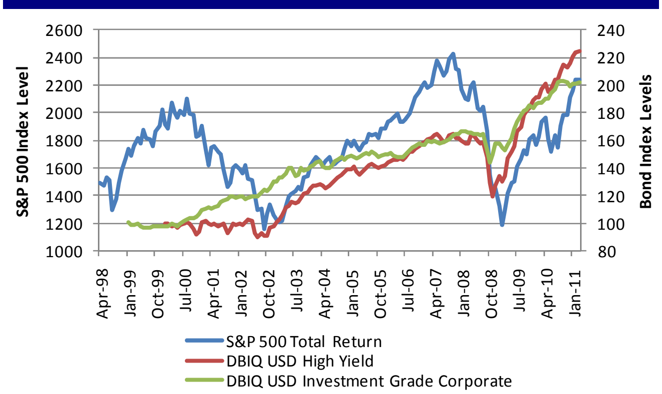
Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Coming out of the crisis, investment grade credit rallied first, followed by high yield credit, and then finally equities

We start our analysis by looking at the relative performance of bonds and stocks around the junk rally. In Figure 34 we show the S&P 500 index performance along with the performance of investment grade and high yield corporate debt. Interestingly we see that the first index to recover out of the crisis was investment grade credit, followed by high yield debt, and then finally the equity market a few months later. At first glance, this would seem to support the turnaround story – bonds did indeed give an early indication of where the equity market was going, so why the extreme underperformance of the ABM factor?

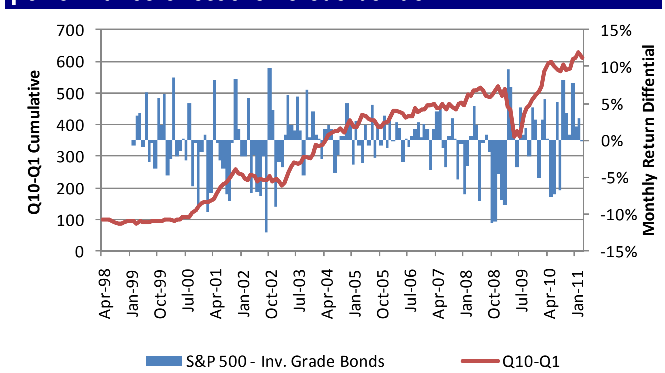
In Figure 35 we try to answer this be showing the factor performance overlaid with the relative performance of equities versus debt. Unfortunately this does not really clear things up, because it turns out there is little correlation between the factor performance and the relative performance of equity versus debt at an asset class level. In other words, the factor performance is not tied to whether debt or equity is outperforming as an asset class.

Figure 34: Stock versus bond performance



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

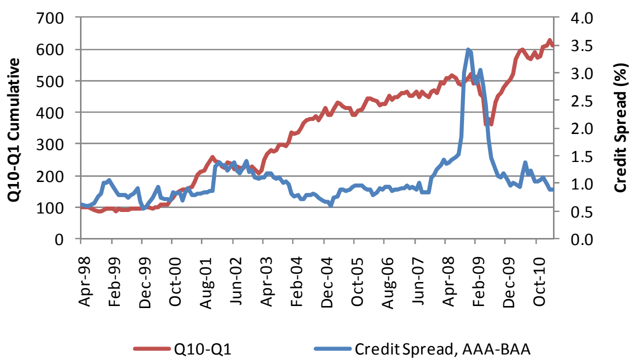
Figure 35: Factor performance versus relative performance of stocks versus bonds



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

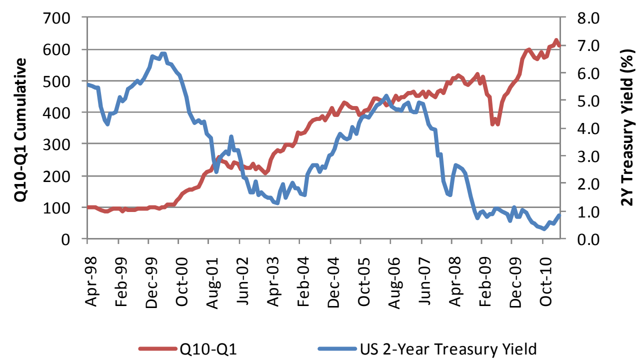
In Figure 36 and Figure 37 we plot similar charts, looking at the performance of the factor compared to credit spreads and Treasury yields respectively. The first chart does suggest the factor had its major drawdown when credit spreads collapsed as the market re-risked out of the credit crisis. On the other hand, the second chart shows there was little relationship between Treasury yields and the factor's junk rally drawdown.

