Pairing Market Risk and 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, represented via VECM parameters, are positive in all 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. Ericsson, Jacobs, and Oviedo (2009) and Cambell and Tasker (2003) focused on the effect of equity historical volatility on credit spreads. Zhang, Zhou and Zhu (2009) documented statistically and economically significant effects of (long term) historical volatility and (short term) realized volatility on credit spreads. Cao, Yu and Zhaodong (2010) and Cremers et al. (2008) analyzed the relationship between CDS and equity implied volatility 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 classical asset pricing theory as envisaged in the work of Merton, where credit spreads are functions of financial leverage and firm asset volatility, which both increase stock price volatility.

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, Goldstein and Martin 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.

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

In response to this literature, we use an exclusive European credit derivative data set to provide the first price discovery analysis between European credit risk and the VIX index. For a broad sample of 47 individual company iTraxx /CDSs covering a 5 to 7 years, we propose a no-arbitrage relation between European CDSs and the VIX volatility index in an equilibrium demand and supply framework with a common non stationary factor. Our work focuses on the adjustment of two cointegrated series to any event that causes divergences (between VIX and iTraxx/ CDS) from the equilibrium relationship driven by arbitrage in the two markets. 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.

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.

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 family of iTraxx indexes form a large sector of the overall credit derivative market covering regions of Europe, Australia, Japan and non Japan Asia. 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 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. It is subject to certain sector rules as determined by the International Index Company (IIC) and also as determined by the SEC.

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.

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 with firm level and portfolio CDS, we find that profits from pairs strategies outperform profits from investing in VIX or iTraxx /CDSs alone.

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 the CDS and VIX markets and showing that VIX is leading in 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, Goldstain and Martin

(2001) and Carr and Wu (2010) among others. It also adds to the current debate on whether credit risk and equity (option) volatility are integrated (see Cremers Driessen and Maenhout 2008). 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 Huppers and Menkveld (2002) and Pascual et al (2006). Our work is related to these papers although it does not focus the analysis on 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.

Cointegration is important because, as shown in Engle and Granger (1987), the presence of common stochastic trends require VECM representations. These models show that current period price changes depend on how far the system was out of long-run equilibrium last period. While a large strand of literature empirically analyses the existence of cointegration in financial assets, comparatively little has been done to examine the theoretical reasons for cointegration in financial markets (see Brener and Kroner 1995 and references therein). Notable exceptions include Campbell and Shiller (1987) and Bossaerts (1988). Brenner and Kroner (1995) use only widely accepted no-arbitrage arguments to explain why some markets, such as currency spot and forward markets are cointegrated, while other markets, such as commodity spot and forward (futures) markets, are not cointegrated. A more recent example includes the work by Figuerola-Gonzalo (2010), (FG thereafter) which introduces an equilibrium framework that leads to an economically meaningful interpretation of the VECM model. While FG base their model on the existence of arbitrage between spot and future commodity prices,

our work describes arbitrage strategies between VIX and CDS markets on the basis of pairs trading in the two integrated markets. Profits from pairs strategies exist only when deviations are short lived but equilibrium adjustment is not immediate, in which case VIX and CDS dynamics are represented in a VECM model. This framework allows us to build pairs strategies that offer improved performance than investing on VIX or credit spreads alone.

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. 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 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. Graphs and additional tables are collected in appendix A.2.

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 when there is temporary misspricing. The participants in the VIX markets are those individuals who invest directly the index or that trade derivatives on the VIX index. Participants in the CDS markets 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 describe how this process leads to market integration.

Let x_t be the price of a credit derivative or a credit derivative index in time t. Let v_t be the contemporaneous price 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 is 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 its mean and auto covariances are different for every realization of *t*.

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

$$x_t = g_0 + g_1 v_t + z_t \tag{1}$$

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 credit derivatives and credit derivative portfolios can be replicated with positions in the VIX derivative 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 mispricings. When the spread between VIX and CDS widens, there is positive profit potential that can be exploited by an arbitrageur that shorts the winner and buys the

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

loser. If the long and short components measure a common non stationary factor, the prices will restore equilibrium providing positive average profits.

