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Pairing Market Risk with Credit Risk*

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Abstract

This paper uses an exclusive proprietary data set of European Credit Derivatives and VIX markets, covering a sample of 5 to 7 years, to study the nature of the link between credit risk and market risk, widely acknowledged in the academic literature. This allows us to establish cointegration in the VIX and iTraxx/CDS markets in a framework where arbitrageurs exploit temporary equilibrium mispricing following pairs strategies. Expected profits, defined in terms of VECM parameters, are positive for all VIX-iTraxx pairs strategies considered. Markets are integrated in that price discovery on both sides of the Atlantic reflect the same underlying information with predominant price leadership of the VIX market over the European CDS market.

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1. Introduction

Over the last few years, the relationship between credit spreads and equity volatility has been widely studied in the financial empirical literature in a framework where credit risk is priced in terms of its theoretical determinants. Ericsson, Jacobs, and Oviedo (2009) explain 60% of the variation of swap spread levels using a measure of leverage, historical volatility and the risk free rate. Different results were obtained by Collin-Dufresne, Goldstain and Martin (2001) who investigate changes in bond yield spreads and conclude that factors suggested by traditional models explain only about one quarter of the variation of credit spreads. Cambell and Tasker (2003) focused on the effect of equity historical volatility on corporate bond spreads and conclude that the effects of volatility are important. Zhang, Zhou and Zhu (2009) used default swap data and documented statistically and economically significant effects of (long term) historical volatility, (short term) realized volatility and various jump measures on credit spreads. Cao, Yu and Zhaodong (2010) and Cremers, Driessen, Maenhout, and Weinbaum (2008ab) analyzed the relationship between bond spreads, equity at-the-money option implied volatility, and jump risk acknowledging the forward looking information inherent in stock options. In a related work, Carr and Wu (2010) propose a dynamically consistent framework allowing joint valuation of stock options and CDS at the individual entity level. The main conclusion of these studies is that volatility increases the probability of default and therefore the spreads. This is consistent with the predictions classical asset pricing theory as envisaged in the framework of Merton (1974), where stock price volatility increases credit spreads.

An interesting finding within this literature is that option implied volatility dominates historical volatility in explaining variation in credit spreads. [1] Related to this empirical relationship is the recognized role of the VIX index in determining credit spreads (see for example Collin-Dufresne et al. 2001, Schaefer and Strebulaev 2008, among others). VIX has also been acknowledged as an important determinant of credit risk premium from sovereign CDS spreads (see Pan and Singleton 2008, and Longstaff, Pan Pedersen, Singleton 2011). VIX is in this context a widely watched measure of event risk in credit markets. Bao Pan and Wang (2011) find a close connection between the VIX index and an aggregate illiquidity measure constructed with corporate bond data.

In response to this literature, we use an exclusive European credit derivative data set we investigate the link between credit risk and forward market volatility in absence of other explanatory variables. For a broad sample of 47 individual company iTraxx /CDSs covering 5 to 7 years, we propose a no-arbitrage relation between European CDSs and the VIX volatility index within equilibrium demand and supply framework proposed by Figuerola-Gonzalo 2010 (FG thereafter). This model develops the dynamics in two distinct but cointegrated markets and shows how market participants exploit temporary mispricing performing arbitrage strategies. Our paper focuses on the adjustment of the two cointegrated series to any event that causes divergences from the long run equilibrium. It evolves around the speed by which arbitrageours restore disequilibria allowing measurement of price discovery and arbitrage profit determination. Within this framework we find short lived deviations from long term equilibrium between market risk and credit risk and a lead of VIX over the CDS market in the price discovery process. Our results are therefore consistent with market integration for geographically distinct markets such as Europe and the US.

[1] See Cao et al. (2010) for the CDS case and Cremers et al. (2008ab) for bond yield data.

Credit risk can be defined as the risk of loss resulting from failures of counterparties or borrowers to fulfil their obligations. Credit risk appears in almost all financial activities, so it is important to measure, price and manage it precisely. Credit risk is hedged via credit derivatives, which are financial contracts that transfer the (credit) risk and return of an underlying asset from one counterparty to another without actually transferring the underlying asset.

The value of any credit derivative is linked to the probability of the underlying reference entity being exposed to a credit risk event (bankruptcy, delayed payment, restructuring, etc) at some point in the future. The most important credit derivative market is the credit default swaps (CDS) market, which makes about half of the total credit derivatives trading volume. A credit default swap is essentially an insurance contract providing protection against losses arising from a credit event. The market for credit derivatives came into existence in 1992 and has been growing exponentially during the past decade, reaching $62 trillion in notional amount outstanding by the end of 2007. This a amount was reduced in the post-crises period to $36 trillion in 2011.

Large exposures to a diversified pool of credit risk are now much easier to gain thanks to the high liquidity of the iTraxx market. The iTraxx suite of indexes are owned, managed, compiled and published by Markit, who also license market makers. ITraxx indexes are standardized contracts and reference a fixed number of obligors with shared characteristics. Investors can be long or short the index which is equivalent to being protection sellers or buyers. The most widely traded of the family of iTraxx indices is the iTraxx Europe index (iTraxx thereafter), a portfolio of the 125 most liquid CDS of European Investment Grade rated companies in the market.

We study the nature of the relationship between VIX and iTraxx/CDS markets by proposing pairs trading strategies in cointegrated markets. The CBOE implied volatility index VIX, is a key measure of market expectations of near-term volatility conveyed by S&P 500 stock index option prices. Since its introduction in 1993, VIX has been considered by many to be the world's premier barometer of investor sentiment and market volatility.[2] On March 2004 the CBOE launched the futures in the VIX index. As volatility became a recognized asset class, VIX futures volume and open interest continued to set new records. As a result, the exchange changed the start time for the trading of futures on the CBOE Volatility Index (VIX) from 8:30 a.m. (Chicago time) to 7:20 a.m. The closing time remains 3:15 p.m. (Chicago time) for VIX futures. VIX options were introduced in 2006 and they have been the most successful contract in the history of the exchange.[3] There is therefore a potential four hour overlap of trading between the VIX and the European CDS market over the sample period analyzed.

The differences between iTraxx and VIX derivatives trading are important. While iTraxx CDS contracts are mainly traded OTC (with recent incorporation into NYSE Euronext Bclear Platform) trading at CBOE is carried out by the exchange's Hybrid system, which has both open outcry and electronic orders.[4] While CBOE trading is an open trading platform with complete access to market participants, iTraxx (and CDS) trading is restricted to institutional investors including hedge funds and capital structure arbitrageurs. The markets do however have a potential for being integrated for the following reasons. First, both markets have experienced recent surge in volumes of trading. Second, there are low regulatory constraints preventing cross trading between

[2] http://www.cboe.com/micro/VIX/vixintro.aspx
[3] Option trading takes place from 8:30 to 3:15 (Chicago time).
[4] Eurex launched exchange-traded futures (not CDS) contracts based upon the iTraxx Europe Main, HiVol and Crossover 5 year indices in 2007, but these products achieved minimal volume at launch and do not currently trade.

VIX derivative products and European CDS derivatives. It has now been widely acknowledged by market participants that credit risk and market volatility are closely related. Market integration is assessed by modeling price discovery over our sample period.

Exploring deeper into the information content of the VIX index, we address the following question: can we capitalize on our cointegration and price discovery results to make arbitrage profits? To answer this question, we focus on “pairs trading” strategies. These are Wall Street investment strategies that belong to the proprietary “statistical arbitrage” tools currently implemented by investment banks and hedge funds. Forming pairs of VIX futures with portfolio CDS, we find that profits from pairs strategies outperform profits from investing in VIX futures or iTraxx alone. A series of out of sample tests show that our results are robust to the extension of the data set.

Our paper contributes to the existent literature in a number of ways. We reconsider the underlying relationship between credit risk and volatility widely acknowledged in the academic community and model it in a price discovery framework establishing cointegration in the two integrated markets. Several credit risk price discovery studies have focused exclusively on information from just a single or at most two financial markets. Longstaff, Mithal and Neiss (2003) studied a sample of US bonds and found that information in equity markets leads information in debt markets. Blanco, Brennnan and Marsh (2005) analysed a set of European and US bonds using CDS prices and credit spreads in the bond cash market and found that the CDS market is the leader in the price discovery process. We contribute to the credit risk price discovery literature by focusing on two proxies for the aggregate market condition: market risk and credit risk and showing that market risk as captured by the VIX index leads the price discovery process. This allows recognition of the important role of implied volatility in the determination of credit risk as envisaged in Collin-Dufresne et al (2001) and Carr and Wu (2010) among others.

This paper also adds to the current debate on whether credit risk and equity (option) volatility are integrated (see Cremers et al. 2008b). We therefore advance in the cointegration and price discovery literature by suggesting market integration across asset classes (credit risk and market risk) and across geographical sites (Europe versus US). Geographical market integration is assessed in Hupperets and Menkveld (2002) and Pascual et al (2006). This paper relates to their work but it does not focus on the analysis of the overlapping trading hours. Instead, it relies on a full day perspective based on available daily data. In addition, the global contribution of the VIX index is acknowledged, to propose pairs strategies between CDS and VIX markets whose profits are explained within VECM dynamics.

By testing cointegration and the existence of abnormal returns we shed light to empirical literature on price efficiency. Brennan and Wang (2010) integrate the empirical price efficiency and the asset pricing literature by showing that expected rates of return depend on fundamental risk as well as asset mispricing. Our work relates to this literature in that it decomposes observed prices of cointegrated series into a common fundamental value and a transitory component reflecting market frictions. We are interested in arbitrage strategies that exploit temporary misspricing in related assets. Relative pricing means that two securities that are close substitutes for each other should sell for the same price. The law of one price (see Ingersoll 1987 and Chen and Knez 1995) can be applied to relative pricing. This is potentially useful to researchers because, despite considerable theory about market efficiency, economists have little empirical information of how efficiency is maintained in practice. In this paper we shed light to the empirical literature on price efficiency and propose pairs trading strategies built upon the existence of temporary mispricing.

The rest of the paper is organized as follows. Section 2 relates the VECM to the construction of pairs trading strategies. This requires a description of preliminaries and main result of the FG model applied to credit risk and market risk (detailed exposition of the model is presented in Appendix A.1). Data and empirical results on cointegration and price discovery are presented in section 3. In section 4 we report profits from "pairs trading" strategies. Section 5 performs an out-of-sample analysis to test for robustness of results. Section 6 concludes. Additional tables and graphs are collected in appendix A.2 and A.3 respectively..

2. VECM Dynamics, Price Discovery and Pairs Strategies

The goal of this section is to characterize the dynamics of VIX and iTraxx/CDS in an equilibrium framework based on the existence of pairs strategies. We focus on the adjustment of VIX and CDS prices under the existence of temporary misspricing. Following the recent empirical literature on credit risk we choose CDS spreads as a direct measure of credit risk because it has several advantages over bond spreads. First, as noted by Zhang et al. (2009) as well as Ericsson et al. (2009), CDS spreads provide relatively pure pricing of default risk and are typically traded on standardized basis. Second, bond spreads are usually more affected by differences in contractual arrangements, such as differences related to seniority, embedded options and coupon rates. Third, as was shown by Blanco Brennan and March (2005) the absence of funding and short-sale restrictions in the derivatives market, allows the CDS market to adjust faster to changes in credit risk conditions than the corporate bond market.

Participation in the VIX markets is open to all individuals who trade in CBOE hybrid system. Participants in the CDS markets are institutional investors that take positions on the (iTraxx) index or on individual CDSs. Knowledge about the characteristics of the joint dynamics between VIX derivatives and CDS index markets is crucial to arbitrageurs which, will exploit (short lived) deviations from equilibrium in search for benefit from pairs strategies. This process is expected to lead into market integration, which arises from cointegration in the underlying markets. In this section we analytically describe cross market dynamics.

Let x_t be the spread underlying a credit derivative or a credit derivative index in time t. Let v_t be the contemporaneous value of VIX forward looking volatility index. In order to find the non-arbitrage equilibrium condition the following set of standard assumptions apply in this section:

- (a.1) No limitations on borrowing.
- (a.2) No cost other than arbitrage transaction cost.
- (a.3) No limitations on short sale.
- (a.4) Transaction costs between credit derivatives and the VIX derivatives markets are determined by the stationary process z_t. [5] Transaction costs consist of commissions involved in opening and closing positions in the CDS and the VIX portfolio.
- (a.5) Credit derivatives and VIX derivative prices are I(1), implying that their mean and auto covariances are different for every realization of t.