Figure 36: Factor performance versus credit spreads



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 37: Factor performance versus 2Y Treasury yield

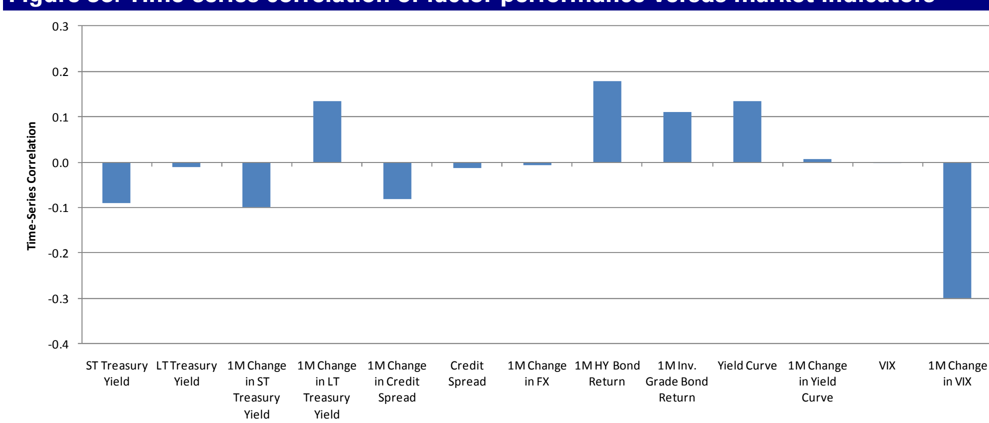


Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

The performance of the ABM factor is relatively independent of the underlying market and interest rate environment

If we expand this type of analysis to a whole host of potential explanatory variables (Figure 38), we find that none of the variables we considered have a particularly high correlation with the performance of the ABM factor. The biggest absolute correlation is a negative 30% correlation with 1-month changes in the VIX index. This implies the factor actually does better when market-wide risk is rising and poorly when risk is falling (like it did in the junk rally).

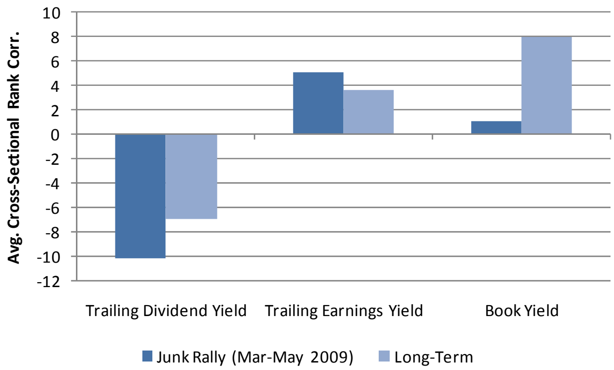
Figure 38: Time-series correlation of factor performance versus market indicators



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

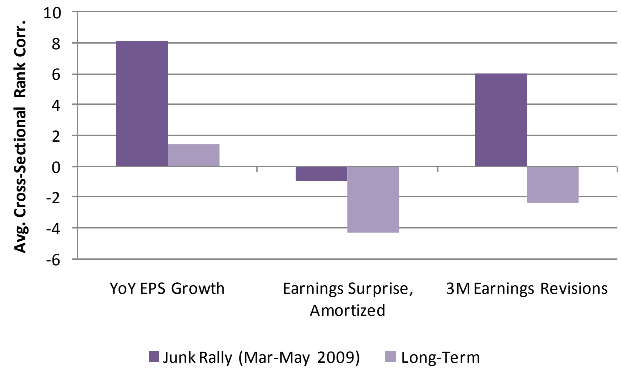
However, these results do not really give us a satisfactory economic reason for the severe underperformance of the factor. The correlations are interesting, but we really need to understand cause and effect if we are going to have confidence in the factor. With that in mind, we return to the exposure analysis that we conducted before, except this time we also show separately the average exposure during the junk rally (see Figure 39 to Figure 43, below).

