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Investing in Corporate Credit Using Quantitative Tools

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Abstract

Corporate credit is an important investment class with potentially attractive returns. The asymmetric nature of corporate bond returns implies that investing in credit is not about picking "winners," but rather about avoiding "losers" (i.e., defaults and spreads blow-ups). Investors can utilize quantitative measures of credit risk to minimize the risk of such events.

This paper demonstrates how investors can use Moody's Analytics EDF™ (Expected Default Frequency) credit measures and fair-value spread (FVS) framework to minimize risk and exploit asset mispricing. We show that both investment grade and high yield portfolios constructed utilizing EDF measures and FVS criteria outperform their respective benchmarks, even after controlling for transaction costs.

Further, we develop portfolios consisting only of high yield bonds that outperform an investment grade index with less risk. We also show that portfolio weights significantly affect returns and risk trade-offs. While it is not the objective of this study to recommend specific investment strategies, our results suggest that quantitative metrics such as EDF measures and FVS can be used as powerful tools for investing in corporate credit.

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1 Overview

Corporate credit presents potentially attractive investment opportunities. For example, the cumulative returns of the Merrill Lynch corporate bond indices, both investment grade and high yield, are higher than those of the S&P 500 and the Dow Jones 30 during January 1990–January 2009. This is shown in Figure 1 and Figure 2, respectively.

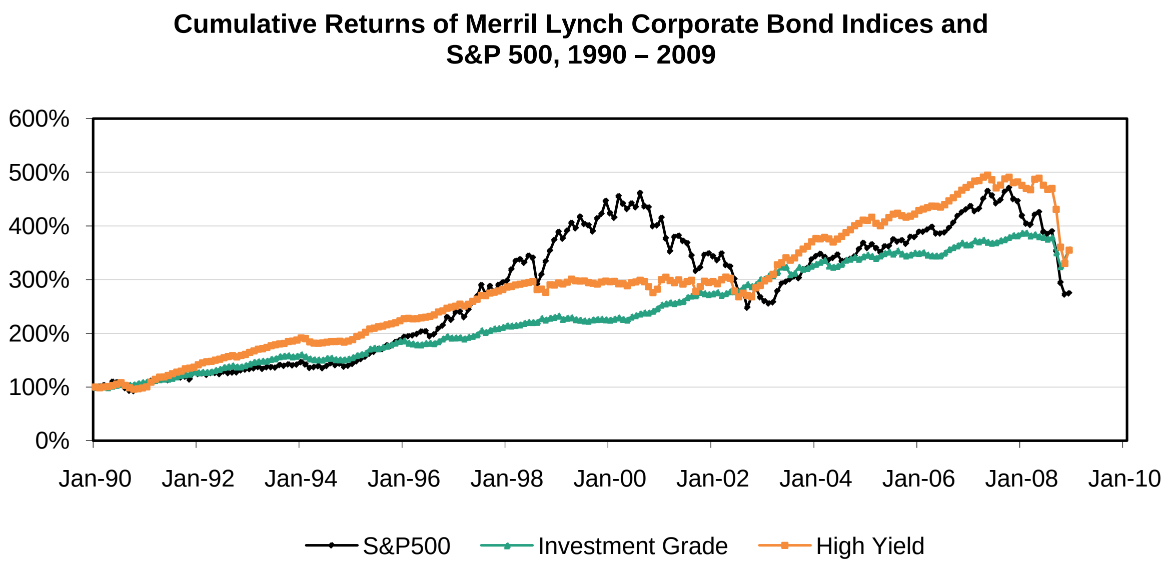

Figure 1 Cumulative returns of Merrill Lynch corporate bond indices and the S&P 500

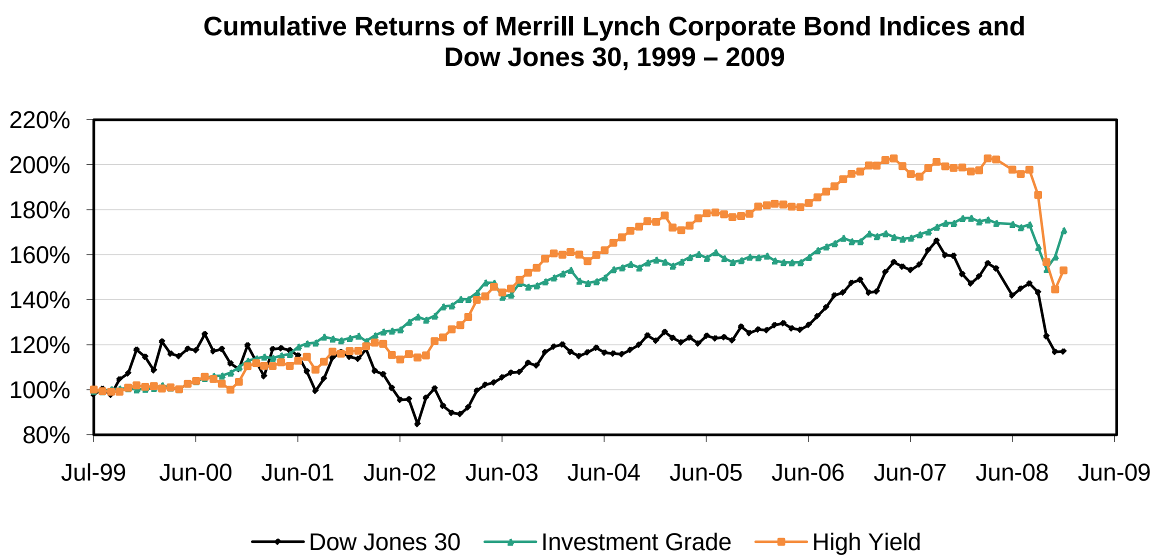

Figure 2 The cumulative returns of both the investment grade and high yield bond indices outperformed the Dow Jones 30 Index.

While a rigorous comparison of the risk-adjusted returns of equities versus corporate bonds falls beyond the scope of this paper, Figure 1 and Figure 2 remind us that corporate credit is an important and potentially attractive investment class.

Both equity and bonds represent claims on the underlying cash flows of the issuing firm, but their return distributions are quite different. In principle, an equity investor can lose everything, but potentially receive an unlimited upside. On the other hand, the best return a bondholder can achieve is the return of principal plus coupon, assuming the bond trades close to par. Distressed debt offers the possibility for high returns, but such issues perform more like equity because of their low prices relative to the principal and coupon. On the downside, a bondholder can lose both the principal and future coupons, minus the recovery. Because the downside is much more extreme, a number of positive returns followed by a large negative return can wipe out all previous gains. The different nature of equity and bond return distributions highlights an important difference in the investment approaches for each.

To illustrate this distinction, we conduct the following exercise:

1. Take the Merrill Lynch Investment Grade and High Yield indices.
2. Remove 10% of the bonds with the best and worst total returns each month.
3. Calculate the cumulative returns of the truncated indices.

We complete the same exercise using the Dow Jones 30 equity index.

Figure 3 and Figure 4 show that truncation results in higher cumulative returns for the investment grade index and the high yield index during July 1999–January 2009.

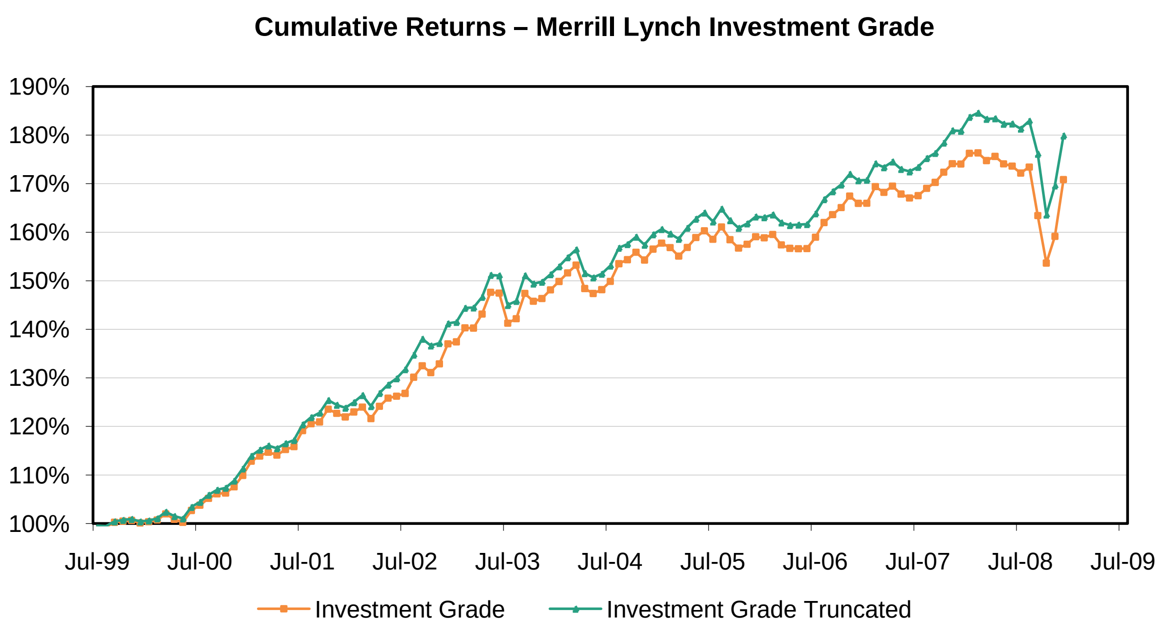

Figure 3 The truncated investment grade index achieves a higher cumulative return than the Original Index; the worst returns have a larger impact than the best returns.

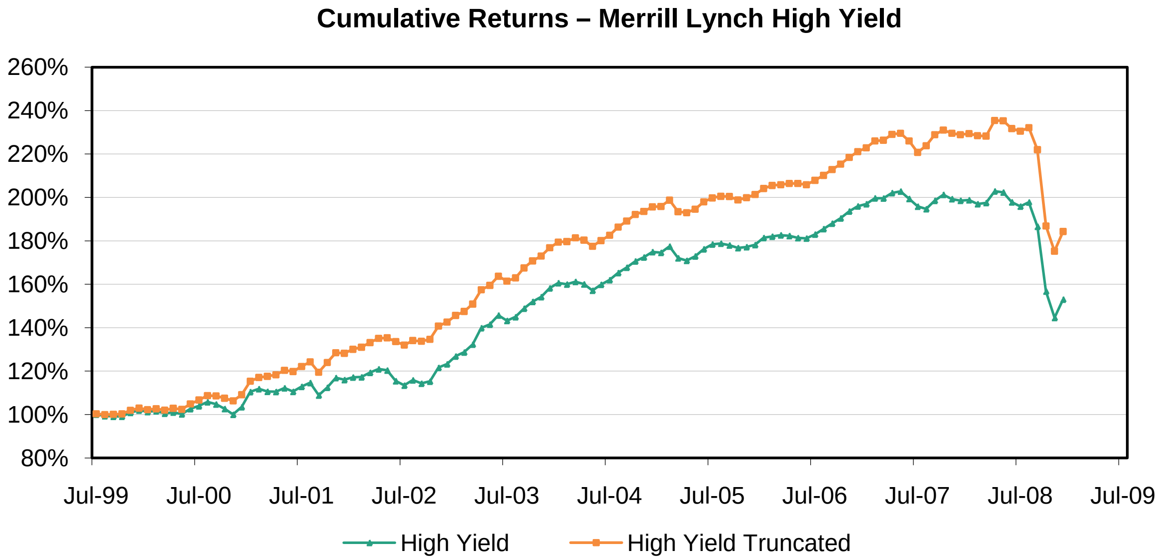

Figure 4 The truncated high yield index achieves a much higher cumulative return than the Original Index due to the reduction in downside.

It is worth mentioning that the difference is even more pronounced for the high yield index. In contrast, Figure 5 shows that the truncated stock index underperforms the Original Index during the same period.

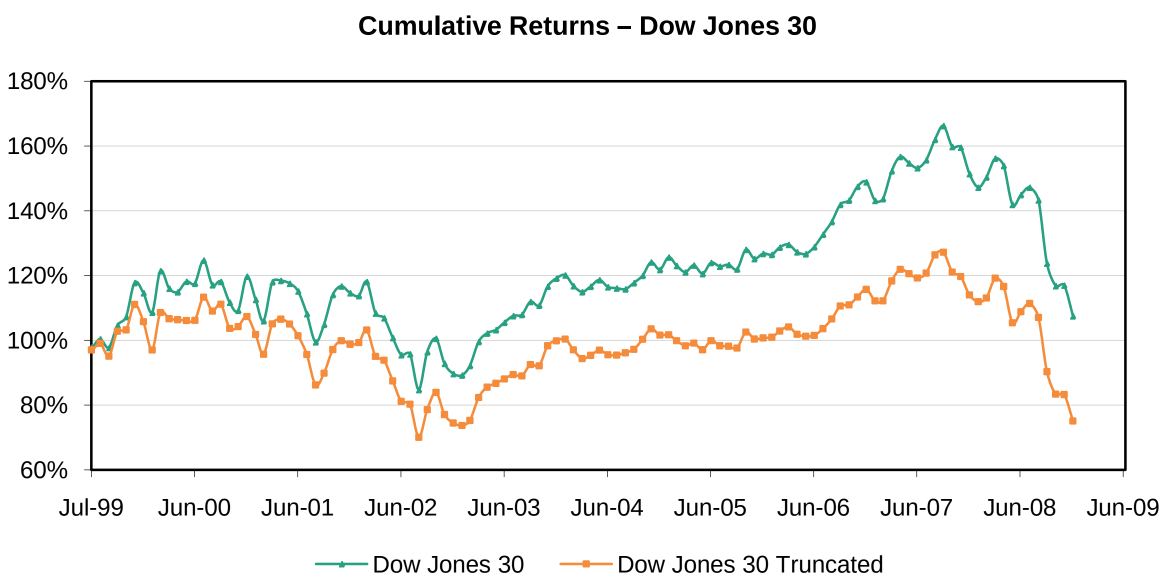

Figure 5 The truncated stock index has a lower cumulative return than the Original Index.

This particular study in itself is not an investment strategy, since it is not possible to pinpoint the worst performers *ex ante*. Rather, our work illustrates the characteristics of the return distributions and the implications of investing in these asset classes. Unlike equity, investing in credit is not about picking "winners," but rather about avoiding "losers" (i.e., avoiding defaults and spreads blow-ups). Another implication is the importance of diversification in credit portfolios, because a few concentrated defaults can be extremely detrimental to a portfolio's performance.

To avoid defaults and spreads blow-ups, investors can conduct a fundamental analysis of a borrower's credit risk. An alternative and complementary approach is to utilize quantitative measures of credit risk. Our paper focuses on this subject. Specifically, we examine using Moody's Analytics EDF measures and fair-value spread (FVS) framework to add value when investing in corporate credits.

1.1 EDF Credit Measures and the FVS Framework

We apply EDF credit measures and use the FVS framework to construct portfolios with attractive return-risk trade-offs using bonds in the Merrill Lynch corporate bond indices. We show that EDF measures and FVS can help improve corporate credit portfolio performance by controlling for risk and/or exploiting relative value opportunities. Both investment grade and high yield portfolios constructed using EDF measures and FVS criteria outperform their respective benchmarks in multiple measures, including average annual return, standard deviation, and cumulative return over the long run, while controlling downside risk. We achieve superior performance by controlling for credit risk. Exploiting relative value opportunities offers the potential to add additional returns. These results hold true for both U.S. and European corporate bonds. Similar strategies can also be used to construct model portfolios consisting only of high yield bonds that outperform an investment grade index with the same multiple measures. Furthermore, these strategies performed well during the crisis period in 2007 and 2008. To make our exercise more realistic, we factor transaction costs into our study.

The EDF credit measure is calculated using a structural framework conceptually similar to the Black-Scholes-Merton (BSM) framework.[1] Moody's Analytics implements the Vasicek-Kealhofer (VK) version of this model to calculate the EDF credit measure.[2] Over the past two decades, the EDF credit measure has become the *de facto* standard for market-based quantitative measurement of default risk and has proved to be a powerful and forward-looking indicator of corporate defaults.[3] Beyond predicting defaults, another important application of any quantitative credit risk measure is valuing credit instruments such as corporate bonds, loans, and credit derivatives. Moody's Analytics FVS framework represents such an important application. With the EDF metric as the measure of default risk, the FVS framework incorporates recovery risk, market risk premium, term, and other drivers to derive a modeled spread for the instrument being valued.[4] This modeled spread can be compared with the observed spread, and the gap can be used as a relative value indicator in the investment process.

While the constructed portfolios show superior performance relative to their benchmarks, it is important to note that it is not our objective to recommend any specific investment strategy in this study. Our intention is to demonstrate that quantitative tools such as EDF measures and FVS can add value to the process of investing in corporate credit. In addition to fundamental analysis, portfolio managers and analysts can use these tools to screen for early warning, to identify problematic names and sectors, and to spot relative value opportunities.

[1] See Black and Scholes (1973), and Merton (1974) for modeling corporate liabilities.

[2] See Kealhofer (2003a) for details.

[3] See Miller (1998), Dwyer and Korablev (2007), and Korablev and Qu (2009).

[4] See Appendix A for the details of the framework.

2 Data

Before we discuss how we construct these portfolios, we first present our data sources. We use Merrill Lynch (ML) U.S. bond indices (investment grade and high yield) as starting points.[5] We focus on the traded universe to make the exercises as realistic as possible. Below, we introduce the data, benchmark construction, and return calculations.

2.1 Data Sources

The Merrill Lynch U.S. Investment Grade Bond Index (C0A0) tracks the performance of dollar-denominated corporate bonds issued in the U.S. that have these characteristics.

- An investment grade rating (based on Moody's or S&P)
- At least one year remaining term to maturity
- Fixed coupon schedule
- Minimum amount outstanding of $150 million before 2005 and $250 million after 2005

The Merrill Lynch U.S. High Yield Bond Index (H0A0) tracks the performance of dollar-denominated corporate bonds issued in the U.S. that have these characteristics.

- Below investment grade rating (based on Moody's or S&P)
- At least one year remaining term to maturity
- Fixed coupon schedule
- Minimum amount outstanding of $100 million

We include bonds from the original Merrill Lynch Investment Grade corporate bond indices in the investment pool if they satisfy the following conditions.

- The issuer of the bond is a publicly traded company with an EDF credit measure.
- The bond pays a fixed coupon and has no special features, i.e., is not convertible, put-able, etc.
- The bond has been traded recently, according to CAI (Capital Access International) or TRACE dataset.
- We filter out issues with these potential data errors:
    - Bonds with extremely low prices compared to bonds with the same rating.
    - Bonds with extremely high EDF measures compared to bonds with the same rating.

We define the *Pseudo Index* as the market value-weighted average of bonds in the above investment pool. Likewise, a high yield pool and a Pseudo Index of high yield bonds are constructed from the Merrill Lynch High Yield Corporate Bond Index. Figure 6 and Figure 7 show the differences in the number of bonds between the Pseudo Indices and the respective original indices. These graphs show that the investment pool universe remains reasonably large after data filtering. As shown in Figure 8 and Figure 9, the Pseudo Indices have either comparable or better cumulative returns than their respective original indices during 1999–2009.

To avoid potential survivorship bias, defaulted bonds remain unfiltered until time of default. For example, the Pseudo Index includes WorldCom during the early period. If a bond defaults before delisting from the Merrill Lynch index, then its price post-default already reflects the loss and is used to calculate its return. Since we calculate returns based on price, a defaulted bond would simply have a very low price (and a negative return). If a bond in the ML indices defaults, the bond's history before default is not deleted from the database. If a bond defaulted before the month we form the portfolio, we retain the bond's history until the point at which it defaulted, or when its EDF measure ends because its equity is delisted. We then calculate the returns accordingly. If we know a bond is in default when forming our portfolio, we exclude it during the subsequent analysis.

[5] We present data sources, analyses, and results for European bonds in Appendix B.