[5] See Brennan and Schwartz (1990) for an exposition of optimal arbitrage strategies with transaction costs and position limits.

By the above assumptions (a.1-a.5), non-arbitrage equilibrium conditions imply:

$$x_t = \gamma_0 + \gamma_1 v_t + z_t \tag{1}$$

where γ_0 is the (constant) cash amount invested to buy γ_1 units of VIX (required to replicate spreads in the CDS portfolio). Therefore γ_1 reflects the size of the position that has to be taken in the VIX portfolio to replicate returns in the CDS market.

Equation 1, implies that x_t and v_t are cointegrated suggesting that there is market integration. The arbitrage relationship specified in (1) shows how spreads of credit derivatives and credit derivative portfolios can be replicated with positions in the VIX market. z_t reflects transaction costs, incurred in pursuing pairs strategies in both markets or any other related factors or imperfections that generate a random difference in the VIX and CDS spreads levels.

To study the mechanism lying behind market integration in the CDS and VIX markets, we adapt the FG theoretical model to focus on how pair strategists restore temporary misspricings. When the spread between VIX and CDS widens, there is a positive profit potential that can be exploited by an arbitrageur that shorts the winner and buys the loser. If the long and short components measure a common non stationary factor, the prices will restore equilibrium providing positive average (and cumulative) profits.

When convergence to long run equilibrium is immediate, there is very limited opportunity to profit from pairs strategies. This happens when there is an infinite elasticity of demand for pursuing pairs strategies (H).[6] In this case, there is an immediate price adjustment to divergences between the CDS and the replicating VIX portfolio. As a

[6] This requires H$\rightarrow\infty$ in equation (2). This elasticity measures the proportional change in demand for “pairs strategies” for a given change in the quantity of arbitrage services.

consequence, potential profits represented by z_t in equation (1), are zero. However, there are a number of cases in which the elasticity of demand for pairs strategies is not infinite in the real world. Many factors, mainly arising from transaction costs, significant position limits, differential tax treatment in the CDS and VIX markets, restrictions in the short run availability of capital, may limit the supply of arbitrage services for pursuing pairs strategies, by making arbitrage transactions between both markets risky (which implies $H>0$ and $z_t \neq 0$). This complicates the dynamics between market risk and credit risk.

The model developed in appendix A.1 describes the interaction between agents that trade in the credit derivatives and the VIX market, when there is finite elasticity of demand for pursuing pairs strategies. Under this more realistic case, the dynamics between the VIX and iTraxx markets may be represented as:

$$\begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \frac{H}{d} \begin{pmatrix} -N_v \\ N_x \end{pmatrix} \begin{pmatrix} 1 & -\gamma_1 & -\gamma_0 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ v_{t-1} \\ 1 \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \tag{2}$$

with

$$d = (H + AN_x)N_v + \gamma_1 HN_x \tag{3}$$

Where there are N_x participants in the credit derivatives market and N_v participants in VIX market and, as previously specified, the elasticity of demand for pursuing pairs strategies is noted by H.

We rewrite the theoretical result in (2) as[7]

$$\Delta Y_t = \begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} \hat{z}_{t-1} + u_t, \tag{4}$$

[7] Note that in the empirical part lags of ΔY are chosen in order to obtain white noise errors.

with $z_t = x_t - \gamma_0 - \gamma_1 v_t$ and u_t a vector white noise with i.i.d shocks.

In order for the VECM to be well defined and “pairs strategies” between VIX and iTraxx/CDS to work, the following conditions should be satisfied:

I. If α_1 and α_2 are both statistically significant, they must have opposite signs, as predicted by the theoretical result in (2). This implies that, if there is a change in the equilibrium error, so that for instance x_t is greater than its replicating VIX portfolio (z_t>0), in order to restore equilibrium x_t is expected to fall in the next period while v_t is expected to increase. In this case α_1 will be negative and α_2 positive, so pairs strategists will short the CDS (outperformer) and buy VIX (underperformer) to exploit price divergences. This allows positive profits until temporary mispricing disappears.

II. If z_t>0 and the CDS market were contributing significantly to price discovery, α_2 will be positive and statistically significant as the VIX market adjusts to incorporate new information. Similarly, if the VIX market is an important venue for price discovery then α_1 would be negative and statistically significant. If both coefficients are significant then both markets contribute to price discovery. The existence of cointegration (and market integration) means that at least one market has to restore long run equilibrium, implying that the given market is short term inefficient, so that profits from pairs strategies can be achieved. If the adjustment of both prices is immediate and independent of the cointegrating error (α_1=α_2=0), the elasticity of demand for pairs strategies is infinite ($H \rightarrow \infty$),[8] and there is no VECM, no price discovery, and no profit from "pairs strategies."

III. In the VECM framework, VIX and CDS markets are modelled to converge to each other to restore equilibrium. The coefficients α_1 and α_2 are the adjustment coefficients, and measure the speed by which VIX and CDS spreads adjust to long run equilibrim. This is slow when the parameter is close to 0, and fast when it is close to 1. In the case where α_1#0 and α_2=0, the VIX market does not adjust to the CDS market as it is essentially the common factor or efficient price. (The reverse is true when α_1=0 and α_2#0.

The analysis of price discovery in the FG framework lies on a decomposition of cointegrated prices into a common permanent factor and a transitory component which captures the effects of illiquidity and other market imperfections.[9] The permanent component or common factor (CF_t) represents the fundamental factor and is a linear combination of x_t and v_t weighted by their corresponding price discovery metrics,

$$CF_t = PD_x x_t + PD_v v_t \tag{5}$$

It can be shown from VECM in (2) and (3), that the contribution to price discovery in the CDS and VIX markets is: [10]

$$PD_x = \frac{\alpha_2}{\alpha_2 - \alpha_1} = \frac{N_x}{N_x + N_v} \tag{6}$$

[8] In this case both markets are perfect substitutes and prices are "discovered" in both markets simultaneously. The model is not sustainable for this case.
[9] See also Hasbrouck (1995), Gonzalo and Granger (1995), and Lehman (2002).
[10] See Booth et al. (2002) and Blanco et al. (2005) for an equivalent representation of the price discovery parameters.

$$PD_V = \frac{-\alpha_1}{\alpha_2 - \alpha_1} = \frac{N_v}{N_x + N_v} \tag{7}$$

Price discovery depends on the relative number of players in the VIX and CDS market. Because CBOE trading is an open trading platform with complete access to market participants, and iTraxx (and CDS) trading is restricted to institutional investors, our model suggests that price discovery is expected to take place in the VIX market.

If new information from both markets is incorporated into the common factor,

$0 \leq PD_i \leq 1$ for $i = x, v$. If $PD_x=1$ and $PD_v=0$ then there is a predominance of credit risk market in the price discovery process. If $PD_x=0$ and $PD_v=1$ there is predominance of the VIX market in the price discovery process. [11]

In order to describe profits from pairs strategies we define the cointegration error as:

$z_t = x_t - \gamma_0 - \gamma_1 v_t$

If $z_{t-1} > 0$, so that the CDS on the previous period was above its equilibrium level, an investor is expected to short the CDS and long VIX in order to profit from pairs strategies. Profits from this strategy may be defined as:

$$\Pi_t = M(-\Delta x_t + \gamma_1 \Delta v_t) = -M \Delta z_t \tag{8}$$

Where Π_t are measured in \$, x_t are credit spreads mesured in bps, v_t is the value of the volatility index measured in volatility points and M is the amount invested (in \$). Substituting the result in equation (3), we get :

[11] Predominance in this context implies that the common factor is driven solely from the dominant price

$$\Delta x_t = \alpha_1 z_{t-1}$$
$$\Delta v_t = \alpha_2 z_{t-1} \qquad (9)$$
$$\Pi_t = M(-\alpha_1 + \gamma_1 \alpha_2) z_{t-1}$$

When $z_{t-1} > 0$, for the VECM to work α_1 must be negative $(-N_v)$ and α_2 positive (N_x) as indicated in our theoretical framework (2). This guarantees that expected theoretical profits from pairs strategies are always positive. We test this proposition empirically in section 5.

3. Cointegration and Price Discovery

We have daily data for the VIX and 3 year, 5 year and 10 year maturity and iTraxx indexes for the period dating from June 2004 to the 8th of December of 2009. The data source is Bloomberg for VIX and Markit for iTraxx. The Markit iTraxx Europe Index is composed of 125 investment grade entities from 6 sectors: Autos, Consumers, Energy, Financials, Industrials, and TMT. The composition of each Markit iTraxx index is determined by the International Index Company according to the Index Rules. Markit iTraxx indices roll every 6 months in March and September. New series of iTraxx have been realized every six months since its introduction. Over our sample period there have been 11 different series of the iTraxx index. We use information in each of these series to select the 50 most representative iTraxx companies.[12] These are those for which CDS have been traded in all 11 iTraxx series. Data for individual CDS is available from July 2002 for 3, 5, and 10 year maturities. These are measured in bps and each bp[1] in CDS represents €1000 to protect €10m of debt. We use a sample dating from July 2002 to December 2009 when looking at VIX and individual CDS. Figures 1-3 show the time series plot of both iTraxx, VIX and France Telecom CDS for the three maturities over the

[12] Markit failed to provide data on CDS in 3 out of the 50 selected, Deutsche Lufthansa AG, Union Fenosa, and CIE Fin Michelin. Therefore the analysis involves 47 companies.

2004-2009 period. The three figures suggest that VIX, iTraxx, as well as individual company CDS are highly related for all maturities. In particular, their value increased by 400% over the period ranging from early 2007 to mid-2008 signalling the degree of global fear in the economy.

In what it follows, we show that VIX and iTraxx as well as VIX and individual CDSs are cointegrated. The mechanism behind this relationship lies on the existence of arbitrage strategies in the form of pairs trading strategies. This requires investment positions in the VIX and CDS markets.

ITraxx indices are tradable instruments in their own right, with pre-determined fixed rates, and the prices set by market demand. Official pricing is collected on-behalf of International Index Company by Markit Group Limited on a daily basis by polling the trading desks at banks that are licensed market makers. Positions on VIX can be gained either directly through the investable volatility index or via positions on VIX derivatives. Futures on VIX provide a pure play on implied volatility independent of the direction and level of stock prices. VIX futures may also provide an effective way to hedge equity returns, to diversify portfolios, and to spread implied against realized volatility.[13]

The VIX options contract is the first product on market volatility to be listed on an SEC-regulated securities exchange. This new product, which can be traded from an options-approved securities account, follows the introduction of VIX Futures on the CBOE Futures Exchange (CFE). Many investors consider the VIX Index to be the world's

[13] A detailed discussion on VIX futures is provided in section 4. Exposure to VIX futures is also possible through ETFs such as ETF Spotlight on iPath S&P 500 VIX Short-Term Futures ETN. The funds seek to replicate the S&P 500 VIX Short-Term Futures Total Return and the S&P 500 VIX Mid-Term Futures Total Return indexes.

premier barometer of investor sentiment and market volatility, and VIX options are very powerful risk management tools.

Our empirical analysis is based on the VECM specified in equation (3). Econometric details of the estimation and inference of (3) can be found in Johansen (1996), and Juselius (2006). We report cointegration and price discovery results when we consider (i) VIX and iTraxx and (ii) VIX with each of the 47 individual CDS. Results for for 5 year maturities are reported in Tables I-II of the main text. Cointegration and price discovery results for 3 year and 10 year maturities are reported in tables Ia to IVa in the appendix.

The first step is to perform a unit root test. Unit roots are a necessary condition for cointegration. Practitioners and theoreticians often refer to VIX and other volatility measures as being "mean reverting," which is a statistical way of saying that at historically low VIX levels there is a high probability that the next big move will be up rather than down. Conversely, at historically high VIX levels, the next move is likely to be down rather than up. However VIX is an implied volatility index, meaning that it is a reflection of option price quotations. In fact, VIX is calculated directly from the price quotations of nearby and second nearby S&P 500 index options spanning a wide range of strike prices. The VIX calculation is independent of any theoretical pricing model, using a formula that averages the weighted prices of at-the-money and out-of-the money puts and calls to derive expected volatility. [14] The statistical properties of the VIX index will therefore be determined by the distribution of weighted average option prices. In this paper we determine whether VIX is mean reverting, empirically.

