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Forecasting and Trading iTraxx and CDX Indices

Matteo Catillo

Abstract

Plenty of researches on the CDS market have focused on the identification of the fundamental components explaining credit spread changes, while very few analyses have investigated the practical opportunity to forecast CDS indices' spread changes, that is, identifying a predicting component in the dynamics of spread changes.

This working paper addresses for the first time, forecasting tasks in the European and U.S credit markets, both in the investment grade and high yield markets, in reference to the iTraxx Europe, iTraxx Crossover, North America CDX IG and North America CDX HY.

Keywords: CDS index, iTraxx, CDX, structural model, rolling-forecast, trading strategies, active management, back-testing

Introduction

Although Credit Default Swaps (CDS) have existed since back in 1997, their use raised from 2003, reaching the "*Golden Age*" during the heart of the 2007-2008 financial crisis, when the outstanding notional amount reached the peak-record of $58 trillion.

The CDS indices were introduced by JP Morgan in 2001 to improve the liquidity in the CDS market, and to provide a "cheaper" single instrument aimed to hedge a portfolio of corporate bonds or single name CDSs as well. Since then, CDS indices have raised interest in the world of finance and in the last years many researches have cast attention merely on the identification of the main determinants of credit spread changes, while very few studies have analyzed the practical opportunity to forecast CDS indices' spread changes.

Thus, this working paper represents one of the first attempts to investigate the existence of forward-looking variables aimed to predict future CDS indices' spread changes.

The identification of a predicting component in the CDS spreads would be supportive to the dynamics of pricing credit derivatives and to portfolio management, which may benefit in terms of hedging purposes and performing active management.

This paper addresses the European and U.S credit markets, specifically the investment grade and high yield markets, in the form of *iTraxx Europe*, *iTraxx Crossover*, *North America CDX IG* and *North America CDX HY*. These indices have been elected benchmarks of the creditworthiness of the European and U.S credit markets.

The rest of the paper is organized as follows:

- The 1^{st} section addresses a detailed *statistical descriptive analysis*, with particular reference to the autocorrelation analysis, aimed to examine the informational efficiency of the CDS indices market.
- The 2^{nd} section involves the development of the forecasting models by employing a *60-month rolling forecast technique*. The forecasting framework implies the use of *Linear Structural models* and *Autoregressive AR(3) models* as benchmarks. The *statistical performance* is examined by looking at statistical indicators as *RMSE*, *MAE* and *MCP* and by analyzing the 60-month rolling correlation to test the forecasting ability over time.
- The 3^{rd} section regards the *economic performance* of the structural models by implementing static and dynamic trading strategies according to the trading signals issued by the models and by *backtesting* such strategies looking at the cumulative wealth of portfolios invested in these credit indices.

1. Credit Default Swap indices: iTraxx and CDX

Credit Default Swaps (CDS) market has experienced an extreme growth since their introduction from the genius of Blythe Masters in the 1997. In a short time, these financial instruments have raised the interest of the financial sector because they allow investors to diversify and to trade credit exposure. Formerly, trading credit exposure was doable only via the cash market. Even so, short positions in the cash market were unfeasible because of the tight liquidity of the repo market and the maturity of the agreements was rather short. [1]

These shortcomings of the cash market allowed *Credit Default Swaps* to assert themselves as the unique financial products able to trade, in an easy and transparent way, credit risk.

A Credit Default Swap (CDS) is essentially an OTC derivative, two-sides insurance contract, where the protection buyer pays fixed periodic fees, usually on a quarterly basis, to a protection seller, who receives the payments in exchange of protection to the buyer in case of default of the underlying bond[2].

Similar to the basket-names CDSs, a *CDS index* is an insurance contract providing protection against a pool of reference entities included in the index. However, in contrast to the basket-names CDSs, a credit event of an entity belonging to the index, does not imply the unwinding of the contract, but the defaulting name is pulled off from the pool of credit entities and the index continues to trade until maturity with a reduced notional[3].

Credit Default Swap Indices emerged in 2001 when JPMorgan launched the JECI and Hydi indices. In the wake of this latter, Morgan Stanley created the Synthetic TRACERS. In 2003 both indices merged forming the Trac-X name. Meanwhile, iBoxx launched similar indices, the iBoxx CDS indices. In 2004 Trac-X name and iBoxx merged forming the current traded CDS indices, the CDX in North America and iTraxx in Europe and Asia. Both indices were acquired by Markit in 2007, becoming the unique owner and manager of Markit iTraxx, Markit CDX, Markit iTraxx SovX, Markit iTraxx LevX, and Markit LCDX as well as Markit iBoxx cash bond indices[4].

It is worthwhile to highlight the differences between a credit index and a single-name CDS. Firstly, a contract on a credit index does not terminate after a credit event of a member but it is alike a new contract on the remaining entities with a reduced notional amount (specifically,

[1] Avino D., Nneji O. – *Are CDS spreads predictable? An analysis of linear and non-linear forecasting models*, March 2014
[2] Markit – *Markit Credit Indices – A Primer*, July 2014
[3] Alexander C., Kaeck A. – *Regime dependent determinants of Credit Default Swap spreads*, September 2007
[4] Markit – *Markit Credit Indices – A Primer*, July 2014

after a credit event the defaulted entity is pulled off from the index and a "new version" of the index is issued)[5].

Secondly, for both CDS contracts and credit index contracts, payment and maturity dates do follow the standard ISDA dates, namely 20th March, 20th June, 20th September and 20th December[6] and accrue on actual/360 basis. A difference lies in the time to maturity because, for example a 5-year CDS contract matures the earliest ISDA date after 5 years from the issuing date. This leads to the fact that the time to maturity of the CDS contract is not fixed but it is comprised in 5 years and 5.25 years. Similarly, a contract on a credit index with a 5-year tenor, because of its rolling issuing frequency (a new series of the credit index is issued on a rollover semiannual basis), has a time to maturity that ranges from 4.75 years to 5.25 years[7].

Thirdly, although both CDS contracts and credit index contracts are quoted on a spread basis, an important difference laid in the trading convention prior of 2009: a single-names CDS was traded on running-premium basis, meaning that no upfront payment was needed and each trading day the premium was adjusted in order to reflect the market value of credit risk. Conversely, a contract on a credit index was traded on an upfront and running-premium basis, meaning that the premium was fixed and set at the inception of the trade and each trading day, the upfront payment was updated reflecting the creditworthiness of the underlying reference entities of the index[8].To date, both CDS contracts and credit index contract are traded on an upfront and running-premium basis[9].

Finally, other differences lie in the categorization of the credit events, namely which events should be contemplated as credit events. Particularly, differences regard the clauses of restructuring events of CDSs and credit index contracts written on non-investment grade entities. In contrast, CDSs and credit index contracts on investment grade names present same clauses regarding credit events[10]. Among CDS indices, the most important ones are the *iTraxx indices* and *CDX indices*. The iTraxx index category is made up by indices grouping the most liquid CDS contracts in Europe, Asia and Emerging Markets. Equivalently, the CDX index category comprises the most liquid CDS contracts in North America and Emerging Markets.

The iTraxx Europe and iTraxx Crossover are two benchmark indices giving an overview of the European credit market: the *iTraxx Europe* encompasses the 125 most liquid equally-

[5] Couderc F. – *Measuring Risk on Credit Indices: On the Use of the Basis*, Winter 2007
[6] Couderc F. – *Measuring Risk on Credit Indices: On the Use of the Basis*, Winter 2007
[7] Couderc F. – *Measuring Risk on Credit Indices: On the Use of the Basis*, Winter 2007
[8] Couderc F. – *Measuring Risk on Credit Indices: On the Use of the Basis,* Winter 2007
[9] Markit – *Markit Credit Indices – A Primer*, July 2014
[10] Couderc F. – *Measuring Risk on Credit Indices: On the Use of the Basis*, Winter 2007

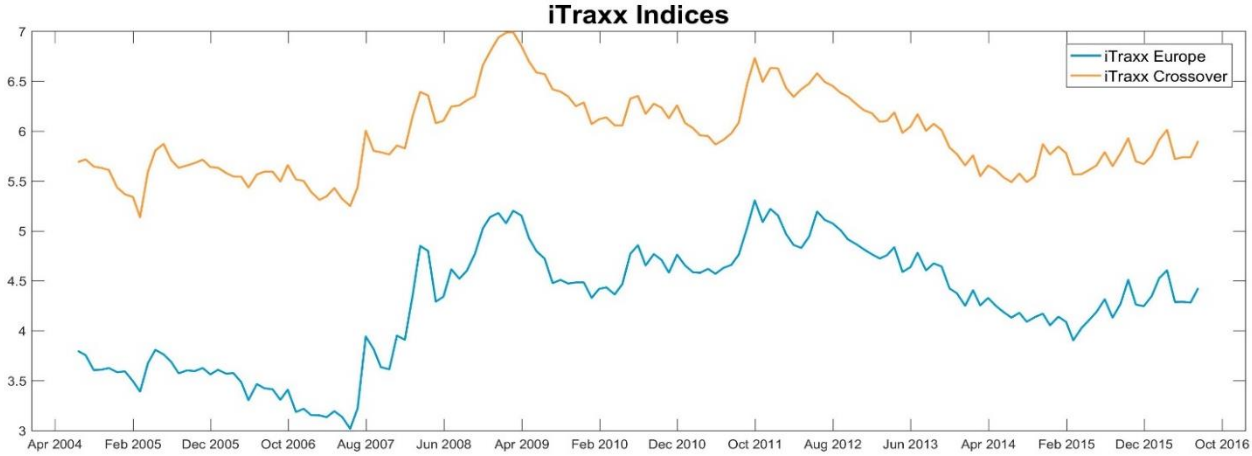
weighted European investment grade entities. It trades with a running coupon of 100 bps and with maturities of 3, 5, 7 and 10 years; the *iTraxx Crossover* groups the 75 most liquid European sub-investment grade names. Given the riskier nature of the underlying entities, the index trades with a running coupon of 500 bps and with same maturities of the previous one.[11]
Equivalently, the North America CDX IG and HY indices represent a gauge of the investment grade and high yield credit trend in the North American market: *North America CDX Investment Grade*, shorten in CDX.NA.IG, consists of the 125 most liquid equally-weighted North American reference names with a rating of investment grade. It trades with a running coupon of 100 bps and with a more complete set of maturities than iTraxx Europe, namely 1, 2, 3, 4, 5, 7, 10 years; *North America CDX High Yield*, shorten in CDX.NA.HY, is formed by the 100 most liquid high-yield reference names of the North American credit market. It trades with a running coupon of 500 bps and maturities ranging in 3, 5, 7 and 10 years.[12]
This working paper is focused respectively on the iTraxx Europe and iTraxx Crossover for the European market and on the North America CDX IG and HY for the North American one, with a tenor of 5 years, being the most liquid.
The dataset consists of monthly bid, mid and ask quotes for the first 25 series of the European indices from June 2004 to June 2016 counting 144 observations and for the first 26 series of the North America Investment Grade from September 2004 to June 2016 counting 142 observations. Monthly quotes for the North America High Yield are available (on the Bloomberg platform[13]) only in terms of price from May 2005 to June 2016, counting 134 observations.
The following paragraphs address a detailed descriptive statistics analysis for the iTraxx and CDX indices.

