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A fundamental bond index including solvency criteria

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Abstract

Doubts are rising whether bond indices, in the way they are constructed, are effective in their role of representing the markets they are designed for. Since index constituents are defined on market shares –the larger the debt obligation, the larger the share in the index– it may be that certain risks related to a high level of indebtedness are being accentuated which are not necessarily representative for the market as a whole.

Undue debt levels would in theory not arise in an information-efficient market, however, if prices are distorted, it makes sense to compensate for that and add elementary information on the debt issuers to the index construction process. We test how that works out on corporate bonds. We build a bond index that is based on firm accounting data rather than debt size, and give evidence that it may serve as a market proxy.

JEL codes : G10, G11, G14

Keywords: fundamental indexing, alternative corporate bond index, solvency criteria, market efficiency

1 – Market efficiency and market share

The supposition that indices designed to represent the capital markets, respect the proportions between the assets that are traded, can be related back to the fundamental axioms of finance theory. The founding Capital Asset Pricing Model (Sharpe, 1964), asserts that the markets, in the way they are configured, are efficiently priced. An asset would not be on offer, if there were no demand for it. More generally, assets would not actually be issued in the observed proportions and traded at the observed prices, if there were no buyer-and-seller’s interest to do so. Trade determines relevance, and in the standing definition of the market indices this principle is strictly respected.

For corporate bond indices in particular, it means that firms exist by the market valuation of their outstanding debt. From the viewpoint of a bond investor, a firm’s share of debt defines its market-neutral position, or *beta* position in CAPM terms. We recall that this model presumes an information-efficient market in the strong form, as defined by Fama (1970), meaning that all assessments made by market participants are fully reflected in the bond price. In such perfect market the way a firm is financed is irrelevant, according to Modigliani and Miller’s (1958) founding theorem. The principle of debt-weighted indices stands thus by the assumption that the markets are strongly information-efficient

Is that a reasonable assumption? The question gives, and continues to give, food for heated debate in the finance literature. It is generally recognized, see e.g. Kwan (1996), Downing et al. (2009), Moles et al. (2011) and Roncalli (2013), that the way the corporate bond markets are structured, through local networks and over-the-counter trading, is not conducive. The absence of a centralized platform is regarded as a serious obstacle for information-efficient pricing. The lack of market liquidity which is manifest for corporate bonds, adds to that (Das, et al., 2014). Given the state of the corporate bond markets today, the pricing efficiency is more likely to be weak than strong, as by Fama’s definition.

If the efficiency assumption is relaxed, so is the principle of strict proportionality in the market indices. It opens the door to alternatively-weighted indices that may be as valid as a market reference. Since a few years new indices are being tried and commented in the literature. We take a new step in this field and propose an index that is defined by the overall financial situation of firms rather than by debt size. As a matter of fact, we believe that the Modigliani-Miller theorem does not hold since we reject the market efficiency hypothesis and that consequently the capital structure is actually relevant for the pricing of firm debt (see

Modigliani-Miller, 1958). We use a set of solvency criteria that we apply systematically onto all firms. We have selected criteria that are commonly used by market participants, by buy- and sell-side analysts alike, in the supposition that they jointly make up the information that is relevant in the market equilibrium pricing process. We make an inversion in a way: instead of relying on market prices to induce information, we rely on information to induce market prices.

In empirical tests we study the risk and return behaviour of the index we build. The analysis is carried out on a US Corporate bond index provided by the Bank of America Merrill Lynch, from 2000 to 2014. Our study objective is to gain insight in the (imperfect) equilibrium pricing process for corporate bonds; we do not search for tactical performance opportunity. The intention is to redefine what is referred to as *beta* positions, which can be called enhanced or smart *beta*, but not *alpha*.

The rest of the paper is organised as follows. Section 2 gives the status on fundamental indexing, both in the literature and in practice. The tests we do are described in section 3, the results of which are presented in section 4. Section 5 concludes.

2 – Fundamental indexing : literature and practice

The flows of capital on the investment markets mark the growing interest in funds that rely on alternative market indices and smart beta strategies. While investors are starving for yield, inflows into such funds grew by 30% in 2014 compared to 2013, corresponding to a sum of $350 billion as reported by Balchunas (2014). Those funds are sold on the premise that they outperform traditional market indices, as shortcomings in their weighting schemes based on market share, are overcome; see Amenc et al. (2012) among others. As Chow et al. (2011) and DeMiguel et al. (2007) put it, smart investment strategies conserve the benefits of traditional benchmarks, giving vast market exposure and access to liquidity, while possessing a potential to perform better. It seems that the general market shift marks the end of an era where capitalisation-weighted indexing was the norm.

Alternative indexing breaks the chain between the asset weights in an index and their market valuation. Two approaches are being deployed in the literature, the fundamental- and the risk-based approach. While the former weighs assets as a function of accounting figures and as such disconnects from an asset pricing component, the latter is related to an improved understanding of the risk structure in the index constituents. Alternative indexing refers thus to the application of weighting schemes that purposely shift away from market pricing towards valuation-free metrics.

Among the early pioneers pursuing the fundamental approach are Arnott et al. (2005). They built a fundamentally-weighted equity index on the US market where weights notionally depend on "Main street measures rather than Wall Street measures". They show their RAFI index, which they commercialized, to outperform the capitalisation-weighted S&P500 systematically, independently of business cycles. They hold this result as evidence that fundamental indices are mean-variance superior to cap-weighted indices.

