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On the Efficiency of the Benchmarks Used in the Asset Management

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Chapter 1: Introduction

The aim of this work is to study the efficiency of the benchmarks used in the asset management industry.

The capitalization weighted indexes are by far the most common indexes used as a benchmark for active and passive investments. As assessed by Arnott et al. (2005), capitalization weighting has many benefits:

1) Capitalization weighting is a passive strategy requiring little trading; therefore, indexing to a cap-weighted index incurs far lower trading costs and fees than active management. Cap-weighted portfolios automatically rebalance as security prices fluctuate. Apart from the impact of stock buybacks and secondary equity offering, the only rebalancing cost associated with executing this strategy is the cost of replacing a constituent security in the portfolio. The cap-weighted indexes require material adjustment only when new companies become large enough to merit inclusion in an index or when others disappear trough merger, failure, or relative changes in capitalization, collectively referred to as "reconstruction".
2) A cap-weighted index provides a convenient way to participate in a broad equity market. Capitalization weighting seeks to assign the greatest weights to the large companies. These companies are typically among the largest as also measured by metrics of size other than capitalization.
3) Market capitalization is highly correlated with trading liquidity, so cap weighting tends to emphasize the more heavily traded stocks, thereby reducing portfolio transaction costs.

4) Because market capitalization is also highly correlated with investment capacity, cap weightings tends to emphasize the stocks with greater investment capacity, thus allowing the use of passive indexing on an immense scale by large pension funds and institutions.

Arnott et al. (2005) and Hsu (2004) point out also that under a “standard” interpretation of the Capital Asset Pricing Model a broad-based cap-weighted portfolio (a “market” portfolio) is automatically Sharpe Ratio maximized (or mean-variance optimality). That is why a huge amount of passive equity investments are done using a cap-weighted index as a benchmark.

As Hsu (2004) says, if equity prices are more volatile than warranted by changes in firm value, a stock is either too expensive or too cheap relative to its fundamental value. If stocks prices are inefficient in the sense that they do not fully reflect firm fundamentals, then under-priced stocks will have a smaller capitalization than their fair value and similarly over-priced stocks will have a larger capitalization than their fair value. A cap-weighted portfolio would have on average shift additional weights into the over-priced stocks and shift weights away from the under-priced stocks. As long as these pricing errors are not persistent, market prices will collapse toward fair value over time and a cap-weighted portfolio would tend to experience greater price decline than other non-price-weighted portfolios due to its heavier exposure to stocks with positive pricing error.

The noisy stock price assumption of Hsu (2004) suggests that stock returns are serially negatively correlated, which imply mean reversion.

Perold (2007) points out that noisy market hypothesis effectively anchors on fair value. To do so is to presuppose systematic reversals in stock prices, an assertion that does not follow from stocks being randomly mispriced. Because market capitalization does not reveal whether a stock is overvalued or undervalued, the random mispricing of stocks does not systematically shift the portfolio weights toward overvalued stocks.

The real debate, then, is whether one subscribes to the efficient market hypothesis or the noise-in-price hypothesis. The former suggests that valuation-indifferent weightings is mean-variance superior to cap-weighting because it takes on non-Gaussian hidden risks that are correlated with small-cap and value exposure. The latter remains controversial because it suggests a financial market free lunch.

As a consequence of the idea of Arnott et al. (2005) and Hsu (2004) that a cap-weighted index is not a mean-variance optimal portfolio in the last years we had an impressive development of new indexes with the idea to have a better benchmark for passive investments.

Following Perold (2007) and Siegel (2003) we must first remember that capitalization weighting is the only strategy that all investors can follow. Because the collective holdings of investors (by definition) aggregate to the market portfolio, for every investor who is underweight a stock, another is overweight that stock, and between them, it is at best a zero-sum game. So many new indexes are seeking to position an active management strategy in a passive management framework.

Chow et al. (2011) give a good framework of alternative approaches to passive equity investing which claiming to offer risk-adjusted performance superior to that of traditional market-capitalization-weighted indices.

The strategies can be classified into two categories: (1) heuristic-based-weighting methodologies and (2) optimization-based-methodologies. Heuristic-based strategies are ad hoc weighting schemes established on simple and, arguably, sensible rules. Optimization-based strategies are predicated on an exercise to maximize the portfolio’s ex ante Sharpe ratio, subject to practical investment constraints.

Heuristic-Based Weighting Strategies:

1) Equally weighting. In an equal-weighted portfolio, constituents are selected from the largest N = 1,000 stocks sorted by descending market capitalization on the reconstitution date. The weight of each stock is set to 1/N. A notable feature of equal weighting is that the resulting portfolio risk-return characteristics are highly sensitive to the number of included stocks.

2) Risk-cluster equal weighting. The method improves upon the simple equal-weighted scheme by equally weighting risk clusters instead of individual stocks. The advantage over simple equal weighting is the robustness of the resulting portfolio to the size of the chosen stock universe.

3) Diversity weighting. Two other potential concerns with equal weighting are relatively high tracking error against the cap-weighted benchmark and excess portfolio turnover. A simple solution is to blend portfolios on the basis of equal weighting and cap weighting in order to attenuate the levels of tracking error and turnover. Intuitively, diversity weighting can be viewed as a method for interpolating between cap weighting and equally weighting. Generally, this process redistributes weights from the larger names in the cap-weighted portfolio to the smaller names.

4) Fundamental weighting. Arnott et al. (2005) described a methodology for weighting stock indices by constituent companies' accounting size, measured by such reported financial variables as total sales and book value. Their aim was to propose weighting measures that are uncorrelated with the companies' market valuations. They argued that weighting by accounting-based measures of size improves upon equal weighting by reducing relative tracking error against the

cap-weighted index and turnover while enhancing portfolio liquidity and capacity from equally weighting.

Optimization-Based Weighting Strategies:

In theory, mean-variance optimization is a fantastic way to form passive portfolios, yet it frequently falls short of its targets when applied in practice. The two inputs required to generate an optimal mean-variance portfolio (all the stocks' expected returns and their covariance matrix) are notoriously difficult to estimate.

1) Minimum-variance strategies. Because forecasting returns is so difficult and the potential for error so large, Chopra and Ziemba (1993) suggested that portfolio outcomes could be improved by assuming that all stocks have the same expected returns. Under this seemingly stark assumption, the optimal portfolio is the minimum-variance portfolio.
2) Maximum Sharpe ratio I. To improve upon a minimum-variance strategy, investors need to incorporate useful information on future stock returns. Choueifaty and Coignard (2008) proposed a simple linear relationship between the expected premium for a stock and its return volatility. That represents a departure from standard finance theory, which states that only the no diversifiable component of volatility (systematic risk) should earn a premium. When applied to stocks and portfolios of stocks it becomes internally inconsistent; it suggests that all stocks and portfolios should have the same Sharpe ratio and, therefore, that volatilities are linearly additive in equilibrium, which cannot be correct.
3) Maximum Sharpe ratio II. Amenc et al. (2010) developed a related portfolio approach that assumes a stock's expected returns are linearly related to its

downside semi-volatility. They argued that investors are more concerned with portfolio losses than with gains. Thus, risk premium should be related to downside risk (semi-deviation below zero) as opposed to volatility. This assumption serves as a foundation for the EDHEC-Risk Efficient Equity Indeces. Amenc et al. (2010) used a two-stage estimation heuristic to estimate the semi-volatility of stocks. Under their method, one first computes empirical semi-volatilities and sort stocks by these estimates into deciles; then one sets the semi-volatility of stocks in the same decile equal to the median value of the containing decile.

While a lot of work has done for the equity indexes used as benchmarks for equity investments, less has done for bond indexes.

Arnott et al. (2010) used a similar approach as the fundamental indexation of equity indexes to U.S. investment-grade corporate bonds, U.S. high-yield bonds, and hard-currency emerging market bonds. For the first two markets they use they use five factors to construct the weightings: total cash flow, total dividends, book value of assets, sales, and face value of the debt issue. For the emerging market bonds they use: total population, square root of land area (as a crude proxy for land resources), total gross domestic product (GDP), and energy consumption.

The contribution of this work to the literature is as follow:

1) In chapter 2 it is presented a study on the efficiency of Government Bond Indexes, where it is analyzed the equally weighting and GDP weighting systems for country weights.
2) In chapter 3 it is presented a study on the use of a derivatives index to invest in the European corporate bond market and its differences with the cash index.

3) In chapter 4 it is analyzed the impact of fallen angels on the corporate bond portfolios, with the rules of the benchmark indexes which can determine a loss of value for the investors.
4) In chapter 5 it is presented a comparison between the equally weighted and capitalization weighted method for the European equity market, with an analysis of the best rebalancing frequency and of the alpha after adjusting for the value and size factors.

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Chapter 2: On the Efficiency of Government Bond Market Indexes for Eurozone and Emerging Markets

Introduction

The aim of this chapter is to understand if there are alternative indexes to use as a benchmark for the Government bond markets.

The most used benchmarks are the capitalization weighted indexes, where each bond is weighted by its market value, and the weight of each country is the result of the sum of the market value of the bonds issued by the country.

There are two problems arising:

1. A low diversification of the issuer risk, in case some large countries have a high weight in the index. In fact, if something happens to a large country, such as an external shock or an economic crisis, investors will have a heavy impact on their investments.
2. If a country is highly indebted, it will have a weight in the index higher than the economic relevance of the country, while a low indebted country will have a lower weight in the index. That is a problem because we usually have a positive correlation between a high debt level and the default risk.

These problems are well analyzed by Arnott et al. (2010) and Siegel (2003).

A possible answer to the diversification problem is to use an equally weight method for the country weights. In this case we have a higher diversification of the country risk.

Another way is to use a diversified index such as the one constructed by JPM for the Emerging Market Bond Index. This way, the weight of a bigger issuer is reduced and the weight of a smaller issuer is increased in order to raise the diversification.

To solve the problem of high indebted countries, Arnott et al. [2010] suggests using alternative weights rather than the capitalization weights. GDP, population, land area and energy consumption are used as proxies of the country economic relevance and these values are taken to construct the index weights.

It is important to point out that these two problems are related to the default risk of a country, not to the currency risk of investing in a bond issued in a specific currency.

This is important because in case a country faces some difficulties in managing its debt it has four options at its disposal, which are the following:

1. Financial austerity, in order to improve its balance sheet and restore confidence in the market, the one that can pay back its debt.
2. Monetization of debt, with the Central Bank buying the debt and increasing the money supply. The consequences can be a higher inflation and the risk of a currency crisis if there is a lack of confidence in the currency.
3. Upload of captive investors with the bond supply absorbed by those investors who have restrictions and have no other choice than buying these bonds. In this case captive investors' bear a loss because, on their investments, they earn an interest rate lower than the market interest rate.
4. Default or debt restructuring.

If a country chooses option 2), it can avoid a default or a restructuring of the debt but a foreign investor will incur a loss due to the currency devaluation.

If the debt is in a foreign currency option 2) is not available, because the Central Bank cannot increase the money supply and has no access to the printing machine.

In case of a debt in a foreign currency the default risk of a country is very important and the two problems, namely low diversification of the issuer risk and the weight of highly indebted country are particularly relevant.

Therefore, we restrict our analysis to two kinds of government markets, the emerging market bonds issued in US dollars and the Eurozone Government bond market, in which countries do not have the option of monetizing their debts.

For these two markets, we analyze four kinds of indexes:

1. A capitalization weighted index, by far the most common kind of benchmark for these markets.
2. A country equally weighted index, in order to maximize the diversification of default risk.
3. A diversified index, where the weights are constructed in order to reduce the weights of the bigger issuers and to increase the diversification.
4. A GDP weighted index, in order to avoid the problem of the high weights of high indebted countries and in order to use weights more related to the economic size of a country.

At first, we explain in detail the data and the methodology we use to construct the four indexes referred to the two markets we take into consideration.

Subsequently, we analyze the results in terms of total return, volatility and Sharpe ratio of the indexes, using different sub periods in order to understand if the behavior of the indexes changes in different market conditions.

Finally, we make our conclusions on which index is more efficient as a benchmark for the two markets.

Data and Methodology

For our analysis, we start with two widely used capitalization weighted indexes for the two markets, the Bank of America Merrill Lynch Euro Government Bond Index (Bloomberg ticker EG00, as follows ML) and the JPM Emerging Market Bond Index Global (Bloomberg ticker JPEGSOSD, hereinafter EMBIG).

We use Bloomberg to collect all our data.

The EMBIG includes the US dollar-denominated Brady bonds, the Eurobonds, and traded loans issued by sovereign and quasi-sovereign entities. The EMBIG defines emerging markets countries with a combination of World Bank-defined per capita income brackets and each country's debt restructuring history. These two criteria allow the EMBIG to include a number of higher-rated countries that international investors have nevertheless considered part of the emerging market universe.

While the EMBIG index uses a traditional market capitalization approach to determine the weight of each individual issue, as well as the resulting country index allocation, the JPM one also calculates a diversified index (EMBIGD) for the emerging market bonds in US dollars, which distribute country weights more evenly. The EMBIGD limits the weights of those index countries with larger debt stocks by including only a specified portion of these countries' eligible current face amounts of debt outstanding.

The calculation process of the EMBIGD bond allocation starts with each EMBIG country current face amount of debt outstanding, for each the EMBIGD includes:

1. 100% of the first US$5 billion of the eligible debt stock.
2. 75% of the eligible debt stock that exceeds US$5 billion, but does not exceed US$10 billion.

3. 50% of the eligible debt stock that exceeds US$10 billion, but does not exceed US$15 billion.
4. 25% of the eligible debt stock that exceeds US$15 billion, but does not exceed US$25 billion.
5. 10% of the eligible debt stock that exceeds US$25 billion, but does not exceed US$35 billion.
6. 0% of the eligible debt stock that exceeds US$35 billion.

While both the EMBIG and the EMBIGD always contain the same list of debt instruments, the constraining process of the EMBIGD instrument allocation generates instruments and country weights, which are different than those of the EMBIG.

Countries with large current face amounts outstanding of the index-eligible debt will have their EMBIGD instrument allocations and, thus, index market capitalization weights are reduced (relative to the EMBIG) by the allocation-constrain process described above. Conversely, countries with relatively small current face amounts outstanding of total eligible debt will have a larger market capitalization weight in the EMBIGD than in the EMBIG, as their instruments allocation will not be reduced as much by this process.

We construct a GDP weighted index for both markets using, for each country, the GDP weight of the previous year. Annual GDP data are usually available in April, therefore, starting from the month of May we have a new GDP weight updating the data. GDP is nominal in current price and in US dollars, in order to have a value which best represents the current economic size of the country. For each month, we take the list of countries included in the EMBIG and calculate their respective GDP's weights. We use the JPM country sub-indexes total return and with the GDP's weights we have the monthly total return of our index. Starting from the monthly total return time series we can construct an index GDP weighted. Finally, an equally weighted index for the emerging markets is constructed using the weight 1/n, where n is the number of countries included in the index for a certain month.

For the Eurozone government bond market, we use the Bank of America Merrill Lynch Euro Government Index which tracks the performance of euro denominated sovereign debt publicly issued by Euro member countries on either the Eurobond market or the issuer's own domestic market. Qualifying countries should be Euro members and should have an investment grade foreign currency long-term sovereign debt rating, which is based on an average of Moody's, S&P and Fitch. Qualification with respect to Euro membership is determined annually effective as of December 31.
As for the EMBIGD, we construct a diversified index for the Eurozone market with the following rules for each country:

1. The weight up to 5% is fully included in the index.
2. The weight between 5% and 10% is included in the index with a cut of 25%.
3. The weight between 10% and 15% is included in the index with a cut of 75%.
4. The weight over 15% is excluded from the index.
5. Finally the weights as rebalanced in order to have a sum of 100% for all the countries.

If we change the rules, we can have a higher/lower diversification, but this does not change the final results considering that our aim is to understand whether or not this diversification improves the risk/return profile of the index.

We construct a GDP weighted index for both markets using their respective GDP weight of the previous year. Annual GDP data are usually available in April; therefore, starting from the month of May we have a new GDP weight which updates the data. GDP is nominal in current price and in Euro currency in order to have a value which best represents the current economic size of the country.

For each month, we take the list of countries included in the ML and calculate their respective GDP’s weights. We use the ML’s country sub-indexes total return and with the GDP’s weights we have the monthly total return of our index. Starting from the monthly total return time series we can construct an index GDP weighted. Finally, an equally weighted index for the Eurozone market is constructed using the weight 1/n where n is the number of countries included in the index for a certain month.

For the emerging markets, historical data are available from 1/1/1994 to 12/31/2011 because JPM data are available only since 1994; for the Eurozone market they are available from 1/1/1999 to 12/31/2011 because the Euro was introduced in 1999. We have four indexes for each market, namely the traditional capitalization weighted index, the diversified index, and the GDP weighted index and the equally weighted index. We analyze the logarithmic monthly returns, the standard deviation of the returns, the skewness, the excess returns on the risk free and the Sharpe ratio of the different indexes. As a risk free, we take the 1 month Euro Libor for the Euro market and the 1 month US$ Libor for the emerging market.

We also analyze two sub-periods for each market. For the emerging markets we have a first sub-period starting 01/1994 and ending 12/2002 where the spreads of the market over the risk free US Treasury Bond was volatile and not falling, and a sub-period starting 01/2003 and ending 12/2011 with a sharp reduction in the spread, and so therefore, a bull market for emerging market bonds. For the Eurozone market we have a first sub-period starting 01/1999 and ending 12/2007 with a stable spread between the German Bund and other countries bonds, and a sub-period starting 01/2008 and ending 12/2011 with a sharp increase in the spread within Eurozone countries.

Finally, we verify if the relative performance of the different indexes is significantly impacted by the different sub-periods running a regression with a dummy for the two different regimes.

Results

The results for the emerging markets are detailed in exhibit no. 1, and for the entire period of time we can state the following:

1. The equally weighted index (EW) has the highest excess return, but a higher standard deviation than the EMBIG.
2. The GDP weighted index (GDP) has the lowest standard deviation, but a lower excess return than the EMBIG.
3. The EW and the GDP indexes have the same Sharpe ratio, which is higher than the EMBIG one.
4. The EMBIGD has a higher Sharpe ratio than the EMBIG because has a slightly higher excess return and a lower volatility, but its Sharpe ratio is lower than the EW and the GDP ones.

