UNIVERSIDAD CARLOS III DE MADRID

TESIS DOCTORAL

FOUR ESSAYS ON THE INTERACTION BETWEEN CREDIT DERIVATIVES AND FIXED INCOME MARKETS

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Esta tesis recoge el trabajo de investigación que he realizado durante los últimos años. En ella analizo la interacción entre los mercados, tanto a nivel corporativo como soberano, de Derivados de Crédito y Renta Fija desde distintas perspectivas. Para el caso corporativo, se realiza un análisis de arbitraje, liderazgo en la formación de precios e integración financiera en los mercados anteriormente mencionados. Para el caso soberano, el estudio se centra en el mercado de bonos soberanos de la Unión Monetaria Europea (EMU) y se analiza el impacto que la posible llegada de un tipo de interés libre de riesgo común para todos los países de la EMU tendría sobre sus costes financieros, así como las consecuencias que de ello se podrían derivar. El desarrollo de cada uno de estos cuatro análisis se ha basado en una combinación de aprendizaje, entusiasmo y esfuerzo pero también en la ayuda inestimable de varias personas. Por tanto, no sólo la palabra interacción se puede utilizar para definir y titular este trabajo sino también para destacar las ideas y energía que he recibido de las personas que a continuación detallo.

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"Essentially, all models are wrong,

but some are useful."

Box and Draper (1987)

ABSTRACT

In this thesis, I study the interaction between Credit Derivatives and Fixed Income Markets, both corporate and sovereign, from different perspectives. In the case of corporate, I study arbitrage, price discovery and financial integration. In the case of sovereign, I focus on the European Monetary Union (EMU) sovereign bond market and analyze the potential arrival of a common risk free rate for the EMU and the advantages derived from it.

First, we analyze long-run and statistical arbitrage opportunities in credit derivatives markets using strategies combining Credit Default Swaps (CDSs) and Asset Swaps (ASPs). We present a new statistical arbitrage test which has lower Type I error and selects arbitrage opportunities with lower downside risk than existing alternatives. This test allows us to study for arbitrage opportunities in the appropriate way by focusing our analysis on the cases in which long positions in CDSs and ASPs are needed. Using four different databases from 2005 to 2009, we find long-run and statistical arbitrage opportunities before the current crisis in 27% and 29% of the cases, respectively. During the crisis, they decrease to 9% and 17%, respectively. Specifically, CDS spreads are too low in comparison with asset swap spreads. This fact puts into question the efficiency of this segment of the CDS market. After considering funding and trading costs, we find SA opportunities in 16% of the cases before the crisis but never during the crisis. Thus, once the crisis started, noticeable deviations from the parity relation appeared although the increase in funding costs makes the apparent arbitrage opportunities non profitable. Finally, we find that arbitrage opportunities are more frequent in low rated

bonds.

Second, we analyze whether liquidity affects the price discovery process in credit derivatives markets and we find that it does. Specifically, we focus on the credit derivatives markets in the context of the subprime crisis. We fill a gap in the price discovery literature in credit markets, because no analysis of the price discovery process between ASPs or bonds and CDSs has been carried out up to now. The goal of the price discovery model is to analyze the dynamics and interaction between CDS and ASP or bond spreads in an equilibrium non-arbitrage model. Thus, this paper contributes to the price discovery literature by considering another facet of the credit markets (ASPs) and by adapting Garbade and Silver (1983) model to this segment of credit markets. We first present an agent-based theoretical price discovery model for the ASP, bond and CDS markets that allows for simultaneous agent participation in different markets. We then empirically test this model and obtain that the CDS market leads the ASP market in the price discovery process before the crisis (the high liquid scenario). This result changes with the appearance of the subprime crisis. Thus, during the crisis (the low liquid scenario) the ASP leads price discovery. We obtain similar results when we relate the CDS and bond markets. The difference in the relative liquidity between CDS and ASP/bond markets helps to explain these results. We also extend our analysis to test the suggestion that ASP spreads are a more accurate measure of credit risk than bond spreads. Our results indicate that ASP spreads consistently lead bond spreads up to the point that according to Garbade and Silver (1983) terms, we find that the bond spread is a “pure satellite” of the ASP spread.

Third, we analyze the internal (intra-market) and external (inter-market) integration of three European corporate credit markets (corporate bonds, asset swap packages and corporate credit default swaps) in the context of the current financial crisis. For this aim, we use a DCC-GARCH model for each market's innovations which are obtained after subtracting from the credit spreads the effect of the fundamentals of the underlying entities. Our measure of internal market integration is based on the average DCCs between an individual (firm-specific) credit spread innovation, and the corresponding average market credit spread innovations. Similarly, our measure of external market integration is based on the average DCCs between the two individual credit spreads innovations of the same firm but in different markets. The higher the innovations' correlation, the stronger is the market integration. We find that credit spread changes are largely driven by firm-specific innovations and to a lesser extent by changes in fundamentals. Internal market integration increases during the crisis for CDSs but decreases for bonds and ASPs. External market integration decreases during the crisis between the CDS and the other two markets. Both facts suggest that the CDS market tends to follow its own way to a considerable extent in times of financial distress. The degree of internal and external integration is significantly affected by liquidity and global risk factors.

Finally, we study the impact of a hypothetical common European Monetary Union (EMU) sovereign bond yielding a common European Monetary Union risk free rate. The possibility of a common European bond has attracted the interest of the financial press and is receiving increased attention from policy makers. However, there is no published quantification of a common risk free rate, nor a detailed comparison with other possible alternatives is available. This paper addresses both questions and presents a tentative

estimate of this common risk free for the European Monetary Union countries from 2004 to 2009 using variables motivated by a theoretical portfolio selection model. First, we analyze the determinants of EMU sovereign yield spreads and find significant effects of the credit quality, macro, correlation, liquidity and interaction variables. Robustness tests with different data frequencies, benchmarks, liquidity and risk variables, cross section regressions, balanced panels and maturities confirm the initial results. Motivated by these results, we present a tentative estimate of the common risk free rate which will be free, at least to some extent, from the effect of the risk factors (credit, liquidity, macro, correlation) that influence the yield of individual sovereign bonds. Finally, we find tentative evidence in favour of the hypothesis that a common bond and a common risk free rate in the EMU could produce substantial savings in borrowing costs for all the countries involved. Of course, there are many institutional design features that must be resolved (seniority, amount relative to total debt issues, guarantee fund, etc.) before such a common bond can be launched. But our paper provides a first insight into one central issue.

RESUMEN

En esta tesis estudio la interacción entre los mercados, tanto a nivel corporativo como soberano, de Derivados de Crédito y Renta Fija desde distintas perspectivas. Para el caso corporativo se realiza un análisis de arbitraje, liderazgo en la formación de precios e integración financiera en los mercados anteriormente mencionados. Para el caso soberano el estudio se centra en el mercado de bonos soberanos de la Unión Monetaria Europea (EMU) y se analiza el impacto que la posible llegada de un tipo de interés libre de riesgo común para todos los países de la EMU tendría sobre sus costes financieros, así como las consecuencias que de ello se podrían derivar.

En primer lugar, analizamos las oportunidades de arbitraje en el largo plazo y arbitraje estadístico en los mercados de derivados de crédito usando estrategias que combinan Credit Default Swaps (CDSs) y Asset Swaps (ASPs). Para ello presentamos un nuevo test de arbitraje estadístico que tiene menor error Tipo I y selecciona las oportunidades de arbitraje con un menor riesgo de pérdida que las alternativas existentes. Dicho test nos permite estudiar las oportunidades de arbitraje, centrando nuestro análisis sólo en los casos en los que se necesitan posiciones largas en CDSs y ASPs. Usando cuatro bases de datos diferentes que comprenden el periodo que se extiende de 2005 a 2009, encontramos oportunidades de arbitraje en el largo plazo y arbitraje estadístico en un 27% y 29% de los casos, respectivamente, antes de la reciente crisis. Durante la crisis, el porcentaje de oportunidades de arbitraje desciende al 9% y 17%, respectivamente. Específicamente, estos resultados reflejan que las primas de crédito del CDS son demasiado bajas en comparación con las primas de crédito del ASP. Este resultado

arroja dudas sobre la eficiencia del mercado de CDSs. Tras la inclusión de costes de financiación y de transacción, encontramos oportunidades de arbitraje estadístico en un 16% de los casos antes de la crisis pero en ningún caso durante la crisis. Por tanto, tras el comienzo de la crisis aparecieron desviaciones notables de la relación de equivalencia o paridad entre las primas de crédito de los CDSs y ASPs aunque el aumento de los costes de financiación convierte en no beneficiosas las aparentes oportunidades de arbitraje. Por último, encontramos que las oportunidades de arbitraje son más frecuentes entre los bonos con bajo rating.

En segundo lugar, analizamos si la liquidez afecta al proceso de liderazgo en la formación de precios (LFP en adelante) en los mercados de derivados de crédito y encontramos que sí lo hace. Concretamente, nos centramos en los mercados de derivados de crédito en el contexto de la actual crisis financiera. Gracias a este análisis cubrimos un vacío en la literatura de LFP en los mercados de derivados de crédito dado que ningún análisis del proceso de LFP entre los ASPs o bonos y CDSs ha sido desarrollado hasta la fecha. El objetivo del modelo de LFP consiste en el análisis de la dinámica e interacción entre las primas de crédito de los CDS y ASP o bonos en un modelo de equilibrio basado en la relación de no arbitraje. Por tanto, este estudio contribuye a la literatura de LFP considerando una nueva vertiente de los mercados de crédito (ASPs) y adaptando el modelo de Garbade y Silver (1983) a este segmento de los mercados de crédito. En primer lugar presentamos un modelo teórico de LFP basado en agentes para los mercados de ASPs, bonos y CDSs que permite la participación simultánea de los agentes en distintos mercados. Posteriormente, contrastamos teóricamente dicho modelo y obtenemos que antes de la crisis (escenario de alta liquidez) el mercado de

CDSs lidera al mercado de ASPs en el proceso de LFP. Este resultado cambia tras la aparición de la actual crisis de forma que durante dicha crisis (escenario de baja liquidez) el mercado de ASPs lidera el proceso de LFP. Resultados similares se obtienen cuando comparamos el mercado de CDSs y el mercado de bonos. La diferencia en la liquidez relativa entre los mercados de CDSs y ASPs/bonos nos ayuda a explicar e interpretar estos resultados. Extendemos nuestro análisis para contrastar la teoría de que la prima de crédito del ASP es una medida de riesgo de crédito más adecuada que la prima de crédito del bono. Nuestros resultados indican que la prima de crédito del ASP lidera, de forma consistente, a la prima de crédito de los bonos hasta el punto que siguiendo la terminología de Garbade y Silver (1983) obtenemos que la prima de crédito del bono es un "satélite puro" de la del ASP.