When convergence to long run equilibrium is almost 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 consequence, potential profits represented by and 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 ? 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 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:

$$\begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \frac{H}{d} \begin{pmatrix} -N_v \\ N_x \end{pmatrix} \begin{pmatrix} 1 & -g_1 & -g_0 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ v_{t-1} \\ 1 \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \tag{2}$$

with

[6] This requires H→∞ in equation (2). The elasticity measures in this context the proportional change in deand for "pairs strategies" for a given change in the quantity of arbitrage services.

$$d = (H + N_x) N_v + g_1 H N_x \tag{3}$$

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]

$$\Delta Y_t = \begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} \hat{z}_{t-1} + u_t, \tag{4}$$

with $z_t = x_t - g_0 - g_1 v_t$ 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

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

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 ($\alpha_1=\alpha_2=0$), the elasticity of demand for pairs strategies is infinite ($H\rightarrow\infty$), 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 $\alpha_2=0$, the VIX market does not adjust to the CDS market as it is essentially the common factor or efficient price.

The Analysis of price discovery lies on a decomposition of cointegrated prices into a common permanent factor and a transitory component.[8] As proposed in FG, in this framework, the permanent component or common factor (CF_t) 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 are:[9]

[8] The two popular Price discovery metrics are the Information Shares of Hasbrouck (1995) and the Permanent Transitory Decomposition of Gonzalo Granger (1995).(See also Lehman 2002 special issue in the Journal of Financial Markets).

[9] See Booth et al. (2002) and Blanco et al. (2005) for an equivalent representation of the price discovery parameters.

$$PD_x = \frac{a_2}{a_2 - a_1} = \frac{N_x}{N_x + N_v} \tag{6}$$

$$PD_V = \frac{-a_1}{a_2 - a_1} = \frac{N_v}{N_x + N_v} \tag{7}$$

Therefore price discovery depends on the relative number of players in the VIX and CDS market. If new information from both markets is incorporated into the common factor,

0£ PD_i £1 for *i= x, v.* If $PD_x=1$ and $PD_v=0$ then there is a predominance[10] 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.

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

$$z_t = x_t - g_0 - g_1 v_t$$

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

$$\Pi_t = M(-\Delta x_t + g_1 \Delta v_t) = -M \Delta z_t \tag{8}$$

Where P_t are measured in \$ x_t is measured in basis points, v_t is measured in volatility points, and M is the amount invested (in \$). Substituting the result in equation (3), we get :

$$\begin{aligned} \Delta x_t &= a_1 z_{t-1} \\ \Delta v_t &= a_2 z_{t-1} \\ \Pi_t &= M(-a_1 + g_1 a_2) z_{t-1} \end{aligned} \tag{9}$$

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

When $z_{t-1} > 0$, for the VECM to work α_1 must negative $(-N_v)$ and α_2 positive (N_x) as indicated in our theoretical framework (2). This guarantees that expected profits from pairs strategies are always positive (see for instance Bossaerts 1988 and Gatev et al. 2006). 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 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.[11] 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 basis points.[12] Therefore 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 (5 year) iTraxx, VIX and France Telecom CDS for the three maturities over the 2004-2009 period. While VIX is measured in volatility points the iTraxx measure is in index points. The three figures suggest that VIX, iTraxx, as well as individual company CDS are highly related for all

[11] 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.
[12] Each basis point in CDS represents €1000 to protect €10m of debt.

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. Exposure to VIX futures is 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.

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

The Investable Volatility Index allows market players to take a position on the spot rather than the derivatives volatility market. The index is built up from VIX-like components computed from the four major quarterly S&P500 option expirations (Mar, Jun, Sep, Dec). It is designed to measure the return of an investment in the forward implied volatility of the S&P 500 Index. The index, created by Bank of America Merrill Lynch and calculated by CBOE is designed to offer direct exposure to equity market volatility.

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. [13] 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.

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.[14] Results are robust to the iTraxx/CDS maturity chosen.[15]

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 (Dx_t Dv_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 (in basis points) with γ_1 units of the VIX portfolio (in

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

[14] 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). A more detailed analysis is provided in section 5.