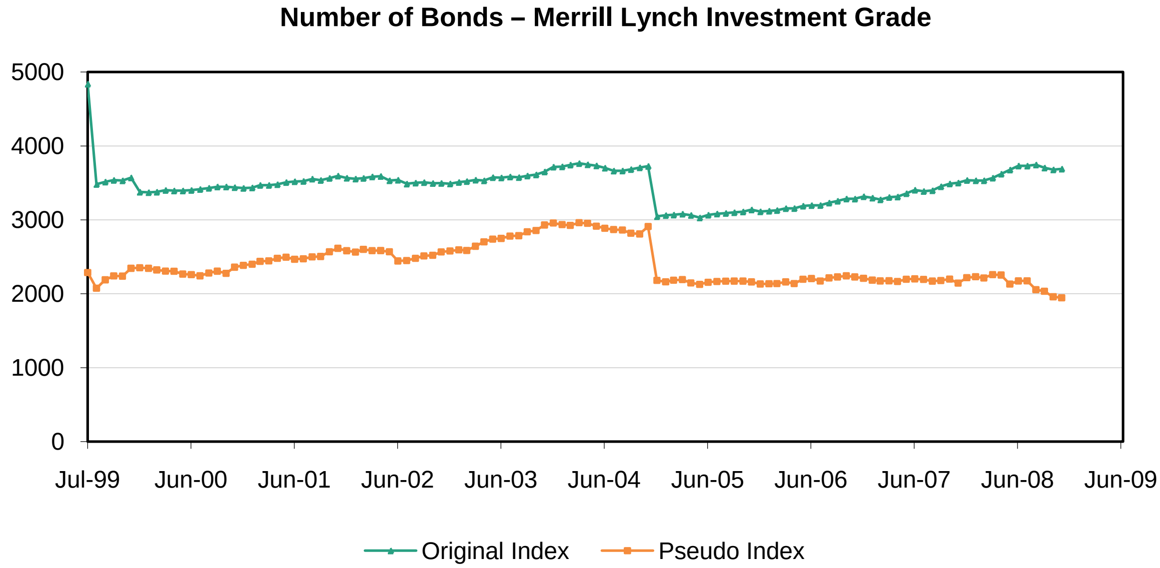

Figure 6 Difference in the number of bonds between the Original Index and Pseudo Index, investment grade.

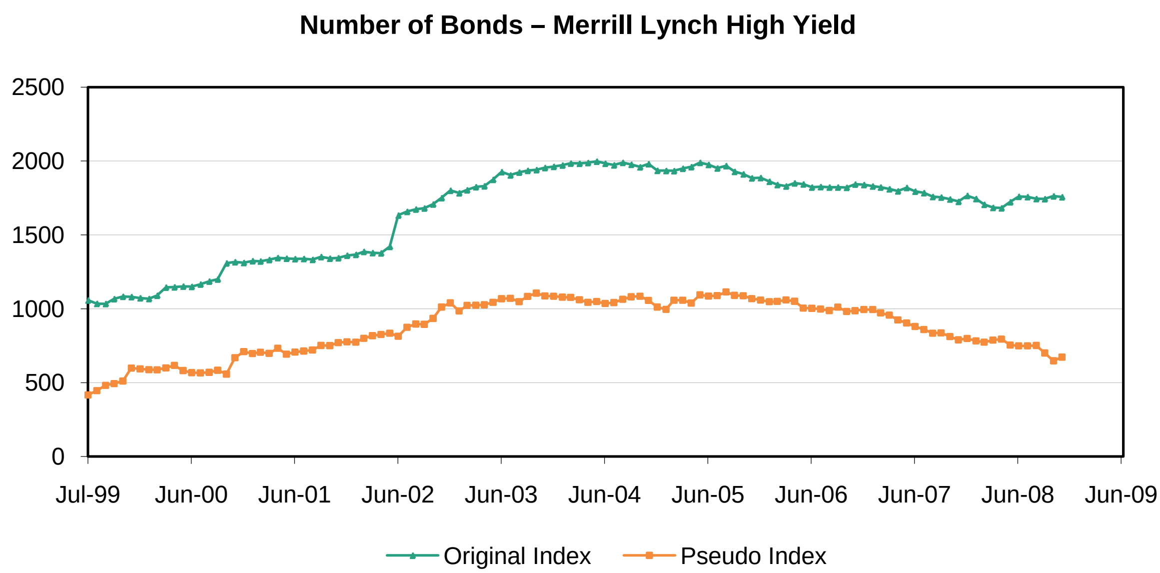

Figure 7 Difference in the number of bonds between Original Index and Pseudo Index, high yield.

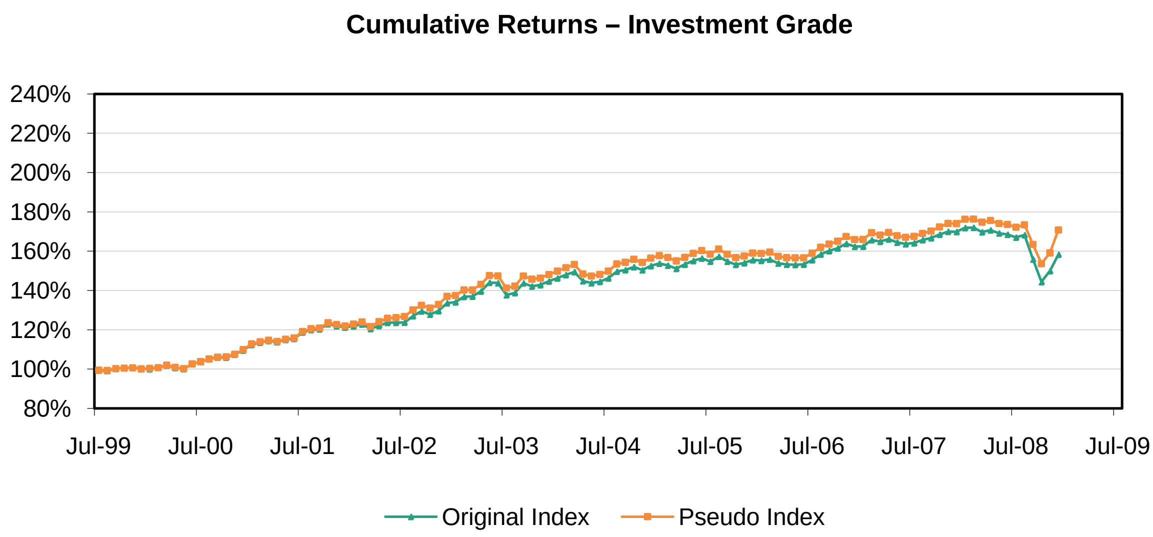

Figure 8 Investment grade cumulative total returns, Original Index and Pseudo Index, 1999–2009.

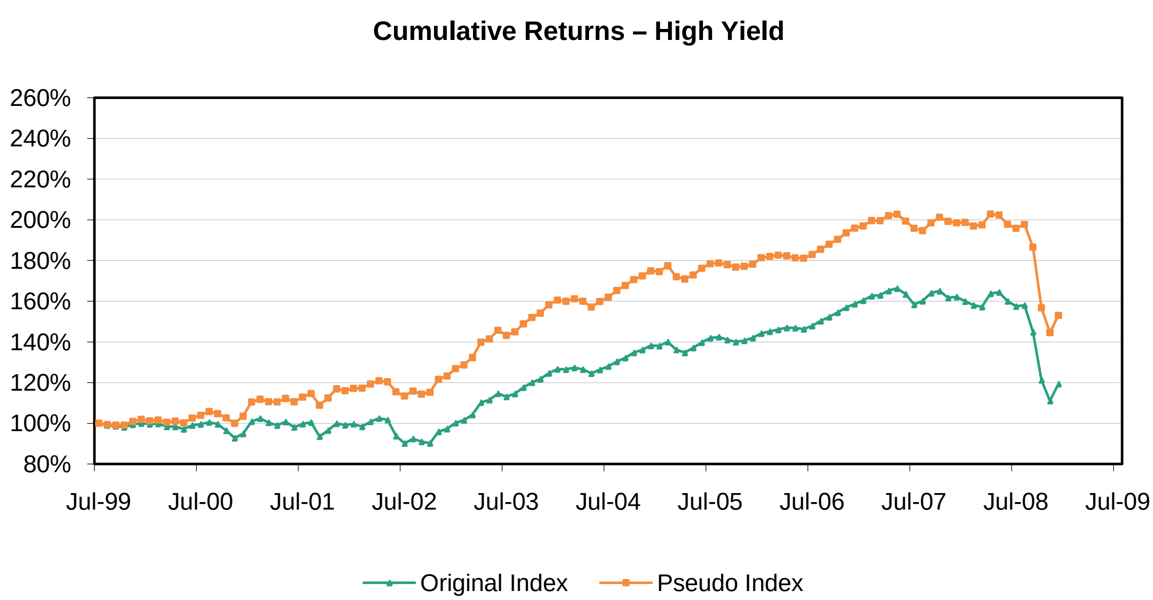

Figure 9 High yield cumulative total returns, Original Index and Pseudo Index, 1999–2009.

3 Using EDF Credit Measures and FVS in Corporate Bond Investment

In this section, we show how to use EDF credit measures and the FVS framework to construct corporate bond portfolios with attractive risk and return trade-offs.

3.1 Constructing Portfolios that Outperform Benchmarks

We first define the investment strategies and then present performance.

3.1.1 Investment Strategies

The basic intuition behind the investment strategies is straightforward: overweight bonds with attractive spreads relative to their credit risk (as expressed by the issuers' EDF measures), which creates a good compromise between "actively" over-weighting certain bonds, while minimizing transaction costs.

In order to achieve this basic setup, we utilize our measure of default risk and relative value. For default risk, we employ EDF credit measures. For relative value, we use fair-value spreads.

Defining the investment strategies and detailing portfolio construction

As shown in the following steps, we first define the risk- and valuation-based strategies, and then detail portfolio construction.

1. Define the strategies: risk-based and valuation-based. The risk-based strategy defines bonds' attractiveness in terms of their spread per unit of expected loss, calculated using EDF measures and loss given default (LGD). For notational purposes, we denote this measure of "attractiveness" by "Gamma." We then construct portfolios using the Gamma values as inputs. For the Risk-based strategy, Gamma is defined by:

   Gamma=OAS/(EDF*LGD)

   The valuation-based strategy defines bonds' Gamma in terms of a bond's OAS spread in excess of its FVS, per unit of expected loss. For this strategy, Gamma is defined by:

   (OAS-FVS)/(EDF*LGD)

2. Rank bonds by their Gamma values. Divide all the bonds into 10 buckets with increasing Gamma values. The dividing points are percentiles of 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95%, 99%. Namely, place the bonds with the lower 1st percentile Gamma values into the first bucket, and then place the bonds with Gamma values between the lower 1st and 5th percentile into the second bucket (i.e. n=1), etc. To take a conservative investment approach and to achieve more robust results, we form larger buckets in the middle of the rankings and smaller buckets on the ends, as extreme values are more likely to be outliers.

3. Assign number n=0 to 9 to the 10 buckets. The larger n, the higher the Gamma values of the bonds inside the bucket. Thus, the bucket with n=0 contains bonds with the lowest Gammas (0-1% of the ranking), the bucket with n=2 contains bonds with the next lowest Gammas (2-5% of the ranking), and so on.

4. Define weighting control parameter c=1 to 19 with an increment of three.

5. Let the weight of the ith individual bond inside the bucket n be $m_{n,i} = n^c$. That is, raise n to the c-th power (a larger c means more weights toward bonds with a higher Gamma value). The total weight of a portfolio is:

$$S = \sum_{n=1}^{9} \sum_{i=1}^{T_n} m_{n,i} \tag{1}$$

   Where T_n is the total number of bonds in bucket n.

6. Normalize the weight for each bond to obtain its final weight, $w_{n,i} = m_{n,i} / S$. This step ensures the sum of the weights for the individual bonds adds up to 100%; or equally, we assume the dollar amount of the portfolio is $1. Weights are adjusted monthly.

Commentary

While the fundamental idea behind the strategies is to overweight those bonds with higher Gamma values, we provide the following commentary on the details of the steps listed in.

- We construct portfolios using Gammas measured at the end of month *t-1*, and returns are calculated during month *t*. Portfolios are rebalanced monthly.
- This setup allows us to study the performance of multiple portfolios and the impacts of portfolio weights on return-risk trade-off and further helps ensure the robustness of our study. Each *c* value implies a portfolio strategy. Results are reported as functions of *c*. Each portfolio strategy can be thought of as beginning with a certain dollar amount of investment at month 0 and growing the portfolio over time according to the weights of the bonds dictated by the above steps.
- Parameter *c* determines how heavily the bonds with large Gamma values are weighted. A higher *c* means a higher concentration in bonds with larger Gammas. *c* values used in this study: 1, 4, 7, 10, 13, 16, and 19.[6] In general, concentrated portfolios tend to be more volatile than diversified portfolios. Increasing the control parameter *c* places more weight on those bonds with larger Gamma values, i.e., those bonds with higher return-risk trade-off, thus increasing the return. However, for a reasonable range of *c* values, this may not necessarily increase the portfolio risk, because bonds with high Gamma values tend to have smaller EDF values, i.e., they tend to be safer bonds. Of course, we should not pick huge values of *c* because the resulting portfolio will be too concentrated, and that is one reason that we stop at *c*=19.
- The time horizons of EDF measures and FVS are set to match the duration of the bond. Duration varies between 1 and 10 years.

To illustrate this, Figure 10 shows the distribution of weights over the gamma buckets across different values of *c* for the investment grade universe for the month of May 2008. Higher *c* values increase the weights in bonds with large gamma values. *c*=0 implies an equally weighted portfolio; portfolios with *c*=19 have bonds mostly from high gamma buckets.

[6] Although the incremental value of three for *c* values seems arbitrary here, we choose it in order to have a reasonable number of different portfolios while trying to contain the scope of the study. As it can be inferred later, choosing a different *c* value does not materially change the conclusion of our study.

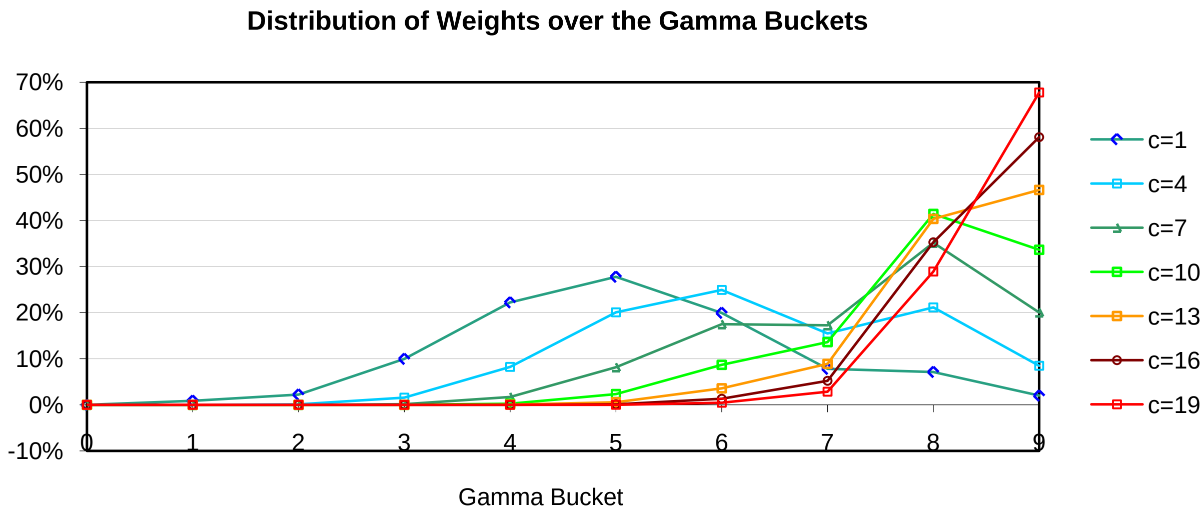

Figure 10 Distribution of weights over the Gamma buckets across different values of *c*.

To make the portfolio construction as realistic as possible, we account for transaction costs. Before 2008, we assume a 15 bps transaction cost roundtrip for investment grade and 30 bps for high yield, based on previous academic research; after 2008, we assume 50 bps for investment grade and 60 bps for high yield, based on our empirical study of TRACE data.[7]

For these strategies, we calculate total returns, including price changes and coupon income, which includes accrued interest. For simplicity, we exclude income from reinvestment.[8] We calculate the bond return for month *t* as follows.

$$R_t = \frac{P_t + C \times \delta - P_{t-1}}{P_{t-1} + AI_{t-1}} \tag{2}$$

Where P_{t-1} is the price of the bond at the end of month *t-1*;

AIt-1 is the accrued interest at the end of month *t-1*;

P_t is the price of the bond at the end of month *t*;

C is the coupon payment;

δ is the number of days in month *t* /365.25

Coupon payments are assumed at month's end.

The return of a bond portfolio for month *t* is calculated as follows.

$$R_t^p = \sum_{i=1}^{N_t} w_{it} \times R_{it} \tag{3}$$

Where N_t is the number of bonds in the sample in month *t*;

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[7] While one can question how broadly the transaction cost assumption applies, it is worth noting that the benchmark indices do not account for transaction costs.

[8] Including the reinvestment income would increase strategy returns and does not change the conclusion of our results.

R_{it} is the return on bond *i* for month *t*.

3.1.2 Empirical Results: Investment Grade

For investment grade names, both the risk-based and the valuation-based strategies achieve higher average annual returns and lower standard deviations than the Pseudo Indices across different values of *c*, as shown in Figure 11 and Figure 12, respectively.

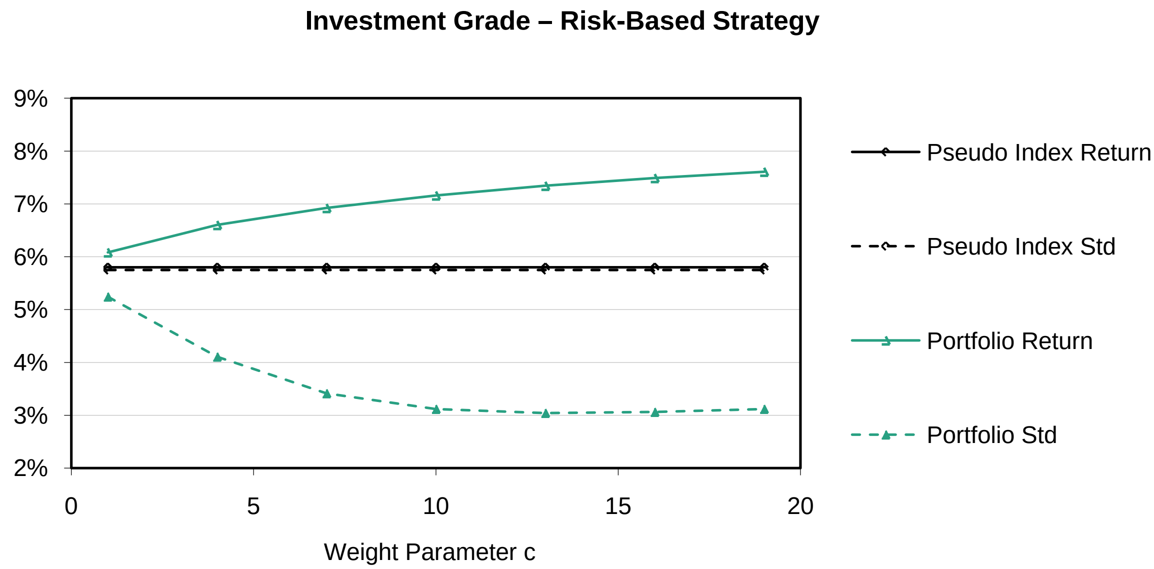

Figure 11 For investment grade names, the risk-based strategy outperforms the Pseudo Index in both average annual return and standard deviation, across different values of *c*. Please note, the annualized return and standard deviation for the Pseudo Index are 5.75% and 5.80%, respectively, shown in both Figure 11 and Figure 12.

