The dynamic relation beetween CDS markets and the VIX index

Isabel Figuerola-Ferretti[A]

Ioannis Paraskevopoulos[B]

Abstract

This study uses a comprehensive data set of VIX and CDS markets to propose pairs trading strategies that represent the dynamic relation between market risk and credit risk in an equilibrium framework with non stationary factors. This involves the analysis of price discovery between VIX and the 47 most traded iTraxx companies. We find cointegration between market risk and credit risk and predominant price leadership in the VIX market. CDS spreads can thus be replicated through positions in the VIX derivatives markets. We demonstrate how one can capitalize on the price discovery between market and credit risk by building a pairs arbitrage strategy whose profits are driven by the common price discovery factor. The respective portfolios are tested against statistical arbitrage. (JEL: C13, C51, G12, G13, G14)

1. Introduction

In this paper we model pairs trading strategies between the VIX volatility index and Credit Default Swaps (CDS) in an equilibrium asset pricing framework with non stationary common factors. Our work focuses on the adjustment of two cointegrated series to any event that causes divergences from the long run relationship driven by arbitrage between 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 CDS in the price discovery process. This allows us to identify the common factor that drives profits in pairs trading strategies based on "statistical arbitrage" of cointegrated price series.

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, and it is important to measure, price and manage accurately. 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.

[A] Business Department, Carlos III University, Madrid. ifgarrig@emp.uc3m.es
[B] Quantitative Development, Treasury, Caja Madrid. iparaske@cajamadrid.es

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 the total credit derivatives trading volume. A credit default swap is essentially an insurance contract providing protection against losses arising from a credit event. Recently tradeable CDX indexes have been introduced to allow investors to quickly and easily buy and sell sectoral credit risk. In June 21 2004 the two main CDS indexes iBoxx and Trac-x, were merged into the Dow Jones iTraxx index that since has set a new standard when it comes to liquidity transparency and diversification. 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 index is a portfolio of the 125 most liquid CDS of European Investment Grade rated companies in the market. It is the main reference European credit Index.

Both the VIX and Itraxx indexes increased their value by 400% over the course of 2008 reflecting high generalized fear in the economy, inherent in both credit risk and market risk measures.

For entities with traded equity the default probabilities are often estimated using information from the stock market. The CBOE volatility index VIX, a gauge of risk aversion, has become the factor benchmark for stock market volatility. The VIX index measures a weighted average of option prices on the S&P 500 index across all strikes at two nearby maturities. On March 2004 the CBOE launched the Chicago futures exchange to start trading futures on the new VIX. Options on the VIX were launched on 2006. They have been the most successful contract in the history of the exchange. As a result, VIX is now the premier benchmark for world stock market risk

This paper tests the validity of “pairs trading” strategies in an equilibrium factor model relating market risks to credit risk for a comprehensive sample of 47 iTraxx companies, and the iTraxx index for three five and ten year maturities. We find that there are long term arbitrage relationships between VIX and CDS for most companies implying that excess returns may be earned using “pairs trading” strategies in the sense of Gatev et al. (2006). This is the first contribution of our paper. Our result points to the existence of a systematic factor that influences the profitability of pairs trading over time. We attribute this result to a clear lead of VIX over CDS in the price discovery process, implying that CDS adjust to market risk when there is temporary mispricing from the long term equilibrium. This is the second contribution of our paper.

Statistical arbitrage may be defined as long horizon opportunity that generates a riskless profit see Hogan et al (2004). Pairs trading is a Wall Street investment strategy that belongs to the proprietary “statistical arbitrage” tools currently implemented by investment banks and hedge funds “. Gatev et al. (2004) test pair trading strategies using US equity data for the 1962-2002 period. They find average annualized returns of about 11% for top pairs portfolios. Additionally, they find evidence suggesting that there is a systematic factor that influences the profitability of pairs trading over time. Our contribution relative to this paper is to use the FG price discovery framework to identify the common factor leading profits in pairs strategies.

The link between credit and stock markets was first acknowledged by Merton (1974), who firm modelled default probabilities as a function of stock market related variables. More recently, CDS spreads and stock market prices were analysed, as well as the link between CDS spreads and return volatilities (see Bystrom 2005 and references therein). However this is the first paper that looks at price discovery between CDS and stock volatility indexes. We are interested in unveiling the dynamic components underlying VIX and iTraxx prices. This allows us to infer how market risk and credit risk are related and what credit risk information can be inferred from forward volatility of equity markets. If similar economic fundamentals affect the value of the two risk indexes, rational long run interdependency exists between their prices. Since prices set in efficient speculative markets contain unit roots, this argument states that VIX and iTraxx prices are cointegrated.

While VIX is often referred as the “fear index” and used to hedge portfolio volatility exposures, credit indexes reflect joint distributions of default risk across firms. We are interested in the component of joint distributions that contributes to systematic risks of “credit crunches” and liquidity crunches, which is captured by identifying the common factor in a long term price discovery framework.

Price discovery is the process of uncovering and asset´s full information or permanent value. The unobservable permanent price reflects the fundamental value the underlying asset. It is distinct from the observable price, which can be decomposed into its fundamental value and a transitory component reflecting temporary effects such as bid ask bounces or short lived order imbalances. In this paper we provide evidence of a long run relationship between the iTraxx CDS market and the VIX index, and suggest that VIX is information dominant.

If the VIX and iTraxx CDS are cointegrated, price discovery may be regarded as a dynamic process in search for an equilibrium state. This requires the sudden adjustment of both indexes to new equilibrium for a given arrival of new information. If both markets do not react to new information in the same manner, one may lead the other. When such a lead-lag relationship appears, the leading market is said to provide price discovery.

The analysis of price discovery has traditionally been confined to the study of spot and future commodity markets. Within the last decade, the research on price discovery has focused on microstructure models and on methods to measure it. This line of literature applies two methodologies (see Lehman, 2002; special issue of Journal of Financial Markets), the Gonzalo-Granger (1995) Permanent-Transitory decomposition (PT thereafter) and Information Shares of Hasbrouck (1995) (IS thereafter).

More recently, the literature on price discovery has also focused on credit risk markets. These applications analyze the relative informational efficiency of the CDS and bond markets in the sense of Blanco et al. (2005) or Zhu (2006) who conclude that CDS market dominates the bond market. Based on iTraxx companies, Dotz (2007) finds that both markets contribute to price discovery. In general the consensus is that price discovery depends on the relative liquidity of the given markets.

The issue of reconciling price discovery with asset pricing models has generally been met with limited success. Figuerola and Gonzalo (2010) (FG thereafter) provide an equilibrium commodity price discovery model suggesting that price discovery depends on the relative volumes traded in spot and future markets. Their economically meaningful Vector Error Correction Representation provides a justification for the use of the PT measure as a metric for price discovery and proposes a factor model that drives spot and future prices. In this paper we show that the FG common factor model can be based on the existence of "pairs strategies" and may be used to identify the common factor leading pairs strategies in Gatev et al (2006). Our common asset pricing factor is the VIX index.

The rest of the paper is organized as follows. The second section discusses price discovery between equity markets, and CDS markets. In section 3 we relate 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). Data and empirical results are presented in section 5. In section 6 we show modified Sharpe Ratios from “pairs trading” strategies based on cointegrating relationships and test for the existence of statistical arbitrage. Section 7 concludes. Graphs are collected in the appendix.

2. CDS index spreads Equity Forward Volatility and Price Discovery

Credit risk is a crucial parameter for CDS pricing. This is the probability of default associated with the underlying reference entity. To quantify credit risk, agents can rely on rating agencies, traditional scoring models, or extract information about credit risk from the market. We focus on the third alternative by arguing that if credit risk is reflected by the market, then there must be ways of filtering the information contained in stock market risk indicators such a the VIX index, to get measures of credit risk.

The most well known stock market based credit risk model is the Merton (1974) model. In this model a firm´s liabilities (equity and debt) are assumed to be contingent claims issued against a firm underlying asset. The default probability in the Merton (1974) model is a nonlinear function of the firm´s stock price, stock price volatility and the leverage ratio. Simplified versions of the standard Merton model can be found in Hall and Miles (1990) and Clare and Priestley (2002). In the Hall and Miles framework the default probability is a function of stock price volatility.

Since the most important determinant of the CDS price is the likelihood that a credit event occurs and since the literature tells us that this probability should be linked to stock return volatility, it is natural to investigate the link between forward looking stock market volatility index (i.e. the VIX) and a credit risk traded index such iTraxx.

There are earlier studies that deal with related issues. Fama and French (1993) find some commonalty in risk factors affecting the stock and the bond market. Kwan (1996) looks at the relationship between the corporate bond market and the stock market. Campbell and Taksler (2002) look at the relationship between stock return volatilities and bond yields show that firm-level volatility can explain much of the variation of US corporate bond yields. Bystrom (2005) provides some early evidence of a link between the iTraxx and the stock market. Other related papers, including Collin-Dufresne et al. (2001), Goldstein and Martin (2001), Elton et al. (2001), and Huang and Huang (2003) show that corporate credit spreads are driven by firm-specific factors as well as broader economic forces.

The relationship between credit risk with market risk related variables has, in many instances, been studied using price discovery models. Price discovery research in credit risk has experienced a paradigm shift from traditional fundamental approaches to focusing on credit risk based on financial market information. The structural model framework assumes the equity market is efficient in impounding credit risk information, while reduced form model relies on the debt market as the main source of credit risk information.

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 lead information in debt markets. Blanco, Brennnan and Marsh (2005) analyzed a set of European and US bonds using CDS prices and credit spreads in the bond cash market and found that the CDS market was the leader in the price discovery process.

Another strand of literature deals with efficiency performance of relative asset pricing activities. 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. Pairs trading strategies in the sense of Gatev et al. (2006) shed light to this literature by suggesting that excess returns may be gained from temporary mispricing of close substitutes.

In this paper, we provide a link between the price discovery and the pairs strategies literature taking the CDS and VIX markets as close substitutes in a relative pricing framework. The underlying assumption is that prices from substitute markets are cointegrated.