[11] Markit – *Markit Credit Indices – A Primer*, July 2014
[12] Markit – *Markit CDX High Yield & Markit CDX Investment Grade Index Rules*, August 2015
[13] The followings are the *current tickers* on the Bloomberg Platform:

- iTraxx Europe: ITRX EUR CDSI S25 5Y Corp;
- iTraxx Crossover: ITRX XOVER CDSI S25 5Y Corp;
- North America CDX IG: CDX NA IG S26 5Y Corp;
- North America CDX HY: CDX NA HY S26 5Y Corp.

iTraxx indices

Figure 1.1: Performance of the iTraxx Europe and iTraxx Crossover



Firstly, both indices have a similar trend over the entire sample period. Obviously the iTraxx Crossover, representing the non-investment grade segment of the credit market, shows the widest spreads compared to the iTraxx Europe. This result proves the theoretical findings, according to which credit ratings are one of the most significant determinants of the creditworthiness of corporates and hence of the CDS spread[14].It is worth noting the downward trend experienced before the April 2005, when there were the downgrades of General Motors (GM) and Ford, two major worldwide auto-manufacturers[15]. Before the downgrades occurred, their aggregate outstanding debt amounted to $450 billion (General Motors with $290 billion and Ford with $160 billion)[16]. The extent of the economic contagion of the downgrades shook not only the U.S market but also the European market, leading to a soaring of the CDS spreads[17].

Secondly, both time series show an upward trend hitting the record level in the run up of the U.S Subprime Mortgages Crisis leading to a significant spread widening: the iTraxx Europe spread jumped from 25 bps to 181 bps rising by 623% and the iTraxx Crossover spread surged from 230 bps to 1084 bps, an increase of 372%.

[14] Bhar R., Colwell D., Wang P – *Component Structure of Credit Default Swap Spreads and their Determinants,* September 2008

[15] Couderc F. – *Measuring Risk on Credit Indices: On the Use of the Basis*, Winter 2007

[16] Bhar R., Colwell D., Wang P. – *Component Structure of Credit Default Swap Spreads and their Determinants,* September 2008

[17] Bhar R., Colwell D., Wang P – *Component Structure of Credit Default Swap Spreads and their Determinants,* September 2008

Thirdly, both iTraxx indices peaked in the mid of 2011 in light of the worsening of the European Sovereign Debt Crisis, particularly the support to the Sovereign Greek Debt intensified. Since then, the spreads have witnessed to a downward trend in conjunction with the Quantitative Easing's Program of Mario Draghi, that reached the historical peak of €3 trillion in the mid of 2012. Moreover, at the same time the ban of naked CDSs across the European Union was imposed[18] in order to control market volatility and to support the price discovering process, namely efficiency in the financial markets, the market confidence and financial stability.

Finally, since the beginning of 2015 the European credit market has also suffered from the Chinese stock market disruption implying a climb of the credit spreads. At the same time, the withdrawal of the United Kingdom from the European Union (Brexit) has rallied the upward trend leading to a climbing of spreads.

Being the CDS spread a compensation for credit risk, it would be opportune to investigate the time-varying credit risk premium, over the sample period[19]. As a rough measure of *Credit Risk Premium* (CRP), the difference between the CDS spread of the iTraxx Crossover (being a gauge of the high yield market) and the investment grade spread of the iTraxx Europe has been taken into account: the CRP peaked during the global financial turmoil and it continued to be high also during the European Sovereign Debt Crisis. It recovered to pre-crisis levels only in the last two years. It is rewarding to highlight the peak that both indices, particularly the iTraxx Crossover experienced during February 2010, when there was the market sentiment of the imminent sovereign default of Greece.

Descriptive statistics of the iTraxx Europe and iTraxx Crossover are provided below.

The iTraxx Europe spread levels range from a minimum value of 20 bps in May 2007 to a maximum value of 201 bps in September 2011 with a mean value of 84 bps over the sample period. Instead the iTraxx Europe changes range from a minimum value of -51% reached in May 2008 to a maximum value of 72% in July 2007 with a mean of 0.4%.

Similarly, minimum and maximum iTraxx Crossover spread levels are comprised between 170 bps in February 2005 and 1084 bps in February 2009 with a mean of 420 bps. Instead minimum and maximum iTraxx Crossover spread changes range between -29% in March 2016 and 57% in July 2007 with a mean of 0.15%.

[18] Barker A. – *EU ban on "naked" CDS to become permanent* – Financial Times, October 2011

[19] Bhar R., Colwell D., Wang P. – *Component Structure of Credit Default Swap Spreads and their Determinants,* September 2008

Table 1.1: Descriptive statistics of the iTraxx Europe and iTraxx Crossover

	iTraxx Europe Levels	iTraxx Europe Changes	iTraxx Crossover Levels	iTraxx Crossover Changes
Mean	83.63	0.004	420.30	0.001
Median	78.47	-0.01	365.33	-0.01
Minimum	20.46	-0.51	170.05	-0.29
Maximum	201.38	0.72	1084.12	0.57
Stand. Deviation	43.71	0.16	186.97	0.14
Skewness	0.54	0.85	1.35	0.87
Kurtosis	2.55	6.25	4.79	4.90
ADF Test (1lag)	-0.77	-10.28***	-0.87	-9.13***
ADF Test (2lags)	-0.81	-7.39***	-0.81	-7.09***
ADF Test (3lags)	-0.63	-6.01***	-0.89	-6.24***
JB Test	8.32**	80.61***	63.11***	40.00***
LBQ Test (1lag)	131.37***	0.22	131.22***	0.05
LBQ Test (2lags)	246.40***	7.26**	243.66***	1.50
LBQ Test (3lags)	350.24***	7.31*	339.19***	1.50
LBQ Test (6lags)	593.46***	9.42	532.87***	2.26
LBQ Test (12lags)	897.08***	12.79	704.77***	2.83

Note: 1%, 5%, 10% significance levels are indicated by ***, **, * respectively.

It should be highlighted that, while iTraxx Europe and Crossover changes present a similar level of volatility in terms of standard deviation, 16% vs 14% per month, iTraxx Europe and Crossover levels diverge significantly with the iTraxx Crossover volatility four times that one of the iTraxx Europe, 44 bps vs 187 bps per month, evidencing the riskier nature of the iTraxx Crossover.

The iTraxx Europe levels and changes present a non-zero level of skewness, specifically both of them are skewed to the right. Moreover, they are characterized by a discrete level of positive kurtosis, meaning that the distributions of levels and changes are leptokurtic.

The iTraxx Crossover levels and spreads are characterized by identical results, although the distribution of both is more skewed to the right compared to the iTraxx Europe one. Instead, the kurtosis is broadly equal for both iTraxx Crossover levels and changes. The most pronounced level of "tailedness", is shown for the iTraxx Europe changes.

At first, these results allow to assert that the spread levels and changes do not come from a normal distribution. In order to confirm these preliminary results, the Jarque-Bera Test (JB Test) was performed, for the purpose of testing whether the sample data provides a skewness and kurtosis' level matching that one of a normal distribution. The achieved findings reject for the iTraxx Europe spread changes and iTraxx Crossover spread levels and changes, the hypothesis of normal distribution at a 1% significance level. Instead, for the iTraxx Europe spread levels the null hypothesis of normal distribution is only rejected at 5% significance level.

It is valuable here to assess the stationarity of time series of the iTraxx Europe and Crossover spread levels and changes in view of the development of the forecasting framework of the iTraxx indices in the next chapter.

Therefore, the Augmented Dickey-Fuller Test (ADF Test) was performed, employing different models of specification and different number of lags. In the table above, only the results for unit root test of autoregressive model with maximum 3 lags are listed, as similar results are found with several models of specification such as an autoregressive with drift model and trend stationary model.

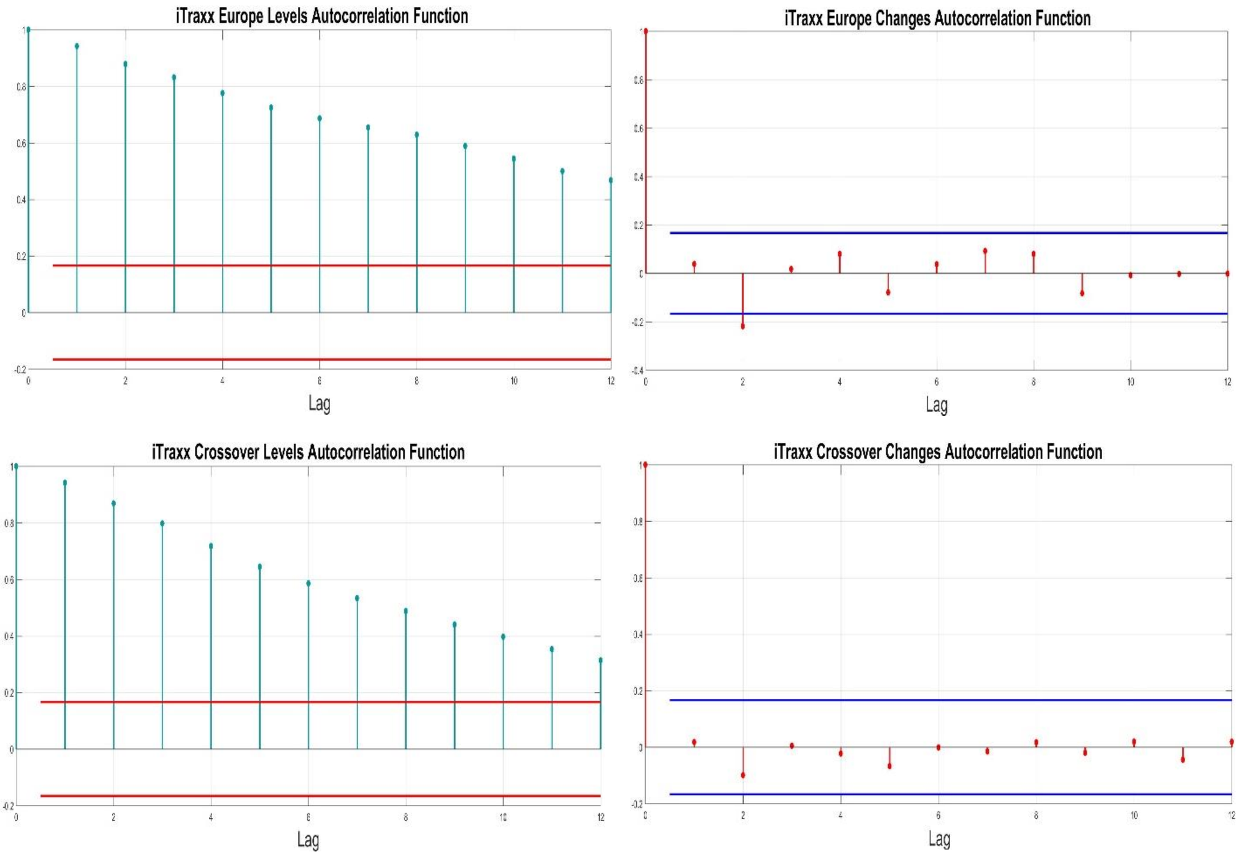
The findings show that the iTraxx Europe and Crossover changes are stationary at 1% significance level, whereas the iTraxx Europe and Crossover levels are found to be non-stationary. Therefore, this allows to affirm that CDS spread changes are led by a *mean-reverting pattern*.