A series of articles confirm the evidence in the international arena. Hemminki and Puttonen (2008) run similar tests on European equities. Tamura and Shimizu (2005), Estrada (2008), and Walkshusl and Lobe (2010) cover other developed countries. Evidence is further corroborated by Chen et al. (2007), who deploy time-smoothed cap weightings as an alternative measure of fundamental values, relying on the hypothesis that prices reverse systematically. Hsu and Campollo's (2006) as well as Houwer and Plantinga's (2009) papers add to the list of evidence of superior risk-adjusted performance in an international framework in the equity world.

Arnott et al. (2005)'s paper does not make unanimity though. A paper written by Perold (2007) entitled "Fundamentally flawed indexing" sparked an animated debate in the Financial Analysts Journal columns. Perold disputed the idea put forward by Arnott et al. (2005), and subsequently defended by Hsu (2006) and by Treynor (2008), that the cap-weighted index suffers a performance drag compared to fundamental indices, for the fact that the pricing error, which exists under the price inefficiency hypothesis, is uncorrelated with the (unobservable) fair value. In that situation a cap-weighted index is biased towards overvalued assets (relative to their fundamentals) while underexposed to undervalued assets. According to Hsu (2006) the higher the price inefficiency, the higher the performance drag. Perold (2007) refutes this explanation; since pricing error is not only independent from fair value, but also from market price, a performance drag of this kind cannot exist. Dijkstra (2015) unnerves the debate by pointing at a weakness in Perold's demonstration who relies on fair values being log-uniformly distributed, which is too strong an assumption.

While the majority of alternative indices are introduced for the equity markets, there is an eagerness among investors to enlarge the scope to other asset classes, notably to bonds. Again among the early pioneers are Arnott et al. (2010) who built fundamentally-weighted sovereign- and corporate bond indices. They weigh sovereign bonds by a set of criteria that measure the strength of the underlying economy, the 'economic footprint' so to speak, that is GDP, population (as a proxy for the labour force), energy consumption (reflecting economic activity) and rescaled land area (to assess natural resources). Barclays (2010) produces 'fiscal strength' sovereign bond indices in a similar spirit, alongside their more basic GDP-weighted indices. Other investment houses have launched fundamental bond indices as well, such as PIMCO, AXA, Blackrock and Lombard Odier.

As to their corporate bond index, Arnott et al. (2010) brought the focus back to firm size, taking five "Main street measures", namely total cash flow, total dividends, book value, sales and the face value of the outstanding debt. Shepherd (2015) built a similar index using corporate cash flows and long-term assets. De Jong and Wu (2014) took a leaner approach, building a corporate bond index on sales revenues alone. Size is an elemental measure to proxy market relevance. Meanwhile it is an effective criterion to capture solvency as well, since sizeable companies are, protected by their scale of operations, less likely to face financial distress.

We expand on the studies of size-focused indices and build a more complete picture of the 'economic footprint' of firms. In the same way that GDP is not all-informative for a country's indebtedness, firm size may be too narrow as a basis, as Kaplan (2008) suggests. Adding creditworthiness, or more precisely the ability to repay contracted debt, is a way, we believe, to accomplish the fundamental indexing approach.

3 – Building a solvency-based market index

3.1. Data

We work on the Bank of America Merrill Lynch US Large Cap Corporate Bond Index, retrieved via Bloomberg, over a fifteen-year period from 31/01/2000 to 31/12/2014. The dataset contains the total returns and principal bond characteristics of the index members on a monthly data frequency. We have retrieved the annual accounting data of the underlying firms in the index from Factset, as published in the financial reports after the fiscal years' close. To avoid survivorship bias we use the "as of" data, meaning that mergers and acquisitions have not been backfilled, and reports not restated. The accounting data have been matched with the market dataset taking a reporting delay of three months into account. Though the bond index dates back to January 1997 originally, the poor accounting data coverage at the beginning of the period has confined us to start tests in 2000.

In all we have obtained fundamentals data for 655 US firms over the period corresponding to a total of 5484 bond issues; that is 91% of the benchmark. We find that an acceptable rate considering that most of the bonds for which no information is available are in fact entities that possess no meaningful accounts, like university endowments (Princeton, Harvard, MIT) or state-owned firms, e.g. Petroleos Mexicanos. After aligning the fundamental metrics with the bond market data, we have recalculated the cap-weighted benchmark onto the successfully-matched universe. We have verified that the exclusion (9%) does not introduce a notable bias or disruption in the test dataset. Data-checking procedures have been applied by which extreme values have been eliminated.

One should bear in mind that our test universe is defined by Merrill Lynch, who applies a "solvency" filter for determining index membership and who strictly respects the "investment grade" constraint as well. Dropping from BBB- to BB+ implies that a firm leaves the index for the high yield world . Many companies, even "blue chips" such as Ford and Time Warner went in and out during our estimation period (also known as the "fallen angels" phenomenon, see Staal et al., 2015), which can interfere with our test objectives

3.2 . Solvency scores

3.2.1 Selecting the accounting variables

The accounting dataset divides into two sets of variables. One set expresses the size of the firms, in the spirit of Arnott et al. (2010), and contains three variables: asset value, sales revenues and equity value. The variables are elementary, common to all sectors of the economy and are relatively easily collected. Among the 655 successfully-matched companies, we have data entries for the three size measures for 93 %, otherwise we have two or sometimes one data entry. We purposely use a composite measure for size, since it smoothes out data inaccuracies and a few cases of 'creative accounting' we have come across. From a practical standpoint, using a composite measure for building an index tends to keep the turnover down, as Hsu (2011) points out.