[14] More information and a sample calculation may be found at http://www.cboe.com/micro/vix/vixwhite.pdf.

We apply the Augmented Dickey Fuller test to all series in our sample. Neither VIX, iTraxx or individual CDS, exhibit mean reversion over our sample period. Results are robust to extension of the sample period and the iTraxx/CDS maturity chosen. [15] A detailed analysis using recursive samples is developed in section 5.

Before testing the rank of cointegration in the VECM specified in (3) two decisions are to be taken: i) selecting the number of lags of (Δx_t Δv_t) necessary to obtain white noise errors, and ii) deciding how to model the deterministic elements in the VECM. For the former, we use the information criterion, AIC, and for the latter, following our theoretical model, we restrict the constant term to be inside the cointegrating relationship.

We report Johansen cointegration test results for VIX and iTraxx as well as VIX and each reference entity CDS with 5 year maturities are presented in Table I. Critical values are taken from Juselius (2006). As predicted by our model, we find evidence of cointegration between x_t and v_t, which implies that VIX and 5 year iTraxx are linked via a long term arbitrage relationship under the imposed restriction that the error term (z_t) is stationary. The (constant) cash amount γ_0 required to replicate the iTraxx portfolio is negative (reported with a positive sign in the table), suggesting that γ_0 units of cash are borrowed to replicate 5 year iTraxx with γ_1 units of the VIX portfolio. This is also the case for all but eight of the cointegrated individual 5 year CDS. [16]

We find cointegration at the 5% level between for VIX and each reference entity CDS in 41 out of the 47 companies considered. The remaining 5 show cointegration at the

[15] ADF tests with optimal lag length chosen under the AIC criteria fail to be reject the unit root null hypothesis for VIX and 5 year iTraxx at the 5% significance level (with p values equal to 0.161 and 0.2532 respectively). ADF test results for 3 year and 10 year maturities can be provided upon request.

[16] Out of the 12 positive signs in the table, 4 are not significant.

10% significance level. Conflicting signs in VECM estimates for Eurpn Aero Defence, Metro AG, and Repsol YPF SA confirms 38 out of the 41 cases of cointegration at 5% significance level.[17]

We report Johansen cointegration test results for VIX and iTraxx for 3 and 10 year maturities in Tables Ia and IIIa in the appendix. We find evidence of cointegration between VIX and iTraxx for 3 and 10 year maturities, suggesting that there is a long term relationship between VIX and credit risk which is robust to the iTraxx maturity chosen. The constant term γ_0 is negative for the 10 year iTraxx maturity whereas positive for the 3 year maturity iTraxx. As it is the case with the 5 year iTraxx, short cash positions are required to replicate 10 year iTraxx with the VIX portfolio. Long cash positions (and a smaller proportion of the VIX portfolio than in the 5 year case) are required to replicate 3 year iTraxx. We find positive signs for the γ_0 parameter in only 2 cases of the VIX and 3 year individual CDS analysed,[18] and in 17 out of the 35 VIX and 10 year individual CDS analysed, although 4 were not significant.

We find evidence of cointegration between VIX and firm level CDS for 3 year and 10 year maturities. Estimates reported in table Table Ia fail to reject cointegration at the 5% level for all companies analysed apart from Vodafone and Royal Bank of Scotland.[19] Conflicting signs in the VECM error correction estimates for LVMH Moet Hennessy, Eurpn Aero Defence, Koninklijke Philips Electrs N V, Metro AG, and Repsol YPF SA confirm 40 out of the 47 cases of cointegration at 5% significance level.

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[17] Conflicting signs imply that estimates of adjustment vector coefficients (α_1 and α_2) are equal signaling evidence of no cointegration .

[18] Four coefficients had positive sign and two of them were not significant.

[19] Royal Bank of Scotland was intervened in 2008. Vodafone´s CDS are found not to be cointegrated with swap spreads in Blanco et al. (2005), suggesting that they are not an accurate measure of credit risk.

Table IIIa in the appendix reports cointegration results for VIX and 10 year CDS. We find evidence of cointegration at the 5% significance level in 39 out of the 47 pairs considered. Conflicting signs in the VECM error correction estimates for Bayer, Eurpn Aero Defence, Hellenic Telecom Org, Metro AG, Repsol YPF SA and Tesco Plc confirms 33 out of the 47 pairs analysed. Cointegration results are therefore also robust to the CDS maturity chosen. [20]

Looking at the first rows of tables I, Ia and IIIa, we can compare iTraxx sensitivity to VIX (γ_1) for the different maturities. Not surprisingly, we can see some difference is the point estimates across maturities. Estimated (γ_1) are 2.97, 4.12 and 4.89 for 3, 5 and 10 years maturities, implying that point estimates for volatility are bigger for longer maturity CDSs.[21] Our results therefore capture the volatility term structure, a general feature of credit spread structure models which is consistent with Merton´s model for low-leverage borrowers. [22] Within this framework, leverage is expected to be positively linked to credit spreads, with default triggered when the leverage ratio approaches unity and a subsequent positive volatility term structure under low leverage levels.[23] The reported coefficients for γ_1 therefore suggest that, ceteris paribus, the sensitivity of spread changes to volatility increases with time to maturity, resulting in upward sloping volatility term structure.

Table I: The long Run Relation between the Price of 5 year Credit Risk in CDS and VIX markets
Samples June 2004-December 2009 (iTraxx)
July 2002- December 2009 (CDS)

[20] Robustness is also found with respect to lag length.
[21] Note that point estimates of γ_0 decrease with time to maturity implying that higher volatility exposure $\gamma_1$require greater amount of cash for iTraxx/CDS portfolio replicating purposes.
[22] See also structural models based on firm value such as Hull, Nelken and White (2004) and Collin-Dufresne, P. and Goldstein, R. S. (2001b) or reduced type models such as Carr and Wu (2010)
[23] We thank Andrea Resti for this comment.

t-statistics are given in parenthesis					
	Number of Cointe vectors			Estimated coefficients $(1, -\gamma_1, -\gamma_o)$, $z_t = x_t - \gamma_0 - \gamma_1 v_t$	
	None (95% c.v. 20.16)	At Most one (95% c.v. 9.14)	1	$-\gamma_1$	$-\gamma_o$
iTraxx5	**32.193**	**2.907**		**-4.121**	**20.625**
				(-14.12)	**(2.98)**
AB Volvo	34.704	4.352		-14.882	209.584
				(-9.37)	(5.61)
ACCOR	20.710	5.923		-5.719	28.935
				(-5.14)	(1.09)
AKZO Nobel N V	39.645	4.325		-2.742	9.159
				(-12.11)	(1.72)
Aegon N.V.	28.511	4.529		-10.125	127.413
				(-11.02)	(5.83)
Aviva plc	34.896	6.303		-7.356	89.989
				(-8.36)	(4.33)
Bay Motoren Werke AG	32.231	4.004		-9.200	124.109
				(-11.09)	(6.37)
Bayer AG	29.641	8.754		-2.588	5.038
				(-6.52)	(0.53)
Bca Monte dei Paschi	28.403	2.474		-3.261	28.944
				(-8.49)	(3.16)
Bertelsmann AG	39.255	6.506		-7.875	80.627
				(-9.59)	(4.17)
Brit Amern Tob plc	22.290	7.107		-2.836	-3.630
				-(4.94)	(-0.27)
Brit Telecom PLC	21.115	6.420		-4.864	29.212
				(-6.95)	(1.75)
Carrefour	38.484	3.169		-2.032	5.933
				(-14.69)	(1.82)
Cie de St Gobain	47.432	2.580		-9.493	106.276
				(-16.88)	(7.98)
Commerzbank AG	23.499	4.332		-3.965	32.828
				(-6.14)	(2.14)
Compass Gp PLC	19.424	5.395		-0.153	-50.573
				(-0.30)	(-4.25)
Deutsche Bk AG	22.400	1.734		-4.217	44.653
				(-8.32)	(3.73)
Deutsche Telekom AG	29.957	7.955		-2.769	-3.874
				(-2.94)	(-0.17)
Diageo PLC	20.132	4.505		-2.545	14.828
				(-7.00)	(1.73)
E.ON AG	28.384	4.633		-2.613	15.656
				(-11.63)	(2.96)
ENEL S p A	36.256	5.339		-10.024	141.982
				(-9.52)	(5.68)
Eurpn Aero Defence	70.688	5.674		-6.996	80.004
				(-18.51)	(8.91)
Fortum Oyj	47.032	3.615		-2.132	3.773

			(-15.18)	(1.17)
France Telecom	52.662	6.030	-1.086	-26.492
			(-1.06)	(-1.10)
Hannover Ruck AG	19.416	4.386	-2.171	4.064
			(-5.77)	(0.47)
Hellenic Telecom SA	42.173	6.685	-0.251	-0.987
			(-10.95)	(-1.81)
Iberdrola S A	34.573	5.268	-0.4208	3.656
			(-14.74)	(5.45)
Koninklijke KPN N V	50.534	6.171	-1.089	-40.325
			(-2.17)	(-3.41)
Koninklijke Philips Electrs N V	36.487	6.914	-2.946	11.614
			(-9. 80)	(1.62)
LVMH Moet Hennessy Louis Vuitton	44.424	6.719	-3.410	16.841
			(-13.51)	(2.81)
METRO AG	69.130	5.251	-6.483	52.853
			(-16.76)	(5.84)
Marks & Spencer p l c	18.953	3.501	-8.148	37.250
			(-4.92)	(0.97)
Munich Re	22.492	6.462	-1.717	2.143
			(-6.00)	(0.32)
RWE AG	26.272	5.352	-2.475	15.223
			(-7.72)	(2.06)
Repsol YPF SA	53.389	6.237	-7.887	-82.60
			(-16.20)	(-7.10)
Royal Bk Scotland plc	18.044	1.598	-6.350	81.830
			(-6.35)	(3.50)
Siemens AG	39.369	4.272	-3.880	36.870
			(-16.17)	(6.59)
Telecom Italia SpA	29.453	7.324	-2.840	-20.100
			(-5.57)	(-1.63)
Telefonica S A	29.453	7.324	-2.840	-2.010
			(-5.57)	(-0.16)
Tesco PLC	29.089	2.807	-0.433	49.92
			(-0.88)	(4.34)
Unilever N V	39.635	5.882	-1.280	-0.365
			(-128.0)	(0.15)
Utd Utils plc	19.554	3.847	-2.370	5.16
			(-5.27)	(0.48)
Vattenfall AB	41.319	5.960	-1.890	4.12
			(11.81)	(1.11)
Veolia Environment	30.242	4.786	-3.650	15.48
			(-11.41)	(2.15)
Vodafone Gp PLC	27.749	6.805	-3.920	25.83
			(-11.88)	(3.27)
Volkswagen AG	24.479	3.705	-7.140	67.85
			(8.60)	(3.46)
WPP 2005 Ltd	48.003	3.183	-11.260	0.01275
			(17.87)	(7.68)

Wolters Kluwer N V	29.82	20.262	-1.210 (41.72)	-30.070 (4.49)

The first two columns of Table I present Johansen trace test statistics for the number of cointegrating relations between the CDS price and the credit spread over swap rates. In line with the theoretical prediction a constant is included in the long term statistical relation The number of lags is optimized using the AIC criteria for each company. The third and fourth columns present the estimated cointegrating relationship coefficients γ_0 and γ_1 .t ratios are given in parenthesis

It might be argued that the predominance of cointegration in the pairs considered arises due to the lack of robustness of the Johansen and Dickey Fuller test under the presence of stochastic volatility or GARCH errors in the VIX series. Lee and Tse (1996) examine the performance of Johansen´s (1988) likelihood ratio test for cointegration in the presence of a GARCH process, and compare it with competing cointegration test. They conclude that, although the tests tend to over reject the null hypothesis of no cointegration in favour of finding cointegration, the problem is generally not very serious. Therefore we can conclude that cointegration in the VIX and CDS markets is robust to the existence stochastic volatility. Given the Granger (1981) representation theorem, the dynamics of two cointegrated variables are represented by the VECM in (3). z_{t-1} is the long term relationship that governs both variables and the adjustment coefficient or adjustment vector describes how fast VIX and iTraxx/individual CDSs adjust when there are (short lived) deviations from the equilibrium relationship.

