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Lauren Stagnol[1]

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 and not necessarily representative of 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 market value, 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

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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 recognised; 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. In the last few years new indices have been tried and commented in the literature. Fundamental indexing is now a well-documented approach in the equity world (Arnott et al. 2005, Chen et al. 2007, Hsu and Campollo 2006). Still, the bond market has not attracted as much attention. Arnott et al (2010) were among the pioneers in that domain and proposed a corporate bond index based on accounting data, however giving a special focus to size-related metrics. 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, this way introducing what could be called a "quality tilt". 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 select 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.

Empirical tests we undertake can be decomposed into two sub-sections. Firstly on the basis of the relevant literature, we select a few accounting variables that aim at reflecting solvency. We verify they do so by testing if accounting metrics do impact spreads (used as a proxy for firm's ability to service its debt) in a panel framework. We find that size, profitability, liquidity, leverage, margin and financial distress metrics are determinants of credit risk, in lines with the literature. Secondly, using that set of balance-sheet data, we build a fundamental index that focuses on the issuer's creditworthiness and compare its performance to the traditional capitalization-weighted benchmark. The analysis is carried out on a US Corporate bond index provided by the Bank of America Merrill Lynch, from 2000 to 2014. Results show that the solvency based, fundamental index outperforms the cap-weighted benchmark. In that sense, this study corroborates previous results found in the corporate bond universe: disconnecting the weighting scheme from debt towards fundamentals measures allows substantial gains. However, we go further than the current literature by not restricting ourselves to firm size metrics, but by augmenting it with information reflecting issuer's ability to service its debt.

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*. We are thus dealing with market exposure, not with active returns due to firm selection also known as *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. Sections 3 and 4 respectively deal with the design of a solvency score and its empirical validation in an econometric framework while the layout of our index and its performance analysis are carried out in section 5. Section 6 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). In this paper, we take the stance to use the term "smart beta" as defined in Arnott and Kose (2014): "A category of valuation-indifferent strategies that consciously and deliberately break the link between the price of an asset and its weight in the portfolio, seeking to earn excess returns over the cap-weighted benchmark by no longer weighting assets proportional to their popularity, while retaining most of the positive attributes of passive indexing". Smart beta 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. The exercise we intend in this paper is part of the fundamental approach

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 towards the latters. 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 which 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, protected by their scale of operations, are 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 (Investment Grade), 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 retrieve 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 are 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 confine us to start tests in 2000.

In all we obtain 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 recalculate the cap-weighted benchmark onto the successfully-matched universe. We verify that the exclusion (9%) does not introduce a notable bias or disruption in the test dataset. As a matter of fact, the tracking error between the two indices is very low: 6 basis points (see Appendix C, Figure C1 and Table C1). Thus, for simplicity in the rest of this paper, when mentioning the "capitalisation-weighted benchmark" we will refer to its adjusted version. Additionally, abnormal values are eliminated this way tackling potential data processing errors.

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: assets, sales and equity. We argue it captures the "structural", size-related solvency. 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 (namely the average of assets, sales and equity scores) since it smoothes out data inaccuracies or potential 'creative accounting' cases. 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 that should be expressed by the bond prices in an efficient market 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 that would reflect this "cyclical" solvency. We deliberately stay with a fixed set of common variables in the purpose of capturing the commonly-shared market information. Applying a fixed set onto a diverse sample of firms tends to oversimplify of course. Aeronautic is 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 do make an exception for the financial sector, for the fact that some accounting figures are simply not meaningful for financial firms. We tailor certain variables to suit banks and insurance companies. The precise sets of variables are given in the Appendix A, Table A1 and A2, with a short description for each, while summarised below in Table 1.

TABLE 1 — VARIABLES USED IN THE CYCLICAL SOLVENCY SCORE CONSTRUCTION, FOR EACH INDUSTRY, FOLLOWED BY THE SIGN OF THEIR EXPECTED IMPACT ON CREDITWORTHINESS

	Industrials	**Banking**	**Insurance**
Profitability & revenues	EBITDA growth (+)	ROE (+)	ROE (+)
Liquidity	Cash ratio (+)	Cash ratio (+)	Cash ratio (+)
Leverage	Net debt / EBITDA (-)	Debt / Equity (-)	Debt / Equity (-)
Margin	EBITDA margin (+)	Operating margin (+)	Operating margin (+)
Financial distress	Interest coverage ratio (+)	Tier 1 capital (+) Coverage ratio (+) Non-performing loans to total loans (-)	Reserves ratio (+)

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, standard 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 discriminating successfully between failing and non-failing firms. Altman (1968) asserts that appraising working capital permits to gauge both liquidity and size factors, and is statistically significant to predict default. We chose to use cash & cash equivalents divided by short-term debt as measure of liquidity, as we believe it allows capturing the cash's adequateness to imminent debt repayment.

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-taxes-depreciation-and-amortization (EBITDA), have predictive power. Falcon (2007) suggests looking at profit margins and Bakshi et al. (2006) at operating income. Hence, we decide to use both margins (EBITDA margin and operating margin for industrials and financials respectively) and profitability measures (EBITDA growth – to capture a more dynamic aspect and return on equity (ROE) for industrials and financials respectively) to account for profitability.

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. As far as we are concerned, we decide to use net debt to EBITDA and debt to equity for industrials and financials respectively.

On top of the three axes put forward by Altman, we add two, namely size and financial distress. 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). Consequently, we select assets, sales and equity.

Financial distress 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). Therefore, we add the coverage ratio, tier 1 capital, non-performing loans for banks, and the reserves ratio for insurance companies. For the industrials we choose to use interest payment coverage, as a way to account for financial distress.

3.2.2 Building the solvency scores

3.2.2.1. The "structural" component

For the construction of the structural component of our solvency score, we proceed as follows. We begin by ranking firms by each size metric 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. Then, the structural solvency score is simply the average over the three variables' Z-score, or less if not all data is available. We are thus left with a size-related, "structural" solvency score (see Table A1 in Appendix A).

3.2.2.2. The "cyclical" component

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 accounting for industry specific ratio which is crucial for balance-sheet risk appraisal (see Table A2 in Appendix A). Figures D1-D3 presented in Appendix D show that the cyclical solvency score permits to capture the major trends of the recent economic environment (such as the dot com bubble from 2000 onwards, the automobile crisis starting in 2006, the telecom crash in 2001 or the financial crisis of 2007-2008) which supports our scoring methodological approach.

3.2.2.3. Final solvency score

The final score is simply the sum of the structural and the cyclical solvency scores.[2] 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

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[2] For each issuer i : $Score\ SIZE_{it} = \frac{Z\ assets_{it} + Z\ sales_{it} + Z\ equity_{it}}{3} \quad \forall\ i$

For $\forall\ i \in$ Industrials :

$$Score\ CYCLE_{it} = \frac{Z\ ebitda\ growth_{it} + Z\ cash\ ratio_{it} + Z\ net\ debt/ebitda_{it} + Z\ ebitda\ margin_{it} + +Z\ interest\ coverage_{it}}{5}$$

For $\forall\ i \in$ Banking :

$$Score\ CYCLE_{it} = \frac{Z\ ROE_{it} + Z\ cash\ ratio_{it} + Z\ debt/equity_{it} + Z\ operating\ margin_{it} + Z\ Tiers\ 1\ capital_{it} + Z\ coverage\ ratio_{it} + Z\ non\ performing\ loans/gross\ loans_{it}}{7}$$

For $\forall\ i \in$ Insurance :

$$Score\ CYCLE_{it} = \frac{Z\ ROE_{it} + Z\ cash\ ratio_{it} + Z\ debt/equity_{it} + Z\ operating\ margin_{it} + +Z\ reserves\ ratio_{it}}{5}$$

For each issuer i ; $Solency\ score_{it} = Score\ SIZE_{it} + Score\ CYCLE_{it} \quad \forall\ i$

cyclical fundamentals go bad one year for a big firm, size will cushion the impact. Of course we sum 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 verify 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 timeliest. In the other months we let the weights drift by the price movements, as in the classical indices.

4 - Empirical testing of the accounting variables

For the sake of completeness, we are keen to test empirically the pertinence of the variables we use in the construction of our index. Indeed, we selected a set of metrics that aims at reflecting the solvency of the issuing firm on the basis of the relevant literature. These metrics are supposed to be representative of profitability, liquidity, leverage, margins as well as financial distress. But are they backed by empirical evidences and meaningful determinants of creditworthiness?

It is generally recognized that spreads are a good proxy for insolvency (Gatfaoui 2008, Ayache, et al. 2005). Indeed, the spread reflects the difference between the yield of a corporate bond, and a risk free bond (typically Treasury bond) of similar maturity. Corporate bond yields are systematically higher than those of US government bonds in the sense that their issuers – companies- are generally considered more likely to default than the government. The mechanism is as follow: the lower the creditworthiness of the issuing company, the higher compensation will be required by a bond owner for taking such risk (i.e.: buying its debt). Therefore we want to investigate if the accounting metrics we have chosen are accurate determinants of spreads.

4.1. Data issues

We face a first problem: multiple bond issues. As a matter of fact, most of the firms in our database issue more than one bond, implying that there are many spreads for a given firm at a time t. Another complication relates to the fact that spreads data we possess are on a monthly basis, while accounting data are only modified once a year. Consequently, to tackle such monthly spreads "noise" as well as multiple securities for a firm, we decide to undertake an aggregation of our data. We create an annual database, where we average out the securities spreads for a given firm across them on a monthly basis and then compute the average of the 12 months constituting a year, thus getting an "annual spread" for each issuer in the database.