The second set of variables focuses on the creditworthiness of firms. The set is meant to encompass the information which in an efficient market should be expressed by the bond prices and which in lack of that we deduce from the fundamentals with best efforts. In the remainder of this section we elaborate on our pick of variables. We deliberately stay with a fixed set of common variables in the purpose to capture the commonly-shared market information. Applying a fixed set onto a diverse sample of firms tends to oversimplify of course. Aeronautics are being mixed with consumer staples, healthcare and IT, despite their distinct levels of capital intensity, profit margin, etc. However we have built the set of variables such that biases cancel out to a certain extent. For example, the telecom industry is structurally intensive in capital, weighing negatively in a solvency assessment, yet has high profit margins, which compensates.

We did make an exception for the financial sector, for the fact that some accounting figures are simply not meaningful for financial firms. We have tailored certain variables to suit banks and insurance companies. The precise sets of variables are given in the appendix, with a short description of each.

Assessing the financial state of firms by accounting ratios is common knowledge that is extensively studied in the literature. In fact, investigating a company's solvency position makes one turn to default probability estimation, which brings us back to the founding pricing models of Black and Scholes (1973) and Merton (1974). Their models gravitate toward the notion of "firm value", by which debt and equity are contingent claims on the asset value (Huang and Huang, 2003). We are keen to identify the broad fundamental factors evocated in the literature, without getting side-tracked by specific expert issues. It is not in the scope to consider the plethora of variables that have been studied by academics in credit risk analyses. A few proxies are selected that are easy in terms of data collection, universal and reflect broad fundamental factors, while not leaving out any important component. As a guideline we follow Altman (1968) who advises to use three categories of ratios when studying bankruptcy-prediction, namely liquidity, profitability and leverage.

The first category, liquidity, has been widely studied in the context of bankruptcy analysis. A firm's inability to meet its short-term obligations can cause great financial distress (Campbell et al, 2011). Beaver (1966) shows that the proportion of liquid assets to current debt allows to discriminate successfully between failing and non-failing firms. Altman (1968) asserts that appraising working capital allows to gauge both liquidity and size factors, and is statistically significant to predict default.

The second category, profitability, is about how effective the firm is at generating returns. Altman (1968) gives evidence that earnings, or more precisely earnings-before-interest-taxesdepreciation-and-amortization (EBITDA), have predictive power. Falcon (2007) suggests to look at profit margins, and Bakshi et al. (2006) at operating income. The third category, leverage, indicates the level of risk-taking. Collin-Dufresne et al. (2001) study the relation between the degree of leverage and risk. Ohlson (1980) and Campbell et al. (2011) investigate the proportion of liabilities to the total asset value as a proxy for indebtedness and showcase that this ratio is highly significant, while Bakshi et al. (2006) demonstrates that leverage captured by book-value-to-debt is a key determinant of default.

On top of the three axes put forward by Altman, we have added two, namely size, as mentioned above, and asset quality. Firm size is an input for determining default likelihood, both for academics and practitioners (Campbell et al 2011, Falcon 2007, and Ohlson 1980). Total assets are commonly used as a proxy (Beaver 1966 and Ohlson 1980), while measures such as sales and equity value are often added as accompanying proxies (Al-Khazali and Zoubi, 2011).

Asset quality is an essential criterion in the banking industry. When appraising a bank's creditworthiness, the quality of the balance-sheet (loans) is key (Whalen and Thomson, 1988). We have therefore added the coverage ratio, tier 1 capital, non-performing loans for banks, and we have added the reserves ratio for insurance companies. For the industrials we have chosen to use interest payment coverage, as a way to account for financial distress.

3.2.2 Building the solvency scores

In order to construct an overall solvency score per firm we proceed as follows. We begin by ranking firms by size over the entire sample. For each of the three size variables, i.e. sales, assets and equity, we compute a Z-score per company per period scaled over a range from 0 to 10. The lower the score, the smaller the company and thus the less solvent. The overall size score is simply the average over the three variables, or less if not all data is available. We then build Z-scores for the other assessment variables in a similar manner, by which we rank within the three industry categories that we distinguish, i.e. industrials, banking and insurance. It would be inappropriate to compare certain accounting measures across those categories and such separation allows to account for industry specific ratio which is key for balance-sheet risk appraisal.

The final score is simply the sum of the size- and the solvency score. By taking the sum we combine a relatively structural component with a more time-cyclical solvency component.

The effect is that the index weighting scheme is somewhat stabilised; typically, if cyclical fundamentals go bad one year for a big firm, size will cushion the impact. Of course we have summed all variables with the appropriate signs, e.g. high sales will conduct to a high score for the size metric, while high debt will lead to a low score on the leverage metric.

The scores determine the firm weights, which are then to be distributed over the actual bonds in the index. We have chosen to conserve the debt structure of firms, meaning that we redistribute the weight of a firm over its bond issues in proportion to the market valuation of the debts, as in the classical indices. It would be an option to use the bonds' face values instead, as do Arnott et al. (2010), however, we prefer to concentrate in our study on discriminating between firms on the basis of creditworthiness, not individual bonds.