3. Pairs strategies and the VECM model: Dynamics and Price Discovery between VIX and iTraxx markets

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. The participants in the VIX markets are those individuals that trade derivatives on the VIX index. Futures on VIX, CBOE's trademark Market Volatility Index have been traded since the beginning of 2004. They 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. On February 24, 2006, options on the CBOE Volatility Index (VIX) began trading on the Chicago Board Options Exchange. 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.

Credit derivatives and CDS came into existence in 1992 and by the end of 2002 the total gross notional value of outstanding credit derivatives was around U.S. $1.9 trillion. The iTraxx index was launched in June 2004 and it has set a new standard in the CDS market in terms of exposure liquidity and diversification. Participants in the iTraxx market take large exposures to a diversified pool of credit risks, which are now much easier to obtain. The liquidity of the iTraxx market has attracted new participants such as hedge funds and capital structure arbitrageurs. Exposures on the iTraxx market can be gained via a new credit derivative ETF on the NYSE Euronext market in Paris the EasyETF iTraxx Europe Main. This includes EasyEFT iTraxx Europe HiVol, EasyETF iTraxx Crossover, and the new tracker on the European credit derivative market, the EasyETF iTraxx Europe Main. (see www.easyetf.com)

Knowledge about the characteristics on the joint dynamics between VIX derivatives and CDS index markets is crucial to arbitrageurs which will benefit from pairs strategies between the two substitutes markets. In this section we provide a framework that describes their equilibrium dynamics, which are dependent on degree of the elasticity of arbitrage services.

3.1. Equilibrium Prices with Infinitely Elastic Supply of Arbitrage Services

Let x_t be the price of a credit derivative or a credit index in time t. Let v_t be the contemporaneous price of a derivative written on the 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 taxes or transaction costs.
- (a.2) No limitations on borrowing.
- (a.3) No cost other than arbitrage risk cost
- (a.4) No limitations on short sale.
- (a.5) Arbitrage risk cost differential between credit derivatives and the VIX derivatives markets is determined by the process $c_t = g_0 + I(0)$ where γ_0 is the mean of c_t and I(0) is a stationary process with mean zero and finite positive variance.
- (a.6) Credit derivatives and VIX derivative prices are I(1)

By the above assumptions (a.1-a.6), non-arbitrage equilibrium conditions imply

$$x_t = g_0 + g_1 v_t + I(0) \tag{1}$$

equation 1, implies that x_t and v_t are cointegrated and shows how the credit derivatives and credit derivative portfolios can be replicated with positions in the VIX derivative market. γ_0 reflects mean arbitrage risk cost differentials, including in dividend yield differentials and positions required in risk free asset to finance the replicating strategy. γ_1 reflects the position that has to be taken in the VIX derivative market to replicate returns in the CDS market, or the degree of substitutability of positions between both markets. In what follows, we propose that because x_t and v_t are cointegrated price convergence is achieved via “pairs trading strategies.” The idea is that when the spread between both prices widens we short the winner and buy the loser. If the long and short components fluctuate with common non stationary factors then the prices of the component portfolios are cointegrated and the pairs trading strategy is expected to work.

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 arbitrage services. However there are a number of cases in which the elasticity of arbitrage services is not infinite in the real world. Many factors, mainly arising from contractual differences between both instruments, transaction costs differentials or restrictions in the short run availability of capital may limit the supply of arbitrage services by making arbitrage transactions between both markets risky.

3.2. Equilibrium Prices with Finitely Elastic Supply of Arbitrage Services

To describe the interaction between credit and VIX derivatives we must first specify the behavior of agents in the marketplace with finite elasticity of arbitrage services, which is described in Appendix A. Under this more realistic case, the dynamics between the VIX and iTraxx markets may be represented as

$$\begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \frac{H_1}{d} \begin{pmatrix} -N_v \\ N_x \end{pmatrix} \begin{pmatrix} 1 & -g_1 & -g_0 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ v_{t-1} \\ 1 \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \qquad (2)$$

with

$$d = \left(H + N_x\right) N_v + g_1 H N_x$$

Where there are N_x participants in the credit derivatives market and N_v participants in VIX derivatives market and H is the elasticity of arbitrage services.

Applying the PT decomposition in this VECM, the permanent component will be the linear combination of x_t and v_t formed by the orthogonal vector (properly scaled) of the adjustment matrix $(-N_v, N_x)$. In other words the permanent component or common factor model for CDS and VIX markets is

$$f_t = \frac{N_x}{N_x + N_v} x_t + \frac{N_v}{N_x + N_v} v_t. \quad (3)$$

This is the price discovery metric proposed by FG applied to credit derivatives and stock volatility derivatives market prices. The measure does not depend neither on g_1 nor on the finite value of the elasticities A and *H (>0)*. These elasticities do not affect the long-run equilibrium relationship, only the adjustment process and the error structure. For modelling purposes is important to notice that the long run equilibrium is determined by expression (1), and it is the rest of the VECM (adjustment processes and error structure) that is affected by the different market assumptions on elasticities, participants, etc.

3.3. Pairs strategies and Price Discovery

Let´s rewrite the theoretical result in (2) as

$$\begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} \hat{z}_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta X_{t-i} + u_t, \quad (4)$$

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 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 then returns on iTraxx will be higher than those of VIX, so pairs strategists will short iTraxx (outperformer) and buy VIX making profits exploiting differentials in cointegrating relationship until they restore equilibrium. Because pair strategists long one asset and short the replicating asset, the adjustment coefficients have opposite signs as shown in equation (3). Long run differentials exist for a period of three to four days when the elasticity of arbitrage services H is finite.

II. If the CDS market were contributing significantly to price discovery, then α_2 will be positive and statistically significant as the VIX market adjusts to incorporate this 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 means that at least one market has to adjust to the long run equilibrium implying that that market is inefficient, so that there can be profits from pairs strategies. If the adjustment is immediate, elasticities from arbitrage services are infinite, and there is no VECM, no price discovery and no profit from "pairs strategies."

The Gonzalo-Granger price Discovery Metric requires calculation of the orthogonal vector to the adjustment vector. In fact, it can be shown that the contribution of price discovery in the iTraxx market is

$$GG_x = \frac{a_{\perp 1}}{a_{1,\perp} + a_{2,\perp,}} = \frac{a_2}{a_2 - a_1} = \frac{N_x}{N_x + N_v} \qquad (5)$$

Given that we short iTraxx and we long VIX, we now relate profits from pairs strategies to the VECM in (4) by writing our betting portfolio as $\Pi_t = M(-\Delta x + \Delta v)$, M being the investment amount, which is the same for both assets. Substituting the result in equation (4), we get

$$\Pi_t = M(-a_1 + a_2)\hat{z}_{t-1} = M(N_v + N_x)\hat{z}_{t-1} \qquad (6)$$

Thus if M=1, total profits will be given by $(-\alpha_{1+}\alpha_2)= N_v + N_x$, then from (6) contributions to total portfolio profits from taking short positions on iTraxx will be $-\alpha_1 /(-\alpha_1+\alpha_2)=N_v/(N_v + N_x)$and contribution to total profits from taking long positions on Vix will be $\alpha_2 /(\alpha_1+\alpha_2)=N_x/(N_v + N_x)$ .Thus if $(-\alpha_1+\alpha_2)$ is not equal to 0 ie $N_v + N_x \pm 0$ we will have profits from pairs strategies, and then total contributions to total profits will be $-\alpha_1 /(-\alpha_1+\alpha_2) +\alpha_2 /-(\alpha_1+\alpha_2) =1$.

The differential in the alphas determined by the sum in the number of participants in each market, determine whether there is investment opportunity. If this difference is big means that VIX and CDS/Itraxx are drifting apart and there is room to benefit from pair strategies because adjustment is not inmediate.. As we measured, on average they need

4 days to return to equilibrium. Therefore a pair bet on the two following the VECM in (4) is placed to exploit short term differentials.

Hogan et al. (2004) develop a methodology to test for statistical arbitrage. This requires that P&L increments ($\Delta\Pi$) follow a normal distribution with adjusted first and second moments,

$$\Delta\Pi_i = mi^J + s\, i^l z_i\,,\ \forall i = 1,2,...,n\,,$$

where z_i are i.i.d $N(0,1)$ random variables. $\Pi(t_0), \Delta\Pi_0, z_0$ are all zero.

$$\Pi(t_n) = \sum_{i=1}^{n} \Delta\Pi_i \sim dN\left(m\sum_{i=1}^{n} i^J, s^2 \sum_{i=1}^{n} i^{2l} \right) \tag{7}$$

with mean increments of P&L, $E(\Delta\Pi) = m \cdot i^J$, and variance of P&L increments, $Var(\Delta\Pi) = s^2 i^{2l}$. It turns out that μ can be related to the adjustment vector in the VECM specified in (4) in particular we can write $\mu=(-\alpha_{1}+\alpha_2)$, so that expected returns from pairs strategies will also depend on how iTraxx and VIX react to equilibrium error.

4. Dataset and Empirical 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 and for both series. 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 & 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 iTraxx index. We use information in each of these series to select the 50 most representative iTraxx companies.[1] These are those for which CDS have been traded in all 11 iTraxx series. Data for CDS and iTraxx are for 3, 5, and 10 year maturities. Figures 1-3 shows the time series plot of both iTraxx, VIX and France

[1] 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.

Telecom CDS for the three maturities. It suggests that VIX, iTraxx indexes as well as individual companies CDS they 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.

Our empirical analysis is based on the corresponding VECM (17). Econometric details of the estimation and inference of (25) can be found in Johansen (1996), and Juselius (2006), and the procedure to estimate $a_{\wedge}$ and to test hypotheses on it are in Gonzalo and Granger (1995). We report in the main text cointegration and price discovery results for VIX and and iTraxx as well as VIX and individual CDS, for 5 year maturities. Results are presented in Tables 1-3. Cointegration and price discovery results for 3 year and 10 year maturities are reported in tables Ia-IVa in the appendix.

The first step is to perform unit-root tests. We apply the Augmented Dickey Fuller test to all series and we fail to reject the null hypothesis of a unit root for VIX, iTraxx, and individual CDS. We argue that VIX is an implied option volatility index, and thus a proxy for option prices. This explains why we find unit root behaviour. Results are available upon request.