[15] Results are available upon request.

volatility points). This is also the case for all but six of the cointegrated individual 5 year CDS. [16]

We find cointegration at the 5% level between for VIX and each reference entity CDS in 42 out of the 47 companies considered. The remaining 5 show cointegration at the 10% significance level. [17] Conflicting signs in VECM estimates for Eurpn Aero Defence, Metro AG, and Repsol YPF SA confirms 39 out of the 42 cases of cointegration at 5% significance level.[18]

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 on average to replicate 10 year CDS with the VIX portfolio. Long cash positions are required to replicate 3 year CDS. We find positive signs for the γ_0 parameter in only 3 cases of the VIX and 3 year individual CDS analysed,[19] and in 10 out of the 35 VIX and 10 year individual CDS analysed.

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. Conflicting signs in the VECM error correction estimates for LVMH Moet Hennessy, Eurpn Aero Defence,

[16] Out of the 6 positive signs in the table, 4 are not significant.
[17] Note that the p value for the trace statistic for no cointegration is 5.2% and we take it as significant at the 5% level.
[18] Conflicting signs imply that estimates of adjustment vector coefficients (α_1 and α_2) are equal signaling evidence of no cointegration.
[19] Four coefficients had positive sign and two of them were not significant.

Koninklijke Philips Electrs N V, Metro AG and Repsol YPF SA confirm 41 out of the 47 cases of cointegration at 5% significance level.

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]

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)
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)

[20] Robustness is also found with respect to lag length.

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	-30.070
			(41.72)	(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 heteroskedasticity 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 heteroskedasticity. 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. Following the definition in Kim (2005), we determine the half-life in 5 year iTraxx and VIX to be equal to 3.1 days, indicating a smooth convergence to equilibrium. This allows opportunities to benefit from pairs strategies within a three week period range.

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. [21] 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.

[21] 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.

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. [22] 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. In this case the common factor is driven solely by the CDS.[23] In seven cases both the VIX market and the CDS market contribute significantly to price discovery. In 30 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 (a_1 and a_2) in all of these cases, a_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 34 out of 41 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

[22] 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

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

market PD_v is greater than one in eight of the individual company cases analyzed. Again, this arises because the estimated a_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 22 cases. The CDS market is the sole contributor to price discovery in two cases Deutche Bank and Utd Utils plc and both, the VIX market and the CDS market contribute in the price discovery process for 9 out of the 33 cases.[24]

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 later analyze price discovery of shares cross listed in US and Europe concentrating on the (two hour) daily overlapping interval. The former 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

[24] 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 (a_1 and a_2). However, as for the 3 and 5 years CDS, in all cases a_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. On the basis of theoretical framework, as underlined in equation (2) this implies that a) the VIX derivatives market has a higher number of participants than the credit risk market, suggesting that it trades at higher volumes b) arbitrageurs will benefit from riskless profits as long as credit risk adjustment to deviations from equilibrium is not immediate (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). [25] 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. 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 between VIX and iTraxx markets. These are calculated following changes in VIX and iTraxx. 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 P_t is expressed in Euros. Investments in iTraxx are done either directly investing in the CDSs or through ETFs, while investments in VIX can be done via VIX derivatives (futures and options on futures), and via ETFs including the investable volatility index of Merill Lynch(see section 2). The profit (or loss) of an investment in VIX or iTraxx can be estimated from the delta of the derivative used for

[25] 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.

investment, assuming all other factors remain the same.[26] For example, if the deltas for iTraxx and VIX investment are both equal to one, this implies that 100% of the changes will have an impact in the portfolio's profit (or loss). If $z_{t-1} > 0$, Dv_t is two points, and Dx_t is 50bps and we invest 1 € in iTraxx and 1 € in VIX, then profits will consist of 2*1= €2 from our position in VIX and 50*1= €50 from our position in iTraxx. Total profits from pairs strategies are defined as $P_t = Dv_t - Dx_t = 2-50 = -€48$.

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. Deltas are expected to be high and close to one for VIX futures and for the Merril Lynch investable Volatility index, and lower for VIX options and remaining ETF 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 rate. 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 VIX derivatives with unit delta,

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

iii) and investing in pairs strategies that combine 1€ invested in a delta one VIX derivative, and 1€ in a derivative written on iTraxx with deltas equal to iii) 1, iv) 0.6, and v) 0.4.