< insert Exhibit 1 here >

We can conclude that if we wish to minimize the risk, the GDP weighted index is the best one to be used, while the EW index is best suited to maximize the excess return.

If we take into consideration the two sub-periods from 1994 to 2002 with volatile spreads, and from 2003 to 2011 with falling spreads, we come to different conclusions:

1. For the 1994-2002 sub-periods, the EMBIG performance is disappointing, with the lowest excess return and the highest standard deviation of the four indexes,

and the EW index is the best one as far as the excess return and Sharpe ratio are concerned.

2. For the 2003-2011 sub-periods the EMBIG shows the best performance in terms of excess return and Sharpe ratio. Therefore, we can affirm that the capitalization weighted EMBIG is the worst index during volatile markets but the best one when markets arise like in the second sub-period.

The outcome does not come as a surprise. In fact, a capitalization weighted index usually has a higher weight in highly indebted countries, which are more risky, and this characteristic pays higher returns when the market performs well and risk is rewarded. When the market is volatile or when the spreads trend is higher, a capitalization weighted index can incur in higher losses.

For the Eurozone market, we reach different results (exhibit no. 2):

1. The GDP weighted index has the highest excess return and the highest Sharpe ratio.
2. The EW index has the lowest excess return and lowest Sharpe ratio.
3. The standard deviation is similar between the indexes, and the excess return explains the differences between Sharpe ratios.

< insert Exhibit 2 here >

When we analyze the two sub-periods from 1999 to 2007 with stable and low spreads and from 2008 to 2011 with increasing spread of the countries, we come to the following conclusions:

1. In the first period the behavior of the indexes is very similar, with no differences in excess returns and standard deviations.

2. In the second period of rising spreads the GDP weighted index has a higher excess return and a higher Sharpe ratio, while the EW index has a lower excess return and a lower Sharpe ratio.

For the Eurozone market, the index weighting system is not important during stable years, but in times of economic crises, such as the one that started in 2008 the GDP weighted is clearly the best one because it avoids the problem of the high weights of high indebted countries and uses weights more related to the economic size of a country. There is no evidence of the benefits from diversification arising from the EW index.

Subsequently, we run a series of regressions to understand if it is statistically significant to divide the time series in two different periods. For the Emerging Markets, we use a dummy with value zero from 1994 to 2002 and with value one from 2003 to 2011. We run regressions with the excess return on the risk free for the different indexes as a dependent variable, and the excess return on the risk free of the EMBIG and Dummy as independent variables.

The results of the three regressions are detailed in exhibit no.3 (GDP index), no. 4 (EW index) and no. 5 (EMBIGD index). The p-values for the dummy are between 0.10 and 0.16, therefore, we cannot assert that it is statistically significant to divide the time period in two sub-periods.

< insert Exhibit 3 here >

< insert Exhibit 4 here >

< insert Exhibit 5 here >

For the Eurozone Market we do the same, and we use a dummy with value zero from 1999 to 2007 and with value one from 2008 to 2011.

We run regressions with the excess return on the risk free of the different indexes as a dependent variable, and the excess return on the risk free of the ML index and Dummy as independent variables.

The results of the three regressions are detailed in exhibit no. 6 (GDP index), no. 7 (EW index) and no. 8 (DIVERSIFIED index). The p-values for the dummy are significant at 99% for the GDP index and at 90% for the EW and the Diversified indexes, thus, we can affirm that it is statistically significant to separate the time period into two sub-periods.

< insert Exhibit 6 here >

< insert Exhibit 7 here >

< insert Exhibit 8 here >

Conclusions

For the Emerging Market Bonds we find that it is better to use an EW index than a capitalization weighted one in order to maximize the total return, while a GDP index is to be used when we wish to minimize volatility, and both have a higher Sharpe ratio than the capitalization weighted index.

If we divide our analysis into two sub-periods, we discover that the GDP index is always the best one in order to reduce volatility. However, it showed a lower total return during the bull market from 2003 to 2011, and during the entire period from 1994 to 2011. In terms of Sharpe ratio the GDP index is superior to the capitalization index during the volatile markets from 1994 to 2002 and only slightly inferior during the bull market from 2003 to 2011.

For the EW index we find a large out-performance relative to the EMBIG capitalization index during the first period from 1994 to 2002, and a slight under-performance during the second period from 2003 to 2011. The first period is characterized by high volatility of the market due to the several economic crises occurred, i.e. the outright default for Russia, Ecuador and Argentina, debt restructuring under a coercive threat of default in Ukraine, Pakistan and Uruguay, large scale IMF financial support for Mexico, Brazil and Turkey. During that period of time, a high level of diversification of country risk like in the EW index was a key element of outperformance. The second period is characterized by a more stable environment and the EW index delivers a lower performance than the EMBIG.

We can conclude that the EMBIG is suited for investors who have a bullish view on the market, but in the long run the EW and the GDP weighted indexes are preferable as benchmarks.

The GDP index has a higher Sharpe ratio because has a lower volatility, and the EW index has a higher Sharpe ratio because has a higher total return during volatile markets. An investor can choose between the GDP if he/she wants a lower volatility and the EW index if he/she wishes to maximize the total return in the long run.

With regards to the liquidity and/or the capacity problem of the indexes, we can face some restrictions in the use of the EW and the GDP weighted indexes. Small countries or countries with a low amount of debt could find difficult to have a high proportion of a portfolio allocated to them or to have the portfolio rebalanced frequently. A large scale of passive investments in EW or GDP indexes could be problematic from a liquidity point of view.

These indexes can be used more widely as benchmarks by an active portfolio manager, who can select the countries in which to invest and then use an equally weighted method for the countries weights or can select the underweights and overweights related to a GDP index.

The Diversified index has results in terms of Sharpe ratio and returns which are between the capitalization index and the GDP index, and a less important liquidity and/or capacity problem because it is only a deviation from the EMBIGD, therefore, it can be more easily used for a passive investment on the market.

For the Eurozone market we have different results. In fact, the GDP index is the best one in terms of total return and Sharpe ratio and the EW index is the worst one.

For such a market the diversification through an EW index is not effective in reducing volatility and during the economic crisis from 2008 to 2011 the total return is lower than the capitalization index.

Far more effective, it is to reduce the risk related to the high weights of highly indebted countries using a GDP index, which gives a higher total return and a slightly lower volatility during a period of economic crisis.

It is important to note that during the period of time prior to the economic crisis from 1999 to 2007 the various indexes have a very similar performance and volatility. It is only during the economic crisis that the diverse constructions lead to a better performance of the GDP index and a bad performance of an EW index.

We can conclude that a GDP index can be a better benchmark for an active portfolio manager because it is more efficient in the long run. As mentioned before, a GDP index has a liquidity or capacity problem because of the use of passive investments on a large scale.

To introduce the different results for the two markets we have studied, we can start from the different kind of economic crises that can happen, as described by Manasse and Roubini [2005].

Debt crises can be classified into three types:

1. Episodes of insolvency or debt unsustainability due to high debt and illiquidity.

2. Episodes of illiquidity, where near default is driven by large stocks of short term liabilities relative to foreign reserves.
3. Episodes of macro and exchange rate weaknesses (large overvaluation and negative growth shocks).

Manasse and Roubini assert that low external debt is by no means a key element in order to avoid an economic crisis in emerging markets.

Their study shows that despite intermediate external debt level, the joint effect of short-term debt (exceeding 130 percent of reserves), relatively rigid exchange rates (low volatility) and political uncertainty, concur to raise the probability of an economic crises up to 41 percent.

Because of that, an EW method can work well for Emerging Markets investments. In fact, the level of debt is not sufficient to access the issuer risk, and maximum diversification is a good method to avoid idiosyncratic risks.

In the Eurozone, episodes of economic crisis for illiquidity are avoided through the intervention of other countries and of the European Central Bank. The problems are more related to debt unsustainability (point 1) and macro and exchange rate weaknesses (point 3).

As a consequence, for the Eurozone government bond market a careful look at the debt level using a GDP index is probably more effective than an EW index.

EXHIBIT 1- EMERGING MARKETS DATA

1/1994-12/2011				
	EMBIG	EMBIGD	GDP	EW
monthly performance	0,80%	0,82%	0,77%	0,90%
standard deviation	4,15%	3,95%	3,27%	4,05%
skweness	-2,93	-3,03	-3,03	-2,88
excess return	0,53%	0,54%	0,49%	0,62%
sharpe ratio	0,13	0,14	0,15	0,15
total return	467	484	422	593

1/1994-12/2002				
	EMBIG	EMBIGD	GDP	EW
monthly performance	0,75%	0,82%	0,83%	0,99%
standard deviation	5,22%	4,89%	4,05%	4,88%
skweness	-2,60	-2,71	-2,85	-2,42
excess return	0,38%	0,44%	0,45%	0,61%
sharpe ratio	0,07	0,09	0,11	0,13
total return	125	142	144	190

1/2003-12/2011				
	EMBIG	EMBIGD	GDP	EW
monthly performance	0,86%	0,82%	0,70%	0,81%
standard deviation	2,69%	2,73%	2,25%	3,03%
skweness	-2,58	-3,01	-2,42	-4,02
excess return	0,68%	0,64%	0,53%	0,63%
sharpe ratio	0,25	0,24	0,24	0,21
total return	152	141	114	139

EXHIBIT 2- EUROZONE MARKET DATA

1/1999-12/2011				
	ML	EW	GDP	Diversified
monthly performance	0,36%	0,35%	0,37%	0,36%
standard deviation	1,10%	1,13%	1,09%	1,12%
skweness	0,10	-0,12	0,15	0,11
excess return	0,13%	0,11%	0,14%	0,12%
sharpe ratio	0,12	0,10	0,13	0,11
total return	72,96	68,57	77,05	71,96
1/1999-12/2007				
	ML	EW	GDP	Diversified
monthly performance	0,35%	0,35%	0,35%	0,35%
standard deviation	0,92%	0,93%	0,92%	0,92%
skweness	-0,24	-0,22	-0,24	-0,23
excess return	0,09%	0,09%	0,09%	0,09%
sharpe ratio	0,10	0,10	0,09	0,10
total return	45,41	46,00	45,21	45,57
1/2008-12/2011				
	ML	EW	GDP	Diversified
monthly performance	0,36%	0,30%	0,41%	0,35%
standard deviation	1,44%	1,49%	1,41%	1,48%
skweness	0,31	-0,01	0,35	0,31
excess return	0,22%	0,16%	0,27%	0,20%
sharpe ratio	0,15	0,10	0,19	0,14
total return	16,24	12,75	19,15	15,44

EXHIBIT 3 – REGRESSION GDP-EMBIG

OLS, 1994:01-2011:12 (T = 216)

Variable: GDP

	Coefficient	Std. Error	t stat	p-value
Const	0.002	0.001	2.392	0.018 **
EMBIG	0.771	0.012	66.90	<0.000 ***
Dummy	-0.002	0.001	-1.645	0.101
R-square	0.955			

EXHIBIT 4 – REGRESSION EW-EMBIG

OLS, 1994:01-2011:12 (T = 216)

Variable: EW

	Coefficient	Std. Error	t stat	p-value
Const	0.003	0.001	2.165	0.032 **
EMBIG	0.931	0.021	45.40	<0.000 ***
Dummy	-0.003	0.002	-1.544	0.124
R-square	0.906			

EXHIBIT 5 – REGRESSION EMBIGD-EMBIG

OLS, 1994:01-2011:12 (T = 216)

Variable: EMBIGD

	Coefficient	Std. Error	t stat	p-value
Const	0.001	0.000	1.908	0.058 *
EMBIG	0.947	0.008	120.91	<0.000 ***
Dummy	-0.001	0.001	-1.408	0.161
R-square	0.986			

EXHIBIT 6 – REGRESSION GDP-ML

OLS, 1999:01-2011:12 (T = 156)

Variable: GDP

	Coefficient	Std. Error	t stat	p-value
Const	0.000	0.000	-0.037	0.979
ML	0.989	0.006	169.31	<0.000 ***
Dummy	-0.001	0.001	-1.408	0.000 ***
R-square	0.995			

EXHIBIT 7 – REGRESSION EW-ML

OLS, 1999:01-2011:12 (T = 156)

Variable: EW

	Coefficient	Std. Error	t stat	p-value
Const	0.000	0.000	0.168	0.867
ML	1.007	0.014	69.98	<0.000 ***
Dummy	-0.001	0.000	-1.957	0.052 *
R-square	0.970			

EXHIBIT 8 – REGRESSION DIVERSIFIED-ML

OLS, 1999:01-2011:12 (T = 156)

Variable: DIVERSIFIED

	Coefficient	Std. Error	t stat	p-value
Const	0.000	0.000	-0.058	0.954
ML	1.015	0.004	245.97	<0.000 ***
Dummy	-0.000	0.000	-1.779	0.077 *
R-square	0.997			

References

Arnott Robert, Hsu Jason, Li Feifei, Shepherd Shane: "Valuation-Indifferent Weighting for Bonds" *Journal of Portfolio Management*, spring 2010

Manasse Paolo, Roubini Nouriel: "Rules of Thumb for Sovereign Debt Crises" *IMF Working Paper*, March 2005

Siegel L.B.: "Benchmarks and investment management" *The Research Foundation of the Association for Investment Management and Research* 2003

Chapter 3: Alternative investments in the euro corporate bonds market: cash and CDS indexes

Introduction

The aim of this chapter is to compare an index that is widely used as a benchmark for the euro corporate bond market – the Bank of America Merrill Lynch EMU Corporate Index (ML) – with an index used as a reference for the credit default swap (CDS) market, namely the Markit Itraxx Europe 5-year Index.

An investor can take exposure to the corporate bond market by choosing between single bonds in the cash market or CDS contracts of these issuers. The market for CDS indexes, where an index represents a position in a basket of single CDS contracts, has become very important in recent years, and is now a valid alternative to the cash market for institutional investors.

The Itraxx Europe 5-year Index is now the most popular and liquid index, with Markit giving a daily reference level and a total return index as well, measuring the performance of holding the respective on-the-run Itraxx Europe 5-year contract. The index reflects a long credit position, that is selling protection on the Itraxx Europe index. Therefore, it replicates the behavior of a fictitious portfolio that buys one Itraxx Europe contract and invests the notional remainder in money market instruments (Euro OverNight Index Average, EONIA). Each time a new Itraxx series is issued, due to a regular index roll (every year on 20th March and 20th September) or due to a default in the current series, the position in the reference portfolio is rolled into the on-the-run index position (the roll cost is 1% of the respective “old” series coupon plus 1% of the respective “new” series coupon). Any coupons paid are immediately reinvested.

An exchange-traded fund (ETF) is now available that uses the Markit Total Return Index as a benchmark; therefore, retail investors can also use this index if they want to invest in the corporate bond market. Institutional investors also use the Itraxx Europe Index as a tool to hedge the credit risk in their portfolios, buying protection while holding a position in corporate bonds.

Given these two uses, the alternative ways of investing in the market and as a hedge tool for a portfolio, we think it is important to analyze in depth the different behaviors of the two indexes in order to understand the risks associated with either investment decision.

The academic literature on the differences between investing in cash bonds and CDSs only looks at the single firm level (Blanco et al. [2005] and Norden and Weber [2009] and not at the index level so our aim is to try to develop an analysis for the indexes.

We start by describing the data we used and the methodology for our analysis. After that, we compare the features of the two indexes and their consequent different exposures to risk factors such as duration, asset swap spread, sector weights and rating bucket weights. Then we analyze the risk/return profiles of the two indexes and the tracking error between them. We follow this with a time series analysis, and study the autocorrelation properties of the index series and the difference in the performance of the two indexes. We conclude by developing a risk factor analysis in order to understand which factors can best explain these differences in performance.

Data and Methodology

For our analysis we choose two indexes that are widely used in the financial industry: the Bank of America Merril Lynch European Monetary Union Corporate

Index (the ML Index, Bloomberg ticker ER00) and the Itraxx Europe Total Return Index (Bloomberg ticker ITRXTE5I).

We use monthly data starting with September 2006, the first month in which the Itraxx Europe Total Return Index is available, and ending with September 2011. We take the end of month value for each series. All data are collected from Bloomberg.

In order to compare these two investment options, that are the indexes, we need to adjust the Itraxx Europe Index and add the interest rate risk component to the credit risk component. Therefore, we create a new index called Derivatives which invests in the Itraxx Europe 5-year Total Return Index and at the same time in the Bobl (the German 5-year government bond) on-the-run future contract (with a rollover every 3 months).

We perform a descriptive analysis of the two indexes showing their different characteristics and risk/return profiles. We use logarithmic data to calculate the monthly performance. To develop our time series analysis, we follow Reilly et al. [1992] to study the autocorrelation. We first use the Akaike criteria in order to choose the number of lags, so we run an autoregressive (AR) model to see whether autocorrelation exists and whether or not the prices follow a random walk.

Our second time series analysis consists of a vector autoregression (VAR) model to show a possible lead-lag relationship between the two indexes, as studied by Blanco et al. [2005] and Norden and Weber [2009] at the single firm level. We first perform the Engle-Granger test to find out whether there is cointegration and determine which model (ECM or VAR) to use for the analysis. We start off by using monthly data but, as it is well known that the dynamics between the bond cash market and the derivatives market are only relevant at a high data frequency, we also use daily data for the VAR model.

Next, we use a regression model to understand which of the identified differences between the indexes are most relevant in determining the difference in performance. We perform a factor analysis, as in Fama and French [1993], using monthly data and the tracking error (TE, the difference in performance between the Derivatives index and the ML index) as a dependent variable.

Features of the ML and Derivatives Indexes

The two indexes, ML and Itraxx Europe, are constructed using different rules, which are described in Exhibit 1. The main difference between the two indexes is the weighting method: the ML is capitalization-weighted and Itraxx is equally weighted. The capitalization weighting method assigns a weight to each bond depending on its market value. Thus, the weightings of different buckets of ratings, of sectors and of curve buckets are a consequence of the issues made by the companies. The Itraxx Europe has 125 members, much fewer than the approximately 1,700 in the ML, but with the equally weighted method the idiosyncratic risk is still low because the weights are limited to 0.8% for each member.