Before testing the rank of cointegration in the VECM specified in (25 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 we restrict the constant term to be inside the cointegrating relationship, Results on the Trace test are presented in Table I. Critical values are taken from Juselius (2006). As it is predicted by our model, x_t and v_t are clearly cointegrated, which implies that VIX and iTraxx are linked via a long term arbitrage relationship. Arbitrage risk cost differential is negative suggesting short positions in the risk free asset are required to finance the replicating portfolio. Moreover this table suggests that there is cointegration at the 5% level between VIX and individual CDS for 42 out of the 47 companies considered. The remaining 5 show cointegration at the 10% significance level. Conflicting signs in the

VECM error correction estimates for Eurpn Aero Defence, Metro AG, and Repsol YPF SA confirms 39 out of the 42 cases of cointegration at 5% significance level. [2]

Tables Ia and IIIa in the appendix show cointegration between VIX and iTraxx for 3 and 10 year maturities, suggesting that there is a long term relationship between market and credit risk which is independent of the time horizon. The constant term is negative for the 10 year maturity whereas but positive for the three year iTraxx. This suggests that financing costs are lower for shorter maturities.

Cointegration between VIX and firm level CDS is also present for 3 year and 10 year maturities. Estimates reported in table Table Ia fail to reject cointegration at the 5% level for all companies analyzed apart from Vodafone. 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 confirms 41 out of the 47 cases of cointegration at 5% significance level.

Cointegration is also present between ten year maturity CDS and the VIX index. Results are reported in table IIIa in the appendix. We fail to reject the hypothesis of cointegration in 41 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 35 out of the 47 pairs analyzed.

Table I: The long Run Relation between the Price of Credit Risk in CDS and VIX markets

	Number of Cointe vectors			Estimated coefficients $(1, -\gamma_1, -\gamma_o)$	
	None (95% c.v. 20.16)	At Most one (95% c.v. 9.14)	1	$-\gamma_1$	$-\gamma_o$
AB Volvo	34.704	4.352	1.000	-14.882	209.584
				(-9.366)	(5.608)
ACCOR	20.710	5.923	1.000	-5.719	28.935
				(-5.134)	(1.093)
AKZO Nobel N V	39.645	4.325	1.000	-2.742	9.159
				(-12.107)	(1.720)
Aegon N.V.	28.511	4.529	1.000	-10.125	127.413
				(-11.019)	(5.827)
Aviva plc	34.896	6.303	1.000	-7.356	89.989
				(-8.358)	(4.323)

[2] 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.

Bay Motoren Werke AG	32.231	4.004	1.000	-9.200	124.109
				(-11.092)	(6.373)
Bayer AG	29.641	8.754	1.000	-2.588	5.038
				(-6.517)	(0.534)
Bca Monte dei Paschi	28.403	2.474	1.000	-3.261	28.944
				(-8.486)	(3.163)
Bertelsmann AG	39.255	6.506	1.000	-7.875	80.627
				(-9.590)	(4.168)
Brit Amern Tob plc	22.290	7.107	1.000	-2.836	-3.630
				-(4.940)	(-0.266)
Brit Telecom PLC	21.115	6.420	1.000	-4.864	29.212
				(-6.951)	(1.749)
Carrefour	38.484	3.169	1.000	-2.032	5.933
				(-14.694)	(1.816)
Cie de St Gobain	47.432	2.580	1.000	-9.493	106.276
				(-16.884)	(7.980)
Commerzbank AG	23.499	4.332	1.000	-3.965	32.828
				(-6.137)	(2.143)
Compass Gp PLC	19.424	5.395	1.000	-0.153	-50.573
				(-0.299)	(-4.252)
Deutsche Bk AG	22.400	1.734	1.000	-4.217	44.653
				(-8.317)	(3.733)
Deutsche Telekom AG	29.957	7.955	1.000	-2.769	-3.874
				(-2.938)	(-0.172)
Diageo PLC	20.132	4.505	1.000	-2.545	14.828
				(-6.997)	(1.729)
E.ON AG	28.384	4.633	1.000	-2.613	15.656
				(-11.626)	(2.956)
ENEL S p A	36.256	5.339	1.000	-10.024	141.982
				(-9.521)	(5.679)
Eurpn Aero Defence	70.688	5.674	1.000	-6.996	80.004
				(-18.513)	(8.906)
Fortum Oyj	47.032	3.615	1.000	-2.132	3.773
				(-15.176)	(1.162)
France Telecom	52.662	6.030	1.000	-1.086	-26.492
				(-1.064)	(-1.103)
Hannover Ruck AG	19.416	4.386	1.000	-2.171	4.06393
				(-5.771)	(0.470)
Hellenic Telecom SA	42.173	6.685	1.000	-0.251	-0.987
				(-10.953)	(-1.811)
Iberdrola S A	34.573	5.268	1.000	-0.4208	3.65546
				(-14.739)	(5.45)
iTraxx5	**29.213**	**2.458**	**1.000**	**-4.148**	**21.144**
				(-13.610)	**(2.925)**
Koninklijke KPN N V	50.534	6.171	1.000	-1.089	-40.325
				(-2.173)	(-3.411)
Koninklijke Philips Electrs N V	36.487	6.914	1.000	-2.946	11.614
				(-9.798)	(1.622)
LVMH Moet Hennessy Louis Vuitton	44.424	6.719	1.000	-3.410	16.841

				(-13.513)	(2.808)
METRO AG	69.130	5.251	1.000	-6.483	52.853
				(-16.763)	(5.841)
Marks & Spencer p l c	18.953	3.501	1.000	-8.148	37.250
				(-4.921)	(0.969)
Munich Re	22.492	6.462	1.000	-1.717	2.143
				(-6.001)	(0.317)
RWE AG	26.272	5.352	1.000	-2.475	15.223
				(-7.724)	(2.006)
Repsol YPF SA	53.389	6.237	1.000	-7.887	-82.60
				(-16.197)	(-7.100)
Royal Bk Scotland plc	18.044	1.598	1.000	-6.350	81.830
				(-6.350)	3.497
Siemens AG	39.369	4.272	1.000	-3.880	36.870
				(-16.167)	(6.584)
Telecom Italia SpA	29.453	7.324	1.000	-2.840	-20.100
				(-5.569)	(-1.634)
Telefonica S A	29.453	7.324	1.000	-2.840	-2.010
				(-5.569)	(-0.163)
Tesco PLC	29.089	2.807	1.000	-0.433	49.92
				(-0.884)	(4.341)
Unilever N V	39.635	5.882	1.000	-1.280	-0.365
				(-128.00)	(0.146)
Utd Utils plc	19.554	3.847	1.000	-2.370	5.16
				(-5.267)	(0.482)
Vattenfall AB	41.319	5.960	1.000	-1.890	4.12
				(11.813)	(1.114)
Veolia Environnement	30.242	4.786	1.000	-3.650	15.48
				(-11.406)	(2.150)
Vodafone Gp PLC	27.749	6.805	1.000	-3.920	25.83
				(-11.879)	(3.270)
Volkswagen AG	24.479	3.705	1.000	-7.140	67.85
				(8.602)	(3.462)
WPP 2005 Ltd	48.003	3.183	1.000	-11.260	0.01275
				(17.873)	(7.680)
Wolters Kluwer N V	29.82	20.262	1.000	-1.210	-30.070
				(41.724)	(4.488)

Results from estimating the VECM in 17 are reported in Table III (t-statistics are given in parenthesis) and tables IIa and IVa in the appendix.

The existence of cointegration implies a long term relationship between VIX and iTraxx indexes as well as VIX and individual iTraxx companies. Estimates in Table II can be interpreted as the market vega sensitivity of the credit portfolio (Π). When the credit portfolio is the 5 year iTraxx $\frac{\Delta\Pi(;VIX)}{\Delta VIX} = \frac{\Pi(Vix+\Delta Vix)-\Pi(Vix)}{\Delta VIX} = 4.15BP$.

Meaning, that if market risk goes up by 1 volatility point the cost of insuring a credit portfolio, on average will go up by 4.15 bps. Note that our results are robust to the lag length and to the log specification. Because both variables are cointegrated, by the Granger representation theorem, both variables may be represented by the VECM in (17). z_{t-1} is the long term relationship that governs both variables and the adjustment coefficient or adjustment vector describes how VIX and iTraxx react to deviations from the long term equilibrium. If a given shock to the long term relationship makes $z_{t-1} > 0$ this implies that iTraxx will fall and VIX will increase to restore equilibrium.

Results in table III also show that the VIX index does not react significatively to the equilibrium error, whereas the iTraxx index does, indicating that the VIX market leads the credit risk market. Note that this is true for 3 year and 10 year CDS as can be seen in tables IIa and IVa. VIX therefore dominates iTraxx in terms of price discovery, and this is independent of the iTraxx maturity chosen.

This is confirmed by the price discovery results between VIX an individual CDS. In 36 out of the 39 companies analysed α_1 is significantly positive indicating that the VIX market contributes to price discovery. [3] The CDS market appears to have a significant role in 9 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). In 8 cases both the VIX market and the CDS market contribute significantly to price discovery. In 27 cases we fail to reject the hypothesis that VIX is the sole contributor to price discovery and therefore a GG common factor weight is reported to be 1. [4] In the three year CDS case we fail to reject the hypothesis of VIX being the sole contributor to price discovery in 31 out of 41 cointegrated pairs. Moreover, the three year CDS market does not dominate in any of the examples analyzed. For the 10 year CDS out of the cointegrated 35 cases, VIX dominates in terms of price discovery in 25 cases and the CDS market is the sole contributor to price discovery in two cases Deutche Bank and Utd Utils plc and. Therefore similar conclusions are obtained for 3 year and 10 year CDS maturities

Table III: VECM estimates and Contribution to Price Discovery

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

[4] Note that we have not discussed price discovery results for those pairs cointegrated at the 10% significance level. The GG metric is reported in italics for these cases.