The construction of pairs strategies requires some measurement of the adjustment speed in number of trading days within a given sample. We define the half-life of the cointegrating error, as the number of periods required for a 1 standard deviation shock to dissipate by one-half in its first-order autoregression. Our results show that that half-lives decrease with iTraxx maturities, which implies a positive term structure of the speed of reversion. The effect of a shock is one half of its size in 14, 13, and 11 days for 3, 5 and 10 year iTraxx maturities respectively. Our findings therefore suggest that equilibrium price convergence is fastest for 10 year iTraxx, which is also the most sensitive portfolio to forward volatility changes. On average, there is smooth convergence to equilibrium implying that there will be opportunities to benefit from pairs strategies. We investigate this possibility for the 5 year case.

The first row in table II reports VECM and price discovery estimates for VIX and 5 year iTraxx. The adjustment coefficient for iTraxx (α_1) suggests that the partial effect of one unit increase in the cointegrating error, is an expected adjustment of iTraxx by 2%. The corresponding point estimate for VIX (α_2) is not significantly different from zero. This suggests that iTraxx clearly does all the adjustment in terms of restoring arbitrage equilibrium. The VIX market does not adjust to the iTraxx market, implying that it is the determinant factor in the price discovery process. [24] The predominance of VIX in the price discovery process is robust to the iTraxx maturity chosen as it is shown in the first rows of tables IIa and IV a in the appendix.

The remaining rows of table II, report VECM estimates and VIX´s price discovery metric (PD_v) for cointegrated pairs of VIX and individual company CDSs. In 38 out of the 39 companies analysed α_1 is significantly positive indicating that the VIX market contributes to price discovery. [25] The CDS market appears to have a significant role in eight out of the 39 cases. Of these cases, the CDS market in the only source of all information in only one case (Deutche Bank AG). This shows that Deutche Bank CDS adjust faster to event risk conditions than the VIX market does, reflecting the global nature of Deuche Bank´s portfolio. Deutsche has leading positions in virtually every segment of trading-driven investment banking in the US and Europe as well as in the fast-

[24] This means that VIX is essentially (weakly) exogenous with respect to the cointegration relationship, meaning that it adjusts instantaneously to its new equilibrium level. Although the point price discovery estimate for VIX PDv is 0.847, t statistics indicate that common factor weights are $PD_x=0$ and $PD_v=1$ respectively.

[25] Note due to their conflicting signs, we do not report PD_v estimates for Eurpn Aero Defence, Metro AG Repsol YPF and thus exclude them from the discussion of price discovery results

growing markets of Asia. Deutsche is Europe's biggest bank by assets and therefore Deutche´s individual company CDSs are expected to trade with high liquidity. We can see from table II that common factor in this case is driven solely by the CDS.[26] In seven cases both the VIX market and the CDS market contribute significantly to price discovery. In 31 pairs analysed we find that α_2 is not significant while α_1 is significantly different from zero, implying that VIX is the leader in the price discovery process with common factor weights $PD_x = 0$ and $PD_v = 1$. Note that in 8 out of the 39 companies analysed the PD_v measure produces a statistic greater than one which is difficult to interpret since, as specified in (6) and (7) both price discovery metrics should be positive and add up to one ($PD_x = 1 - PD_v$). Although it arises due to negative signs in both speed of adjustment coefficients (α_1 and α_2) in all of these cases, α_2 is not significantly different from zero, indicating price leadership in the VIX market.

In the three year CDS case we find that VIX is the sole contributor to price discovery in 32 out of 40 cointegrated pairs. Moreover, the three year CDS market does not dominate in any of the examples analysed. Both, the VIX market and the CDS market contribute to price discovery in seven cases. The price discovery metric for the VIX market PD_v is greater than one in eight of the individual company cases analyzed. Again, this arises because the estimated α_2 is negative but not significantly different from zero.

Estimates in table IVa in the appendix show that, for the 10 year CDSs, out of the 33 cointegrated cases, VIX dominates in terms of price discovery in 24 cases. The CDS market is the sole contributor to price discovery in two cases Deutche Bank and Utd Utils

[26] The point estimate for *PDv* is 0.457 and t statistics indicate that common factor weights are $PD_x=1$ and $PD_v=0$.

plc and both, the VIX market and the CDS market contribute in the price discovery process for 9 out of the 33 cases.[27]

Another interesting result from the analysis of price discovery lies on the term structure of the contribution to price discovery of the VIX index *PDv*. Point estimates are 0.811 0.847 and 0.897 for 3, 5, and 10 year iTraxx maturities. This suggest that the VIX dominance in the price discovery process increases with credit spreads maturities and is consistent with the term structure observed the γ_1 coefficients.

The VIX index and iTraxx as well as individual CDSs are traded asynchronously mainly due to the difference in trading times in Europe and the US (4 to 5 hours). There is large amount of literature that has studied price discovery in related securities (see Hasbrouck 2003) or cross listed shares (see Pascual et al. 2006 and Hupperest and Menkveld 2002). The former analyze price discovery of shares cross listed in NYSE and the Spanish Stock Exchange concentrating on the (two hour) daily overlapping interval. The later analyze trading in the (one hour) overlapping period between NYSE and Amsterdam Stock Exchange. The general conclusion is that European listed stocks are leaders in the price discovery process. On the basis of these results, we are able to confirm that the predominance of VIX (US) over iTraxx/CDS (Europe) does not arise due to the existence of non synchronous trading.

The study of market integration could be reduced to the analysis across asset classes and (not distinct geographical areas) by analyzing iTraxx CDSs and European stock market volatility indexes such as the VSTOXX Indices. These are based on EURO

[27] Note that in 7 out of the 33 companies analyzed the *PDv* measure produces a statistic greater than one. This arises due to negative signs in both speed of adjustment coefficients (α_1 and α_2). However, as for the 3 and 5 years CDS, in all cases α_2 is not significantly different from zero, indicating price leadership in the VIX market.

STOXX 50 real time options prices and are designed to reflect the market expectations of near-term up to long-term European volatility. These indexes lacked of liquidity prior to 2009 and therefore presented significant challenges for investors seeking to trade European volatility. Although liquidity for the VSTOXX indices improved significantly from 2010, our general claim is that VIX is the most appropriate measure of world wide benchmark of stock market volatility.

Table II: VECM estimates and Contribution to Price Discovery (5 year iTraxx and CDS maturity) Samples June 2004-December 2009 (iTraxx) July 2002- December 2009 (CDS)

	Number of Cointe vectors		
	α_1	α_2	PD_v
iTraxx5	**-0.020**	**0.004**	**0.847**
	(-4.12)	**(1.39)**	
AB Volvo	-0.008	0.000	0.958
	(-4.91)	(0.77)	
ACCOR	-0.005	0.001	0.819
	(-3.21)	(1.398)	
AKZO Nobel N V	-0.020	-0.001	1.047
	(-5.78)	(-0.328)	
Aegon N.V.	-0.009	0.002	0.803**
	(-2.81)	(2.98)	
Aviva plc	-0.011	0.001	0.954
	(-4.97)	(0.71)	
Bay Motoren Werke AG	-0.011	0.002	0.868**
	(-4.04)	(1.98)	
Bayer AG	-0.014	-0.001	1.078
	(-4.37)	(-0.51)	
Bca Monte dei Paschi di Siena S p A	-0.012	0.004	0.750**
	(-3.82)	(2.23)	
Bertelsmann AG	-0.010	0.000	0.990
	(-5.58)	(0.14)	
Brit Amern Tob plc	-0.009	0.002	0.858
	(-3.46)	(0.92)	
Brit Telecom PLC	-0.008	0.001	0.854
	(-3.06)	(1.03)	
Carrefour	-0.022	0.008	0.720**
	(-4.65)	(1.88)	
Cie de Saint Gobain	-0.015	0.003	0.845**
	(-5.08)	(2.90)	
CommerceBank AG	-0.090	0.003	0.786**

	(-3.261)	(2.06)	
Deutche Bk AG	-0.005	0.006	0.457**
	(1.41)	(3.64)	
Deutsche Telekom AG	-0.007	0.000	0.991
	(-4.22)	(0.08)	
ENEL S p A	-0.010	0.001	0.948
	(-5.23)	(0.879)	
Fortum Oyj	-0.024	-0.001	1.037
	(-5.90)	(-0.21)	
France Telecom	-0.007	0.000	1.057
	(-6.74)	(-0.70)	
Hellenic Telecom Org SA	-0.026	-0.014	2.215
	(-5.84)	(-0.52)	
Iberdrola S A	-0.018	0.035	0.333
	(-4.64)	(1.49)	
Koninklijke KPN N V	-0.011	-0.001	1.112
	(-6.59)	(-1.01)	
Koninklijke Philips Electrs N V	-0.013	-0.002	1.147
	(-5.37)	(-0.76)	
LVMH Moet	(-6.07)	(-1.55)	1.202
Munich Re	-0.015	0.001	0.911
	(-3.61)	(0.47)	
RWE AG	-0.010	0.003	0.774
	(-3. 90)	(1.17)	
Siemens AG	-0.016	0.006	0.707**
	(-4.41)	(2.50)	
Telecom Italia SpA	-0.012	-0.006	1.872
	(-4.47)	(-0.37)	
Telefonica S A	-0.012	-0.001	1.049
	(-4.47)	(-0.37)	
Tesco PLC	0.000	0.000	0.798
	(4.31)	(-1.24)	
Unilever N V	-0.023	0.008	0.736
	(-5.17)	(1.37)	
Vattenfall AB	-0.020	0.002	0.899
	(-5.83)	(-0.57)	
Veolia Environnement	-0.019	0.002	0.987
	(-4.84)	(0.10)	
Vodafone Gp PLC	-0.010	0.006	0.500**
	(-2.91)	(2.54)	
Volkswagen AG	-0.010	0.013	0.884
	(-3.54)	(1.31)	
WPP 2005 Ltd	-0.023	-0.001	1.004
	(-6.58)	(-0.67)	
Wolters Kluwer N V	-0.016	0.000	0.980
	(-4.62)	(0.12)	

This table presents (point) estimates of the adjustment vector in the VECM specified in (3) as well as the contribution of the Price Discovery in the VIX market (PD_v) as specified in (5). ** denote rejection of predominance of VIX leadership in the price discovery process $(PD_x=0, PD_v=1)$ at the 5% significance level on the basis of reported t statistics. In order for $(PD_x=0, PD_v=1)$ to be accepted we require that α_1 is significantly different from zero (at 5%) level while α_2 not being significantly different from zero.

Estimates in table II, show that in most cases analysed the VIX index is the dominant contributor to the common factor in the price discovery process suggesting that market risk (as measured by the VIX index) adjusts faster to changes in the common factor underlying the two integrated markets. This is true for all iTraxx/CDS maturities considered, although stronger for the 5 and 3 year case. This implies that, on average, if there is temporary mispricing between VIX and credit risk market $(z_t > 0)$ it is the credit derivatives market that does the adjustment to the new equilibrium and not the VIX market. An explanation to this result can be obtained from the theoretical result specified in (2), where price discovery is defined in terms of relative number of participants. In this framework VIX leads the price discovery process if it has (relatively) higher number of market participants. While the VIX derivatives market is open to all market participants the CDS markets is restricted to OTC trading across institutional investors. Exchange based VIX trading leads to price leadership in the price discovery process. Arbitrageurs benefit from this process by obtaining riskless profits in a context of slow convergence to long run equilibrium (i.e. $z_t \pm 0$).

4. Proposed "pairs trading" strategies

In this section we investigate the possibility of earning abnormal profits pursuing pairs trading strategies in the VIX and CDS markets. This is a classic trading strategy for speculators or hedge funds. It relies on a well known trading rule for cointegrated price series based on the following proposition: an investor should open a long-short position when the paired prices have diverged by a certain amount and close the position when prices have reverted (see for instance Gatev Goezman and Rouwenhorst 2006). [28] When an investor has opened a position he shorts the out-performer and longs the underperformer, hoping that eventually they will converge to their long run equilibrium level. Theoretical profits are defined by return differentials as specified in (8) and (9). Once there is equilibrium reversion, the trading position is closed.