En tercer lugar, analizamos la integración interna (dentro de un mercado) y externa (entre mercados) de tres mercados europeos de crédito a nivel corporativo (bonos, asset swap packages y credit default swaps corporativos) en el contexto de la actual crisis financiera. Para tal fin, empleamos un modelo DCC-GARCH para las innovaciones de cada mercado que a su vez se obtienen tras extraer de las primas de crédito el efecto de los fundamentales de las entidades subyacentes. Nuestra medida de la integración interna del mercado se basa en la media de los DCCs existentes entre la innovación de una prima de crédito individual (específica de la empresa) y las innovaciones correspondientes a la prima de crédito media del mercado. De igual forma, nuestra medida de la integración externa del mercado se basa en la media de los DCCs existentes entre las innovaciones de dos primas de crédito individuales de la misma empresa pero correspondientes a distintos mercados. De esta forma, cuanto mayor es la correlación de las innovaciones, mayor es la integración de los mercados. Nuestros resultados muestran que los cambios en las primas de crédito se deben en gran medida a innovaciones específicas de las empresas y en un menor grado a cambios en los fundamentales. La integración interna del mercado aumenta durante la crisis para el caso del mercado de CDSs pero decae para el caso de los bonos y ASPs. La integración externa del mercado entre el mercado de CDSs y los otros dos mercados disminuye durante la crisis. Estos hechos sugieren que el mercado de CDSs tiende a seguir su propio camino de forma considerable en épocas de crisis financiera. El grado de integración interna y externa se ve afectado de forma significativa por factores de liquidez y riesgo global.

Finalmente, estudiamos el impacto de un hipotético bono soberano común en la Unión Monetaria Europea (UME) que a su vez daría lugar a un tipo de interés libre riesgo común en la Unión Monetaria Europea. Un posible bono común europeo ha atraído el interés de la prensa financiera y está recibiendo una atención creciente de los reguladores. Sin embargo, hasta la fecha no se dispone de ninguna cuantificación de este tipo de interés libre de riesgo común al igual que no se ha realizado una comparación detallada con otras posibles alternativas. Este estudio trata ambas cuestiones y presenta una estimación de este tipo de interés libre de riesgo común para los países de la UME durante el periodo de 2004 a 2009 usando variables que vienen motivadas de un modelo teórico de selección de cartera. Así, en primer lugar analizamos los determinantes de los diferenciales de las rentabilidades de los bonos soberanos en la UME y encontramos un efecto significativo de las variables referentes a la calidad crediticia, situación macro, correlación, liquidez y términos interacción. Estos resultados se ven confirmados gracias a distintos tests de robustez en los que se emplean otras frecuencias en los datos, distintos bonos de referencia (benchmarks), otras alternativas para las variables relacionadas con el riesgo y la liquidez, regresiones de sección cruzada, paneles balanceados y diferentes vencimientos. A partir de estos resultados, presentamos una estimación del tipo de interés libre de riesgo que estaría libre, al menos hasta cierto punto, del efecto de factores de riesgo (crédito, liquidez, macro, correlación) que influyen sobre el diferencial de los bonos soberanos individuales. Por último, encontramos evidencia a favor de la hipótesis de que un bono común y por tanto de un tipo de interés común en la UME propiciaría ahorros substanciales referentes al coste de financiación de la deuda para todos los países involucrados. Por supuesto, existen muchos aspectos relacionados con el diseño institucional que deberían resolverse (prioridad relativa a otros bonos, cantidad relativa al total de la emisión, fondo de garantía, etc.) antes de que dicho bono común empezara su andadura. Sin embargo, nuestro estudio ofrece una primera aproximación a una cuestión fundamental.

CONTENTS

CHAPTER 1

GENERAL INTRODUCTION

In this thesis, I study the interaction between Credit Derivatives and Fixed Income Markets, both corporate and sovereign, from different perspectives. In the case of corporate, I study arbitrage, price discovery and financial integration. In the case of sovereign, I focus on the European Monetary Union (EMU) sovereign bond market and analyze the potential arrival of a common risk free rate for the EMU and the advantages derived from it.

In Chapter 2 we analyze the existence of arbitrage opportunities in credit derivatives markets using self-financing strategies combining Credit Default Swaps (CDSs) and Asset Swaps Packages (ASPs). More concretely, we analyze the mispricings between CDSs and ASPs. Credit Default Swaps are insurance contracts which provide protection in exchange for the CDS spread while the Asset Swaps are compounded by a bond and an IRS which swaps the bond coupon into Euribor plus the asset swap spread. The underlying idea is that both the CDS and the ASP spreads are prices for the same credit risk and for this reason there should be an equivalence relation between both spreads to avoid arbitrage opportunities. The analysis of arbitrage opportunities is based on two different perspectives, the long run arbitrage and the statistical arbitrage perspective.

The first perspective is based on the cointegration methodology and analyzes if both spreads are equivalent in the long run. This perspective has also been employed to analyze the no-arbitrage relationship between bonds and CDSs in Blanco, Brennan and Marsh (2005) or Zhu (2006) among others. We use ASP instead of bond spreads given that they allow a more precise analysis parity relation between CDS and bond spreads. The cointegration analysis is based on the assumption that bonds and ASPs can be shorted. However, this option is not always feasible and so we extend the analysis of arbitrage opportunities by focusing in the cases in which long positions in CDSs and ASPs are needed. To develop this extension we use the statistical arbitrage methodology.

The second perspective is then based on the statistical arbitrage test. The statistical arbitrage analysis is designed to exploit persistent anomalies and was firstly introduced by Hogan, Jarrow, Teo and Warachka (2004) and later improved in Jarrow, Teo, Tse and Warachka (2007). Both studies analyze statistical arbitrage opportunities in the stock market. Statistical arbitrage represents a zero cost, self-financing trading opportunity that has positive expected cumulative trading profits with a declining variance and a probability of loss that converges to zero. Hogan et al. (2004) and Jarrow et al. (2007) are based on the stationary bootstrap methodology. However, we present a new statistical arbitrage test based on the subsampling methodology introduced in Politis, Romano and Wolf (1995) and (1997) and extended in Politis, Romano and Wolf (1999) and (2001). Our test allows a more general structure in the residuals and which has lower Type I error and selects arbitrage opportunities with lower downside risk than existing alternatives.

Using four different data sources for CDS spreads covering the period from 2005 to 2009, long-run (cointegration) and statistical arbitrage analysis are performed. Before the subprime crisis, we find long-run and statistical arbitrage opportunities in 27% and

29% of the cases, respectively. During the crisis, arbitrage opportunities decrease to 9% and 17%, respectively. Specifically, CDS spreads are too low in comparison with asset swap spreads. This fact puts into question the efficiency of this segment of the CDS market. Employing Hogan et al. (2004) or Jarrow et al. (2007) methodology we find statistical arbitrage opportunities in 49% and 24% of the cases before the crisis and during the crisis, respectively. We find that arbitrageurs engaging in arbitrage opportunities detected by Jarrow et al. (2007) test (but not detected by our test) are exposed to significant downside risk that is even more extreme during the crisis period. This is an economically relevant difference between Jarrow et al. (2007) test and our test besides its better statistical properties. We find that our test is more conservative than Jarrow et al. (2007) test and it rejects statistical arbitrage in some cases where there exist risk and the other tests (Jarrow et al. (2007) and long-run) support the existence of statistical arbitrage. After considering funding and trading costs, we find statistical arbitrage opportunities in 16% of the cases before the crisis but never during the crisis. Arbitrage opportunities are more frequent in the case of relatively low rated bonds. The ongoing financial crisis and its possible consequences for the regulation of financial markets and for the investment strategies makes the study of the possible persistent mispricing in credit derivatives markets a topic of salient relevance. Our results can be interpreted as tentative evidence in favour of the hypothesis that before the crisis some persistent mispricings can be found in this segment of the credit derivatives markets. However once the crisis started, noticeable deviations from the parity relation appeared although the increase in funding costs makes the apparent arbitrage opportunities non profitable.

Some interesting economic and regulatory implications follow from these results. For example, persistent mispricing in credit derivatives markets suggests potential inefficiencies in these markets. The existence of statistical arbitrage opportunities before the crisis, even after adjusting by market frictions, puts into question the efficiency of this segment of the CDS market and highlights the interest of this analysis for financial regulators. Moreover, these results also sheds light on the risk and profitability of the strategy which is commonly known as "trading the basis" and which has been employed by some investors during the last years.[1] Finally, one economic implication derived from our new test is that the arbitrageurs engaging in arbitrage opportunities detected by the previous tests but not detected by ours will be exposed to significant downside risk. This risk is even more extreme during the crisis period. Traders using our test will not take into account those apparent (but risky) arbitrage opportunities. Thus, there is an economically relevant difference between the previous tests and our test besides its better statistical properties (our test has lower Type I error).

The primary focus of Chapter 3 is to examine the role that liquidity plays in the price discovery mechanism of credit derivatives markets in the context of the subprime crisis. As Yan and Zivot (2007) state, an efficient price discovery process is characterized by the fast adjustment of market prices from the old equilibrium to the new equilibrium with the arrival of new information. The new equilibrium is achieved by means of the interactions of buyers and sellers. Thus, the financial instrument price's that contributes more and newer information to the price discovery process should be the one with the highest number of informed market participants. We analyze it based on an agent-based

[1] Basis trades exploit the different pricing of ASP/bond and CDS on the same underlying company and they have been a popular investment strategy during the last years.

theoretical model for the asset swap package (ASP) or bond and CDS markets in the spirit of Garbade and Silver (1983) estimated in an econometric framework associated with the work of Gonzalo and Granger (1995).

Although there is no a formal theoretical model to understand the price discovery process in credit derivatives markets there are some applications based on Hasbrouck (1995) and Gonzalo and Granger (1995) methodologies that analyze the efficiency of both CDS and bond markets in terms of price discovery. Norden and Weber (2004), Blanco, Brennan and Marsh (2005) or Zhu (2006) among others obtain that the CDS market reflects the information more accurately and quickly than the bond market. Other analyses of price discovery based on bonds and CDS such as Ammer and Cai (2007) and Dötz (2007) find that the bond market also make net contributions to price discovery.