	Number of Cointe vectors			3 year cds
	α_1	α_2	GG	AIC
AB Volvo	-0.008	0.000	1.000	24.000
	[-4.91313]	[0.77225]		
ACCOR	-0.005	0.001	1.000	17.000
	[-3.20801]	[1.39789]		
AKZO Nobel N V	-0.020	-0.001	1.000	25.000
	[-5.78379]	[-0.32759]		
Aegon N.V.	-0.009	0.002	0.803	25.000
	[-2.81075]	[2.97813]		
Aviva plc	-0.011	0.001	1.000	17.000
	[-4.97367]	[0.71115]		
Bay Motoren Werke AG	-0.011	0.002	0.868	25.000
	[-4.03724]	[1.98110]		
Bayer AG	-0.014	-0.001	1.000	17.000
	[-4.36800]	[-0.50875]		
Bca Monte dei Paschi di Siena S p A	-0.012	0.004	0.750	25.000
	[-3.81582]	[2.22503]		
Bertelsmann AG	-0.010	0.000	1.000	25.000
	[-5.58220]	[0.13756]		
Brit Amern Tob plc	-0.009	0.002	1.000	19.000
	[-3.46272]	[0.92021]		
Brit Telecom PLC	-0.008	0.001	1.000	22.000
	[-3.06433]	[1.02745]		
Carrefour	-0.022	0.008	0.720	25.000
	[-4.650]	[1.879]		
Cie de Saint Gobain	-0.015	0.003	0.845	25.000
	[-5.07943]	[2.89728]		
	-0.009			
CommerceBank AG	-0.090	0.003	0.786	25.000
	[-3.26079]	[2.05756]		
Compass Gp PLC	-0.009	-0.003	*1.000*	24.000
	[-3.63795]	[-1.48466]		
Deutche Bk AG	-0.005	0.006	0.457	25.000
	[1.407]	[3.639]		
Deutsche Telekom AG	-0.007	0.000	1.000	21.000
	[-4.22478]	[0.07615]		
Diageo PLC	-0.010	0.003	*1.000*	25.000
	[-3.44794]	[1.10341]		
ENEL S p A	-0.010	0.001	1.000	25.000
	[-5.22609]	[0.87940]		
Fortum Oyj	-0.024	-0.001	1.000	25.000
	[-5.89584]	[-0.21247]	1.000	
France Telecom	-0.007	0.000	1.000	25.000
	[-6.74436]	[-0.70118]		
Hannover Ruck AG	-0.015	0.002	*1.000*	25.000
	[-3.43943]	[0.77033]		
Hellenic Telecom Org SA	-0.026	-0.014	1.000	21.000
	[-5.83628]	[-0.51930]		

Iberdrola S A	-0.018	0.035	1.000	25.000
	[-4.64099]	[1.48516]		
iTraxx5	0.082	-0.015	1.000	25.000
	[3.96049]	[-1.30730]		
Koninklijke KPN N V	-0.011	-0.001	1.000	25.000
	[-6.59430]	[-1.01436]		
Koninklijke Philips Electrs N V	-0.013	-0.002	1.000	19.000
	[-5.37022]	[-0.76323]		
Marks & Spencer plc	-0.005	0.001	*0.820*	25.000
	[-2.15744]	[2.09254]		
Munich Re	-0.015	0.001	1.000	25.000
	[-3.60796]	[0.47486]		
RWE AG	-0.010	0.003	0.774	24.000
	[-3.89766]	[1.16517]		
Royal Bk Scotland plc	0.000	0.000	*0.287*	25.000
	[0.01763]	[-0.14477]		
Siemens AG	-0.016	0.006	0.707	24.000
	[-4.41337]	[2.49906]		
Telecom Italia SpA	-0.012	-0.006	1.000	24.000
	[-4.46879]	[-0.37033]		
Telefonica S A	-0.012	-0.001	1.000	25.000
	[-4.46879]	[-0.37033]		
Tesco PLC	0.000	0.000	1.000	25.000
	[4.31457]	[-1.23993]		
Unilever N V	-0.023	0.008	1.000	25.000
	[-5.16712]	[1.37032]		
Utd Utils plc	-0.005	0.005	*0.484*	25.000
	[-2.32114]	[2.66905]		
Vattenfall AB	-0.020	0.002	1.000	25.000
	[-5.82833]	[-0.56951]		
Veolia Environnement	-0.019	2.534	1.000	25.000
	[-4.84478]	[0.10187]		
Vodafone Gp PLC	-0.010	0.006	0.500	25.000
	[-2.90866]	[2.53870]		
Volkswagen AG	-0.010	12.667	1.000	25.000
	[-3.54009]	[1.30882]		
WPP 2005 Ltd	-0.023	-0.001	1.000	25.000
	[-6.58273]	[-0.67084]		
Wolters Kluwer N V	-0.016	0.000	1.000	24.000
	[-4.62298]	[0.11777]		

The VIX index is the sole contributor to the common factor in the price discovery process implying that market risk dominates credit risk in terms of price discovery. This is true for all iTraxx maturities studied, although stronger for the 5 and 3 year case. This implies that, on average if there is a long run disequilibria between VIX and credit risk market it is the credit derivatives market that does the adjustment to the new equilibria and not the stock volatility derivatives market. Taking the result in equation (4) we can conclude that a) the VIX derivatives market is more liquid (has a higher number of participants) that the credit risk market since it has a higher number of participants and b) arbitrageurs will benefit from riskless profits as long as credit risk adjustment to long run disequilibria are not immediate.

5. Statistical Arbitrage and Proposed "pairs trading" strategy

The finding of cointegration between credit risk and market risk, suggest that we can have abnormal profits pursuing a pairs trading strategy. Gatev et al. (2006) use a trading rule for cointegrated price series based on the following proposition: we open a long-short position when the paired prices have diverged by a certain amount and close the position when prices have reverted. This is a classic trading strategy for speculators or hedge funds.

We follow their pairs strategy rule by exploiting deviations from the long term cointegrating relationship. When VIX or Itraxx/CDS deviate for their the long run relationship, the correlation between the two diminishes, and therefore move the opposite way, we can go SHORT the out-performer and LONG the underperformer, hoping that eventually they will converge back to their long run level. Gatev et al. (2006) we define deviations in terms of one historical standard deviations away from the long term equilibrium. We take 1 standard deviation to be significant.

Pairs strategies have certain characteristics. Typically, they are neutral to market crashes. That's because if the market goes down we lose from the long position and we win from the short position. From the nature of them, we bet on the long run relationship of the two, so our strategy is mean reverting. In theory, they are also zero cost strategies, as we 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 start drifting away from each other or away from long run relationship, we will occur a loss.

The spread of alphas, determine whether there is investment opportunity. If this difference is large means that VIX and CDS/Itraxx are drifting apart. As measured, they will need 4 days on average to back to equilibrium. Therefore a pair bet on the two is placed as described above.

Table III reports average daily excess returns and (simplified) Sharpe ratios from pursuing the "pairs strategy" or investing in VIX or iTraxx alone. We can see that the pairs strategy delivers improved average returns and performance.

Table III	Expected Profit Returns and Performance Measures			
	Mean	**Var**	**Vol**	**Sharpe Ratio**
Itraxx	0.001	0.001	0.038	0.029
Vix	0.002	0.004	0.066	0.036
Pairs Strategy	0.015	30.721	5.543	0.066

Gatev (2006), suggest that there is a latent systematic factor influencing the profitability of pairs trading over time. They do however fail to identify this factor. The existence of price discovery in cointegrated price series does allow the identification of this factor. Results in section 4 suggest that VIX is the leader in terms of price discovery. This implies that it is the only factor contributing to price discovery and therefore we propose that it should also be the latent factor driving our pairs strategy profit returns. Figure 5 in the appendix suggests that this might be the case. Additionally, a regression analysis that use VIX to explain profitability from pairs strategy are reported in table IV in the appendix. They confirm our view, suggesting that VIX is a common factor explaining "paired strategies" returns.

We go a step further than the usual testing strategy for positive excess returns that are performed in studies like Gatev et al. (2006), by testing whether our pairs strategy P&L, for each company in our sample, constitute a credible statistical arbitrage in the sense of Hogan et al. (2004). The P&L increments ($\Delta\Pi$) follow the normal distribution with adjusted first and second moments as specified in (6).

To test for statistical arbitrage, we perform a maximum likelihood estimation to identify (m, s, l, J) out of the pair-strategy P&L series and then proceed to check the Hogan et al. (2004) unconstrained hypotheses, please check for relevant parameter discussion:

$$\begin{aligned} &H_1 : \hat{m} > 0 \\ &H_2 : \hat{l} < 0 \\ &H_3 : \hat{J} > \hat{l} - \frac{1}{2} \end{aligned}$$

Also the sum of the p values should be less than $1-a$.

Fig 6. In the appendix we offer a goodness of fit example of the pair strategy for ITRAXX Its P&L histogram is shown along with the fitted probability distribution function (7). There is a suggestion that the fit is also good for the CDS case.

Table IV, summarizes our findings and confirm that our pair strategies lead to positive excess returns, and in fact constitute a statistical arbitrage in the sense of Hogan et al (2004).