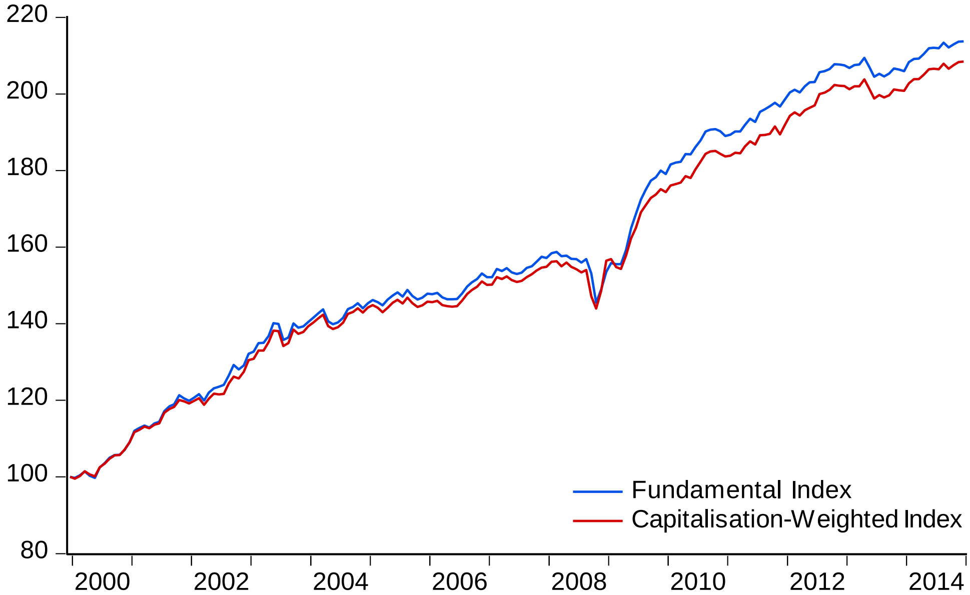
We rebalance the index once a year in March, when the majority of companies publish their annual reports. We have verified that most companies in the study sample end their fiscal year in December or January and comply to the SEC rule to publish results within three months. In March the fundamental data are thus the most timely. In the other months we let the weights drift by the price movements, as in the classical indices.

4 – Empirical tests

4.1. Return performance

The performance of the fundamental index (FI hereafter) based on the solvency scoring scheme, is compared with that of the cap-weighted market index (CW hereafter) in Figure 1, Table 1 and Table 2. We remind that the official index has been reconstituted onto the sub-universe for which accounting data is available. The monthly Total Rate of Return figures (TRR) as provided by Merrill Lynch have been used in the calculations.

Figure 1: Total returns



Source: Authors calculations based on BoA ML and Factset data

The FI outperformances the market index by 35 basis points per year on average with a tracking error of 39 basis points, and with a slightly inferior total volatility. This result adds to the stream of evidence that cap-weighted indices may not be return-risk efficient. Indeed, we show that shifting away from a traditional weighting scheme allows to enhance performance and ultimately to "beat the cap-weighted benchmark", at least during our time span, which in turn pulls into question the market efficiency hypothesis for corporate bonds.

We note that the duration of the FI is slightly longer on average, which is in line with the connotation that creditworthy companies tend to issue longer-dated bonds (Shepherd, 2015). One could suspect the outperformance to stem from the higher duration, which has been a favourable feature over the observation period, however, when adjusting for this fortuitous effect by taking a risk-adjusted measure, namely the Treynor ratio, superior performance remains. For one unit of risk, the FI provides a 6.4% return versus 5.5% for the CW index. These results are validated by the calculations made on returns in excess of the sovereign interest-rate returns, displayed in Table 2, which are by construction duration neutral.

TABLE 1-: RESULTS ON TOTAL RETURNS

	Fundamental Index	Capitalisation-Weighted Index
Total returns	113.70%	108.45%
Geometric returns	100.42%	100.41%
Total returns annualised	7.58%	7.23%
Annual volatility	3.62%	3.66%
Sharpe ratio	1.62	1.51
Maximum drawdown	-8.33%	-9.32%
Average duration	6.14	6.04
Average credit rating[1]	A/BBB	A/BBB
Treynor ratio	6.39	5.53
TE	0.39%	
Information ratio	0.90	
Beta	0.92	
Alpha	0.56%	
Alpha t-stat	1.50	

TABLE 2: RESULTS ON EXCESS RETURNS

	Fundamental Index	Capitalisation-Weighted Index
Total excess returns	24.45%	20.73%
Total excess returns annualised	1.63%	1.38%
Annual volatility	4.82%	4.91%

Notes: TE stands for « Tracking Error » which is the standard deviation of the difference between the returns of a portfolio and the benchmark. Sharpe ratio corresponds to the return of the portfolio minus the risk-free rate, divided by the standard deviation of the returns. 4-week T-bill rates were averaged over the study period to obtain a risk-free rate of 1.72%. Information ratio is the difference between the portfolio return and those of the benchmark, divided by the tracking error. Treynor ratio represents the difference between the return of a portfolio and the risk free rate, divided by its beta (so adjusted from duration risk). The "Capitalisation-weighted index" refers to Merrill Lynch reconstituted benchmark.

In the remainder of this section we analyse to what the outperformance is due. More precisely, we investigate potential sector bias, concentration effects, diversification, sensitivity to risk factors and to the macroeconomic cycle, a traditional analysis framework for such exercise.