We fill a gap in the price discovery literature in credit markets, because, as far as we know, no analysis of the price discovery process between ASPs or bonds and CDSs has been carried out up to now. Moreover, there is no an empirical analysis that relates the ASP and bond markets. The goal of the price discovery model that we present is to analyze the dynamics and interaction between CDS and ASP or bond spreads in an equilibrium non-arbitrage model. Garbade and Silver (1983) posit a formal agent-based theoretical model to analyze the process of price discovery and show empirically that this process is led by the markets where the number of participants is higher, in their case the futures market in comparison with the spot market. We adapt Garbade and Silver (1983) model to credit markets and extend it to reflect, as realistically as possible, the behaviour of market participants in the corresponding market place. Thus, we consider five different types of market participants instead of three as Garbade and Silver (1983). Each agent that participates in the market place can be classified into one of the following groups: (i) Arbitrageurs who try to exploit possible discrepancies among CDS and ASP prices. (ii) Agents that only take positions in the asset swap market such as insurance firms or pension funds that invest in bonds or asset swaps as a "buy and hold" strategy. (iii) Agents that only participate in the CDS market either as protection sellers or buyers such as the CDO issuers. Some examples of these agents are hedge funds that benefit from CDSs leverage effect. (iv) Agents that participate in both financial markets as market makers or as financial intermediaries who manage portfolios for different customers or simply as investors in credit markets. (v) Agents that use the CDS market to hedge their positions in corporate debt contrary to the individuals in group iii) who do not have any underlying bond or ASP. Garbade and Silver (1983) assume that the only individuals that operate in both markets are the arbitrageurs. We offer a more general model that includes participants that operate in both markets (iii) and hedgers (v) and so, both markets are not only linked by arbitrageurs as in GS but by the two additional groups of individuals.

Once we have defined the demand scheduled for the different market participants we set the clearing market conditions and find the equilibrium prices. We use Figuerola-Ferretti and Gonzalo (2009) methodology to match the theoretical model and the econometric framework. The equilibrium prices can be defined in first differences according to a VECM such that by means of the Gonzalo and Granger (1995) permanent-transitory decomposition we obtain the price discovery metrics. The metrics represent the relative contribution of a given markets relative to the other in terms of price discovery. They represent a liquidity measure and are defined in terms of the relative number of participants in a given market, i. e. the number of agents operating in one market relative to the number of participants in another market. Assuming that in a given market the highest the overall number of market participants, the highest the number of informed agents and given that the overall number of market participants is a measure of market liquidity, we state that liquidity is the common element in price discovery analyses that determines which market reveals information more efficiently. This measure can be easily related with other commonly employed liquidity measures like the number of contracts or traded volume in a given market relative to the other. Our empirical application confirms the theoretical model's insights.

Cointegration is tested for and where found, we undertake the VECM analysis yielding a price discovery metric consistent with the Gonzalo and Granger (1995) methodology. The empirical results find that the CDS market is more efficient than the ASP market in regards to price discovery in 87.5% of the cases which are studied before the crisis (the high liquid scenario). Interestingly, this result is very sensitive to the appearance of the subprime crisis. Thus, we find that during the subprime crisis (the low liquid scenario) the ASP spreads reflect credit risk more efficiently in 71.9% of the cases. We obtain similar results when we relate the CDS and bond markets. The difference in the relative liquidity between CDS and ASP/bond markets helps to explain these results. We also extend our analysis to test the suggestion that ASP spreads are a more accurate measure of credit risk than bond spreads. Our results indicate that ASP spreads consistently lead bond spreads up to the point that according to GS (1983) terms, we find that the bond spread is a "pure satellite" of the ASP spread.

The paper contributes to the price discovery literature by considering another facet of the credit markets (Asset Swap Packages) and by adapting Garbade and Silver (1983) model to this segment of credit markets. This model reveals the importance of liquidity to the price discovery process in addition to the role of arbitrageurs in reducing deviations from long-run equilibrium. Moreover the results presented yield thought provoking ramifications for the measurement of credit risk in times of financial distress. Actually, we hypothesize that the presence of a cheapest-to-deliver option, a liquidity premium or counterparty risk among other aspects in CDS spreads may cloud the role of these spreads as reliable credit risk measure and may difficult inferences from CDS spreads to monitor credit risk during periods of financial distress. For this reason, it seems more convenient to use the ASP spread as an alternative or as a complement to the CDS spread, rather than the bond spread which is favoured in the literature, in turbulent times.

In summary, the main economic and financial implications are the following. First, during the crisis the ASP market reveals credit risk more efficiently that the CDS market. Reasons explaining this finding include the cheapest-to-deliver option embedded in the CDS spread, the liquidity premium and the counterparty risk in CDSs. The key implication of this result is that inferences on the creditworthiness of a given firm based solely in CDS spreads in periods of high market turbulence and low liquidity are bound to be misleading. Second, the ASP spread leads the price discovery process of credit risk more efficiently than the bond spread, before and during the crisis. For this reason, it is more appropriate to use the ASP spread as an alternative or as a complement to the CDS spread as a measure of credit risk rather than the bond spread. However, most of the existing literature has focused primarily on the bond and CDS spreads ignoring the role of the ASP spread as a credit risk indicator. Third, our theoretical model and empirical results highlight the importance of the agents that operate in both markets in order to provide stability to the credit markets. The arbitrageurs also play a special role in these markets given that their demands are defined in terms of a long-run equivalence or adjustment which could reduce deviations from the equilibrium prices.

In Chapter 4 we analyze the internal and external integration of three European corporate credit markets (Corporate Bonds, Asset Swap Packages and Corporate Credit Default Swaps) in the context of the current financial crisis based on the information on credit risk for fifty firms using the prices in CDS, ASP and Bonds from November 2005 to September 2008. Unlike a number of previous studies, we do not restrict ourselves to few particular aggregate market indexes. The reason for taking a broader perspective is to provide an insight into the integration process of financial markets at the micro level rather than simply a narrower integration within or among overall markets. In this chapter we define market integration in terms of the correlation structures estimated between two credit spreads innovations obtained after subtracting from the credit spreads the effect of the fundamentals of the underlying entities. The reason for using the innovations as in Acharya et al. (2007) according to the Acharya and Johnson's (2007) econometric methodology is that changes in fundamentals should have affected in a similar way all credit spreads in fixed-income markets. The innovations are computed using a non-linear equation derived from a structural model of credit risk such as Merton (1974). To capture the characteristics of time-varying correlations we employ the Dynamic Conditional Correlation (DCC-GARCH) model of Engle and Sheppard

(2001) and Engle (2002), which is particularly well suited to examine correlation dynamics among assets. The DCC models have been employed to study the integration or co-movement among different financial markets and among different economic areas. The higher the innovation's correlation, the stronger is the market integration. We test both the internal or intra-market integration (within a given market) and the external or inter-market integration (between two given markets). Our measure of internal market integration is based on the average DCCs between an individual (firm-specific) credit spread innovation, and the corresponding average market credit spread innovations. Similarly, our measure of external market integration is based on the average DCCs between the two individual credit spreads innovations of the same firm but in different markets.

In related research, Acharya and Schaefer (2006) and Acharya et al. (2007) analyze the existence of correlation risk in credit markets during the Ford and GM downgrades episode in May 2005. Coudert and Gex (2008) study the variations in the correlation between CDS premium around the same episode using different measures such as the DCC-GARCH model. Both analyses find a significant increase in CDS premium co-movements or correlations (internal market integration) during the previous episode. The current financial crisis represents an illiquid scenario even more severe than the one analyzed by Coudert and Gex (2008) to extend the analysis to other credit markets (ASP and bond markets) and test the correlation dynamics among credit markets.

Our main findings in this chapter are as follows. Credit spread changes are largely driven by firm-specific innovations and to a much lesser extent by changes in fundamentals. Internal market integration increases during the crisis for CDSs but decreases for

Bonds and ASPs. External market integration decreases during the crisis between the CDS and the other two markets. Reasons justifying these results are the concentration of some players in the CDS market, the "extinction" of a portion of individuals operating in various markets, the heterogeneity and the disperse distribution of the remaining market players in ASP and Bond markets, and the drastic change in liquidity in the CDS market. These results suggest that the CDS market tends to follow its own way to a considerable extent in times of financial distress. This finding combined with the fact of the relatively low liquidity of CDS market in comparison with Bonds and ASP casts some doubts on the representativeness of market prices quoted in this market. The degree of internal and external integration is significantly affected by liquidity and global risk factors.

These results have a number of important economic implications. For example, they suggest that a substantial portion of the changes in corporate credit risk is not related with changes in economic fundamentals and may not be diversifiable. This has clear implications for portfolio choice and the cost of corporate debt capital. Furthermore and given the fact of the relatively low liquidity of CDS market in comparison with Bonds and ASP, our results cast some doubts on the representativeness of market prices quoted in the CDS market.

In Chapter 5 we deal with some of the effects of a hypothetical common European Monetary Union (EMU) sovereign bond yielding a common European Monetary Union risk free rate. Thus, we present a tentative estimate of this new financial variable: the common risk free rate of interest for the EMU members. We show how to estimate it for a given set of countries and discuss its uses for monetary policy management and its implication for financial markets' integration.

The possibility of a common European bond has attracted the interest of the financial press and is receiving increased attention from policy makers. There are potential wider benefits for the Eurozone as well as specific benefits for market agents such as issuers, dealers, and investors. A large common bond issue could have benefits even for countries with low credit risk (Germany, France), as it could rival American's treasuries market for liquidity. Moreover a single issuer would make EMU bonds more attractive to investors in large foreign-exchange reserves (China, Japan) and enhance the euro's standing as a reserve currency, as well as lowering borrowing costs for all countries that took part in it. On the other hand, some arguments against it have been raised focusing on the possible increase in moral hazard as well as the technical and institutional difficulties of managing a common bond issuance. However, as far as we know, there is no published quantification of a common risk free rate, nor a detailed comparison with other possible alternatives is available. This paper addresses both questions.

A common risk free rate could be used as a benchmark for measuring the benefits from financial market integration in the EMU. We conjecture and provide some evidence that our estimate of this rate would be close to what a common EMU-based single bond would yield for a specified maturity. We can then compare actual rates offered by the different EMU countries with sovereign bonds with this common rate. This allows us to compute the savings in terms of financing costs per year for the different EMU members. Of course, there are many institutional design features that must be resolved (seniority, amount relative to total debt issues, guarantee fund, etc.) before such a common bond can be launched. But our paper provides a first insight into one central issue.