Figure 39: Value exposures



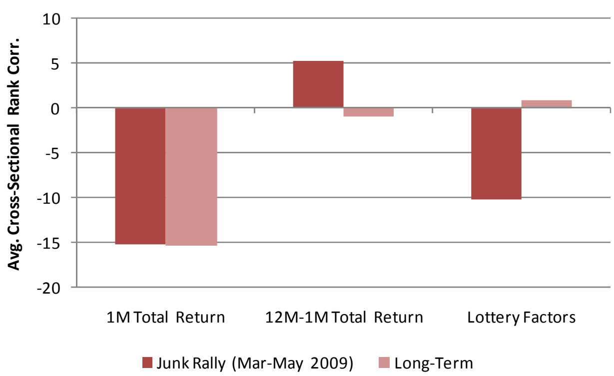
Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 40: Growth & Sentiment exposures



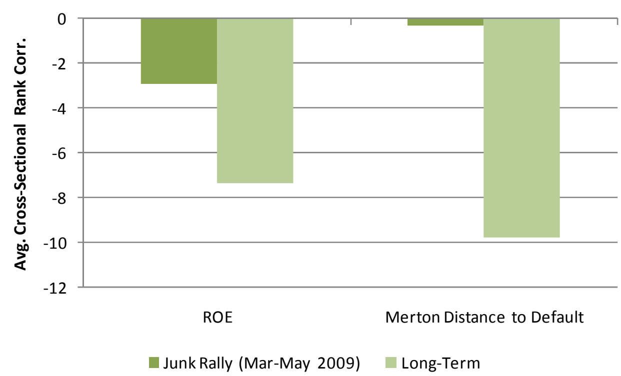
Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 41: Momentum/Reversal exposures



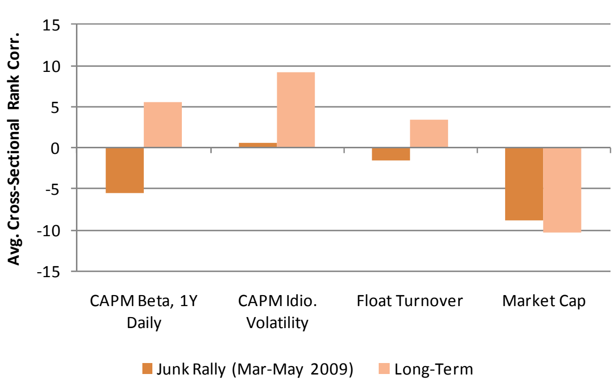
Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 42: Quality exposures



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 43: Technicals exposures



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

The real reason the factor underperformed is because it rotated into quality at precisely the wrong time

The results are fascinating. It turns out that the ABM factor made a very pronounced rotation towards quality stocks through the junk rally. While the factor is on average an anti-quant bet, through the junk rally period the factor rotated towards stocks with better earnings growth prospects, positive earnings revisions, better ROE, and lower default risk. It also shifted away from high beta and high volatility stocks, and pulled back on its small cap exposure.

This rotation towards safer, low beta, large cap, quality stocks is the real driver of the severe underperformance through the junk rally; the factor could not have picked a worse time to move away from its normal anti-quant exposure than this three month period. Had the factor maintained its normal value trap positioning, it would have performed spectacularly well in the three months from March – May 2009 instead of having its worse drawdown in ten years.

This rotation happened because in the debt world "quality" recovered first, but in the equity world "junk" rallied hard

Of course, the next question is: why did the factor move away from its normal exposures over that short time-frame? It turns out the answer was already at our fingertips back in Figure 34. In that chart we saw that it was investment grade credit that recovered first, followed by high yield credit, and finally equities. It turns out that in the bond market, it was actually "quality" that recovered first, but in the stock market the opposite happened -- "junk" recovered first. The ABM factor was favoring stocks with high quality, investment grade debt at a time when the equity market was favoring the most beaten down, low quality stocks. This disconnect was the root cause of the severe drawdown the factor experienced through this period.

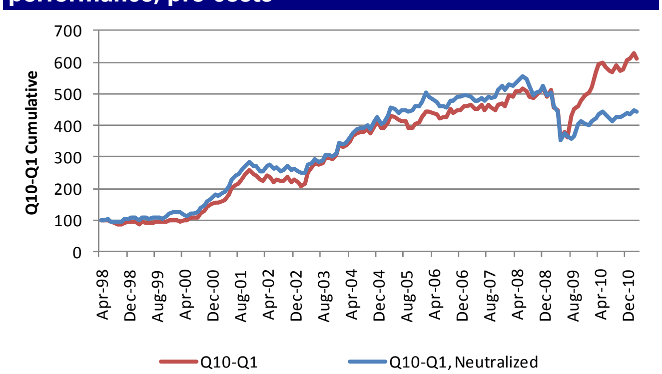
Potential improvement 1: Factor neutralization

A test whether removing the cross-sectional exposure to volatility in the factor would have helped; the results suggest the answer is no

Is there any way we can mitigate the factor performance to this type of turning point? One potential solution is a technique we call factor neutralization. In our past research, we showed that most quant factors have an inherent exposure to volatility, and that this exposure can lead to dramatic reversals in factor performance at turning points in risk appetite, such as the 2009 junk rally (see Luo et al. [2010b]). This is certainly the case with the adjusted bond momentum factor – in Figure 31 we saw the factor has a consistent positive tilt towards volatility over time.