Pairs strategies have certain characteristics. Typically, they are not highly exposed to market crashes. This is because, if the market goes down, the investor looses from the long position and wins from the short position. From the nature of their construction, one can bet on the long run relationship of the two, so the strategy is mean reverting. They are also low cost strategies, as an investor can bet the proceedings from the short position to finance the long position. However, they do not imply a risk-free portfolio, when VIX and CDSs move away from their long term equilibrium, the holder of pairs strategies will incur a loss if there is no short term reversion.

In what follows we report profits (or losses) for pairs strategies pursued between VIX and iTraxx markets. These are calculated following changes in VIX and iTraxx derivatives. The strategy consists of taking two positions in t (one short and one long) in response to observed price differentials in $t-1$. If iTraxx is above its long term equilibrium in $t-1$ i.e. $z_{t-1} > 0$ profits at the end of day in t are given by (8) where Π_t is expressed in

[28] Gatev Goezman and Rouwenhorst 2006 define deviations in terms of two historical standard deviations away from the long term equilibrium. We take 1 standard deviation to be significant.

Euros. Investments in iTraxx are done by directly investing in the CDSs,[29] while investments in VIX are done via VIX derivatives (futures and options on futures).

We estimate the profit (or loss) from an investment in VIX by looking at VIX futures price differentials. For this purpose we use a continuous series of front month VIX future prices. CBOE VIX futures trade in consecutive calendar months and expire before the contract month. The rollover of the front month VIX futures contract is made at the expiry date.[30] We have futures daily data from the 26th of March 2004 to the 26th of December 2011. Figure 4 in the appendix depicts the time series plot for VIX and VIX futures for the 2004-2011 period. It is clear from the graph that both series move closely together, although the spot series looks more volatile than the futures series.

In this section we use data from March 2004 to December 2009 to set up pairs trading strategies between VIX futures and iTraxx CDS. In what follows we refer to v_t as the front month VIX future while x_t remains the CDS spread.

In the absence of derivative prices on iTraxx we calculate the profit (or loss) of an investment in iTraxx using different delta (δ) scenarios assuming all other factors remain the same. [31] For example, if the delta for iTraxx is equal to one (δ=1), this implies that 100% of the changes will have an impact in the portfolio's profit (or loss). If $z_{t-1} > 0$, Δv_t is two points, and Δx_t is 50bps and we invest €1 in iTraxx and €1 in VIX futures, then profits will consist of 2*1= €2 from our position in VIX futures and 50*1= €50 from our position in iTraxx. Total profits from pairs strategies are defined as $\Pi_t = \gamma_1 \Delta v_t - \Delta x_t$.

[29] Investment in iTraxx can also be pursued through ETFs. See for example the Easy ETFs provided by Paribas.

[30] VIX CBOE continuous future data source is data stream. THE CBOE futures exchange Exchange lists for trading up to nine near-term serial months and five months on the February quarterly cycle for the VIX futures contract.

[31] The delta of a derivative is defined as the rate of change of the option price with respect to the price of the underlying asset. See C. D. Smith 2008 for a description of profit determination via delta.

When $\gamma_1=1$, $\Pi_t = 2-50 = -€48$. Note that because €1 is shorted and €1 is invested, pairs strategies require low (or zero) initial investment.

We analyze profits attained from investing in five different generic portfolios whose profit and losses depend on the underlying evolution of different delta scenarios or products. Investments in iTraxx are done directly on the index or through an ETF. Profits from trading an iTraxx CDS will depend on the delta of the CDS with respect to the underlying spread. In what follows we allow deltas of the iTraxx investment to vary from 0.4 to 1. In particular, we consider the following five strategies:

i) €1 invested in front month VIX futures (VIXF),

ii) €1 invested in iTraxx derivatives with unit delta,

iii) and investing in pairs strategies that combine €1 invested in front month VIX futures, and €1 in a derivative written on iTraxx with deltas equal to iii) 1, iv) 0.6, and v) 0.4. Note that because they combine €1 long with €1 short, positions pairs strategies require lower initial investment than strategies specified in (i) and (ii).

We denote the last three pairs strategies in (iii) as delta 1 strategies, delta 0.6 strategies, and delta 0.4 strategies. [32] Table III summarizes positions taken in the five strategies considered.

[32] We allow delta to vary in the iTraxx case. An example of non delta one strategy is provided by Bloomberg which provides prices for CDS written on iTraxx CDSs with a delta in the order of 0.4.

Table III: Description of investment strategies		
Strategy (1€ investment)	**VIXF**	**iTraxx**
(i) VIXF	$1\Delta v_t$	
(ii) iTraxx		$1\Delta x_t$
(iii) delta 1	+ (-1)$1\Delta v_t$	- (+) Δx_t
(iv) delta 0.6	+ (-1) $1\Delta v_t$	- (+) $0.4\Delta x_t$
(v) delta 0.4	+ (-1) $1\Delta v_t$	- (+) $0.6\Delta x_t$

This table provides a description of the five proposed strategies. Strategies that combine 1 € investment (with opposite positions) in VIXF and iTraxx are pairs strategies.

Columns 1-3 in table IV report annual average profits and volatilities as well as (simplified) Sharpe Ratios. Column 4 reports annualized cumulative profits, assuming zero risk free rates for the sample period analysed. Rows 3-5 report performance results from investments in delta 1, delta 0.6, and delta 0.4 pairs strategies. Reported figures in table III show that, over our sample period, simplified annual Sharpe ratios and cumulative profits have been positive for all five strategies considered. Sharpe Ratios are simplified in that zero rates are assumed over the sample period analyzed. Both, Sharpe ratios and end of the sample cumulative profits are maximized by investing in delta 0.4 pairs strategies. All the pairs strategies considered deliver higher Sharpe Ratios and cumulative profits than those that are obtained from investing in iTraxx or VIX alone.

Table IV: Annual Simplified Sharpe Ratios and Annual Cumulative Trading Profits for five proposed trading strategies (June 2004-December 2009)

	μ	**σ**	**Sharpe Ratio**	**Cumulative Profits**
iTraxx	0.280	0.597	0.468	0.279
VIXF	0.219	0.545	0.401	0.218
Pairs 1	337.78	112.71	2.997	88.35
Pairs 0.6	348.07	96.52	3.606	91.05
Pairs 0.4	353.21	92.36	3.824	92.39

This table reports mean annual profits, volatility (measured by the standard deviation), simplified Sharpe Ratios and annualized cumulative profits for three strategies i) €1 invested in long position iTraxx ii) € 1invested in a long position in VIX futures iii) delta 1, delta 0.4 and delta 0.6 pairs strategies that combine a € 1 long position with a 1€ short position in replicating VIX futures portfolio

Simplified yearly Sharpe ratios and cumulative profits are also calculated for all cointegrated pairs of VIX and individual company CDSs over the 2002-2009 period. Due to the absence of VIX futures prices for the 2002-2004 period, we generate srategies with direct positions in the VIX index[33] and not VIX futures. Calculated profits are reported in table IVa in the appendix. Pairs strategies deliver positive mean profits, Sharpe ratios and Cummulative profits for all but two cointegrated pairs analysed. We can therefore state that pairs strategies deliver positive Sharpe Ratios and Cummulative retruns in about 92% of the individual CDS pairs analyzed.

5. Robustness Checks

We have updated our sample to include VIX and 5 year iTraxx data from 10th of December 2009 to the 26th of December 2011. This allows testing for robustness to the inclusion of post crisis periods. We do this for the following reasons a) given the short time series for both the VIX and CDS spreads, it is important to test whether the non stationary assumption is a correct assumption especially given that the sample ends in the credit crisis period. b) the VIX and the iTraxx CDS index are based on "refreshed" pools of large, high-quality firms, which may make it more likely that over longer term spans the VIX and CDS index series are stationary.

As a first robustness check we perform recursive Augmented Dickey Fuller test unit root tests on the VIX and iTraxx indexes. Figure 4 in the appendix reports recursive p

[33] See for instance the investable volatility index of Meryll Lynch

values obtained from ADF unit root test on VIX and 5 year iTraxx with optimal lag length chosen recursively using the AIC criteria. It demonstrates that we fail to reject the null hypothesis of unit roots for VIX and iTraxx for the 514 extended daily samples considered which range from June2004-Dec2009 to June2004-Dec2011. In the light of reported figures, we can conclude that results from unit roots tests are not sample dependent.

We have additionally performed a recursive unit root test on the estimated cointegrating error prevalent over our (in) sample period for the VIX and 5 year iTraxx relationship. Parameter estimates for this error are specified in Table I. The robustness check on the cointegrating error covers data from June 2004 to December 2011, which includes 1942 observations. Halve of these, i.e. 971 observations are used as the initial sample for the recursive test. The initial sample runs up to March 2008 and therefore covers four and a half years underlying the pre-crises period. Fig 4 in the appendix reports resulting p values for the recursive test. It shows that we reject the null hypothesis of unit root in the cointegrating error for all but two of the recursive samples that follow the Lehman´s episode.

In view of updated sample ADF results we perform an out of sample performance analysis of the proposed strategies over the Jan 2010-2011 period. We do this using the cointegration relation between 5 year iTraxx and VIX prevailing over our sample period. Results, reported in table V may be summarized as follows. All strategies involving VIX futures and iTraxx provide positive Sharpe ratios and cumulative profits. The later are maximized with delta 0.6 pairs strategies while the former are highest for 0.4 pairs strategies.

Table V: Robustness Check: Expected Returns, Volatilities Performance Measures and Cumulative for different trading Strategies (December 2009-December 2011)

	μ	**σ**	**Sharpe Ratio**	**Cumulative Profits**
iTraxx	0.499	0.539	0.925	0.498
VIXF	0.244	0.729	0.335	0.244
Pairs 1	253.11	135.42	1.869	42.02
Pairs 0.6	253.01	94.43	2.679	166.81
Pairs 0.4	252.96	87.17	2.902	158.50

This table reports mean annual profits, volatility (measured by the standard deviation), simplified Sharpe Ratios and annualized cumulative profits for three strategies i) 1€ invested in long position in iTraxx ii) €1 invested in a long position in VIX futures (VIXF) iii) pairs strategies between the VIXF replicating portfolio and iTraxx that invest €1 in a long position and €1 in a short position resulting in lower investment cost than i) and ii)

We can therefore establish that profits from pairs strategies are not sample dependent. Cointegration remains and pairs strategies between VIX and 5 year iTraxx provide positive Sharpe ratios during the 2010-2011 period which is governed by positive average US stock market returns.[34]

6. Conclusion

This article exploits a highly comprehensive data set on European iTraxx/CDSs and VIX to analyse the nature of the link between market risk and credit risk, the two proxies for the aggregate market condition. We apply a solid model based on arbitrage trading and contribute to the empirical literature that associates implied option volatility and CDS markets by reporting the following findings:

[34] Average yearly returns for the S&P500 index were 9.65% during the Jan 2010-Dec2011 period.

First, the empirical link between credit risk and market risk, now widely acknowledged by market participants can be explained on the basis of a cointegrating relation between VIX and credit risk at portfolio and individual company level. A demand and supply model for VIX and CDS market participants is used to demonstrate how arbitrageurs restore equilibrium mispricing pursuing pairs trading strategies.

Second, profits from pairs strategies can be represented through parameters in VECM model, in a framework where only under significant transaction costs and slow equilibrium convergence, there is room to benefit from pairs strategies.

Third, the VIX market leads the CDS market in the price discovery process. This implies that VIX adjusts faster to changes in event risk conditions than the CDS market and holds for CDS portfolios and individual company CDS. Out of the 39 cointegrated pairs, we find that in 30 cases the VIX market is the leader in the price discovery process. This result is robust to different CDS maturity chosen and suggests that the VIX and CDS markets are integrated across distinct geographical areas as well as distinct asset classes.

Fourth, we generate profits from pairs strategies and show that Sharpe Ratios and cumulative profits from pairs strategies are always positive. This is robust to the extension of our data set to include periods of positive average market returns.