Since the formation of the European Monetary Union (EMU henceforth) the topic of the determinants of the sovereign bonds' yield spreads within the EMU has been the subject of intense and increasing research. Researchers have tried to find out which are the factors that explain the differences between sovereign yields in the EMU countries, but so far no clear consensus has emerged. Codogno, Favero and Misale (2003) find that for most EMU countries only international risk factors have explanatory power. Geyer, Kossmeier and Pichler (2004) report that EMU government bond spreads are related to common factors whereas they do not find evidence for a significant impact of macroeconomic or liquidity related variables. Bernoth, von Hagen and Schuknecht (2006) report that global risk factors as well as idiosyncratic macroeconomic factors affect yield spreads, whereas liquidity plays a marginal role. Favero, Pagano and Von Thadden (2008) find that one aggregate risk factor is consistently priced, that liquidity differentials are priced for a subset of countries, and that the interaction of liquidity differentials with the risk factor is consistently priced. In all these papers the benchmark for comparing the yield spreads is based on the German 10-year bund or German zero coupon curves. Beber, Brandt and Kavajecz (2009), however, use as benchmark the Euro-swap curve and show that the bulk of yield spread is explained by differences in credit quality as measured by the CDS, whereas liquidity plays a nontrivial role especially for low credit risk countries and in times of high market uncertainty. Thus, first of all and motivated by a simple theoretical portfolio selection model, we analyze the determinants of EMU sovereign yield spreads during the period which spans from 2004 and 2009 by fitting an unbalanced panel model. The yield spreads are defined as the difference between a given sovereign bond yield and the benchmark reference yield which is constructed as a weighted average of the total gross debt at nominal value issued by the general governments of the different EMU members.[2] We find significant effects of the credit quality, macro, correlation, and liquidity variables. Robustness tests with different data frequencies, benchmarks, liquidity and risk variables, cross section regressions, balanced panels and maturities confirm the initial results.

Secondly, motivated by these results we try to answer the following question: What should be the yield of a common Euro zone bond, free, at least to some extent, from the effect of the risk factors (credit, liquidity, macro, correlation) that influence the yield of individual sovereign bonds? We consider that a given country X should be required to pay a compensation to the actual issuer (let's assume that the issuer is the ECB or other EMU-wide agency) to be allowed to share a given issue of the EMU-based single bonds. We argue that this compensation should be the Credit Default Swap (CDS) spread on X's sovereign bonds such that we define the "Hedge Yield" of the sovereign debt of a country as the difference of actual yield and the corresponding CDS spread. The benefits for country X in using the common bond (instead of the sovereign bond) will be the enhanced rating and liquidity the common bond would provide plus additional premiums for country X's macro fundamentals. Based on these hedged yields we present an estimation of this hypothetical common risk free rate and show that average savings in borrowing costs for all EMU countries are positive irrespective of the maturity of the

[2]The selection of the appropriate benchmark reference, however, has not received extensive attention in the literature. Analysts who take this view accept that the appropriate criterion for benchmark status is that this is the security against which others are priced, and they simply assume that the security with lowest yield takes that role. A plausible alternative, however, is to interpret benchmark to mean the most liquid security. Dunne, Moore and Portes (2002) consider in detail the meaning of the term "benchmark" bond. They suggest looking for benchmark portfolios rather than a single benchmark security. This may be particularly appropriate in this partially integrated market and it is the approach we take in this paper.

common risk free rate measure employed.

Summing up, the most salient economic implication in this chapter is the estimation of the possible savings in borrowing costs arising from the issuance of common bonds in the EMU. We find that the average savings in borrowing costs are positive irrespective of the country and maturity. Our estimations suggest that the average annual savings for the EMU in the period that spans from September 2005 to February 2009 might be around €19.52 billion with the Common Risk Free Rate. Moreover, the average annual savings for the EMU obtained from the Euro-denominated sovereign bonds issued during the sample period (2004 – 2009) and with a maturity equal or lower than 11 years at the issuance date are roughly €1.1 billion. Contrary to the idea that a common bond would generate an implicit debt guarantee by some countries in favour of others, our results show tentative evidence in favour of the hypothesis that a common bond in the EMU could produce substantial savings in borrowing costs for all the countries involved.

As a last remark, this thesis was elaborated in a way that any of the following four chapters can be read independently. In this sense, Chapters 2, 3, 4 and 5 present complete researches that, although based on the interactions or relationships between the different credit markets under study, consider different contexts and lead to independent conclusions.

CHAPTER 2

ARE THERE ARBITRAGE OPPORTUNITIES IN CREDIT DERIVATIVES MARKETS? A NEW TEST AND AN APPLICATION TO THE CASE OF CDS AND ASPS

2.1 Introduction

This chapter analyzes potential arbitrage opportunities arising from a cash-and-carry strategy in which the arbitrageur trades two self-financing portfolios based in credit derivatives. The first portfolio contains a long position in a Credit Default Swap (CDS) while the second contains a long position in an Asset Swap Package (ASP) funded at Euribor. Note that this second portfolio is equivalent to a synthetic short position in a CDS. For this reason, there should be an equivalence relation between the payoffs of both portfolios, which are given by the CDS premium and the asset swap spread, respectively. If for a given pair of payments the equivalence does not hold, there exists an arbitrage opportunity. The existence of arbitrage opportunities is studied from two different perspectives. The first perspective analyzes possible long-run (cointegration) arbitrage opportunities while the second one tests the existence of statistical arbitrage opportunities.

Other arbitrage strategies in fixed income markets such as swap spread arbitrage, yield curve arbitrage, mortgage arbitrage, volatility arbitrage and capital structure arbitrage are addressed in Duarte, Longstaff, and Yu (2007). They find that all the five previous strategies yield positive excess returns which are positively skewed. On the basis of these results, they suggest that there could be more economic substance to fixed income arbitrage than simply "picking up nickels in front of a steamroller". Capital structure arbitrage is usually based on strategies trading equity instruments against CDSs. Yu (2005), Bajlum and Larsen (2007), and Cserna and Imbierowicz (2008) find significant positive capital structure arbitrage returns.

The existence of long-run arbitrage opportunities is analyzed using the cointegration test proposed by Engle and Granger (1987). Given that both credit derivatives price credit risk, we expect them to be closely linked in the long-run. Blanco, Brennan, and Marsh (2005) analyze this equivalence relation for CDS and bond spreads and find support, in general, for the parity relation as a long-run equilibrium condition. Zhu (2006), in a similar study, finds similar results and also analyzes the determinants of the basis, defined as the difference between the CDS and bond spreads. He finds that both spreads respond differently to credit conditions such as rating events. De Wit (2006) analyzes the basis calculated as the difference between par ASP and CDS spreads and applies a cointegration test to show that the basis is usually stationary. In fact, ASP spreads should be a more accurate measure of credit risk than bond spreads. This idea is supported by De Wit (2006), Felsenheimer (2004), Francis, Kakodkar, and Martin (2003), and in the next chapter of this thesis.

Statistical arbitrage represents a zero cost, self-financing trading opportunity that has positive expected cumulative trading profits with a declining time-averaged variance and a probability of loss that converges to zero. The statistical arbitrage analysis is designed to exploit persistent anomalies and was firstly introduced by Hogan, Jarrow, Teo, and Warachka (2004) (HJTW henceforth) and later improved in Jarrow, Teo, Tse, and Warachka (2007) (JTTW henceforth). They test statistical arbitrage on stock markets. HJTW analyzes momentum and value trading strategies while JTTW extends the analysis to stock liquidity and industry momentum strategies. Both studies find that these strategies generate statistical arbitrage opportunities even after adjusting for market frictions such as transaction costs, margin requirements, liquidity buffers for the marking-to-market of short-sales and borrowing rates, although momentum and value strategies offer the most profitable trading opportunities.

HJTW and JTTW tests are based on the behavior of the increment in cumulative trading profits associated with the corresponding strategies. In both studies, innovations are assumed to be weakly dependent and stationary. Therefore, JTTW use a stationary bootstrap methodology to compute the test statistic's empirical distribution. Stationarity is a very convenient assumption but also a restrictive one when modeling financial time series. Just as it is also restrictive to treat the errors in any empirical econometric work as homoskedastic. The first contribution of this chapter is to present a new test that allows for nonstationarity in incremental trading profits series and also for nonnormal, autocorrelated, heteroskedastic and possibly nonstationary innovations. This new test is based on the subsampling methodology introduced in Politis, Romano, and Wolf (1995) and (1997) and extended in Politis, Romano, and Wolf (1999a, 1999b) and (2001). This technique is based on asymptotic inference and provides an asymptotically valid test under weak assumptions. Extensive simulation exercises suggest that our test has lower Type I error (false positive) and chooses arbitrage opportunities with lower downside risk than existing alternatives. Moreover, to the best of our knowledge, ours is the first study that applies the statistical arbitrage methodology to analyze the relation between two credit derivatives (CDSs and ASPs) whose spreads, or prices for credit risk, should be similar.[1] The use of asset swap spreads should allow a more precise analysis of the parity relation between CDS and bond spreads. This is our second contribution.

Our third contribution relates to the appropriate way of testing for arbitrage opportunities. Usually arbitrage analysis is based on the assumption that financial instruments (in our case bonds and ASPs) can be shorted. Nevertheless, according to Schonbucher (2003) and Mengle (2007) shorting a corporate bond or ASP is not always a feasible option. Therefore, we focus our analysis to testing the cases in which long positions in CDSs and ASPs are needed. Moreover, we extend the study to test the strategies that are based on bonds or ASPs short-sales. To take into account the effects of the ongoing financial crisis, we analyze two different subperiods which cover the periods before and during the subprime crisis. It should be emphasized that our test is only applied when there is trading activity and liquid enough prices. The results suggest that arbitrage opportunities decreased substantially during the crisis because of the considerable increase in funding costs traders faced in this period. This is our fourth contribution.

Using four different CDS databases (GFI, CMA, Reuters, and J.P. Morgan) and a sample of 55 cases, corresponding to the same number of bonds, which span from November 2005 to August 2007, we find 15 long-run arbitrage opportunities with the

[1] Yu (2006) uses the HJTW procedure to detect statistical arbitrage in monthly capital structure arbitrage returns generated with CDS and stock price data.

cointegration test. Using the methodology of HJTW and JTTW, 27 statistical arbitrage opportunities are found. The new test finds 16 statistical arbitrage opportunities. Employing a sample of 46 cases which covers the crisis period and spans from August 2007 to June 2009, we find four long-run arbitrage opportunities and eight statistical arbitrage opportunities with the new test. Employing HJTW and JTTW methodology, we find 11 statistical arbitrage opportunities. We find that arbitrageurs engaging in arbitrage opportunities detected by JTTW's test (but not detected by our test) are exposed to significant downside risk that is even more extreme during the crisis period. Thus, there is an economically relevant difference between JTTW's test and our test besides its better statistical properties. After considering funding and trading costs, we find nine statistical arbitrage opportunities during the first subperiod but none during the crisis. As far as we know, ours is the first paper showing formally the effect of the increased funding costs in arbitrage opportunities in credit markets, due to the credit squeeze of the recent financial crisis. Moreover, we find that arbitrage opportunities are more frequent in the case of bonds with relatively low issuer rating. Therefore, there seems to be one salient factor that determines the existence of statistical arbitrage: the issuer's relative credit risk. This is our fifth contribution.