[26] 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.

We denote the last three pairs strategies as delta 1 strategies, delta 0.6 strategies, and delta 0.4 strategies.[27] Table III summarizes positions taken in the five strategies considered.

Table III: Description of investment strategies

Strategy (1€ investment)	**VIX**	**iTraxx**
(i) VIX	Δ_1	
(ii) iTraxx		Δ_1
(iii) delta 1	+ (-1)Δ_1	- (+) Δ_1
(iv) delta 0.6	+ (-1) Δ_1	- (+) $\Delta_{0.6}$
(v) delta 0.4	+ (-1) Δ_1	- (+) $\Delta_{0.6}$

This table provides a description of the five proposed strategies. Strategies that combine 1 € investment (with opposite positions) in VIX 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, Sharpe ratios and cumulative returns have been positive for all five strategies considered. Sharpe Ratios are maximized when we invest in delta 1 pairs strategies. End of the sample cumulative profits are maximized by investing in delta 0.6 pairs strategies. Reported figures suggest that pairs strategies deliver improved cumulative profits than those that are obtained from investing in iTraxx or VIX alone.

[27] Delta one strategies for the VIX index include investment in VIX futures, under the presumption of zero risk free rate. We allow delta to vary in the iTraxx case. An example of non delta one strategy is provided by Bloomberg which provides a prices for an ETF written on a basket of iTraxx CDSs with a delta in the order of 0.44.

Table IV: Expected Returns, Volatilities Performance Measures and Cummulativefor different trading Strategies (June 2004-December 2009)

	μ	s	Sharpe Ratio	Cummulative Profits
Itraxx	0.280	0.597	0.468	0.279
VIX	0.605	1.049	0.577	0.605
Pairs 1	84.539	91.540	0.924	15.473
Pairs 0.6	15.601	35.751	0.436	15.579
Pairs 0.4	11.338	30.314	0.374	11.322

This table reports mean annual profits, volatility (measured by the standard deviation), simplified Sharpe Ratios and annualized cumulative profits for three strategies i) long position iTraxx ii) long position in VIX iii) delta 1, delta 0.4 and delta 0.6 pairs strategies

Average profits and volatilities as well as Sharpe ratios are also calculated for all cointegrated pairs of VIX and individual company CDSs, assuming a delta equal to one for the investment in VIX as well as individual CDS. Calculated profits are reported in table IVa in the appendix. Pairs strategies deliver positive mean profits for all cointegrated pairs analysed. As it is the case for the CDS portfolio, performance from pairs strategies, as measured by the simplified Sharpe Ratios, are superior than betting on VIX or iTraxx alone.

5. Robustness Checks

We have updated our sample to include VIX and 5 year iTraxx data from end of December 2009 to end of December 2011. This allows testing for robustness to the inclusion of post crisis periods. As a first robustness check we perform recursive Augmented Dickey Fuller test unit root tests VIX and iTraxx indexes. Figure 4 in the appendix reports recursive p values 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.

In view of updated sample ADF results we perform an out of sample performance analysis of the proposed strategies over the Jan2009-2011 period. [28] We do this using the cointegration relation prevailing over our sample period. Results, reported in table V may be summarized as follows. All strategies involving iTraxx provide positive Sharpe ratios and cumulative profits. The later are maximized when with delta 0.4 pairs strategies while the former are highest for strategies that invest 1€ in iTraxx. VIX performs poorly over the updated period while pairs strategies provide positive earnings.

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

	μ	s	Sharpe Ratio	Cummulative Profits
Itraxx	0.352	0.542	0.650	0.352
VIX	-0.013	1.240	-0.010	-0.013
Pairs 1	18.260	60.431	0.302	15.069
Pairs 0.6	18.607	39.170	0.475	15.355
Pairs 0.4	18.781	32.097	0.585	15.499

This table reports mean daily profits, volatility (measured by the standard deviation), simplified Sharpe Ratios and annualized cumulative profits for three strategies i) long position iTraxx ii) long position in VIX iii) pairs strategies between VIX and iTraxx

[28] This supports the existence of a liner relationship between VIX and iTraxx.

We can therefore establish that profits from pairs strategies are not sample dependent.