We now turn our attention to the industry classification we have chosen to apply in our weighting scheme. Indeed, we separate out industrials, banking and insurance companies, thus leaving us with three distinct databases, their number of cross-sections being respectively 508, 98 and 49. Descriptive statistics are presented in Table A3 in Appendix A. Each industry having its peculiarities in terms of creditworthiness metrics we have to treat them separately.

4.2. Unit root analysis

First, we need to investigate if the variables we study are stationary, since it can impact the estimation method subsequently used. In order to do so, we perform different panel unit root tests, namely Levin-Lin-Chu (2002), Im, Pesaran & Shin (2003) as well as Augmented Dickey Fuller and Phillips-Perron panel unit root test types (see Maddala & Wu, 1999 and Choi, 2001). While the former tests the null hypothesis of common unit root process to all cross-sections, the other tests investigate the existence of an individual unit root. The results presented in Appendix B Table B1 demonstrate that none of the series - some of them being taken in logarithm, contains a unit root.

4.3. Causality tests

Then, we undertake empirical testing of Granger Causality between creditworthiness and accounting variables. Investigating Granger Causality between variables X and Y implies testing if the values of X help predicting values of Y, and vice versa. Indeed from a theoretical point of view, we suspect some bilateral causality (endogeneity), in the sense that financial accounts are obvious determinants of solvency, but in turn a degradation of creditworthiness might affect accounting reports (increased difficulties to re-finance etc…). Tests have been carried out on the entire sample, without distinguishing between industries. Despite the fact that our database is in a panel framework, we investigate “common coefficients”, which implies testing causality on stacked data.[3] The results are presented in Table 2:

TABLE 2 — GRANGER CAUSALITY TEST
SAMPLE 2000-2014, ALL INDUSTRIES

Cat.	Null Hypothesis	Obs	F Stat	P-Value	Cat.	Null Hypothesis	Obs	F Stat	P-Value
Size	Sales => Spread	2767	7.97	<0.01	**Margin**	EBITDA Margin => Spread	1996	5.04	<0.01
	Spread => Sales	2767	3.55	0.03		Spread => EBITDA Margin	1996	0.95	0.39
	Equity => Spread	2682	10.20	<0.01		Operating Margin => Spread	2636	54.07	<0.01
	Spread => Equity	2682	6.58	<0.01		Spread => Operating Margin	2636	0.92	0.40
	Assets => Spread	2777	2.44	0.09	**Financial distress**	Interest Coverage ratio => Spread	1945	10.61	<0.01
	Spread => Assets	2777	1.86	0.16		Spread => Interest Coverage ratio	1945	10.24	<0.01
	Score Size => Spread	2833	14.84	<0.01		Tiers 1 Capital => Spread	265	4.74	<0.01
	Spread => Score Size	2833	3.48	0.03		Spread => Tiers 1 Capital	265	0.95	0.39
Profitability	EBITDA Growth => Spread	1669	13.55	<0.01		Non-Performing Loans to Gross loans => Spread	232	10.20	<0.01
	Spread => EBITDA Growth	1669	1.63	0.20		Spread => Non-Performing Loans to Gross loans	232	1.25	0.30
	ROE => Spread	2606	54.45	<0.01		Coverage ratio => Spread	270	43.47	<0.01
	Spread => ROE	2606	7.94	<0.01		Spread=> Coverage ratio	270	0.47	0.63
Leverage	Debt to Equity => Spread	2568	2.29	0.10		Reserves ratio => Spread	140	1.20	0.31
	Spread => Debt to Equity	2568	11.01	<0.01		Spread => Reserves ratio	140	0.54	0.59
	Net Debt EBIDTA => Spread	2034	1.38	0.25	**Liquidity**	Cash ratio => Spread	2389	0.60	0.55
	Spread => Net Debt EBIDTA	2034	2.32	0.10		Spread => Cash ratio	2389	0.77	0.46

Notes: Considering that we work on annual data, we have chosen to use two lags in the tests.
Source: Author calculations

The first point we can make is that most of the variables we have chosen in our scoring strategy seem to be potential determinants of spread. Such result demonstrates that our combination of broad axis (profitability, leverage etc…) for assessing creditworthiness is mostly sensible, and that using adequate metrics as a proxy for those categories in the construction of a solvency score has empirical grounds. Indeed size, profitability, liquidity, debt, margins and financial distress metrics all seem to “Granger cause” spread. Still, when

[3] Indeed, our panel data being unbalanced, we cannot apply Dumitrescu-Hurlin (2012) test for individual coefficients

going into the variable details, we came across some surprising results at a first sight, such as our inability to conclude when considering debt to equity. It seems that a bidirectional causality exits between the spread and the level of leverage of a company. Indeed, being highly indebted implies that markets might anticipate future financial difficulties for a company, resulting in a higher spread. Subsequently, if those anticipated financial difficulties actually occur it may force the firm to again raise indebtedness. The idea is reinforced by another bi-directional causality between interest rate coverage and spread. A high interest rate coverage ratio is a good signal to bondholders, which puts a downward pressure on spreads. However, as the spread for a given company increases, it becomes more expensive to refinance in the sense that interest rates paid to lenders have to increase in pace with the creditworthiness deterioration, which *in-fine* widens the interest expense As far as the other variables are concerned, it seems that there is endogeneity between spread and equity levels, as well as with size metrics which is in line with theory (Campbell et al. 2011, Falcon 2007 and Ohlson 1980).

4.4 Model estimation

As explained before, in that study we have three distinct databases, one for each industry: industrials, insurance and banking. However, they all share common statistical properties, namely having a low T (we have annual data from 2000 to 2014, leaving a maximum of T=15), and high N. Therefore we are in the case of micro-panel datasets, that are on top of that unbalanced (this is due to working on a financial index whose index constituents evolve every month). All series taken in logarithm are stationary, as shown before. The dependent variable – the spread - is likely to be persistent so we will focus on a specification with the lagged dependent variable on the right hand side of the equation as in Gerlach et al (2010). Additionally, considering our firm level database and our period of analysis, we believe that unobserved heterogeneity has to be accounted for, on both the cross-sectional and period levels. Last but not least, as suggested by the Granger causality tests in Table 2, endogeneity materialises between some fundamental variables and credit spread. All these elements are likely to lead to dynamic panel bias if inappropriate estimation methods are employed. However we cannot use OLS because the estimator is likely to be biased and inconsistent, particularly due the Nickel bias that only approaches 0 when T is very large (Bun and Sarafidis, 2013). Instead, we should consider the General Method of Moments. Indeed GMM has been widely used because it allows achieving optimal asymptotic properties, without having to make too strong statistical assumptions on homoscedasticity and distributional properties. On top of that, GMM is often viewed as superior to the standard Instrument Variables method if we are facing a problem of endogeneity (as we suspect for size, debt to equity and interest coverage).

Arellano and Bond (1991) developed a consistent GMM dynamic panel data estimator. The basic idea is to improve efficiency by using all of the available information (contained in lagged values) for each observation as instrument. The first step is to take the regressors in difference (or through orthogonal deviations as later proposed by Arellano and Bover, 1995): this allows eliminating cross-section fixed effects. This leaves a differentiated equation for each period. Then, the aim is to instrument explanatory variables of the latter equations by their own lagged values. These equations translate into moment conditions that allow deriving parameters estimates. Indeed, the GMM core idea is that moments conditions can be exploited to test a model specification, but also to estimate the model parameters.

We decide to estimate the following model for the "industrials" database:

$$\begin{gathered} Spread_{it} = \alpha_i + \delta_t + \beta_1 Spread_{i,t-1} + \beta_2 Size_{it} + \beta_3 EBITDA\ Growth_{it}\ + \\ \beta_4 Cash\ _{it} + \beta_5 \left(\frac{Net\ Debt}{EBITDA}\right)_{it} + \beta_6 EBITDA\ Margin_{it} + \beta_7 Interest\ Coverage_{it} + \varepsilon_{it} \end{gathered} \tag{1}$$

We choose to use period dummy variables, denoted δ_t, in order to account for tension in spreads during the recent crisis. We also use cross-section fixed effects, α_i to tackle unobserved individual heterogeneity. Additionally and as explained before, we fear our model may suffer from endogeneity problem and thus decide to use instrumental variables, including dynamic instruments. We use GMM estimation with Arellano and Bond GMM weights. The weighting matrix employed is known as "White period" implying that the residuals can have a serial correlation structure that varies across cross-section. Its estimation is achieved in two steps, as in Arellano and Bond (1991). Finally we apply robust standard errors. As far as the transformation of the above specification is concerned, we use forward orthogonal deviations instead of traditional differences to control for fixed effects.[4] We do this for two reasons: first it is suggested that the estimator applied to orthogonal deviations might be more performant (Hayakawa, 2009). Second, we believe that such method allows reducing the loss in degrees of freedom, which is an important concern in an unbalanced panel data model. Results are presented in Table 3.

[4] This implies that for each current observation, we subtract the mean of its future values, this way eliminating fixed effects.