The chapter is divided into eight sections. Section 2 defines the cash-and-carry arbitrage strategy. Section 3 presents the long-run arbitrage test. In Section 4 we address the concept of statistical arbitrage and its application. In Section 5 we introduce the new test. Section 6 describes the data. Section 7 presents the results for long-run arbitrage and statistical arbitrage analyses. Section 8 includes robustness tests and extensions and Section 9 concludes the chapter.

2.2 Cash-and-carry arbitrage strategy

2.2.1 Credit default swaps

A CDS is as a traded insurance contract which provides protection against credit risk until the occurrence of a credit event or the maturity date of the contract, whichever is first, in exchange for periodic premium payments (the CDS premium or CDS spread) and/or an upfront payment. We analyze the case in which the CDSs trade on a full running format (i.e. no upfront). It means that the CDS contract that we employ is unfunded and so, investors do not make an upfront payment (ignoring dealer margins and transaction costs). Thus, the traded CDS premium is an at-market annuity premium rate $\overline{s}$ such that the market value of the CDS is zero at origination. In the event of default, CDSs are settled in one of two ways: by physical settlement or by cash settlement.

The British Bankers' Association estimates that CDSs accounted for 33% of the market share of credit derivatives in 2006. According to the ISDA statistics, the CDS market exploded over the past decade from a notional amount outstanding of \$8.42 trillion at the end of 2004 to more than \$45 trillion in mid-2007 and more than \$62 trillion at the end of 2007. However, the notional amount outstanding decreased to \$38.6 trillion at the end of 2008. Most CDSs are quoted for a benchmark time-to-maturity of five years but since CDSs are traded Over the Counter (OTC) any maturity is possible. The spread is quoted in annual terms but standard premium payments are settled in quarterly terms with an "actual/360" day count convention.

2.2.2 Asset swap packages

An ASP contains a defaultable coupon bond with coupon $\bar{c}$ and an interest rate swap (IRS) that swaps the bond's coupon into Euribor plus the asset swap spread rate s^A. The spread is chosen such that the value of the whole package is the par value of the defaultable bond. Thus, an upfront payment must be added to the bond's price at the investment period to ensure that the value of the whole package is the bond face value. The upfront payment represents the net present value of the swap. The asset swap's fixed leg $\left(\bar{c}\right)$ represents the buyer's periodic fixed rate payments, while its floating leg (Euribor + s^A) represents the seller's potential payment.[2] According to Schonbucher (2003), it is even easier to trade an ASP than the underlying defaultable bond alone.

2.2.3 Cash-and-carry strategy

A combined long position in a CDS (buy protection) and an ASP is hedged against bond's default risk and should therefore trade close to the price of an equivalent default free bond. This is the intuition behind the cash-and-carry arbitrage pricing of CDSs. From cash-and-carry strategies, we construct two equivalent portfolios which should produce the same payments and then analyze the existence of possible arbitrage opportunities.

Portfolio I:

- Long position in a CDS with an annual full running premium equals to $\bar{s}$ which is paid quarterly.

[2] According to the California Debt and Investment Advisory Commission (CDIAC), floating-rate payment intervals in a IRS need not coincide with fixed-rate payment intervals, although they often do. Thus, the ASP investors could make the fixed rate payments dates to coincide with the defaultable bond's coupon payments dates while the floating payments, Euribor plus asset swap spread, could be made quarterly.

Portfolio II:

- Long position in an ASP whose cost is equal to the bond's par value. The investor pays to the counterparty the bond's coupon at the coupon dates in exchange for receiving every quarter the 3-month Euribor rate (E_{3m}) plus the asset swap spread (s^A). The quarterly payment dates coincide with the CDS premium payment dates.

- Loan (principal equals to the bond's face value) at 3-month Euribor. Interest payment dates coincide with both CDS premium and ASP floating leg payment dates.

We first assume that the investor can borrow money at Euribor flat for the entire duration of the trade and after, we relax this assumption and estimate the critical level of average funding costs which delimits the existence/absence of statistical arbitrage.

Portfolio II is equivalent to a synthetic short position in a CDS and so, there should be an equivalence relation between CDS and asset swap spreads. Otherwise, arbitrage opportunities could appear.

As CDSs are OTC instruments, we assume that the investor can buy a CDS contract whose maturity coincides with the bond's maturity and whose premium payments timing is agreed by the parties.[3] Thus, we take advantage of the range of CDSs maturities to fit a CDS curve using a Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) algorithm that permits us to match ASP and CDS maturities. This method is also used in Levin, Perli, and Zakrajšek (2005).

[3] As the bond's maturity date approaches, the use of CDSs with a 5 years constant maturity would lead to an overhedging, given that the maturity dates of CDSs and asset swaps do not coincide. The consequence is that the investor will pay a CDS spread above the one needed to be fully hedged.

At origination the cost of both portfolios is zero, and so the net payoff is also zero. CDS' premium is paid quarterly and the first payment takes place a quarter after origination. At this date and at every subsequent quarter, the investor pays the CDS premium ($\overline{s}_t$), receives the floating leg payment of the ASP ($E_{3m,t} + s_t^A$) and pays the interest associated with the loan ($E_{3m,t}$). The net payment is equal to the difference between ASP and CDS spreads ($s_t^A - \overline{s}_t$) converted into quarterly terms using an "actual/360" day count convention. The previous difference is known as the basis.[4] This payment is repeated every quarter up to maturity or default, whichever comes first. The existence of funding costs (F) would transform the net payment into ($s_t^A - \overline{s}_t - F$).

At the coupon payment dates, the investor receives the coupon ($\overline{c}$) from the underlying bond and delivers it to the asset swap counterparty as the fixed leg payment. Thus, net payoff at the coupon payment date is zero.

At the bond's maturity, the investor receives the bond's face value plus the final coupon payment. The coupon is delivered to the ASP counterparty as the IRS fixed leg payment while the bond's face value is employed to refund the loan's principal. From the IRS floating leg, the investor receives 3-month Euribor rate plus the ASP spread. The former is employed to pay the loan's interest. Finally, the investor must pay the CDS spread, which is the price for credit risk protection. Then, the net payoff is also equal to the basis.

In case of default, at a given date τ, the investor recovers a portion of the bond face value $R(\tau)$, and through the protection bought in the CDS, the investor receives the difference between the bond face value and the recovery rate ($FV - R(\tau)$). The

[4] Note that the bond-CDS basis is often calculated as the difference between the CDS and bond spreads. The strategy's net payment is equivalent to the opposite of the bond-CDS basis.

investor employs the amount equal to the bond face value FV to refund the loan. The net payment at default is then composed by: (i) the value of the IRS included in the ASP which remains alive after default and must be serviced or unwound at market value; (ii) the payment of the CDS accrued premium from the last payment date to the credit event; (iii) the payment of the loan accrued interest from the last payment date to the credit event; (iv) the value of the cheapest-to-deliver (CTD) option which appears because in the event of a default, not only the underlying bond but a given number of bonds, some of them cheaper than the underlying, can be delivered. The strategy net payments are equal to the basis, $s_t^A - \overline{s}_t$, except in case of default.[5]

This strategy is known as trading the basis. Basis trades exploit the different pricing of ASP/bond and CDS on the same underlying company. According to Elizalde, Doctor, and Saltuk (2009), the basis trades based on long positions in ASPs/bonds and CDSs have been a popular investment strategy during the last years. In fact, they represent one of the closest trading techniques in the credit market to an "arbitrage free" trade given that the investor is not exposed to risk but still receives the difference between the ASP and CDS spreads.

An adequate arbitrage's analysis under the cointegration methodology is based on the assumption that short positions in the asset swap market are possible to guarantee that the equivalence relation holds. Nevertheless, shorting a corporate bond or an ASP with a required maturity, even years, is unfeasible.[6] It implies that traders might

[5] In practice the asset swap spread plus Libor tends to be greater than the bond coupon and in the event of a default, the investor will usually continue to receive a small annual income from the trade. Other potential assumption, for simplicity, could be to assume that the asset swap is a "perfect asset swap" and the future cash flows disappear upon default.

[6] The short sale of bonds or ASPs could be done via a repurchase agreement (repo) but as Blanco, Brennan, and Marsh (2005) explain, it is impossible to borrow a bond via a repo. The reason is that repo market for corporate bonds is illiquid and even if it were possible to short a bond via a repo, the

not be able to exploit deviations in the equivalence relation when the CDS premium is higher than the asset swap spread and so, ASP short sales are necessary. This asymmetry could affect the dynamic adjustment of credit spreads. A cointegration test as the one employed in Blanco, Brennan, and Marsh (2005) cannot isolate strategies in which an ASP short sale is involved because it is based on both types of deviations from the equivalence relation. However, a statistical arbitrage test permits us to study unilaterally the existence of statistical arbitrage whenever long positions in ASPs are needed. Hence, due to the complications associated with ASPs or bonds short sales and due to the potential high costs of going short in ASPs, we focus on long positions.

We employ a long-run investment strategy to detect the existence of possible persistent anomalies instead of punctual deviations between credit spreads. For this reason, the same self-financing strategy based on the same individual bond should be repeated across time, maintaining all the terms and conditions. Thus, the payment on a given date is added to the cumulative trading profits from the first investment date to the day before, which were invested or borrowed at the risk-free rate a day ago.

We employ CDSs with a notional equal to €500,000 and assume that the strategy stops if the total investment in a given bond exceeds 25% of the bond's issued amount, if there are two downgrades which place the firm in BBB- rating category, or if the total expected future losses exceed €25,000.[7] Once the strategy's investments stop, future

tenor of the agreement would be short. Schonbucher (2003) states that this limitation could be solved by issuing credit-linked notes linked to the corresponding bond and selling them to the investors in the asset swap market. This alternative presents other limitations given that the issuance of credit-linked notes takes time and implies high fixed costs.

[7] The CDS typical notional amount is €10-20 million for investment grade credits and €1-5 million for high yield credits and the standard bond's face value is €1,000. Successive repetitions of this strategy might imply high demand of a given bond that could exceed the issued amount. For this reason, we employ CDSs with a notional equal to €500,000. This notional is high enough to deal with fixed costs and is of adequate size to guarantee that a substantial number of investments can be made.

payments are fully known because both CDS and asset swap spreads are set at the investment date. Moreover, we assume that the market segmentation does not affect the arbitrageur, who has no restriction on participating in the CDSs market.