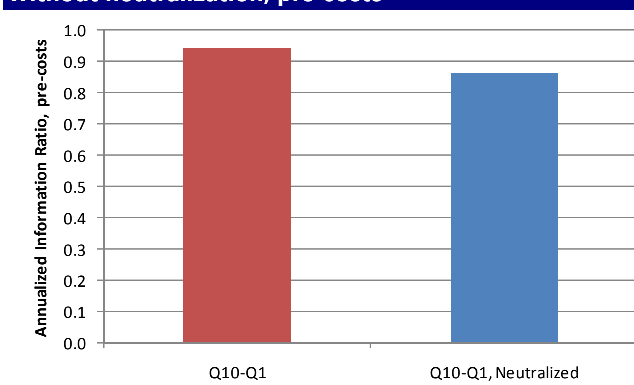
Unfortunately, in this instance neutralization does not help very much. Figure 44 and Figure 45 show the time-series and risk-adjusted performance of the factor, with and without neutralization. It turns out neutralization actually hurts the performance of the factor in the long run.

Figure 44: Neutralized versus non-neutralized performance, pre-costs



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 45: Annualized information ratio with and without neutralization, pre-costs



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

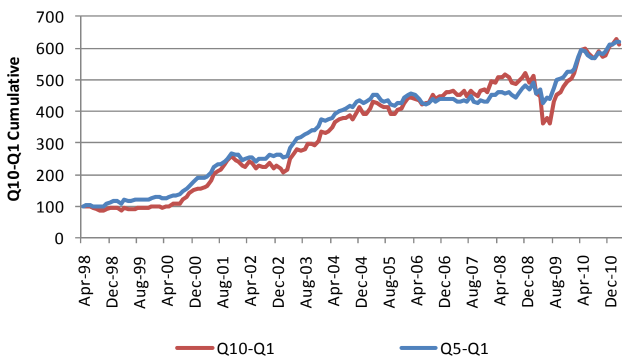
Potential improvement 2: Better diversification

Simply increasing the diversification of the implementation was a better way to mitigate the large drawdown

A second obvious, but surprisingly effective, improvement is to seek better diversification. In the previous analysis we focused on simple decile portfolios. However, given the size of the universe (only around 500 stocks) these decile portfolios are actually quite concentrated by quant standards, since the long and short portfolios have only around 50 stocks each.

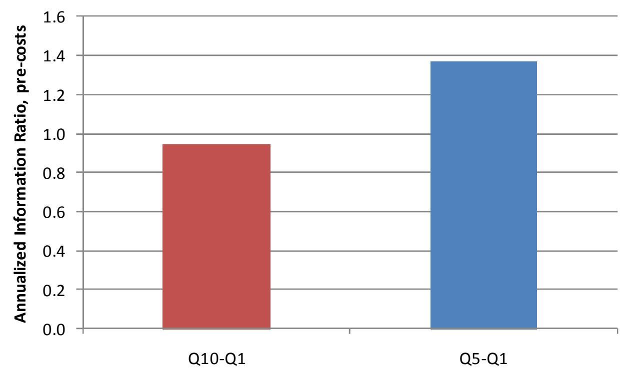
If we use quintile portfolios instead of deciles, the drawdown is less severe (Figure 46) and the risk-adjusted performance (Figure 47) is substantially improved. Later on, in the final section of this report, we will continue this analysis by examining a more real-world portfolio simulation with realistic costs and institutional constraints.

Figure 46: Deciles versus quintiles performance, pre-costs



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 47: Annualized information ratio using deciles and quintiles, pre-costs



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Broadening the universe

Can we overcome the limited breadth?

One of the limitations of the bond database we are using is the limited breadth. While our backtesting suggests there is enough breadth to generate quite promising performance, one of the key questions is whether we can extend the factor to cover the whole universe. In this section we examine two potential solutions to this problem.