TABLE 3 — DEPENDENT VARIABLE: SPREAD
SAMPLE 2000-2014, INDUSTRIALS

	GMM (1)	GMM (2)	GMM (3)	GMM(4)	GMM(5)
Spread(-1)	0.635***	0.618***	0.613***	0.599***	0.609***
Size	-0.502***	-0.013	-0.593***	-0.129	-0.545***
EBITDA Growth	-0.001***	0.001	-0.001**	-0.001	-0.001
Cash ratio	-0.009**	-0.028**	-0.011***	-0.044***	-0.012***
Net Debt / EBITDA	0.125***	0.061**	0.063***	0.136***	0.062***
EBITDA Margin	-0.151***	-0.192**	-0.173***	-0.229**	-0.197***
Interest Coverage	0.108***	0.032	0.087***	0.128***	0.094***
Period dummy	YES	YES	YES	YES	YES
Cross-section effects specification	Orthogonal deviations	Orthogonal deviations	Orthogonal deviations	Orthogonal deviations	Orthogonal deviations
Instrument rank	110	110	110	110	110
Hansen J statistics (p-value)	96.23 (0.31)	116.40 (0.03)	98.49 (0.26)	105.96 (0.12)	99.82 (0.23)
SSR	97.62	99.45	102.28	110.57	102.50
Cross-sections	264	270	269	271	269
Observations	1470	1505	1514	1530	1514
Instruments Transformation	Orthogonal deviations	Levels	Orthogonal deviations	Levels	Orthogonal deviations
Instruments	Dependent variable (dynamic) Score size, Net debt EBITDA, Interest coverage endogenous Cash ratio, EBITDA growth and EBITDA margin exogenous	Dependent variable (dynamic) Score size, Net debt EBITDA, Interest coverage endogenous Cash ratio, EBITDA growth and EBITDA margin exogenous	Dependent variable (dynamic) Score size, Interest coverage endogenous Net debt / EBITDA, Cash ratio, EBITDA growth and EBITDA margin exogenous	Dependent variable (dynamic) Score size, Interest coverage endogenous Net debt / EBITDA, Cash ratio, EBITDA growth and EBITDA margin exogenous	Dependent variable (dynamic) Score size, Interest coverage endogenous Net debt / EBITDA, Cash ratio, EBITDA growth(level) and EBITDA margin exogenous

Notes: We recall that size is a composite measure of assets, equity and sales. All variables are taken in logarithm, except EBITDA growth.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Source: Author calculations

Different specifications are tested, with varying transformation methods and instruments. More precisely, we try two versions: one where net debt / EBITDA is exogenous – as suggested through Granger Causality test (models (3) (4) (5)), and another one where it is endogenous (models (1) (2)). Indeed the bilateral relationship between spread and debt to equity tends to support the idea that leverage could also be a determinant of spread, so we try that hypothesis as well. As far as instrument transformation methods are concerned, we test orthogonal deviations, levels as well as combination of both to tackle "growth" variables (see model (5)). We observe that the validity of the instruments is not rejected by the Hansen test of over-identifying restrictions across the different instrument specifications, except for the

GMM (2) at a 99 % confidence level. [5] Additionally, one should note that these approaches convey analogous coefficient estimations that are relatively stable across models, which tends to corroborate our results robustness.

In our analysis, we simplify the mechanism, and assume that a high spread implies financial distress, and thus a higher probability of default. We observe that the estimated coefficients have the expected signs. For instance, size proxied by assets, equity and sales diminishes the credit risk in models (1), (3) and (5), as argued by Ohlson (1980). Additionally, having liquidity and strong margins appears to strengthen creditworthiness, as measured by spreads, in all specifications, so are rising revenues in models (1) and (3), supporting Altman (1968) argument. Oddly, being able to service its debt seems to have a positive impact on spread in our GMM specification (see models (1) (3) (4) (5)) which contradicts preliminary OLS results displayed in Table B2. Finally, and as expected being highly leveraged is a bad signal for financial markets, which require a higher spread in compensation for such risk, a result which goes in lines in lines with Collin-Dufresne et al. (2001). Finally, we perform simple OLS estimates, regressing each variable separately on spread in Table B2 and the model specified in equation (1) estimated via OLS, is presented with the Variance Inflation Factors (VIF) for each coefficient in Table B3. We perform this extra step to ensure that collinearity is not responsible for the variables' significance. The results demonstrate that this is not the case: all the explanatory variables have the expected sign in Table B2 while the VIF in Table B3, displayed for the basic model and for different dummy specifications are below the threshold value of 5 (O'brien, 2007).

As far as banking and insurance are concerned we have much less cross-sections available, which is likely to decrease the efficiency of the GMM estimator. Consequently, we decide to treat them together, considering that they share five common variables in our scoring scheme and estimate the following model:

$$Spread_{it} = \alpha_i + \delta_t + \beta_1 Spread_{i,t-1} + \beta_2 Size_{it} + \beta_3 ROE_{it} + \beta_4\, Cash_{\,it} + \beta_5 \left(\frac{Debt}{Equity}\right)_{it} + \beta_6 Operating\ Margin_{it} + \varepsilon_{it} \quad (2)$$

[5] The test principle is to regress the errors from the GMM regression on instruments used. Under the null hypothesis, all instruments are uncorrelated to the residuals. And hence, instruments can be considered as valid (Hansen, 1982)

Remaining industry specific variables will have to be treated separately. The results are presented in Table 4.

TABLE 4 — DEPENDENT VARIABLES: SPREAD
SAMPLE 2000-2014, FINANCIALS

	GMM (6)	**GMM (7)**	**GMM (8)**	**GMM (9)**	**GMM (10)**
Spread(-1)	0.399**	0.400***	0.305***	0.292***	0.305***
Size	-0.741***	-0.777***	-0.922***	-0.462	-0.925***
ROE	-0.049***	-0.009	-0.434*	-0.046**	-0.044*
Cash ratio	-0.041***	-0.094***	-0.029***	-0.071***	-0.029**
Debt to Equity	0.039**	0.043**	0.072***	0.044**	0.072***
Operating Margin	-0.002**	-0.002**	0.002	-0.005***	0.002
Period dummy	YES	YES	YES	YES	YES
Cross-section effects specification	Orthogonal deviations	Orthogonal deviations	Orthogonal deviations	Orthogonal deviations	Orthogonal deviations
Instrument rank	90	92	87	90	87
Hansen J statistics (p-value)	76.60 (0.30)	71.59 (0.53)	68.76 (0.45)	70.08 (0.51)	68.79 (0.45)
SSR	46.90	49.68	45.92	48.49	45.92
Cross-sections	90	92	87	90	87
Observations	452	464	421	441	421
Instruments transformation	Orthogonal deviations	Levels	Orthogonal deviations	Levels	Orthogonal deviations
Instruments	Dependent variable (dynamic) Score size and Debt to Equity endogenous Cash ratio, ROE and Operating margin exogenous	Dependent variable (dynamic) Score size and Debt to Equity endogenous Cash ratio, ROE and Operating margin exogenous	Dependent variable (dynamic) Score size, ROE, Debt to Equity endogenous Cash ratio exogenous	Dependent variable (dynamic) Score size, ROE Debt to Equity endogenous Cash ratio and operating margin(transformed) exogenous	Dependent variable (dynamic) Score size, ROE, Debt to Equity endogenous Cash ratio, Operating margin (in level) exogenous

Notes: We recall that size is a composite measure of assets, equity and sales. All variables are taken in logarithm, except operating margin.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Source: Author calculations

As in the industrial database analysis, the results presented here display different methods for instruments transformation in addition to diverse instrument sets. According to the Granger Causality test, ROE and spread are endogenous. However the test carried on EBITDA growth for the non-financial firms does not support a bi-directional causality between profitability and spread, so for the banking and insurance sample we try two alternatives: ROE being considered as endogenous / exogenous. This time, according to the Hansen test, we reject the null hypothesis of over-identifying restrictions for all specifications, implying the validity of the instruments used. As in the industrial case, we note that the coefficients are somewhat stable across specifications. We notice that the coefficient for size (models (6) (7) (8) (10)) is negative while debt to equity has a positive effect on probability of default in all models, in lines with the literature (Campbell et al. 2011). ROE and operating margin tend to demonstrate a negative influence on spread in most of our specifications (see models (6) (8) (9) (10) and (6) (7) (9) respectively) as expected (Falcon, 2007). Moreover, the cash ratio appears significant in all specifications and seems negatively correlated with spread (models (6)-(10)), a result that corroborates Beaver‘s (1966) analysis. Finally, and as a robustness check to collinearity, we display in Appendix B in Table B4 and B5 the OLS estimates for the variables taken separately as well as for the whole model specified in equation (2), controlled for different set of dummy variables. We reach the same conclusion as in the industrials study: most of the variables have the correct sign – even though results have to be nuanced for “financial distress” metrics which could be attributed to the lower number of observations; and finally the VIF are in the 0-3 range, dismissing strong collinearity issues in the estimation.

4.5. Capital requirement ratios analysis

In order to preserve the estimator efficiency, we decide to treat tier-1 capital, coverage ratio, non-performing loans to gross loans and reserves ratio separately. A first encouraging result is provided by the Granger causality tests presented above, where most of these variables appear to “Granger cause” spread. Still, those measures present some distinctiveness compared to standard accounting variables. As a matter of fact, we believe that those metrics are often scrutinized by the legislator, a situation that is likely to be exacerbated following a crisis since bank and insurance regulators often tighten the rules in terms of capital requirements during such troublesome periods (such as Basel II for banks in 2010). During a crisis, there is a general upward movement in spreads, as well as an increased surveillance of balance sheet ratios. This might imply that when a crisis occurs, firms are under pressure to reinforce their capital reserves.