The cumulative trading profits obtained at every period are discounted up to the initial date. Thus, we obtain the increment in the discounted cumulative trading profits at a given date t, $\Delta v(t)$, as the difference between the discounted cumulative trading profits at t and at $t-1$.[8]

2.3 Long-run arbitrage

The cointegration test proposed by Engle and Granger (1987) has been widely used to study the long-term relation among nonstationary financial series. The most common example where this test is used is the spot price at t and the forward (futures) contract at time $t-k$, which expires at time t, see Brenner and Kroner (1995). Blanco, Brennan, and Marsh (2005), Forte and Peña (2009), Norden and Weber (2004), and Zhu (2006) analyze and, in general, find support for the existence of an equivalence relation between bond and CDS markets in the long-run by means of a cointegration test.[9] The cointegration methodology is also a popular tool among practitioners such as hedge fund managers [see Alexander, Giblin, and Weddington (2001) or Alexander and Dimitriu (2004)].

The arbitrage based equivalence of CDSs premiums and asset swaps spreads implies

[8] It should be mentioned that a simpler methodology to test for arbitrage would implement a buy-and-hold strategy that ends after five years. However and given that a standard arbitrage opportunity is a special case of statistical arbitrage our procedure will detect any simpler arbitrage opportunities.

[9] These papers use different bonds with different maturities to construct a synthetic 5-year bond spread to be compared with the 5-year CDS spread. This synthetic bond is not traded in financial markets and cannot be used for arbitrage strategies.

that credit risk tends to be priced equally in both credit markets in the long-run. By means of the cointegration methodology, we test if a given pair of credit spreads shares a common stochastic trend. As the companies included in our database are free from credit events, the payments are defined as the difference between both credit spreads. Thus, the existence of long-run arbitrage opportunities will be tested through a cointegration analysis based on the cash-and-carry strategy payments from Portfolio I (CDS spread) and Portfolio II (ASP spread).

Firstly, we study the series stationarity applying the standard Dickey-Fuller unit root test. Subsequently, the existence of a cointegration relation is tested based on the following long-run relation:

$$s_t^A = \alpha + \beta \overline{s}_t \tag{2.1}$$

Assuming that both series are integrated with order one, $I(1)$, both markets should price credit risk equally in the long-run and so, both spreads should be cointegrated with a cointegrating vector $[1, -1, c]$. According to equation (2.1), it means that β should be equal to one. Parameter α should be equal to zero to assure that no long-run arbitrage exists, but as there could be transaction costs or other market frictions and even misspecifications, we do not impose this condition and α can be different from zero and equal to a given constant c. This is equivalent to saying that the basis should be stationary to support the absence of long-run arbitrage.

2.4 Statistical arbitrage

2.4.1 Definition

Following JTTW's definition, statistical arbitrage is a zero initial cost, self-financing trading strategy with a cumulative discounted trading profits $v(t)$ such that:

(i) $v(0) = 0$

(ii) $\lim_{t\to\infty} E^P[v(t)] > 0$

(iii) $\lim_{t\to\infty} P(v(t) < 0) = 0$, and

(iv) $\lim_{t\to\infty} Var[\Delta v(t) \mid \Delta v(t) < 0] = 0$

Statistical arbitrage requires that the expected cumulative discounted profits, $v(t)$, are positive, the probability of loss converges to zero and the variance of the incremental trading profits $\Delta v(t)$ also converges to zero. The fourth condition suggests that investors are only concerned about the variance of a potential decrease in wealth. Whenever the incremental trading profits are nonnegative, their variability is not penalized. In other words, and as JTTW state, this condition avoids penalizing positive profits deviations from their expected values, given that investors benefit from these deviations. A statistical arbitrage opportunity implies that the amount invested in the risk-free asset becomes more important over time than the daily investments.

Although statistical arbitrage is defined over an infinite time horizon, there is a finite timepoint t^*, such that the probability of a loss is arbitrarily small, $P(v(t^*) < 0) = \varepsilon$. Standard arbitrage is a special case of statistical arbitrage with a zero cost trading strategy that offers the possibility of a gain with no possibility of a loss. Hence, the probability of a loss should be equal to zero at the timepoint t^*, $P(v(t^*) < 0) = 0$. Thus, statistical arbitrage converges to standard arbitrage in the limit (as t tends to infinity).

It is important to emphasize that albeit statistical arbitrage is a procedure suitable for long run investment periods, investors can benefit from statistical arbitrage in shorter time horizons. For instance, Bondarenko (2003) apply statistical arbitrage methods to index futures options data in the period from 1987 to 2000 where he finds that selling unhedged put options one month before maturity would have resulted in high and statistically significant average excess returns. Investors with finite time horizon (in our case five years) view statistical arbitrage opportunities as remarkably attractive as they offer positive expected discounted profits, variance that becomes arbitrary small, and decreasing risk of a loss.

2.4.2 Implementation

The methodology for analyzing the existence of a statistical arbitrage opportunity is based on HJTW, later improved in JTTW. This methodology is based on the incremental discounted cumulative trading profits Δv_i measured at equidistant time points. Firstly, we employ a process denoted as the unconstrained mean (UM) model where Δv_i is assumed to evolve over time as:

$$\Delta v_i = \mu i^{\theta} + \sigma i^{\lambda} z_i \tag{2.2}$$

for $i = 1, 2, ..., n$ where z_i are the innovations such that $z_0 = 0$ and so, both $v(t_0)$ and Δv_0 are zero. Parameters θ and λ indicate whether the expected trading profits and the volatility, respectively, are decreasing or increasing over time and their intensity. Under the assumption that innovations z_i are i.i.d. $N(0,1)$ random variables, the expectation and variance of the discounted incremental trading profits in equation (2.2) are $E[\Delta v_i] = \mu i^{\theta}$ and $Var[\Delta v_i] = \sigma^2 i^{2\lambda}$.

The discounted cumulative trading profits generated by a given strategy are:

$$v(t_n) = \sum_{i=1}^{n} \Delta v_i \overset{d}{\sim} N(\mu \sum_{i=1}^{n} i^{\theta}, \sigma^2 \sum_{i=1}^{n} i^{2\lambda}) \tag{2.3}$$

while the log likelihood function for the increments in equation (2.2) is:

$$\log L(\mu, \sigma^2, \lambda, \theta \mid \Delta v) = -\frac{1}{2}\sum_{i=1}^{n} \log(\sigma^2 i^{2\lambda}) - \frac{1}{2\sigma^2}\sum_{i=1}^{n} \frac{1}{i^{2\lambda}}(\Delta v_i - \mu i^{\theta})^2 \tag{2.4}$$

The parameters are estimated by maximizing the previous log likelihood function from a nonlinear optimization method based on a Quasi-Newton-type algorithm.

The cash-and-carry strategy generates statistical arbitrage opportunities if incremental trading profits satisfy simultaneously the following hypotheses:

H1: $\mu > 0$,

H2: $\lambda < 0$ or $\theta > \lambda$

H3: $\theta > \max\{\lambda - \frac{1}{2}, -1\}$.

The first hypothesis is due to the second property of statistical arbitrage which requires that the expectation of the discounted cumulative trading profits is positive. The second hypothesis is obtained from the fourth property and ensures that the variance of the incremental trading profits, given a potential drop in them, converges to zero. The third hypothesis involves the trend in expected profits and the trend in volatility and its expression comes from the convergence of $P(v(t) < 0)$ to zero. It ensures that any potential decline in expected trading profits do not prevent convergence to arbitrage.

As in JTTW, a more restrictive version of model (2.2) is also employed in the analysis. It is based on constant expected profits over time and it implies that the parameter θ is set to zero. This model is defined as the constrained mean (CM) model. Under this assumption, the process for the evolution of the incremental trading profits is:

$$\Delta v_i = \mu + \sigma i^{\lambda} z_i \tag{2.5}$$

And the required hypotheses to be satisfied for the existence of statistical arbitrage opportunities are:

H1: $\mu > 0$,

H2: $\lambda < 0$.

2.4.3 Hypothesis testing

Under the assumption that the trading profits evolve as a UM model, all the following restrictions must be satisfied simultaneously to have a statistical arbitrage opportunity:

$R_1 : \mu > 0$ and

$R_2 : \lambda < 0$ or $\theta - \lambda > 0$, and

$R_3 : \theta - \lambda + \frac{1}{2} > 0$ and

$R_4 : \theta + 1 > 0$.

Nevertheless, if the trading profits evolve as a CM model (5) the restrictions to be satisfied simultaneously become:

$R_1 : \mu > 0$ and

$R_2 : \lambda < 0$.

The existence of statistical arbitrage is thus based on an intersection of subhypothesis. On the other hand, the absence of statistical arbitrage is based on a union of four subhypotheses which are given by the complementary of the previous four hypotheses. We set the null hypothesis as the absence of statistical arbitrage and then, the restrictions for the UM model become:

$R_1^c : \mu \leq 0$ or

$R_2^c : \lambda \geq 0$ and $\theta - \lambda \leq 0$, or

$R_3^c : \theta - \lambda + \frac{1}{2} \leq 0$ or

$R_4^c : \theta + 1 \leq 0$.

While for the CM model the restrictions are:

$R_1^c : \mu \leq 0$ or

$R_2^c : \lambda \geq 0$.

If one of the previous restrictions is satisfied, we conclude that no statistical arbitrage opportunities exist.

2.4.4 Statistical arbitrage tests

The results obtained by HJTW could be influenced by the limitations of the Bonferroni approach employed in the paper. Their test presents a low statistical power to reject an incorrect null hypothesis in every case. In fact, the statistical power decreases as the number of restrictions increases, leading to an unacceptable level of Type II error. JTTW overcome these limitations by introducing the Min-t test methodology[10] and employing the stationary bootstrap procedure proposed by Politis and Romano (1994), which allows for time dependence and stationary residuals, to estimate the *p-values*. The assumption that the incremental trading profits innovations are normal and uncorrelated seems very restrictive as Affleck-Graves and McDonald (1989) and Lo and MacKinlay (1988) reveal. For this reason, JTTW test the case in which the innovations z_i follow a stationary weakly dependent process. Thus, both HJTW and JTTW impose a MA(1) process for z_i to test if it could improve the statistical efficiency of the remaining parameter estimates and avoid inappropriate standard errors. Nevertheless, JTTW show that allowing for this serial correlation does not change their conclusions significantly.

2.5 A new test of statistical arbitrage

This paper presents an enhancement with respect to JTTW methodology. The reason is that assuming stationarity seems restrictive when modeling financial time series. Just as it is also restrictive to treat the errors in any empirical econometric work as homoskedastic. We allow incremental trading profits series to be nonstationary and innovations z_i to be nonnormal, autocorrelated, heteroskedastic and possibly nonstationary. In this more general situation, the use of the stationary bootstrap is

[10] As the four restrictions R_i must be simultaneously satisfied to reject the null hypothesis of no statistical arbitrage, the minimum of their associated t-statistics serves as a rejection criterion. Thus, Min-t test considers separately the t-statistics associated with the four restrictions R_1, R_2, R_3 and R_4 and finds the minimum.

not advisable for estimating the *p-values* for the Min-t statistics.[11] Thus, we employ a new test from the use of the subsampling method introduced in Politis, Romano, and Wolf (1995) and (1997) and extended in Politis, Romano, and Wolf (1999a, 1999b) and (2001).[12] We construct an asymptotically valid test for UM and CM models based on test statistics which are formed from the quasi-maximum likelihood (QML) estimators in equation (2.4).