For the risk-based strategy, returns are an increasing function of weight parameter *c*; as more weight is placed on high Gamma bonds, returns increase. Risk is a decreasing function. High Gamma bonds are issues with low EDF measures and higher spreads. When picking these bonds, we find better returns and lower standard deviations than the benchmark.

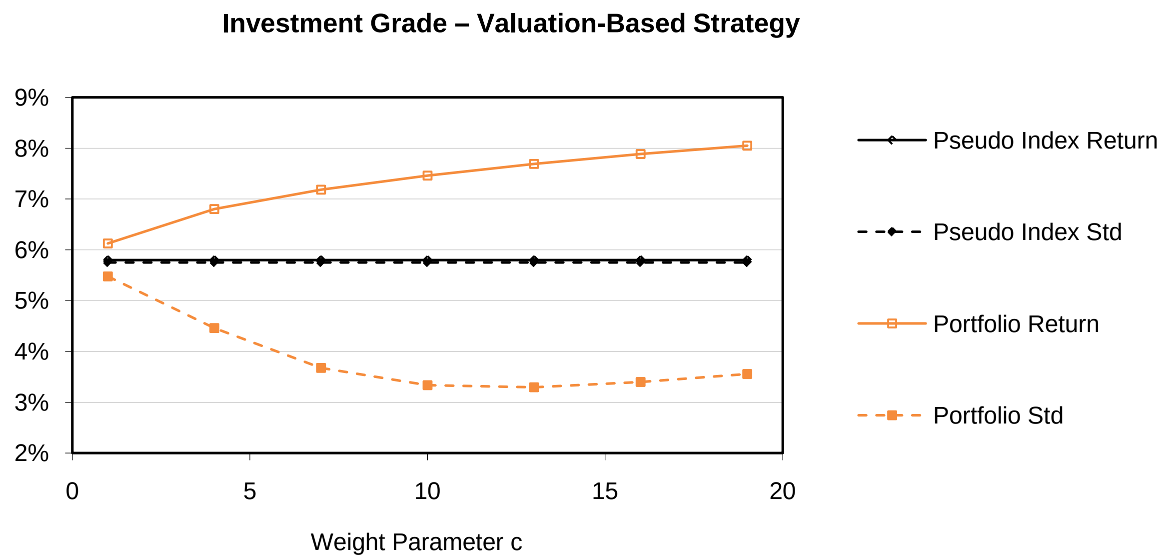

Figure 12 With investment grade names, the valuation-based strategy outperforms the Pseudo Index in average annual return and standard deviation, across different values of *c*.

The results for the valuation-based strategy are very similar. Return is also an increasing function of weight and decreasing volatility. Returns for the valuation-based strategy are slightly higher, using the difference between the FVS and the OAS and exploiting mispricing while controlling for risk.

To place these results within the context of comparison to the Original Index, the cumulative returns for the two strategies over the years (for example, with *c*=1, 13, and 19) are much higher than that of the original Merrill Lynch index, shown in Figure 13, Figure 14, and Figure 15.

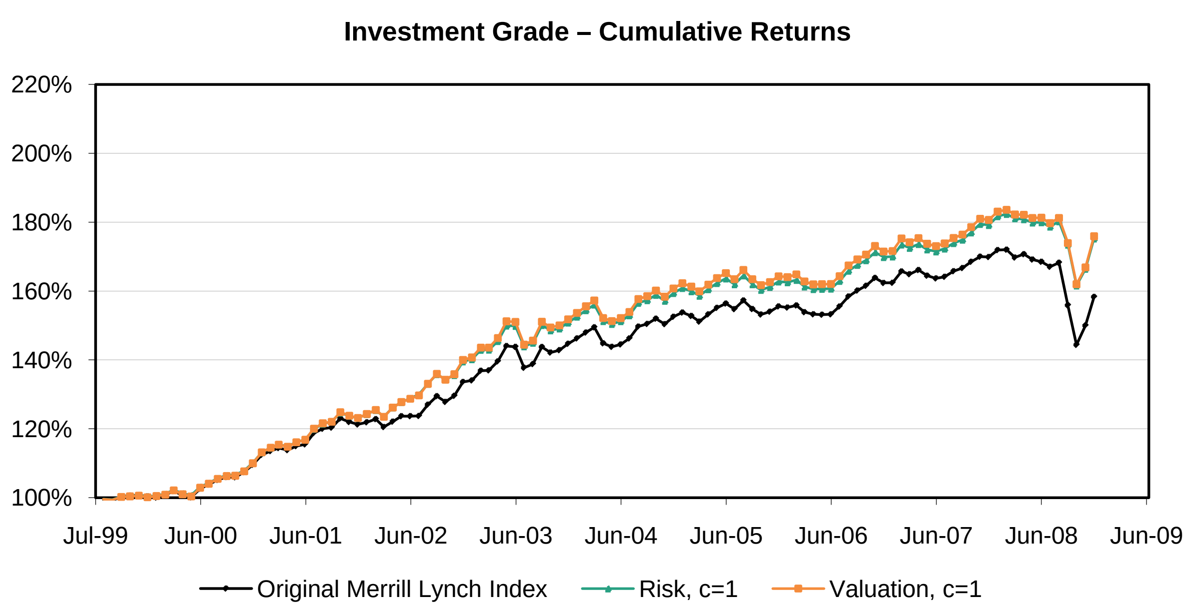

Figure 13 For investment grade names, the cumulative returns for the two strategies over the years with *c*=1 are much higher than the original Merrill Lynch index. The annualized excess returns for the risk and valuation strategy are 1.13% and 1.17%, respectively.

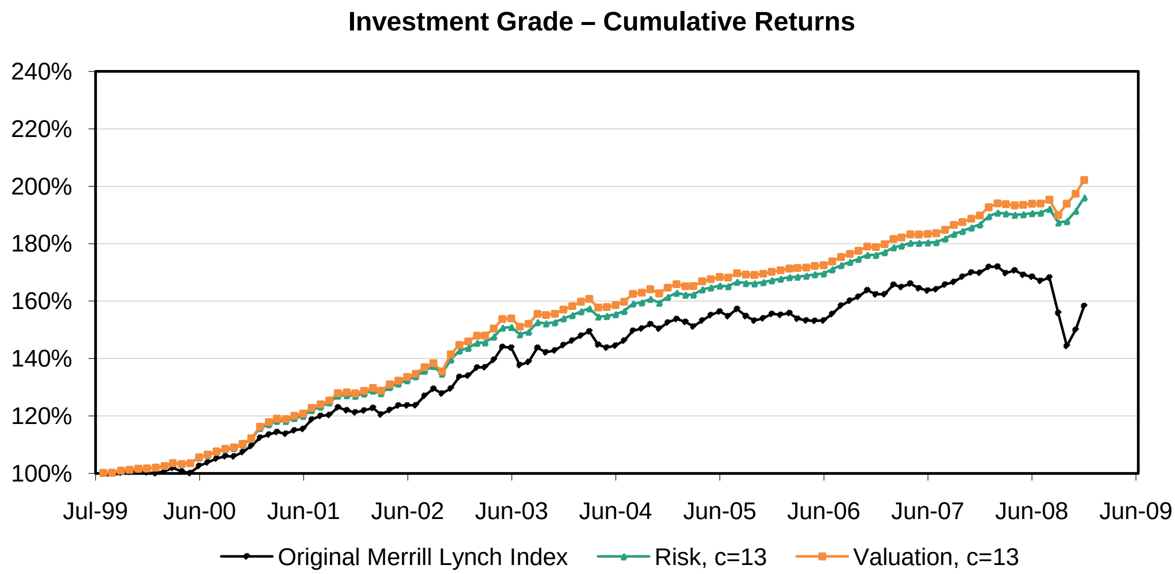

Figure 14 For investment grade names, the cumulative returns for the two strategies over the years with *c*=13 are much higher than the original Merrill Lynch index. The annualized excess returns for the risk and valuation strategy are 2.39% and 2.74%, respectively.

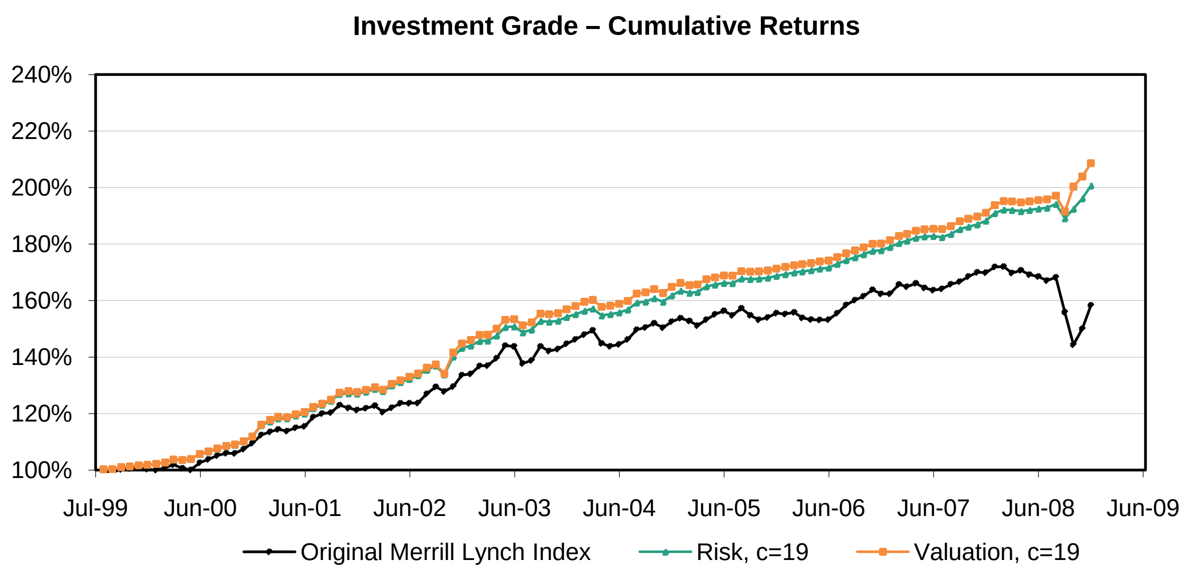

Figure 15 For investment grade names, the cumulative returns for the two strategies over the years with *c*=19 are much higher than the original Merrill Lynch index. The annualized excess returns for the risk and valuation strategy are 2.65% and 3.09%, respectively.

To provide more details, we show the annual returns between the two trading strategies and the benchmark (original Merrill Lynch index), year by year, with *c*=19. The two strategies outperform the benchmark's indices most years, as shown in Figure 16, even during the recent crisis, while slightly trailing the benchmark in 2003 and 2004, when spreads narrowed. It is worth mentioning that the Merrill Lynch index does not account for transaction costs, while our two trading strategies do. Including transaction costs for the benchmark index would make the performance difference larger.

When we change the benchmark to the Pseudo Index, we find similar results, shown in Figure 17. Furthermore, the two strategies performed well during 2008, amidst the financial crisis. As seen in Figure 18, these strategies yield portfolios that were less volatile, did not "overreact" in September 2008, and posted positive returns in October 2008.

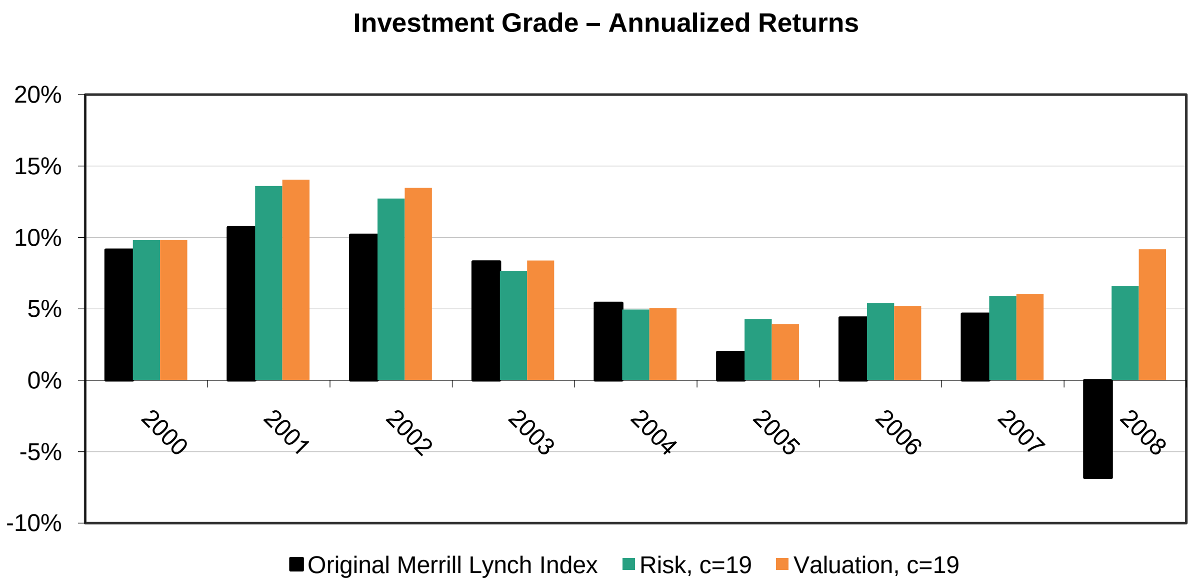

Figure 16 The annual returns for the two strategies are higher than that of the benchmark (original Merrill Lynch index) most of the years, even during the recent financial crisis. The two strategies slightly trailed the benchmark in 2003 and 2004, when spreads narrowed. Also, the two trading strategies account for transaction costs, while the benchmark does not.

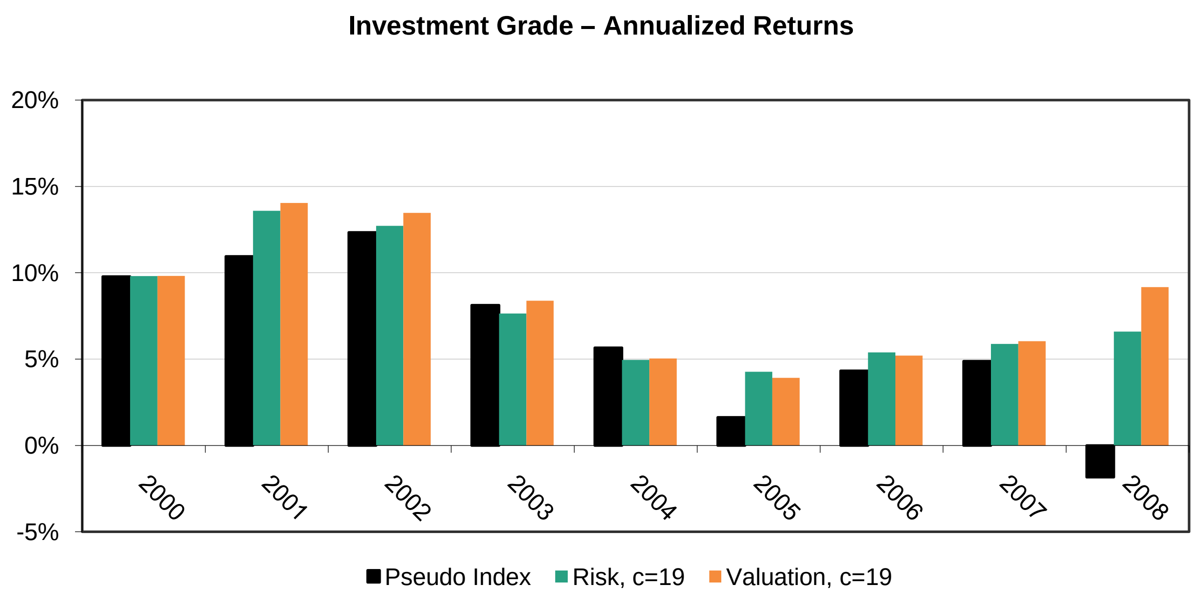

Figure 17 We see similar results when the benchmark is changed to the Pseudo Index.

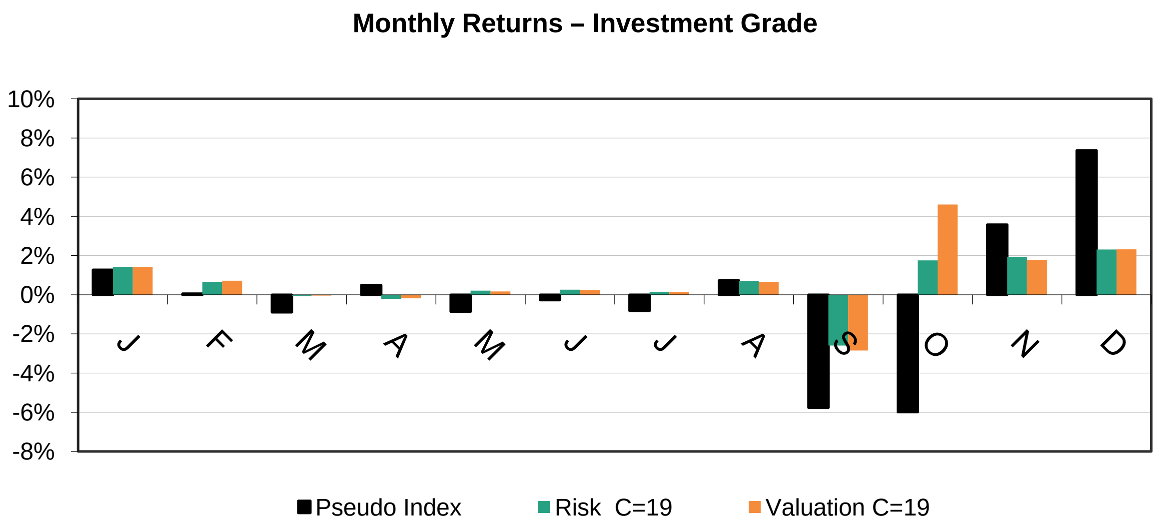

Figure 18 The strategy performed well in 2008 because it did not "overreact" in September and turned positive in October.

After viewing these results, we ask the following question: are these better returns achieved at the expense of higher risk? Although we have shown that these portfolios have smaller standard deviations and are therefore less volatile, it is prudent to examine additional risk measures such as systematic risk and downside risk.[9]

To assess the degree of systematic risk (i.e., the degree of the correlation between a portfolio and its index), we regress the returns of these strategies against their benchmark returns and find low beta and positive alpha across different values of c, shown in Figure 19 and Figure 20.

Figure 19 shows that when we regress portfolio returns against the benchmark, both trading strategies achieve positive alphas. In Figure 20, we see that when we regress portfolio returns against systematic risk, both trading strategies have low beta loadings.

These results suggest the strategies deliver consistent, positive excess returns across the board, while incurring less correlation risk with the market.

[9] We also compare the durations of our portfolios to those of the benchmarks and do not find significant differences.