6. Conclusion

This article exploits a highly comprehensive data set on European iTraxx/CDSs and VIX to analyse the nature of the link between credit risk and market risk. We contribute to the empirical literature that associates implied option volatility and CDS markets by reporting the following findings:

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, 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 average and cumulative profits from pairs strategies are always positive and higher than profits from investing in VIX or iTraxx alone. This is robust to changes in the delta of the investment vehicle used and to out of sample estimations including data from January 2010 to December 2011.

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

Let´s 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 ith 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 ith 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 relevant results in our theoretical framework are robust to a more general structure of the elasticity of demand, such as, $A_i = A + a_i$, where a_i is an independent random variable, with $E(a_i) = 0$ and $V(a_i) = s^2_i < 8$.

The demand schedule for the jth 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

$$\begin{aligned} & H\left((g_1 v_t + g_0) - x_t\right), && H > 0, \\ & = H(z_t), && H > 0, \end{aligned} \tag{A1.3}$$

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,

$$\sum_{i=1}^{N_x} P_{i,t} = \sum_{i=1}^{N_x} \left(P_{i,t} - A\left(x_t - B_{i,t} \right) \right) + H\left(\left(g_1 v_t + g_0 \right) - x_t \right) \qquad H > 0, \tag{A1.4}$$

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

$$\sum_{j=1}^{Nv} P_{j,t} = \sum_{i=1}^{N_v} \left(P_{j,t} - A\left(v_t - B_{j,t} \right) \right) - H\left(\left(g_1 v_t + g_0 \right) - x_t \right) \tag{A1.5}$$

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

$$\begin{aligned} x_t &= \frac{(AN_v + Hg_1)N_x B_t^x + HN_v g_1 B_t^v + HN_v g_0}{(H + AN_x)N_v + HN_x g_1}, \\ v_t &= \frac{HN_x B_t^x + (H + AN_x)N_v B_t^v - HN_x g_0}{(H + AN_x)N_v + HN_x g_1}. \end{aligned} \tag{A1.6}$$

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 ith 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

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

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 ith 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 ith participant ($w_{i,t}$). The equations in (A.1.7) imply that the mean bid price in each market in period t will be

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

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.1.6) into (A.1.6) yields the following vector model

$$\begin{pmatrix} x_t \\ v_t \end{pmatrix} = \frac{Hg_0}{d}\begin{pmatrix} N_v \\ -N_x \end{pmatrix} + (M)\begin{pmatrix} x_{t-1} \\ v_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \tag{A1.9}$$

where

$$\begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} = (M)\begin{pmatrix} e_t + w^x \\ e_t + w_t^v \end{pmatrix} \tag{A1.10}$$

$$M = \frac{1}{d}\begin{bmatrix} N_x(g_1 H + AN_v) & g_1 HN_V \\ HN_x & ((H + AN_x)N_v \end{bmatrix} \tag{A1.11}$$

And

$$d = (H + N_x)N_v + g_1 HN_x \tag{A1.12}$$

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

$$\begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \frac{Hg_0}{d} \begin{pmatrix} N_v \\ -N_x \end{pmatrix} + (M - I) \begin{pmatrix} x_{t-1} \\ v_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \tag{A1.13}$$

$$M - I = \frac{1}{d} \begin{bmatrix} -HN_V & g_1 HN_v \\ HN_x & -HN_x g_1 \end{bmatrix} \tag{A1.14}$$

Rearranging terms,

$$\begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \frac{H}{d} \begin{pmatrix} -N_v \\ N_x \end{pmatrix} \begin{pmatrix} 1 & -g_1 & -g_0 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ v_{t-1} \\ 1 \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \tag{A1.15}$$

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)

	a_1	a_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 None (95% c.v. 20.16)	at Most one (95% c.v. 9.14)	Estimated Coefficients (1, $-\gamma_1$, $-\gamma_0$) $z_t = x_t - \gamma_0 - \gamma_1 v_t$ $-\gamma_1$		$-\gamma_0$	
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	(-112.335)		
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)	-165.023	(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	(-6540)
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)

	a_1	a_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.