Let $(x_1, ..., x_n)$ be a sample of n observations that are distributed in a sample space S. The common unknown distribution generating the data is denoted by P, the null hypothesis H_0 asserts $P \in P_0$, and the alternative hypothesis H_1 is $P \in P_1$, where $P_j \subset P \; for \; j = 0, 1$, and $P_0 \cup P_1 = P$. Our purpose is to create an asymptotically valid test based on a given test statistic for the case in which the null hypothesis translates into a null hypothesis about a real-valued parameter $\xi_i(P)$. The test statistic is defined as:

$$T_{i,n} = \tau_n t_{i,n}(X_1, ..., X_n) = \tau_n(\hat{\xi}_{i,n}(X_1, ..., X_n) - \xi_{i,0}) \qquad for \; i = (1, 2, 3, 4) \tag{2.6}$$

where τ_n is a normalizing constant and, as in regular cases, we set $\tau_n = n^{\frac{1}{2}}$, $\hat{\xi}_{i,n} = \hat{\xi}_{i,n}(X_1, ..., X_n)$ is the estimator of $\xi_{i,n}(P_i) \in \mathbb{R}$, which is the parameter of interest,

[11] Stationary bootstrap is generally applicable for stationary weakly dependent time series. Subsampling allows for a more general structure in the innovations. Thus, in Politis, Romano, and Wolf (1997), it is shown that in the presence of heteroskedasticity in residuals, subsampling gives better results for "the right choice" than moving blocks bootstrap methods. This choice is not affected materially by the degree of dependence in the residuals. Moreover, one should obtain better information about the sampling distribution of the statistic using the subsampling methodology. The reason is that, while the subsample statistics are always generated from the true model, bootstrap data come from an approximation to the true model. Another advantage of subsampling is that it has been shown to be valid under very weak assumptions.

[12] One could expect that both the increment in the discounted cumulative trading profits and the innovations should be stationary. Nevertheless, our sample only spans two years and a unit root test in this case usually has low power [see Shiller and Perron (1985)]. It should be noted however, that subsampling methodology allows for a more general process both in profits and innovations and even for nonstationarity in some cases.

P_i denotes the underlying probability distribution of the *ith statistic* and $\xi_{i,0}$ is the value of $\xi_{i,n}$ under the null hypothesis. Each of the four statistics are defined from the restrictions R_i^c in Subsection 4.3 which lead to four contrasts of hypothesis based on real-valued parameters such that:

$$\begin{cases} H_0 : \xi_i(P) \leqslant \xi_{i,0} \\ H_1 : \xi_i(P) > \xi_{i,0} \end{cases} \qquad for \quad i = (1, 2, 3, 4) \tag{2.7}$$

where $\xi_{i,0}$ is equal to zero in our analysis. The test is applied to the union of restrictions R_i^c and so, the non rejection of one of the four null hypotheses automatically confirms the absence of statistical arbitrage.

The distribution of the *ith* statistic $T_{i,n}$ under P_i can be denoted by:

$$G_{i,n}(x,P_i) = \text{Prob}_{P_i}\{T_{i,n}(X_1,..., X_n) \leq x\} \tag{2.8}$$

where $G_{i,n}(.,P_i)$ converges in distribution at least for $P_i \in P_{i,0}$, where $P_{i,0}$ denotes the probability distribution under H_0.

Because P_i is unknown, $G_{i,n}(.,P_i)$ is unknown and the sampling distribution of $T_{i,n}$ is approximated by:

$$\hat{G}_{i,n,b}(x) = \frac{1}{n-b+1} \sum_{t=1}^{n-b+1} 1| \{\tau_b t_{i,n,b,t}(X_1,..., X_n) \leq x\} \tag{2.9}$$

where $1|$ is an indicator function, $\tau_b = b^{\frac{1}{2}}$ such that $\frac{\tau_b}{\tau_n} \longrightarrow 0$ as n$\longrightarrow \infty$, $n - b + 1$ indicates the number of subsets of $(X_1,..., X_n)$ and $t_{i,n,b,t}(X_1,..., X_n)$ is the statistic evaluated at the block of data $(X_t,..., X_{t+b-1})$ which is defined as:

$$t_{i,n,b,t}(X_1,...,X_n) = \overset{\wedge}{\xi}_{i,n,b,t}(X_t,...,X_{t+b-1}) - \overset{\wedge}{\xi}_{i,n,t} \tag{2.10}$$

where $\overset{\wedge}{\xi}_{i,n,b,t}$is the estimator of $\xi_{i,n}(P_i) \in \mathbb{R}$ based on the subsample $(X_t,...,X_{t+b-1})$ and $\overset{\wedge}{\xi}_{i,n,t}$ is the estimator of $\xi_{i,n}$ for the whole sample.

The only assumptions that will be needed to consistently estimate the cumulative distribution function $G_{i,n}(x, P_i)$ are the following:

(i) The estimator, properly normalized, has a limiting distribution.

(ii) For large n, the distribution function of the normalized estimator based on the subsamples will be, on average, close to the distribution function of the normalized estimator based on the entire sample.

Using this estimated sampling distribution, we can compute the critical value for the test at least under the null hypothesis. It is obtained as the $1 - \alpha$ quantile of $\hat{G}_{i,n,b}(x)$:

$$g_{i,n,b}(1-\alpha) = \inf\{x : \hat{G}_{i,n,b}(x) \geqslant 1-\alpha\} \tag{2.11}$$

Our purpose is to test if T_n is rejected at a level of significance α depending on whether the statistic exceeds the exact $1 - \alpha$ quantile of the true sampling distribution $G_n(x,P)$, that is $g_n(1-\alpha, P)$. Of course, P is unknown and so is $g_n(1-\alpha, P)$. However and according to Politis, Romano, and Wolf (1999a), the asymptotic power of the subsampling test against a sequence of contiguous alternatives $\{P^n\}$ to P with P in P_0 is the same as the asymptotic power of this fictitious test against the same sequence of alternatives. For this reason and given that there is no loss in efficiency in terms of power, we test the statistic T_n against the $1-\alpha$ quantile under P_0, $g(1-\alpha, P_0)$.

The steps in which subsampling technique is applied in this study are as follows:

1. Once the parameters have been estimated by QML, we calculate the test statistic for the whole sample:

$$T_{i,n}= \tau_n(\hat{\xi}_{i,n}(\Delta v_1, ..., \Delta v_n) - \xi_{i,0}) \qquad for\ i = (1,2,3,4) \tag{2.12}$$

   and the estimated residuals $\hat{z}_i$:[13]

$$\hat{z}_i = \frac{\Delta v_i - \hat{\mu} i^{\hat{\theta}}}{\hat{\sigma} i^{\hat{\lambda}}} \qquad for\ i = 1, ...n \tag{2.13}$$

2. We create subsamples of consecutive blocks of data with length b such that the first subsample of residuals is defined by $(\hat{z}_1, ..., \hat{z}_b)$, and so on.

3. We generate $n-b+1$ successive subsamples of trading profits $(\Delta v_i^*, ..., \Delta v_{i+b-1}^*)$ from the corresponding residuals $(\hat{z}_i, ..., \hat{z}_{i+b})$ for $i = 1, ..., n-b$. The trading profits are calculated with the parameters under the null hypothesis such that their values bind the restrictions. Thus, the parameter values are $(\mu, \sigma, \theta, \lambda) = (-10^{-6}, \hat{\sigma}, -1, -0.5)$ for the UM model and $(\mu, \sigma, \lambda) = (0, \hat{\sigma}, 0)$ for the CM model:[14]

$$\Delta v_i^* = \mu i^{\theta} + \hat{\sigma} i^{\lambda} \hat{z}_i \tag{2.14}$$

[13]We find that the residuals follow ARMA processes and, in some cases, they even present heteroskedasticity. It confirms that it is very restrictive to impose a $MA(1)$ process for z_i.

[14]For the UM model, five restrictions should be simultaneously satisfied to prove the existence of statistical arbitrage. However, these five restrictions involve three parameters and not all the restrictions are necessarily binding. As HJTW suggest, a model within the null family and on the boundary of all the inequality restrictions is not available. We employed other values of μ such as -0.0001 or -10^{-8} to have θ in the equation, but results are similar in the three cases. The values of parameters θ and λ bind the third restriction and we employ them due to their good properties in JTTW. Parameter $\hat{\sigma}$ does not appear in the restrictions and we use the value of the QML estimator for σ in the whole sample.

4. We estimate $n - b + 1$ times by QML the parameters for the successive blocks and for every block we calculate the statistic $t_{i,n,b,t}$ such that we have $n - b + 1$ statistics.

5. Finally we approximate the sampling distribution of $T_{i,n}$ by means of the estimated sampling distribution $\widehat{G}_{i,n,b}(x)$ as in equation (2.9) and compute the critical values $g_i(1-\alpha, P_0)$ as in equation (2.11) under the null hypothesis. We reject the null hypothesis at a degree of significance of α if and only if $T_{i,n}$ exceeds the corresponding critical value $g_i(1-\alpha, P_0)$.

There is not a universal prescription for the choice of the optimal block size. Moreover, Politis, Romano, and Wolf (1999a) show that subsampling works quite well even with a data-driven choice of block size. Block sizes should not be too large or small but the effect of different choices of b diminishes as the sample size increases.[15]

In the correct range of b, the confidence intervals should be "stable" when considered as a function of the block size. For this reason, we use the method defined by Politis, Romano, and Wolf (1999a) as the Minimum Volatility Method to select the optimum b :

1. Compute a subsampling quantile $g_{n,b}(1-\alpha)$ for $b = b_{small} = n^{\frac{4}{10}}$ to $b = b_{big} = n^{\frac{9}{10}}$.

2. For each b compute a volatility index as the standard deviation of the quantiles in a neighborhood of b, $VI(g_{n,b-k}(1-\alpha), g_{n,b}(1-\alpha), g_{n,b+k}(1-\alpha))$ with $k = 2$.

3. Pick the value b^* corresponding to the smallest volatility index and use $g_{n,b^*}(1-\alpha)$ as the critical value of the test.

[15] For b too close to n all subsample statistics $\overset{\wedge}{\xi}_{i,n,b,t}$ will be almost equal to $\overset{\wedge}{\xi}_{i,n}$, resulting in the subsampling distribution being too tight and in undercoverage of subsampling confidence intervals. For b too small, the intervals can undercover or overcover depending on the state of nature.