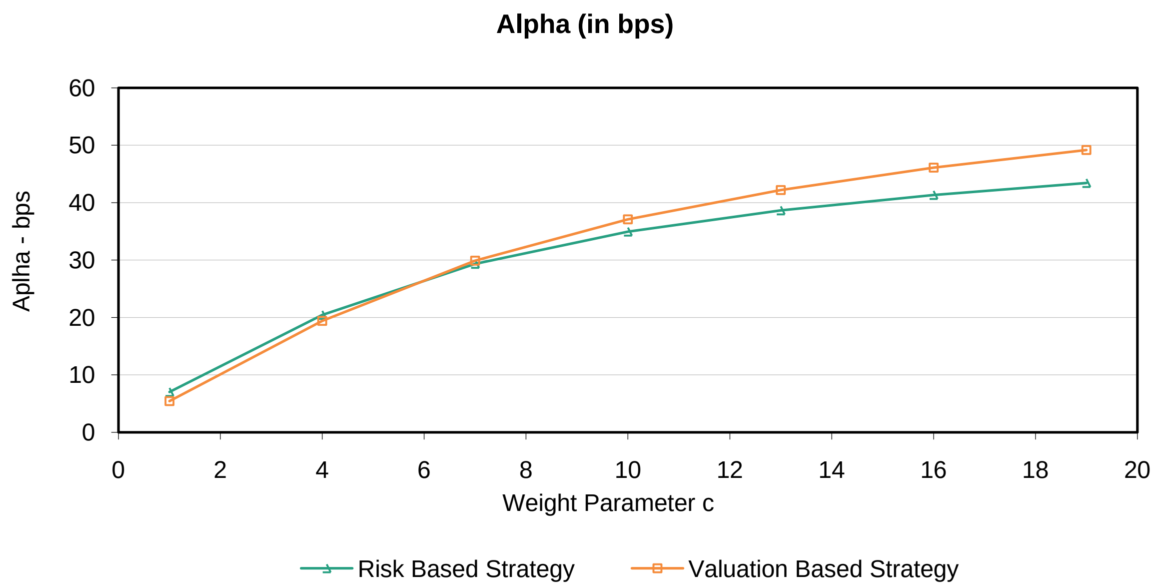

Figure 19 Regressing portfolio returns against the benchmark, both trading strategies achieve positive alphas.

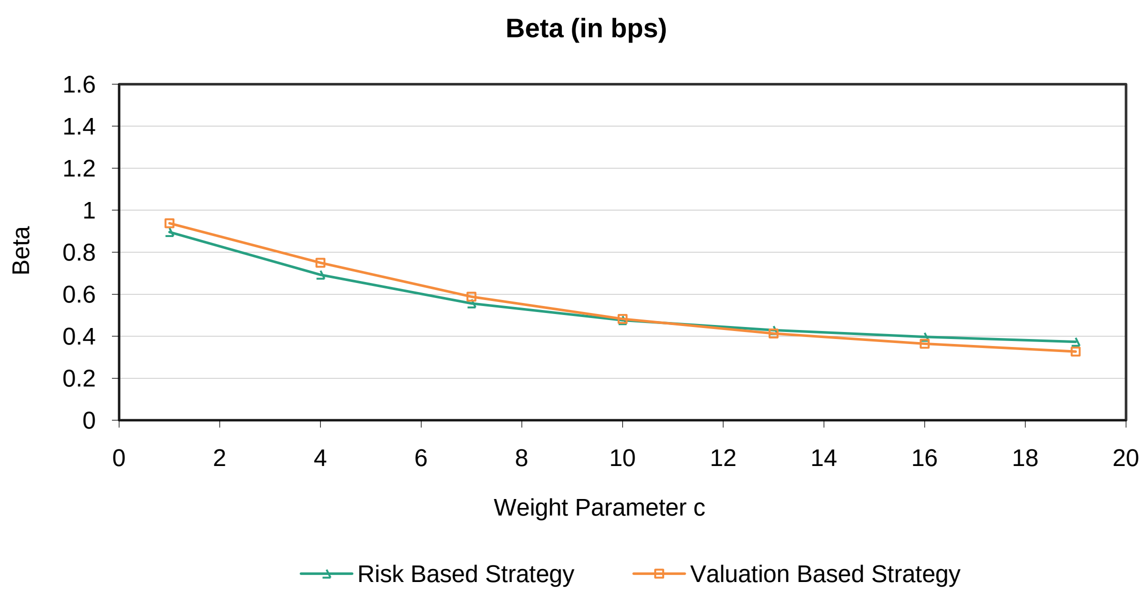

Figure 20 Regressing portfolio returns against systematic risk, both trading strategies have low beta loadings.

We now compare the downside risk of our portfolios with the benchmark. We calculate the worst monthly return, the 5th percentile worst monthly return, and the 10th percentile worst monthly return of the two strategies. We then compare returns with the benchmark across different values of c. We find the constructed portfolios have much smaller negative returns than the benchmark, and they protect against downside risk, outperforming the benchmark except in one case, where c=1.

We also compare the worst monthly returns. Figure 21 shows the worst monthly returns of the two strategies compared with the Pseudo Index. Figure 22 shows the 5th percentile worst monthly returns of the two strategies compared with the Pseudo Index, and Figure 23 shows the 10th percentile worst monthly returns of the two strategies compared with the Pseudo Index.

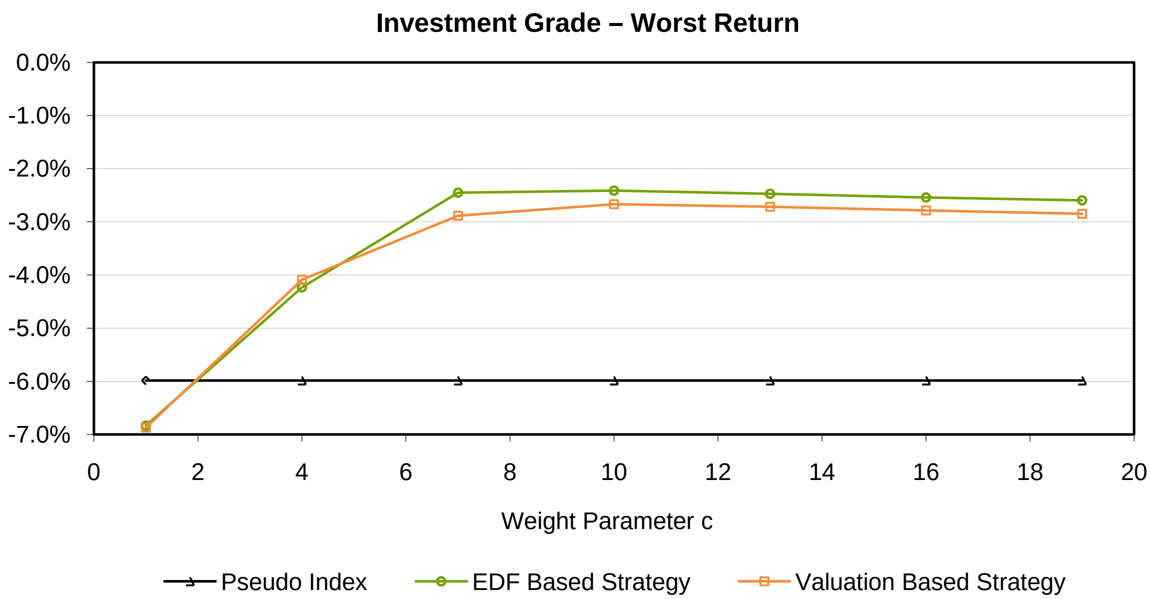

Figure 21 Worst monthly returns of the two strategies compared with the Pseudo Index.

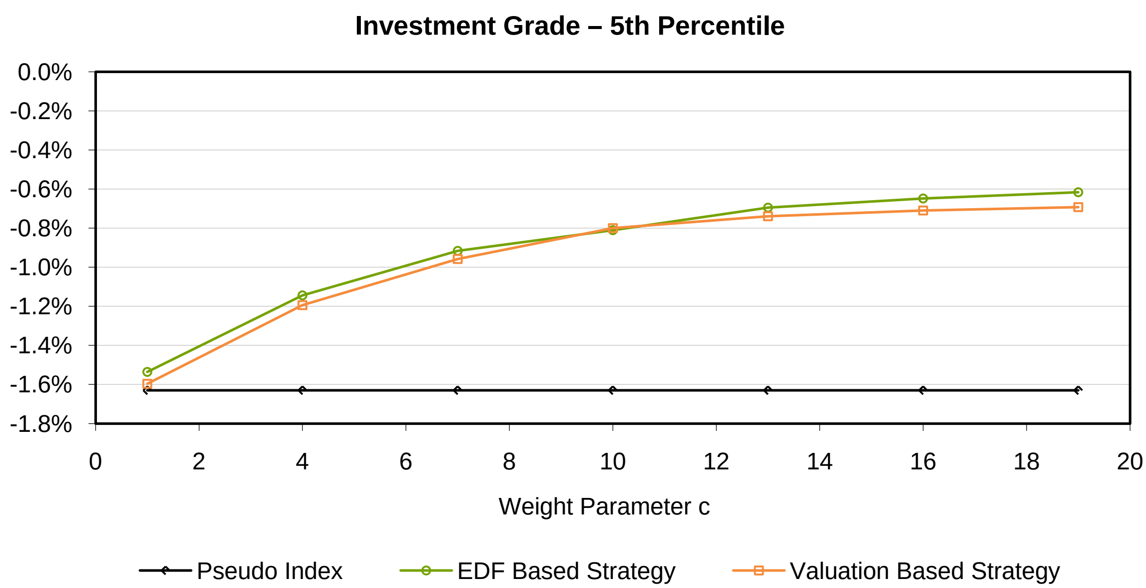

Figure 22 5th percentile worst monthly returns of the two strategies compared with the Pseudo Index.

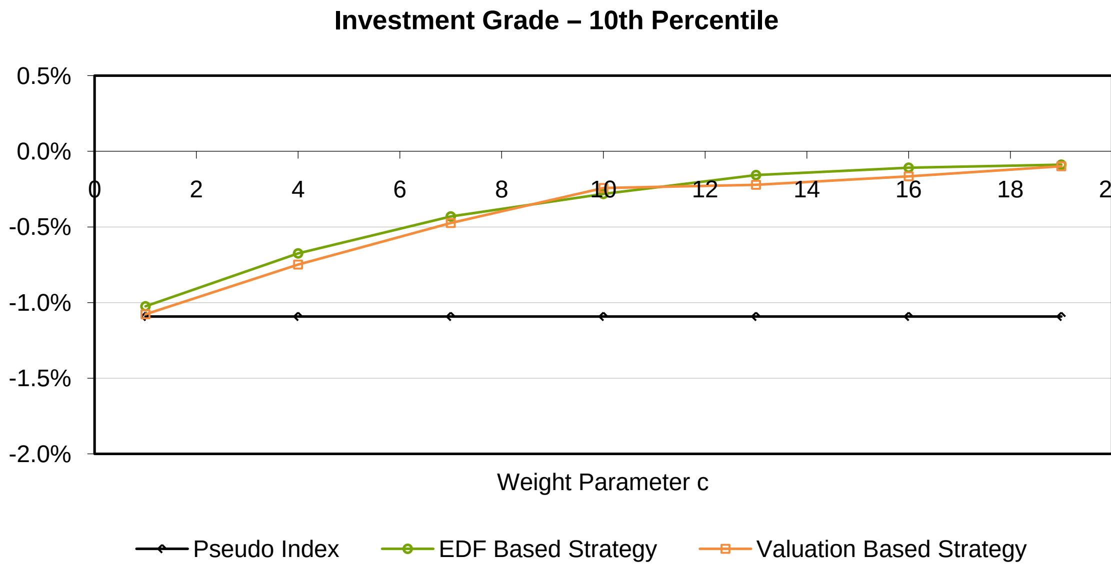

Figure 23 10th percentile worst monthly returns of the two strategies compared with the Pseudo Index.

Figure 24 shows the information ratio of the two trading strategies across different values of *c* for investment grade names, with the Merrill Lynch Investment Grade Index as the benchmark. The information ratio is calculated as the excess returns over the standard deviation of the tracking errors.

While the information ratios of these two strategies are positive, they are relatively small, usually ranging between 0.1 and 0.2. As shown in previous graphs, the primary reason is that portfolios from these two strategies possess different risk characteristics than the benchmark. Hence, the standard deviations of the tracking error tend to be significant

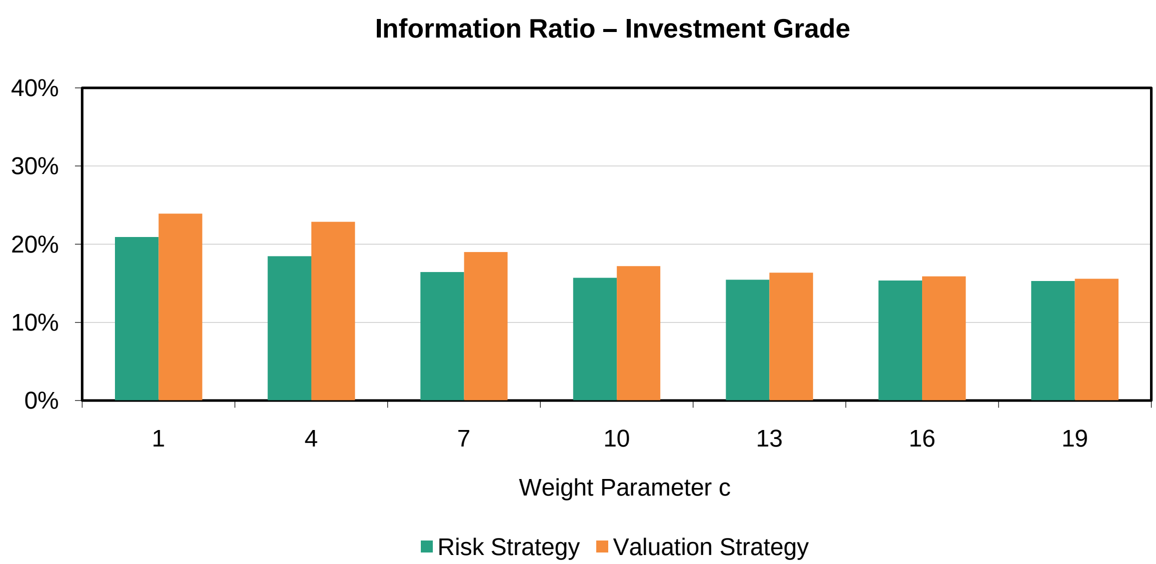

Figure 24 For investment grade names, the information ratio of the two trading strategies across different values of *c*, with the Merrill Lynch Investment Grade index as the benchmark.

3.1.3 Empirical Results: High Yield

All the results shown so far are for investment grade. Results for high yield are similar, while the out-performance is even more pronounced. The EDF measure's option-theoretical framework is especially powerful for high yield names, because the spreads of riskier names are more sensitive to default risk. The high yield universe also tends to be more inefficient.

For high yield names, both strategies (risk-based and valuation-based) achieve higher average annual returns and lower standard deviations than the Pseudo Indices across different values of *c*, shown in Figure 25 and Figure 26.

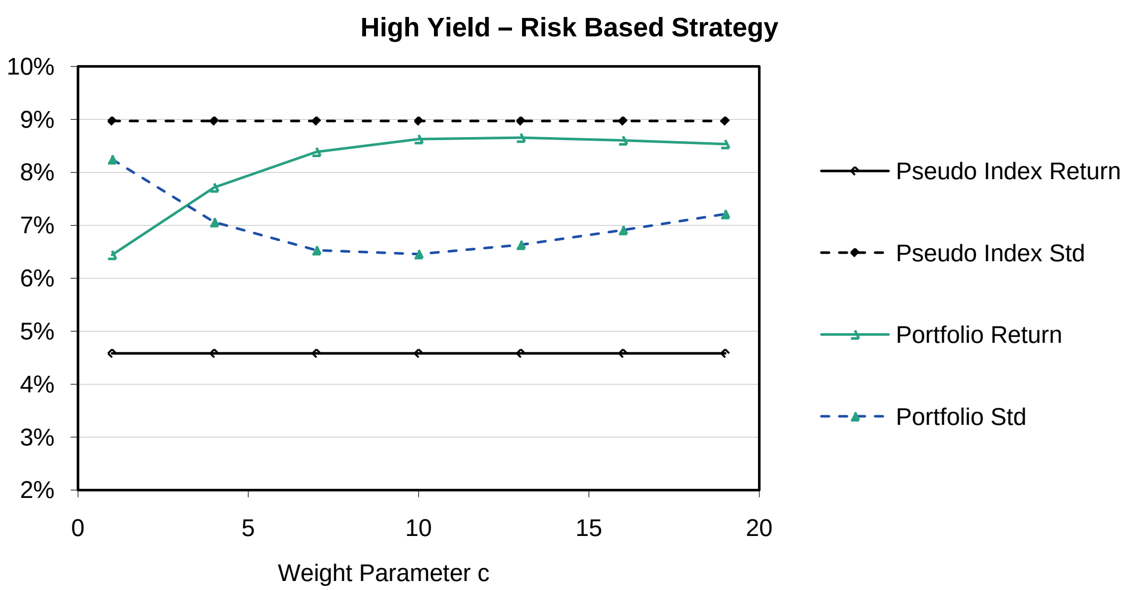

Figure 25 For high yield names, the risk-based strategy outperforms the Pseudo Index in both average annual return and standard deviation, across different values of *c*.

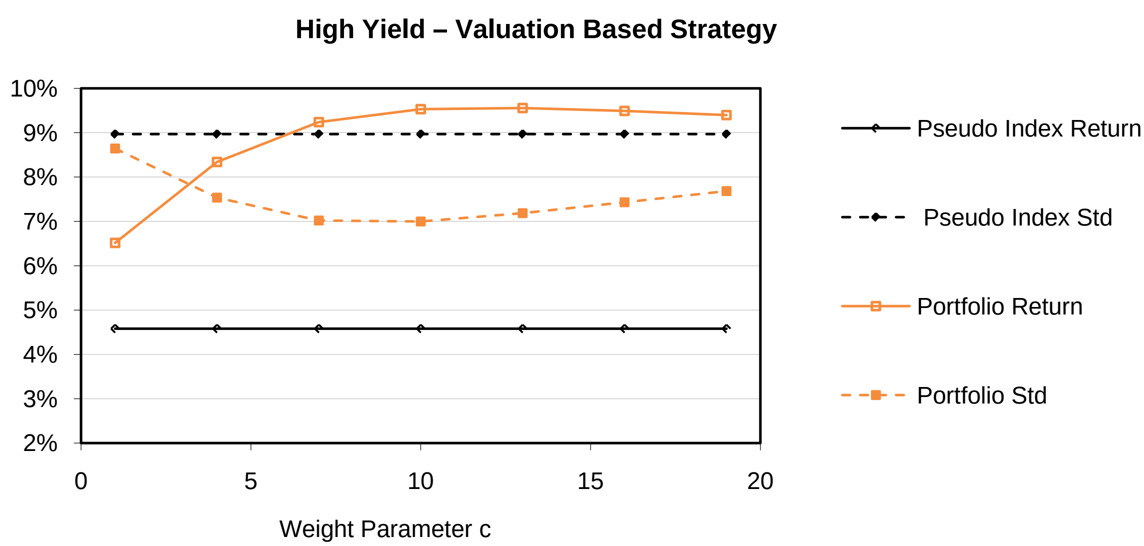

Figure 26 For high yield names, the valuation strategy outperforms the Pseudo Index in both average annual return and standard deviation across different values of *c*.

For high yield names, the cumulative returns for the two strategies over the years for *c*=1, 10, and 19 are higher than that of the original Merrill Lynch index, as is shown in Figure 27, Figure 28, and Figure 29. The annualized excess returns for the risk and valuation strategy are 4.56% and 4.63%, respectively.