As far as the coverage ratio is concerned, we believe it is a good measure of banking solvency in the sense that a high ratio implies that the firm loan loss provision as a proportion of total loans is strong, which augurs well in case of systemic financial hardship. Concerning capital buffers (tier-1 capital for banks and reserves ratio for insurances respectively) we can make a similar observation. Indeed, regulatory capital requirements allow covering for “unexpected losses” and thus serve as a “cushion” during tough economic climate. Analogically, incorporating non-performing loans in our scoring scheme permits to capture potential bank’s inability to cope with a general deterioration of the economy. As a matter of fact, we believe that these three variables, dealing with financial distress for financials companies, all share a common feature: pro-cyclicality. While the first two (coverage ratio and capital buffers) are likely to be highly scrutinized and regulated by the legislator during a financial crisis, the latter (non-performing loans) does depend from the real economy. This idea is reinforced by the Figures D4 and D5, where it can be observed that these measures evolve in lines with the spread. We argue that such pro-cyclical characteristic makes the regression analysis challenging for these metrics, considering that our dependent variable is the spread, itself extremely sensible to the economic climate. Still, since by construction our scoring scheme discriminates between firms on a given metric at a given date –and thus free of pro-cyclicality timing- we believe that we accurately take into account the benefits from high regulatory capital and low non-performing loans to gross loans ratio on the creditworthiness score.

To conclude, it appears that our choice of variables is pertinent to explain corporate bond spread. Being able to understand what the credit risk drivers are allows us to develop an effective solvency scoring scheme. Still, we do not argue that those metrics are the "best-in-class". As a matter of fact, we select those variables on the basis of the literature, and ahead of any empirical investigations. Our aim in this paper is to demonstrate that selecting a few simple metrics that roughly reflect creditworthiness might lead to substantial gains in performance when constructing a corporate bond index.

5 –Index empirical tests

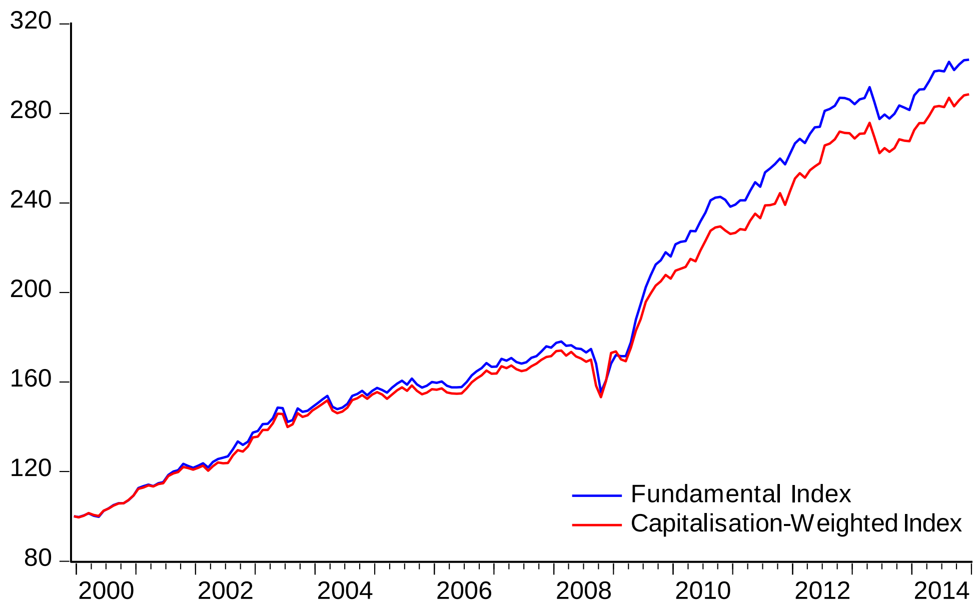
5.1. Return performance

In the following section, we investigate the various implications from using a solvency based criterion to construct a corporate bond index. More precisely, at each rebalancing date, a company weight in the index is defined by its contribution to the global portfolio's solvency. [6]

[6] Capitalisation-weighted index performance : $TRR_{CW,t} = \sum_{i=1}^{n} \vartheta_{i,t} TRR_{i,t}$
where $\sum_{i=1}^{n} \vartheta_{i,t} = 1$, i=bond and $\vartheta_{i,t}$ represents the weight attributed to a bond at a time t on the basis of its capitalization (debt amount)
Fundamental index performance : $TRR_{FI,t} = \sum_{i=1}^{n} \omega_{i,t} TRR_{i,t}$
where $\sum_{i=1}^{n} \omega_{i,t} = 1$, i= bond and $\omega_{i,t}$ represents the weight attributed to a bond at a time t on the basis of its solvency score
We should highlight that a bond weight $\omega_{i,t}$, belonging to an issuer A decomposed into $\omega_{i,t}^{A} = Solvency\ score_{t}^{A} \times \frac{\vartheta_{i,t}^{A}}{\sum_{i=1}^{i} \vartheta_{i,t}^{A}}$
It implies that we only modify the issuer weight, that we redistribute as the capitalization weighted index between the issuer's bonds
For both indexes we have $Index\ Value_{t+1} = Index\ Value_{t} \times (1 + TRR_{t+1})$ with $Index\ Value_{t} = 100$ for $t = 31/12/1999$

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 5 and Table 6. We remind that the official index is reconstituted onto the sub-universe for which accounting data is available. The monthly Total Rate of Return figures (TRR) as provided by Merrill Lynch are used in the calculations.

FIGURE 1: TOTAL RETURNS



Notes: Vertical axis represents index value, with base 100 =31/12/1999. Calculations based on "Total Rate of Returns"
Source: Authors calculations based on BoA ML and Factset data

As shown in Table 5, the FI outperformances the market index by 37 basis points per year on average with a tracking error of 60 basis points, and with a slightly inferior total volatility. [7] 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

[7] Annual returns FI – Annual returns CW= 7.69% -7.32 % = 37 bps

effect by taking a risk-adjusted measure, namely the Treynor ratio, superior performance remains. For one unit of risk, the FI provides a 6.5% return versus 5.6% for the CW index.[8] These results are validated by the calculations made on returns in excess of the sovereign interest-rate returns, displayed in Table 6, which are by construction duration neutral.

TABLE 5 — RESULTS ON TOTAL RETURNS

	Fundamental Index	Capitalisation-Weighted Index
Total returns	204.03%	188.53%
Annualised returns	7.69%	7.32%
Volatility	5.36%	5.40%
Sharpe ratio	1.11	1.04
Maximum drawdown	-12.73%	-13.94%
Average duration	6.14	6.04
Average credit rating	A/BBB	A/BBB
VaR 95	-1.15%	-1.59%
VaR 99	-4.80%	-5.26%
Treynor ratio	6.50	5.60
TE	0.60%	
Information ratio	0.62	
Beta	0.92	
	[32.48]	
Alpha	0.94%	
	[1.66]	

TABLE 6 — RESULTS ON EXCESS RETURNS

	Fundamental Index	Capitalisation-Weighted Index
Total excess returns	25.62%	20.90%
Excess returns annualised	1.53%	1.27%
Volatility	4.66%	4.81%
TE	0.60%	

Notes: TE stands for « Tracking Error » which is the standard deviation of the difference between the returns of a portfolio and a given 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%. Maximum drawdown represents the maximum loss during a specific period of time delimitated by the highest peak and the lowest trough. VaR refers to parametric Value-at-Risk. 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. Information ratio is the difference between the portfolio return and those of the benchmark, divided by the tracking error. The numbers in the brackets refer to the t-stat for alpha and beta.

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 (Arnott et al, 2010; Hsu and Campollo, 2006; Shepherd, 2015)

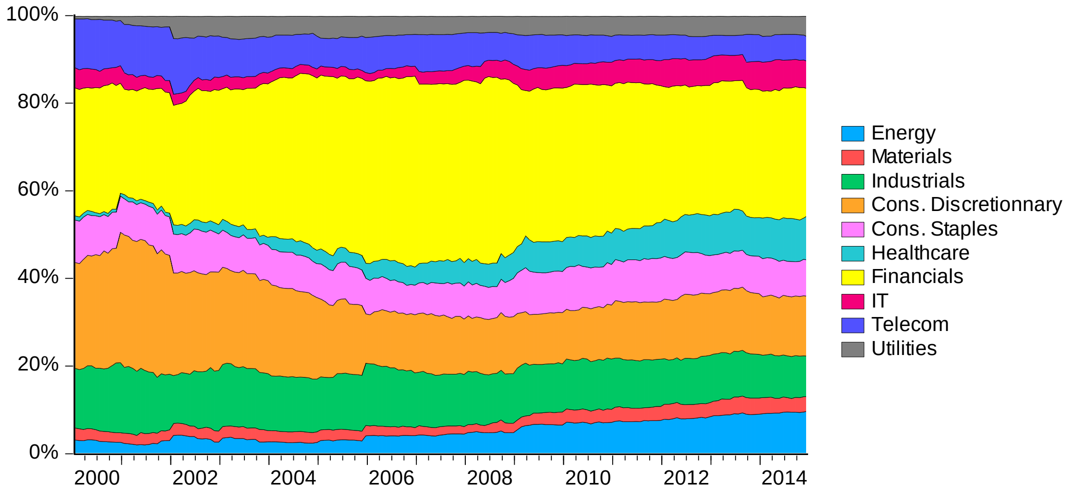
5.2 Sector analysis

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.