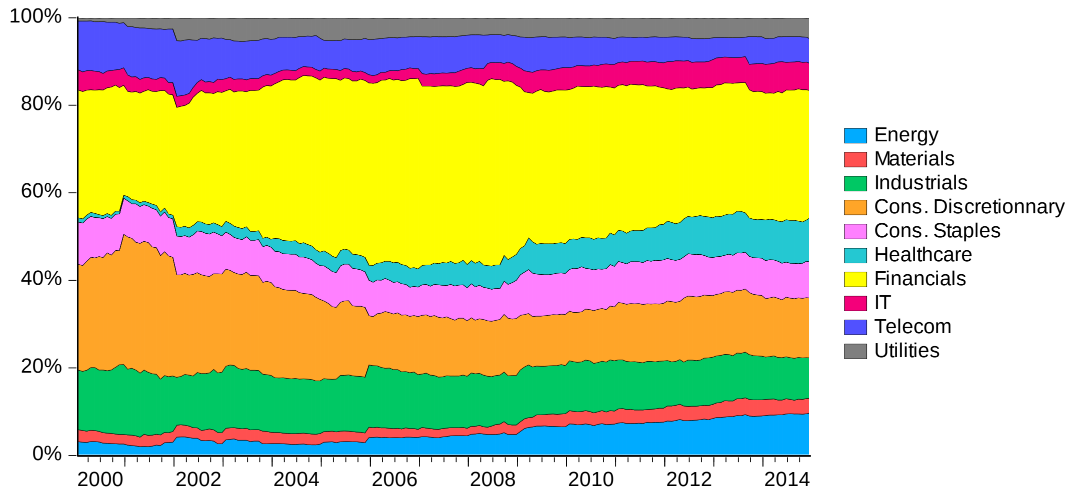
4.2 Sector analysis

Figure 2 compares the economic sector breakdown of the two indices over the test period, as per Merrill Lynch's sector definition. Most apparently the weight of the financial sector diminishes when using solvency weights. This diminution is compensated for fairly equally by the other sectors. Within that, the weights of *consumer discretionary* and *telecom* shrink, while *utilities* and *healthcare* expand.

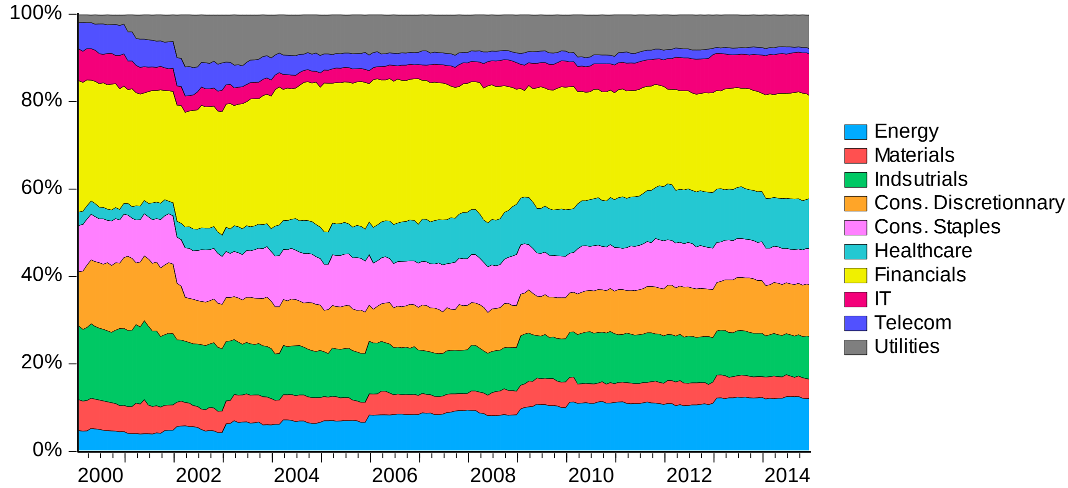
[2] The methodology developed by Morningstar © has been applied to calculate the average credit rating https://prnedelivery.morningstar.com/Average_credit_Quality_Methodology_Change_2010.pdf

Figure 2: Economic sector breakdown

(a) Cap-weighted index



(b) Fundamentally-weighted index



Source: BoA ML data (sector definition level 3). Authors calculations.

Interestingly, we find that the sector biases that are incurred do not explain the outperformance of the FI. We give proof by building two auxiliary indices: (i) cap-weighted on sector level while fundamentally weighted on issuer level, and (ii) the inverse. When comparing the return performances of these indices, in Table 3, it can be seen that the outperformance is generated by the first one, where sector weights have remained unchanged. Its information ratio is greatly superior and higher than the overall FI as well. We thus do not reach the same conclusion as Jacob and Levy (2015), who attribute the success of smart beta strategies essentially to unintended sector biases. Our result gives credit to the "quality tilt" we purposely aim for in our weighting scheme.

TABLE 3: RESULTS FOR THE AUXIILIARY INDICES

	(i) Sectors cap weighted, issuers fundamentally weighted	(ii) Sectors fundamentally weighted, issuers cap weighted
Total returns	116.00%	108.53%
Total returns annualised	7.73%	7.24%
Annual volatility	3.73%	3.70%
Sharpe ratio	1.61	1.49
Information ratio	1.12	0.03
Maximum drawdown	-9.09%	-9.20%