Idea 1: Factor replication

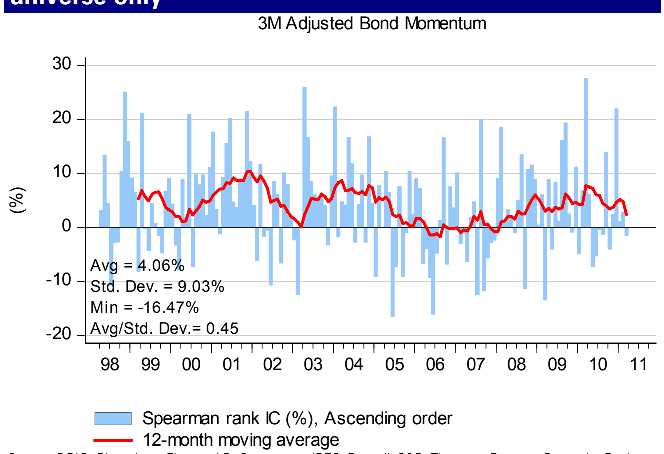
Can we use a linear combination of existing quant factors to extrapolate the factor to those stocks without bond data?

Our first idea is borrowed from the large body of literature on hedge fund replication. In that field of study, the goal is to try to replicate the returns of hedge funds through a systematic factor-timing approach. The rationale is that a significant portion of hedge fund returns come from exposures to underlying factors, and that by uncovering these exposures and replicating them, one can capture a portion of hedge fund alpha at a much lower cost.

In our case, we are applying the same idea to our ABM factor. As we saw in our exposure analysis, the bond factor loads up on common quant factors in a time-varying way. Suppose at each point we first take the universe of stocks for which we have bond data, and project (i.e. regress) the ABM factor onto our common factors cross-sectionally. In other words, we are saying that our bond factor can be approximated as a linear combination of our common quant factors. Then, for stocks where we don't have bond data, we can approximate the bond factor by using the linear combination of common factors that we uncovered using the subset of stocks that do have bond data.[5] This is also similar to a statistical technique for filling in missing data called multiple imputation.

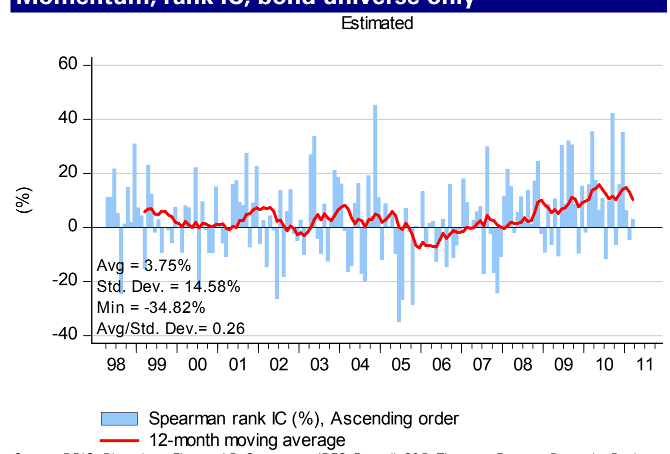
In the charts below we try this idea. First, Figure 48 reprises the performance of the ABM factor purely for comparison purposes. Next, Figure 49 shows the performance of our regression estimated bond factor, *within the universe of stocks that have bond data*.

Figure 48: 3M Adjusted Bond Momentum, rank IC, bond universe only



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 49: Regression estimated 3M Adjusted Bond Momentum, rank IC, bond universe only



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

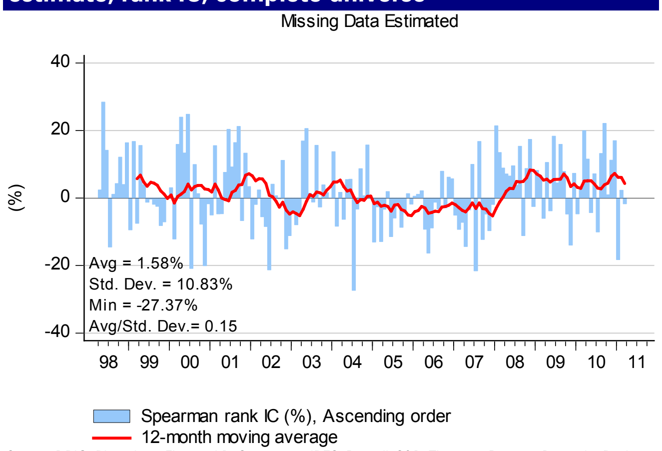
[5] We thank our colleague Khoi Le Binh from our Asian quant team for this excellent suggestion.

The results so far are interesting. Within the universe of stocks that have bonds, we destroy most of the performance of the factor, on a risk-adjusted basis, when we approximate it using a time-varying linear combination of common factors instead of the factor itself. However, this is not that surprising. Of course we will do worse within the bond universe if we throw out the actual bond data and use the linear combination instead.