Two previous researches have studied and analyzed the behaviour of the iTraxx indices. Especially, Byström (2006) found that the Europe sector indices, including iTraxx Industrials, iTraxx Financials, iTraxx Auto, iTraxx TMT, iTraxx Energy, etc and iTraxx Crossover, during the period coming from June 2004 to March 2006, were characterized by a positive and significant first-order daily autocorrelation[20]. Afterward, Alexander and Kaeck (2007) has validated the Byström's (2006) findings regarding the first-order autocorrelation. Furthermore, they studied the relationship between several CDS spread determinants and iTraxx spread in different contingent economic states[21].

In the wake of these studies, in this working paper the autocorrelation of the iTraxx Europe and Crossover changes and levels has been analyzed. The figures below show the autocorrelation patterns of spread levels and changes over the sample, employing a capped number of lags equal to 12 lags (namely, on a yearly time horizon). The focus should be cast on the spread changes: the iTraxx Europe spread changes exhibit a significant negative second-order autocorrelation (at 5% significance level) and a positive third-order autocorrelation (at 10% significance level) in monthly data.

[20] Byström H. – *Credit Default Swap and Equity Prices: the iTraxx CDS Index Market,* May 2005
[21] Alexander C., Kaeck A. – *Regime dependent determinants of Credit Default Swap spreads,* September 2007

Figures 1.2, 1.3, 1.4 and 1.5: Autocorrelation Function of the iTraxx Europe and iTraxx Crossover's spread levels and changes



This result is going to play a key role in the predictability ability of past spreads. Otherwise, the autocorrelation of the iTraxx Crossover spread changes over different lags is found to be non-significant. The autocorrelation curves for the iTraxx Europe and Crossover spread changes do not decay "rapidly" to zero, highlighting the potential forecasting ability of past CDS spreads. Obviously, the autocorrelation functions for the iTraxx Europe and Crossover spread levels are positive and significant at all lags.

As a consequence, the European 5-year CDS market, especially the investment grade segment, reveals a certain degree of inefficiency that may be exploited away in fixed income arbitrages[22]. In order to validate these findings, the Ljung-Box test (LBQ test) has been performed among different lags, specifically 1 lag (monthly), 2 lags (bi-monthly), 3 lags (quarterly), 6 lags (semiyearly) and 12 lags (yearly).

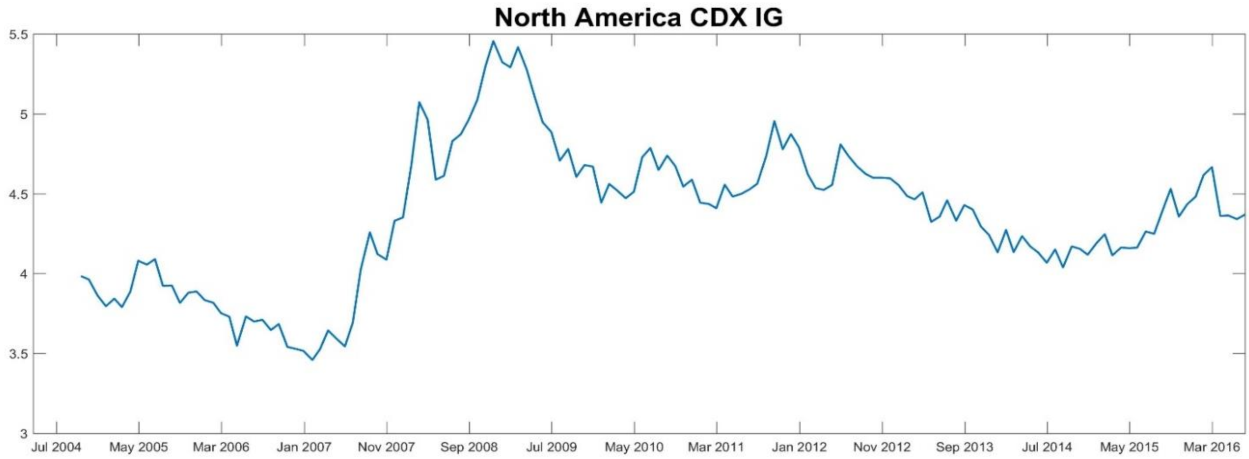
The Ljung-Box test is a Portmanteau test, testing whether the autocorrelations of residuals of a time series are statistically different from zero. Clearly, the autocorrelations of the residuals

[22] Byström H. – *Credit Default Swap and Equity Prices: the iTraxx CDS Index Market*, May 2005

of the iTraxx Europe and Crossover spread levels are significantly different from zero at 1% significance level: the LBQ test values are much wide, ranging from 131.37 for Q (1) to 897.08 for Q (12) for the iTraxx Europe levels, and from 131.22 for Q (1) to 704.77 for Q (12) for the iTraxx Crossover levels. Regarding the autocorrelations of the residuals of spread changes, only the residuals at 2nd lag and 3rd lag of the iTraxx Europe spread changes are significantly different from zero, respectively at 5% and 10% significance level, with a Q(2) and Q(3) equal to 7.26 and 7.31. Negative results are achieved for the autocorrelation test of the iTraxx Crossover spread changes.

CDX indices

Figures 1.6 and 1.7: Performance of the North America CDX IG and CDX HY



Note: North America CDX IG is quoted in terms of spread and North America CDX HY is quoted in terms of price.

Firstly, the North American indices are characterized by a similar behavior and shock-moves over the entire sample period. In the opening of both time series, the North American indices were shaken by the downgrades of the two auto-makers, General Motors (GM) and Ford, happened during April 2005. The shock struck the U.S credit market determining a widening of the spread of many reference names included in the basket. As mentioned in the previous section, the extent of the contagion exceeded the internal U.S market spreading all around the European credit market[23].

The autos-sector afterward suffered by the default of Delphi (March 2005) and Collin & Aikman (mid 2005), respectively a spin-off of General Motors and a manufacturer of interior components and systems for autos. In this case the movements of the indices differ: as the downgrade of Delphi from investment grade to high yield grade occurred, it shifted, being no longer member of the CDX IG index but of the new series CDX HY[24]. As a consequence, the CDX IG spread fell because of removing of Delphi from the basket names.

Secondly, both North American CDX indices peaked amid the U.S Subprime Mortgages Crisis reaching a record level of 234 bps for the CDX IG and 1575 bps for the CDX HY. It is worth noting that spread levels were much higher for the North American indices than the European one: 29% higher for the North America CDX IG and 45% for the CDX HY one. Thus, in the peak of the global financial distress, global markets assessed the U.S credit market much riskier than the European counterparty.

In response to the financial meltdown of 2007, Federal Reserve, in the person of Ben Bernanke, announced on November 2008 the beginning of the Quantitative Easing Era in the United States, with the so-called *QE1 program*, in conjunction with the adoption of a *Zero Interest Rate* policy, aimed to lower the benchmark federal funds rate to closely zero[25]. These economic shocks pointed in the direction of restoring a discrete quality in the money and credit markets.

An additional exogenous monetary shock came from the FOMC's announcement of the *Operation Twist*, a monetary policy program sought to manage the level and hence the slope of the yield curve by buying and selling short-term and long-term bonds[26]. It was primarily performed in September 2011 by shorting short-term bonds and by buying long-term bonds in order to lower long-term interest rates.

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[23] Bhar R., Colwell D., Wang P. – *Component Structure of Credit Default Swap Spreads and their Determinants,* September 2008

[24] Couderc F. – *Measuring Risk on Credit Indices: On the Use of the Basis,* Winter 2007

[25] For more details, please see http://www.investopedia.com/articles/investing/031815/what-zero-interestrate-policy-zirp.asp

[26] http://www.investopedia.com/terms/o/operation-twist.asp

In effect, the U.S credit market witnessed from the mid of 2009 to a downward trend leading to tightening of the spread levels, sign that the monetary policies were working relatively well and market's fear in the credit market was moving down.

Thirdly, at the end of 2011, a manipulation by JP Morgan of the North America CDX IG index was found out, put in place by the nicknamed "London Whale", the JP Morgan's trader Bruno Iksil[27]. He opened huge positions (that are short positions) in the CDX IG index, in order to bet on an improving of the state of the economy. The positions' size was such that the CDX IG was trading at very low levels, diverging from the market's expectations. Nevertheless, the unexpected European Sovereign Debt Crisis at the end of 2011, moved the credit market against the JP Morgan's positions (a sharp increase in spread levels), forcing the investment bank to unwind the positions, reporting a trading loss of more than $7 billion. The winners in "this story" were hedge funds that were the counterparties in the JP Morgan's transactions[28].

Finally, since the end of 2013 both North American indices experienced a downward trend, reaching the record low level from the bursting of the financial crisis of 57 bps in August 2014 for the CDX IG and about 303 bps for the CDX HY. All of this is a sign that the U.S credit market is recovering from the damages caused by the 2007 Subprime Crisis.

Descriptive statistics of the North America CDX IG and CDX HY are provided in the table 1.2, in levels and changes terms. It should bear in mind that the CDX IG is quoted in terms of spread, whereas the CDX HY is quoted in terms of price.

The CDX IG levels range from a minimum of 32 bps in January 2007 to a maximum of 234bps in November 2008 with a mean value of 86 bps. Concerning the CDX IG changes, they range from a minimum of -38% in April 2008 to a maximum value of 39% peaked in February 2008, with a mean of 0.3%.

Analogously, minimum and maximum CDX HY levels are comprised between 71%, about 1444 bps, in March 2009 to 109%, about 303 bps, in June 2014, with a mean price of 99%. Regarding CDX HY changes, they range from a minimum of -15% reached in February 2009 to a maximum value of 11% peaked in April 2009.

[27] Braithwaite T., Alloway T., Mackenzie M. – *JPMorgan offloads "whale" holdings* – Financial Times, June 2012

[28] https://en.wikipedia.org/wiki/2012_JPMorgan_Chase_trading_loss

Table 1.2: Descriptive statistics of the North America CDX IG and CDX HY

	NA CDX IG Levels	NA CDX IG Changes	NA CDX HY Levels	NA CDX HY Changes
Mean	85.84	0.003	99.28	0.0004
Median	81.31	-0.01	100.35	0.0002
Minimum	31.79	-0.38	70.63	-0.15
Maximum	234.00	0.39	108.71	0.11
Stand. Deviation	39.69	0.12	6.87	0.03
Skewness	1.33	0.28	-1.55	-0.78
Kurtosis	5.32	3.66	6.48	10.28
ADF Test (1lag)	-0.80	-8.84***	0.02	-8.74***
ADF Test (2lags)	-0.63	-6.81***	-0.02	-5.32***
ADF Test (3lags)	-0.74	-5.85***	-0.09	-5.54***
JB Test	73.54***	4.42*	121.24***	306.95***
LBQ Test (1lag)	129.03***	0.21	118.16***	0.05
LBQ Test (2lags)	240.81***	1.15	221.27***	0.78
LBQ Test (3lags)	340.03***	1.25	311.92***	9.60**
LBQ Test (6lags)	557.07***	2.16	490.34***	14.83**
LBQ Test (12lags)	753.69***	4.52	649.37***	29.09***

Note: 1%, 5%, 10% significance levels are indicated by ***, **, * respectively.