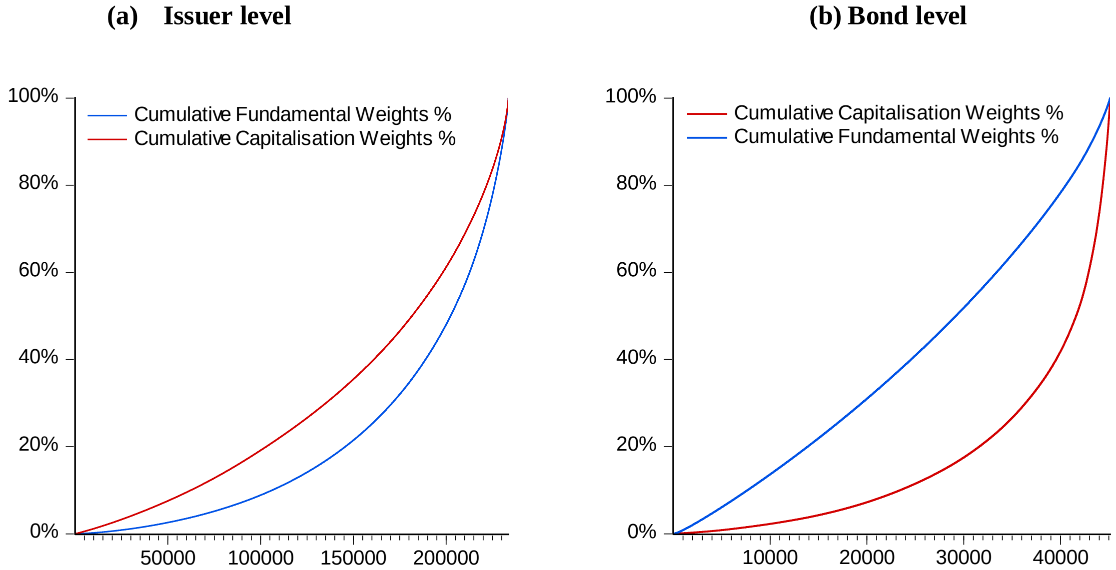
4.3 Concentration

We investigate whether the concentration differs between the two indices and whether that explains the difference in performance. In Figure 3 the index concentrations are depicted in terms of Lorenz curves. The higher the degree of convexity, the higher the concentration. Calculations are made on firm level in (a) and on bond level in (b). Note first that the CW index is highly concentrated on firm level whereas much less on bond level

Compared to the benchmark, note in (a) that the FI is much less concentrated on firm level. Risk is better diversified across firms in this index, which gives support to the idea that alternative indices allow to reduce the concentration risk inherent to traditional indexing (Amenc et al, 2013). Note in (b) that the FI appears more concentrated on bond level. This result is inherent to our choice of conserving the debt structures of firms. Traditionally issuer's weight in the CW index is positively correlated with the variety of bonds it offers: firms can be penalised if they issue only one bond. In the FI construction, we are keen to eliminate such bias and hence a bond weight is not constrained: it can be high if its issuer displays strong fundamentals, even though it has a unique bond issuance which in-fine might lead to a higher concentration at the securities level. We have made an attempt to correct for that, by imposing maximum bond weights, yet found that it did not change the test results in a significant way.[2]

[2] Calculations available from the authors upon request.

Figure 3: Lorenz curves



Calculation method : entities' weights are ranked in ascending order and cumulative weights are displayed

In Table 4 two additional concentration measures are displayed, namely a weight entropy and the so-called Herfindhal-Hirschman index. The latter is simply the sum of squared weights: the lower the value, the less concentrated the index. The weight entropy is the sum of weights multiplied by their log-values. This measures reads the other way round: the lower the value, the higher the concentration. Both confirm the results given by the Lorenz curves.

TABLE 4: CONCENTRATION MEASURES

		Weight entropy	Herfindhal-Hirschman
ISSUER	Capitalisation Weighted Index	361.39	3.47
	Fundamental Index	425.87	0.85
BOND	Capitalisation Weighted Index	538.23	0.26
	Fundamental Index	513.95	0.39

Let us make a direct comparison between the two indices at a given date. In Table 5 the top twenty firms are listed for each index as of March 2014 with their solvency scores.

TABLE 5: TOP 20 ISSUERS, MARCH 31ST, 2014

Capitalisation Weighted Index				Fundamental Index					
No.	Description	Weight	Score	No.	Description	Weight	Score	Score size	Score cycle
1	General Electric	3.91%	11.1	1	Apple	0.34%	13.1	6.9	6.2
2	Bank of America	3.90%	12.7	2	MidAmerican Energy	0.34%	13.0	7.3	5.7
3	Bank One	3.59%	10.0	3	BNSF Railway	0.34%	13.0	7.3	5.7
4	Verizon Communications	3.48%	12.4	4	Google	0.34%	13.0	6.3	6.7
5	Goldman Sachs	3.33%	11.4	5	Chevron	0.34%	12.8	7.0	5.8
6	Citigroup	2.59%	10.8	6	Microsoft	0.33%	12.7	6.4	6.3
7	Morgan Stanley	2.56%	11.0	7	Bank of America	0.33%	12.7	7.6	5.1
8	Wells Fargo	2.05%	9.6	8	HSBC	0.33%	12.7	7.5	5.2
9	AT&T	2.03%	12.3	9	Santander	0.33%	12.5	7.0	5.5
10	Time Warner	1.92%	10.6	10	Johnson & Johnson	0.33%	12.5	6.4	6.1
11	Comcast	1.85%	11.6	11	Verizon Communications	0.32%	12.4	6.7	5.7
12	Wal-Mart	1.50%	12.1	12	Motiva Enterprises	0.32%	12.3	7.3	5.0
13	Ford	1.42%	10.6	13	AT&T	0.32%	12.3	6.7	5.6
14	AIG	1.02%	12.0	14	Occidental Petroleum	0.32%	12.3	5.9	6.4
15	IBM	1.00%	11.5	15	Intel	0.32%	12.2	6.1	6.0
16	MetLife	0.97%	11.8	16	Oracle	0.32%	12.2	6.0	6.1
17	American Express	0.92%	11.6	17	Cisco	0.32%	12.1	6.1	6.0
18	Pepsi	0.89%	11.1	18	Kohlberg Kravis Roberts	0.32%	12.1	5.4	6.8
19	Oracle	0.87%	12.1	19	Wal-Mart	0.32%	12.1	7.2	4.8
20	Amgen	0.82%	11.0	20	AIG	0.31%	12.0	6.7	5.3

The FI is much less concentrated in the top 20, weights being nearly 10 times smaller than in the CW index. The solvency scores appear quite homogeneous in both top 20s. The overlap is low; there are only six companies in common. Big debt does not stand for high solvency, so it appears when comparing these two lists. The bias towards financials in the CW index, made apparent in previous section, shows. The FI is rather biased to IT firms in 2014. This tendency cannot be the result of a hypothetical tech bubble, since the scoring scheme is value-indifferent and thus not related to prices. In fact, the bias indicates that the IT firms had strong fundamentals in 2014.