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Appendix A1: Theoretical model for dynamics of VIX and CDS Markets

Let x_t be the spread underlying a credit derivative or a credit derivative index in time t. Let v_t be the contemporaneous value of VIX forward looking volatility index. We assume that there are N_x participants in the credit derivatives market and N_v participants in VIX derivatives market. Let $P_{i,t}$ be the net position of the i^{th} participant immediately prior to period t and $B_{i,t}$ the bid price at which that participant is willing to hold the position $P_{i,t}$. Then the demand schedule of the i^{th} participant in the credit derivatives market in period t is

$$P_{i,t} - A(x_t - B_{i,t}), \qquad A > 0, \quad \mathrm{i} = 1,....,N_x, \tag{A1.1}$$

where A is the elasticity of demand, assumed to be the same for all participants. Note that due to the dynamic structure to be imposed to the bid price, $B_{i,t}$,

The demand schedule for the j^{th} participant in the VIX market is

$$P_{i,t} - A(v_t - B_{j,t}), \qquad A > 0, \quad \mathrm{j} = 1,....,N_v, \tag{A1.2}$$

The aggregate market demand schedule of agents pursuing pairs strategies in the credit and VIX markets in period t is

$$\begin{aligned} &H\left(\left(\gamma_1 v_t + \gamma_0\right) - x_t\right), && H > 0, \\ &= H(z_t), && H > 0, \end{aligned} \tag{A1.3}$$

where z_t represents the transaction costs involved in opening and closing positions in the CDS and VIX portfolio, and H is the elasticity of market demand for pair strategies. As previously discussed, it is finite when the arbitrage transactions of buying in the credit market and selling in the VIX derivatives market or vice versa are not risk less.

The credit market will clear at the value of x_t that solves,

$$\sum_{i=1}^{N_x} P_{i,t} = \sum_{i=1}^{N_x}\left(P_{i,t} - A\left(x_t - B_{i,t}\right)\right) + H\left(\left(\gamma_1 v_t + \gamma_0\right) - x_t\right) \qquad H > 0, \tag{A1.4}$$

The VIX derivatives market will clear at the value of v_t such that

$$\sum_{j=1}^{N_v} P_{j,t} = \sum_{j=1}^{N_v}\left(P_{j,t} - A\left(v_t - B_{j,t}\right)\right) + H\left(\left(\gamma_1 v_t + \gamma_0\right) - x_t\right) \tag{A1.5}$$

Solving equations (A.1.4) and (A.1.5) for x_t and v_t as a function of the mean bid price set by credit derivatives market participants $\left(B_t^x = N_x^{-1} \sum_{i=1}^{Nx} B_{i,t}\right)$ and the mean bid price for VIX market participants $\left(B_t^v = N_v^{-1} \sum_{j=1}^{N_v} B_{j,t}\right)$, we obtain

$$\begin{aligned} x_t &= \frac{(AN_v + H\gamma_1)N_x B_t^x + HN_v\gamma_1 B_t^v + HN_v\gamma_0}{(H + AN_x)N_v + HN_x\gamma_1}, \\ v_t &= \frac{HN_x B_t^{\,x} + (H + AN_x)N_v B_t^v - HN_x\gamma_0}{(H + AN_x)N_v + HN_x\gamma_1}. \end{aligned} \tag{A1.6}$$

To derive the dynamic price relationships, the model in equation (A.1.6) must be characterized with a description of the evolution of bid prices. It is assumed that immediately after the market clearing period *t-1* the i^{th} CDS market participant was willing to hold a position $P_{i,t}$ at a price x_{t-1}. Following FG, this implies that x_{t-1} was his bid price after that clearing. We assume that this bid price changes to $B_{i,t}$ according to the equation

$$\begin{aligned} &B_{i,t} = x_{t-1} + e_t + w_{i,t}, \quad i = 1, \ldots, N_x, \\ &B_{j,t} = v_{t-1} + e_t + w_{j,t}, \quad j = 1, \ldots, N_v, \\ &\operatorname{cov}(e_t, w_{i,t}) = 0, \quad \forall_i, \\ &\operatorname{cov}(w_{i,t}, w_{f,t}) = 0, \quad \forall i \neq f, \end{aligned} \tag{A1.7}$$

where the vector $\left(e_t, w_{i,t}, w_{j,t}\right)$ is vector white noise with finite variance.

The price change $B_{i,t}$ - x_{t-1} reflects the arrival of new information between period *t-1* and period *t* which changes the price at which the i^{th} participant is willing to hold the position $P_{i,t}$ in the credit derivatives market. This price change has a component common to all participants (e_t) and a component idiosyncratic to the i^{th} participant ($w_{i,t}$). The equations in (A.1.7) imply that the mean bid price in each market in period *t* will be

$$\begin{aligned} B^x{}_t &= x_{t-1} + e_t + w^x{}_t, \quad i = 1, ..., \ N_x, \\ B^v{}_t &= v_{t-1} + e_t + w^v{}_t, \quad j = 1, ..., N_v, \end{aligned} \qquad \text{(A1.8)}$$

where, $w_t^x = \dfrac{\sum_{i=1}^{N_x} w_{i,t}^x}{N_x}, w_t^v = \dfrac{\sum_{j=1}^{N_v} w_{j,t}^v}{N_v}$. Substituting expressions (A.1.8) into (A.1.6) yields the following vector model

$$\begin{pmatrix} x_t \\ v_t \end{pmatrix} = \frac{H\gamma_0}{d}\begin{pmatrix} N_v \\ -N_x \end{pmatrix} + \left(M\right)\begin{pmatrix} x_{t-1} \\ v_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \qquad \text{(A1.9)}$$

where

$$\begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} = \left(M\right)\begin{pmatrix} e_t + w_t^x \\ e_t + w_t^v \end{pmatrix} \qquad \text{(A1.10)}$$

$$M = \frac{1}{d}\begin{bmatrix} N_x\left(\gamma_1 H + AN_v\right) & \gamma_1 HN_V \\ HN_x & \left((H + AN_x\right)N_v \end{bmatrix} \qquad \text{(A1.11)}$$

And

$$d = \left(H + AN_x\right)N_v + \gamma_1 HN_x \qquad \text{(A1.12)}$$

We now convert (A.1.9) into a Vector Error Correction Model (VECM) by subtracting *(x_{t-1}, v_{t-1})´* from both sides, with

$$\begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \frac{H\gamma_0}{d}\begin{pmatrix} N_v \\ -N_x \end{pmatrix} + (M-I)\begin{pmatrix} x_{t-1} \\ v_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \tag{A1.13}$$

$$M - I = \frac{1}{d}\begin{bmatrix} -HN_V & \gamma_1 HN_v \\ HN_x & -HN_x\gamma_1 \end{bmatrix} \tag{A1.14}$$

Rearranging terms,

$$\begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \frac{H}{d}\begin{pmatrix} -N_v \\ N_x \end{pmatrix}(1 \quad -\gamma_1 \quad -\gamma_0)\begin{pmatrix} x_{t-1} \\ v_{t-1} \\ 1 \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \tag{A1.15}$$

Appendix A.2 Empirical Cointegration and Price Discovery Results

Table I a:
The long Lun Relationship between the Price of 3 year CDS and VIX markets
Samples June 2004-December 2009 (iTraxx)
July 2002- December 2009 (CDS)

	None 95% c.v=20.26	At Most one 95% c.v= 9.14	Estimated Coefficients $(1, -\gamma_1, -\gamma_0)$ $z_t = x_t - \gamma_0 - \gamma_1 v_t$ $-\gamma_1$	$-\gamma_0$
iTraxx3	**23.622**	**2.735**	**-2.971**	**-15.501**
			(0.278)	**(6.627)**
AB Volvo	35.210	4.976	-15.791	238.828
			(-9.479)	(6.097)
ACCOR	26.083	5.990	-0.189	-7.172
			(-5.777)	(-2.522)
AKZO Nobel N V	36.985	4.741	-0.322	2.900
			(0.028)	(0.662)
Aegon N.V.	27.794	4.783	-10.472	143.856
			-(10.702)	(6.181)
Aviva plc	35.235	6.465	-7.584	102.116
			(-8.122)	(4.631)
Bay Motoren Werke AG	24.932	4.830	-9.893	146.666
			(-8.553)	(5.357)
Bayer AG	34.101	8.617	-2.953	22.050
			(0.362)	(2.565)
Bca Monte dei Paschi di Siena	36.433	2.648	-3.265	34.859
			(-10.209)	(4.639)
Bertelsmann AG	66.430	7.124	-7.322	85.084
			(-12.887)	(6.290)
Brit Amern Tob plc	26.973	6.150	-3.229	17.542
			(-6.512)	(1.492)
Brit Telecom PLC	25.469	6.924	-4.878	44.807
			(-8.916)	(3.435)
Carrefour	59.616	3.859	-2.152	16.276
			(-20.998)	(6.731)
Cie de St Gobain	52.070	3.259	-10.526	138.361
			(-17.435)	(9.688)
Commerzbank AG	25.546	4.470	-3.778	37.881
			(-6.919)	(2.927)
Compass Gp PLC	22.909	6.094	-1.045	-18.199
			(0.321)	(7.427)
Deutsche Bk AG	27.765	2.175	-4.142	50.146
			(-9.445)	(4.849)
Deutsche Telekom AG	34.111	6.857	-3.902	31.465
			(-5.111)	(1.731)
Diageo PLC	31.738	5.892	-2.452	21.469

			(-10.729)	(3.997)
E.ON AG	47.494	4.874	-2.805	26.012
			(-19.904)	(7.852)
ENEL S p A	36.298	5.587	-10.979	167.637
			(-9.202)	(5.920)
Eurpn Aero Defence	57.624	5.654	-7.667	102.410
			(-15.272)	(8.591)
Fortum Oyj	64.768	3.624	-2.461	17.599
			(0.113)	(2.623)
France Telecom	48.911	6.277	-1.955	5.023
			(-1.537)	(0.167)
Hannover Ruck AG	22.892	4.369	-2.393	16.410
			(-8.142)	(2.431)
Hellenic Telecom Org SA	57.855	5.410	-3.092	14.420
			-(16.107)	(3.210)
Iberdrola S A	41.147	5.315	-4.620	52.353
			(-16.923)	(8.151)
Koninklijke KPN N V	55.315	6.437	-1.957	-6.746
			(-4.557)	(-0.663)
Koninklijke Philips Electrs N V	59.375	6.111	-3.201	25.740
			(-14.938)	(5.057)
LVMH Moet Hennessy Louis Vuitton	54.852	6.809	-3.768	33.989
			(16.780)	(6.376)
METRO AG	68.010	5.850	-6.970	76.028
			(-16.780)	(6.376)
Marks & Spencer p l c	26.301	2.846	-10.252	119.406
			(-8.846)	(4.449)
Munich Re	26.824	6.334	-1.842	11.396
			(0.214)	(5.011)
RWE AG	39.079	5.574	-2.559	23.708
			(-11.011)	(4.313)
Repsol YPF SA	59.643	8.460	-8.370	102.060
		0.068	(-144.310	(7.450)
Royal Bk Scotland plc	18.855	2.124	-6.190	83.700
			(-6.516)	(3.805)
Siemens AG	42.361	4.051	-4.110	48.790
			(-17.870)	(8.871)
Telecom Italia SpA	32.988	7.348	-3.600	23.970
			(-8.571)	(2.421)
Telefonica S A	32.112	6.975	-3.730	26.860
			(-9.098)	(2.741)
Tesco PLC	41.362	3.945	4.080	52.340
			(12.000)	(6.710)
Unilever N V	49.268	4.884	-1.390	0.821
			(-15.618)	(0.391)
Utd Utils plc	26.434	3.469	-2.440	15.590
			(-8.133)	(2.196)
Vattenfall AB	51.863	6.859	-0.205	14.520
			(0.140)	(3.300)

Veolia Environnement	37.362	5.026	-4.350	39.020
			(-140.323)	(5.574)
Vodafone Gp PLC	38.552	20.262	-4.370	45.120
			(-16.808)	(7.277)
Volkswagen AG	29.616	4.245	-7.830	94.370
			(10.303)	(5.302)
WPP 2005 Ltd	45.698	3.503	-11.800	155.100
			(17.101)	(8.617)
Wolters Kluwer N V	45.223	6.314	-0.180	-5.020
			(9.000)	(1.046)

The first two columns of Table Ia present Johansen trace test statistics for the number of cointegrating relations between the CDS price and the credit spread over swap rates. In line with the theoretical prediction a constant is included in the long term statistical relation The number of lags is optimized using the AIC criteria for each company. The third and fourth columns present the estimated cointegrating relationship coefficients γ_0 and γ_1 .t ratios are given in parenthesis

Table II a: VECM estimates and Contribution to price Discovery 3 year CDS
Samples June 2004-December 2009 (iTraxx)
July 2002- December 2009 (CDS)