Table IV: **Testing for Statistical Arbitrage on the Pairs-Startegy of Individual CDS**

Companies	Mu	Sigma	lamda	Theta	SA
AB Volvo	0,193889	2,20459	-1,70128	-1,90582	YES
ACCOR	0,102578	1,49813	-1,82702	-1,34494	YES
AKZO Nobel N V	0,105259	1,42499	-1,80229	1-,37773	YES
Aviva plc	0,105259	1,42499	-1,80229	1-,37773	YES
Bay Motoren Werke AG	0,0827992	1,42225	-1,74787	-1,34254	YES
Bca Monte dei Paschi di Siena S p A	0,0721668	1,47565	-1,85043	-1,43942	YES
Bertelsmann AG	0,0632485	1,40308	-1,69226	-1,27028	YES
Brit Amern Tob plc	0,0632485	1,40308	-1,69226	-1,27028	YES
Carrefour	0,0674085	1,45086	-1,83037	-1,43154	YES
Cie de St Gobain	0,0879797	1,29119	-1,52871	-1,45884	YES
Commerzbank AG	0,122152	148.556	-2,04511	-1,57361	YES
Deutsche Bk AG	0,0922026	1,43399	-1,98656	-1,63361	YES
Deutsche Telekom AG	0,110774	1,43381	-2,0649	-1,66986	YES
E.ON AG	0,0923684	1,46619	-1,75023	-1,32633	YES
Fortum Oyj	0,0864427	1,54574	-1,77366	-1,30537	YES
France Telecom	0,0703334	1,38766	-1,65833	-1,281713	YES
Hannover Ruck AG	0,0743825	1,4456	-1,71056	-1,30216	YES
Hellenic Telecom Org SA	0,0682092	1,39946	-2,03354	-1,62426	YES
Koninklijke Philips Electrs N V	0,0541238	1,32973	-1,39609	-1,06424	YES
Marks & Spencer p l c	0,0751467	1,27166	-1,40841	-1,27907	YES
Munich Re	0,121534	1,43567	-2,10135	-1,68611	YES
Repsol	0,11892	1,55668	-2,06112	-1,55687	YES

Telefonica S A	0,0517091	1,4044	-1,67885	-1,26179	YES
Tesco PLC	0,0468379	1,39912	-1,60046	-1,17217	YES
Vattenfall AB	0,0619239	1,40068	-1,62048	-1,24489	YES
Vodafone Gp PLC	0,0680684	1,28416	-1,56455	-1,36059	YES
WPP 2005 Ltd	0,126894	1,63576	-1,7454	-1,24191	YES

6. Implications of results and Conclusions

In this paper test the validity of pairs trading strategies between VIX and CDS markets using the FG price discovery framework. This requires us to establish the link between VECM price discovery parameters and the positions taken in the two substitute markets in search for abnormal profits.

Using a comprehensive data set of VIX, iTraxx and 47 individual company CDSs the following results are obtained:

i) VIX and iTraxx as well as individual CDS are cointegrated verifying that they are indeed substitute assets. VECM estimates suggest that VIX dominates the credit risk market. These results are robust to all maturities considered and hold when looking at the credit portfolio measured by the iTraxx index as well as for individual company´s CDS.

ii) Profits obtained from pairs trading strategies between VIX and iTraxx outperform investments on VIX or iTraxx alone. Such profits are related to our price discovery common factor. The contribution of each substitute asset to total profits can be related to the price discovery parameters.

iii) Pairs strategies are consistent with statistical arbitrage as defined by Hogan (2004). This is true for Vix and iTraxx as well as Vix and individual CDS

Our results suggest that because of its price discovery leadership, VIX be treated as the explanatory variable in one factor asset pricing models.

7. Bibliography

Baillie R., G. Goffrey, Y. Tse, and T. Zabobina (2002). "Price discovery and common factor models." *Journal of Financial Markets*, 5, 309-325.

Blanco, R., Brenan, S. and Marsh, I. W (2005). " An Empirical Analysis of the Dynamic Relationship Between Investment Grade Bonds and Credit Default Swaps." *Journal of Finance*, 60, 2255-2281.

Bystrom, H. "Credit default swaps and equity prices: the iTraxx CDS index market." *Working Paper. Department of Economics. Lund University*.

Cambell, J. and Taskler, G. (2002), "Equity Volatility and Corporate Bond Yields." Working Paper. Harvard University.

Clare, A. and Priestley, R. (2002). "Calculating the probability of Failure of the Norwegian Banking Sector." Journal of Multinational Financial Management (12), 1, 21-40.

Collin-Dufresne, P., Goldstein, R. and R. Martin, J (2001). "The determinants of spread changes." *Journal of Finance*, 56, 2177-2207.

Dotz, N. (2007). " Time Varying contributions by the corporate bond and CDS market to credit risk price discovery." Discussion paper Series 2. Banking and Financial Studies No 08. Deutche Bundesbank.

Elton, E. J. Gruber M. K., Agrawal D. and C. Mann (2001). "Explaining the rate spread on corporate bonds, *The Journal of Finance*, 56, 247-277

Fama , E. and French K. (1993), "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*.

Figuerola-Ferretti, I., and J. Gonzalo (2010). "Modeling and measuring price discovery in commodity markets." *Journal of Econometrics*, 158, 95-107.

Garbade, K.D., and W.L. Silber (1983). "Price movements and price discovery in futures and cash markets." *Review of Economics and Statistics*, 65, 289-297.

Goldstein, R.S. N, Ju, and H. E. Leland (2001). "An EBIT-based model of dynamic capital structure." *Journal of Business.*

Harris, F.H., T.H. McInish, and R.A. Wood (1997). "Common long-memory components of intraday stock prices: A measure of price discovery." *Working Paper, Wake Forest University*.

Harris, F. H., T.H. McInish, and R.A. Wood (2002). "Security price adjustment across exchanges: an investigation of common factor components for Dow stocks." *Journal of Financial Markets,* 5, 277-308.

Hogan, S. R. A. Jarrow, M. Teo and M. Warachka (2004). "Testing Market Efficiency using Statistical Arbitrage with Applications to Momentum and Value Strategies," Journal of Financial Economics 73, 525-565.

Huang. J. and M. Huang (2003). "How much of the corporate Treasure yield-spread is due to credit risk? Working paper. Pen state University.

Gatev E., Goetzmann W. and Rouwenhorst Geert (2006). "Pairs trading: performance of a relative-value arbitrage rule" Review of Financial Studies, 19, pp 797-827.

Gonzalo, J., and C.W.J. Granger (1995). "Estimation of common long-memory components in cointegrated systems." *Journal of Business and Economic Statistics*, 13, 27-36.

Hasbrouck, J. (1995). "One security, many markets: Determining the contributions to price discovery." *Journal of Finance*, 50, 1175-1199.

Hall, S. and Miles, D. (1990). Measuring the Risk of Financial Institution´s Portfolios: Some suggestions for alternative techniques Using Stock Prices, in "Henry, S.G.B., Patterson K.D. Eds. Economic Modelling at the Bank of England. Chapman and Hall.

Johansen, S. (1996). *Likelihood-based Inference in Cointegrated Vector Autoregressive Models (2nd edition)*. Oxford University Press, Oxford.

Juselius, K. (2006). *The Cointegrated VAR Model: Methodology and Applications*. Oxford University Press, Oxford.

Lehman, B. N. (2002). Special issue of *Journal of Financial Markets*, 5, 3.

Longstaff, F. A., Mithal, S and Neis, E. (2003). "Corporate Yield Spreads. Default Risk or Liquidity? New evidence from the credit swap market." Journal of Finance, 60, 2213-2253.

Merton, R. (1974), "On the Pricing of Corporate Debt: The risk structure of Interest Rates." Journal of Finance 2(2), 449-470.

Kwan, S. (1996), "Firm specific information and correlation between individual Stocks and Bonds." *Journal of Financial Economics,* 40, 63-80.

Yan, B., and E. Zivot (2007). "The dynamics of price discovery." *Working Paper*, *Department of Economics, University of Washington*.

Zhu, H. (2006). "An Empirical Comparison of Credit Spreads between the Bond Market and the Credit Default Swap Market." *Journal of Financial Services Research*

8. Appendix A: Theoretical model for dynamics of VIX and iTraxx Markets

Following FG, 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

$$P_{i,t} - A(x_t - B_{i,t}), \qquad A > 0, \quad \mathrm{i} = 1,...., N_x, \qquad (2a)$$

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

$$H((g_1 v_t + g_0) - x_t), \qquad H > 0, \qquad (3a)$$

where H is the elasticity of derivatives market demand by arbitrageurs. As previously discussed, it is finite when the arbitrage transactions of buying in the credit derivatives market and selling in the VIX derivatives market or vice versa are not risk less.

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

$$\sum_{i=1}^{N_x} P_{i,t} = \sum_{i=1}^{N_x} \left(P_{i,t} - A\left(x_t - B^x{}_{i,t}\right)\right) + H\left((g_1 v_t + g_0) - x_t\right) \qquad H > 0, \qquad (4a)$$

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

$$\sum_{i=1}^{Nv} P_{i,t} = \sum_{i=1}^{N_v} \left(P_{i,t} - A\left(v_t - B^v{}_{i,t}\right)\right) - H\left((g_1 v_t + g_0) - x_t\right) \qquad (5a)$$

Solving equations (4a) and (5a) for v_t and x_t as a function of the mean bid price of VIX market participants $\left(B_t^x = N_x^{-1}\sum_{i=1}^{Nx} B_{i,t}\right)$ and the mean bid price for credit derivatives market participants $\left(B_t^v = N_v^{-1}\sum_{j=1}^{N_v} B_{j,t}\right)$, we obtain

$$x_t = \frac{(AN_v + Hg_1)N_x B_t^x + HN_v g_1 B_t^v + HN_v g_0}{(H + AN_x)N_v + HN_x g_1}, \qquad (6a)$$
$$v_t = \frac{HN_x B_t^x + (H + AN_x)N_v B_t^v - HN_x g_0}{(H + AN_x)N_v + HN_x g_1}.$$

To derive the dynamic price relationships, the model in equation (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

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

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 (7) imply that the mean bid price in each market in period *t* will be

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

where, $w_t^x = \frac{\sum_{i=1}^{N_x} w_{i,t}^x}{N_x}, w_t^v = \frac{\sum_{j=1}^{N_v} w_{j,t}^v}{N_v}$. Substituting expressions (8a) into (6a) yields the following vector model

$$\begin{pmatrix} x_t \\ v_t \end{pmatrix} = \frac{Hg_2}{d}\begin{pmatrix} N_v \\ -N_x \end{pmatrix} + (M)\begin{pmatrix} x_{t-1} \\ v_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix}, \tag{9a}$$

where

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

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

And

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

We now convert (9a) into a Vector Error Correction Model (VECM) by subtracting *(x_{t-1}, v_{t-1})´* from both sides,

$$\begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \frac{Hg_1}{d}\begin{pmatrix} N_v \\ -N_x \end{pmatrix} + (M - I)\begin{pmatrix} x_{t-1} \\ v_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \tag{13a}$$

with

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

Rearranging terms,

$$\begin{pmatrix} \Delta x_t \\ \Delta v_t \end{pmatrix} = \frac{H_1}{d} \begin{pmatrix} -N_v \\ N_x \end{pmatrix} \begin{pmatrix} 1 & -g_1 & -g_0 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ v_{t-1} \\ 1 \end{pmatrix} + \begin{pmatrix} u_t^x \\ u_t^v \end{pmatrix} \quad (15a)$$