We find we lose too much information when we try to extrapolate ABM to stocks without data

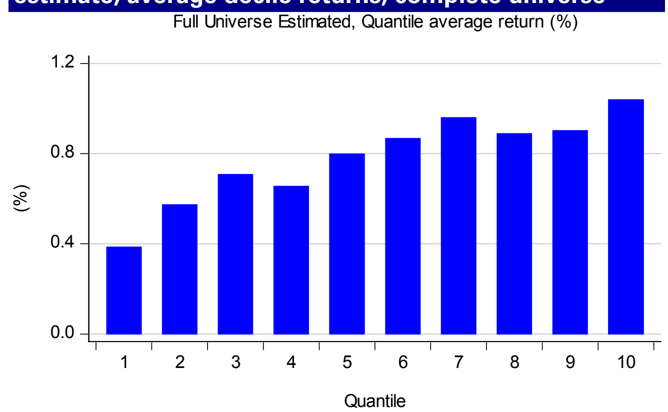
The real test comes in Figure 50 and Figure 51. Here we use the ABM where it is available, *but for stocks with no bond data we fill in the missing scores using the linear combination instead*. Recall the linear combination is estimated by cross-sectionally regressing the bond factor onto the common factors at each point in time So for stocks without bond data, we are effectively saying that perhaps the bond factor does a good job at timing the exposures to common factors. Unfortunately this does not appear to the case. The performance of this hybrid factor over the whole universe is merely adequate.

Figure 50: Missing data filled in with regression estimate, rank IC, complete universe



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

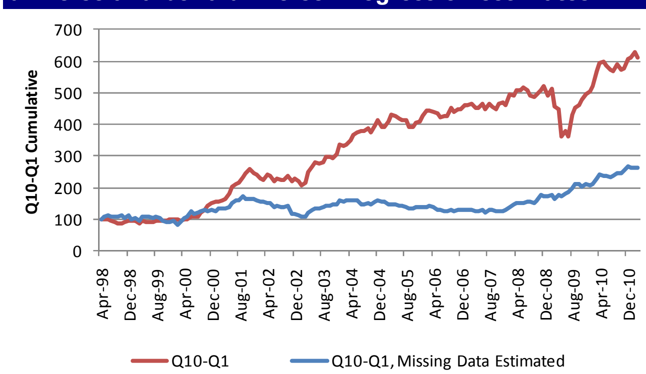
Figure 51: Missing data filled in with regression estimate, average decile returns, complete universe



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

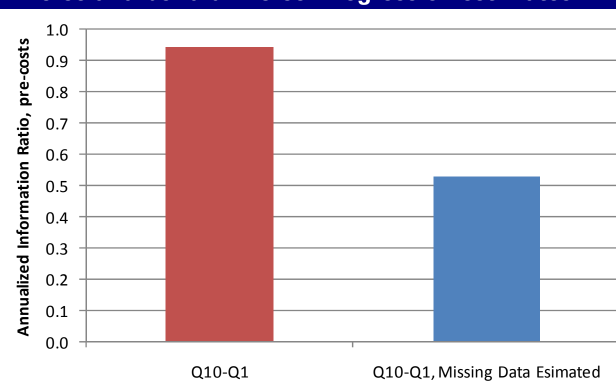
We can see the same result if we compare the performance of the bond factor within the universe of stocks with bonds, to the performance of the extrapolated factor in the whole universe (Figure 52 and Figure 53). Again, the evidence suggests that too much information is "lost in translation" when we try to extrapolate the factor out to stocks without bond data.

Figure 52: Cumulative Q10-Q1 performance for bond universe and bond universe + regression estimates



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 53: Annualized information ratio using bond universe and bond universe + regression estimates



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

At least the failure of this experiment suggests something positive: the new factor is not just a proxy for other known quant factors

On reflection, the fact that this approach does not work is actually quite heartening, because it lends further support to our hypothesis that the bond information is the key ingredient that helps time the entry point of value trap trades. Without the bond information, we are effectively just buying low quality companies, a strategy that of course fails to pay off over the long run.

Incidentally, this analysis has also accomplished the same thing that we normally do with our correlation analysis. Every time we propose a new factor in *Signal Processing*, we are always careful to examine the correlation of the new factor with common quant factors, to make sure that it is really capturing new information and is not just a combination of factors we already have in our model. Here we omit that standard section because we have just shown the same thing – the ABM factor is actually different from all our common factors, because it cannot be represented using a linear combination of the common factors.