	α_1	α_2	PD_v
iTraxx3	**-0.021**	**0.005**	**0.811**
	(-3.296)	(1.431)	
AB Volvo	-0.008	0.000	0.988
	(-5.10)	(0.225)	
ACCOR	-0.008	0.000	0.964
	(-4.272)	(0.310)	
AKZO Nobel N V	-0.003	-0.024	2.365
	(-5.534)	(-0.421)	
Aegon N.V.	-0.013	0.002	0.894**
	(-3.560)	(2.076)	
Aviva plc	-0.011	0.000	0.983
	(-4.864)	(0.258)	
Bay Motoren Werke AG	-0.009	0.001	0.925
	(-3.803)	(0.991)	
Bayer AG	-0.016	-0.001	1.093
	(-5.005)	(-0.660)	
Bca Monte dei Paschi di Siena S p A	-0.016	0.003	0.827**
	(-5.001)	(1.646)	
Bertelsmann AG	-0.018	-0.001	1.057
	(-7.656)	(-1.145)	
Brit Amern Tob plc	-0.011	0.001	0.912
	(-4.289)	(0.646)	

Brit Telecom PLC	-0.012	0.001	0.949
	(-4.052)	(0.410)	
Carrefour	-0.031	0.003	0.914
	(-6.804)	(0.604)	
Cie de St Gobain	-0.017	0.002	0.919**
	(-6.184)	(1.736)	
Commerzbank AG	-0.012	0.002	0.845
	(-3.774)	(1.522)	
Compass Gp PLC	-0.013	-0.004	1.368
	(-4.019)	(-1.229)	
Deutsche Bk AG	-0.011	0.005	0.673**
	(-3.063)	(3.206)	
Deutsche Telekom AG	-0.008	0.000	1.007
	(-5.087)	(-0.061)	
Diageo PLC	-0.016	0.001	0.963
	(-4.868)	(0.191)	
E.ON AG	-0.025	0.006	0.798**
	(-5.553)	(1.604)	
ENEL S p A	-0.010	0.000	0.971
	(-5.311)	(0.539)	
Fortum Oyj	-0.035	-0.004	1.128
	(-7.669)	(-0.883)	
France Telecom	-0.006	0.000	1.060
	(-6.468)	(-0.815)	
Hannover Ruck AG	-0.019	0.001	0.930
	(-4.014)	(0.475)	
Hellenic Telecom	-0.030	-0.004	1.154
	(-7.191)	(-1.452)	
Iberdrola S A	-0.019	0.002	0.900
	(-5.436)	(0.947)	
Koninklijke KPN N V	-0.011	-0.001	1.135
	(-6.797)	(-1.168)	
Marks & Spencer p l c	-0.010	0.001	0.878
	(-3.634)	(2.037)	
Munich Re	-0.021	0.002	0.900
	(-4.160)	(0.608)	
RWE AG	-0.014	0.002	0.861
	(-5.316)	(0.820)	
Royal Bk Scotland plc	-0.006	0.003	0.671**
	(-1.854)	(3.053)	
Siemens AG	-0.000	0.000	0.827
	(5.260)	(1.560)	
Telecom Italia SpA	0.000	0.000	0.968
	(5.0283)	(-0.507)	
Telefonica S A	-0.011	0.000	1.042
	(-3.980)	(-0.289)	

Tesco PLC	-0.012	0.000	0.987
	(-5.796)	(0.084)	
Unilever N V	-0.032	-0.002	1.081
	(-6.535)	(-0.389)	
Utd Utils plc	-0.009	0.007	0.571**
	(-3.491)	(2.641)	
Vattenfall AB	-0.025	-0.060	1.328
	(-6.946)	(-1.500)	
Veolia Environnement	-0.020	-0.0009	1.047
	(-5.540)	(-0.406)	
Volkswagen AG	-0.012	0.001	1.000
	(-4.206)	(0.858)	
WPP 2005 Ltd	-0.022	-0.001	1.062
	(-6.397)	(-1.066)	
Wolters Kluwer N V	-0.024	0.000	1.015
	(-6.040)	(-0.125)	

This table presents (point) estimates of the adjustment vector in the VECM specified in (3) as well as the contribution of the Price Discovery in the VIX market (PD_v) as specified in (5). ** denote rejection of predominance of VIX leadership in the price discovery process *(PD_x=0, PD_v=1)* at the 5% significance level on the basis of reported t statistics. In order for *(PD_x=0, PD_v=1)* to be accepted we require that α_1 is significantly different from zero (at 5%) level while α_2 not being significantly different from zero.

Table III a: The Long Run Relation between the Price of 10 year Credit Risk in CDS and ViX Markets

Samples June 2004-December 2009 (iTraxx)
July 2002- December 2009 (CDS)

	Number of Cointe vectors		Estimated Coefficients (1, $-\gamma_1$, $-\gamma_0$) $z_t = x_t - \gamma_0 - \gamma_1 v_t$			
	None (95% c.v. 20.16)	at Most one (95% c.v. 9.14)	$-\gamma_1$		$-\gamma_0$	
iTraxx10	**39.690**	**3.051**	**-4.891**	**(-18.539)**	**48.594**	**(7.418)**
AB Volvo	31.421	4.044	-12.430	(-8.940)	147.884	(4.551)
ACCOR	18.434	6.815	-4.288	(-3.930)	-18.574	(-0.714)
AKZO Nobel N V	38.177	5.507	-1.662	(-8.770)	-25.151	(-5.585)
Aegon N.V.	28.232	4.442	-9.405	(-11.279)	105.807	(5.329)
Aviva plc	32.467	6.741	-7.255	(-8.296)	80.158	(3.935)
Bay Motoren Werke AG	27.492	3.848	-7.287	(-10.028)	77.296	(4.532)
Bayer AG	22.651	8.386	-0.955	(-2.012)	-41.694	(-3.691)
Bca Monte dei Paschi di Siena S p A	28.591	2.445	-3.009	(-8.393)	16.222	(1.908)
Bertelsmann AG	32.024	6.764	-7.044	(-7.600)	46.671	(2.134)
Brit Amern Tob plc	22.046	5.553	-0.935	(-2.104)	-59.699	(-5.646)
Brit Telecom PLC	16.488	6.717	-4.998	(-4.466)	7.961	(0.300)

Carrefour	33.112	4.333	-9.825	(-17.519)	-4.897	
Cie de St Gobain	41.675	2.521	-8.020	(-15.146)	63.833	(5.108)
Commerzbank AG	21.772	4.594	-3.719	(-5.294)	21.289	(1.284)
Compass Gp PLC	12.474	3.428	2.037	(0.997)	2.037	(-112.3)
Deutsche Bk AG	20.601	1.718	-3.957	(-7.821)	33.732	(2.827)
Deutsche Telekom AG	29.496	6.397	-1.025	(-1.107)	-60.688	(-2.760)
Diageo PLC	23.965	5.686	-1.706	(-5.969)	-12.300	(-1.788)
E.ON AG	17.327	4.744	-2.041	(-5.910)	-6.146	(-0.758)
ENEL S p A	34.382	4.213	-9.070	(-9.981)	111.267	(5.222)
Eurpn Aero	86.147	5.074	-5.969	(-21.064)	45.821	(6.865)
Fortum Oyj	31.245	3.997	-1.566	(-8.220)	-18.643	(-4.216)
France Telecom	39.495	5.316	0.437	(0.380)	-79.734	(-2.947)
Hannover Ruck AG	21.622	4.374	-1.645	(-5.126)	-14.045	(-1.900)
Hellenic Telecom Org SA	37.137	4.743	-0.141	(-6.897)	-5.309	(-11.238)
Iberdrola S A	27.093	5.353	-3.319	(-10.114)	8.724	1.135
Koninklijke KPN N V	24.078	5.802	16.986	(3.936)	-165.02	(4.012)
Koninklijke Philips Electrs N V	31.950	7.182	-2.119	(-6.492)	-20.178	(-2.595)
LVMH Moet Hennessy Louis Vuitton	38.388	6.073	-2.630	(-9.223)	-11.317	(-1.678)
METRO AG	69.130	5.251	-5.060	(17.233)	8.457	(1.241)
Marks & Spencer p l c	18.953	3.501	-8.148	(-4.921)	37.250	(0.969)
Munich Re	21.251	5.369	-1.286	(-4.483)	-14.371	(-2.138)
RWE AG	16.536	3.893	-2.246	(-4.768)	-0.298	(-0.027)
Repsol YPF SA	68.976	6.441	-6.374	(14.196)	39.106	(3.643)
Royal Bk Scotland plc	17.828	1.485	-6.130	(-6.320)	73.060	(3.233)
Siemens AG	39.722	4.548	-3.280	(-14.261)	14.130	(2.666)
Telecom Italia SpA	32.775	4.450	-6.760	(-13.000)	6.910	(0.576)
Telefonica S A	26.259	6.098	-1.340	(-2.310)	-50.790	(-3.735)
Tesco PLC	20.241	2.201	-4.280	(-6.485)	36.780	(2.358)
Unilever N V	34.900	6.289	-0.762	(-6.927)	-21.860	(-8.408)
Utd Utils plc	20.233	5.881	-2.120	(4.157)	-13.520	(-1.099)
Vattenfall AB	28.497	6.261	-1.390	(-6.318)	-17.160	(-3.365)
Veolia Environnement	28.528	5.128	-2.510	(-9.296)	-21.150	(-3.467)
Vodafone Gp PLC	21.582	6.427	-3.140	(7.476)	-6.540	(-0.600)
Volkswagen AG	18.858	4.313	-6.150	(6.276)	34.120	(1.471)
WPP 2005 Ltd	43.207	3.166	-10.180	(16.419)	85.600	(5.252)
Wolters Kluwer N V	25.425	6.314	-0.100	(0.263)	-71.880	(-7.987)

The first two columns of Table IIIa present Johansen trace test statistics for the number of cointegrating relations between the CDS price and the credit spread over swap rates. In line with the theoretical prediction a constant is included in the long term statistical relation The number of lags is optimized using the AIC criteria for each company. The third and fourth columns present the estimated cointegrating relationship coefficients γ_0 and γ_1 .t ratios are given in parenthesis

Table IV a: VECM estimates and Contribution to price Discovery 10 year CDS
Samples June 2004-December 2009 (iTraxx)
July 2002- December 2009 (CDS)

	α_1	α_1	PD_v
iTraxx10	**-0.028**	**0.003**	**0.897**
	(-4.893)	(1.085)	
AB Volvo	-0.008	0.000	0.849
	(-4.561)	(0.896)	
AKZO Nobel N V	-0.025	-0.001	1.034
	(-5.557)	(-0.246)	
Aegon N.V.	-0.011	0.002	0.821**
	(-2.977)	(2.766)	
Aviva plc	-0.012	0.001	0.937
	(-4.708)	(0.934)	
Bay Motoren Werke AG	-0.012	0.002	0.878
	(-3.751)	(1.615)	
Bca Monte dei Paschi	-0.014	0.005	0.746**
	(-3.838)	(2.390)	
Bertelsmann AG	-0.009	0.000	0.980
	(-4.872)	(0.238)	
Brit Amern Tob plc	-0.013	-0.003	1.244
	(-4.024)	(-1.313)	
Carrefour	-0.021	0.010	0.672**
	(-3.947)	(2.250)	
Cie de St Gobain	-0.014	0.004	0.774**
	(-4.022)	(3.622)	
Commerzbank AG	-0.009	0.002	0.793**
	(-3.167)	(1.912)	
Deutsche Bk AG	-0.005	0.006	0.491**
	(-1.561)	(3.522)	
Deutsche Telekom AG	-0.008	-0.001	1.093
	(-4.732)	(-0.774)	
Diageo PLC	-0.008	0.003	0.750
	(-2.231)	(0.860)	
Enel	-0.012	0.001	0.919
	(-4.928)	(1.364)	
Fortum Oyj	-0.023	-0.001	1.032
	(-4.992)	(-0.173)	
France Telecom	-0.005	0.0002	0.954
	(-4.333)	(0.432)	
Hannover Ruck AG	-0.020	0.002	0.917
	(-3.829)	(0.613)	
Iberdrola S A	-0.016	0.004	0.816
	(-3.876)	(1.462)	
Koninklijke KPN N V	-0.007	0.001	0.899
	(-3.349)	(0.600)	
Koninklijke Philips Electrs N V	-0.014	-0.002	1.181
	(-4.938)	(-0.944)	
LVMH Moet Hennessy Louis Vuitton	-0.020	-0.003	1.187
	(-5.626)	(-1.411)	

Munich Re	-0.020	-0.001	1.038
	(-3.904)	(-0.227)	
Siemens AG	0.000	-0.000	0.652
	(4.66)	(0.627)	
Telecom Italia SpA	0.000	-0.0001	0.958
	(4.092)	(-0.080)	
Telefonica S A	-0.012	0.000	1.011
	(-4.092)	(-0.080)	
Unilever N V	-0.027	0.009	1.000
	(-4.740)	(1.432)	
Utd Utils plc	-0.003	0.006	0.483**
	(-1.318)	(3.295)	
Vattenfall AB	-0.017	-0.002	1.141
	(-4.643)	(-0.567)	
Veolia Environment	-0.019	0.000	0.987
	(-4.845)	(0.102)	
Vodafone Gp PLC	-0.006	0.006	0.500**
	(-1.958)	(2.602)	
WPP 2005 Ltd	-0.022	-0.001	1.036
	(-6.191)	(-0.562)	
Wolters Kluwer N V	-0.013	0.000	0.992
	(-4.192)	(0.0468)	

This table presents (point) estimates of the adjustment vector in the VECM specified in (3) as well as the contribution of the Price Discovery in the VIX market (PD_v) as specified in (5). ** denote rejection of predominance of VIX leadership in the price discovery process $(PD_x=0, PD_v=1)$at the 5% significance level on the basis of reported t statistics. In order for $(PD_x=0, PD_v=1)$to be accepted we require that α_1 is significantly different from zero (at 5%) level while α_2 not being significantly different from zero.