9. Appendix B: Empirical Cointegration and Price Discovery Results

Table I a:
The long Lun Relationship between the Price of 3 year CDS and ViX markets

	None 95% c.v=20.26	At Most one 95% c.v= 9.14	Estimated Coefficients $(1, -\gamma_1, -\gamma_0)$	$-\gamma_1$	$-\gamma_0$
AB Volvo	35.210	4.976	1	-15.791	238.828
			1	(-9.479)	(6.097)
ACCOR	26.083	5.990	1	-0.189	-7.172
			1	(-5.777)	(-2.522)
AKZO Nobel N V	36.985	4.741	1	-0.322	2.900
			1	(0.028)	(0.662)
Aegon N.V.	27.794	4.783	1	-10.472	143.856
			1	-(10.702)	(6.181)
Aviva plc	35.235	6.465	1	-7.584	102.116
			1	(-8.122)	(4.631)
Bay Motoren Werke AG	24.932	4.830	1	-9.893	146.666
			1	(-8.553)	(5.357)
Bayer AG	34.101	8.617	1	-2.953	22.050
			1	(0.362)	(2.565)
Bca Monte dei Paschi di Siena	36.433	2.648	1	-3.265	34.859
			1	(-10.209)	(4.639)
Bertelsmann AG	66.430	7.124	1	-7.322	85.084
			1	(-12.887)	(6.290)
Brit Amern Tob plc	26.973	6.150	1	-3.229	17.542
			1	(-6.512)	(1.492)
Brit Telecom PLC	25.469	6.924	1	-4.878	44.807
			1	(-8.916)	(3.435)
Carrefour	59.616	3.859	1	-2.152	16.276
			1	(-20.998)	(6.731)
Cie de St Gobain	52.070	3.259	1	-10.526	138.361
			1	(-17.435)	(9.688)
Commerzbank AG	25.546	4.470	1	-3.778	37.881
			1	(-6.919)	(2.927)
Compass Gp PLC	22.909	6.094	1	-1.045	-18.199
			1	(0.321)	(7.427)
Deutsche Bk AG	27.765	2.175	1	-4.142	50.146
			1	(-9.445)	(4.849)
Deutsche Telekom AG	34.111	6.857	1	-3.902	31.465
			1	(-5.111)	(1.731)
Diageo PLC	31.738	5.892	1	-2.452	21.469
			1	(-10.729)	(3.997)
E.ON AG	47.494	4.874	1	-2.805	26.012
			1	(-19.904)	(7.852)
ENEL S p A	36.298	5.587	1	-10.979	167.637
			1	(-9.202)	(5.920)
Eurpn Aero Defence	57.624	5.654	1	-7.667	102.410
			1	(-15.272)	(8.591)
Fortum Oyj	64.768	3.624	1	-2.461	17.599

			1	(0.113)	(2.623)
France Telecom	48.911	6.277	1	-1.955	5.023
			1	(-1.537)	(0.167)
Hannover Ruck AG	22.892	4.369	1	-2.393	16.410
			1	(-8.142)	(2.431)
Hellenic Telecom Org SA	57.855	5.410	1	-3.092	14.420
	5.410		1	-(16.107)	(3.210)
Iberdrola S A	41.147	5.315	1	-4.620	52.353
			1	(-16.923)	(8.151)
iTraxx3	23.622	2.735	1	-2.971	-15.501
			1	(0.278)	(6.627)
Koninklijke KPN N V	55.315	6.437	1	-1.957	-6.746
			1	(-4.557)	(-0.663)
Koninklijke Philips Electrs N V	59.375	6.111	1	-3.201	25.740
			1	(-14.938)	(5.057)
LVMH Moet Hennessy Louis Vuitton	54.852	6.809	1	-3.768	33.989
			1	(16.780)	(6.376)
METRO AG	68.010	5.850	1	-6.970	76.028
			1	(-16.780)	(6.376)
Marks & Spencer p l c	26.301	2.846	1	-10.252	119.406
			1	(-8.846)	(4.449)
Munich Re	26.824	6.334	1	-1.842	11.396
			1	(0.214)	(5.011)
RWE AG	39.079	5.574	1	-2.559	23.708
			1	(-11.011)	(4.313)
Repsol YPF SA	59.643	8.460	1	-8.370	102.060
		0.068	1	(-144.310	(7.450)
Royal Bk Scotland plc	18.855	2.124	1	-6.190	83.700
			1	(-6.516)	(3.805)
Siemens AG	42.361	4.051	1	-4.110	48.790
			1	(-17.870)	(8.871)
Telecom Italia SpA	32.988	7.348	1	-3.600	23.970
			1	(-8.571)	(2.421)
Telefonica S A	32.112	6.975	1	-3.730	26.860
			1	(-9.098)	(2.741)
Tesco PLC	41.362	3.945	1	4.080	52.340
			1	(12.000)	(6.710)
Unilever N V	49.268	4.884	1	-1.390	0.821
			1	(-15.618)	(0.391)
Utd Utils plc	26.434	3.469	1	-2.440	15.590
			1	(-8.133)	(2.196)
Vattenfall AB	51.863	6.859	1	-0.205	14.520
			1	(0.140)	(3.300)
Veolia Environnement	37.362	5.026	1	-4.350	39.020
			1	(-140.323)	(5.574)
Vodafone Gp PLC	38.552	20.262	1	-4.370	45.120
				(-16.808)	(7.277)
Volkswagen AG	29.616	4.245	1	-7.830	94.370
				(10.303)	(5.302)
WPP 2005 Ltd	45.698	3.503	1	-11.800	155.100
			1	(17.101)	(8.617)

Wolters Kluwer N V	45.223	6.314	1	-0.180	-5.020
			1	(9.000)	(1.046)

Table II a: VECM estimates and Contribution to price Discovery 3 year CDS

	a_1	a_2	**GG**	**AIC**
AB Volvo	-0.008	0.000	1.000	24
	[-5.10040]	[0.22539]		
ACCOR	-0.008	0.000	1.000	25
	[-4.27271]	[0.30968]		
AKZO Nobel N V	-0.003	-0.024	1.000	23
	[-5.53439]	[-0.42102]		
Aegon N.V.	-0.013	0.002	0.894	25
	[-3.55802]	[2.07606]		
Aviva plc	-0.011	0.000	1.000	24
	[-4.86430]	[0.25794]		
Bay Motoren Werke AG	-0.009	0.001	1.000	25
	[-3.80312]	[0.99111]		
Bayer AG	-0.016	-0.001	1.000	17
	[-5.00580]	[-0.66017]		
Bca Monte dei Paschi di Siena S p A	-0.016	0.003	0.827	24
	[-5.00150]	[1.64619]		
Bertelsmann AG	-0.018	-0.001	1.000	25
	[-7.65601]	[-1.14589]		
Brit Amern Tob plc	-0.011	0.001	1.000	20
	[-4.28948]	[0.64581]		
Brit Telecom PLC	-0.012	0.001	1.000	22
	[-4.05201]	[0.41005]		
Carrefour	-0.031	0.003	0.914	25
	[-6.80449]	[0.60427]		
Cie de St Gobain	-0.017	0.002	0.919	25
	[-6.18366]	[1.73580]		
Commerzbank AG	-0.012	0.002	0.845	25
	[-3.77475]	[1.52190]		
Compass Gp PLC	-0.013	-0.004	1.000	24
	[-4.01929]	[-1.22919]		
Deutsche Bk AG	-0.011	0.005	0.673	25
	[-3.06293]	[3.20618]		
Deutsche Telekom AG	-0.008	0.000	1.000	24
	[-5.08675]	[-0.06161]		
Diageo PLC	-0.016	0.001	1.000	25
	[-4.86815]	[0.19139]		
E.ON AG	-0.025	0.006	0.798	25
	[-5.55366]	[1.60490]		

ENEL S p A	-0.010	0.000	1.000	25
	[-5.31136]	[0.53948]		
Eurpn Aero Defence	-0.018	-0.002	N.A	
	[-7.27889]	[-1.90337]		
Fortum Oyj	-0.035492	-0.004033	1.000	25
	[-7.66931]	[-0.88333]		
France Telecom	-0.006	0.000	1.000	25
	[-6.46773]	[-0.81558]		
Hannover Ruck AG	-0.019	0.001	1.000	25
	[-4.01438]	[0.47458]		
Hellenic Telecom	-0.030	-0.004	1.000	24
	[-7.19088]	[-1.45219]		
Iberdrola S A	-0.019	0.002	1.000	25
	[-5.43624]	[0.94788]		
iTraxx3	-0.021	0.005	0.811	25
	[-3.29628]	[1.43172]		
Koninklijke KPN N V	-0.011	-0.001	1.000	24
	[-6.79719]	[-1.16845]		
Koninklijke Philips Electrs N V	-0.020	-0.006	N.A	24
	[-7.23231]	[-2.34251]		24
LVMH Moet Hennessy Louis Vuitton	-0.024	-0.004	N.A.	25
	[-6.86933]	[-1.76198]		
METRO AG	-0.027	-0.003	N.A.	25
	[-7.83202]	[-2.37263]		
Marks & Spencer p l c	-0.010	0.001	0.878	25
	[-3.63386]	[2.03691]		
Munich Re	-0.021	0.002	1.000	25
	[-4.15966]	[0.60855]		
RWE AG	-0.014	0.002	1.000	24
	[-5.31664]	[0.82019]		
Repsol YPF SA	-0.019	-30.144	N.A.	24
10	[-6.80785]	[-3.43737]		
Royal Bk Scotland plc	-0.006	0.003	0.671	25
	[-1.85357]	[3.05262]		
Siemens AG	0.000	0.000	0.827	25
	[5.26023]	[-1.55864]		
Telecom Italia SpA	0.000	0.000	1.000	24
	[5.02836]	[-0.50654]		
Telefonica S A	-0.011	0.000	1.000	25
	[-3.97952]	[-0.28946]		
Tesco PLC	-0.012	0.000	1.000	25
	[-5.79556]	[0.08401]		
Unilever N V	-0.032	-0.002	1.000	25
	[-6.53514]	[-0.38799]		
Utd Utils plc	-0.032	-0.002	1.000	25
	[-6.53514]	[-0.38799]		
Vattenfall AB	-0.009	0.007	0.579	25