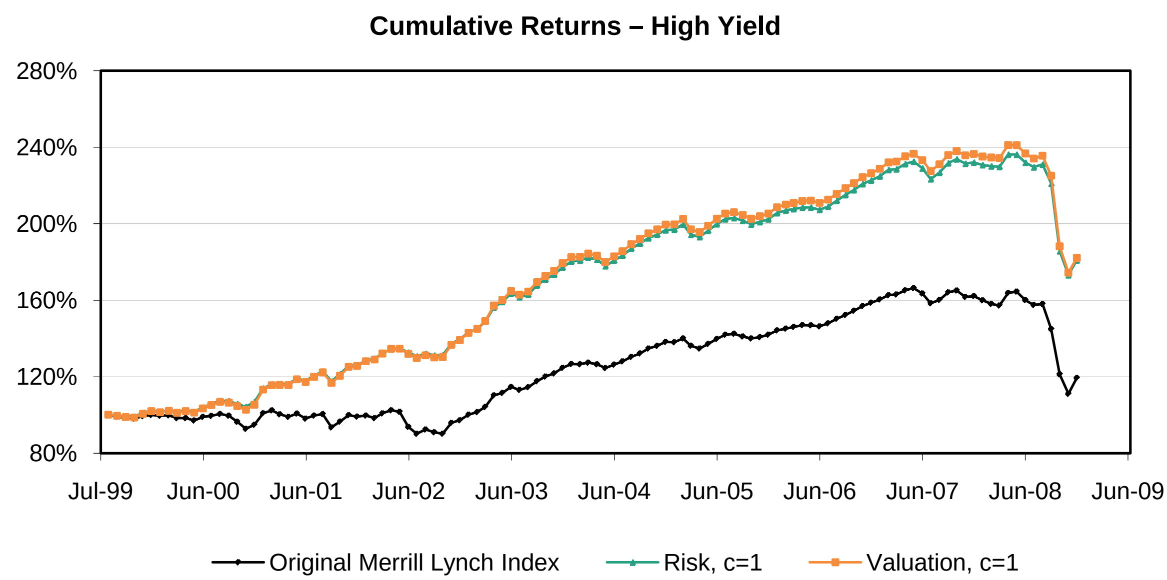

Figure 27 For high yield names, the cumulative returns for the two strategies over the years with *c*=1 are much higher than the original Merrill Lynch index.

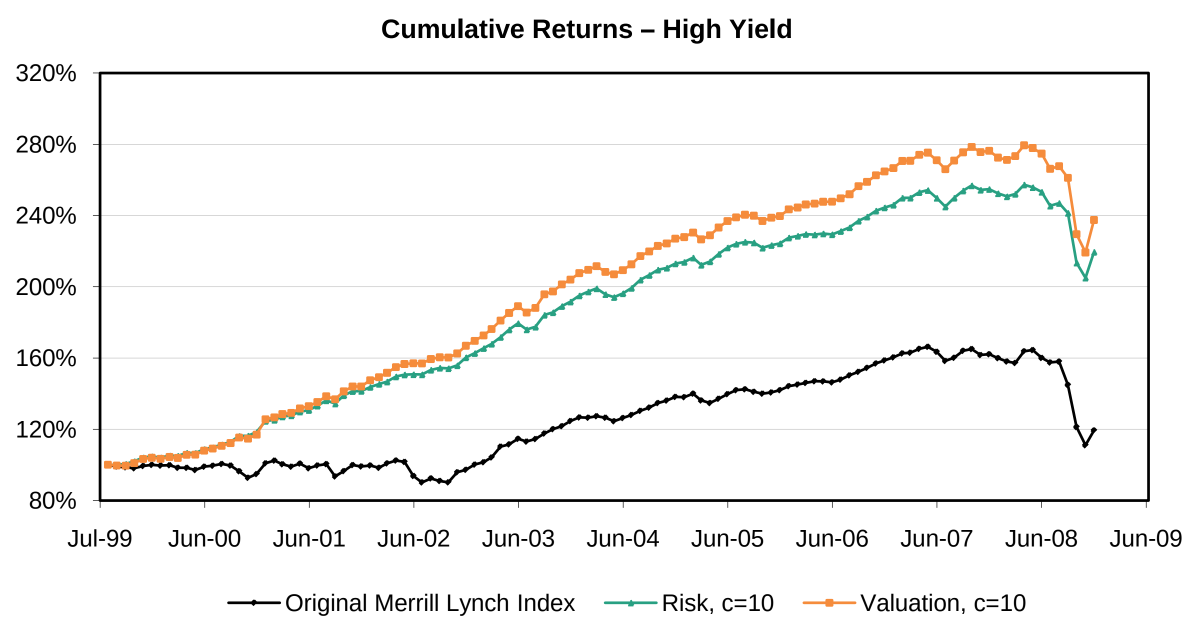

Figure 28 For high yield names, the cumulative returns for the two strategies over the years with *c*=10 are much higher than that of the original Merrill Lynch index. The annualized excess returns for the risk and valuation strategy are 6.75% and 7.65%, respectively.

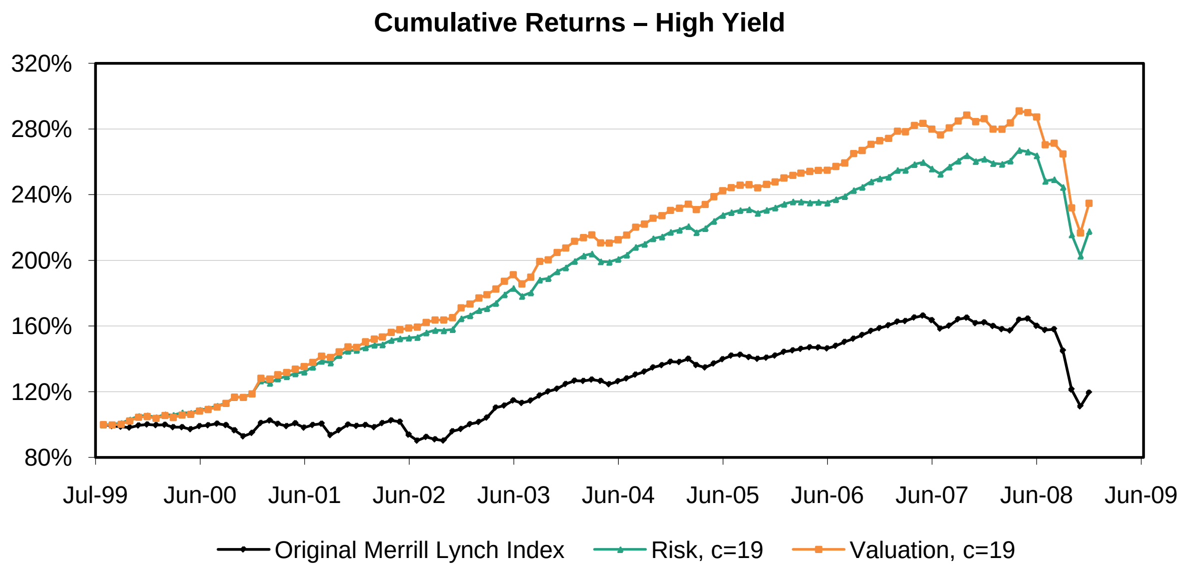

Figure 29 For high yield names, the cumulative returns for the two strategies over the years with *c*=19 are much higher than the original Merrill Lynch index. The annualized excess returns for the risk and valuation strategy are 6.65% and 7.52%, respectively.

To provide more details, we compare the annual, January–December returns between the two trading strategies and the benchmark (original Merrill Lynch index), year by year, with *c*=19. The two strategies outperform the benchmark's indices in most of the years, shown in Figure 16, even during the recent crisis, while slightly trailing the benchmark in 2003, 2004, and 2006, when spreads narrowed. Figure 30 shows the comparison.

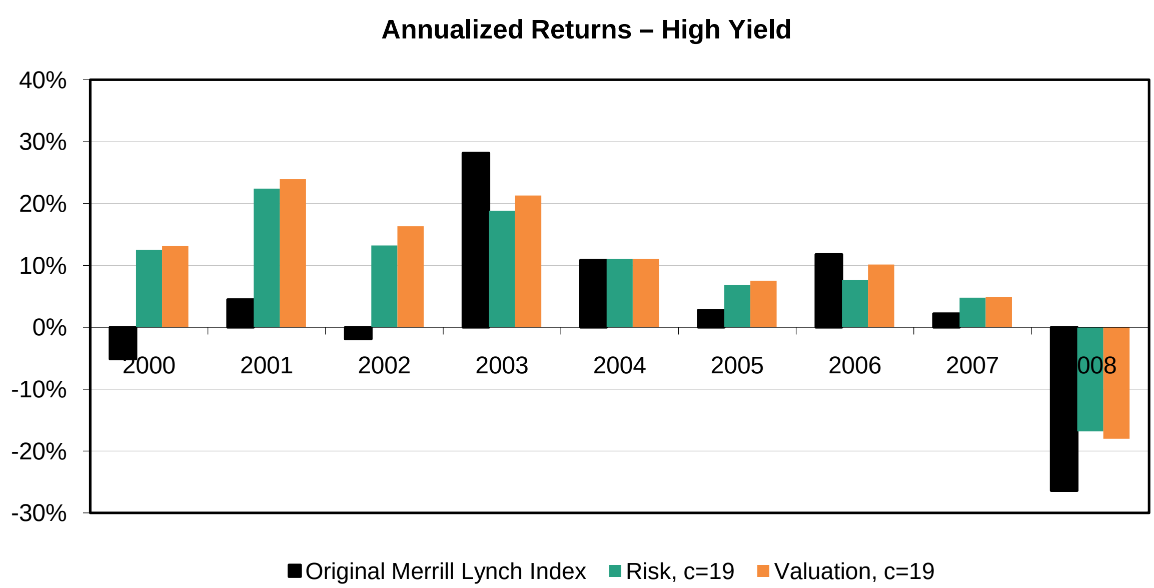

Figure 30 For investment grade names, with *c*=19 the annual returns for the two strategies are higher than the benchmark (the original Merrill Lynch index) most years, even during the recent crisis. The two strategies slightly trailed the benchmark in 2003, 2004, and 2006, when spreads narrowed. Also, the two trading strategies account for transaction costs; the benchmark does not.

We change the benchmark to the Pseudo Index and find similar results, shown in Figure 31.

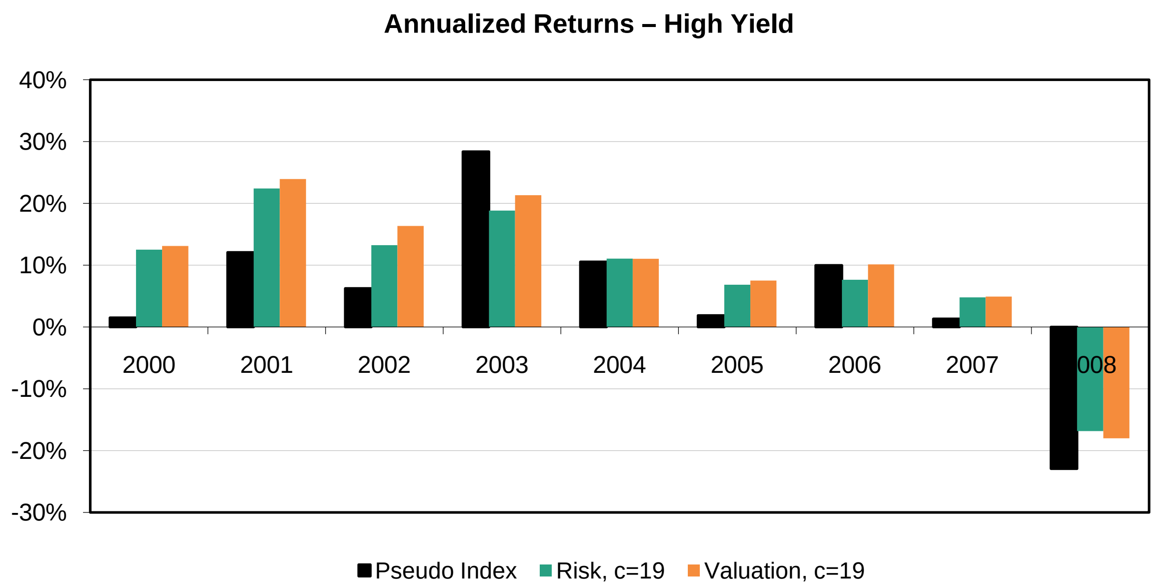

Figure 31 We see similar results when the benchmark is changed to the Pseudo Index.

Next, we document the positive information ratios of the two trading strategies across different values of *c*, using the Merrill Lynch High Yield Index as the benchmark. Figure 32 shows the results.

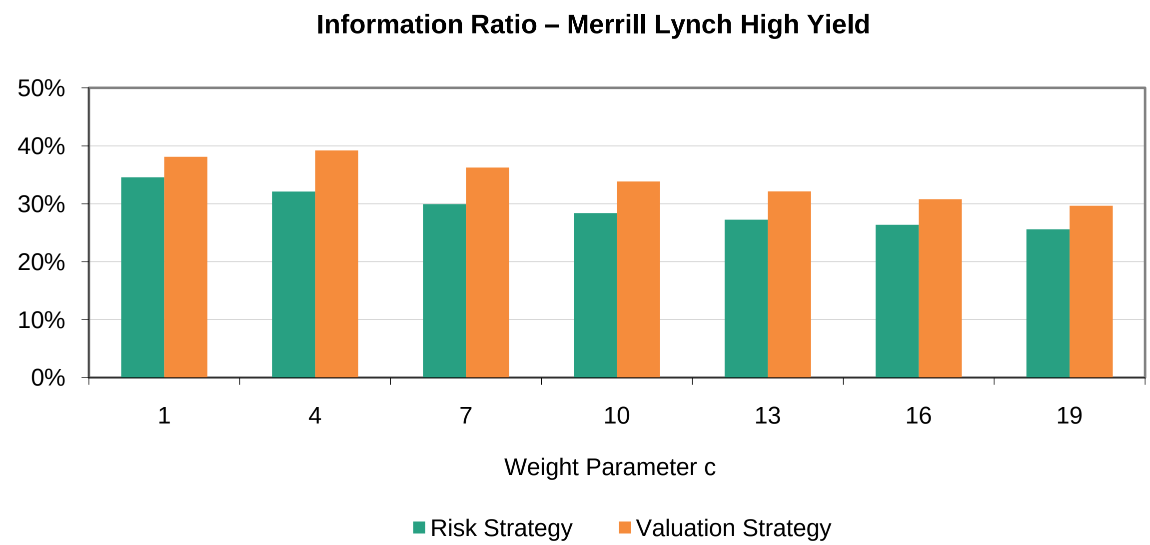

Figure 32 For high yield names, the information ratio of the two trading strategies across different values of *c*, with the Merrill Lynch Investment Grade index as the benchmark.

When the returns of the two strategies are regressed against systematic risk, we find low beta and positive alpha across different values of *c*, shown in Figure 33 and Figure 34.

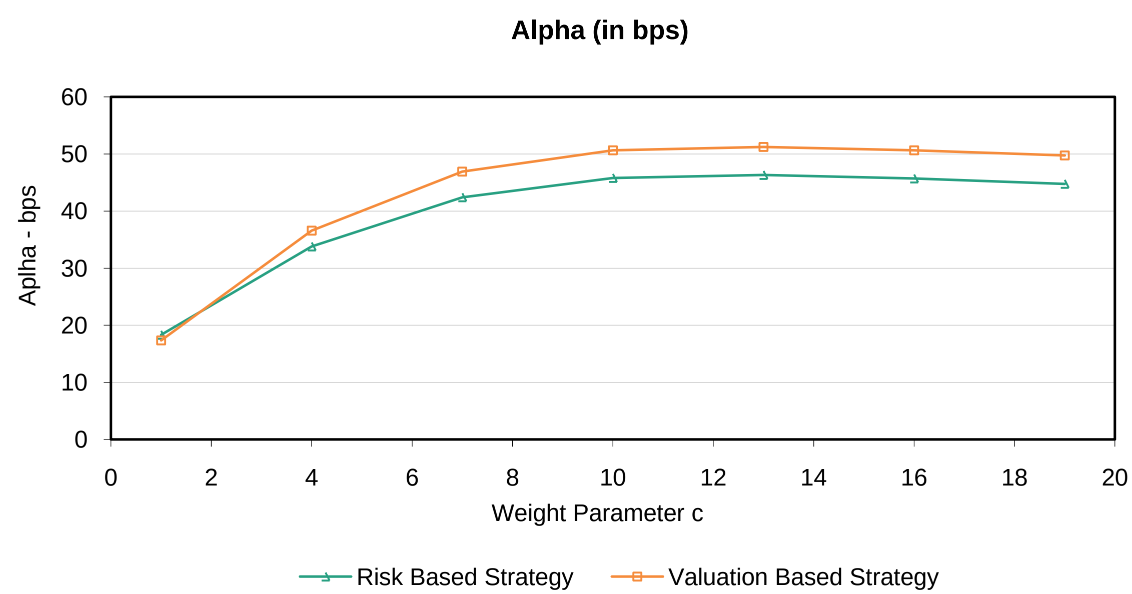

Figure 33 Regressing portfolio returns against systematic risk, both trading strategies achieve positive alphas.

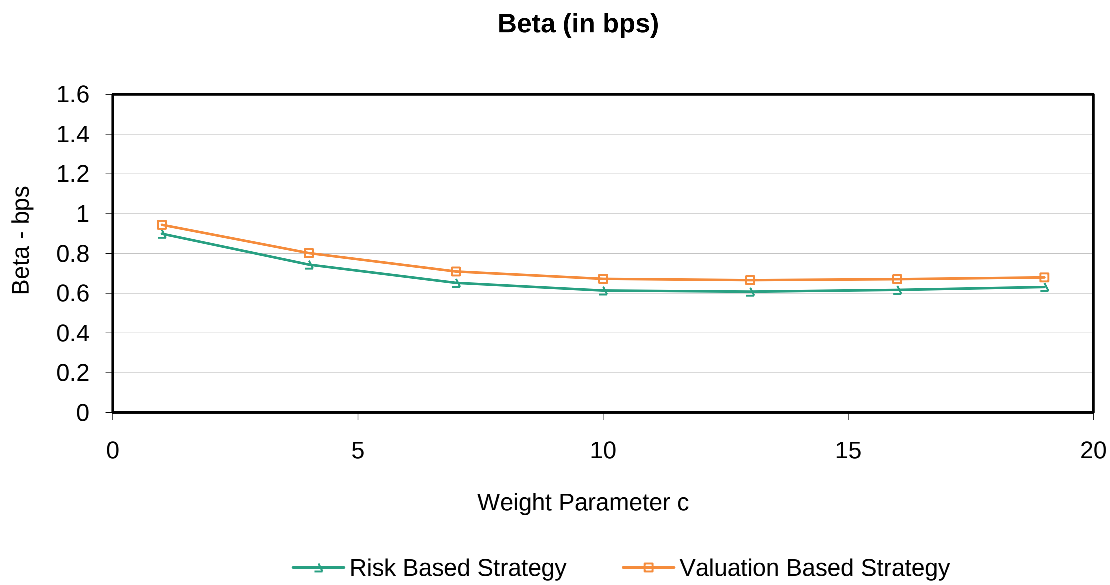

Figure 34 Regressing portfolio returns against systematic risk, both trading strategies have low beta loadings.

We now compare the downside risk of our portfolios with the benchmark. We calculate the worst monthly return, the 5th percentile worst monthly return, and the 10th percentile worst monthly return for the two strategies and then compare them with the benchmark across different values of *c*. Both strategies outperform the benchmark except in one case, where c=1.

We also compare the worst monthly return. Figure 35, Figure 36, and Figure 37 show the results.

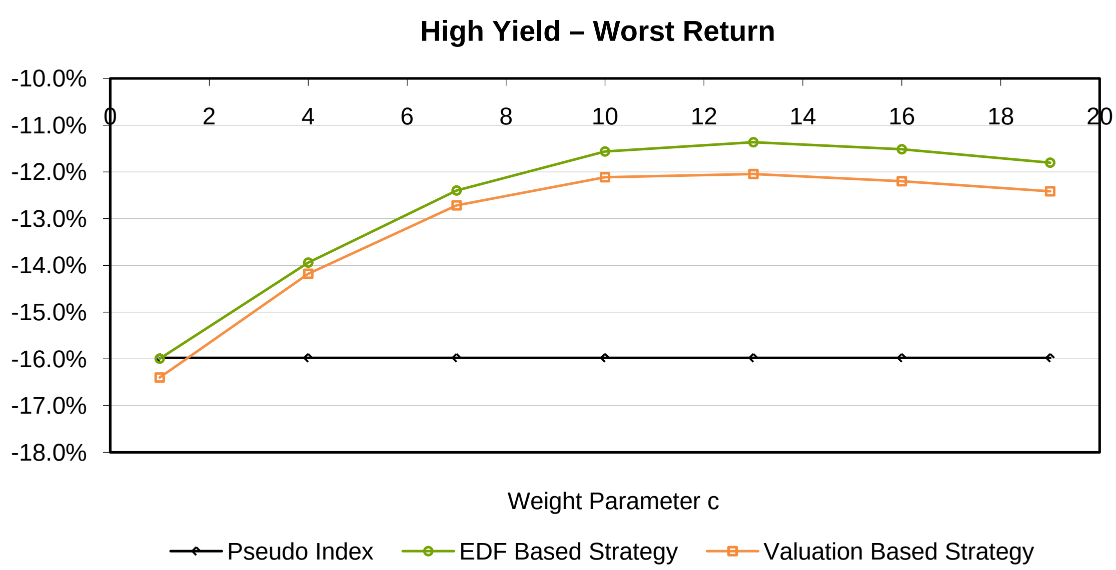

Figure 35 The worst monthly returns of the two strategies compared with the Pseudo Index.