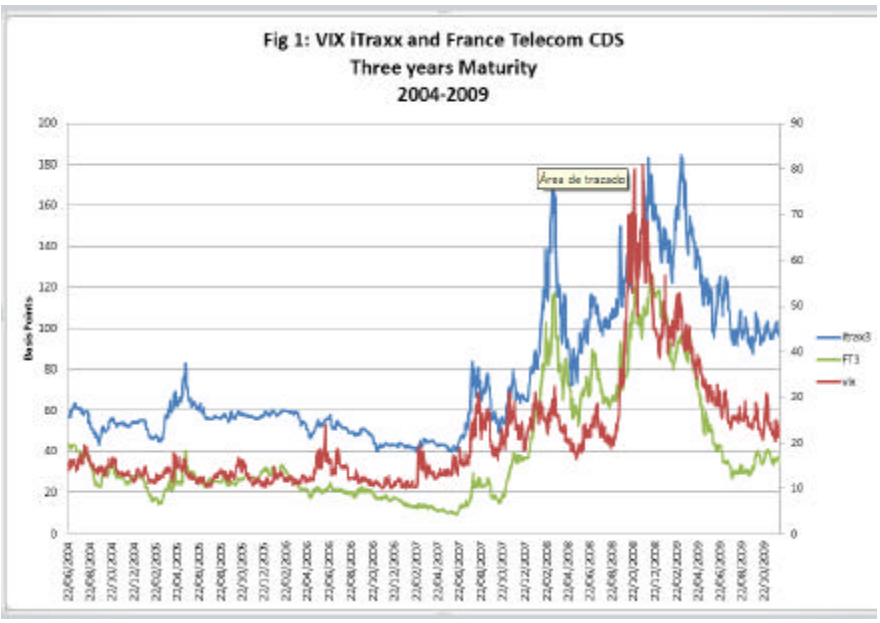
Table IV: Expected daily Returns, Volatilities and Performance Measures for Pairs strategies between VIX and individual CDS (August 2002-December 2009)

	μ	s	**Sharpe Ratio**
VIX	0.000	0.060	-0.005
AB Volvo	0.3337	5.540	0.061
ACCOR	0.000	0.000	0.185
AKZO Nobel N V	0.289	2.715	0.106
Aviva plc	0.143	2.085	0.069
Aegeon	0.242	2.577	0.094
Bay Motoren Werke AG	0.324	2.495	0.130
Bayer	0.230	3.254	0.071
Bca Monte dei Paschi	0.197	2.411	0.082
Bertelsmann AG	0.118	2.833	0.042

Brit Amern Tob plc	0.186	2.339	0.080
British Telecom	0.163	1.933	0.085
Carrefour	0.186	2.339	0.080
Cie de St Gobain	0.234	1.988	0.118
Commerzbank AG	0.282	2.378	0.119
Deutsche Bk AG	0.200	2.232	0.090
Deutsche Telekom AG	0.171	1.971	0.087
Diageo	0.184	3.827	0.048
Enel	0.120	2.118	0.057
E.ON AG	0.301	2.422	0.124
Fortum Oyj	0.292	2.682	0.109
France Telecom	0.249	2.216	0.112
Hannover Ruck AG	0.251	2.377	0.106
Hellenic Telecom Org SA	0.149	2.113	0.071
Koninklijke Philips Electrs N	0.308	2.211	0.139
Marks & Spencer p l c	0.264	2.012	0.131
Iberdrola	0.115	1.804	0.064
LVMH Moet	0.245	2.785	0.088
Munich Re	0.251	2.207	0.114
Repsol	0.280	2.606	0.108
RWE AG	0.212	2.694	0.079
Telefonica S A	0.190	2.259	0.084
Siemens	0.110	1.769	0.062
Telecom Italia SPA	0.261	3.421	0.076
Uniliver	0.116	1.865	0.062
Veolia	0.076	1.893	0.040
Vattenfall AB	0.160	2.737	0.058
Vodafone Gp PLC	0.210	1.945	0.108
Volswagen AG	0.258	2.335	0.111
Wolters Kluwer SA	0.085	0.866	0.098
WPP 2005 Ltd	0.159	2.682	0.059

This table reports mean daily 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