<insert Exhibit 1 here >

Our aim is to compare an investment in the ML index with an investment in the Itraxx Europe and the Bobl future on-the-run Derivatives index. Thus, we look at the different exposures of these indexes to the main risk factors. Exhibit 2 shows the yield to maturity of the two indexes and in Exhibit 3 we show the trend in this measure. We can see that the ML has a higher mean value but also a higher volatility than the Derivatives index.

< insert Exhibits 2 and 3 here >

Next, we see that the indexes' durations are quite similar (see Exhibits 4 and 5), but, also for this measure, in the ML case volatility is higher. The volatility of derivatives is due mainly to the quarterly roll of the Bobl future.

< insert Exhibits 4 and 5 here >

The asset swap spreads of the two indexes are compared in Exhibits 6 and 7. The ML has a higher value, consistent with a higher yield to maturity, as well as a higher volatility of the value.

< insert Exhibits 6 and 7 here >

The sector exposure of the two indexes is very different. For the ML this is a result of using the capitalization of the bonds outstanding, whereas the sector exposure is fixed by the index rules for the Itraxx. Exhibit 8 shows the differences for the main macro sectors, from which we can see that the biggest difference is in the weights for the financial sector, which are fixed at 20% for the Itraxx and vary between 52% and 60% (with a mean value of 55%) for the ML.

< insert Exhibit 8 here >

Exposure to the different ratings buckets is not fixed for either the ML or the Itraxx Index. Both have means close to A, as Exhibits 9 and 10 show. The scale used assigns 4 to BBB, 3 to A, 2 to AA and 1 to AAA, and the mean value is between 2.6 and 2.9 for the ML Index and between 3.2 and 3.5 for the Itraxx Index so that the mean is higher for the ML but both are still closest to an A rating. We can conclude that the difference between the mean ratings of the two indexes is small but the ML Index has a slightly better rating on average.

< insert Exhibits 9 and 10 here >

From our analysis we can state that the cap-weighted methodology used for the ML Index produces higher volatilities of the various risk exposure indicators (duration, sector weights and mean ratings) than for the Derivatives Index. Companies issuing bonds might display opportunistic behavior in issuing long maturity bonds when the interest rates are low and short maturity bonds when interest rates are high. A cap-weighted index that modifies its duration on the basis of the bonds issued could lead to a loss of value for investors if the opportunistic behavior of the issuers is profitable.

Another problem related to the cap weighting methodology is the so-called ‘bums’ problem (Siegel [2003]), which is a result of a large share of the total debt market being made up of issuers with a large amount of outstanding debt, issuers whose creditworthiness and total debt volume are usually negatively related. The problem is not limited to individual issues; it can also occur if a specific segment is adversely affected. In the financial sector, for example, the sector weight for the ML Index had risen to 60% by the second half of 2008, just before the collapse of Lehman Brothers and the explosion of the financial bubble. As we can see in Exhibit 11, the financial sector weights started to decline from there and went down to 51% in December 2011.

< insert Exhibit 11 here >

The effects of the cap-weighting methodology are well explained in Arnott et al. [2010]. The equal weighting methodology used for the Itraxx Index and the fixed sector weights rule allow this index to avoid the problem.

Indexes’ Risk/Return Profiles

In order to compare the performances of the two alternative investment choices, we create time series for both portfolios, starting on 09/29/2006 and ending on 09/30/2011, one investing in the ML Index and the other in the Itraxx Europe Total Return Index and the Bobl future on-the-run. The Itraxx Europe Total Return Index is calculated by Markit and represents the payoff of a funded investment in the Itraxx Europe Index on-the-run. Over the 5-year period we find the total return for the ML to be 17.71%, and that for the Derivatives Index to be 19.62%, as Exhibit 12 shows.

< insert Exhibit 12 here >

The monthly data are summarized in Exhibit 13, where the logarithmic values show an almost identical mean performance. When we compare the risk of the two indexes, we can see, however, that the ML has a higher standard deviation as well as more pronounced skewness and kurtosis. Therefore, it is more risky than the Derivatives Index. Finally, the Derivatives Index has a better Sharpe ratio due to its slightly higher performance (excess return over the risk free rate) and lower volatility.

< insert Exhibit 13 here >

We calculate the tracking error (TE) between the two indexes in order to identify any short-run divergence in performance; the data are shown in Exhibit 14. The one-month TE is 4% annualized, a high value considering the monthly annualized performance of 3.6% for the indexes. The TE is not only high, but also rises as we look at the values for 2, 3, 4, 5, and 6 months using no overlapping data. This would be important for someone using index derivatives to hedge a bond portfolio because, due to the TE, they may incur losses over many months.

< insert Exhibit 14 here >

Time Series Analysis

In the previous section, we demonstrated the performance of the indexes, and now we analyze their time series. We follow Reilly et al. [1992] and study the autocorrelation in the time series because, if autocorrelation exists, it is an indication that prices do not follow a random walk pattern but the past performance has forecasting power for the future. Autocorrelation is estimated through an AR(3) model. If the lagging variables are statistically significant, it means that there is autocorrelation in the series. The number of lags (3) is suggested by the Akaike criteria. Exhibit 15 shows the results for the Derivatives Index, where no autocorrelation is found and none of the lagging variables are statistically significant.

< insert Exhibit 15 here >

In Exhibit 16 we can see that for the ML Index we have statistically significant autocorrelation for the lagging variables 1 and 3. Thus, the past performance of the index has forecasting power for the future. The presence of autocorrelation in the bond indexes is partially explained by the accrued component, which is constant over time, but the different results for the Derivatives and ML Indexes could indicate a stale pricing problem, too, where prices move with lags due to the bonds' low liquidity, while the derivatives are a more liquid instrument.

< insert Exhibit 16 here >

Exhibit 17 displays the results of an autocorrelation analysis concerning the difference in the performance of the two indexes (TE). We find a positive and statistically significant value for lag 1. This confirms our finding from earlier that the difference in performance between the two indexes tends to increase rather than converge in the short term.

< insert Exhibit 17 here >

In order to examine the lead-lag relationship between the Derivatives and ML Indexes, we use a VAR model, following other studies. Blanco et al. [2005] and Norden and Weber [2009] studied the relationship between investment grade bonds and CDS prices at the single firm level, while Fung et al. [2008] studied the relationship between the CDS market and the US equity market. The aim of these studies was to ascertain which market is more efficient in the price discovery process and so leads the other markets.

Our results from using monthly data can be seen in Exhibit 18. We do not find any relationship between the two indexes, so the lead role of the CDS market found by Blanco et al. [2005] and Norden and Weber [2009] at the single firm level is not confirmed at the index level.

< insert Exhibit 18 here >

We utilize a VAR model because we find no signs of cointegration between the two series using the Engle-Granger test. For the Derivatives index, no lags are significant, while for ML, only ML -1 is significant at the 95% level. If we utilize daily data instead of monthly data (see Exhibit 19), again we find no signs of cointegration and the VAR model has no significant lags for the Derivatives Index, while for ML only ML -1 and ML -2 are significant at the 95% level.

< insert Exhibit 19 here >

We conclude that there is no statistically significant lead-lag relationship between the Derivatives Index and the ML Index during the period between September 2006 and September 2011.

Risk Factor Analysis

We now study the TE (Derivatives performance minus ML performance) using factor analysis, as in Fama and French [1993] in order to find out which variable best explains the different performances of the two indexes. We focus our analysis on the following factors:

1) The excess return of the BBB bonds related to the market index ML, which we call excess_BBB. As we know that the Derivatives Index has a

higher exposure to the BBB bucket, we investigate whether this difference is relevant in explaining the TE.

2) The excess return of the financial sector bonds related to the market index ML, termed excess_Fin. As we know that the Derivatives Index has a lower exposure to the financial sector, we investigate whether this difference is relevant.

3) The excess return of the Bund future (10-year German government bond) relative to the risk free rate (1-month euribor), a factor we call Curve. We investigate whether an unexpected movement in the long-term interest rates has an impact on the TE.

4) Variations in the implicit volatility of the DJ eurostoxx 50 Index (V2X). We investigate whether changes in the expected equity market volatility can explain the TE, due to the fact that equity market volatility is an input into CDS pricing models, as explained by Bedendo et al. [2011].

In Exhibit 20 we present the results of a regression of TE (dependent variable) against the above factors (independent variables). All factors are statistically significant with the exception of Curve.

< insert Exhibit 20 here >

In Exhibits 21 to 24 we show the results of regressing TE against each of the above factors in turn, and again the only factor that is not statistically significant at the 95% level is Curve, a result explained by the fact that the mean durations are similar for ML and Derivatives, as was shown earlier.

< insert Exhibits 21 to 24 here >

Finally, in Exhibit 25 we present a regression of TE against all the above factors except for Curve, from which we can conclude the following:

1) If the variations in V2X, the implicit volatility in the equity market, are positive (higher expected volatility), this leads to a positive TE. Higher implicit volatility in the equity market is usually associated with higher uncertainty and higher spreads in the corporate bond market. This means that the Derivatives Index performs better in a negative environment and is more defensive.

2) As expected, a positive excess return for the financial sector leads to a negative excess return for the Derivatives Index compared to the ML index because the latter has a higher exposure to this sector.

3) If the excess return for the BBB bucket is positive, we have an under-performance by the Derivatives Index, which is not expected due to the lower mean rating for this index compared to the ML Index. The explanation is probably that the Derivatives Index has a lower beta (reactions to market movements) than the ML Index due to its exposure to the 125 most liquid issuers. As a consequence, when the market is doing well (usually meaning that the BBB bucket over-performs), the TE is negative.

<insert Exhibit 25 here >

From our factor analysis we can conclude that the most important element explaining TE is the excess return of the financial sector, which has the highest coefficient with the lowest p-value. Also, the signs of the coefficients for variations in the implicit equity market volatility and excess returns for the BBB bucket indicate that the Derivatives Index has a lower beta than the ML, a characteristic consistent with the lower mean asset swap spread of the Derivatives Index that we saw earlier.

Conclusions

We have compared the ML Index for the EMU corporate bonds market to an index constructed from an investment in the Itraxx Europe and the Bobl future (the "Derivatives Index"). We have shown that these two alternatives for investing in the corporate bond market have different characteristics that lead to different trends over the short term. We have seen that the TE increases as we increase the time frame, and a time series analysis has shown a positive autocorrelation in the difference in performance between the Derivatives Index and the ML Index. This could be important for investors who use derivatives indexes to hedge their corporate bond portfolios.

The two indexes do not differ meaningfully in duration, but the Derivatives Index has a much lower exposure to the financial sector and a lower mean rating than the ML Index. The lower asset swap spread and lower yield to maturity of the Derivatives Index suggest a more defensive composition and a lower beta compared with the ML Index.

The factor analysis shows that the difference in the two indexes' performance is related to the Derivatives Index's lower exposure to the financial sector and lower beta, with the lower beta explained by the importance of changes in the implicit equity market volatility and the excess return of the BBB bucket relative to the market.

We reveal a statistically significant positive autocorrelation for the ML Index and a statistically insignificant value for the Derivatives Index. There is a possible liquidity problem for the ML Index, and also the possibility of stale pricing, which explains the positive autocorrelation. This problem is not present in the Derivatives Index.

We do not find a lead-lag relationship between the two indexes when we apply a VAR model, and the lead role of the CDS market found in other papers at the single firm level is not statistically significant at the index level according to our data.

Finally, we can state that the two indexes are similar in terms of returns, but that the Derivatives Index is less risky because it has a lower volatility, has values of skewness and kurtosis closer to those of a normal distribution and is a more liquid instrument, as the autocorrelation is not significant. The capitalization method used for the ML Index (in contrast to the equal weighting method used for the Derivatives Index) also has risks related to changes in the weights over time, in particular when a sector or an issuer has a high weight because it is highly indebted, as has been experienced by the financial sector recently.

EXHIBIT 1- INDEX CONSTRUCTION RULES

	BofA Merrill Lynch	Itraxx Europe
Inclusions	Only bonds from corporations domiciled in EMU-participating countries. Only fixed coupons (including step-ups). Zero coupons, corporate pay-in-kind securities, and toggle notes are eligible	The most liquid CDSs from European investment-grade issuers
Exclusions	Convertible securities, Bills, inflation-linked and strips. Defaulted securities	Defaulted CDSs
Time-to-Maturity	Minimum 1 year	5 years
Minimum requirements	Minimum amount outstanding of € 250 million	None
Number of Bonds	Floating (1,790 in Dec. 2010)	Fixed at 125
Reinvestment Assumption	Full reinvestment in the index	Full reinvestment in the index
Treatment of Defaults	Defaulted bonds are excluded	Defaulted CDSs are excluded
Index Rebalancing	End of Month	Every 6 months