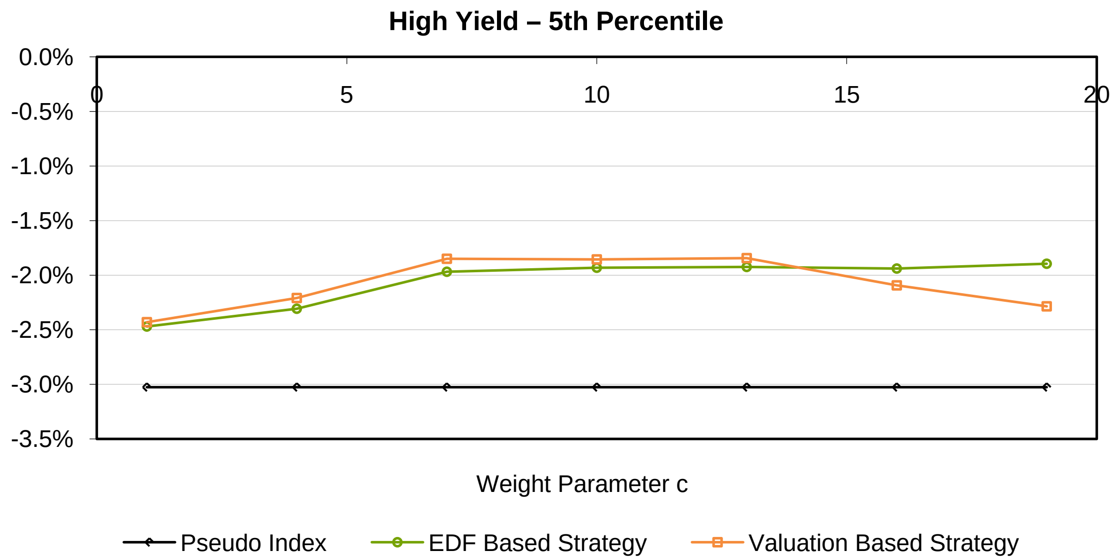

Figure 36 5th percentile worst monthly returns of the two strategies compared with the Pseudo Index.

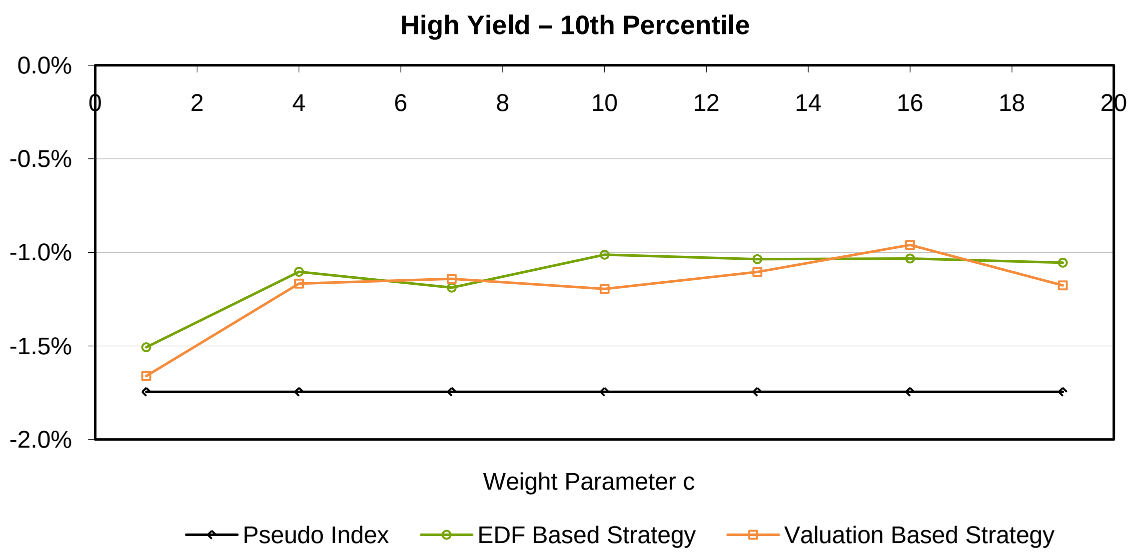

Figure 37 10th percentile worst monthly returns of the two strategies compared with the Pseudo Index.

3.2 Using High Yield Bonds to Construct Investment Grade-like Portfolios

In this section we demonstrate how investors can use high yield bonds to outperform high grade indices with less risk, or how EDF credit measures help construct a portfolio of high yield bonds that outperforms the investment grade index.

3.2.1 Data and Strategies

Bonds from the Investment Grade and High Yield Pseudo Indices are divided into three categories according to their S&P rating: A, BBB, and BB.[10]

We use the following strategies with the same steps introduced in the previous section, but with definitions of Gammas as follows.

- EDF-based strategy: Gamma=1/(EDF*LGD)
- Valuation-based strategy: Gamma = (OAS-FVS)/(EDF*LGD)
- We assign weights in the same way as in the previous part of the analysis, including the weight parameter *c*=1, 4, 7, 10, 13, 16, 19.

3.2.2 Empirical Results

We construct portfolios with BB bonds using the above strategies. It is no surprise that the portfolios have higher cumulative returns over the years than the A index and BBB index (since BB bonds have higher coupon rate), as shown in Figure 38 and Figure 39 for *c*=1 and *c*=19, respectively. What is surprising is that these portfolios can be less risky than the investment benchmark.

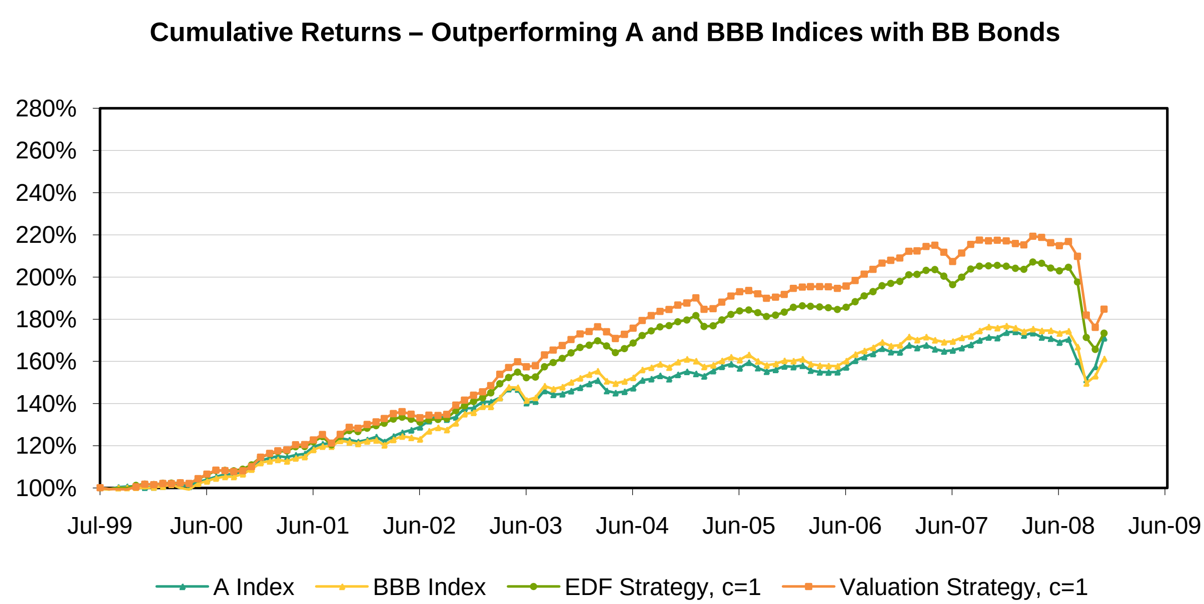

Figure 38 With *c*=1, portfolios constructed using the two trading strategies with BB bonds have a higher cumulative return than the A index and BBB index over the year. The annualized excess returns for the risk and valuation strategy are 0.99% and 1.17%, respectively.

[10] We use S&P ratings because of data availability. We would expect similar results using Moody's ratings.

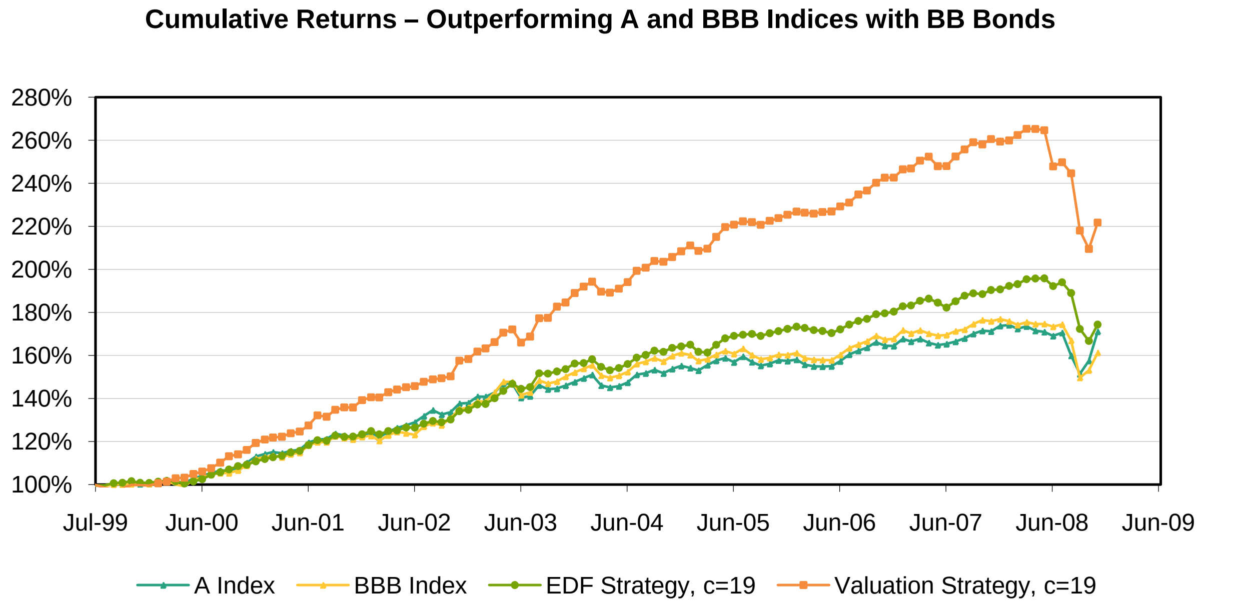

Figure 39 With c=19, portfolios constructed using the two trading strategies with BB bonds have a higher cumulative return than the A index and BBB index over the year. The annualized excess returns for the risk and valuation strategy are 1.06% and 3.78%, respectively.

Both the EDF and valuation based strategies achieve a higher average annual return and lower standard deviation than the A index and BBB index across different values of c, shown in Figure 40 and Figure 41.

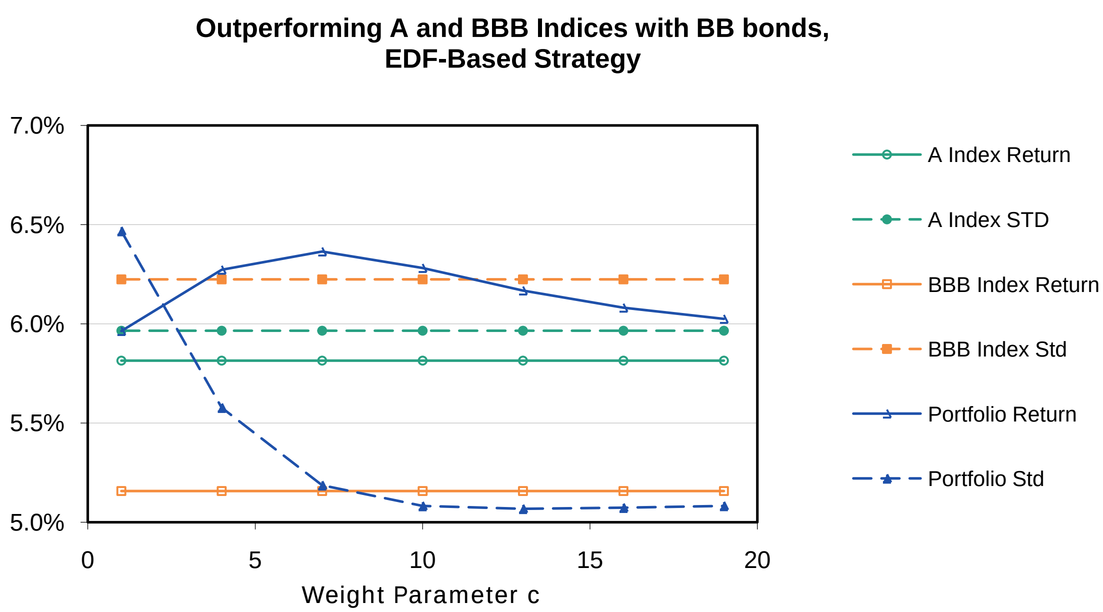

Figure 40 The EDF-based strategy achieves a higher average annual return and lower standard deviation than the A index and BBB index across different values of c.

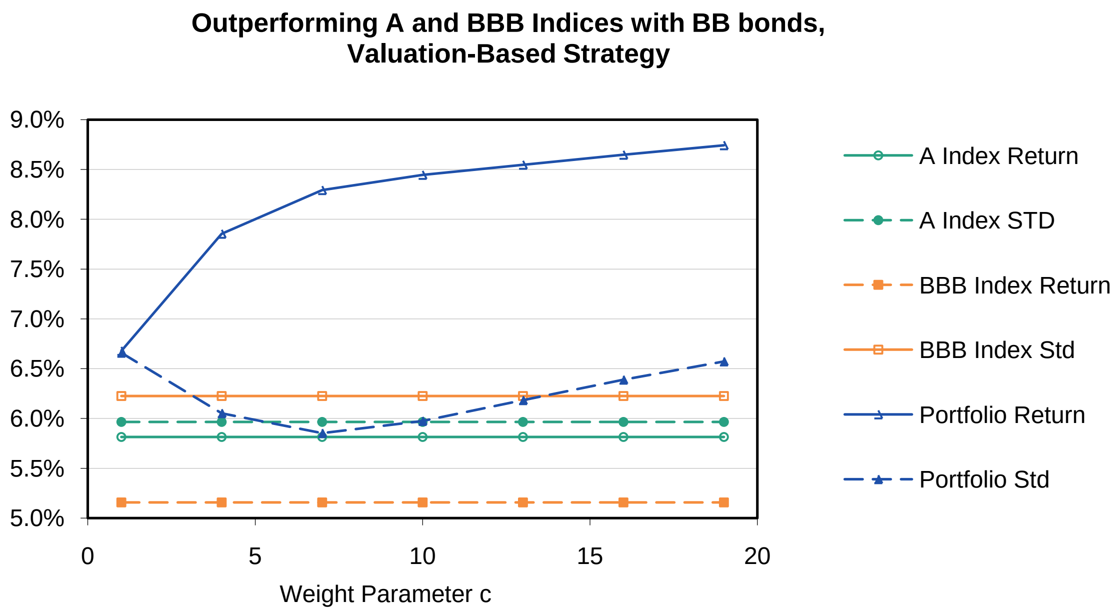

Figure 41 The valuation-based strategy achieves a higher average annual return and lower standard deviation than the A index and BBB index across different values of *c*.

We now compare the downside risk of our portfolios with the Pseudo Index. We calculate the worst monthly return, the 5th percentile worst monthly return, and the 10th percentile worst monthly return of the two strategies, and then compare them with the Pseudo Index across different values of *c*. Both strategies outperform the Pseudo Index. Figure 42, Figure 43, and Figure 44 show the results.

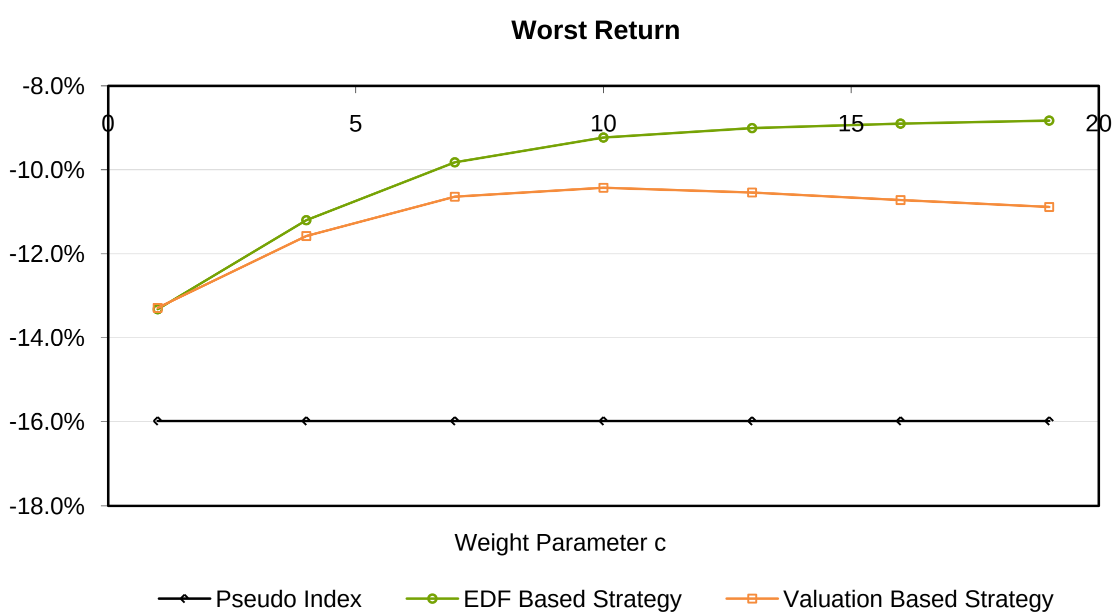

Figure 42 The worst monthly returns of the two strategies compared with the Pseudo Index across different values of *c*.

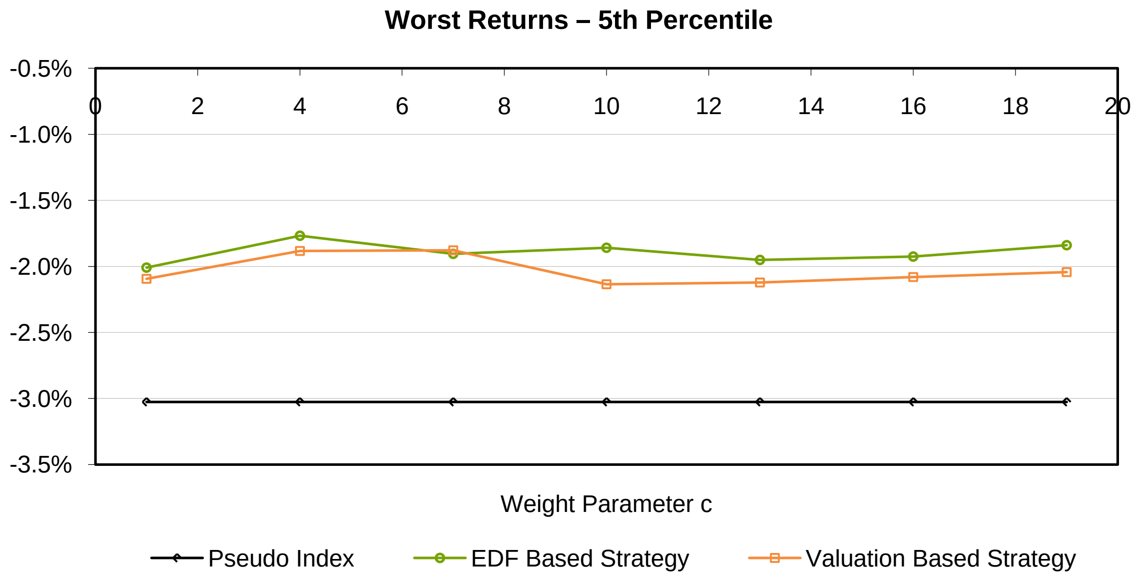

Figure 43 5th percentile worst monthly returns of the two strategies compared with the Pseudo Index.