8. Graphical Appendix



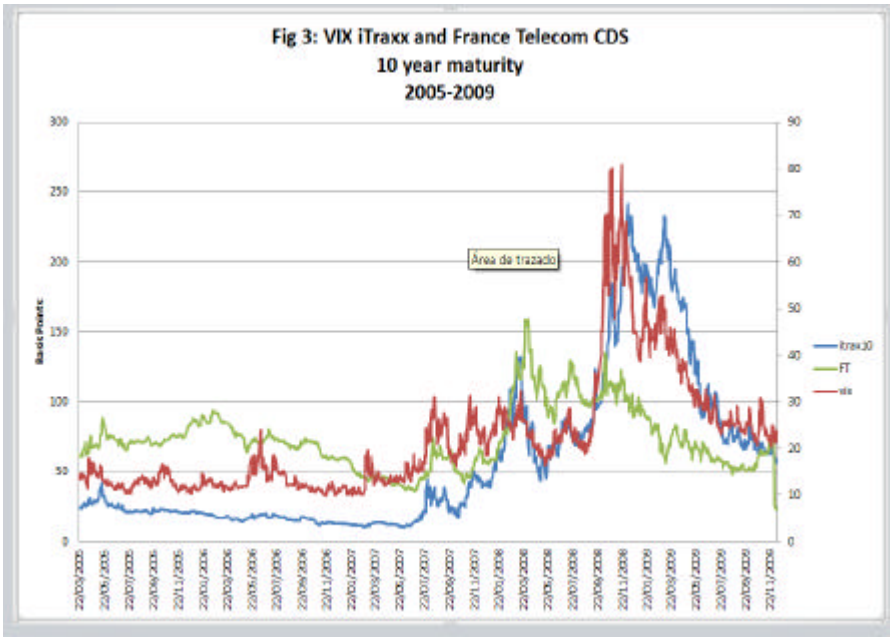
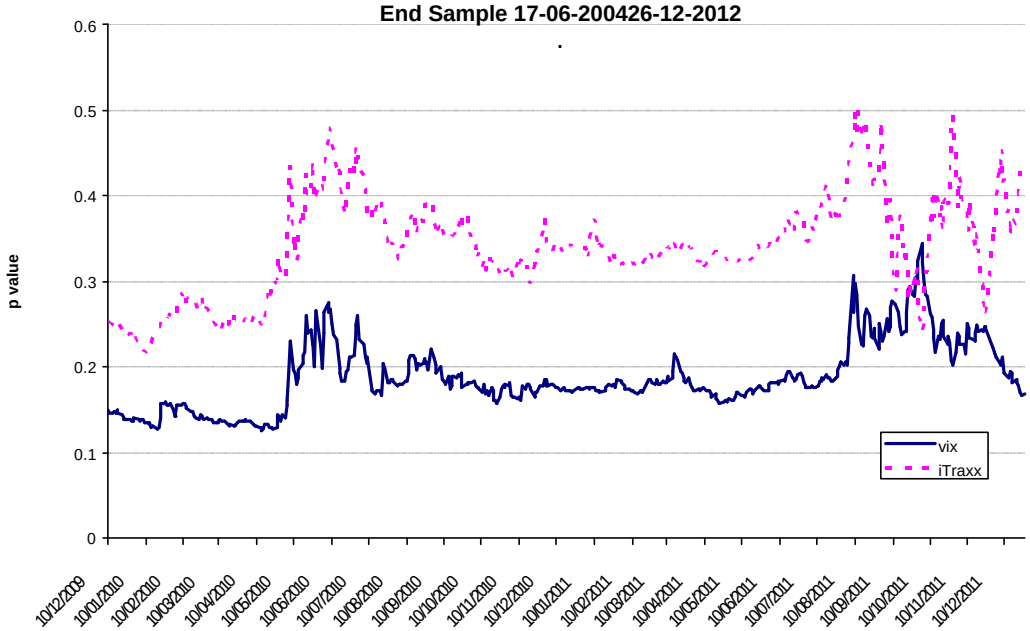



Figure 4: Recursive p values for ADF unit root test VIX and iTraxx indexes
Initial Sample 17-06-2004 to 10-12-2009
End Sample 17-06-200426-12-2012