EXHIBIT 2 – YIELD TO MATURITY

	ML	Derivatives
Mean	4.73	3.94
Stand. Dev.	1.11	0.78
Min	3.08	2.48
Max	7.29	5.69

EXHIBIT 3 – YIELD TO MATURITY

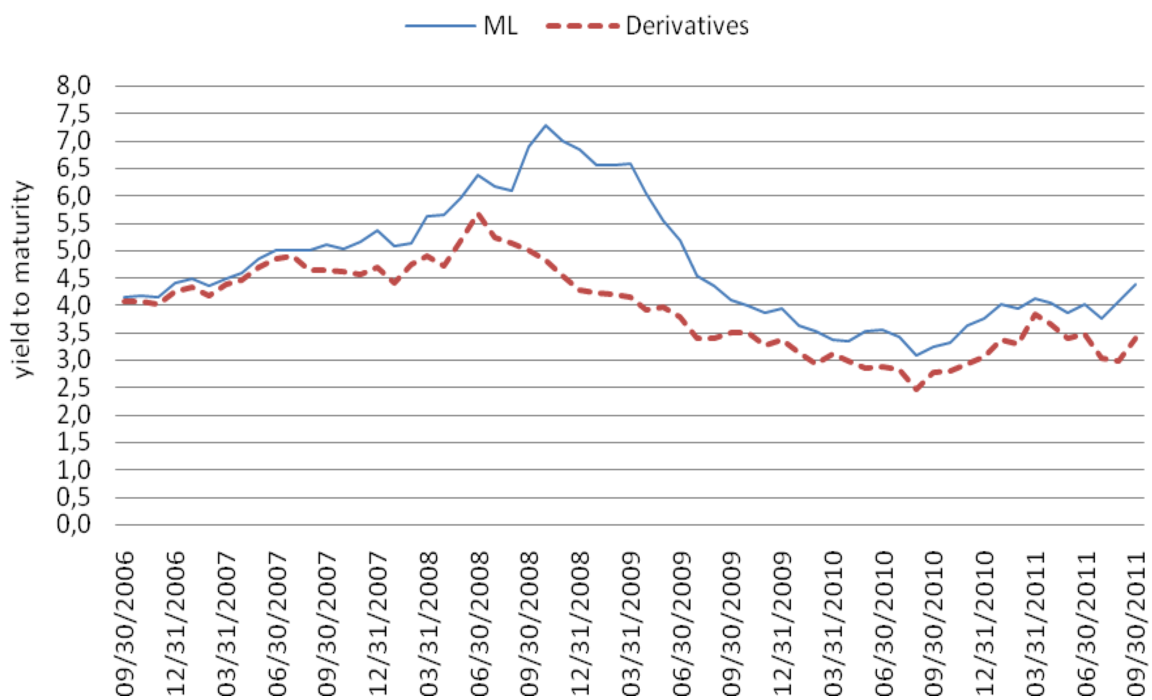

EXHIBIT 4 – DURATION

	ML	Derivatives
Mean	4.33	4.38
Stand. Dev.	0.26	0.16
Min	4.00	4.05
Max	4.77	4.66

EXHIBIT 5 - DURATION

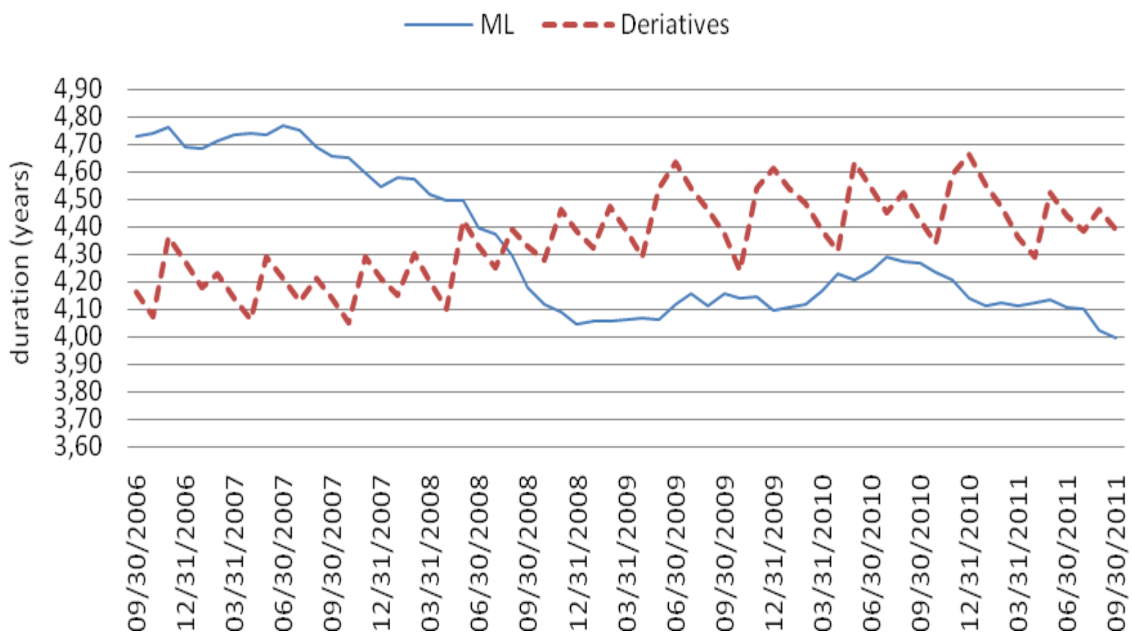

EXHIBIT 6 – SWAP SPREAD

	ML	Derivatives
Mean	139	92
Stand. Dev.	86	45
Min	25	20
Max	348	202

EXHIBIT 7 – SPREAD

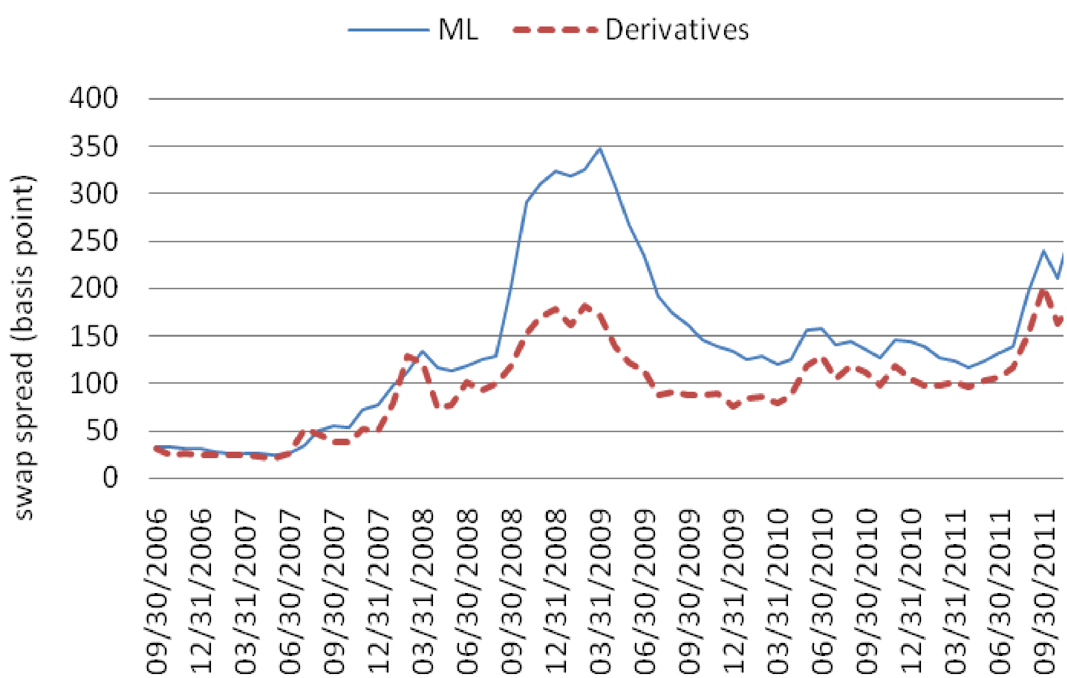

EXHIBIT 8 – SECTOR WEIGHTS

Weights for Financial sector		
	ML	Derivatives
Mean	55	20
Stand. Dev.	2	0
Min	52	20
Max	60	20

Weights for TMT sector		
	ML	Derivatives
Mean	9	16
Stand. Dev.	1	0
Min	8	16
Max	12	16

Weights for Energy&Utilities sector		
	ML	Derivatives
Mean	13	16
Stand. Dev.	2	0
Min	10	16
Max	17	16

Weights for Auto&Industrial sector		
	ML	Derivatives
Mean	16	24
Stand. Dev.	0	0
Min	15	24
Max	16	24

Weights for Consumer (ex auto) sector		
	ML	Derivatives
Mean	7	24
Stand. Dev.	1	0
Min	5	16
Max	8	16

EXHIBIT 9 – RATINGS*

	ML	Derivatives
Mean	2.75	3.35
Stand. Dev.	0.09	0.04
Min	2.63	3.27
Max	2.89	3.43

*1= AAA, 2= AA, 3= A, 4= BBB

EXHIBIT 10 – RATINGS

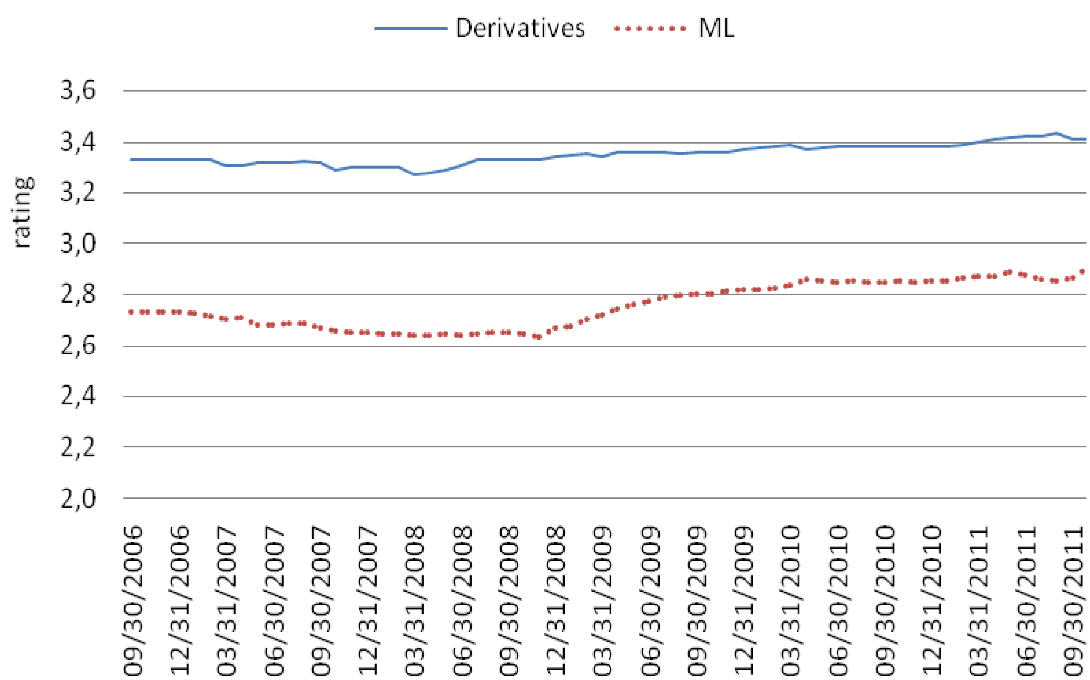

EXHIBIT 11 - PERCENTAGE OF FINANCIALS IN THE ML INDEX

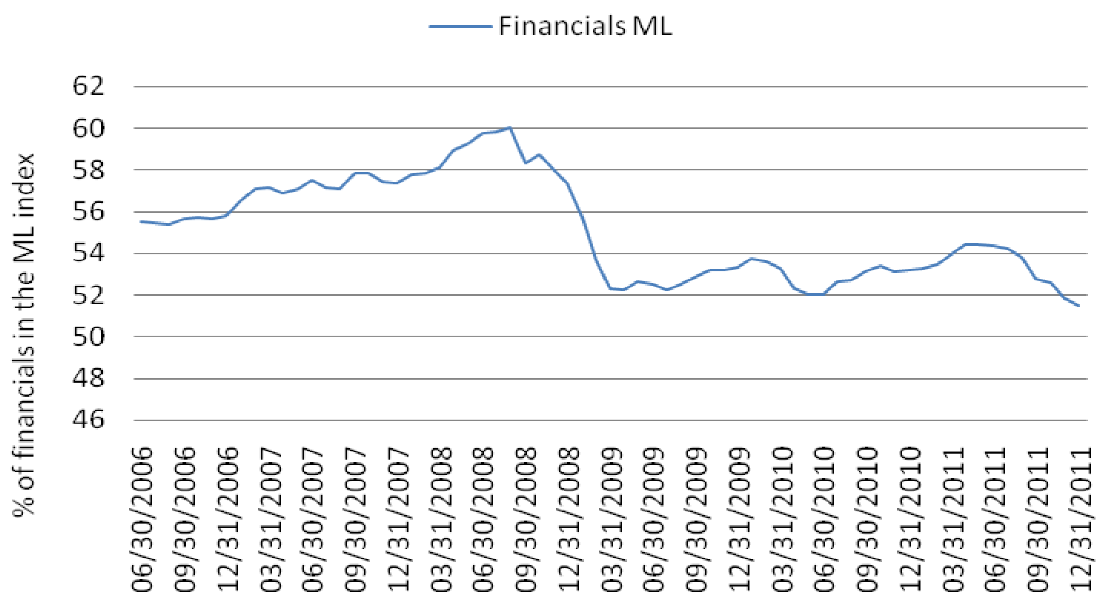

EXHIBIT 12 – PERFORMANCE*

	ML	Derivatives
Mean	0.29%	0.30%
Stand. Dev.	1.18%	1.00%
Skewness	-0.64	-0.30
Excess Kurtosis	2.90	-0.08
Mean annualized	3.56%	3.64%
Stand. Dev. ann.	4.09%	3.46%
Mean Excess Return	0.10%	0.11%
Sharpe ratio	0.09	0.11

*log monthly data

EXHIBIT 13 – PERFORMANCE

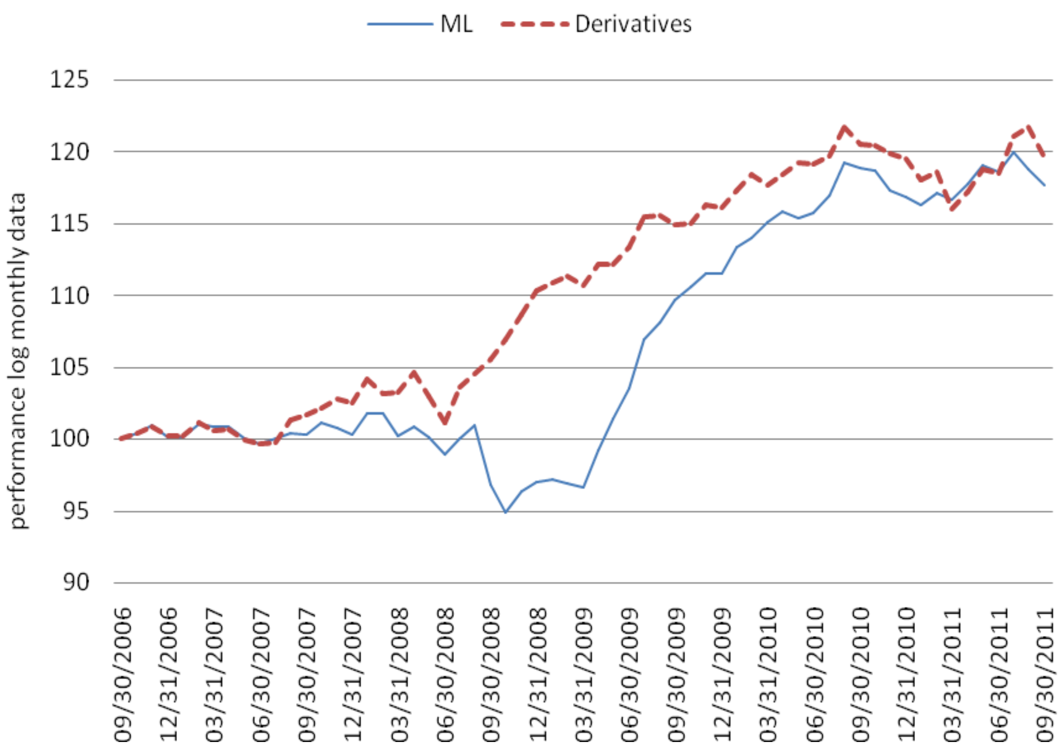

EXHIBIT 14 – TRACKING ERROR*

1 month	2 months	3 months	4 months	5 months	6 months
4.0%	4.2%	5.2%	4.9%	6.1%	6.2%

*annualized mean st.dev. with no overlapping data

EXHIBIT 15 – AUTOCORRELATION OF THE DERIVATIVES INDEX

OLS, 2007:01-2011:09 (T = 57)

Variable: Derivatives

	Coefficient	Std. Error	t stat	p-value
Const	0.003	0.002	1.761	0.084 *
Derivatives_1	-0.049	0.136	-0.361	0.720
Derivatives_2	-0.079	0.136	-0.582	0.563
Derivatives_3	0.271	0.141	1.923	0.060 *
R-square	0.075		R-square corrected	0.023
F (3,53)	1.441		P-value (F)	0.241

EXHIBIT 16 – AUTOCORRELATION OF THE ML INDEX

OLS, 2007:01-2011:09 (T = 57)

Variable: ML

	Coefficient	Std. Error	t stat	p-value
Const	0.002	0.002	1.012	0.314
ML_1	0.329	0.132	2.500	0.016 **
ML_2	-0.173	0.138	-1.251	0.217
ML_3	0.271	0.134	2.018	0.050 **
R-square	0.153		R-square corrected	0.105
F (3,53)	3.195		P-value (F)	0.031

EXHIBIT 17 – AUTOCORRELATION OF THE TRACKING ERROR

OLS, 2007:01-2011:09 (T = 57)

Variable: TE

	Coefficient	Std. Error	t stat	p-value
Const	0.0001	0.002	0.079	0.937
TE_1	0.345	0.138	2.492	0.016 **
TE_2	-0.006	0.149	-0.038	0.970
TE_3	0.127	0.141	0.900	0.372
R-square	0.147		R-square corrected	0.099
F (3,53)	3.046		P-value (F)	0.037

EXHIBIT 18 – THE LEAD-LAG RELATIONSHIP BETWEEN THE DERIVATIVES AND ML INDEXES (MONTHLY DATA)

VAR, 3 lags

OLS, 2007:01-2011:09 (T = 57)

Equation 1: Derivatives

	Coefficient	Std. Error	t stat	p-value
Const	0.003	0.002	1.737	0.089 *
Derivatives_1	-0.059	0.163	-0.362	0.719
Derivatives_2	-0.048	0.169	-0.285	0.788
Derivatives_3	0.275	0.165	1.662	0.103
ML_1	0.004	0.144	0.030	0.976
ML_2	-0.059	0.157	-0.376	0.708
ML_3	-0.003	0.144	-0.020	0.984

R-square	0.079		R-square corrected	-0.031
F (6,50)	0.716		P-value (F)	0.638

Equation 2: ML

	Coefficient	Std. Error	t stat	p-value
Const	0.002	0.002	1.311	0.196
Derivatives_1	-0.311	0.178	-1.750	0.086 *
Derivatives_2	-0.109	0.183	-0.593	0.556
Derivatives_3	0.207	0.179	1.158	0.252
ML_1	0.467	0.156	2.995	0.004 ***
ML_2	-0.175	0.170	-1.028	0.309
ML_3	0.170	0.156	1.091	0.281
R-square	0.226		R-square corrected	0.133
F (6,50)	2.434		P-value (F)	0.038

EXHIBIT 19 – THE LEAD-LAG RELATIONSHIP BETWEEN THE DERIVATIVES AND ML INDEXES (DAILY DATA)

VAR, 3 lags

OLS, daily 2006/10/04-2011/09/30 (T = 1367)

Equation 1: Derivatives

	Coefficient	Std. Error	t stat	p-value

Const	0.0002	0.00007	2.655	0.008 ***
Derivatives_1	0.037	0.036	1.030	0.303
Derivatives_2	-0.021	0.036	-0.583	0.560
Derivatives_3	0.052	0.035	1.469	0.142
ML_1	-0.045	0.047	-0.961	0.337
ML_2	0.062	0.047	1.310	0.191
ML_3	-0.084	0.046	-1.811	0.070 *
R-square	0.004		R-square corrected	-0.0002
F (6,50)	0.947		P-value (F)	0.460

Equation 2: ML

	Coefficient	Std. Error	t stat	p-value
Const	0.0001	0.00005	2.215	0.027 **
Derivatives_1	0.007	0.027	0.261	0.795
Derivatives_2	-0.018	0.027	-0.648	0.517
Derivatives_3	0.019	0.027	0.701	0.484
ML_1	0.150	0.036	4.184	0.00003 ***
ML_2	0.098	0.036	2.712	0.007 ***
ML_3	0.038	0.036	1.060	0.290
R-square	0.043		R-square corrected	0.039
F (6,50)	10.203		P-value (F)	4.57 10^{-11}

EXHIBIT 20 – REGRESSION OF TE (DEPENDENT VARIABLE) AGAINST THE OTHER FACTORS (INDEPENDENT VARIABLES)

OLS, 2006:11-2011:09 (T =59)

Variable: TE

	Coefficient	Std. Error	t stat	p-value
Const	-0.0008	0.001	-0.645	0.522
var_V2X	0.015	0.006	2.437	0.018 **
Excess_BBB	-0.489	0.157	-3.107	0.003 ***
Excess_Fin	-1.063	0.260	-4.086	0.0002 ***
Curve	-0.079	0.073	-1.084	0.283
R-square	0.477		R-square corrected	0.439
F (4,54)	12.336		p-value (F)	3.40 10^{-7}

EXHIBIT 21 – REGRESSION OF TE AGAINST CURVE FACTOR

OLS, 2006:11-2011:09 (T =60)

Variable: TE

	Coefficient	Std. Error	t stat	p-value
Const	0.0002	0.002	0.110	0.913
Curve	0.616	0.081	1.981	0.052 *
R-square	0.063		R-square corrected	0.047
F (1,58)	3.924		p-value (F)	0.052

EXHIBIT 22 – REGRESSION OF TE AGAINST var_V2X FACTOR

OLS, 2006:11-2011:09 (T =59)

Variable: TE

	Coefficient	Std. Error	t stat	p-value
Const	-0.0008	0.001	-0.604	0.549
var_V2X	0.027	0.006	4.546	0.00003 ***
R-square	0.266		R-square corrected	0.253
F (1,57)	20.665		p-value (F)	0.00003

EXHIBIT 23 – REGRESSION OF TE AGAINST Excess_Fin FACTOR

OLS, 2006:11-2011:09 (T =60)

Variable: TE

	Coefficient	Std. Error	t stat	p-value
Const	-0.0008	0.001	-0.579	0.565
Excess_Fin	-1.158	0.265	-4.367	0.00005 ***
R-square	0.247		R-square corrected	0.234
F (1,58)	19.068		p-value (F)	0.00005

EXHIBIT 24 – REGRESSION OF TE AGAINST BBB FACTOR

OLS, 2006:11-2011:09 (T =60)

Variable: TE

	Coefficient	Std. Error	t stat	p-value
Const	0.002	0.001	1.643	0.106
Excess_BBB	-0.451	0.070	-6.475	<0.00001 ***
R-square	0.420		R-square corrected	0.410
F (1,58)	41.929		p-value (F)	2.22 10^{-8}

EXHIBIT 25 – REGRESSION OF TE AGAINST ALL OTHER FACTORS EXCLUDING CURVE

OLS, 2006:11-2011:09 (T =59)

Variable: TE

	Coefficient	Std. Error	t stat	p-value
Const	-0.0007	0.001	-0.634	0.529
var_V2X	0.014	0.006	2.293	0.026 **
Excess_BBB	-0.440	0.151	-2.213	0.005 ***
Excess_Fin	-0.975	0.248	-3.938	0.0002 ***
R-square	0.466		R-square corrected	0.437
F (3,55)	16.006		p-value (F)	1.34 10^{-7}

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Chapter 4: The impact of Fallen Angels on Investment Grade Corporate Bonds portfolios: evidence from the European market

Paper presented at the Multinational Finance Conference, Roma, June 26-29 2011.