	[-3.49184]	[2.64139]		
Veolia Environnement	-0.025	-60.557	1.000	25
	[-6.94655]	[-1.49992]		
Vodafone Gp PLC	-0.015	59.746	0.500	21
	[-4.20732]	[2.36694]		
Volkswagen AG	-0.012	0.001	1.000	25
	[-4.20584]	[0.85803]		
WPP 2005 Ltd	-0.022	-0.001	1.000	25
	[-6.39759]	[-1.06568]		
Wolters Kluwer N V	-0.024	0.000	1.000	25
	[-6.04032]	[-0.12517]		

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

	Number of Cointe vectors			Estimated Coefficients $(1, -\gamma_1, -\gamma_0)$			
	None (95% c.v. 20.16)	at Most one (95% c.v. 9.14)		$-\gamma_1$		$-\gamma_0$	
AB Volvo	31.421	4.044	1	-12.430	(-8.940)	147.884	(4.551)
ACCOR	18.434	6.815	1	-4.288	(-3.930)	-18.574	(-0.714)
AKZO Nobel N V	38.177	5.507	1	-1.662	(-8.770)	-25.151	(-5.585)
Aegon N.V.	28.232	4.442	1	-9.405	(-11.279)	105.807	(5.329)
Aviva plc	32.467	6.741	1	-7.255	(-8.296)	80.158	(3.935)
Bay Motoren Werke AG	27.492	3.848	1	-7.287	(-10.028)	77.296	(4.532)
Bayer AG	22.651	8.386	1	-0.955	(-2.012)	-41.694	(-3.691)
Bca Monte dei Paschi di Siena S p A	28.591	2.445	1	-3.009	(-8.393)	16.222	(1.908)
Bertelsmann AG	32.024	6.764	1	-7.044	(-7.600)	46.671	(2.134)
Brit Amern Tob plc	22.046	5.553	1	-0.935	(-2.104)	-59.699	(-5.646)
Brit Telecom PLC	16.488	6.717	1	-4.998	(-4.466)	7.961	(0.300)
Carrefour	33.112	4.333	1	-9.825	(-17.519)	-4.897	
Cie de St Gobain	41.675	2.521	1	-8.020	(-15.146)	63.833	(5.108)
Commerzbank AG	21.772	4.594	1	-3.719	(-5.294)	21.289	(1.284)
Compass Gp PLC	12.474	3.428	1	2.037	(-112.335)		
Deutsche Bk AG	20.601	1.718	1	-3.957	(-7.821)	33.732	(2.827)
Deutsche Telekom AG	29.496	6.397	1	-1.025	(-1.107)	-60.688	(-2.760)
Diageo PLC	23.965	5.686	1	-1.706	(-5.969)	-12.300	(-1.788)
E.ON AG	17.327	4.744	1	-2.041	(-5.910)	-6.146	(-0.758)
ENEL S p A	34.382	4.213	1	-9.070	(-9.981)	111.267	(5.222)
Eurpn Aero	86.147	5.074	1	-5.969	(-21.064)	45.821	(6.865)
Fortum Oyj	31.245	3.997	1	-1.566	(-8.220)	-18.643	(-4.216)
France Telecom	39.495	5.316	1	0.437	(0.380)	-79.734	(-2.947)
Hannover Ruck AG	21.622	4.374	1	-1.645	(-5.126)	-14.045	(-1.900)
Hellenic Telecom Org SA	37.137	4.743	1	-0.141	(-6.897)	-5.309	(-11.238)
Iberdrola S A	27.093	5.353	1	-3.319	(-10.114)	8.724	1.135
iTraxx10	39.690	3.051	1	-4.891	(-18.539)	48.594	(7.418)
Koninklijke KPN N V	24.078	5.802	1	16.986	(3.936)	-165.023	(4.012)
Koninklijke Philips Electrs N V	31.950	7.182	1	-2.119	(-6.492)	-20.178	(-2.595)
LVMH Moet Hennessy Louis Vuitton	38.388	6.073	1	-2.630	(-9.223)	-11.317	(-1.678)
METRO AG	69.130	5.251	1	-5.060	(17.233)	8.457	(1.241)

Marks & Spencer p l c	18.953	3.501	1	-8.148	(-4.921)	37.250	(0.969)
Munich Re	21.251	5.369	1	-1.286	(-4.483)	-14.371	(-2.138)
RWE AG	16.536	3.893	1	-2.246	(-4.768)	-0.298	(-0.027)
Repsol YPF SA	68.976	6.441	1	-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	1	-3.280	(-14.261)	14.130	(2.666)
Telecom Italia SpA	32.775	4.450	1	-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	1	-4.280	(-6.485)	36.780	(2.358)
Unilever N V	34.900	6.289	1	-0.762	(-6.927)	-21.860	(-8.408)
Utd Utils plc	20.233	5.881	1	-2.120	(4.157)	-13.520	(-1.099)
Vattenfall AB	28.497	6.261	1	-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	1	-3.140	(7.476)	-6.540	(-6540)
Volkswagen AG	18.858	4.313	1	-6.150	(6.276)	34.120	(1.471)
WPP 2005 Ltd	43.207	3.166	1	-10.180	(16.419)	85.600	(5.252)
Wolters Kluwer N V	25.425	6.314	1	-0.100	(0.263)	-71.880	(-7.987)

Table IV a: VECM estimates and Contribution to price Discovery 10 year CDS

	a_1	a_1	**GG**	**AIC**
AB Volvo	-0.008	0.000	1.000	24
	[-4.56051]	[0.89609]		
ACCOR	-0.005	0.001	1.000	17
	[-2.60934]	[0.98645]		
AKZO Nobel N V	-0.025	-0.001	1.000	24
	[-5.55696]	[-0.24645]		
Aegon N.V.	-0.011	0.002	0.821	24
	[-2.97666]	[2.76614]		
Aviva plc	-0.012	0.001	1.000	20
	[-4.70797]	[0.93372]		
Bay Motoren Werke AG	-0.012	0.002	0.878	25
	[-3.75105]	[1.61476]		
Bayer AG	-0.012	-0.004	N.A.	17
	[-3.41217]	[-2.14373]		
Bca Monte dei Paschi	-0.014	0.005	0.746	25
	[-3.83799]	[2.39009]		
Bertelsmann AG	-0.009	0.000	1.000	25
	[-4.87226]	[0.23809]		
Brit Amern Tob plc	-0.013	-0.003	1.000	11
	[-4.02369]	[-1.31278]		
Brit Telecom PLC	-0.004	0.002	0.701	21
	[-2.00755]	[1.72515]		
Carrefour	-0.021	0.010	0.672	25
	[-3.94735]	[2.25032]		
Cie de St Gobain	-0.014	0.004	0.774	25

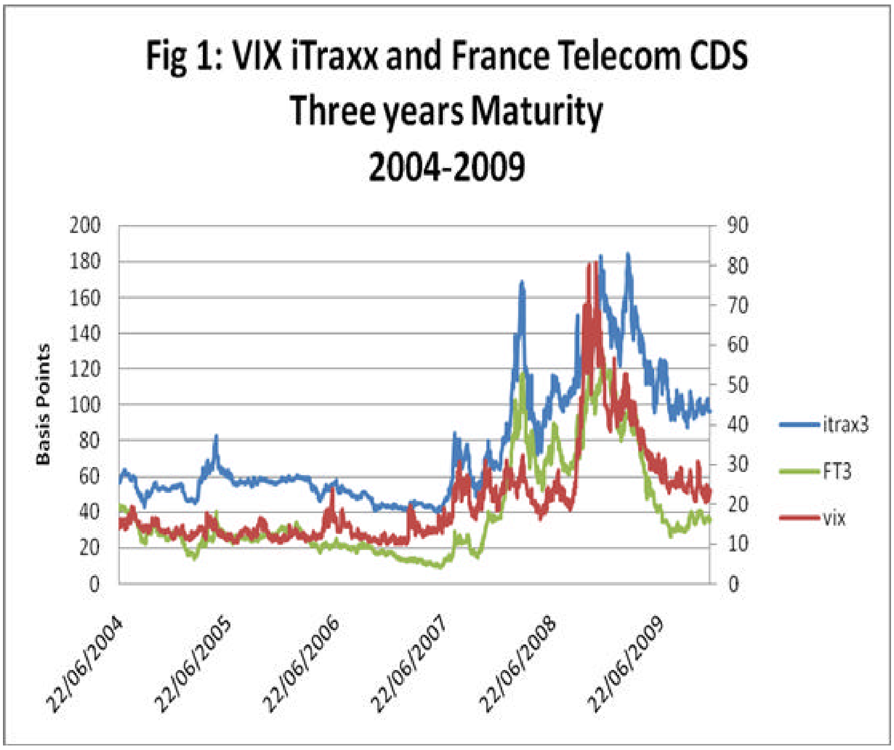
10	[-4.02204]	[3.62272]		
Commerzbank AG	-0.009	0.002	0.793	25
	[-3.16773]	[1.91228]		
Compass Gp PLC				
Deutsche Bk AG	-0.005	0.006	0.491	25
	[-1.56122]	[3.52246]		
Deutsche Telekom AG	-0.008	-0.001	1.00	23
	[-4.73209]	[-0.77386]		
Diageo PLC	-0.008	0.003	0.750	2
	[-2.23123]	[0.86021]		
E.ON AG	-0.008	0.005	0.617	
	[-2.38291]	[1.72695]		
ENEL S p A	-0.012	0.001	1.000	23
	[-4.92805]	[1.36362]		
Eurpn Aero Defence & Space Co Eads N V	-0.031	-0.003	N.A.	25
	[-9.05751]	[-1.72693]		
Fortum Oyj	-0.023	-0.001	1.000	25
	[-4.99267]	[-0.17296]		
France Telecom	-0.005	2.662	1.000	25
	[-4.33372]	[0.43186]		
Hannover Ruck AG	-0.020	0.002	1.000	25
	[-3.82850]	[0.61342]		
Hellenic Telecom Org SA	-0.030	-0.053	N.A.	25
	[-5.63130]	[-1.60048]		
Iberdrola S A	-0.016	0.004	1.000	25
	[-3.87614]	[1.46187]		
iTraxx10	-0.028	0.003	1.000	25
	[-4.89296]	[1.08472]		
Koninklijke KPN N V	-0.007	0.001	1.000	23
	[-3.34851]	[0.60048]		
Koninklijke Philips Electrs N V	-0.014	-0.002	1.000	20
	[-4.93779]	[-0.94357]		
LVMH Moet Hennessy Louis Vuitton	-0.020	-0.003	1.000	25
	[-5.62563]	[-1.41109]		
METRO AG	-0.032	-0.004	N.A.	25
	[-7.48296]	[-2.50384]		
Marks & Spencer p l c	-0.005	0.001	0.820	25
	[-2.15744]	[2.09254]		
Munich Re	-0.020	-0.001	1.000	25
	[-3.90385]	[-0.22654]		
RWE AG	-0.007	0.003	1.000	25
	[-2.86796]	[1.34617]		
Repsol YPF SA	-0.024	-24.995	N.A.	25
	[-7.81790]	[-2.50191]		
Royal Bk Scotland plc	0.000	0.000	0.491	25
	[0.99959]	[-3.36737]		
Siemens AG	0.000	0.000	0.652	25
	[4.09309]	[-3.07299]		
Telecom Italia SpA	-0.012	-1.240	1.000	24
	[-4.09200]	[-0.08014]		
Telefonica S A	-0.012	0.000	1.000	25