Both indices present a moderate positive level of kurtosis, with the greatest value computed for the CDX HY index, meaning that all distributions are leptokurtic. It should be noticed here that the kurtosis of the CDX IG changes is nearly to 3 (that is the kurtosis value of a normal distribution); this is a further evidence that the related changes may be potentially drawn up by a normal distribution.

This explorative analysis allows to evidence that the CDX IG levels and CDX HY levels and changes do not come from a normal distribution. Otherwise, the CDX IG changes appear to be denoted potentially by normality in the distribution.

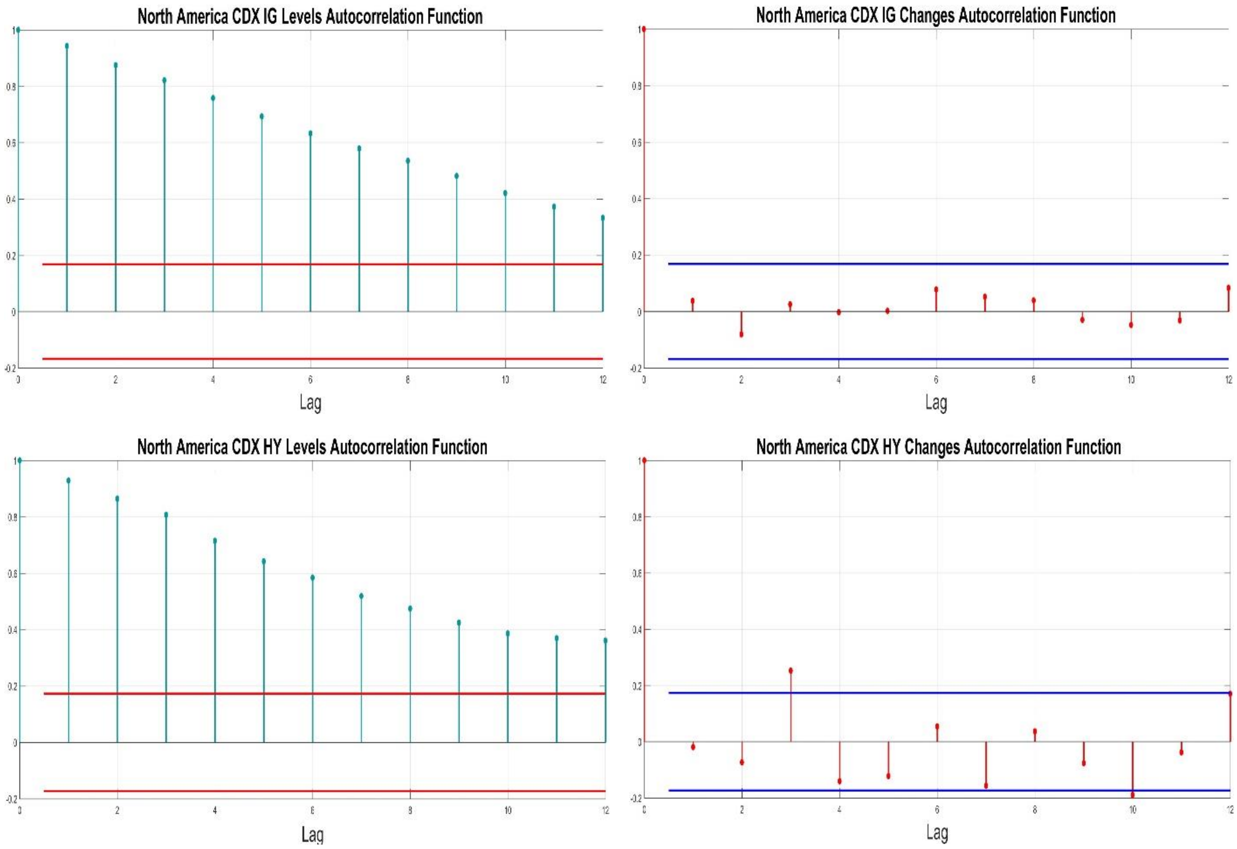
In order to validate this preliminary analysis, as computed for the European counterparty, the Jarque-Bera Test (JB Test) was performed, aimed to test the normality of the distribution. The achieved findings highlight the rejection of the null hypothesis of normal distribution for the CDX IG levels and CDX HY levels and changes at 1% of significance level. The null hypothesis for the CDX IG changes is only rejected at 10% significance level.

The next step in the descriptive analysis is assessing whether North American levels and changes are stationary. Therefore, the Augmented Dickey-Fuller Test (ADF Test) was performed, employing various models of specification with at most 3 lags. In the reported table above only results for unit root test of autoregressive model with maximum 3 lags are included since analogous results are found for autoregressive with drift and trend stationary models of specification.

The findings indicate that both CDX IG and CDX HY changes are stationary at 1% significance level. Obviously, spread levels are found to be non-stationary. Therefore, the pattern of spread changes of the CDX IG and CDX HY have a stationary trend over the entire sample, driven by a *mean-reverting pattern*, as for the European counterparties.

Figures below illustrate the behavior of the autocorrelation functions for the CDX IG and CDX HY spread levels and changes, using a capped number of lags equal to 12, hence on an annual horizon.

Figures 1.8, 1.9, 1.10 and 1.11: Autocorrelation Function of the North America CXD IG and CDX HY's levels and changes



Focusing on spread changes, while the CDX IG exhibits weak levels of autocorrelation over the 12 lags, the CDX HY presents significant levels of autocorrelation comprising between -19% and +25%. This result is relevant in view of forecasting future prices using past CDX HY prices. However, the autocorrelation pattern of the CDX IG decays to zero more "rapidly" compared to the CDX HY one, meaning that the efficiency is more evident in the investment grade segment than in the high yield one.

In order to validate these results, the Ljung-Box Test (LBQ Test) was performed, aimed to investigate whether the residuals are autocorrelated among different lags, specifically 1 lag (monthly), 2 lags (bi-monthly), 3 lags (quarterly), 6 lags (semiyearly) and 12 lags (yearly).

Obviously, for the CDX IG and CDX HY spread levels, the LBQ test values are wide ranging from 129.03 for Q (1) to 753.69 for Q (12) for the CDX IG, and from 121.41 for Q (1) to 649.37 for Q (12) for the CDX HY.

Regarding the spread changes, the LBQ test values are comprised between 0.21 and 4.52 for the CDX IG and 0.05 and 29.1 for the CDX HY. This imply that autocorrelation values for the CDX IG are non-significant at any significance level; whereas for the CDX HY the autocorrelation at 12^{th} lag is significant at 1% and at 3^{th} and 6^{th} at 5% significance level.

It is worth to highlight the divergences in the autocorrelation functions among the U.S and European markets: comparing the autocorrelation curves, it may confirm that:

- the European investment grade market has a certain degree of inefficiency, strengthened by the fact that the autocorrelations converge to zero less “promptly” than the U.S counterparty;
- the U.S high yield market is much less efficient than the European high yield market, since the autocorrelation curves of the CDX HY changes converge to zero “very slowly”.

2. Forecasting CDS indices spreads

The core part of the working paper involves the *forecasting methodology* of CDS indices' spread changes. The forecasting framework is organized in the followings steps:

- analysis of the fundamental determinants of CDS spread changes, in order to determine the set of predictors to be employed in the forecasting models;
- analysis of the underlying forecasting methodology: *Linear Structural models* and *Autoregressive (AR) models* as benchmarks are employed;
- implementation and *statistical performance* of the developed models regarding their accuracy in predicting future CDS indices' spread changes.

Since the iTraxx and CDX are subject to the rollover requirement, a new series (the on-the-run series) is issued on a semiannual basis. With the aim to focus on the most liquid quotes, the dataset has been modelled taking into account only the most recent (read liquid) series.

In the first step, the main explanatory variables as theorized by the structural model of Merton, *Equity*, *Volatility* and *Short-term Risk-Free rate*[29] in addition to the *Slope of the Yield Curve*, *Gold*[30] and *Momentum*[31] have been tested through an OLS estimation aimed to verify whether they are able to explain CDS spread changes.

The following indices are used as proxies for the explanatory variables:

- *Equity:* Dow Jones EURO STOXX 600 and STANDARD & POOR'S 500;
- *Volatility*: Dow Jones VSTOXX 50 and CBOE S&P 500 VIX;
- *Term Spread*: German 10 year-2 year government bond yield spread and US 10 year- 2 year swap spread;
- *Risk-free rate*: 3-month EURIBOR and 3-month USD LIBOR;
- *Gold*: gold prices of the *London Bullion Market Association* in the afternoon time;
- *Momentum*: dummy variable based on a simple moving average of spread changes over the past 3 months with a neutral range of 10% for the European credit market and 5% for the North America one. It simulates a trading strategy consisting of taking long positions

[29] Chu Y., Constantinou N., O'Hara J. – *An analysis of the determinants of the iTraxx CDS spreads using the Skewed Student's t AR-GARCH Model*, February 2010
[30] Breitenfellner B., Wagner N. – *Explaining aggregate Credit Default Swap spreads,* February 2012
[31] Ilmanen A. – *Forecasting U.S Bond returns (Understanding the Yield Curve Part 4),* August 1995

(value of 1) in securities that in the past months have had significant high returns and taking short positions (value of -1) in securities which have poorly performed in the same past months. If the trading strategy implies a neutral position, the momentum variable takes value of 0.

The inclusion of this momentum variable in the structural model aims to exploit existing trends in the credit market.

Table 2.1: Regression results

Betas	iTraxx Europe	iTraxx Crossover	CDX IG	CDX HY
Constant	0.0037	-0.0014	0.0059	-0.0010
Equity	-1.3274***	-1.2375***	-1.2856***	0.3763***
Volatility	0.1276**	0.0690	0.0198	0.0248**
Term Spread	-0.0387*	-0.0374**	0.0055	0.0001
Risk-Free Rate	-0.0037	-0.0179	0.0333	-0.0321**
Gold	0.2125	0.1422	0.1328	-0.0514*
Momentum	0.0746***	0.0797***	0.0659***	0.0265***
R-squared	0.6643	0.6745	0.7104	0.6481
Adj-R-squared	0.6492	0.6599	0.6971	0.6310
F-Test	44.1847	46.2688	53.5480	37.7586
MSE	0.0087	0.0067	0.0047	0.0003

Note: 1%, 5%, 10% significance levels are indicated by ***, **, * respectively

The regression results indicate that, as predicted by the theory, Equity and Volatility represent two of the fundamental determinants of credit spread changes, together with Momentum and Term Spread. All of these variables are able to jointly explain on average more than half of the variation of credit spreads[32].

In the second step, aiming to exploit the information embedded in this set of predicting variables, through the adoption of a *Rolling-Forecast technique* with a 60-month rolling window, the forecasting *Linear Structural models* have been implemented. In addition to the above identified variables (Equity, Volatility, Short-term Risk rate, Term Spread, Gold and Momentum), a lagged variable of past credit spread changes has been included in the forecasting models, aiming to exploit potential significant autocorrelations among credit

[32] Given the number of explanatory variables, the multicollinearity has been tested using the *Variance Inflation Factors* (VIF): the average level of VIFs is less than 2, only in some case it is around 2. Hence, multicollinearity is not a warning in such developed econometric framework.

spread changes: specifically, the models have been calibrated in accordance to the related significant autocorrelations as previously evidenced in the descriptive statistical analysis.