Introduction

Corporate bonds that have suffered a downgrade from the Investment Grade (IG) to the speculative grade category are generally known as *fallen angels* (FA). The advantage of investing in this category of securities has long been debated by academic researchers and investment professionals alike. The rising importance of FA securities grew to become a proper asset class of investment, can be deducted from the trading volume and the relative weight that they acquire within the wider category of the High Yield (HY) bonds. Examining the trading volume of FA we observe that it has increased steadily in recent years, reaching or exceeding the \$100bn in 2002, 2005, and 2008[1]. According to Merrill Lynch data, during the 2004-2008 five year period, FA represented over \$300bn in HY supply, roughly half of the original HY new issuance during the period. In 2009 alone, FA represented \$1 in \$4 dollars of all outstanding HY rising from an average of 10-15% in the period from 1997 to 2002.

Extensive literature aims to investigate the characteristics of FA. The risk-return profile of this asset class have been compared to both the HY and the Original Issue High-yield bonds (OI), defined as those securities that are rated speculative grade at issue. Among the most notable studies, Fridson and Sterling (2006) show that, over the

[1] High Yield Strategy. Fallen Angels: Gems or Empty Shells?. Bank of America – Merrill Lynch, March 2009.

period 1996-2006, OI have produced lower return with higher risk than FA. Besides, Altman and Fanjul (2004) highlight the importance of focusing on these securities especially from the portfolio managers' perspective. They demonstrate that the median weighted average recovery rate on FA defaulting issues is 70% for the period 1982-2003. This compares to about 42.4% for the category of HY and about 29% for OI. They conclude that, from a default loss standpoint, FAs appear to be less risky than OI securities.

It has been observed that institutional investors are the most involved in corporate bond trading activity and are also the major holders of these securities. This evidence is supported by the fact that corporate bonds mainly trade in block size, besides minimum lots are usually too high for retail investors. For this reason, the downgrade to junk bond affects, above all, the investment choices on three categories of institutional portfolios: investment funds characterized by regulatory constraints based on credit rating (i.e. insurance funds), passive investment vehicles (i.e. Exchange Traded Funds, ETF) and mutual funds characterized by tracking error restrictions. The first category of portfolios deals with regulatory constraints that restrict or prohibit the ownership of speculative-grade debt to limit the resources earmarked when they invest in riskier assets besides for reputational considerations (Ambrose et al., 2008). In greater detail, the purpose of rating-based governance rules is to mitigate the agency problems between fund managers and investors as fund managers are discouraged from following opportunistic, high-risk strategies[2]. From an operational perspective the fund's regulation impose the forced sale of all securities that fall below IG regardless of any market price valuation and opportunity. This circumstance is common to the passive investment vehicles that

[2] The theme of the role of credit ratings as tools for portfolio governance has been addressed by Loffler (2004), who evaluates the efficiency rating-based portfolio governance approach comparing it to the market base approach.

track IG indices, as their investment objective is the full replication of the underlying index. The relevance of these funds in the market is demonstrated by their recent growth: out of 28 existing ETFs denominated in euro that track IG corporate bonds indices, 23 have been created during or after 2009. As a consequence, the growth of the assets under management by ETFs provokes an increasingly relevant price pressure on those securities deleted from their underling benchmarks. Similarly, the FAs' exit from the IG indices, although with greater operational flexibility, results in the requirement to sell these securities for those managers who have the obligation of holding securities with an IG rating and/or who have tracking error restrictions.

Mainstream analysis of the impact of the index rebalancing on portfolios has focused so far, to our knowledge, solely on stock market indices. Cai and Houge (2008), for example, assess the impact of index rebalancing on long-term index performance and portfolio evaluation. Examining deletions and additions to the Russell 2000 small-cap index from 1979 to 2004, they notice that a buy-and-hold portfolio significantly outperforms the rebalanced index over five years.

Our study instead analyses the impact of the index rebalancing on the corporate bond market focusing on Euro denominated securities, a segment traditionally reviewed less often than the US Dollar denominated one. Moved by this purpose, we implement an event study aiming to verify the effect of a downgrade that crosses the IG boundary on a bond's price. We examine corporate bonds that exit the Merrill Lynch Emu Non Financial Corporate Index during January 2001 and December 2009 because of a downgrade to junk status by Moody's and/or S&Ps. It is worth highlighting that the rebalancing criteria of the ML Emu Non Financial Corporate Index are common to the ones associated with other corporate bond indices such as the Iboxx EUR Bonds, the underlying benchmark of some Exchange Traded Funds (ETF). For this reason, our results can be easily generalized to the overall index funds category that replicates a corporate bonds index. We adopt the event study methodology using daily data from the Bloomberg database. Our sample consists of the most representative issues of the corporate bond market (in the U.S. and in Europe both denominated in Euro) hence composed only by large and liquid issues. Due to the characteristics of our sample, we assume that the prices provided by Bloomberg correspond to transaction prices rather than matrix prices (refer to Section 3 for an in-depth discussion about issues related to the use of matrix prices and the choice of reliable prices).

We calculate the abnormal returns in three representative analyses. In the first one we examine the effect of the announcement of first downgrade to junk status by one of the two rating agencies. In accordance with the literature (Grier and Katz, 1976; Wansley et al., 1992; Hand et al., 1992; Hite and Warga, 1997; Steiner and Heinke, 2001; May, 2010), we find both abnormal returns statistically significant in correspondence of the announcement day and in the course of the month preceding the downgrade (see Section 2 for an overview). In the second event study we perform, we examine the effect of the second downgrade, which determines the revision of the security to the FA category. Again we record a significant bond market reaction, more amplified than in the previous case.

Widening the existing literature we also focus on the effect of the subsequent bond deletion from the IG benchmark, observing positive and significant ARs in the month following the event. This result indicates that the selling pressure on the bond price decreases at the time of the securities' release from the index. In other words, our original finding is that once the securities leave the IG index they show a significant over-performance compared to the high yields. These insights offer some practical guidelines for those professionals that manage IG and/or HY portfolios.

The rest of the paper is organized as follows: Section 2 reviews the main studies that focus on the impact of downgrades on the bonds' price; Sections 3 and 4 present the data and the details of the methodology we adopted. Section 5 reports the results of the event studies while Section 6 comprises some final remarks and concludes the paper.

Literature overview on the impact of bonds' downgrade

A broad body of research examines the impact of the changes in credit rating on the bond's price using the event study methodology highlighting significant negative average excess returns associated with a downgrade. Examining the price impact on bonds re-rated by S&Ps between 1982 and 1984 through weekly data, Wansley et al. (1992) find a strong negative announcement effect during the week of bond rating reductions. Moreover, although the reaction is concentrated in the week of the rating change, they find a negative response as early as three weeks prior to the week of the press release by the rating agency. In a study published in the same year but using daily data, Hand et al. (1992) find negative average excess bond returns in correspondence of the announcement day to downgrades declared by Moody's Investors Service (Moody's) and Standard & Poor's (S&P) between 1977 and 1982. In addition, they find that the average excess returns are stronger for speculative grade than for IG bonds. Aside from this, Grier and Katz (1976) show that the impact on a bond's price occurs during the post-announcement period and that it is stronger for industrial firms if compared to utility ones. Observing the rating changes in the years 1966-72 and using monthly data, they reveal a price drop that occurs in the month-of and the month-subsequent to a rating reclassification. Similarly, examining the effect of rating changes of industrial firms between 1985 and 1995, and using monthly data, Hite and Warga (1997) show highly significant negative cumulative abnormal returns during the event-month and in the six months after a rating change for downgrades remaining below IG. They also find highly significant positive excess returns for all rating changes in the six months prior to a downgrade. Furthermore, they assert that the magnitude of the downgrading effect increases dramatically, moving from the sample of IG to non-IG firms. Focusing on the German Eurobond market, Steiner and Heinke (2001) examining daily excess returns driven by rating changes in the period 1985-1996 find price movements up to 100 trading days before the downgrade and with the strongest reaction in correspondence of the announcement day. They also find a positive excess returns after the downgrade, between day 15 and 45 post-announcement; this result suggests a bond price behavior that can be explained by the investors' attitude to overreact to downgrades followed by a rebound afterwards. Recently, examining the rating changes during the period 2002-2009, May (2010) provides evidence of negative abnormal bond returns during the month prior to downgrades and a cumulative abnormal return larger in magnitude and highly significant in correspondence of the announcement day. Moreover, May (2010) highlights that bond prices show negative abnormal returns in the 10 days after the firm's downgrade. In accordance, Ben Dor and Xu (2011) show negative monthly excess returns up to 3 quarters before the downgrade and the strongest reaction during the rating event month.

It is worth noting that the methodology used in the mentioned studies has been the subject of an extensive debate. In particular, the presence of conflicting results around the impact of downgrades on a bond's price obtained in less contemporary studies (i.e. Weinstein, 1977) are mainly ascribed to the poor quality of data used in the past. To explain this in more detail, when the availability of data on the Corporate Bond over-the-counter (OTC) market was limited, the data analyzed was deducted from the infrequent bond trades on the NYSE. A further dispute concerning the methodology adopted concerns the use of monthly, as opposed to daily, data (see Brown and Warner, 1985). Bessembinder et al. (2009) address this matter analysing the empirical power and specification of test statistics designed to detect abnormal bond returns in corporate event studies. They find that the use of daily bond data significantly increases the power of the tests compared to the use of monthly data and they demonstrate that most methods implemented in monthly data, lack power to detect abnormal returns. Furthermore, the authors accurately define the appropriate methodology to be used to calculate the daily abnormal bond returns to which we refer in this study.

Data and Sample selection

In this study we examine the dynamics of the Merrill Lynch (ML) Emu Non Financial Corporate Index during January 2001[3] to December 2009. The index's composition is based on a set of publicly disclosed rules aiming to guarantee both the index replicability (in order to avoid illiquid securities) and a credit risk bound to the IG. The index provider releases credit ratings based on a composite of Moody's and S&P[4]. The index is rebalanced on the last calendar day of the month, based on the information available in the marketplace up to and including the third business day prior to the last business day of the month. Rating changes that take place after the third business day prior to the last business day of the month are not taken into consideration until the following rebalancing. ML establishes four criteria that can initiate a bond's deletion from the index: 1) maturity less than one year; 2) illiquidity; 3) a bond's rating unavailability; 4) downgrade from investment to non-investment-grade level. Our

[3] The starting date of our sample has been determined by the data availability of the ratings of the index components.
[4] If a bond is rated by only one service, its composite rating is equal to that individual rating. The calculation of a composite rating is undertaken by an averaging algorithm that is biased to the lower of the two ratings.

analysis is focused on the bonds deleted from the index following the event mentioned in the last of these criteria. Operationally, we monitor the composition of the ML Emu Non Financial Corporate Index every month and we identify the FAs, using the definition provided by Ambrose et al. (2008): *"A fallen angel is a bond that once had an investment-grade rating from Moody's or S&P (not necessarily both) but was downgraded and it no longer possesses an investment-grade rating from either"*. Our sample is composed only by fixed-rate corporate bonds issued by industrial firms and denominated in Euro. Unlike the dataset used in previous studies, our sample is solely composed of benchmarks' constituents, the most representative issues in the corporate bond market and, therefore, the most traded.

At the issue level, the number of FA during the observation period is 149. We exclude from this preliminary sample 56 bonds because of their low liquidity around the event under investigation. Following the approach of Bessembinder et al. (2009) and May (2010) in order to deal with bonds illiquidity, we impose three trading restrictions. Being Day 0 the day of the event, the first one is that, to be part of our data set, a bond has to show a price change at least on ten days during the intervals going from Day -15 to -1 and Day +1 to +15. Moreover, we require price changes on fifteen days in the periods (-30; -1) and (+1; +30). Finally, we require that those bonds are priced every day from Day -1 to Day +1. Although the sample size becomes much smaller we believe that, in case of a downgrade that crosses the IG boundary of a large issuer, the FA's price should change before and after the event to ensure the reliability of the bond data. We also decided to exclude from our sample 8 defaulted bonds issued by Enron (US) and Parmalat (IT) because, in these cases, the downgrade announcement has taken place just before the company default and, thus, before the index rebalancing. This means that the default bonds would not enter into the sample of our third analysis in any case. On the other hand, the exclusion of these bonds from the sample of the first two analyses allows obtaining more conservative results. This choice is also justified by the evidence that the prices of default bonds, being characterized by high bid-ask spread, are not accurate. Furthermore, and in line with Bessembinder et al. (2009), we believe that bankruptcies should not be included in a sample for studies that examine events unrelated to bankruptcy. Finally, to avoid positive correlation from bonds issued from the same firm, we use a portfolio approach to compute firms' abnormal returns and treat each firm downgrade as a single observation. As a result, we obtain a final list of 85 bonds issued by 48 companies, admittedly a biased sample of large firms (with liquid bonds).

In our analysis, we use daily prices from the over-the-counter (OTC) dealer market. The reason lies on the evidence that the corporate bond market is institutional in nature with trading conducted primarily OTC. The problem related to the quality of corporate bond price data has been largely discussed in literature[5]. As described in Warga (1991) and Warga and Welch (1993), the two sources of generally available price quotes are exchange prices and institutional prices from major OTC bond dealers. Exchange prices primarily reflect the odd-lot activities of individual investors and cover only a limited number of corporate issues and a negligible portion of the total trading. On the other hand, institutional data is more comprehensive than exchange data because it covers a larger number of bonds, offering prices at which large positions could have been or indeed were transacted. Warga and Welch (1993) highlighted a potential issue related to the use of institutional data when conducting research in this area: the complication derives from the fact that prices are generally supplied by commercial services (e.g., Bloomberg Financial Services) and are not always trader quotes. These

[5] See Goltz and Campani (2011) for a detailed analysis of the corporate bond price sources.

prices are often determined on the base of an algorithm (so-called “matrix” prices)[6]. They demonstrate that trader-quoted data is preferable in research investigating corporate bond reactions to firm-specific events. As explained by Goltz and Campani (2011) every source of price lack in reliability in the case of rarely traded securities.

In our case, the sample is composed only by large and liquid bonds, and we can assume that prices supplied by commercial services are, in all respects, transaction prices. Encouraged by this, we calculate daily returns using Bloomberg information provider[7]. The choice to use Bloomberg database provides two main benefits to our analysis: first of all it allows us to examine the impact of downgrades using data on a daily basis and secondly it provides figures for the European corporate bond market for the entire period of our investigation.

Methodology

Our work is divided into three different analyses. In the first analysis we calculate abnormal returns considering, as the unit of observation, the first rating change at the firm level. Conventionally, we identify Day 0 as the downgrade announcement day by one or both of Moody’s and S&P rating agencies. We use Bloomberg to identify the rating changes by the two agencies during the sample period. Along with the common announcement window (-1; +1), as in May (2010) we consider two pre-event windows, (-30; -1) and (-15;-1), and the post-event window (+2; +10). We also calculate abnormal

[6] In the case of bonds that do not trade, matrix prices are based on quoted prices for securities with similar coupons, ratings and maturities, rather than on specific bids and offers for the designated security.
[7] It is worth mentioning that Bloomberg prices are market consensus prices, considering all the indicative and executable quotes on its database. These prices are weighted average and tends to apply higher significance to the more robust pricing contributors. Moreover, these prices are generally end-of-day, with occasional intraday updates, created by a proprietary algorithm that needs at least two providers to form.

return in two other post-event windows (+2; +20) and (+2; +30) to observe whether the bonds display ARs after the downgrade event.

In our second study Day 0 coincides with the event of the second downgrade by the rating agencies (if the rate-change does not overlap). In this case, the bond observed becomes an FA in line with Ambrose et al. (2008) definition. In this case Day 0 is the date in which the bond loses the investment-grade rating from both the rating agencies. Furthermore, we calculate abnormal returns on the same event windows of the previous analysis.

The third analysis focuses on the rebalancing of the ML Emu Non Financial Corporate Index where Day 0 is the date of the index rebalancing. Although the bond's deletion from the benchmark cannot be considered an event by its conventional definition, as its occurrence is normally known in advance, we treat it as such to verify whether ARs occur around the index rebalancing. For this reason, we consider the same two pre-event windows as in both our previous analyses, (-30;-1) and (-15;-1), besides the (-1; +1) event window. As post-event windows we consider four intervals starting from the first day following the index rebalancing, Day +1, up to Day +5, +10, +15 and +30.

Consistently with Bessembinder et al. (2009) we define the bond's daily return as follows:

$$Bond\ Return = \frac{P_t - P_{t-1} + AI_t}{P_{t-1}} \tag{1}$$

Where P_{t-1} and P_t are the daily prices on Days $t-1$ and t respectively and AI_t is the interest accrued over Day t[8]. Aiming to compare each bond return with its homogeneous high yield category, we form matching portfolios and we use these as benchmark

[8] The annual coupon is based on a 365 day period. Business days are determined in accordance with a global holiday schedule. AI considers non trading days.

portfolios. Like Bessembinder et al. (2009) we rely on well diversified portfolios of bonds managed by a primary index provider. In particular, we rely on indices representative of the speculative bond market, divided by rating class and provided by Merrill Lynch (ML), to form the matching portfolios. ML classifies speculative grade bonds into three classes of rating: BB, B and CCC & lower rated.