	[-4.09200]	[-0.08014]		
Tesco PLC	0.000	0.000	0.569	25
	[0.76573]	[-0.71152]		
Unilever N V	-0.027	0.009	1.000	25
	[-4.74001]	[1.43189]		
Utd Utils plc	-0.003	0.006	0.483	25
	[-1.31840]	[3.29521]		
Vattenfall AB	-0.017	-0.002	1.000	25
	[-4.64314]	[-0.56743]		
Veolia Environnement	-0.019	0.000	1.000	25
	[-4.84478]	[0.10187]		
Vodafone Gp PLC	-0.006	0.006	0.500	25
	[-1.95764]	[2.60177]		
Volkswagen AG	-0.006	0.002	0.500	19
	[-2.26565]	[2.04956]		
WPP 2005 Ltd	-0.022	-0.001	1.000	25
	[-6.19093]	[-0.56184]		
Wolters Kluwer N V	-0.013	0.000	1.000	25
	[-4.19185]	[0.04676]		

Table V.a: Regression of Profits from pairs strategy on VIX

	Coefficients	*Standard Error*	*t Stat*
Intercept	-0.00161558	0.001833844	-0.88097982
VIX	0.00021432	7.63022E-05	2.80888353
Regression Statistics			
Multiple R	0.0742818	Standard Error	0,03481493
R Square	0.00551779	Observations	1424
Adjusted R Square	0.00481843		

10. Graphical Appendix



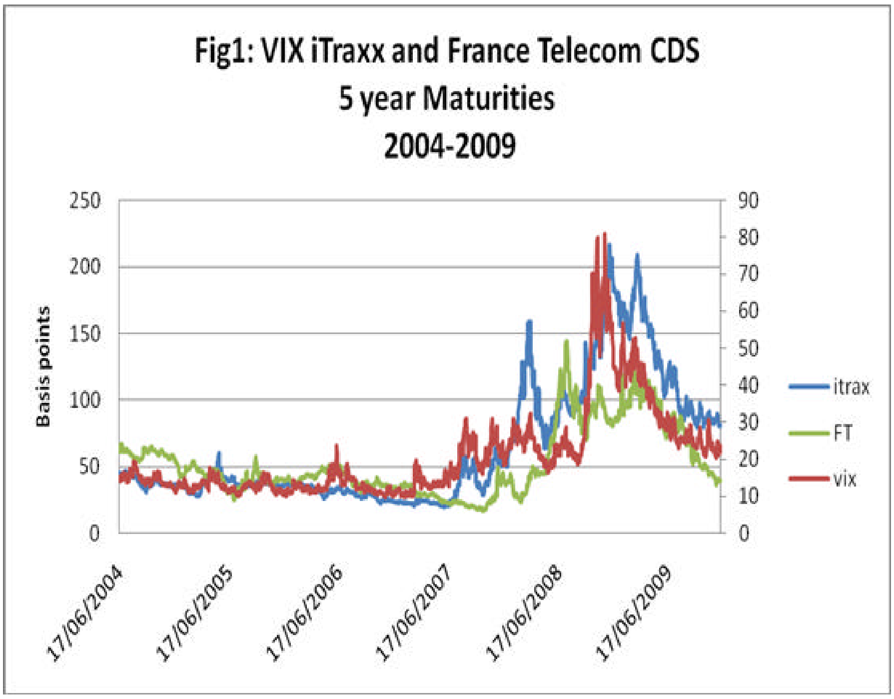


Fig1: VIX iTraxx and France Telecom CDS
5 year Maturities
2004-2009
Basis points
250
200
150
100
50
0
90
80
70
60
50
40
30
20
10
0
itrax
FT
vix
17/06/2004
17/06/2005
17/06/2006
17/06/2007
17/06/2008
17/06/2009

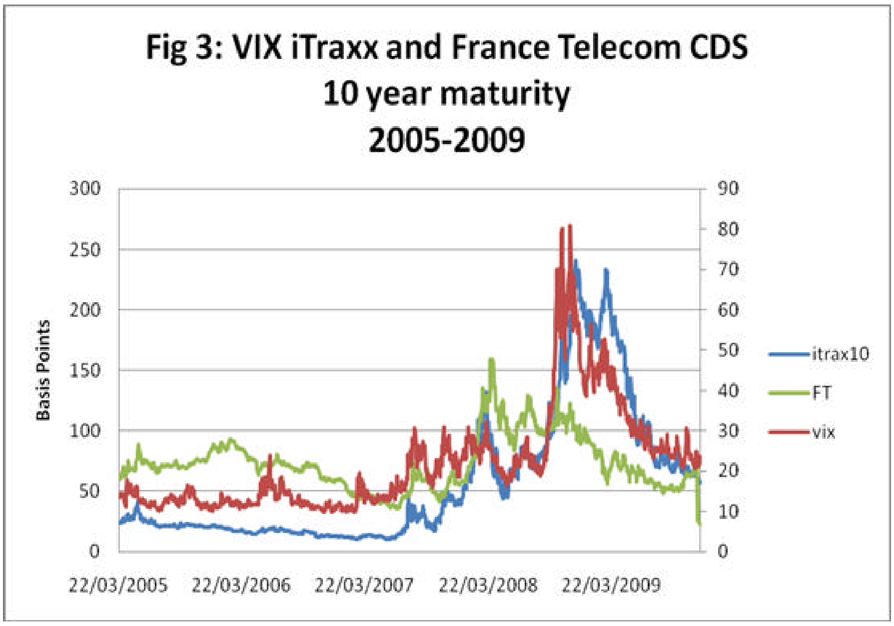


Fig 3: VIX iTraxx and France Telecom CDS
10 year maturity
2005-2009
Basis Points
300
250
200
150
100
50
0
90
80
70
60
50
40
30
20
10
0
itrax10
FT
vix
22/03/2005
22/03/2006
22/03/2007
22/03/2008
22/03/2009

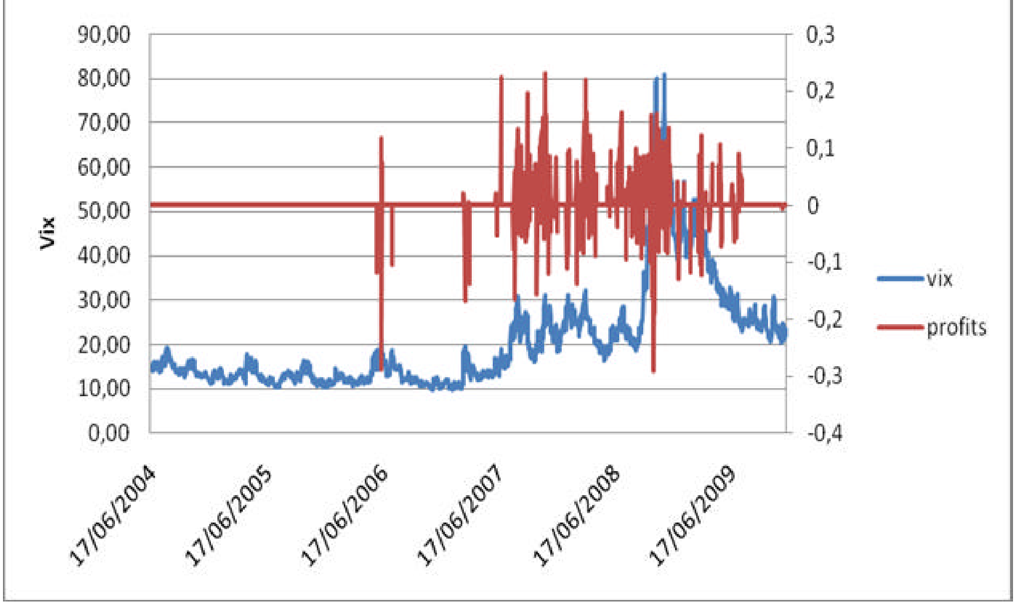


Fig 5: profits from pairs strategy vs the VIX common factor

Fig. 6

Histogram of P&L of ITRAXX replicating portfolio,

$$d\Pi \sim dN(\mu \sum_{i=1}^{n} i^{\theta}, \sigma^2 \sum_{i=1}^{n} i^{2\lambda})$$