Table IV: Expected daily Returns, Volatilities and Performance Measures for Pairs strategies between VIX and individual CDS (August 2002-December 2009)

	Average	Volatility	Sharpe Ratio	Cummulative Profits
Accor	260.29	142.52	1.83	608.62
Aegeon	349.90	283.20	1.24	88.25
Azco	79.68	35.99	2.21	21.88
Aviva	838.01	348.86	2.40	215.35
Bayer	188.38	133.50	1.41	12.44
Bay Motoren	1009.69	397.75	2.54	284.53
BcaMon	79.15	110.85	0.71	20.16
Bertlesman	302.23	378.52	0.80	302.07
Brit Amern	82.70	116.24	0.71	52.59
Brit Tel	589.03	224.82	2.62	157.26
Carrefour	253.20	119.28	2.12	62.36
Cie e Saint Gobain	1403.29	28.16	49.83	362.96
CommerceBank	257.99	191.36	1.35	72.96
Deutche Bank	405.18	194.71	2.08	119.50
Deutche Telecom	126.27	48.48	2.6	3.54
Enel	315.49	338.63	0.93	178.85
Fortum	401.27	126.50	3.17	42.09
LMV5	320.66	148.78	2.16	86.21
France Tel	31.95	103.02	0.31	9.84
Hanover	302.97	144.52	2.10	9.49
Iberdrola	-88.48	59.64	-1.48	-90.51
LMV5	320.66	148.78	2.16	86.21
Hellenic Telecom	-52.80	55.66	-0.95	-52.75
Munich RE	84.95	76.34	1.11	83.33
Repsol	23.12	116.11	0.20	23.03
RWE	118.85	86.35	1.38	117.87
RWE5	198.20	109.11	1.82	54.24
Siemens	499.56	157.22	3.18	171.09
Telefonica	120.40	90.99	1.32	119.84
Telecom Italia	157.32	227.08	0.69	27.02
Tesco	-5.46	58.08	-0.09	-22.33
Uniliver	105.10	83.95	1.25	93.85
Vatten	69.89	39.82	1.76	17.97
Veolia	178.02	157.24	1.13	61.43
Vodafone	178.67	113.65	1.57	177.56
Walters	21.30	13.74	1.55	3.30
Volkswagen	315.42	203.47	1.55	315.10
WPP	40.08	42.57	0.94	29.79

This table reports mean yearly profits, volatility (measured by the standard deviation) and Sharpe Ratios for two strategies i) long position in VIX ii) pairs strategies between VIX and individual company CDSs

Appendix A. 3. Graphs

Fig1: VIX iTraxx and France Telecom CDS
5 year Maturities
2004-2009

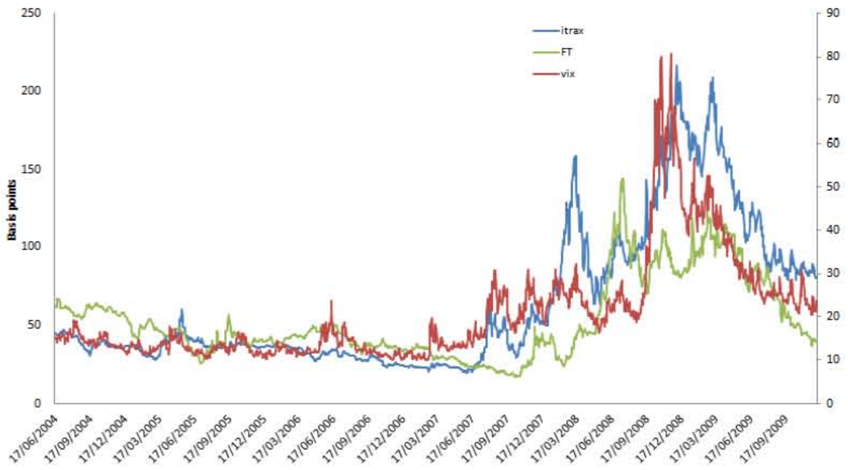

Fig 2: VIX iTraxx and France Telecom CDS
Three years Maturity
2004-2009

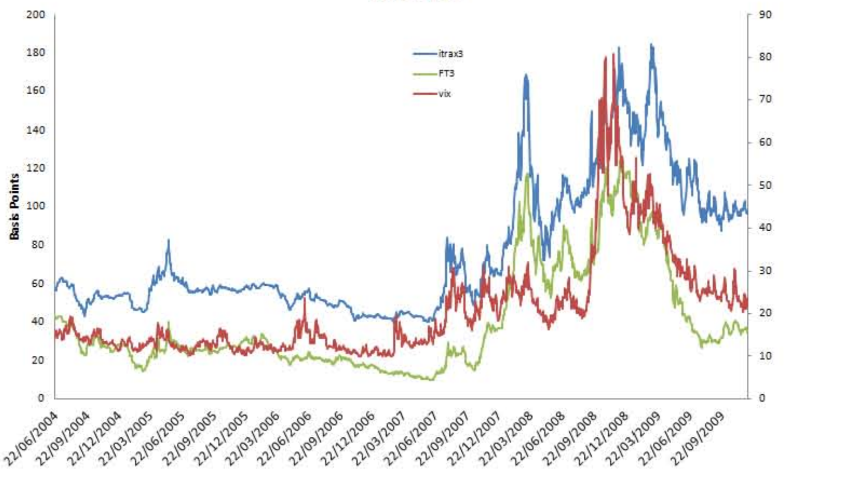

Fig 3: VIX iTraxx and France Telecom CDS
10 year maturity
2005-2009

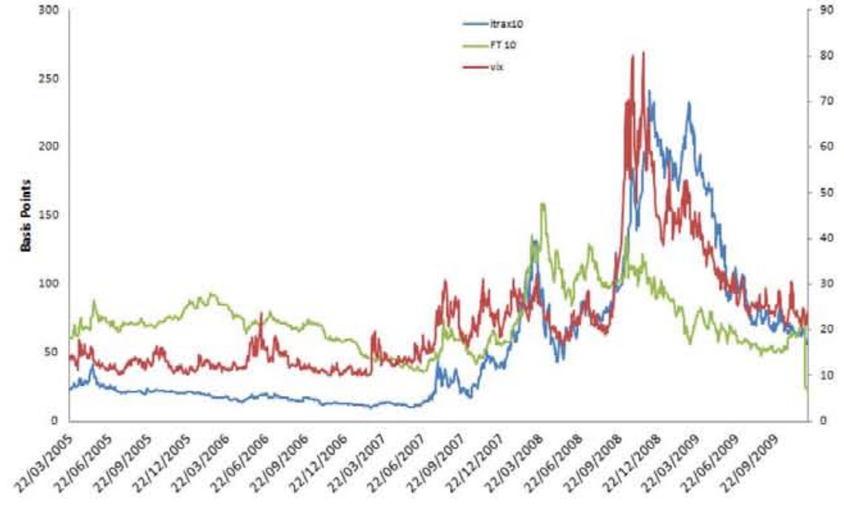

Fig 4: Time series plot of VIX and VIX future prices 2004-2011

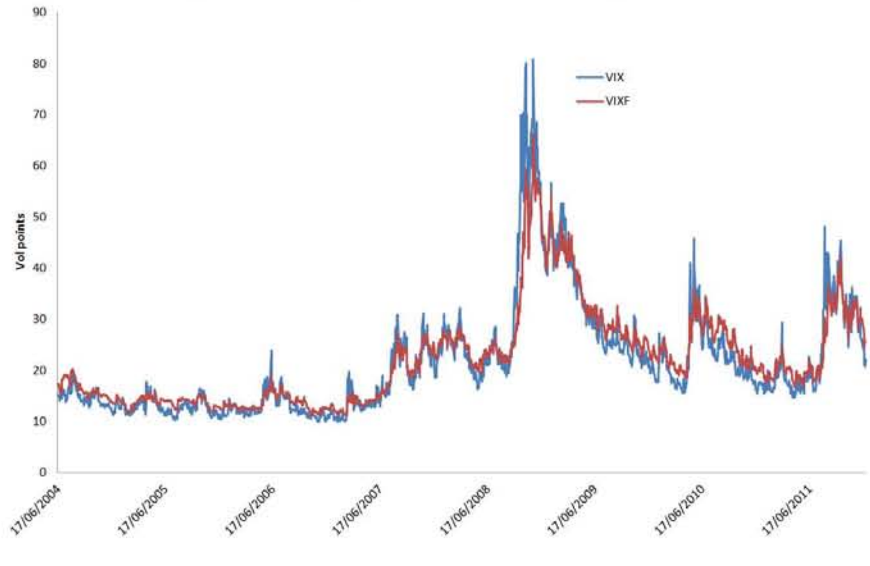

Fig 5: Recursive p values for ADF unit root test VIX and iTraxx indexes
Initial Sample 17-06-2004 to 10-12-2009
End Sample 17-06-2004 to 26-12-2012

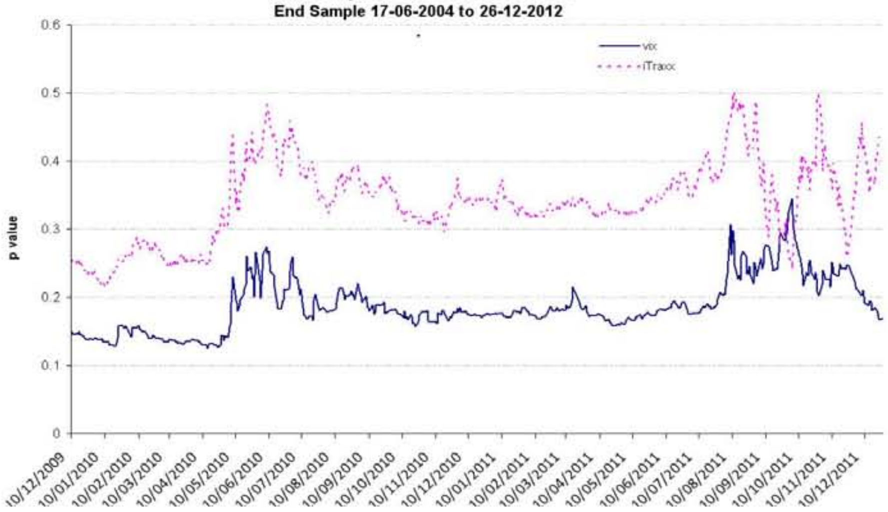

Fig 6: Recursive P values of ADF on the cointegration
error term zt = xt +21.14 - 4.148vt
where xt is 5 year iTraxx and vt is VIX
Initial sample 17-06-2004 to 06-03-2008
End sample 17-06-2004 to 22-12-2011