For each issue we follow the credit rating evolution during the observed event window. Afterwards, we calculate an index able to reflect the daily return of the overall bond's rating category whose daily returns are expressed as:

$$IR_t = \begin{cases} R_{CCC\&lower,t} & \textit{if the bond is rated CCC or lower at date t;} \\ R_{B,t} & \textit{if the bond is rated B at date t;} \\ R_{BB,t} & \textit{if the bond is rated BB at date t;} \\ R_{INV,t} & \textit{if the bond is rated IG at date t .} \end{cases} \quad (3)$$

Where IR_t is the return of matching portfolio at date t; $R_{CCC\&lower,t}$ is the return of the ML Euro CCC & lower rated Index at date t; $R_{B,t}$ is the return of the ML Euro B rated Index at date t; $R_{BB,t}$ is the return of the ML Euro BB rated Index at date t and $R_{INV,t}$ is the return of the ML Emu Non Financial Corporate Index at date t and that represents the return of the investment-grade bond. These dynamic matching portfolios are calculated through the daily compounded performances of the HY indices, homogeneously associated with each bond. If a firm experiences multiple rating changes during the observation period, we include all the rating changes thus allowing a constant match of credit risk. It is worth noting that the HY indices that we use in this comparison follow the same composition rules of the ML Emu Non Financial Corporate

Index; this implies that they consist of the most representative issues of the rating class they are affiliated with. We calculate the daily abnormal return (AR_t) as the difference between bond return (R_t) and the return on an index of rating matched corporate bonds (IR_t):

$$AR_t = R_t - IR_t \quad (4)$$

This comparison gives an evaluation of the difference between the returns registered by the bond with respect to the equivalent class of risk.

As in previous studies for firms in the sample with multiple bonds we treat each firm as a portfolio. According to Grier and Katz (1976) we first averaged (equally) the abnormal returns to all bonds of the same firm and then averaged (equally) across firms. Therefore, the average abnormal bond return for firm k on Day t ($AR_{k,t}$) is calculated as:

$$AR_{k,t} = \frac{\sum_{i=1}^{n} AR_{i,t}}{n} \quad (5)$$

Where n is the number of issues in the sample for firm k, $AR_{i,t}$ is the abnormal return for bond i on day t.

Empirical Results

Table 1 shows the results of our first analysis, where the announcement date (Day 0) coincides with the date of the first downgrade either from Moody's or S&P, or both at the same time. The table provides the mean CARs for each window examined, the t-statistic and the non-parametric Wilcoxon signed-rank test[9]. We find negative CARs in the pre-event windows analyzed. In particular, for both the test statistics we used, the mean (-30; -1) CAR is -4.45%, statistically significant. Moreover, (-15; -1) CAR is -

[9] While the t test is based on the cross sectional standard error, the Wilcoxon test does not rely on the assumption of normal distribution of returns but on a symmetric distribution around the median.

2.38% with a statistical significance of 10% based only on the t-test. These results confirm the findings of Wansley et al. (1992), Hite and Warga (1997), Steiner and Heinke (2001), May (2010)[10] and Ben Dor and Xu (2011) about the negative excess returns registered by the bond's price before the downgrade. As expected, within the announcement window (-1; +1), we observe a highly significant CAR of -3.64%[11]. This result can be explained by a typical mechanism of the asset management industry: whenever a security is removed from the benchmarks, portfolio managers concentrate their selling orders during a small period. The obvious final effect is a more deeply stressed market price. On the other hand, we observe different results from Grier and Katz (1976), Hite and Warga (1997) and May (2010) concerning their findings about the negative excess returns registered in the days after the downgrade. Our results provide the absence of significance of the CARs related to the post event windows (+2; +10), (+2; +20) and (+2; +30).

Table 1

The impact of the downgrade to high yield on corporate bonds price. CARs are calculated considering, as unit of observation, the first rating change (declared by either Moody's or S&Ps) at the firm level. The sample consists of bonds that are deleted from the investment grade ML Emu Non Financial Corporate Index during the period January 2001 to December 2009. The sample is composed of 85 bonds issued by 48 companies. To be included in the sample the data set of each bond has to show at least ten price changes during the intervals going from Day -15 to -1 and Day +1 to +15; at least fifteen price changes in the periods (-30; -1) and (+2;+30) and must be priced every day from Day -1 to Day +1. The analysis is based on daily prices provided by Bloomberg Financial Services. In the case of firms with multiple bonds, each firm is treated as a portfolio. CARs are the sum of the firm's daily abnormal returns over the event windows.

[10] Having used the same event windows, we can consistently compare our findings with the author's results. This comparison is instrumental to confirm the reliability of the prices used in our study. In particular, May (2010) displays, in relation to the speculative grade sample, mean CARs in the intervals (-30;-1) and (-15;-1) of -4.52% and -2.36% respectively. These results are in line with our findings.

[11] It is worth mentioning that the latter result reflects a stronger impact of the downgrade on the bond's price if compared to the one registered by May (2010) within the announcement window (-0.88%). The difference in magnitude can be ascribed to the fact that our study is focused merely on downgrades that cross the investment-grade boundary leading to a deeper market reaction. Thus, confirming Hite and Warga (1997) and Ben Dor and Xu (2011) findings, we prove that moving from the IG to the speculative grade rating the intensity of the bond price reaction is amplified.

Event Window (days)	Mean CAR	t-stat	Signed-rank
(-30;-1)	-4.45%	-2.70***	-2.04*
(-15;-1)	-2.38%	-1.85*	-0.97
(-1;+1)	-3.64%	-2.78***	-2.81***
(+2;+10)	1.20%	1.10	0.74
(+2;+20)	1.62%	1.17	1.52
(+2;+30)	1.29%	0.73	1.28

* Statistical significance at the 10% level in two-tailed tests.
** Statistical significance at the 5% level in two-tailed tests.
*** Statistical significance at the 1% level in two-tailed tests.

Table 2 provides evidence of the second event study we performed. In this case, the event is represented by the downgrade from both rating agencies. According to our preceding analysis, the pre-event windows show negative CARs, statistically significant based on the t-test: the mean (-30; -1) CAR and (-15; -1) CAR are -4.76% and -4.40% respectively. Besides, the short term reaction to the announcement is reflected by the (-1; +1) CAR equal to -3.48%. These results are slightly stronger than those calculated in our previous analysis. Moreover, also in this case we don't register significant CARs in the post-event windows.

Table 2

The impact of the downgrade to high yield on corporate bonds price. The event is represented by the departure of the bond from the investment grade parameters of both the rating agencies (Moody's and S&Ps), therefore becoming an FA. The sample consists of bonds that are deleted from the investment grade ML Emu Non Financial Corporate Index during the period January 2001 to December 2009. The sample is composed of 77 bonds issued by 41 companies. To be included in the sample the data set of each bond has to show at least ten price changes during the intervals going from Day -15 to -1 and Day +1 to +15; at least fifteen price changes in the periods (-30; -1) and (+2;+30) and must be priced every day from Day -1 to Day +1. The analysis is based on daily prices provided by Bloomberg Financial Services. In the case of firms with multiple bonds, each firm is treated as a portfolio. CARs are the sum of the firm's daily abnormal returns over the event windows.

Event Window (days)	Mean CAR	t-stat	Signed-rank
(-30;-1)	-4.76%	-2.23**	-1.15
(-15;-1)	-4.40%	-2.50**	-1.60
(-1;+1)	-3.48%	-2.20**	-1.16
(+2;+10)	0.66%	0.62	-0.33
(+2;+20)	1.62%	1.46	0.56
(+2;+30)	1.18%	0.81	0.30

* Statistical significance at the 10% level in two-tailed tests.
** Statistical significance at the 5% level in two-tailed tests.
*** Statistical significance at the 1% level in two-tailed tests.

Finally, our third analysis investigates the impact of the month's end rebalancing of the IG index examined in this paper. Table 3 summarizes our results: in this case we find a mean CAR in the pre-event window (-30; -1) of -5.00%, statistically significant based on both the t-test and Wilcoxon test. According to the findings of the two previous analyses, this result can be explained by the impact of the downgrade announcement on bond prices at some point during the preceding month of the rebalancing. This proposition is supported by the evidence that, on average, the time that elapses between the first downgrade and the index rebalancing is 24 trading days.

Table 3

The impact of the downgrade to high yield on corporate bonds price. Day 0 is the date of the index rebalancing. The sample consists of bonds that are deleted from the investment grade ML Emu Non Financial Corporate Index during the period January 2001 to December 2009. The sample is composed of 82 bonds issued by 47 companies. To be included in the sample the data set of each bond has to show at least ten price changes during the intervals going from Day -15 to -1 and Day +1 to +15; at least fifteen price changes in the periods (-30; -1) and (+1;+30) and must be priced every day from Day -1 to Day +1. The analysis is based on daily prices provided by Bloomberg Financial Services. In the case of firms with multiple bonds, each firm is treated as a portfolio. CARs are the sum of the firm's daily abnormal returns over the event windows.

Event Window (days)	Mean CAR	t-stat	Signed-rank
(-30;-1)	-5.00%	-2.76***	-2.11**
(-15;-1)	-2.60%	-1.82*	-1.51
(-1;+1)	0.99%	1.81*	1.12
(+1;+5)	1.12%	2.96***	3.03***
(+1;+10)	1.91%	3.27***	2.94***
(+1;+15)	1.59%	2.74***	2.74***
(+1;+30)	0.81%	0.85	2.04**

* Statistical significance at the 10% level in two-tailed tests.
** Statistical significance at the 5% level in two-tailed tests.
*** Statistical significance at the 1% level in two-tailed tests.

As expected, we do not report a significant CAR around the event window (-1; +1). We argue that this evidence is attributable to the fact that the index rebalancing rules are known in advance to the investors; hence the bond's exit from the index does not have any short term impact on their price. More important are the results related to the post-event windows: (+1; +5), (+1; +10) and (+1; +15) display positive mean CARs of +1.12%, +1.91% and +1.59% respectively. These results are highly significant based on both t-test and signed-rank test. The excess returns calculated after the index rebalancing demonstrate that the bond, after the deletion from the benchmark, registers an over-performance versus the category of securities having an equivalent class of risk. This occurrence can be seen as a bond price rebound following the pressure driven by regulatory and investment constraints of both traditional funds and index trackers. Confirming Steiner and Heinke (2001) results, our findings suggest that the price pressure that occurs in correspondence to a downgrade is reabsorbed several days after its announcement. In addition, we argue that the bond price reversal follows the rebalancing of the IG indices.

These insights offer some practical guidelines. Firstly, the positive excess returns with respect to the HY category, observed on the following days of the index rebalancing, show the loss of value paid by a portfolio anchored to the index construction methodology of the underlying benchmark. Secondly, the impact on the bond prices is attributable to the disinvestments made around the downgrade announcement, before the index rebalancing. This evidence suggests a careful market timing evaluation for the portfolio manager following an IG benchmark. The implications are more straightforward when managing a portfolio of HY: our results reveal the opportunity to overweigh FA around the day they are removed from the IG benchmarks. Furthermore, and consistently with Cai and Houge (2008), our results suggest that the index design methodology may provide a structural incentive for portfolio managers to drift from their benchmark.

Conclusions

We have examined the impact of downgrades to high yield on corporate bond prices from January 2001 until December 2009, using daily data on bond transactions provided by Bloomberg Financial Services. Our analysis focuses on a sample of corporate bonds released by the ML Emu Non Financial Corporate Index from the moment when they become HY. The ML Emu Non Financial Corporate Index is representative of the largest and most liquid Euro denominated US and European issues, it is commonly used as the benchmark by IG corporate bond funds and it follows the same rebalancing rules of other corporate bond indices. For these reasons, we can assume that our results can be generalized to the overall index funds category that replicates an IG corporate bonds index.

We calculate the abnormal returns in three different analyses based over a sample composed by 85 bonds issued by 48 companies. In the first, we calculate abnormal returns in the event of the first downgrade (declared by either Moody's or S&Ps) at the firm level. In the second analysis the event is represented by the deletions of the bond from the IG parameters of both the rating agencies (therefore becoming an *FA*). Both of our analyses, according to the major results of the existing literature, prove significant negative CARs in the pre-event windows and in the announcement window. On the other hand, in contrast with the findings of previous studies, we do not find significant negative CARs in the post-event windows.

Widening the existing literature, our third analysis investigates the impact of the month-end rebalancing of the ML Emu Non Financial Corporate Index. In this case, we find a statistically significant negative CAR of -5.00% in the pre-event window (-30; -1). Moreover, in this last case we do not report a significant CAR in the event window (-1;+1): the reason is that the index rebalancing rules are known in advance, hence the bond's deletion from the index does not have any short term impact on their prices. Furthermore, we find positive and statistically significant CARs of +1.12%, +1.91% and +1.59% in the post-event windows respectively (+1; +5), (+1; +10) and (+1; +15).

One possible criticism of this study could be related to the use of Bloomberg prices instead of traders' quotes, based on the argument that prices supplied by commercial services are sometimes determined on the base of an algorithm ("matrix prices") that compromise their reliability. We argue that in our case, Bloomberg prices should coincide with transaction prices as our analysis focuses only on large and liquid issues. Moreover, Bloomberg dataset covers the entire period observed in our analysis for Euro denominated corporate bonds, as opposed to other databases, which take into account shorter time intervals and only US Dollar denominated issues. Furthermore, the novelty of this study lies in our third analysis, focused on the impact of the bonds' deletion from the IG benchmarks. This analysis is based on month-end prices, considered the most reliable, as traders have a strong incentive to provide accurate bid quotes, given the significant amount of trading generated by index trackers funds (Hite and Warga, 1997). The *abnormal returns* recorded after the deletion of the bonds from the index, ***vis-à-vis*** the new risk category, suggest a selling pressure around the downgrade event.

Our findings confirm that the price pressure takes place mostly around the time of the announcement and/or in the preceding trading days. In addition, our results reveal higher abnormal returns for the bonds that become speculative grade for both the rating agencies. This evidence relates to the mandate of some investment professionals to sell high yields due to portfolio governance guidance. It's worth noting that our results can be generalized to take into account the wider issue of the appropriateness of the portfolio management constraints. The study of the impact of regulatory and investment constraints on financial markets is a complex topic, requiring analysis beyond the scope of this work. This work nonetheless can give a contribution to the discussion on the regulation of the investment funds, highlighting how the price pressure generated by these funds is additional to the negative influence on the market generated by the index fund manager, who has the obligation to sell the junk bond at the time of the index rebalancing. The illustrated market effect occurrence is evident when observing our results relative to the over-performance of the deleted bonds after the reconstitution of the IG indices. In other words, the selling pressure reported around the downgrade announcement is followed by a price reversal towards the general matching high yield category after the IG benchmark rebalance.

Our results offer some practical guidelines for both investment and non-IG corporate bonds portfolio managers. First, the positive CARs with respect to the high yield category, observed on the following days of the index rebalancing, show the loss of value paid by a portfolio anchored to the index construction methodology of the underlying benchmark. The impact on the bond prices is attributable to strong disinvestments made around the time of the downgrade announcement. Our results suggest the opportunity for managers of high yield portfolios to overweigh *FAs* around the day they are removed from the IG benchmarks. Furthermore, our results confirm, within the corporate bond indices, the relevance of the findings of Cai and Houdge (2008) regarding the index design methodology on the portfolio evaluation. With our research we demonstrated that there is a structural incentive for corporate bond portfolio managers to drift from their benchmark. Future research should take into account this consideration to design more effective market index composition rules.

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Chapter 5: A comparison between Capitalization-weighted and Equally-weighted indexes in the European equity market

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1. Introduction

This paper aims at comparing two major equity index construction methodologies, i.e. the capitalization-weighted (CW) and the equally-weighted (EW) approaches. In general, the equity benchmarks adopted by mutual funds are CW indexes where the components are weighted according to the total market value of their outstanding shares. From a theoretical perspective, the wide use of this approach is based on the evidence that, under a standard interpretation of the Capital Asset Pricing Model (Sharpe, 1964), a CW portfolio (the "market" portfolio) is automatically Sharpe Ratio maximized.

Operationally, CW portfolios are easy to be implemented because they offer, at the same time, broad diversification and low transaction costs. These operational benefits can be justified by the fact that CW portfolios adjust their constituents' weights automatically as market prices move, resulting in fewer rebalancing trades. As a result, it is not surprising that asset management companies avoid using benchmarks based on a different construction methodology, such as EW indexes for their investment products. The EW approach has been criticized mainly because portfolios created using this methodology are not representative of the aggregate equity market and this approach treats large and mid-small caps regardless of market liquidity (Arnott et al., 2005).

The issue concerning the enhancing of the index construction methodologies is the center of academic debate. Critics of CW indexes point out the fact that, basing index constituents' weights on their market capitalization results in the largest securities having the biggest weights in the index, so much so that the contribution of smaller-capitalization securities can be minimal. An increasing number of studies have rejected the mean-variance efficiency of CW indexes suggesting alternative index weighting methodologies (see Hauger and Baker, 1991; Arnott et al., 2005; Clarke et al., 2006; Hsu, 2006; Choueifaty and Coignard, 2008; Chow et al., 2011). These studies base their critics on the evidence that cap-weighting tends to overweight those stocks whose prices are high in relation to their fundamentals and to underweight stocks which have low prices.

In accordance with Bailey (1992), we believe that the efficacy of the benchmark's choice is mainly related to the context of use. It is worth remembering that the choice of the index construction methodology is an increasingly relevant issue due to the fundamental role played by the benchmark in the asset management industry. Benchmarks have become central to portfolio management with an impact on the investment choices, asset allocation, performance measurement and on the evaluation of the fund managers reward. The role of the benchmark in the industry is even more relevant if we take into consideration the growing role and the impressive amount of assets under management of passive investment vehicles such as Exchange Traded Funds (ETF).