Idea 2: Combining with an existing quant model

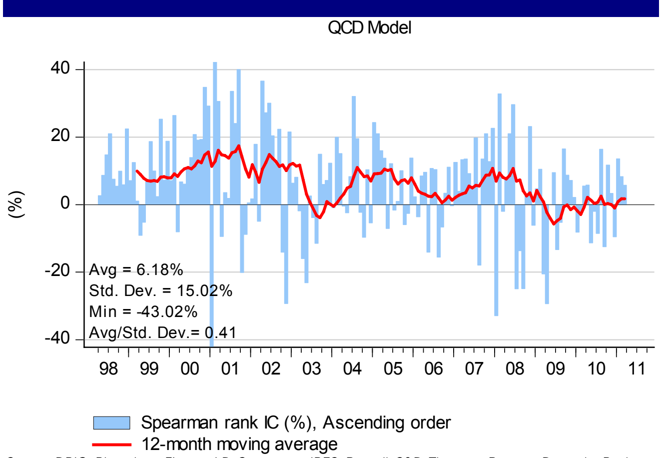
Our second idea for using the factor on a broader universe is much more traditional. Can we take the adjusted bond momentum factor and overlay it on top of an existing alpha model to add some incremental value?

To combine the factor with an existing model we have to be careful; on average the bond factor takes an anti-quant position

It turns out we can, but we need to be a little careful how we do so. The most common way to combine a new signal with an existing model is to add in the new factor as an additional factor in the multifactor alpha model. However, because the bond factor is effectively taking an anti-quant position, this does not make sense in this instance. On average, the existing model will probably be avoiding precisely the kind of low quality, high risk stocks that the bond factor wants to buy. Therefore, adding it linearly into an existing model risks diluting most of the potency of the factor, since the scores will just cancel out.

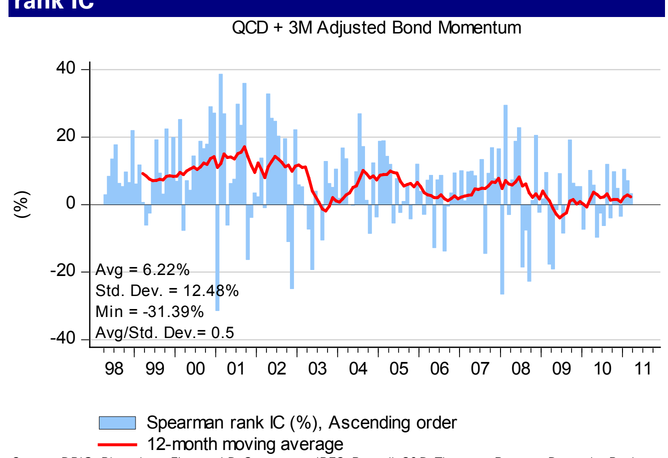
Instead, we follow a very simple approach. If we have bond data for a given stock, we use the ABM z-score as our alpha score; if the stock has no bond data then we use the score from our QCD model (our own in-house stock-selection model) instead. Figure 54 shows the original QCD model performance and Figure 55 shows the performance after adding in the bond factor. We see a significant improvement in risk-adjusted performance, which rises from 0.41 to 0.5. The maximum drawdown is also reduced substantially.

Figure 54: QCD model, rank IC



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

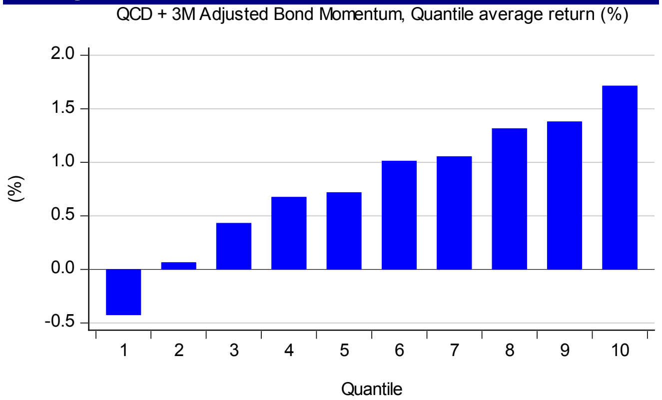
Figure 55: QCD model + 3M Adjusted Bond Momentum, rank IC