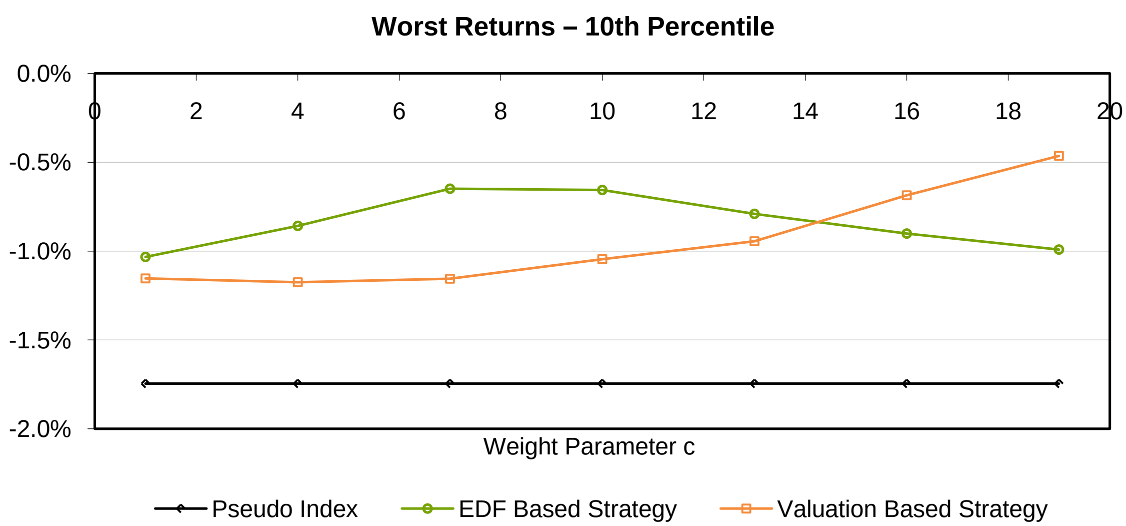

Figure 44 10th percentile worst monthly returns of the two strategies compared with the Pseudo Index.

4 Conclusion

The return distribution of corporate bonds is asymmetric. The best return a bondholder can achieve is the principal and coupon, plus some capped potential price appreciation. On the downside, a bondholder can lose both the principal and future coupons, minus the recovery. Because the downside is much more extreme, a number of periods of positive returns can be wiped out by one large negative return.

This asymmetric nature of the corporate bond return distribution has important implications for investing in corporate bonds. Controlling downside risk is critical in managing a corporate bond portfolio. To help avoid defaults and spreads blow-ups, investors can utilize quantitative measures of credit risk in addition to using fundamental analysis. Moody's Analytics EDF credit measure and FVS provide powerful tools that improve corporate credit portfolio performance by controlling risk, both in the form of return volatility and downside risk, and/or identifying relative values. Both investment grade and high yield portfolios constructed using EDF measures and FVS criteria outperform their respective benchmarks based on multiple measures, including average annual returns, lower standard deviations of returns, and cumulative returns over the long run. The approach also controls downside risk.

Furthermore, a portfolio consisting only of high yield bonds outperforms an investment grade index according to a range of metrics. Portfolio weights significantly affect the return and risk trade-off of portfolios. These strategies performed well during the crisis period in 2008.

While the constructed portfolios show superior performance relative to their benchmarks, it is not our objective to recommend any specific investment strategy in this study. Our objective is to show that quantitative tools such as EDF measures and FVS can add value to the process of investing in corporate credit. Portfolio managers and analysts can use these tools, in addition to fundamental analysis, for early warning screening, identifying problematic names and sectors, and spotting relative value opportunities.

Appendix A Fair-value Spread Framework

On a conceptual level, credit spreads reflect investors' required compensation for taking on credit risk, which predominantly includes both default and recovery risk. Higher default and loss given default translate to higher spreads. Credit spreads also reflect investor attitudes toward risk over time. If investors are more risk averse, say in 2009 than in 2008, they require more spreads for the same amount of default and recovery risk. Furthermore, borrower systematic risk and its correlation within the general economy also have an impact on its credit spreads. Higher systematic risk implies that it is more difficult to diversify away risk; hence, investors require higher spreads to place the bond into their portfolios. Therefore, a model for credit spreads would incorporate at least these inputs: default probabilities, loss given default, risk premium, and systematic risk.

To make the above argument more rigorous, we follow the risk-neutral valuation methodology grounded in the No-Arbitrage principle. More specifically, we compute a transformation that converts our default probabilities under the physical measure (EDF credit measures) to default probabilities under the risk-neutral measure (the Quasi Default Frequencies, or QDFs). The main parameter in this transformation is the *market price of risk* (denoted by λ here). This parameter captures corporate debt investor attitude toward risk. Alternatively, λ can be interpreted as the market Sharpe ratio or the expected excess return demanded by investors per unit of risk. This attitude toward risk for credit market investors is best reflected in the prices (or spreads) of credit risky claims. Consequently, we use these data to calibrate the market Sharpe ratio.

Under the risk-neutral valuation principle, the model spread, or fair-value spread on a defaultable zero-coupon bond, is given by:

$$\begin{aligned} FVS_T &= -\frac{1}{T}\ln(1 - CQDF_T * LGD) \\ &\approx \frac{1}{T} CQDF_T * LGD \end{aligned} \tag{4}$$

Where T is the tenor of the bond, $CQDF$ is the cumulative default probability under the risk-neutral measure, and LGD is the loss given default. Although the above equation is derived for zero-coupon bonds, the relationship works reasonably well for coupon-bearing bonds, with T replaced by its duration.

The above equation suggests that spreads should be approximately equal to expected loss under the risk-neutral measure. To calculate the *CQDFs*, we start with EDF credit measures, our default probabilities under the physical measure. When asset returns are assumed to follow a Geometric Brownian motion process, one can show that $CQDF$ can be obtained from $CEDF$ through the following transformation,[11]

$$CQDF_{iT} = N\left[N^{-1}\left(CEDF_{iT}\right) + \frac{\mu_i - r}{\sigma_i}\sqrt{T}\right] \tag{5}$$

In our current valuation framework, we rewrite this relationship by imposing the Capital Asset Pricing Model (CAPM) on asset returns. CAPM says,

[11] See Agrawal et al (2004) for a derivation.

$$
\begin{aligned}
(\mu_i - r) &= \beta_{im}(\mu_m - r) \\
&= \frac{\rho_{im}\sigma_i\sigma_m}{\sigma_m^2}(\mu_m - r) \\
\frac{(\mu_i - r)}{\sigma_i} &= \rho_{im}\frac{(\mu_m - r)}{\sigma_m} \\
\lambda_i &= \rho_{im}\lambda_m \\
&\Rightarrow \\
CQDF_{iT} &= N\left[N^{-1}(CEDF_{iT}) + \rho_{im}\lambda_m\sqrt{T}\right]
\end{aligned} \tag{6}
$$

Thus,

$$
FVS_T = -\frac{1}{T}\ln(1 - N\left[N^{-1}(CEDF_{iT}) + \rho_{im}\lambda_m\sqrt{T}\right] \times LGD) \tag{7}
$$

Because *CEDF* is known and *LGD* values can be estimated separately, ρ_{im} and λ_m are the two main unknown parameters. ρ_{im} is the correlation coefficient of individual asset returns with the market returns and represents a firm-specific parameter. The market Sharpe ratio is constant across the entire cross-section of assets. Conceptually, both parameters can vary over time.

While the mode in Equation (7) works, in general, one major systematic bias that shows up in the bond spreads is the "size effect." We find that the spreads on bonds issued by smaller firms are systematically higher than those on bonds of larger firms, after controlling for various known spread drivers such as EDF credit measure, agency rating, seniority, tenor, and industry. We take such findings as clear evidence of a size effect in bond spreads, which is not too surprising given the long history of a known size effect in the stock market. We capture the size effect by (a) calibrating the model in Equation (7) to large firms only and (b) including a Size Premium term to explain the spreads for small firms.

Thus, the general model with size premium becomes

$$
S_T = \beta_z f(z_i) - \frac{1}{T}\ln(1 - N\left[N^{-1}(CEDF_{iT}) + \rho_{im}\lambda_m\sqrt{T}\right] \times LGD) \tag{8}
$$

where z is the firm size, $f(z)$ is a size-function whose form is calibrated from the bond data, β_z is the size-premium parameter, and $\beta_z f(z_i)$ is the size premium.

Appendix B Empirical Results for Europe

This appendix reports the results of a pilot study on the European bond universe. Lack of commensurable data, especially for the smaller European nations, poses substantial constraints. To get around this problem, we focus on only three major European nations—Germany, France, and the UK. We obtain results that are similar to, although not as strong as, the U.S. counterparty. This indicates the robustness of the investment value of our methodologies.

Figure 45 and Figure 46 show the European Investment Grade returns for December 2002–September 2009 for the risk-based strategy and the valuation-based strategy, respectively.

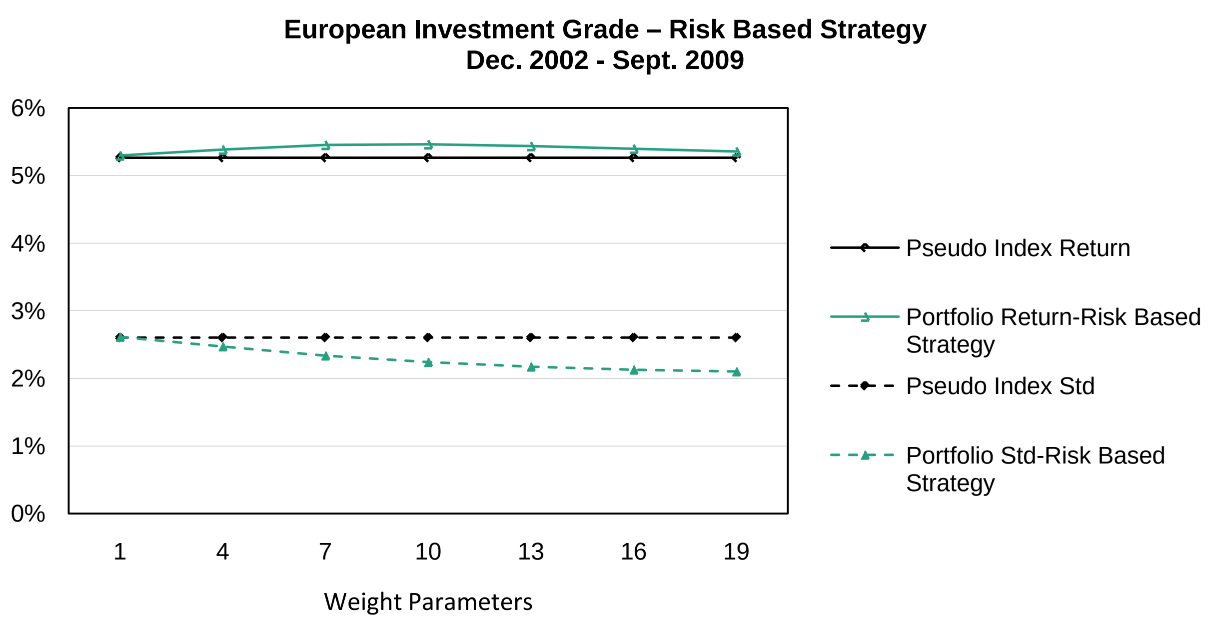

Figure 45 European Investment Grade returns for the risk-based strategy: December 2002–September 2009.

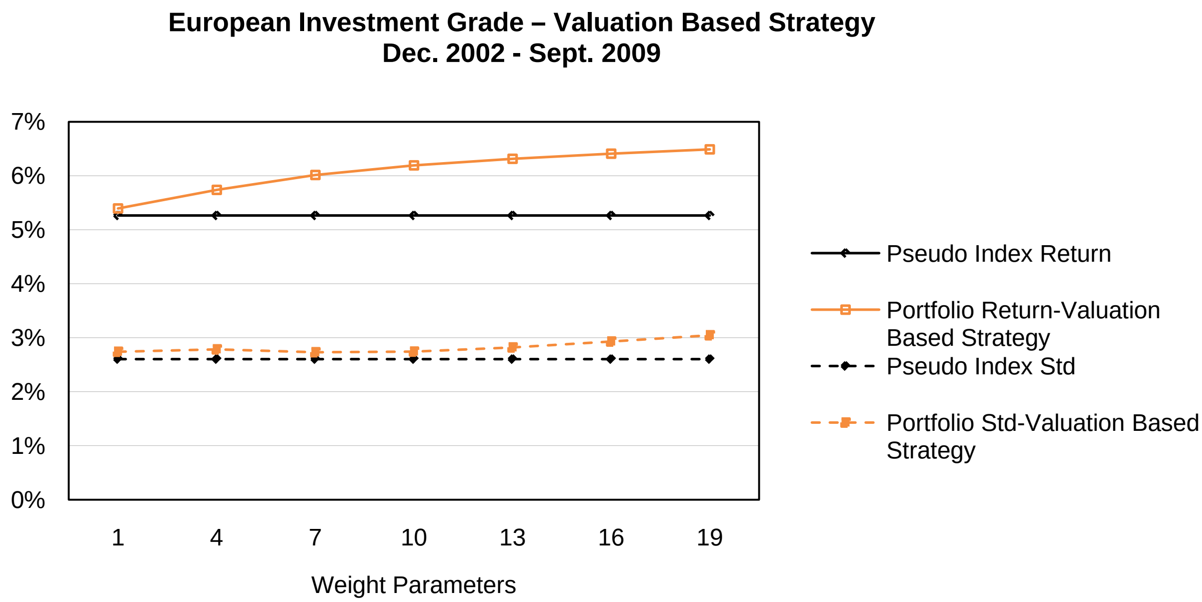

Figure 46 European Investment Grade returns for the valuation-based strategy: December 2002–September 2009.

Figure 47 and Figure 48 show the European Investment Grade returns for January 2007–September 2009 for the risk-based strategy and the valuation-based strategy, respectively.

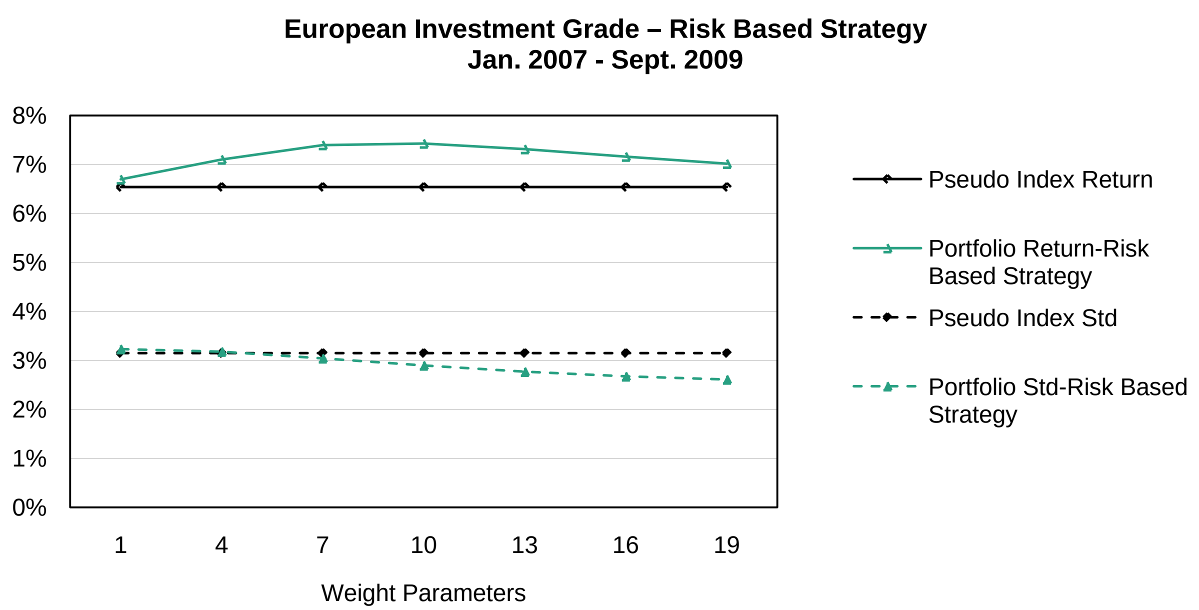

Figure 47 European Investment Grade returns for the risk-based strategy: January 2007–September 2009.

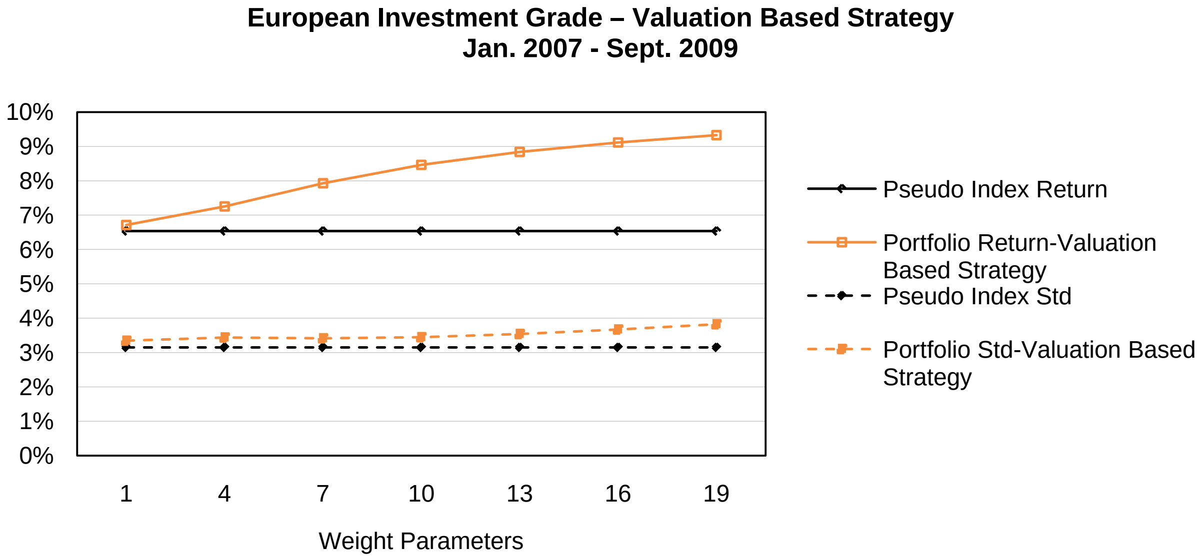

Figure 48 European Investment Grade: Valuation-based strategy for January 2007–September 2009.

Figure 49 shows the year-by-year performance of risk-based strategy and valuation-based strategy compared with the Pseudo Index, c=19. Note that in 2009, we had only nine months of data, therefore, we annualize it to obtain the 2009 return. For all previous years, we take the cumulative return from January–December.