From Perold (2007) we assume that capitalization weighting is associated to a momentum strategy while a rebalancing strategy, including equal weighting, is based on a contrarian strategy. The momentum strategy[12] is based on the empirical evidence that stocks with strong past performance continue to outperform stocks with poor past performance in the subsequent period (Jegadeesh and Titman, 1993). Being the cap-weighting a buy-and-hold investment strategy takes advantage of this effect. On the other hand, a contrarian strategy is based on the attempts to profit by going against the trend selling of the stocks that have shown higher returns and buying the underperforming stocks. The EW methodology implicitly follows a contrarian strategy because it mechanically rebalances away from stocks that increase in price. Dash and Loggie (2008) compare the two approaches focusing on the performance of both the S&P500 Index and the S&P500 Equal Weighted Index between 2003-2008. They provide empirical evidence of the EW index outperformance as a result of different weighting and rebalancing processes. With further research, Dash and Zeng (2010) show the same results related to an international index, the S&P International 700 which is comprised of 700 of the largest, most liquid stocks from outside the United States.

Focusing on the stock market of the Euro area, this paper aims to compare the performance of portfolios constructed using the CW and EW approaches over the period between January 2002 and December 2011. Our study examines the indexes of the Euro equity market since the literature on this topic has focused only on the U.S. market[13]. The comparison between capitalization-weighted and equally-weighted portfolios in the Euro area is particularly relevant when we consider the importance of passive investment products (such as ETFs) in the fund management industry. These funds

[12] See Swinkels (2004) for a survey on momentum investing.
[13] European data are also used by Hemminki and Puttonen (2008) in their study on the benefits of fundamental indexation.

simply mirror the underlying equity market indexes which are cap-weighted. We selected for our analysis the Dow Jones EuroStoxx Index (DJ EURO) and the Dow Jones EuroStoxx 50 Index (DJ EURO50) because they are the underlying assets of the largest ETF specialized in the Euro equity market, the IShare funds[14].

Furthermore, we examined the DJ EURO50 which is a highly concentrated index (representative of the 50 largest stocks in the Euro area) and widely used as benchmark by mutual funds. Among the US equity market indexes, there is not an index showing such characteristics, namely high concentration of members and market weighted. In this study, we examine the large cap index together with the DJ EURO (whose members are about 300) as they are the mainly used stock market indexes denominated in Euro[15].

In this study, we construct EW portfolios using four reweighting frequencies: monthly, quarterly, semiannually and annually. Widening the existing literature on this topic, we test alternative reweighting frequencies in order to identify the one able to maximize the benefits of the contrarian strategy, which is implicit in the EW methodology. The results reveal a superior performance of the EW portfolios in each reweighting time frame we test and for both the indexes examined. This finding suggests that the contrarian effect derived from the stocks reweighting, is stronger than the momentum effect, characterizing CW portfolios. Furthermore, we rely on Fama-French (1992)three-factor regression analysis, we examine the extent to which the difference in performance of the two methodologies can be explained by the size and/or the style biases. We then proceed with a further analysis focused on the “size effect” but

[14] According to the statistics provided by Blackrock, in 2011 the market share of the IShares products in Europe, within the category of ETFs, was 70%. Moreover, in December 2011, the assets under management by the IShares in Europe were € 105.9 billion.

[15] The DJ EuroStoxx and the DJ EuroStoxx 50 are composed only by stocks denominated in Euro. This restriction allows a comparison of the two index construction methodologies without having to consider the trend of the exchange rates (primarily the EUR/GBP).

based on a portfolio approach. We construct quintile-based portfolios sorting all the index members by market capitalization and calculate the excess returns of the top and the bottom quintiles over the CW indexes. Next, we test the presence of a stock return seasonality and, in particular, of the "January size effect" (see Schwert, 1983 for a survey).

A frequent criticism of the EW methodology is related to the transaction costs due to the higher portfolio turnover. We then calculate the impact of the indexes reweighting with respect to a passive investment strategy.

The rest of the paper is organized as follows. Section 2 describes the data and the research methodology. Section 3 presents our main empirical results. Section 4 comprises some final remarks and concludes the paper.

2. Data and methodology

In order to compare the two index construction methodologies, we create EW portfolios using a sample of stocks of the Eurozone. This sample includes all the stocks that have been constituents of the DJEURO index and of the DJEURO50 index during the observation period. In particular, the DJEURO index is composed by a variable number of constituents (approximately 300) and it is weighted by free float market capitalisation reviewed quarterly. The DJEURO50 index is a blue chip index and covers the 50 largest components of the broader DJEURO index. As we discuss later in the paper, the analysis of this blue chip index overcome the problem of the well-known "size effect" that emerges when different portfolios are compared. We focus on the time period from January 2002 to December 2011. The starting date of the observation period coincides with the availability of the index constituents provided by Bloomberg Finance L.P. which is the data set used in this study. We construct EW portfolios with the constituents of the two DJ indexes but by giving equal weights. More in detail, we construct four EW indexes associated with both the market indexes using different reweighting frequencies (monthly, quarterly, semiannually and annually). Each rebalancing day, the weight of each constituent is set to 1/N percent whereas N is the number of constituents in the indexes. The index reweighting is made on the first trading day after the end of the observation period in order to avoid illiquidity problems, characterizing the last trading day of the year.

In our analysis, we assess the return and the risk properties of our EW portfolios and of the market indexes. We derive average returns of each portfolio and calculate the excess returns of the EW portfolio with respect to the equivalent market index. To measure performance, we use total returns which means that returns include dividends and distributions realized over the observation period. Next, we calculate the standard deviation and the Sharpe ratio. The Sharpe ratio reflects the indexes' risk/reward efficiency by adjusting excess returns over the risk-free interest rate by the volatility incurred by the index. As a proxy of the risk-free rate, we use the Euribor rate with maturity at 1, 3, 6 and 12 months in accordance with the time frames of the indexes reweighing. Next, we calculate the Skewness of return distributions and the drawdown, in order to compare the downside risk of each index.

In order to examine the risk-adjusted return of the EW indexes we calculate the Jensen's alpha α_{JEN}, by running the regression:

$$R_t^{EW} - Rf_t = \alpha_{JEN} + b(R_t^{CW} - Rf_t) + \varepsilon_t \qquad (1)$$

where R_t^{EW} is the return of the EW portfolio, R_t^{CW} is the return of the CW index and Rf_t is the return on a risk-free asset. α_{JEN} provides an estimate of the risk-adjusted return, assuming that *b* is an appropriate measure for the systematic risk.

The analysis of risk and return measures yield insights into how the indexes behave. However, it is also interesting to analyze where the return properties come from. The non-cap weighted indexes may take on exposures to common risk factors, such as value, momentum and small-cap exposures. Since the indexes are broadly diversified across constituent stocks, one may in fact expect that the risk and return properties are largely driven by such factor exposures. This leaves only a small fraction of returns that are completely specific to the method of index design (Amec et al., 2011). Therefore, in order to examine the impact of these risk factors on the difference in performance between EW and CW portfolios, we perform a Fama-French (1992) three-factor regression analysis:

$$R_t^{EW} - Rf_t = \alpha + b(R_t^{CW} - Rf_t) + s \cdot SMB_t + h \cdot HML_t + \varepsilon_t \tag{2}$$

where R_t^{EW} is the return of the EW portfolio, R_t^{CW} is the return of the CW index, Rf_t is the return on a risk-free asset, SMB is the small-cap factor and HML is the value factor. In particular, SMB is a portfolio that is long small cap stocks and short large stocks while HML is a portfolio that is long high book-to-price stocks (value stocks) and short low book-to-price stocks (growth stocks). In our analysis, the small-cap factor is measured by means of the excess return of the S&P small cap Eurozone total return index and the DJEURO50 total return index while the value factor is measured as the excess return of the S&P Europe EBI Value total index and the S&P Europe EBI Growth total index.

Afterwards, we proceed with a further analysis which focuses on the “size effect” and is based on a different methodology. Following a portfolio approach, we create quintile-based portfolios, sorting all the index constituents by ascending market capitalization in correspondence of each rebalancing. In particular, we focus on the returns offered by the top and the bottom quintiles portfolios. Therefore, we estimate the excess returns over the CW indexes for top and bottom quintiles, as well as the difference.

Next, we test if the difference in performance between the two portfolios is more prevalent in certain month in accordance with the evidence of the size-related anomalies of stock returns at the beginning of the year. The January premium for smaller companies is one of the best-known academic market anomalies (see Keim 1983). As in Keim (1983), for both the indexes analysed, we test the null hypothesis of equal expected abnormal returns for each month of the year, we use the following regression:

$$R_t^{EW} - R_t^{CW} = \alpha + a_1 D_1 + a_2 D_2 + a_3 D_3 + ... + a_{11} D_{11} + \varepsilon_t \quad (3)$$

where R_t^{EW} - R_t^{CW} is the monthly excess return of the EW portfolio over the CW index for month *t*, and the dummy variables indicate the month of the year in which the excess return is observed (D_1 =January, D_2 =February, etc.). The excess return for December is measured by α, while a_1 through a_{11} represent the differences between the excess return for December and the excess return for the other months. Afterwards, we perform a further regression analysis focused only on the DJEURO index in order to verify if the stock return seasonality is due to the “size effect”, rather than to the index construction methodology. Therefore, adding the small cap factor SMB to equation (3), we use the following regression:

$$R_t^{EW} - R_t^{CW} = \alpha + a_1 D_1 + a_2 D_2 + a_3 D_3 + ... + a_{11} D_{11} + SMB_t + \varepsilon_t \quad (4)$$

Therefore, if the SMB factor is significant, then the seasonality is explained by the “size effect”.

Finally, we estimate the rebalancing costs that must be incurred when an EW strategy is implemented. In particular, we focus on quarterly reweighting of the DJEURO index. In this analysis, we consider two sources of transaction costs. The first arises because of the periodic reweighting of the index constituents to the target weigh characterizing an EW strategy. In this case, the portfolio turnover is generated by the average cross-sectional dispersion of returns of the index's constituents during the observation period:

$$turnover \approx \sum_{t=1}^{M} \frac{\frac{\sum_{i=1}^{N} \left| R_t^i - R_t^{EW} \right|}{N_t}}{M} \qquad (5)$$

where R_t^i is the return the stock *i* in the quarter *t*, R_t^{EW} is the return of the EW portfolio in the quarter *t*, N_t is the number of the portfolio constituents in the quarter *t* and M is the number of quarters examined (which is equal to 36 in our analysis). The second source of transaction costs refers to the loss of the inclusion requirements by the index constituents and the subsequent replacement. This occurs mainly when stocks are replaced due to their small size or in the case of corporate actions (i.e. M&A and spin-offs). We calculate this source of turnover as the number of stocks entering and leaving the index, at each rebalancing, multiplied by the stocks target weight. Afterwards, we average the turnover calculated in each quarter.

3. **Empirical Results**

Table 1 shows the comparison between the returns of the CW indexes (DJEURO and DJEURO50) and the equivalent EW version, from January 2002 to December 2011. Panel A reports the performance of the DJEURO index and each of its four EW versions, constructed using the different reweighting frequencies (monthly, quarterly, semiannually and annually). The results highlight that, for each rebalancing time frame, EW portfolios outperform the corresponding CW index whereas the positive excess returns are statistically significant based on the t-test. We observe the same findings in the comparison between the DJEURO50 index and the corresponding EW portfolios, as shown in Panel B. Being that the DJEURO50 is composed only by blue-chips, these results prove that the EW methodology provides higher returns with respect to the CW one besides any stock's size consideration. Furthermore, both our analyses show that the highest excess returns registered by the EW over the CW indexes are achieved when the indexes are rebalanced on a quarterly basis. In this case, the differences in average annualized returns between EW and the CW indexes are +3.73% and +2.92% for the DJEURO and for the DJEURO50 indexes respectively. The findings suggest that the most efficient time frame for the EW index rebalancing is three months. For this reason, our further analyses focus only on this reweighting frequency.

Table 1

This table shows the average returns of the DJ EuroStoxx (DJEURO) and of the DJ EuroStoxx50 (DJEURO50) indexes and their equally-weighted versions. The statistics are based on a ten-year data from 02/01/02 to 31/12/11. Panel A reports the performance of the EW and CW indexes. EW indexes are constructed using different reweighting periods: monthly, quarterly, semiannually and annually.

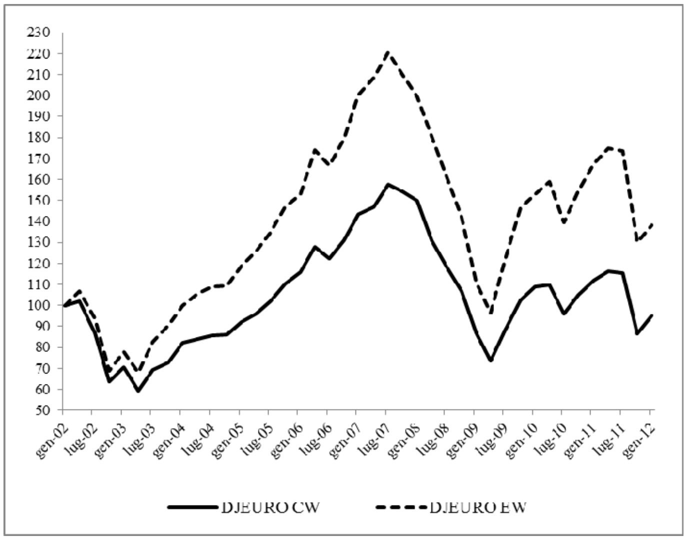
	EW	CW	Difference in average		EW (annualized)	CW (annualized)	Difference in average	No. Obs.
Panel A: DJEURO								
Monthly	0.26%	-0.04%	0.30%	**	3.12%	-0.48%	3.60%	120
Quartely	0.81%	-0.12%	0.93%	**	3.25%	-0.48%	3.73%	40
Semiannually	1.50%	-0.24%	1.74%	**	3.01%	-0.48%	3.49%	20
Annually	3.12%	-0.48%	3.60%	*	3.12%	-0.48%	3.60%	10
Panel B: DJEURO50								
Monthly	0.06%	-0.15%	0.21%	**	0.69%	-1.82%	2.51%	120
Quartely	0.27%	-0.45%	0.73%	**	1.10%	-1.82%	2.92%	40
Semiannually	0.13%	-0.91%	1.04%	***	0.27%	-1.82%	2.09%	20
Annually	0.32%	-1.82%	2.14%	**	0.32%	-1.82%	2.14%	10

* Statistically significant at the 10 percent level
** Statistically significant at the 5 percent level
*** Statistically significant at the 1 percent level

Figure 1 displays the performance of the DJEURO and the equivalent EW portfolio over the observation period. The cumulative return of the EW portfolio was 38.42% compared to -4.70%% of the DJEURO, with a difference equal to 43.12%.

Figure 1

This figure displays the comparison of the cumulative return of the DJ Euro Stoxx index (DJEURO) and the equivalent equally-weighted portfolio rebalanced quarterly. **The graph covers ten years of data from 02/01/02 to 31/12/11.** The dataset is provided by **Bloomberg Finance L.P.**



Similarly, Figure 2 shows the performance of the DJEURO50 index and its EW version. In this case, the cumulative returns of the EW portfolio and of the DJEURO50 index were 11.60% and -16.63% respectively, showing a difference equal to 28.23%.

Figure 2

This figure displays the comparison of the cumulative return of the DJ Euro Stoxx 50 index (DJEURO50) and the equivalent equally-weighted portfolio rebalanced quarterly. **The graph covers ten years of data from 02/01/02 to 31/12/11.** The dataset is provided by **Bloomberg Finance L.P.**

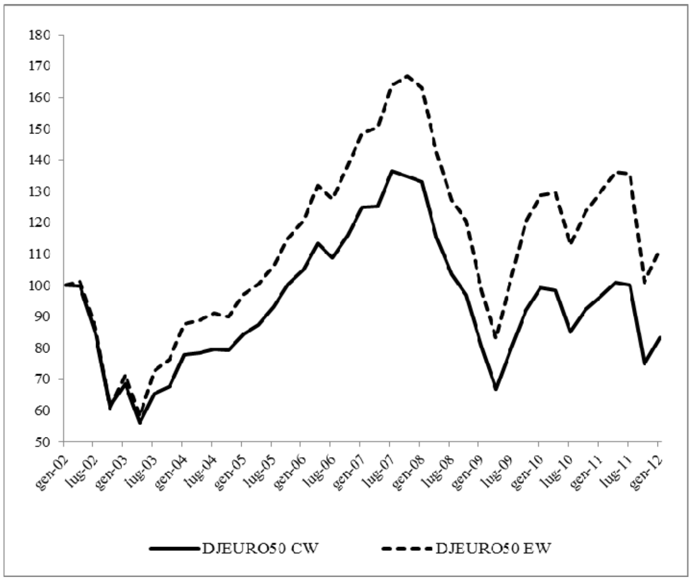


Table 2 reports the mean, median, standard deviation and the extreme values of the performance difference between the EW portfolios and the stock market indexes analyzed in this work. In particular, Panel A is related to the DJEURO index. During the sample period, the performance of the market index is positive for 7 out of 10 years. In each rebalancing scheme, the over performance of the EW portfolios is predominant regardless of the positive or negative performance of the market index. Panel B is related to the DJEURO50 index. It’s not surprising that even in this case, the market performance is positive, for 6 out of 10 years. Similarly, the over performance of the EW is dominant for each reweighing frequency, although smaller than the previous case.

Table 3 presents the risk and return profile of the analysed portfolios over the sample period. The results highlight that EW portfolios show higher standard deviations with respect to the related CW indexes. Calculation of the Sharpe ratios yield values of -

0.064 and -0.091 for the DJEURO index and the DJEURO50 index respectively. On the other hand, the equivalent EW portfolios show higher Sharpe ratios equal to +0.014 and -0.028 respectively. The Sharpe ratio reflects the indexes' risk/reward efficiency by adjusting excess returns over the risk-free rate by the volatility incurred by the index. In this case the CW indexes display lower excess return/volatility ratios than their EW versions. All indexes show a negative Skewness meaning that the left tail of the returns distribution is more pronounced than the right tail. EW indexes show lower Skewness with respect to CW (in particular if we consider the case of the DJEURO) meaning that EW portfolios can be considered less risky in the case of extreme negative events. This result is explained by the higher diversification of the EW portfolios, able to limit their downside risk.