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

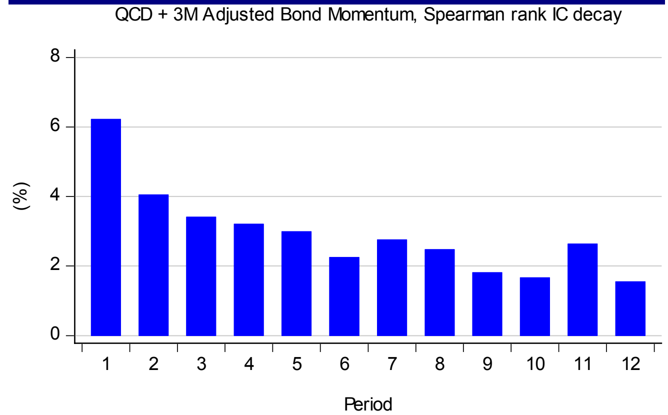
Other performance statistics also look attractive. The average decile returns of the integrated model are nicely monotonic (Figure 56) and the information decay rate is relatively slow, despite the fact the bond factor is a higher turnover factor (Figure 57).

Figure 56: QCD model + 3M Adjusted Bond Momentum, average decile returns



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 57: QCD model + 3M Adjusted Bond Momentum, information decay profile



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Overall, our results here suggest that there is incremental value-add to including bond data into a quant alpha model. In the next section, we check whether this value-add survives a more realistic portfolio simulation with transaction costs and real-world portfolio constraints.

Real world simulation

After cost performance in the presence of constraints

We conduct a realistic portfolio simulation to test if the performance survives transaction costs and real-world constraints

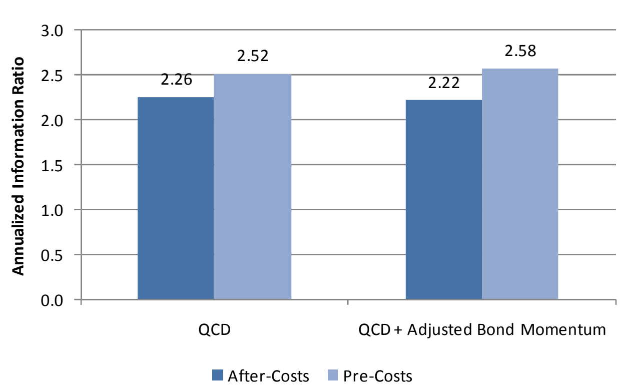
In this sector we conduct a more rigorous, real-world simulation of the adjusted bond momentum factor. In the first instance, we test the factor on a univariate basis, and then we test the factor in conjunction with our QCD model. For all the simulations, we use the Axioma portfolio optimizer to optimize a dollar neutral, long-short portfolio each month. We target a 3% risk level, and constrain turnover to no more than 30% per month one-way. We also use sector and beta neutrality constraints to ensure the portfolio is not taking unintended sector or market exposures. All results in this section are after transaction costs, where we assume 20 bps one-way linear costs (i.e. 40 bps for a round-trip rebalance).

Adjusted bond momentum factor + QCD model

As described in the previous section, we can integrate our bond factor into a generic quant model by replacing the generic alpha score with the bond factor score, for the subset of stocks where we have bond data. Figure 58 shows the information ratio, before and after costs, for both strategies over the entire backtest period. Figure 59 shows the same chart, except only for the last three years.

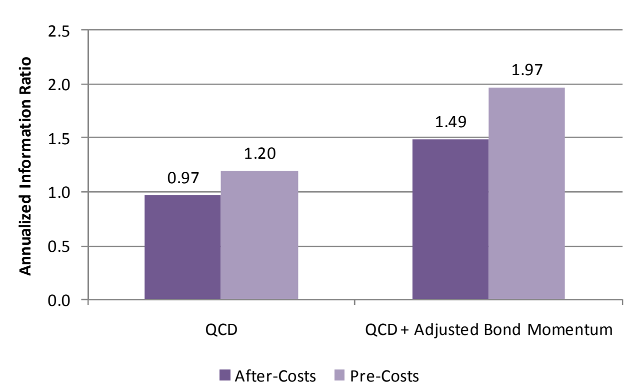
We find that in the long-run, adding the ABM factor to our QCD model does not change performance significantly. However, in more recent years the performance boost has been substantial, with the after-cost information ratio rising from 0.97 to 1.49 (a 54% improvement). This is consistent with what we have seen in many of our research projects. Over the long-run, the QCD model is hard to beat, but since 2007 the value-add from many of the new factors we have researched is substantial. This supports our view that many of the common quant factors – which form the foundation of most multifactor quant models – have suffered from arbitrage and an inhospitable macro environment since 2007. Under "normal" conditions a model like the QCD model can work very well, but in today's tough quant environment the addition of new factors makes a big difference.

Figure 58: Information ratio, 1998-present



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 59: Information ratio, last 3 years



Source: DBIQ, Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

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Appendix 1

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