The following is the expression of the calibrated forecasting model:

$$\Delta CDS_t = \beta_0 + \beta_1 \Delta CDS_{t-k} + \beta_2 \Delta Equity_{t-1} + \beta_3 \Delta Vol_{t-1} + \beta_4 \Delta TermSpread_{t-1} + \beta_5 \Delta RF_{t-1} + \beta_6 \Delta Gold_{t-1} + \beta_7 Momentum_{t-1} + \varepsilon_t$$ [33]

where ΔCDS_t is the credit index spread changes, $\Delta Equity_{t-1}$ is the equity index return, ΔVol_{t-1} is the equity volatility index change, $\Delta TermSpread_{t-1}$ is the change in the slope of the Yield Curve, $\Delta RF_{t-1}$is the change in the short-term Risk-Free Rate, $\Delta Gold_{t-1}$ is the Gold return and finally $Momentum_{t-1}$ is the momentum variable.
Combining the parameters estimated on the (t-1) observations with the observations at time t, the expected credit spread changes for the subsequent period are get, namely, time (t+1). In other words, the analysis implies a rolling-estimation with a 1-step forecast ahead.
Furthermore, from the rolling-forecast technique, Autoregressive AR(3) models with a rolling-window of 5 years have been performed as benchmarks against which evaluate the structural models.

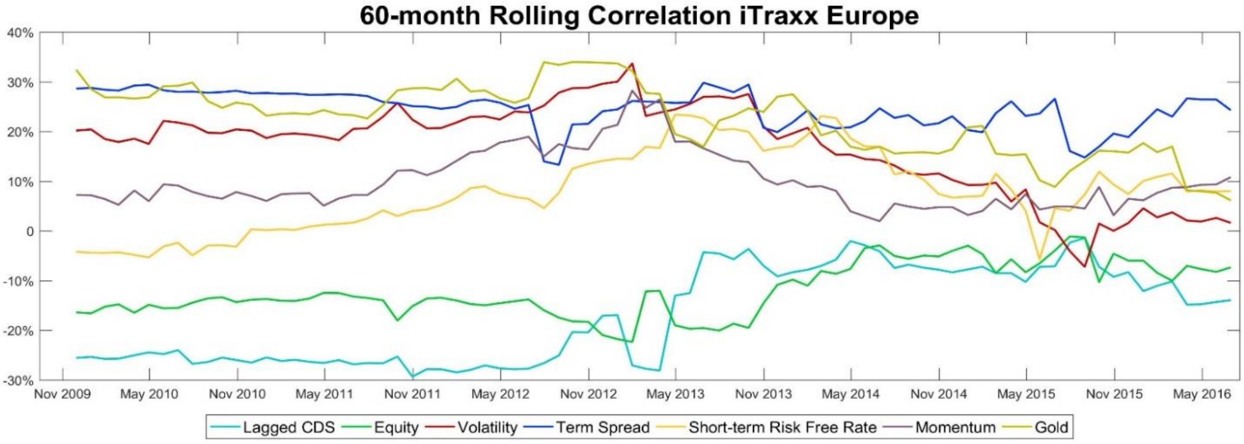
$$\Delta \mathrm{CDS}_{\mathrm{t}} = \mathrm{c} + \varphi_1 \Delta \mathrm{CDS}_{\mathrm{t}-1} + \varphi_2 \Delta \mathrm{CDS}_{\mathrm{t}-2} + \varphi_3 \Delta \mathrm{CDS}_{\mathrm{t}-3} + \varepsilon_{\mathrm{t}}$$

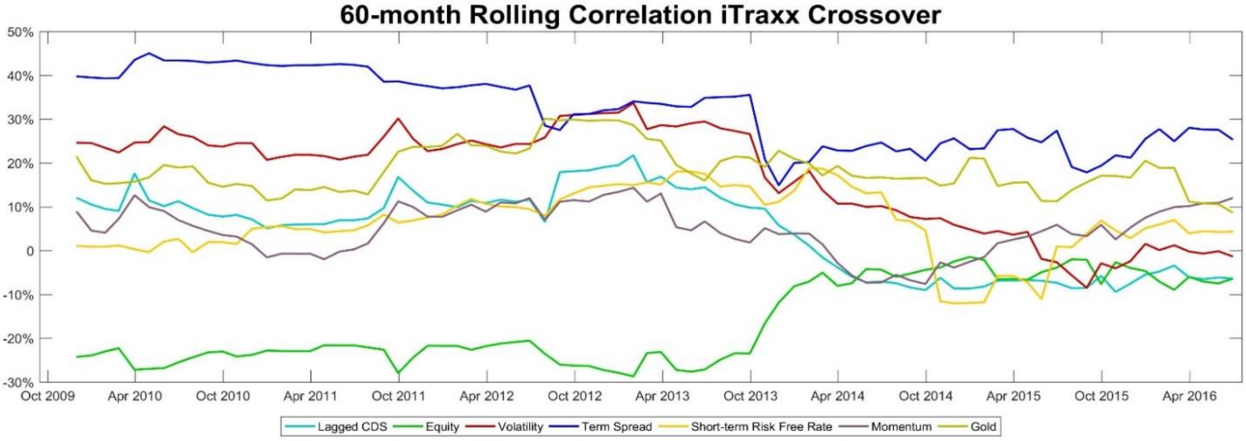
This allows to verify whether future credit spread changes may be forecasted using past credit spread changes, trying to exploit potential inefficiency in the CDS indices market.

In the last step, the *statistical performance* of the developed models has been assessed by looking at the *60-month rolling correlation* of the predictors with the subsequent monthly credit spread changes, aiming to investigate their pattern over time.

[33] The lagged credit spread changes have been calibrated according to the autocorrelation analysis carried out in 1st section. Consequently, k= 2 (meaning 2nd order autocorrelation) for iTraxx Europe, k=3 (meaning 3rd order autocorrelation) for CDX HY, and k=1 (meaning 1st order autocorrelation) for iTraxx Crossover and CDX IG.

Figures 2.1 and 2.2: 60-month rolling correlation of the predicting variables with the subsequent monthly credit spread changes of the iTraxx Europe and iTraxx Crossover



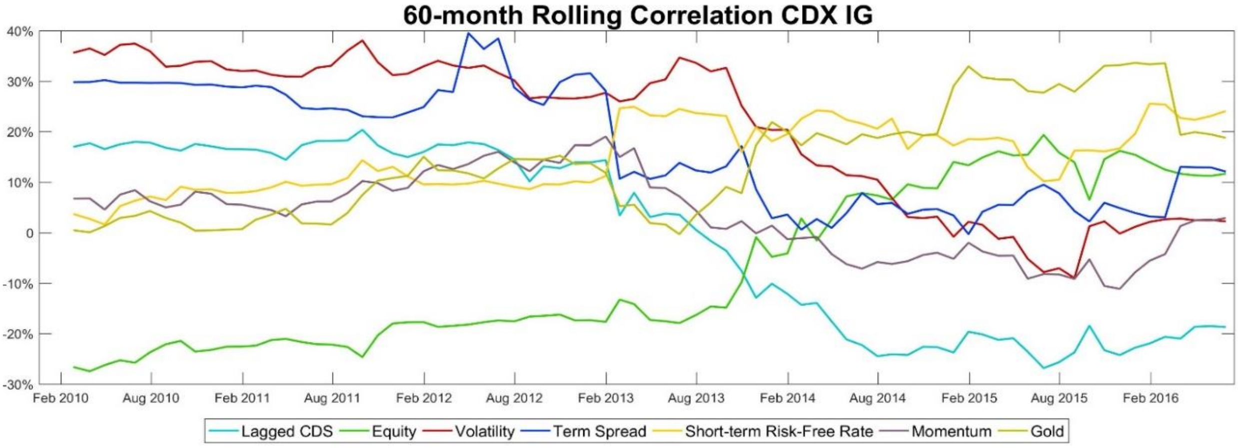


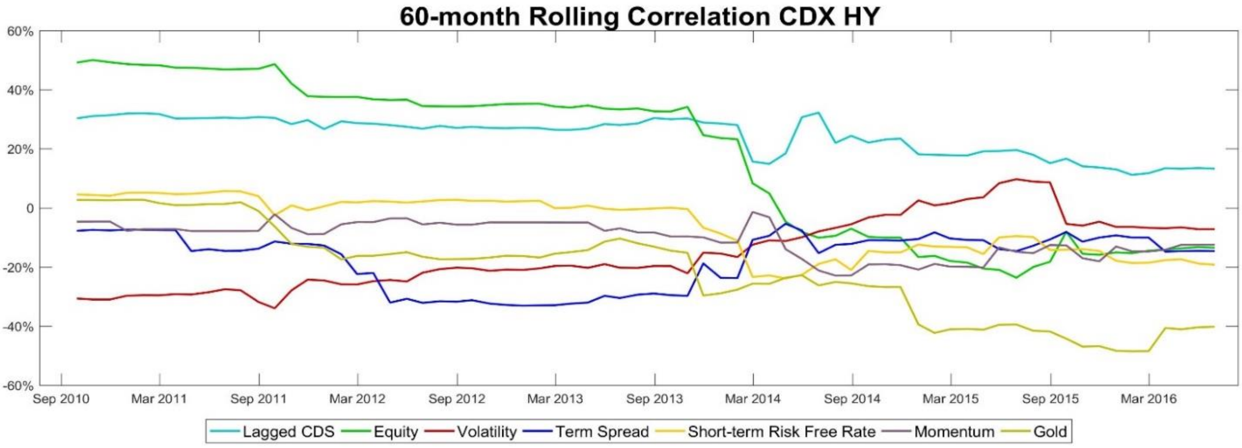
At first sight, the forecasting ability of the predicting variables in respect to the subsequent monthly credit spread changes is not constant over time, but it is rather time-varying.

In the European credit market, Term Spread and Gold are characterized by limited movements, meaning that these predicting variables present a good forecasting ability of credit spread changes over time.

The remaining predicting variables Lagged Credit Spread, Equity, Volatility, Short-term Risk-Free Rate and Momentum show a great forecasting ability until mid-2013. Afterward, one witnesses to a convergence to zero of the 60-month rolling-correlations, evidencing that in the recent years (from 2013 to 2016) such predicting variables are lacking in the ability to forecast the subsequent monthly credit spread changes.