4.4. Performance attribution

4.4.1 Fama-French factors

Motivated by the observation that the strong performance of the FI is essentially due to firm selection, we continue the analysis, trying to establish the driving factors behind the selection process. As Arnott et al (2010) do in their study, we test the Fama and French (1993) three-factor model, a standard reference in equity space, which we augment by two factors that are specific to bonds. Beside the market,- size- and value factor, we build a TERM factor to capture term-structure variations in the yield curve, defined, as Gebhardt (2001) suggests, on a portfolio that is long 10-20 year US Treasury notes and short the 3-month T-bill. And we build a DEF factor for default risk, defined on a portfolio that is long the (full) BoA ML US Large Cap Bond Index and short the 10-year T-bond. Results are presented in Table 6.

TABLE 6: 5 FACTORS ANALYSIS
JANUARY 2000 – DECEMBER 2014

	Coefficients	t-stat	P-Value
Intercept	0.22	12.159	<0.001
Mkt-RF	-0.007	-0.510	0.611
SMB	0.029	1.494	0.137
HML	0.054	2.860	0.005
DEF	0.438	9.741	<0.001
TERM	-0.015	-0.677	0.499
R^2	0.64		
F-stat	24.61	F-test	<0.001

Notes: Mkt-Rf represents the market premium, SMB and HML the size and value factors respectively, while DEF and TERM allows to account for default and duration exposures.. Alpha (the intercept) is annualised

Most interestingly the value factor (HML) loads significantly, which confirms the quality tilt in the fundamentally-weighted index. This result is accompanied by a significant alpha (Intercept), meaning that not all outperformance is explained by the tilt. We therefore only partially agree with Swinkels and Blitz (2008), who argue that smart benchmarking is no more than a “value tilt in disguise”. Default risk (DEF) is the main risk source in bond space and *de facto* replaces the equity market factor (Mkt). The size factor (SMB) does not load significantly, nor does the TERM factor, which is in line with the results given in Table 2.

4.4.2 Sensitivity to macroeconomic cycle

Table 7 shows that the FI consistently delivers equal or superior return across the three distinct interest-rate regimes compared to the CW benchmark. Highest excess returns occur when 4-weeks T-bill rates are falling. Analogous results were obtained with a composite measure of fundamentals developed by Basu and Forbes (2013). It appears that a rising rate environment is most favourable for the FI in terms of risk-adjusted return. In all, the FI outperforms across all interest rate cycles in our test, giving counterevidence to a common criticism addressed to smart beta strategies that performance is inconsistent across time (Jacob and Levy, 2014).

TABLE 7 — PERFORMANCE ACROSS FEDERAL FUND RATE REGIMES

		Fundamental Index	Capitalisation Weighted Index
RISING T-BILL RATE	Total returns annualised	4.12%	3.96%
	Annual volatility	2.81%	3.26%
	Information ratio	1.23	
	Excess returns	0.16%	
	TE	0.13%	
FALLING T-BILL RATE	Total returns annualised	6.11%	5.85%
	Annual volatility	3.84%	3.68%
	Information ratio	1.08	
	Excess returns	0.26%	
	TE	0.24%	
ZERO T-BILL RATE	Total return annualised	4.96%	4.87%
	Annual volatility	3.85%	4.09%
	Information ratio	0.16	
	Excess returns	0.09%	
	TE	0.56%	

Notes: We use 4-Week Treasury Bill: Secondary Market Rate

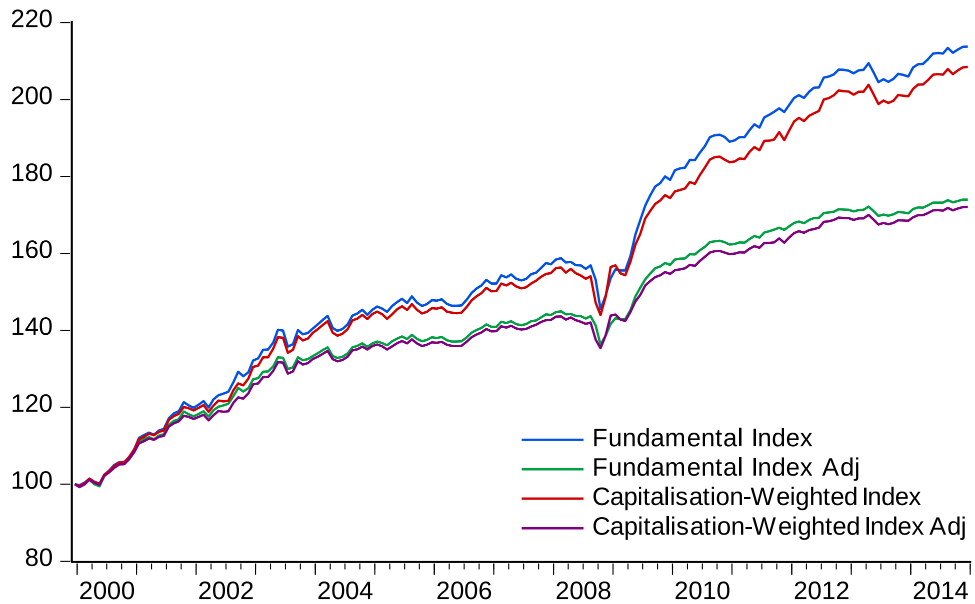
4.4.3 Turnover

We investigate whether the superior performance of the FI can be attributed to the extra turnover stemming from the annual rebalancing in March. Many explain the superior performance of alternative indices by the higher turnover or more generally by liquidity considerations (Jacob and Levy 2015; Malkiel 2014). Yet we have not managed to do so. The annual rebalancing in our test produces an extra turnover of 23%, which is consistent with the literature (Houwer and Plantinga 2009; Hsu and Campollo 2006). When associating a cost of 20bps per trading unit we find that the outperformance by and large persists, see Figure 4.