Table 2

This table presents descriptive statistics regarding the difference between the equally-weighted portfolios and the capitalization-weighted indexes (EW-CW). Panel A shows the comparison related to the DJ EuroStoxx index (DJEURO) while Panel B is related to the DJ EuroStoxx50 index ((DJEURO50). The statistics are based on a ten-year data from 02/01/02 to 31/12/11. EW indexes are constructed using different reweighting periods: monthly, quarterly, semiannually and annually. The dataset is provided by **Bloomberg Finance L.P.**

	No.	Mean	Median	SD	Min	Max		No.	Mean	Median	SD	Min	Max
Panel A: DJEURO							**Panel B: DJEURO50**						
Monthly:							*Monthly:*						
EW-CW>0	74	1.05%	0.89%	0.84%	0.01%	4.45%	EW-CW>0	67	0.80%	0.50%	0.93%	0.03%	4.58%
EW-CW<0	46	-0.91%	-0.61%	0.79%	-2.99%	-0.03%	EW-CW<0	53	-0.54%	-0.26%	0.76%	-3.85%	-0.01%
EW-CW in case of positive index returns	67	0.32%	0.31%	1.07%	-1.86%	4.45%	EW-CW in case of positive index returns	66	0.52%	0.25%	1.07%	-0.87%	4.58%
EW-CW in case of negative index returns	53	0.27%	0.40%	1.47%	-2.99%	3.19%	EW-CW in case of negative index returns	54	-0.17%	-0.06%	0.99%	-3.85%	2.11%
Quarterly:							*Quarterly:*						
EW-CW>0	28	3.21%	2.07%	5.32%	0.12%	29.33%	EW-CW>0	28	1.50%	1.15%	1.56%	0.05%	7.13%
EW-CW<0	12	-2.60%	-2.23%	2.28%	-8.88%	-0.07%	EW-CW<0	12	-1.07%	-0.94%	0.85%	-3.26%	-0.17%
EW-CW in case of positive index returns	26	1.04%	1.55%	2.97%	-8.88%	5.13%	EW-CW in case of positive index returns	23	1.12%	0.63%	1.92%	-0.96%	7.13%
EW-CW in case of negative index returns	14	2.26%	0.32%	8.19%	-4.18%	29.33%	EW-CW in case of negative index returns	17	0.20%	0.70%	1.58%	2.89%	2.89%
Semiannually:							*Semiannually:*						
EW-CW>0	16	3.06%	2.60%	2.43%	0.08%	7.92%	EW-CW>0	16	1.56%	1.17%	1.25%	0.23%	4.68%

EW-CW<0	4	-3.51%	-4.15%	2.50%	-5.65%	-0.09%
EW-CW in case of positive index returns	12	2.35%	1.93%	2.06%	0.08%	7.43%
EW-CW in case of negative index returns	8	0.84%	1.24%	5.18%	-5.65%	7.92%
Annually:						
EW-CW>0	7	6.63%	6.67%	2.38%	2.04%	8.82%
EW-CW<0	3	-3.46%	-3.60%	0.69%	-4.07%	-2.72%
EW-CW in case of positive index returns	7	4.85%	6.14%	4.32%	-3.60%	8.79%
EW-CW in case of negative index returns	3	0.68%	-2.72%	7.08%	-4.07%	8.82%

EW-CW<0	4	-1.01%	-1.11%	0.49%	-1.51%	-0.33%
EW-CW in case of positive index returns	11	0.89%	1.03%	0.83%	-1.04%	1.91%
EW-CW in case of negative index returns	9	1.23%	0.50%	2.17%	-1.51%	4.68%
Annually:						
EW-CW>0	8	2.83%	2.74%	1.75%	0.25%	5.28%
EW-CW<0	2	-0.62%	-0.62%	0.79%	-1.18%	-0.06%
EW-CW in case of positive index returns	6	2.54%	2.57%	2.22%	-0.06%	5.28%
EW-CW in case of negative index returns	4	1.53%	1.69%	2.16%	-1.18%	3.92%

Table 3

This table shows some performance statistics of the indexes DJ EuroStoxx (DJEURO) and DJ EuroStoxx50 (DJEURO50) and their equally-weighted version based on a quarterly reweighting. The statistics are based on 40 observations in the ten-year data from 02/01/02 to 31/12/11. Significance tests are made for each comparison. In particular, the differences in the statistics are tested by the t-test for the average returns, the Fisher test for standard deviations and the Jobson-Korkie test for the Sharpe ratio.

	DJEURO (EW)	DJEURO (CW)	DJEURO (EW - CW)	DJEURO50 (EW)	DJEURO50 (CW)	DJEURO50 (EW - CW)
Average return	3.25%	-0.48%	3.73%	1.10%	-1.82%	2.92%
p-value			*0.017*			*0.015*
Standard deviation	25.01%	23.69%	1.32%	25.73%	23.90%	1.83%
p-value			*0.737*			*0.647*
Sharpe ratio	0.014	-0.064	0.078	-0.028	-0.091	0.063
p-value			*2.540*			*2.956*
Skewness	-0.811	-0.967		-0.890	-0.970	

In order to test the two strategies during negative market phases, we calculate the drawdown of each index. The drawdown is the measure of the decline from a historical peak of the stock price. We focus on the two bear market phases occurred in our observation period: the first includes the interval between 01/01/02 and 01/10/02; the second the interval between 01/07/07 and 01/04/09. The results of the drawdown analysis are shown in Table 4. The figures highlight conflicting results in the two periods examined for the two indexes analysed suggesting that the market direction is not an explanatory variable in our comparison.

Table 5 shows the results of the regression analysis performed to calculate the Jensen’s alpha. Our finding highlights that EW portfolios have a positive coefficient, significantly different from zero.

Table 4

This table shows the results of the drawdown analysis on the **DJ EuroStoxx (DJEURO) and of the DJ EuroStoxx50 (DJEURO50) indexes** during two bear market phases within the sample period (**02/01/02 - 31/12/11).** The dataset is provided by **Bloomberg Finance L.P.**

	DJEURO (EW)	DJEURO (CW)	DJEURO (EW - CW)	DJEURO50 (EW)	DJE+G16URO50 (CW)	DJEURO50 (EW - CW)
01/2002 - 10/2002	-31.1%	-36.4%	5.3%	-39.2%	-38.6%	-0.6%
07/2007 - 04/2009	-56.2%	-53.4%	-2.8%	-49.3%	-51.0%	1.7%

Table 5

This table shows summary statistics for the Jensen’s alpha. Tests are performed on **DJ EuroStoxx (DJEURO) and DJ EuroStoxx50 (DJEURO50) indexes. The statistics are based on a ten-year data from 02/01/02 to 31/12/11. The construction of the EW portfolios is based on a quarterly reweighting. Regressions with Newey-West standard errors.**

	α		*b*		No. Observations
DJEURO	1.013	**	1.057	***	40
t-value	*(2.685)*		*(31.51)*		
DJEURO50	0.867	***	1.076	***	40
t-value	*(3.039)*		*(42.76)*		

* Statistically significant at the 10 percent level

** Statistically significant at the 5 percent level

*** Statistically significant at the 1 percent level

Table 6 shows the results of the regression analysis based on the three-factor model of Fama and French (1992), aimed to capture the size bias by means of the SMB factor (small stocks minus large stocks) and the style bias by means of the HML factor (value stocks minus growth stocks). The findings reveal that EW portfolios have a highly significant size bias in the case of the DJEURO which is composed by roughly 300 stocks. This result confirms previous findings providing strong empirical support that allows to assert that EW indexes tilt toward smaller-cap securities to a statistically significant level (see Velvadapu, 2011). Over the 2002-2011 period, the SMB coefficient is 0.298 for the EW version of the DJEURO. In the case of the DJEURO50 the regression analysis should not reveal any size bias. Actually, we find a negative coefficient of the SMB factor, statistically significant at 10% level. This result indicates that the EW index tilts toward large-cap securities, but this is not a reasonable assertion. Moreover, focusing on the style factor, we find that both the indexes exhibit a value tilt over the ten-year period: the HML coefficients are 0.320 and 0.216 for the EW version of the DJEURO and the DJEURO50 indexes respectively. This result confirms the findings of Arnott et al. (2005) demonstrating that CW indexes tilt toward growth securities.

Table 6

This table shows summary statistics for the three-factor model. Tests are performed on **DJ EuroStoxx (DJEURO) and DJ EuroStoxx50 (DJEURO50) indexes. The parameter *s* is related to the size factor SMB while the parameter h is related to the style factor HML. The statistics are based on a ten-year data from 02/01/02 to 31/12/11. The construction of the EW portfolios is based on a quarterly reweighting.** The dataset is provided by **Bloomberg Finance L.P. Regressions with Newey-West standard errors.**

	α		*b*		*s*		*h*		No. Observations
DJEURO	0.704	**	1.053	***	0.298	***	0.320	***	40
t-value	(2.200)		(48.03)		(4.055)		(4.591)		
DJEURO50	0.715	***	1.041	***	-0.359	***	0.200	***	40
t-value	(3.290)		(63.246)		(-6.604)		(4.011)		

* Statistically significant at the 10 percent level

** Statistically significant at the 5 percent level

*** Statistically significant at the 1 percent level

Table 7 presents the results of our further analysis, based on a portfolio approach, aimed to verify if the stock’s size is able to explain the over performance of the EW portfolios. Our results confirm highly significant excess returns over the CW indexes of the equivalent EW portfolios based on a quarterly reweighting frequency: +1.02% and +0.84% for the DJEURO and the DJEURO50 respectively. On the other hand, the TOP and BOTTOM quintile-based portfolios do not exhibit statistically significant excess returns over the CW indexes. Also the comparison between the BOTTOM and TOP portfolios do not provide significant results. The findings offer additional evidence to the fact that the stock's size is not able to fully explain the excess returns of the EW portfolios over the equivalent CW indexes.

Table 7

This table shows the results of the analysis based on the portfolio approach. Excess returns are calculated over the CW indexes (DJ EuroStoxx and DJ EuroStoxx50) for EW portfolios (EWmCW), for top quintile portfolios (TOPmCW) and for bottom quintile portfolios (BTMmCW). Excess returns are also calculated between top and bottom quintile portfolios (TOPmBTM). The statistics are based on a ten-year data from 02/01/02 to 31/12/11. The construction of the portfolios is based on a quarterly reweighting. The dataset is provided by **Bloomberg Finance L.P.**

	EWmCW		TOPmCW	BTMmCW		TOPmBTM	No. Observations
DJEURO	1.02%	***	-0.07%	1.62%	*	-1.69%	40
t-value	*(2.645)*		*(-0.293)*	*(1.878)*		*(-1.595)*	
DJEURO50	0.84%	***	-0.36%	1.50%		-1.87%	40
t-value	*(2.68)*		*(-0.592)*	*(1.386)*		*(-1.242)*	

* Statistically significant at the 10 percent level

** Statistically significant at the 5 percent level

*** Statistically significant at the 1 percent level

Table 8 shows the results of the analysis designed to examine if the excess returns of the EW portfolios presents a seasonality (Panel A) and if the stock return anomaly is explained by the "size effect" (Panel B). Not surprisingly, we find that highly significant excess returns occur in January, but only for the DJEURO. According to the prevalent literature on this issue, we provide evidence of the "January size effect" being both a positive and highly significant coefficient of the SMB factor (Panel B).

From an operational point of view, the excess return showed by the EW portfolios must be analysed in the light of the higher transaction costs associated with the EW strategy. Focusing on the DJEURO index reweighted quarterly, we estimate two sources of trading costs: the turnover related to the periodic index constituents reweighting and the turnover associated with the index stocks replacement. The first is, on average, equal to 10.51% while the second is equal to 5.04% on a quarterly basis. This statistic is in line with those of Dash and Zeng (2010), who argue that generally the US equity indexes have a turnover in the 15% to 30% range. Relying on the S&P500 index, during the five years period, ending in 2009, the average turnover of the equivalent EW index (also rebalanced quarterly) was 28.1%. In this case of the DJEURO index, if we assume negotiation fees of 10 bps[16] for stock trading, the average transaction costs are limited to nearly 6 bps per year.

4. Conclusions

This paper compares two alternative index design methodologies, i.e. the equally-weighted and the cap-weighted. It focuses on the Euro equity market rather than the more frequently studied US equity market. Our research provides further evidence to the established literature on this topic of the benefits of equal weighting over the market weighting methodology. We highlight the fact that the highest excess return amongst those observed is associated with the quarterly rebalancing of the EW portfolios.

Our findings demonstrate that the "January size effect" is not the only explanatory variable of the difference in performance obtained using the two approaches. The benefit which results from reweighting the portfolio into equal weights can rather be

[16] A negotiation fee equal to 10bps for stock trading is relatively high for institutional investors. Our conservative assumption allows considering the possible additional transaction costs arising from the bid-ask spread characterizing smaller cap stocks.

attributed to the fact that EW portfolios implicitly follow a contrarian investment strategy, because they mechanically rebalance away from stocks that increase in price. According to this strategy, overvalued stocks are sold at each rebalancing, preventing the continued growth of their weight during financial bubbles. These findings are extremely important if we consider that, usually, the benchmarks used in the asset management industry are based on cap-weighting. Moreover, **EW indexes permit a higher diversification of the portfolio by investing a higher proportion of the portfolio in mid- or small-cap stocks. Finally,** we calculate the amount of transaction costs related to the EW portfolios examined in our analyses.

Table 8

This table shows the results of the analysis month-by-month of the average excess returns of the equally-weighted portfolios of the DJ EuroStoxx and DJ EuroStoxx50 over the market-weighted indexes. Panel A presents the results of the regression analysis focused on the stock return seasonality for both the indexes. Panel B presents the results of the regression analysis performed in order to verify the January size effect. The statistics are based on a ten-year data from 02/01/02 to 31/12/11. The dataset is provided by **Bloomberg Finance L.P.**

	January	February	March	April	May	June	July	August	September	October	November	SMB
Panel A												
DJEURO	0.0152 ***	0.00685	0.01068 **	0.0127 **	0.00457	-0.0013	0.00473	0.00429	-0.002	-0.0009	-0.0007	
t-value	*(2.924)*	*(1.313)*	*(2.048)*	*(2.435)*	*(0.876)*	*(-0.252)*	*(0.9073)*	*(0.823)*	*(-0.390)*	*(-0.168)*	*(-0.143)*	
DJEURO50	0.0012	-0.0026	0.00307	0.0093 *	0.00143	-0.0041	0.00226	-0.0015	-0.0053	-0.0027	0.0016	
t-value	*(0.241)*	*(-0.527)*	*(0.620)*	*(1.876)*	*(0.288)*	*(-0.826)*	*(0.455)*	*(-0.311)*	*(-1.062)*	*(-0.553)*	*(0.325)*	
Panel B												
DJEURO	0.00246	-0.0019	0.00489	0.00654	0.00082	-0.0035	0.0013	0.00036	-0.0035	0.00032	-0.0004	0.3751

t-value	*(0.675)*	*(-0.522)*	*(1.390)*	*(1.856)*	*	*(0.235)*	*(-0.999)*	*(0.372)*	*(0.102)*	*(-1.017)*	*(0.093)*	*(-0.121)*	*(11.631)*	***

* Statistically significant at the 10 percent level

** Statistically significant at the 5 percent level

*** Statistically significant at the 1 percent level

Disclaimer

STOXX Limited ("STOXX") is the source of the Dow Jones EuroStoxx Index and the Dow Jones EuroStoxx 50 Index **and STOXX or its third party data providers are the source of the data comprised therein. Neither STOXX nor its third party data providers have been involved in any way in the creation of any reported information and they neither warrant nor assume any liability whatsoever – including without limitation the accuracy, adequateness, correctness, completeness, timeliness, and fitness for any purpose – with respect to any reported information. Any dissemination or further distribution of any such information pertaining to STOXX is prohibited.**

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Chapter 6: Conclusions

In this work we studied the efficiency of the benchmarks used in the asset management industry, with a focus on the difference between capitalization weighted indexes and alternative weighted methods.

In chapter 2 we analyzed the efficiency of the benchmark used for the government bond markets. We found that for the Emerging Market Bonds an equally weighted index for the country weights is probably the more suited because guarantees maximum diversification of country risk and in the long run has a better Sharpe ratio than a capitalization weighted index. For the Eurozone government bond market we found a GDP weighted index is better because the most important matter is to avoid a higher weight for highly indebted countries.

In chapter 3 we analyzed the efficiency of a Derivatives Index to invest in the European corporate bond market instead of a Cash Index. We can state that the two indexes are similar in terms of returns, but that the Derivatives Index is less risky because it has a lower volatility, has values of skewness and kurtosis closer to those of a normal distribution and is a more liquid instrument, as the autocorrelation is not significant. The capitalization method used for the ML Index (in contrast to the equal weighting method used for the Derivatives Index) also has risks related to changes in the weights over time, in particular when a sector or an issuer has a high weight because it is highly indebted, as has been experienced by the financial sector recently.

In chapter 4 it is analyzed the impact of fallen angels on the corporate bond portfolios, with the rules of the benchmark indexes which can determine a loss of value for the investors. Our analysis investigated the impact of the month-end rebalancing of the ML Emu Non Financial Corporate Index for the exit of downgraded bond (the event). In this case, we found a statistically significant negative CAR of -5.00% in the pre-event window (-30; -1). Moreover, we did not report a significant CAR in the event window (-1;+1): the reason is that the index rebalancing rules are known in advance, hence the bond's deletion from the index does not have any short term impact on their prices. Furthermore, we found positive and statistically significant CARs of +1.12%, +1.91% and +1.59% in the post-event windows respectively (+1; +5), (+1; +10) and (+1; +15). We can conclude a flexible approach to the month-end rebalancing is better in order to avoid a loss of valued due to the benchmark construction rules.

In chapter 5 we did a comparison between the equally weighted and capitalization weighted method for the European equity market. The benefit which results from reweighting the portfolio into equal weights can be attributed to the fact that EW portfolios implicitly follow a contrarian investment strategy, because they mechanically rebalance away from stocks that increase in price. According to this strategy, overvalued stocks are sold at each rebalancing, preventing the continued growth of their weight during financial bubbles. Moreover, EW indexes permit a higher diversification of the portfolio by investing a higher proportion of the portfolio in mid- or small-cap stocks.

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