Figures 2.3 and 2.4: 60-month rolling correlation of the predicting variables with the subsequent monthly credit spread changes of the North America CDX IG and CDX HY



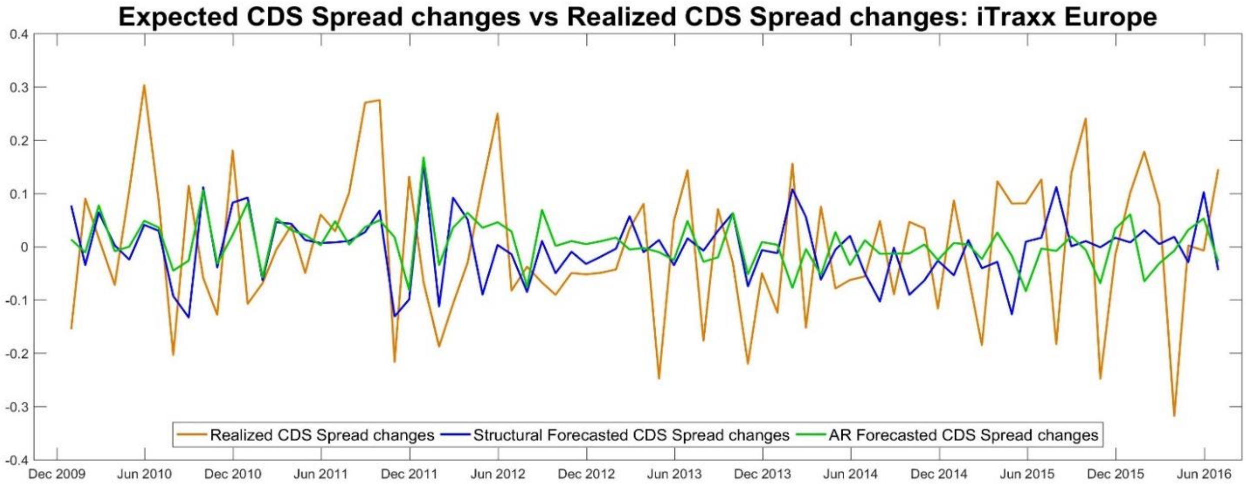


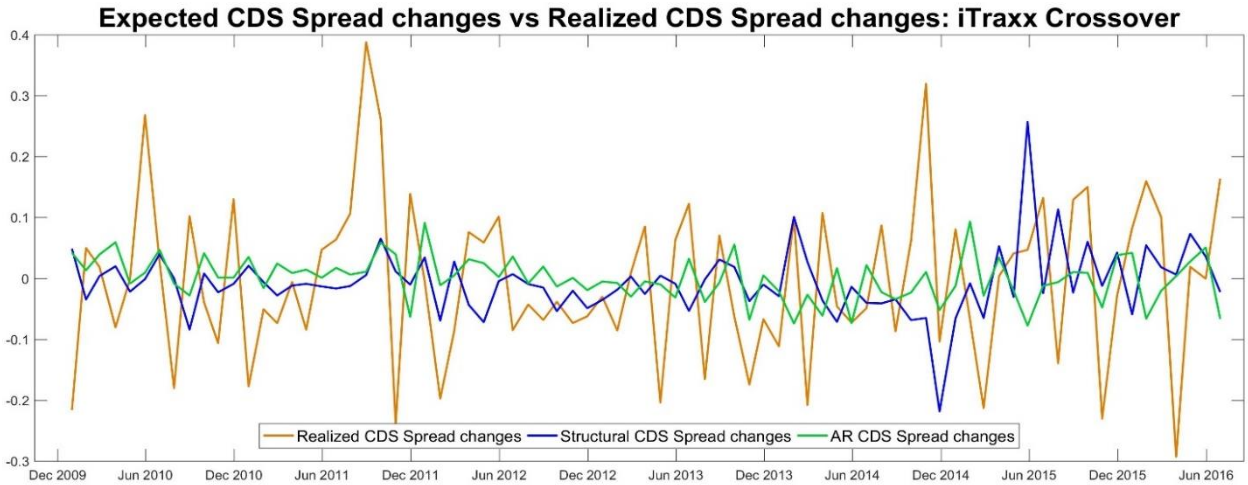
In the North America credit market, the 60-month rolling correlations show a well-established time-varying trend, expect for the CDX HY, where the lagged credit spread exhibits a rather time-constant pattern. In the first years, from 2010 to 2013, the 60-month rolling correlations are characterized by a constant behavior, where the highest correlations are with Lagged credit spread, Equity, Volatility, Term Spread, and Momentum. Since mid-2013, all 60-month rolling correlations tend to move around low levels, highlighting poor forecasting ability of such variables. Surprisingly, the 60-month rolling-correlation related to equity does not keep in negative field but it crosses and moves in positive field from the 2013[34], meaning that positive credit spread changes (that are credit spread widening) are observed in bullish markets, that is when positive equity returns occur.

[34] Since the CDX HY is quoted in terms of price, the relationship with credit spread changes is inverted.

To investigate the performance of the developed forecasting models, it is worth to compare the *forecasted credit spread changes* with the related *realized credit spread changes*.

Figures 2.5 and 2.6: Expected CDS spread changes vs realized spread changes of the iTraxx Europe and Crossover

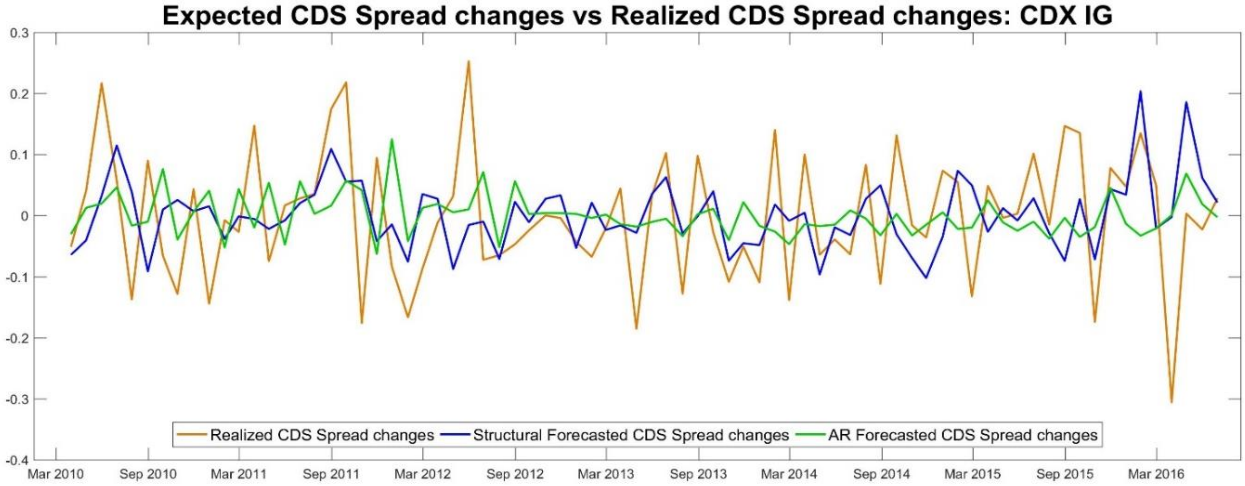


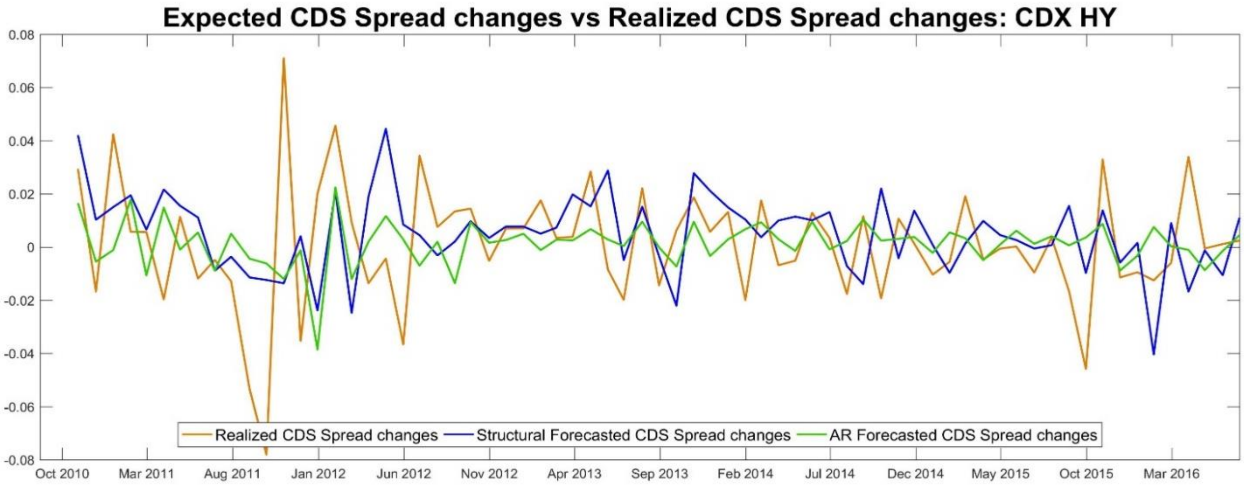


In each figure, realized credit spread changes, together with expected credit spread changes according to the linear structural and autoregressive models are plotted. At first sight one may assert that structural models seem to predict reasonably well the variation and in several events the magnitude, of the credit spread changes, particularly in the North America CDX.

Differently, the autoregressive models appear to predict the direction of the credit spread changes, but they do not capture the effective magnitude of their variation.

Figures 2.7 and 2.8: Expected CDS spread changes vs Realized spread changes of the North America CDX IG and CDX HY





Therefore, preliminarily, structural models present a greater ability in forecasting credit spread changes than autoregressive models.

The statistical performance is concluded by examining the accuracy of the models, through the employment of three different measures *Mean Absolute Error* (MAE), *Root Mean Square Error* (RMSE) and *Mean Correct Prediction* (MCP)[35].

[35] Avino D., Nneji O. – *Are CDS spreads predictable? An analysis of linear and non-linear forecasting models,* March 2014

Table 2.2: Statistical performance results

	iTraxx Europe		iTraxx Crossover		North America CDX IG		North America CDX HY	
	Structural Model	**AR Model**	**Structural Model**	**AR Model**	**Structural Model**	**AR Model**	**Structural Model**	**AR Model**
Mean	0.14%	-0.64%	0.21%	-0.49%	-0.36%	-0.23%	-0.41%	-0.04%
MAE	11.91%	11.68%	11.30%	11.25%	8.27%	8.83%	1.94%	1.69%
RMSE	14.20%	13.52%	14.07%	13.68%	10.68%	10.88%	2.55%	2.38%
MCP	56%	46%	51%	51%	61%	50%	59%	51%

As illustrated in the table above, structural model outperforms for each credit index the autoregressive model in terms of MCP (expect for the iTraxx Crossover where they equally perform), although the latter are characterized by smaller values of RMSE.

The MAE assumes rather low levels for the North American credit market, around 8% for Investment Grade segment and 2% for the High Yield one. Similar results hold in respect to the RMSE. These findings signal a greater accuracy of the forecasting models in the U.S market compared to the European one, confirming the previous arguments.

A further consideration relates to the fact that structural models correctly predict credit spread changes more than 50% of the times. The best results are achieved in the North American credit market, where the structural models are able to predict the correct direction around 60% of the times (61% for the CDX IG and 59% for the CDX HY). However, fairly good results are also obtained in the European market, with a MCP of 56% and 51%.

3. Trading Strategies

The final aim of the working paper is analyzing the *economic performance* of the structural models by implementing certain trading strategies so as to investigate whether investment strategies in the CDS investment grade and high yield markets may exploit such predictability in future credit spreads changes, therefore producing significant profits.

In order to design the structure of the trading strategies, the framework, adopted by the Ilmanen (1995), is followed.