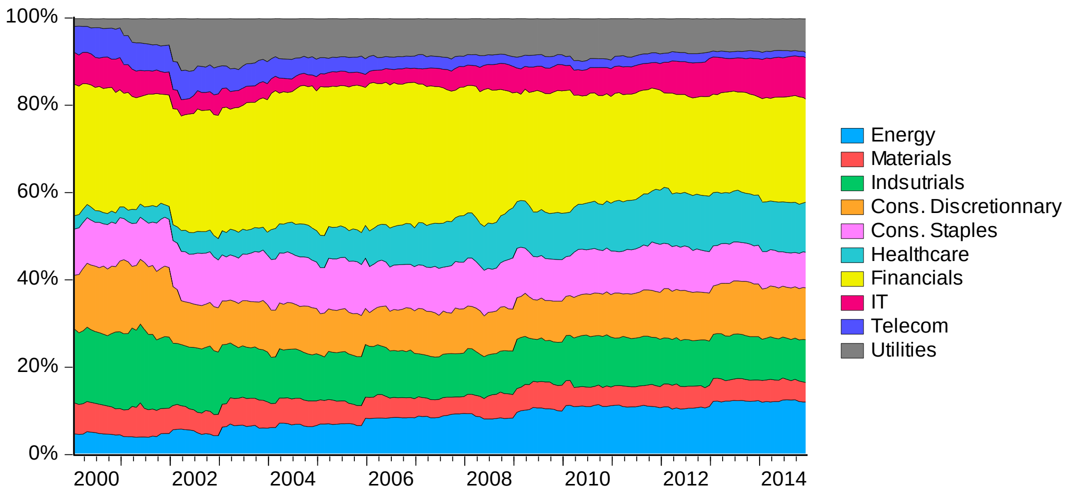
[8] The difference between the risk-adjusted returns series is statistically different from 0 at the 10 % level.

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 7, 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 Jacobs 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 7 — RESULTS FOR THE AUXIILIARY INDICES

	(i) Sectors cap weighted, issuers fundamentally weighted	(ii) Sectors fundamentally weighted, issuers cap weighted
Total returns	210.74 %	188.54%
Annualised returns	7.85%	7.32%
Volatility	3.52%	5.48%
Sharpe ratio	1.11	1.02
Information ratio	0.79	0.00

Notes: For the first index, we compute the monthly weights attributed by the CW index to each sector. Then within each sector, we redistribute bond weights according to their issuer's solvency score. For the second index, we retrieve monthly sector weights from the FI, and then within each sector, weigh bonds in function of their market valuation, that is using the CW weights.

5.3 Concentration

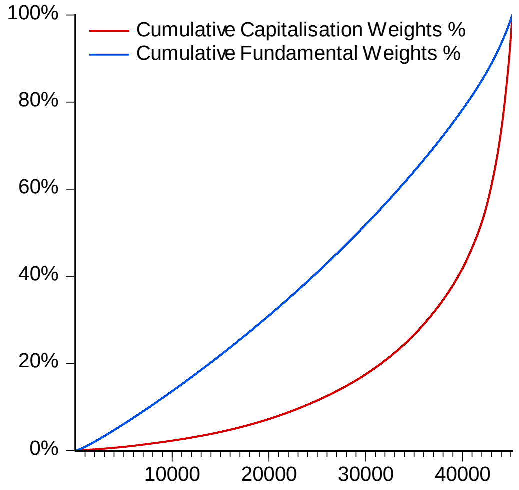
We now turn our attention to a key part of the performance analysis. Is outperformance achieved thanks to a higher diversification or at the contrary, because of high weights given to a few bonds that happened to perform well? We investigate whether the concentration differs between the two indices and 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.[9]

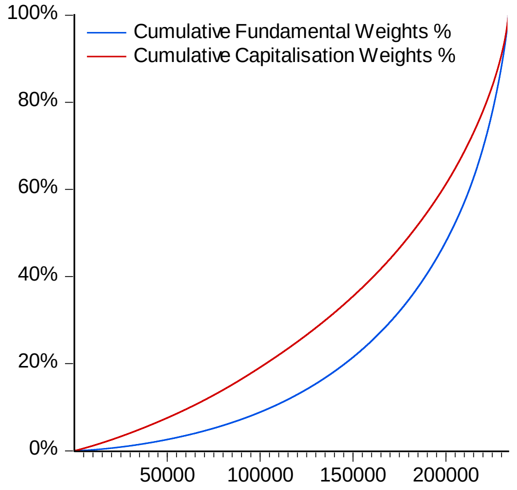
[9] Calculations available from the authors upon request.

FIGURE 3: LORENZ CURVES

(a) Issuer level



(b) Bond level



Notes: Entities' weights are ranked in ascending order and cumulative weights are displayed

In Table 8 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 measure reads the other way round: the lower the value, the higher the concentration. Both confirm the results given by the Lorenz curves.

TABLE 8 — CONCENTRATION MEASURES

		Weight entropy	Herfindhal-Hirschman index
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 9 the top twenty firms are listed for each index as of March 2014 with their solvency scores.

TABLE 9 — 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. On a more general tone, the FI leads to a lower bonds concentration than the CW benchmark, which is a positive aspect in terms of diversification. Moreover, according to Modern portfolio theory, under the assumption that correlations between assets are different from |1|, higher diversification allows to lower risk (Markowitz, 1952). The latter argument is supported in Table 5 by the lower annual volatility for the FI compared to its CW counterpart.

5.4. Performance attribution

5.4.1 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. Indeed, besides the equity market-, size- and value factors, we build a TERM factor to capture term-structure variations in the yield curve, defined, as Gebhardt et al (2004) suggest, on a portfolio that is long 10-20 year US Treasury notes and short the risk-free rate. And we build a DEF factor for default risk, defined on a portfolio that is long the Barclays Long US Corporate Investment Grade Index and short the 10-20 years Barclays US treasuries Index.[10] Results are presented in Table 10.

TABLE 10 — FACTOR ANALYSIS
SAMPLE: JANUARY 2000 – DECEMBER 2014
DEPENDENT VARIABLE: MONTHLY INDICES RETURNS – RISK FREE RATE

	Fundamental Index			**Capitalisation Weighted Index**		
	Coefficients	t-stat	P-Value	Coefficients	t-stat	P-Value
Intercept	2.34	3.82	0.00	2.08	4.15	0.00
Mkt-RF	-0.01	-1.13	0.26	0.00	0.047	0.97
SMB	-0.01	-0.80	0.43	-0.02	-2.03	0.04
HML	-0.01	-0.95	0.34	-0.01	-1.11	0.27
TERM	0.57	24.11	0.00	0.55	28.30	0.00
DEF	0.49	26.99	0.00	0.52	35.11	0.00
R^2	0.83			0.89		
F-stat	171.80	F-test	<0.001	277.46	F-test	<0.001

Notes: Alpha (the intercept) is annualised. It represents excess return (over the risk factors) due to firm selection. Market-Risk Free rate, Small Minus Big, High Minus Low and the Risk Free rate were retrieved from Kenneth French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

As do Gebhardt et al (2004), we find that the factor DEF and TERM load significantly, while Mkt-Rf does not, as expected for a fixed-income universe. Neither the value nor the size factor is significant, challenging Swinkels and Blitz (2008)'s thesis that smart benchmarking is no more than a "value tilt in disguise". The main result of this test lies in the *alpha* (the intercept). The fact that it is higher for the fundamental index implies that the outperformance of this index is due to a superior firm selection.

[10] We use an independent bond market index to avoid too high correlation levels between the DEF factor and the cap-weighted benchmark.

Additionally, we note that exposures to duration and default risks are very similar for the two indices, the fundamental one being marginally more exposed to duration and loading slightly less on default risk, a result we would expect when introducing a solvency criterion in the weighting scheme.

5.4.2 Sensitivity to macroeconomic cycle

In order to challenge our corporate bond index performance robustness across time we decide to compute statistics for three different interest-rate regimes. Table 11 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 where the FI outperformance is enhanced compared to the benchmark, as shown by the information ratio. 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 (Jacobs and Levy, 2014).

TABLE 11 — PERFORMANCE ACROSS FEDERAL FUND RATE REGIMES

		Fundamental Index	**Capitalisation Weighted Index**
RISING T-BILL RATE	Total returns annualised	5.31%	5.05%
	Annual volatility	3.65%	5.05%
	Sharpe ratio	0.98	0.66
	Information ratio	1.72	
	Excess returns	0.26%	
	TE	0.15%	
FALLING T-BILL RATE	Total returns annualised	7.48%	7.10%
	Annual volatility	4.99%	4.78%
	Sharpe ratio	1.15	1.13
	Information ratio	1.20	
	Excess returns	0.38%	
	TE	0.32%	
ZERO T-BILL RATE	Total return annualised	8.97%	8.60%
	Annual volatility	6.35%	6.61%
	Sharpe ratio	1.14	1.04
	Information ratio	0.43	
	Excess returns	0.37%	
	TE	0.87%	

Notes: We use 4-Week Treasury Bill: Secondary Market Rate from the Federal Reserve Bank of St Louis database. Rising T-Bill rate regime corresponds to periods from 31/12/1999 to 31/10/2000 and 31/05/2004-28/02/2007. Falling T-bill rate regime corresponds to 30/11/2000-30/04/2004 and 31/03/2007-31/08/2008. Since 30/09/2008 we consider that we are in the zero T-bill rate regime.

5.4.3 Executability: Turnover, transaction costs and liquidity

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 (Jacobs and Levy 2015, Malkiel 2014). Yet we do not manage to do so. The annual rebalancing in our test produces an extra turnover of 23% compared to the benchmark, which is consistent with the literature (Houwer and Plantinga 2009; Hsu and Campollo 2006).[11] When associating a cost of 20 basis points per trading unit we find that the outperformance by and large persists, see Figure 4.[12] One should realise though that the observation we make is limited by the fact that the market returns that are used are themselves influenced by potential liquidity issues. As a matter of fact, investors will require a higher return (a "liquidity premium") for holding a relatively illiquid bond, considering that opportunities to trade it will be limited.