One should realise though that the observation we make is limited by the fact market returns that are used are themselves influenced by liquidity issues.

In an attempt to stay away from prices, we compare the two market indices on the basis of directly observable bond characteristics that are indicative of their liquidity. Following Houweling et al. (2005) we compare the average residual maturity of bonds, the average face value and the proportion of 'on-the-run' bonds, which all three favour liquidity. According to both the residual maturity, and 'on-the-run' measure, our index is in fact more liquid than the benchmark, while the latter has a higher average face value. In all, the test is not conclusive.

Figure 4: Fundamental and capitalisation weighted indices adjusted for transaction costs and turnover



Source: Authors calculations based on BoA ML and Factset data

5 - Conclusion

The research on *smart benchmarking* to which this paper contributes, is revealing for the definition of *beta*, in the meaning of market-neutral position, that has been practiced for decades in the investment profession. The *beta* position of an asset is defined in a world without transactions costs and strongly efficient prices as its asset value in price equilibrium after market clearance. Any diversion from that falls into the category of *alpha*. Investment activity is organized by this definition; passive management is geared to seizing a *beta* risk premium, while active management seeks tactical performance opportunity brand-marked as *alpha*.

The notion of *smart benchmark* or *smart beta* blurs the frontiers, as mention AlMahdhi (2015). Asness (2006), Blitz and Swinkels (2008), and Jacob and Levy (2014) believe it to be active investment management, since it is based on price behaviour estimation and forecasts of returns. We argue against this. Since the point of alternative indexing is breaking the chain between asset price and market weight, it is typically not based on price estimations or forecasts. Fundamental indexing is to us akin to passive investment, the intention being to hold the market with a low maintenance.

It is interesting that alternative indices tend to superior performances and in our case to a quality tilt as well, which is usually associated to active investment management. Shepherd (2015) says as much: “Smart beta bond strategies combine the transparent, rules-based approach of conventional indices with the active manager’s potential for better investment outcomes.” The debate on how to classify *smart beta* is not settled. A way to judge how the balance is tilting may be to watch the management fees of new *smart beta* funds which are traditionally higher for *alpha* than for *beta* strategies.

We could also reverse the observation. Is it not the quality tilt found in alternative indices pointing at a flaw in the standing definition of *beta*? Is the traditional passive manager investing in a cap-weighted index adequately rewarded for the risks incurred? We think not. Our article contributes to the evidence that the market-neutral *beta* position is ill-defined and that this is rooted in the pricing inefficiencies at play in the bond markets.

In this paper, we make plausible that the broader economic footprint of firms is informational to their market neutral positions. We make use of a parsimonious creditworthiness scoring framework to give demonstration. Our test results echoe with the effectiveness of fiscal strength indices defined on sovereign bonds which incorporate, amongst other criteria, fiscal sustainability, account imbalances and institutional stability. From the empirical evidence we infer that, both in the corporate and sovereign world, a more careful credit-quality bond weighting leads to improved risk-adjusted returns.

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Appendix Definition of the solvency scores

ALL	Impact on scoring	Economic mechanism
Sales	+	Sales allow to estimate the size of the firms as well as its profitability and scale of operation
Assets	+	Measures how much a company owns, which can be a suitable proxy for size
Equity	+	In case of default, equity capital is what is left once debt holders have been repaid. This is thus a measure of capital adequacy : the higher the equity the higher the balance sheet strength

INDUSTRAILS	Impact on scoring	Factor	Economic mechanism
Net debt / EBITDA	-	Leverage	How many years it would take for the company to reimburse its debt if both variables were held constant
EBITDA margin	+	Margin	Profitability of current operations
EBITDA growth	+	Revenues and profitability	Knowing if revenues are growing or not gives key information concerning the firm profitability
Cash & Cash equivalents / Short term debt	+	Liquidity	This measure allows to gauge a company ability to face its short term debt burden with its current cash flows
Interest coverage ratio	+	Balance-sheet quality	This ratio allows to appraise the sustainability of interest expenses

BANKING	Impact on scoring	Factor	Economic mechanism
ROE	+	Revenues and profitability	ROE refers to the ability of a firm to generate profit
Tiers 1 capital	+	Balance-sheet quality	Capital “buffer” against unexpected losses
Coverage ratio	+	Balance-sheet quality	Loan loss provisions / gross loans Allowances for potential losses. A high coverage ratio reduces the probability of default
Operating margin	+	Margin	Amount of revenues generated by every unit of sales
Debt / Equity	-	Leverage	Give an idea of how a firm has been financing its asset. The higher the debt the higher the risk, the lower the solvency on our cyclical metric
Cash & Cash equivalents / Short term debt	+	Liquidity	This measure allows to gauge a company ability to face its short term debt burden with its current cash flows
Non-performing loans / gross loans	-	Balance-sheet quality	Non-performing loans are a bad signal to a bank solvency

INSURANCE	Impact on scoring	Factor	Economic mechanism
ROE	+	Revenues, profitability	ROE refers to the ability of a firm to generate profit
Operating margin	+	Margin	Amount of revenues generated by every unit of sales
Net debt / Equity	-	Leverage	Give an idea of how a firm has been financing its asset. The higher the debt the higher the risk, the lower the solvency on our cyclical metric
Cash & Cash equivalents / Short term debt	+	Liquidity	This measure allows to gauge a company ability to face its short term debt burden with its current cash flows
Reserves ratio	+	Balance-sheet quality	Holding large volume of reserves decreases the probability of default

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