In the implemented trading strategies, the following *assumptions* are made:

- all trades are made taking into account *transactions costs*;
- each position is held for a *holding period* of 1 month and it involves only investing in on-the-run series of the credit indices. Moreover, it is assumed that the running coupon is paid on a monthly frequency, at the end of the related month;
- all positions are default-corrected assuming a *recovery rate* equal to the one set by the credit index.

Opening a position on a credit index requires posting an initial margin as collateral with a CCP Thus, trading CDS indices are essentially l*everaged positions*.

The required initial margin is not constant over time and it is not constant over different launched series of a CDS index[36]. It is a function of several factors among which liquidity charge, interest rate sensitivity, jump-to-default, jump-to-health, etc.[37]

Table 3.1: Initial Margins of opening positions with a CCP

	Buyer Protection	Seller Protection
iTraxx Europe and CDX IG	0.80%	1.61%
iTraxx Crossover	2.16%	3.30%
CDX HY	3.53%	5.00%

[36] The time series of initial margins applied by the CCPs are proprietary data, not publicly available. However, the CME Group provided me the initial margins for the on-the-run series dated only on 13th September 2016. So, it was decided to assume those margins as fixed among the sample period.

[37] For further details regarding the rules governing the posting of collateral and its main determinants, please refer to "*Introduction to the New CDS Model*", CME Group, September 2014

The economic performance is explored through several indicators such as *Sharpe Index*, *Drawdown Measure* and *Zeroes Index*. Moreover, for the purpose of backtesting such trading strategies, the cumulative performance in terms of NAV of different portfolios of a closed-end fund, individually invested in the CDS indices, iTraxx Europe, iTraxx Crossover, North America CDX IG and North America CDX HY, is analyzed[38].
Two different kind of trading strategies were implemented:

- *Static Strategies*: they consist of investing in credit indices, without regard to the effective economic and market conditions and without exploiting the trading signals provided by the forecasting structural models. Hence, such kind of strategy may be attributed to a passive portfolio management.

  This class comprises the so called "*Always Spread Strategy*". It implies being long credit risk (namely being a seller protection) on a notional of $/€ 250000 in the credit indices, irrespective of the financial performance of the markets.
- *Dynamic Strategies*: they involve investing in credit indices, basing the own investing decisions on the trading signals provided by the structural models. As a consequence, these strategies imply actively managing a portfolio on a monthly basis, where its composition depends on the type of forecasting signal issued by the structural models.

  This classification encompasses:
  - *Binary Spread Strategy*: this strategy calibrates the portfolio allocation according to the forecasted credit spread changes: it involves opening a long position (short position) written on a notional of $/€ 250000 when the forecasted credit spreads change is greater (less) than a trading trigger α.

    This strategy essentially exploits the ability of the structural models to predict the credit spread changes in the correct direction, regardless the effective accuracy of the forecasted spread changes;
  - *Scaled Spread Strategy*: this more speculative strategy exploits not only the ability to forecast in the correct direction, but it takes into account also the magnitude of the forecast.

    This strategy tailors the size of the investment to the magnitude of the expected credit spread changes: long and short positions are essentially proportional to the forecasted value of the credit spread changes: the larger the predicted credit spread change in the model is, the greater the notional against which the position is opened.

[38] Ilmanen A. – *Forecasting U.S Bond returns (Understanding the Yield Curve Part 4),* August 1995

In order to set the more feasible and profitable trading triggers α and to evaluate the performance of the trading strategies over the period, a *What-If Scenario Analysis (WISA)*, with several triggers α ranging from 0.50% to 3% with steps of 0.50%, has been implemented. This analysis allowed to evaluate the impact of different trading triggers on the profitability of the strategies and additionally it provides a more reliable investment-tool regarding the forecasting models. By means of it, it was possible to pick the thresholds such that the strategies are more profitable in terms of average annual returns. The WISA thresholds reveal for both strategies *short-biased investors*, meaning that these strategies foster opening more short positions (in other words being a seller protection) than long positions; the latter are opened only when there is strong evidence from the forecasting model that the credit spreads are effectively expected to climb.

In summary, the Scaled Spread Strategy represents the most speculative strategy compared to the Binary Spread Strategy, because in trading it takes into account not only the correct direction of the forecasted credit spread changes, but also the size of such changes.
So, it is expected a greater performance in terms of profitability of the Scaled Spread Strategy.

Tables 3.2, 3.3 and 3.4: Economic performance of the Always Spread strategy, Binary Spread strategy and Scaled Spread strategy

	Always Spread Strategy			
	iTraxx Europe	**iTraxx Crossover**	**North America CDX IG**	**North America CDX HY**
Avg An. Exc. Return	35.7%	134.8%	45.7%	45.3%
Max Return	108.2%	187.4%	82.7%	132.1%
Min Return	-130.9%	-234.5%	-74.5%	-140.7%
Volatility	148.4%	257.4%	98.1%	152.2%
Number of Rebalances	79	79	76	69
Zeros Index	0	0	0	0
Max Drawdown	4.1%	3.1%	0.1%	15.7%
Avg Annual Drawdown	3.1%	6.6%	0.5%	9.7%
Sharpe Ratio	24.1%	52.4%	46.6%	29.7%

	Binary Spread Strategy			
	iTraxx Europe	**iTraxx Crossover**	**North America CDX IG**	**North America CDX HY**
Avg An. Exc. Return	100.5%	64.1%	49.5%	83.8%
Max Return	250.6%	272.4%	138.7%	89.3%
Min Return	-97.9%	-220.5%	-143.6%	-64.9%
Volatility	195.5%	217.3%	129.4%	93.3%
Number of Rebalances	57	61	47	37
Zeros Index	22	18	29	32
Max Drawdown	2.3%	10.9%	1.0%	0.0%
Avg Annual Drawdown	1.1%	5.5%	1.5%	3.7%
Sharpe Ratio	51.4%	29.5%	38.3%	89.8%

	Scaled Spread Strategy			
	iTraxx Europe	**iTraxx Crossover**	**North America CDX IG**	**North America CDX HY**
Avg An. Exc. Return	115.5%	65.2%	60.9%	95.9%
Max Return	250.6%	272.4%	138.7%	89.3%
Min Return	-97.9%	-220.5%	-143.6%	-64.9%
Volatility	196.6%	234.9%	139.0%	102.9%
Number of Rebalances	60	65	60	48
Zeros Index	19	14	16	21
Max Drawdown	2.1%	15.5%	0.9%	0.0%
Avg Annual Drawdown	1.3%	11.0%	3.3%	5.0%
Sharpe Ratio	58.8%	27.8%	43.8%	93.2%

Tables above summarize the economic results of the trading strategies.

The findings unveil that the dynamic strategies, particularly the Scaled Spread Strategy, perform progressively better than the static one, both in terms of average annual excess returns and in terms of Sharpe Ratio in respect to each credit index. This holds expect for the iTraxx Crossover where the best strategy is found in the Always Spread Strategy. This may be explained by the timing of credit events of the underlying reference names: all credit events occurred in the iTraxx Crossover regard off-the-run series, while these implemented trading strategies imply a rollover trading on the most recent on-the-run series.

Let's take a look in detail to the performance for each credit index:

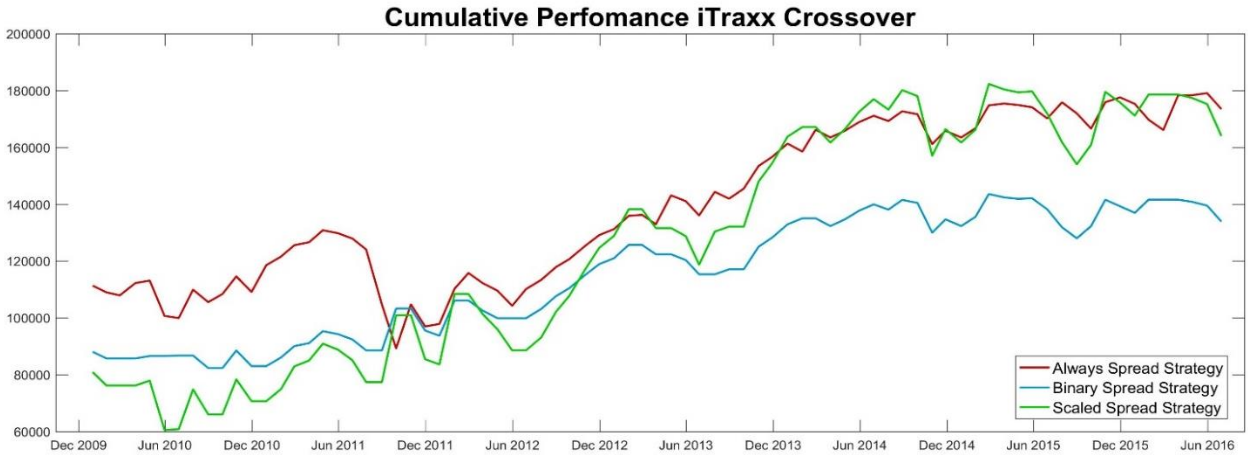
- **iTraxx Europe**: compared to the benchmark Always Spread strategy, both Binary Spread and Scaled Spread are able to perform better, with average annual excess returns 3-4 times of that one of the Always Spread Strategy: from about 36% to 101% for Binary Spread and to 116% for Scaled Spread. This finding is also confirmed by the increasing Sharpe ratios, with the best result of 59% achieved with the Scaled Spread Strategy.
  Regarding the monthly rebalances, the Scaled Spread Strategy requires slightly more rebalances than the Binary Spread one and this fact is also confirmed by the Zeroes index (19 vs 22). Thus, the Scaled Spread Strategy is characterized by a more active component in portfolio management.The maximum and average Drawdown levels are low around 2% and 1%, implying a rather constant profitability of both dynamic strategies.
  All these findings confirm the goodness of the forecasting structural model for the iTraxx Europe index.
- **iTraxx Crossover**: here the dynamic Binary Spread and Scaled Spread underperform the benchmark Always Spread Strategy, in terms of average annual excess return and Sharpe Ratio: the static Always Spread provides an excess return of about 135% with a Sharpe Ratio of 52% in respect to the about 65% of excess return and 29% of Sharpe Ratio of the Binary Spread and Scaled Spread. This may be explained by the timing of credit events of the underlying reference names: all credit events occurred in the iTraxx Crossover index regard off-the-run series, while these implemented trading strategies imply a rollover trading on the most recent on-the-run series of the index. Hence, for the iTraxx Crossover, the most profitable strategy would have to be short in the index, namely being a seller protection: in this way, the investor would have earned all periodic cashflows, without any outflow due to the credit events.
- **North America CDX IG**: the dynamic strategies are found to outperform, particularly the Scaled Spread one, the benchmark Always Spread Strategy: for the Always Spread and Binary Spread the average annual excess return is almost the same, just lightly better for the Binary Spread one (46% vs 50%), instead the Scaled Spread seems to outperform with an average annual excess return of 61%.
  However, it is worthwhile to mention that the static Always Spread presents the best risk-return profile among the related dynamic strategies, with a Sharpe Ratio of 47%, against 38% and 44%, respectively of the Binary Spread and Scaled Spread, due to the lower volatility.