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 in Table 12 the residual maturity of bonds, the proportion of 'on-the-run' bonds, which both favour liquidity as well as the yield volatility. This way, we mix price-based and non-price-based measures. The idea behind is that yield volatility can conduct to large bid-ask spreads, implying a lower liquidity. As far as residual maturity and proportion of on-the-run bonds are concerned, they both echo the notion of a bond life-cycle: a bond that is newly issued will be traded actively, thus very liquid. As he ages, a bond's liquidity declines.

TABLE 12 — LIQUIDITY MEASURES

	Average residual maturity	Average yield volatility	Average proportion of on the run bonds
Fundamental Index	3576	3.57	3.0%
Cap-Weighted Index	3550	2.98	2.8%

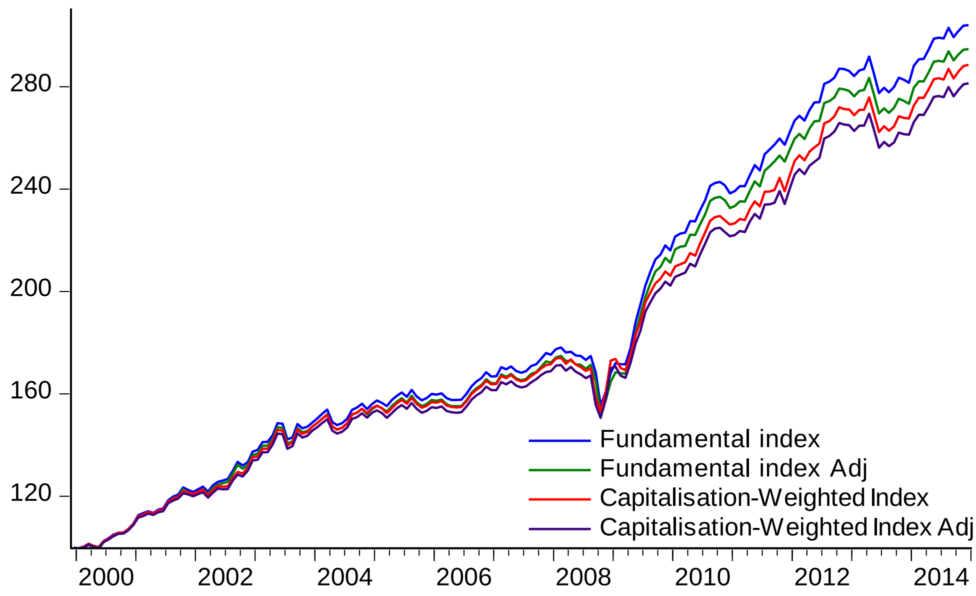
Notes: For each index, we multiply each bond weight by its residual maturity, yield volatility or by one if it is an "on-the-run" bond, 0 otherwise. Values obtained were then divided it by the number of months (180) to ease understanding. Yield volatility is computed for each bond over the whole period.

[11] For each index, we compute the absolute variation in weights for each bond between t and t+1, resulting from entries / exits of constituents as well as rebalancing, that we sum for each date. Over the entire period, the FI sum of weights variations goes up to 15.7 units while the CW index displays a total of 12.8 units

[12] A trading cost of 20 basis point lies within the lines of Chakravarty & Sarkar (2001)

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 lower yield volatility. 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

6 – Conclusion

In this paper, we make plausible that the broader economic footprint of firms is informational to their market neutral positions. More precisely, we show that introducing a notion of solvency in an index building scheme allows outperforming traditional benchmark while ensuring a “quality tilt”. The first part of this paper focuses on the research of variables that effectively reflect creditworthiness. The accounting metrics were chosen on the basis of the relevant literature, and tested subsequently for their explanatory power on spreads, a proxy for default probability. Our empirical results, obtained through econometrics tools, show that variables reflecting size, profitability, liquidity, leverage, margins as well as financial distress are determinant of corporate bond spread. On that basis, we construct a solvency score that decomposed into two parts: a first one relates to the size of the issuing firm (structural solvency score), while the second one gives an account of the balance-sheet viability (cyclical solvency score). This score is then incorporated as a positive function of weight in the index design: the higher the solvency score, the higher the weight. The second part of this paper is then dedicated to the investigation of the solvency-based index's properties: concentration, performance decomposition, sector analysis, exposure to Fama-French factors, performance's robustness across interest rates regimes as well as executability issues are examined. It appears that the fundamental index outperforms the capitalisation-weighted benchmark, the Sharpe ratio being improved. The outperformance is robust across time and does not appear to be resulting from increased exposures to well-known risk factors neither from sector bias. 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.

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. In a world without transactions costs and strongly efficient prices, the *beta* position of an asset is defined as the 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 Jacobs 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.

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Appendix A: Definition of the solvency score

Table A1. Accounting variables used in the "structural solvency score"

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

Table A2. Accounting variables used in the "cyclical solvency score"

INDUSTRAILS	Impact on scoring	Factor	Economic mechanism
EBITDA growth	+	Profitability	Knowing if revenues are growing or not gives key information concerning the firm profitability
Cash ratio	+	Liquidity	Cash & Cash equivalents / Short term debt This measure allows to gauge a company ability to face its short term debt burden with its current cash flows
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
Interest coverage ratio	+	Financial Distress	EBIT / Interest Expense This ratio allows to appraise the sustainability of interest expenses

BANKING	Impact on scoring	Factor	Economic mechanism
ROE	+	Profitability	ROE refers to the ability of a firm to generate profit
Cash ratio	+	Liquidity	Cash & Cash equivalents / Short term debt This measure allows to gauge a company ability to face its short term debt burden with its current cash flows
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
Operating margin	+	Margin	Amount of revenues generated by every unit of sales
Coverage ratio	+	Financial Distress	Loan loss provisions / gross loans Allowances for potential losses. A high coverage ratio reduces the probability of default
Non-performing loans / gross loans	-	Financial Distress	Non-performing loans is a loan in default for more than 90 days. Percentage of non-performing loans raising is a bad signal for bank solvency
Tiers 1 capital	+	Financial Distress	Core capital (equity and disclosed reserves). Capital "buffer" against unexpected losses

INSURANCE	Impact on scoring	Factor	Economic mechanism
ROE	+	Profitability	ROE refers to the ability of a firm to generate profit
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 ratio	+	Liquidity	Cash & Cash equivalents / Short term debt This measure allows to gauge a company ability to face its short term debt burden with its current cash flows
Reserves ratio	+	Financial Distress	Net reserves / Net written premiums Holding large volume of reserves decreases the probability of default

TABLE A3 — DESCRPTIVE STATISTICS
(IN MILLIONS DOLLARS UNLESS OTHERWISE STATED)

	Size			Profitability	Liquidity	Leverage	Margin	Financial distress		
					INDUSTRIALS					
	Assets	Sales	Equity	EBITDA growth %	Cash ratio %	Net debt / EBITDA %	EBITDA Margin %	Interest Coverage %		
Mean	44174	28950	13884	7.17	9.20	1.91	21.43	11.03		
Std. Error	1981	850	403	0.56	0.44	0.04	0.22	0.29		
Kurtosis	148.61	32.23	19.90	10.54	22.12	6.58	0.12	34.62		
Skewness	10.63	4.84	3.95	1.04	4.42	1.26	0.63	4.84		
Count	3116	3120	2967	2500	2832	2911	2857	2763		
					BANKING					
	Assets	Sales	Equity	ROE %	Cash ratio %	Debt to Equity %	Operating Margin %	Tiers 1 Capital	Coverage ratio %	Non-Performing Loans to Gross Loans %
Mean	365626	21263	29071	12.60	3.98	4.05	19.89	30570.	1,13	1,77
Std. Error	21774	1074	1729	0.51	0.64	0.23	0.57	2021	0,09	0,11
Kurtosis	7.98	3.23	7.87	11.72	56.76	10.09	3.93	3.20	26,96	35,80
Skewness	2.54	1.91	2.76	-1.18	6.81	2.90	-0.96	1.99	4,30	4,96
Count	605	593	588	586	566	579	567	363	378	341
					INSURANCE					
	Assets	Sales	Equity	ROE %	Cash ratio %	Debt to Equity %	Operating Margin %	Reserves ratio %		
Mean	208759	30072	17771	8.93	6.97	0.94	13.22	3.87		
Std. Error	12986	1902	1156	0.87	1.02	0.15	0.57	0.29		
Kurtosis	1.56	5.02	10.94	53.51	49.21	53.89	10.23	0.15		
Skewness	1.44	2.13	3.07	-6.09	6.17	7.09	-1.36	1.06		
Count	307	307	278	274	236	275	273	158		