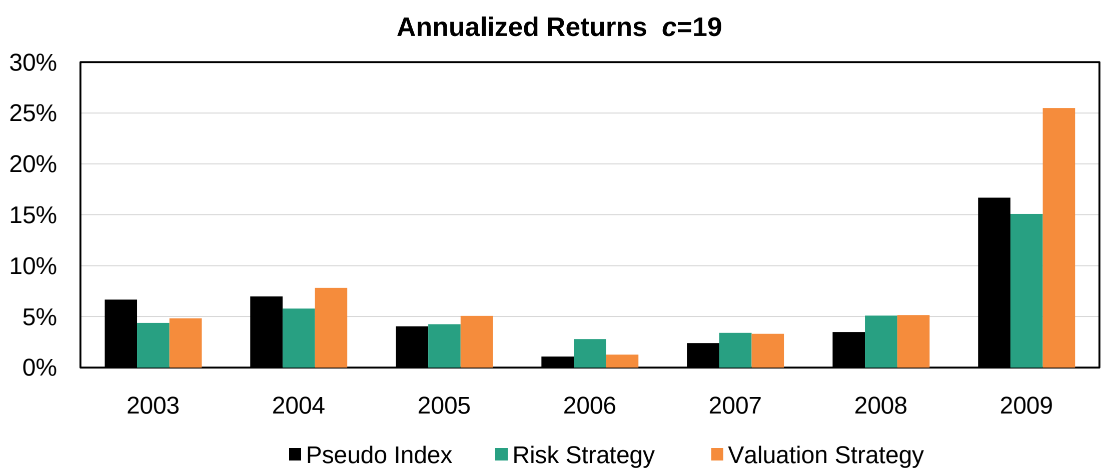

Figure 49 Year-by-year performance of risk-based strategy and valuation-based strategy compared with the Pseudo Index, c=19.

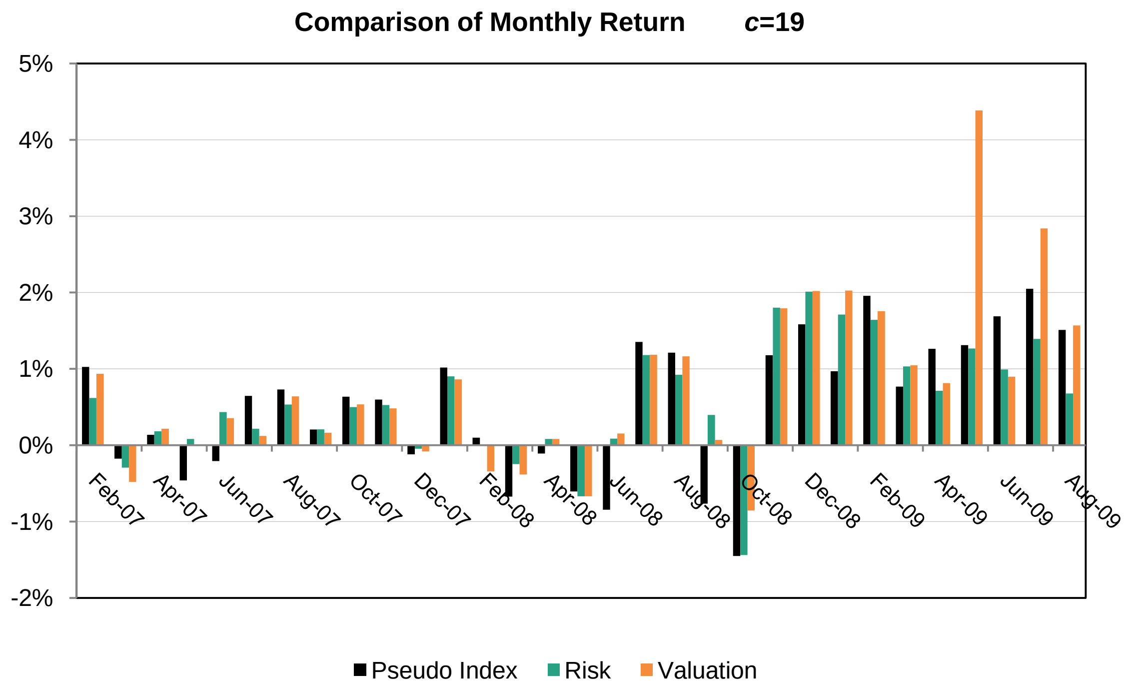

Figure 50 Comparison of monthly returns for Risk-Based Strategy, Valuation-Based Strategy, and Pseudo Index during the recent crisis period, *c*=19.

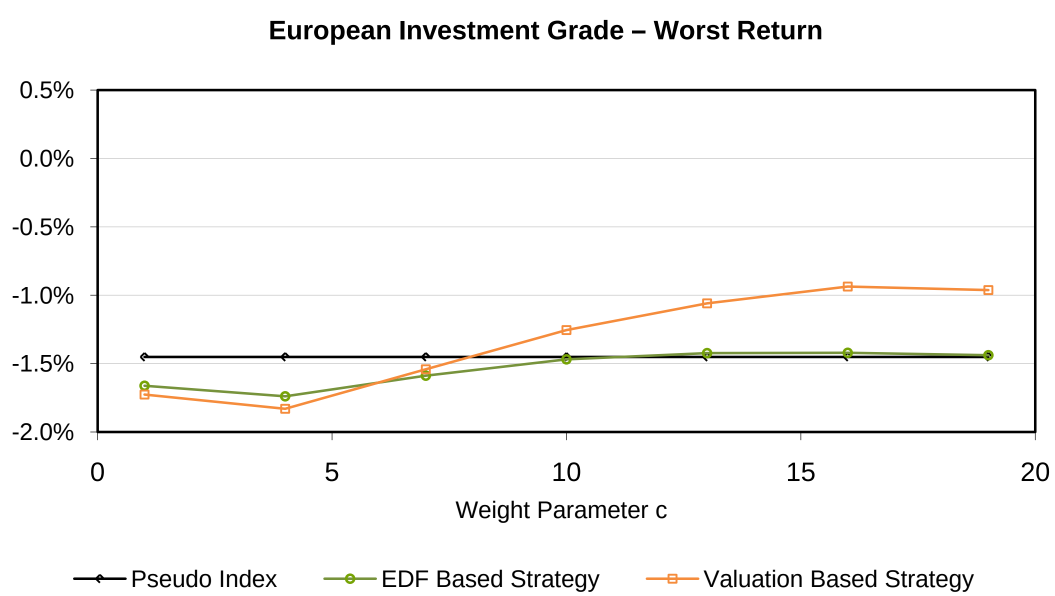

Figure 51 Controlling downside risk, European Investment Grade: Worst return.

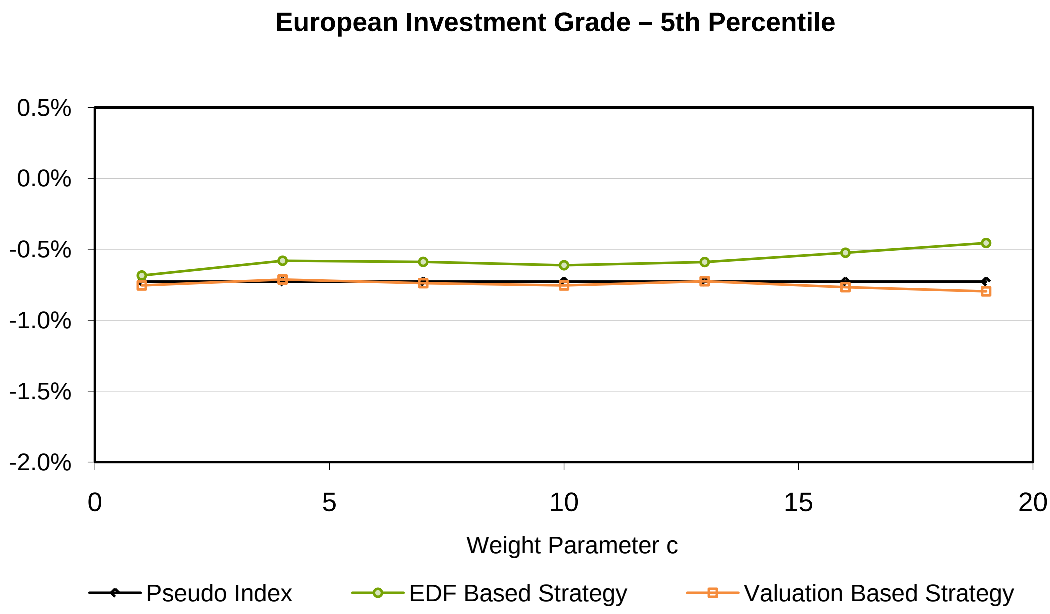

Figure 52 Controlling downside risk, European Investment Grade: 5th percentile return.

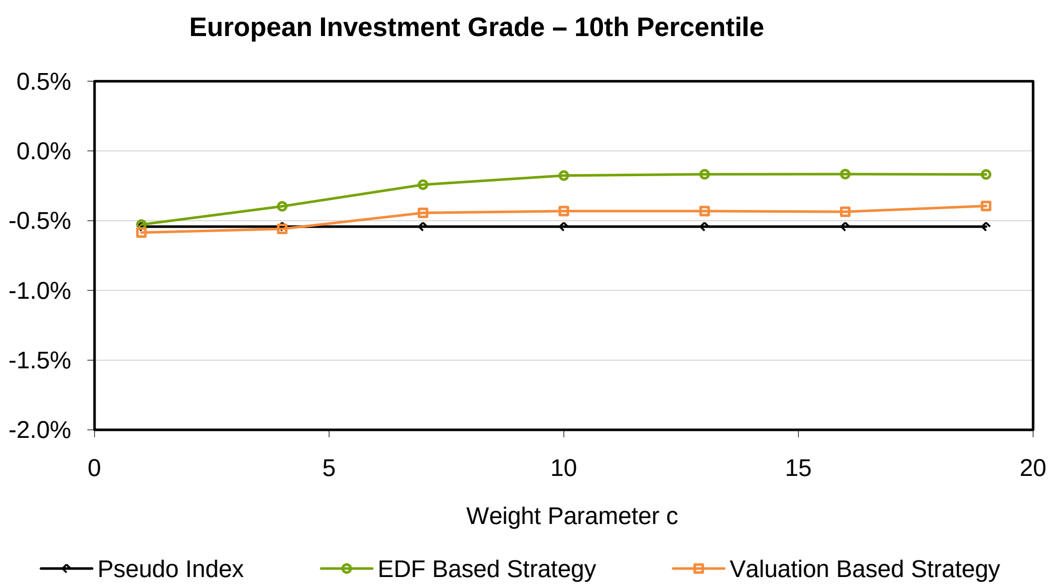

Figure 53 Controlling downside risk, European Investment Grade: 10th percentile return.

We see that the strategies generate positive alpha with smaller systematic risk.

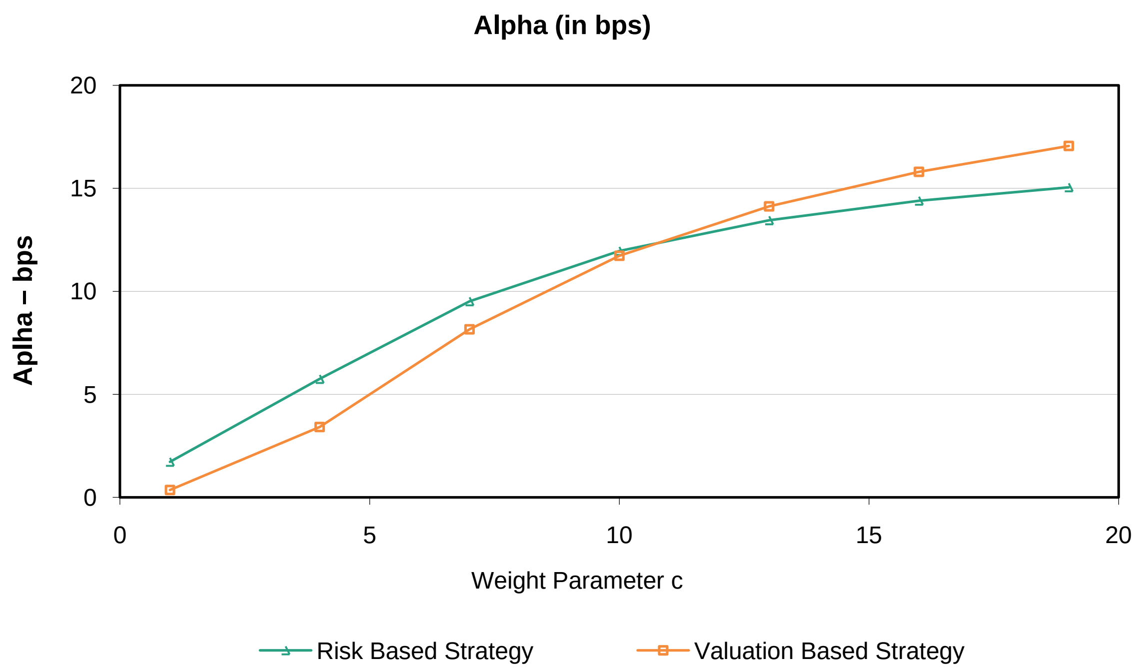

Figure 54 Alphas of Risk-Based Strategy and Valuation-Based Strategy.

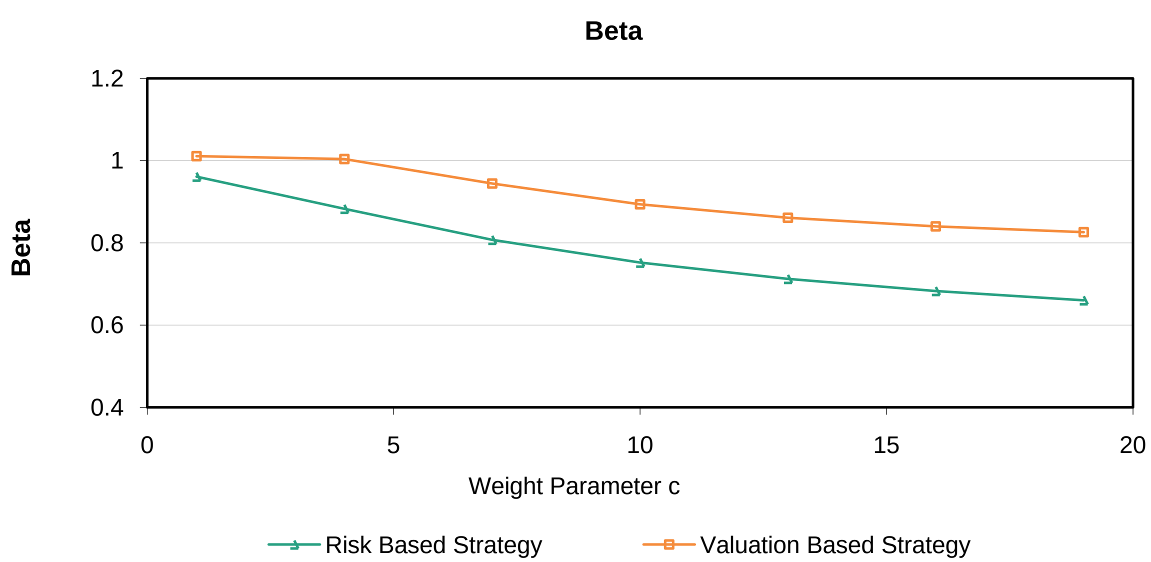

Figure 55 Betas of Risk-Based Strategy and Valuation-Based Strategy.

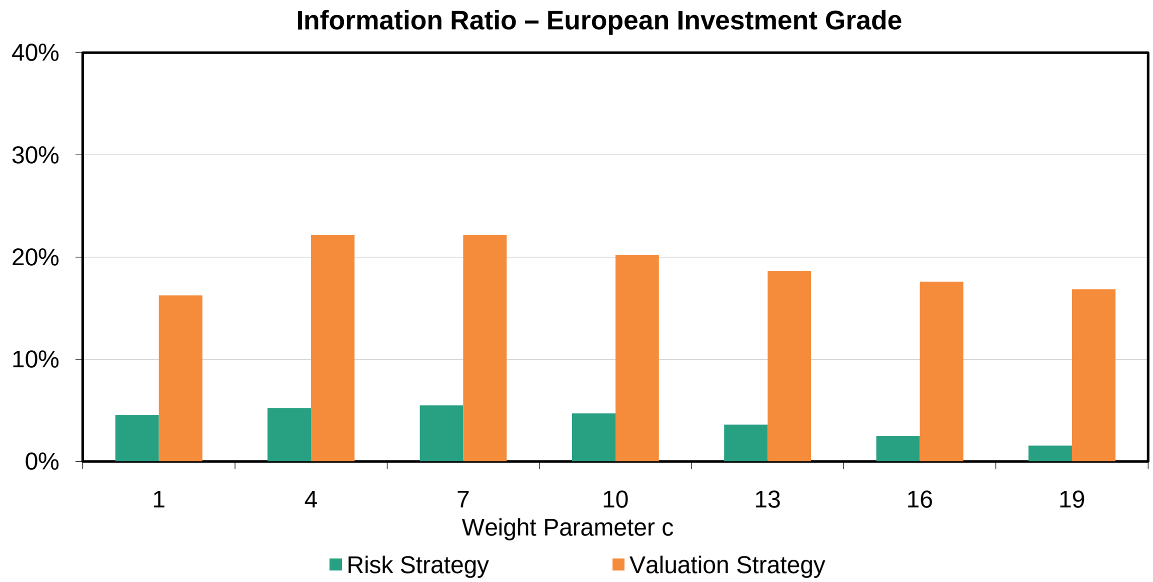

Figure 56 Positive Information Ratio over the Pseudo Index.

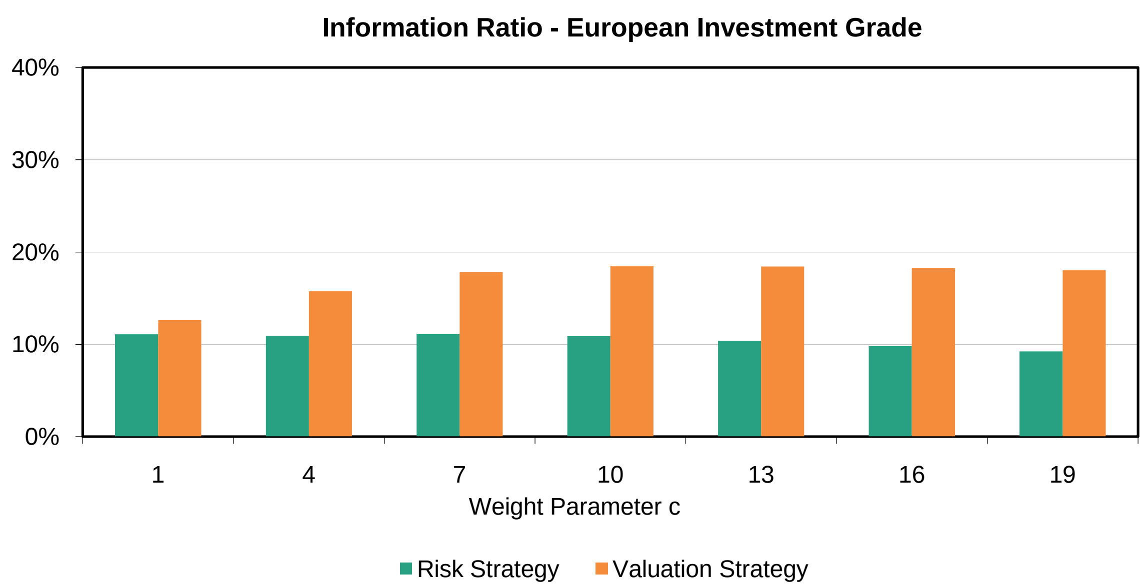

Figure 57 Positive Information Ratio over the Original Index.

EDF measures and FVS can be used to improve corporate credit portfolio performance. We achieve out-performance by controlling for risk and/or exploring for mispricing. The valuation (FVS)-based strategy adds additional returns. These strategies performed well during the recent crisis.

Acknowledgements

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