Although the Scaled Spread Strategy overperforms the other ones, it requests a number of monthly rebalances of 60 against 47 of the Binary Spreads: so, the former strategy needs a more active management from a portfolio manager's point of view.

- **North America CDX HY**: here, the Scaled Spread Strategy achieves better results than the Binary Spread and Always Spread Strategies, both in terms of average annual excess return, 96%, and in terms of risk-profile, with a Sharpe Ratio of about 93%.
  The Always Spread strategy is not very profitable since the credit index suffered since its launch about 8 credit events on its on-the-run series and such strategy prescribes to be always long on the index (that is being constantly a seller protection).
  The dynamic strategies are able to get better returns and to lower the related volatility, causing an improvement in the values of Sharpe ratio, 90% for Binary Spread and 93% for the Scaled Spread. Moreover, the number of monthly rebalances, 48 for the Scaled Spread and 37 for the Binary Spread Strategy, signals an efficient active management for a portfolio manager. Nevertheless, the implementation of such dynamic strategies requires a minimum capital buffer, in order to bear the on-going trading losses, highlighted by the high levels of average drawdown, about 5%.

Furthermore, the *economic performance* has been assessed by "backtesting" the feasibility of the above mentioned trading strategies, supposing the business of a closed-end investment fund that trades separately in the four different credit indices according to the Always Spread Strategy, Binary Spread Strategy and Scaled Spread Strategy.
The backtest is carried out assuming that the investment fund has a minimum capital buffer of $/€ 100000, in order to satisfy the initial and on-going margin requirements and to support the capital drawdowns due to the potential trading losses.
Figures below show the cumulative growth of the NAV (Net Assets Value) of an investment fund holding both static and dynamic portfolios.
At first sight it is possible to assert that the dynamic Binary Spread and Scaled Spread Strategies have shown a greater ability to outperform the static Always Spread Strategy.
Regarding the investment in the iTraxx Europe, the most profitable portfolio in terms of cumulative NAV is the one invested in the Scaled Spread Strategy: during the years end-2009/mid-2011, all portfolios equally perform. Afterward, the Scaled Spread and Binary Spread Strategies are able to "beat" the static Always Spread, achieving a greater NAV.
Concerning the portfolio invested in the iTraxx Crossover, the best portfolio in terms of NAV is the one invested in the Always Spread Strategy.

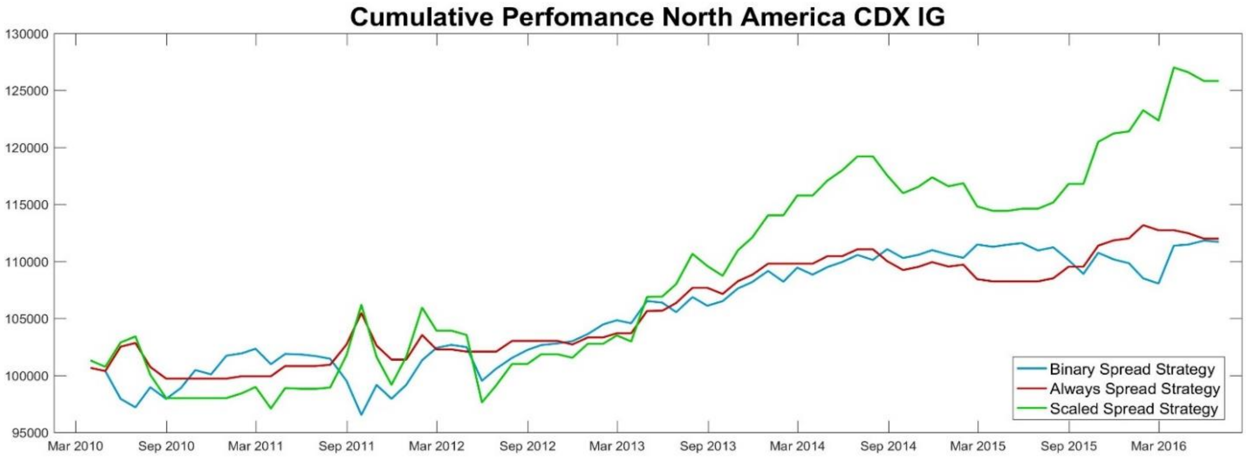
Figures 3.1 and 3.2: Cumulative performance of the iTraxx Europe and iTraxx Crossover



Regarding the investment in the iTraxx Crossover, in the first years of the sample, from December 2009 to September 2011, the dynamic strategies, especially the Scaled Spread, incur in heavy trading losses, signal that in this period the structural model does not work in predicting correctly future spread changes.

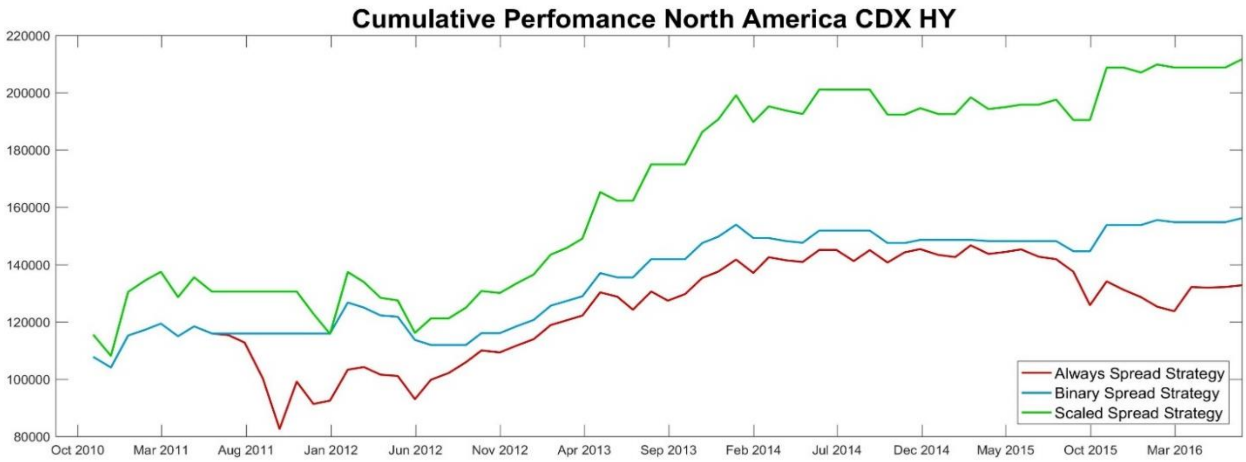
However, from the end of 2011, the Scaled Spread recovers ground, equally performing to the Always Spread, in the last months of the sample. The explanation of the consistent greater performance of the Always Spread strategy is attributed to the lack of credit events in the pool of names of the on-the-run series.

Figure 3.3: Cumulative performance of the North America CDX IG



Here for the North America CDX IG most of the part of the sample period from March 2010 to end-2013, the cumulative NAV of all strategies is performing roughly the same. Just in the last years 2014-2016, the model seems to remarkably work, causing an out-performance of the Scaled Spread Strategy compared to the Binary Spread and Always Spread Strategies. These results allow to assert that the model appears to work in periods which are not affected by the turbulences caused by the 2009 U.S Subprime Mortgages Crisis.

Figure 3.4: Cumulative performance of the North America CDX HY



For the portfolio invested entirely in the CDX HY index, the best results are achieved in terms of NAV, where its value is viewed to double in respect of the beginning of the management of such portfolio. The Scaled Spread strategy outperforms the other ones, the Binary Spread and the Always Spread.

Although the Binary Spread and Always Spread exhibit a quite similar cumulative performance, the former is able not to incur in trading losses in the first years of the sample period.

The above analysis has evidenced a common feature to all managed portfolios invested in credit indices: the forecasting structural models are able to issue reliable signals in periods far away from the 2009 turmoil. All dynamic portfolios are characterized by an equal cumulative performance and in some cases by an underperformance (for example in the portfolio invested in the iTraxx Crossover) in respect to the static portfolio during the years 2009-2011, when the structural models estimate the coefficients using essentially information and signals experienced in the period of disruption of the 2007-2008 financial crisis.

Conclusions

In the last years, most studies relating to CDS markets have cast attention merely on the identification of the main determinants explaining the credit spread changes, while very few studies have analyzed the real opportunity to forecast such credit spread changes of CDS indices.

The main challenge of this analysis has been finding and building the appropriate dataset: from 2007 all of these CDS indices are fully owned and managed by Markit.

Consequently, the related data are proprietary, not fully available for educational purposes.

This working paper represents one of the first attempts to investigate not only the statistical predictability of credit spread changes, employing structural models, but also to assess the economic robustness implementing both static and dynamic strategies.

The first result leads to the conclusion that credit spread changes of CDS indices, on a monthly basis, are not completely unpredictable whereas there is a forecasting component that affects such changes.

The analysis was carried out on the European and North American CDS indices, respectively, iTraxx Europe, iTraxx Crossover, North America CDX IG and North America CDX HY, with a 5-year tenor, representing the most liquid and traded segment of the CDS market.

The investigation included in the first chapter highlighted the presence of a significant second-order and third-order autocorrelations in the iTraxx Europe and a significant autocorrelation structure in the North America CDX HY monthly spreads. This result suggests a degree of inefficiency in the CDS indices markets, where actual credit spread changes seem to be lead-lagged. In order to predict the credit spread changes, Autoregressive AR(3) models as benchmarks and linear forecasting structural models were employed. The latter were calibrated according to the autocorrelation analysis and including the following predicting variables:

- Lagged Credit Spread Changes;
- Equity Value Changes;
- Equity Volatility Changes;
- Term Spread;
- Short-term Risk Free Rate;
- Gold Price Changes;

- Momentum.

The statistical performance was assessed according to the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Correct Prediction (MCP) and 60-month rolling correlation. As in economic variables' forecasting, here the attention is focused on the ability of the models to predict the correct direction of the changes, rather than the effective magnitude. The findings unveil that the developed forecasting structural models are able to outperform the Autoregressive models; additionally, they predict reasonably well the future credit spread changes, with a correct direction prediction of more than 50%.

The economic performance was evaluated by implementing two different kind of strategies:

- Static Strategies: they imply a passive portfolio management where the portfolio composition is statically rebalanced each month being always short on the credit indices;
- Dynamic Strategies: they are characterized by an active portfolio management, where the portfolio composition is essentially rebalanced each month according to the trading signals issued by the forecasting structural models, taking into account both the direction and the magnitude of the changes.

Additionally, the economic performance was tested through a backtest procedure. It was applied to the trading strategies assuming a closed-end investment fund, investing separately in portfolios of CDS indices, and analyzing the cumulative performance or, in other words, the cumulative NAV of the fund.

The trading results have mostly confirmed the findings arisen in the statistical performance, with the best profitable results achieved with the dynamic portfolios, especially in the European and U.S investment grade and high yield markets.

The results have evidenced a certain degree of predictability in the credit spread changes; therefore, the CDS markets cannot be considered to be completely informational efficient.

A portfolio manager may exploit the predicting information embedded in the chosen set of predictors, improving the portfolio performance.

However, it should be remembered that trading CDS indices are leveraged positions and thus highly risky, and consequently the returns and volatility may be significantly high.

To conclude, trading CDS indices request, as highlighted by the levels of drawdown, a minimum capital buffer in order to support the on-going margin requirements and the potential trading losses.

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