Notes: "Count" refers to number of firm x year observations per variable

Appendix B: Panel unit root test and Ordinary Least Square estimates

TABLE B1 — UNIT ROOT TESTS SUMMARY
SAMPLE 2000-2014, ALL INDUSTRIES

	Specification	**Levin, Lin & Chu t***	**Im, Pesaran and Shin W-stat**	**ADF - Fisher Chi-square**	**PP - Fisher Chi-square**
		H0 : Common Unit Root Process	H0 : Individual Unit Root Process		
Log(Spread)	Trend + Intercept	-99.51***	-3.87***	1006.57***	1233.17***
Sales	Intercept	-26.34***	-17.25***	1075.55***	1125.45***
Log(Assets)	Intercept	-17.07***	2.97***	973.95***	1224.51***
Cash ratio	Trend + Intercept	-3.74***	-30.97***	1137.50***	1502.22***
EBITDA growth	Intercept	-119.86***	-31.79***	1546.55***	1514.41***
EBITDA margin	Intercept	-23.78***	-10.69***	933.12***	1023.97***
Interest Coverage	Intercept	-82.50***	-17.80***	1006.22***	1072.68***
Net debt / Ebitda	Intercept	-47.83***	-16.57***	1077.07***	1214.29***
Equity	Trend + Intercept	-9.39***	-6.96***	856.90***	1125.89***
Log(ROE)	Intercept	-25.27***	-16.01***	1315.51***	1452.68***
Log(Tiers 1 capital)	Interecpt	-15.96***	-10.73***	109.60***	91.01***
Coverage ratio	Intercept	-10.51***	-3.37***	154.67***	122.478***
Operating margin	Trend + Intercept	816.25***	-206.64***	907.04***	1179.57***
Debt to equity	Intercept	-81.30***	-20.96***	1324.11***	1463.77***
NPL to gross loans	Intercept	-18.10***	-3.83***	111.5***	97.84**
Reserves ratio	Intercept	-9.86***	-1.40*	61.60*	72.27**
Score size	Intercept	-44.36***	-7.17***	1111.02***	1423.60***

Notes: lag length can vary across series and was selected on the basis of the Schwarz criterion.
*** Significant at 1%
** Significant at 5%
* Significant at 10%
Source: Author calculations

TABLE B2 — DEPENDENT VARIABLE: SPREAD
SAMPLE 2000-2014, INDUSTRIALS

	OLS(1)	OLS(2)	OLS(3)	OLS(4)	OLS(5)	OLS(6)
Constant	6.266***	4.937***	4.911***	5.157***	5.337***	4.888***
Size	-0.848***					
Cash ratio		-0.004				
EBITDA growth			-0.002***			
EBITDA Margin				-0.083***		
Interest coverage					-0.225***	
Net debt / EBITDA						0.123***
Cross sections	508	476	426	467	434	427
N	3138	2832	2500	2847	2731	2587
R^2	0.066	0.000	0.006	0.008	0.132	0.044
F-stat (prob)	220.750 (<0.00)	0.571 (0.449)	15.660 (<0.00)	22.878 (<0.00)	415.75 (<0.00)	119.396 (<0.00)

TABLE B3 — OLS ESTIMATES AND VIF
SAMPLE 2000-2014, INDUSTRIALS
DEPENDENT VARIABLE: SPREAD

	OLS(7)		OLS(8)		OLS(9)		OLS(10)	
	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF
Constant	1.798***		2.278***		1.0423***		3.213***	
Spread(-1)	0.729***	1.261	0.546***	1.077	0.839***	1.463	0.517***	1.132
Size	-0.199***	1.107	0.168	1.021	-0.128***	1.141	-0.413***	1.035
Cash ratio	-0.002	1.358	-0.029***	1.096	0.010**	1.353	0.001	1.081
EBITDA growth	0.001	1.012	0.001	1.092	-0.001**	1.017	-0.003	1.103
EBITDA margin	-0.035**	1.027	-0.113*	1.244	-0.014	1.033	-0.068**	1.258
Interest coverage	-0.046***	1.986	-0.004	1.491	-0.025***	2.145	-0.029	1.514
Net debt / EBITDA	-0.003	2.088	-0.010	1.335	0.021	2.109	0.051***	1.315
Period dummy	NO		NO		YES		YES	
Cross section dummy	NO		YES		NO		YES	
Cross sections	326		326		326		326	
N	1863		1863		1863		1863	
R^2	0.565		0.670		0.844		0.900	
F-stat (prob)	343.724 (<0.00)		9.355 (<0.00)		499.824 (<0.00)		37.548 (<0.00)	

TABLE B4 — DEPENDENT VARIABLE: SPREAD
SAMPLE 2000-2014, FINANCIALS

	OLS(11)	OLS(12)	OLS(13)	OLS(14)	OLS(15)	OLS(16)	OLS(17)	OLS(18)	OLS(19)
Constant	6.055***	5.029***	5.44***	5.374***	5.050***	4.323***	5.686***	5.983***	5.127***
Size	-0.608***								
Cash ratio		0.064***							
ROE			-0.199***						
Operating Margin				-0.020***					
Debt / Equity					-0.044***				
Tier 1 Capital						0.057***			
Non-Performing Loans to Gross Loans							0.190***		
Coverage ratio								0.206***	
Reserves ratio									0.011
Cross sections	147	138	136	135	137	55	54	61	23
N	922	802	793	840	854	363	341	378	158
R^2	0.026	0.029	0.050	0.117	0.009	0.019	0.072	0.126	0.001
F-stat (prob)	24.075 (<0.00)	23.657 (<0.00)	41.950 (<0.00)	111.001 (<0.00)	7.671 (<0.00)	7.061 (<0.00)	26.42 (<0.00)	54.340 (<0.00)	0.065 (0.800)

TABLE B5 — OLS ESTIMATES AND VARIANCE INFLATION FACTORS
SAMPLE 2000-2014, FINANCIALS. DEPENDENT VARIABLE: SPREAD

	OLS(20)		OLS(21)		OLS(22)		OLS(23)	
	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF
Constant	1.576***		1.665**		1.670***		4.085***	
Spread(-1)	0.732***	1.291	0.590***	1.352	0.765***	1.108	0.453***	1.050
Size	-0.097	1.322	0.317	1.859	-0.235***	1.360	-0.729***	2.647
Cash ratio	0.001	1.765	-0.002	1.294	0.005	1.648	-0.012	1.176
ROE	0.043	1.328	0.0869**	1.541	-0.041***	1.214	-0.068***	1.325
Operating Margin	-0.011***	1.235	-0.021***	1.419	-0.001	1.280	-0.001	1.313
Debt / Equity	0.022	1.639	0.009	2.281	0.019**	1.521	0.056***	2.900
Period dummy	NO		NO		TES		YES	
Cross section dmumy	NO		YES		NO		YES	
Cross sections	111		111		111		111	
N	584		584		584		584	
R^2	0.534		0.630		0.880		0.920	
F-stat (prob)	109.957 (<0.00)		6.853 (<0.00)		216.461 (<0.00)		40.034 (<0.00)	

Appendix C: Adjusting the capitalisation-weighted index

FIGURE C1: CAPITALISATION-WEIGHTED INDEX ADJUSTED TO OUR BOND SAMPLE, VERSUS THE PUBLISHED BENCHMARK

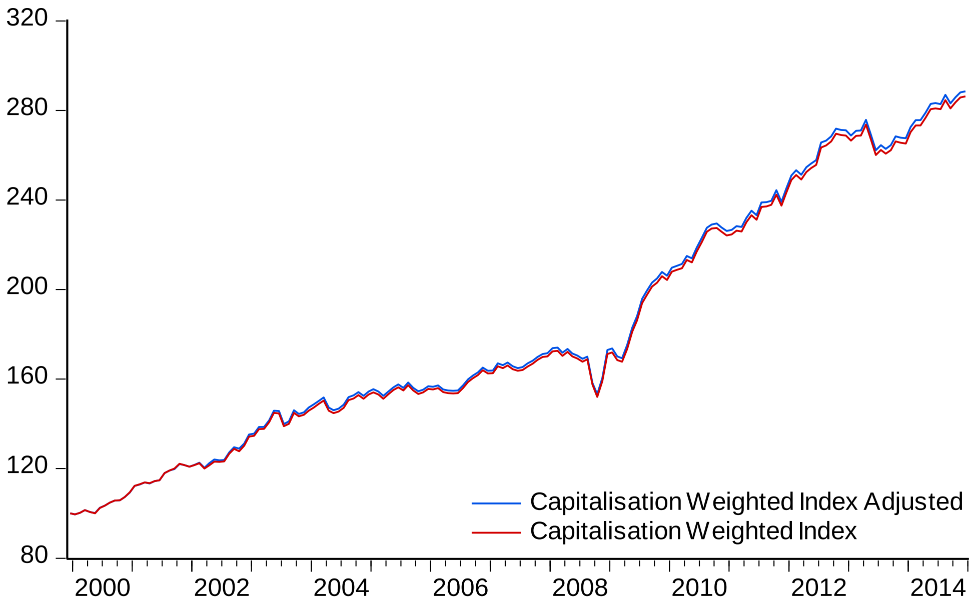


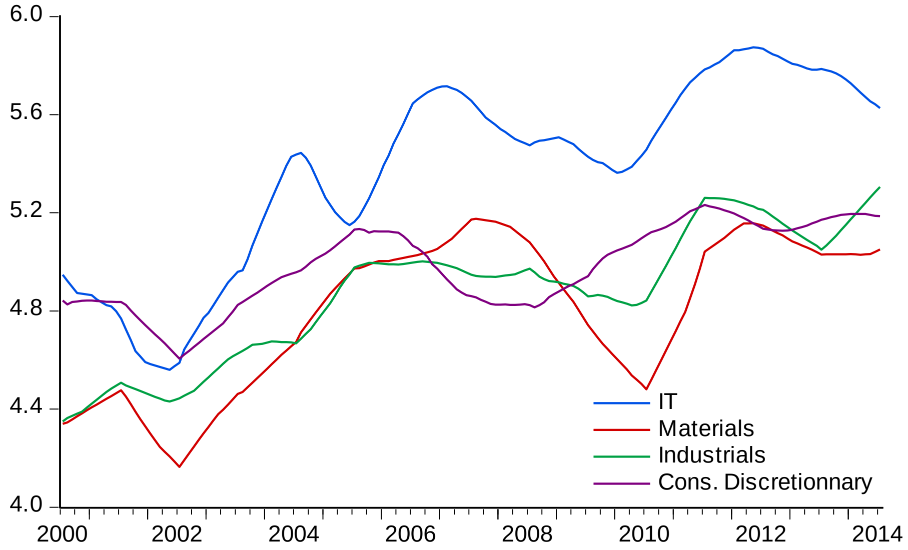
TABLE C1 — RESULTS ON TOTAL RETUNS

	Capitalisation-Weighted index adjusted	Capitalisation-Weighted Index
Total returns	188,53%	186,31%
Annualised returns	7,32%	7,26%
Volatility	5,40%	5,37%
Sharpe ratio	1,04	1,03
TE	0,06%	

Notes: The adjusted benchmark corresponds to index covering our successfully-matched bonds universe. This implies an exclusion of 9 % of the bonds from the published benchmark.

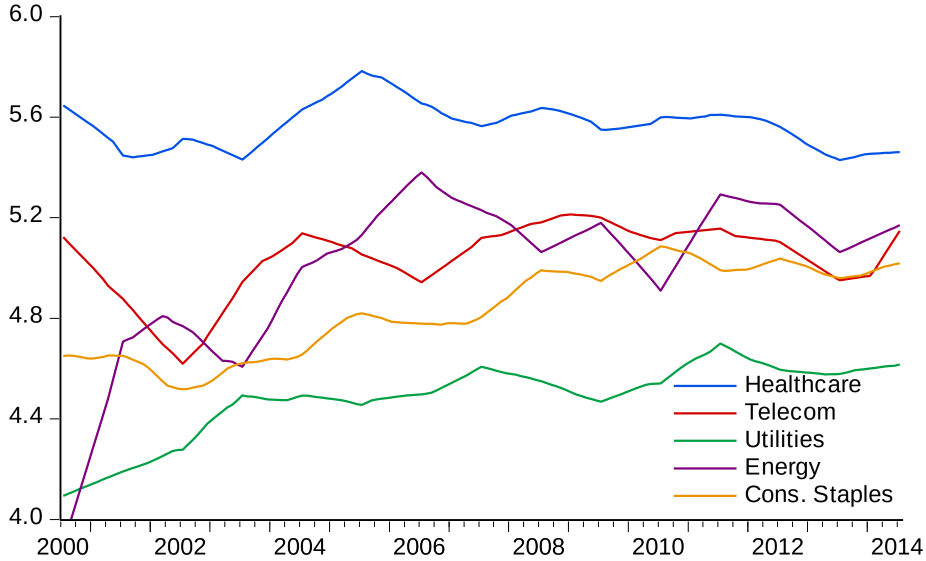
Appendix D: Trends in cyclical solvency score and capital buffers

FIGURE D1: AVERAGE SOLVENCY SCORE FOR "CYCLICAL" INDUSTRIES



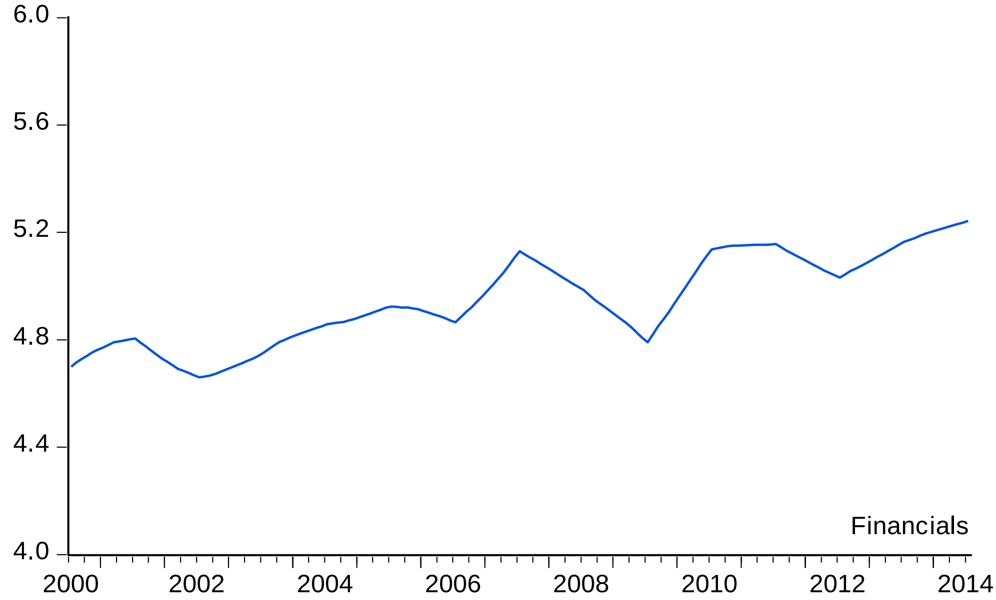
Source: Authors calculations based on Factset data. 12 months moving averages have been used for graphical purposes. Distinction between cyclical and defensive sectors decomposition was used to ease the graphic's reading. This distinction is based on MSCI © (2014) methodological note available at :
https://www.msci.com/eqb/methodology/meth_docs/MSCI_Cyclical_and_Defensive_Sectors_Indexes_Methodology_Jun14.pd

FIGURE D2: AVERAGE SOLVENCY SCORE FOR "DEFENSIVE" INDUSTRIES



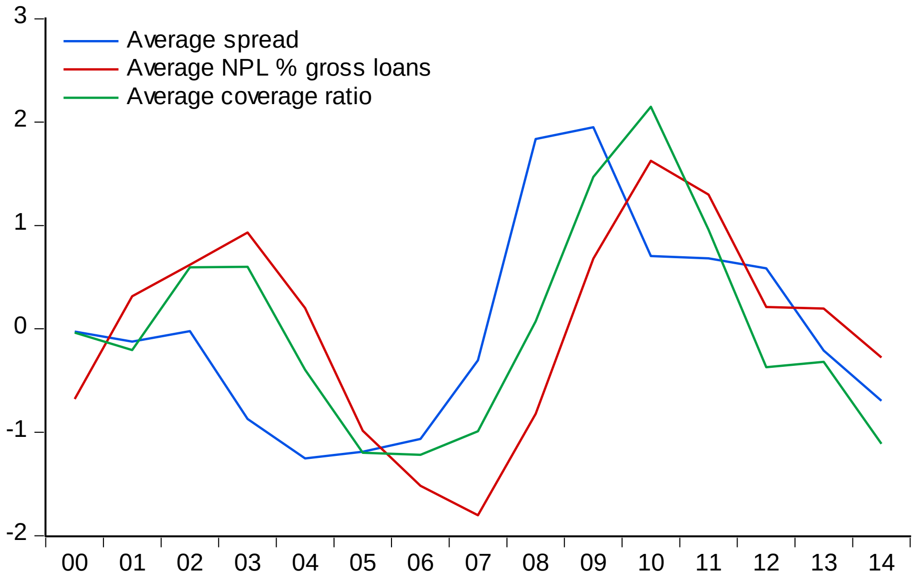
Source: Authors calculations based on Factset data. 12 months moving average have been used for graphical purposes

FIGURE D3: AVERAGE SOLVENCY SCORE FOR THE FINANCIAL INDUSTRY



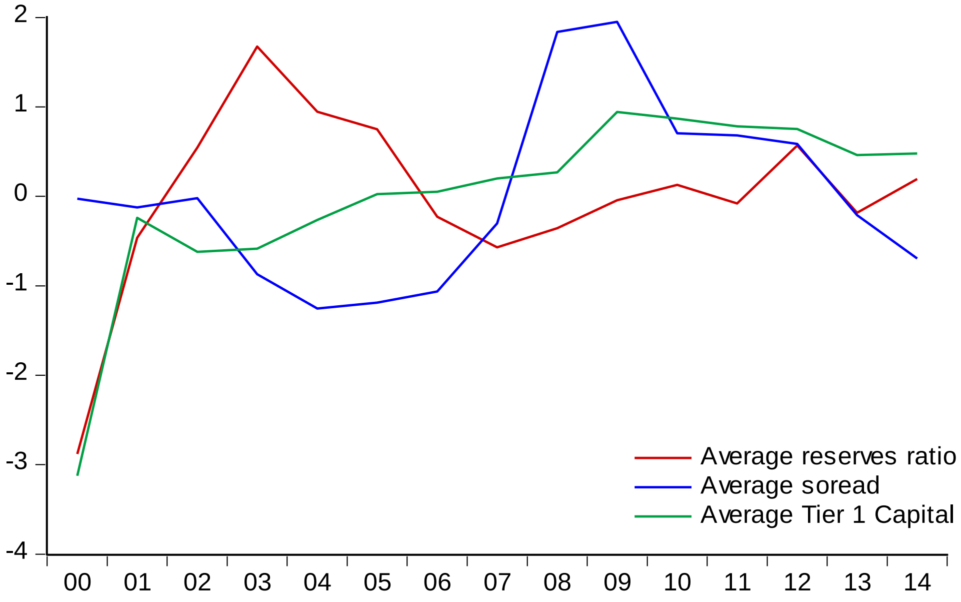
Source: Authors calculations based on Factset data. 12 months moving average have been used for graphical purposes

FIGURE D4: BANKING SECTOR METRICS



Source: Factset data, normalised scale.

Figure D5: Capital “buffers” for banks and insurances



Source: Factset data, normalised scale.