After estimating the optimal block size, we confirm, as expected, that there is not a common optimum block size for every sample. In most cases, the optimum block size is such that the ratio block size/sample size is between 0.15 and 0.5.[16] Longer blocks are needed to capture greater dependence in the innovations.

We now compare the new test with JTTW's looking at their Type I errors. Given that the null hypothesis is no statistical arbitrage opportunities it seems advisable to choose the test with lower "false positive" record (i.e. the most conservative). The absence/existence of statistical arbitrage is based on three hypotheses, each of them associated to different requirements, or equivalently, on four restrictions R_i^c (see Subsection 4.3). We study both tests using simulations of the series of the increment in the discounted cumulative trading profits. These profits are simulated by setting parameters μ, θ and λ such that they hold one given restriction R_i^c, which corresponds to the complementary of one of the three hypotheses in Subsection 4.2, and do not hold the remaining ones. The parameters employed to simulate the profits are close to the limits of the existence/absence of statistical arbitrage to discriminate between both tests in the most detailed way as possible.[17] This allows us to have a further perspective of the individual restrictions. We perform one hundred different simulations with a sample size of 400 observations. This length is close to the average number of observations or

[16] We require that the selected block size, b, can also be obtained from the expression $b = n^x$ with $x < 1$. It guarantees that the required assumption which states that $b \longrightarrow \infty$ as $n \longrightarrow \infty$ and $\frac{b}{n} \longrightarrow 0$ as $n \longrightarrow \infty$ is fulfilled.

[17] The restriction that holds is related with each of the three requirements needed for the existence/absence of statistical arbitrage. We first compare both test using simulations where the first restriction, R_1^c, holds and employing as parameters: $\mu = -0.001$, $\sigma = 1$, $\theta = 0.5$ and $\lambda = -0.5$. The second comparison is based on the ability of the tests to detect the cases in which R_2^c holds and we employ as parameters: $\mu = 1$, $\sigma = 1$, $\theta = 0.1$ and $\lambda = 0.05$. Finally, we evaluate the case in which both R_3^c and R_4^c hold according to the following parameters: $\mu = 1$, $\sigma = 1$, $\theta = -1.05$ and $\lambda = -0.45$. Note that the last case involves two restrictions; the reason is that both of them are associated with the requirement which states that the probability of loss converges to zero.

investment days in the different cases analyzed in this paper. Moreover, as a test of convergence, we simulate a series of profits with a sample length equal to 5,000, and find that the estimated coefficients are exactly the same to the ones employed to do the simulation. As we find that the residuals are neither normal nor follow a $MA(1)$ process, which is the process imposed in JTTW methodology, we compare both test after generating randomly the residuals according to three different processes: *i.i.d.* normal residuals; the residuals follow an $ARMA(1,1)$ process with the AR and MA coefficients equal to 0.9 and 0.75, respectively; or the residuals follow an $ARMA(1,1)$ process such that the coefficients of the AR and MA parts are 0.5 and 0.75, respectively.

We find that both tests are equally effective when either restriction R_1^c, which states that the expected cumulative discounted profits are negative, or restrictions R_3^c and R_4^c, which state that the probability of loss does not converge to zero, hold. When restriction R_2^c, which states that the variance of the incremental trading profits does not converge to zero, hold, we find that our test cannot reject the absence of statistical arbitrage at any standard confidence level. However, JTTW's test signals the existence of statistical arbitrage at confidence levels between 1% and 5%, depending on the residuals process, when in fact there is no arbitrage opportunity. These results suggest that some arbitrage opportunities detected by JTTW's test do not satisfy condition (iv) in page 13 (investors only care about downside risk) whereas that condition is fully satisfied in all cases by our test. This discrepancy between both tests may be due to the different information about the sampling distribution and the dependence structure of the statistic that is employed by the subsampling and the bootstrap methodologies. There is a salient economic implication of this fact: traders relying in JTTW's test will sometimes try to profit from apparent arbitrage opportunities but will incur unknowingly in substantial downside risk. Traders using our test will not take into account those apparent (but risky) arbitrage opportunities.

2.6 Data

Our database contains daily data on Eurobonds and ASPs denominated in Euros and issued by nonfinancial companies that are collected from Reuters and on CDSs also denominated in Euros and issued by the same nonfinancial companies that are obtained from four different databases: GFI, Reuters and Datastream, and J. P. Morgan.

We employ four different CDSs databases to have more robust results and to minimize the possibility that measurement errors could affect our results. This variety of sources also serves as a check of the reliability of our data. The first source we employ is GFI which is a major inter-dealer broker (IDB) specializing in the trading of credit derivatives. GFI data contain single name CDSs market prices for 1, 2, 3, 4, and 5 years maturities. These prices correspond to actual trades, or firm bids and offers where capital is actually committed and so, they are not consensus or indications.[18] Thus, these prices are an accurate indication of where the CDS markets traded and closed for a given day. For some companies and for maturities of two and four years, the data availability is scarce and in these cases, whenever there exist data on CDSs real market prices for the maturity of five years, we employ mid-price quotes from a credit curve also reported by GFI.[19] GFI data have also been used by Hull, Predescu, and White

[18] Consensus and indicative data are trusted less now that the markets are so volatile. There exist differences of up to 100% between consensus prices from leading providers compared to actual trades on GFI systems. The reason is that consensus is inherently slow and the prices originate from back office staff that can be swayed by the positions they hold and they do not have a front office view.

[19] The GFI FENICS® Credit curves are generated each hour for over 1900 reference entities. Data

(2004), Predescu (2006), Saita (2006), Nashikkar and Subrahmanyam (2007), Fulop and Lescourret (2007), or Nashikkar, Subrahmanyam, and Mahanti (2009) among others.

The second source is Reuters. Reuters takes CDS quotes each day from over 30 contributors around the world and offers end of day data for single names CDSs. Before computing a daily composite spread, it applies a rigorous screening procedure to eliminate outliers or doubtful data. According to Longstaff, Mithal, and Neis (2005), as the data include quotations from a variety of credit derivatives dealers, these quotations should be representative of the entire credit derivatives market. Jankowitsch, Pullirsch, and Veža (2008), among others, employ CDSs data from Reuters.

The third source is CMA DataVision(TM) which is available from Datastream. CMA DataVision is consensus data sourced from 30 buy-side firms, including major global Investment Banks, Hedge Funds, and Asset Managers which offers quoted CDS prices (bid, ask and mid). Among the papers that employ CMA data we mention Nashikkar and Subrahmanyam (2007) and Nashikkar, Subrahmanyam, and Mahanti (2009).

Our fourth database, employed also in Aunon-Nerin, Cossin, Hricko, and Huang (2002), Blanco, Brennan, and Marsh (2005), and Chen, Cheng, and Liu (2008) among others, contains mid-market data provided by J. P. Morgan which is one of the leading players and most active traders in the CDS market.

points in each curve can be actual trades or mid prices calculated from the bid/offer quotes, and in their absence GFI will calculate a running point level using the Hull and White methodology to ensure a credit curve always exists for each reference entity. This curve is a good approximation for CDSs at any maturity. The median of the absolute difference in basis points between five years CDS premiums as defined from credit curve and the actual quotes or transaction prices for the period between April 2001 and May 2002, is equal to 1.16, 2.01 and 3.82 bps for AAA/AA, A and BBB ratings for a total of 2,659, 9,585 and 8,170 companies respectively. Moreover, market CDS spread could be different from what we are assuming to be the true CDS spread by as much as 3.725 bps. on average.

Given the four different data sources on CDSs spreads, we cross-check the data using all the sources to confirm the validity of any CDS price. Due to liquidity restrictions and to require that investments take place whenever there is trading activity, these investments are restricted to dates when we observe 5-year CDS actual trades or firm bids and offers where capital is actually committed according to GFI data.[20] The results that we report in the paper are the ones obtained with GFI data.

For each bond there is information on both bid and ask prices, the swap spread, the asset swap spread, the sector of the entity and its geographical location, the currency, the seniority, the rating history (Fitch, S&P, and Moody's ratings), the issuance date and the amount issued, the coupon and coupon dates, and the maturity. We use bonds whose maturity at the investment dates is lower than five years. Several bonds issued by the same company are used whenever they satisfy all the required criteria. The reason is that although CDS spreads quotes are referred to the issuer and not to an individual bond, asset swap spreads are quoted for individual bonds. Due to liquidity considerations, bonds with time to maturity equal to or less than twelve months in the date corresponding to their last observation are excluded. Moreover, our sample contains fixed-rate senior unsecured Euro denominated bonds whose issued quantity exceeds 300 millions of Euros. Other requirements imposed on bonds to be included in the sample are: i) straight bonds , ii) neither callable nor convertible, iii) with rating history available, iv) with constant coupons and with a fixed frequency, v) without a sinking fund, vi) without options, vii) without an odd frequency of coupon payments,

[20] Even when CDS quotes, from any of the data sources, are available at a given date, we do not employ them unless we observe 5-year CDS data from GFI. Thus, these dates do not indicate missing observations in a given source of data, but lack of trading activity.

viii) no government bonds, and ix) no inflation-indexed bonds. We also cross-check the data on bonds with the equivalent data obtained from Datastream.

The data span from November 1st, 2005 to June 29th, 2009. However, we split the data into two subperiods to take into account the possible effects of the ongoing financial crisis. The first subperiod covers the period from November 1st, 2005 to August 8th, 2007 while the second one spans from August 9th, 2007 to June 29th, 2009. Our sample size is comparable to others in the literature on CDS and bond spreads, both in terms of sample size and number of companies.[21] The final sample consists of 49 nonfinancial companies and 64 bonds. In the first subsample we employ 55 bonds and 41 companies while in the second one we use 46 bonds and 36 companies.[22] Table I presents information about all issuers, ASPs, bonds, and CDSs in the two different periods under study. As shown in Panel B of Table I, there is a great deal of variation in the amount issued and, in the first period, in the sample size. This panel shows that bonds traded, on average, above par in the first period and below par in the second one. Panels C1 and C2 include descriptive statistics for CDS, ASP, and bond spreads for the first and second subperiod, respectively. On average, the CDS spreads seem to be lower (higher) and less (more) volatile than the ASP spreads before the crisis (during the crisis). The last column in this panel also reveals that both CDSs and

[21] Longstaff, Mithal, and Neis (2005) include 68 firms from March 2001 to October 2002, Blanco, Brennan, and Marsh (2005) use 33 American and European companies from January 2001 to June 2002, Zhu (2006) use 24 investment grade companies from January 1999 to December 2002, and Forte and Peña (2009) employ data for 20 companies from September 2001 to June 2003.

[22] Our initial sample was formed by 301 corporate bond issuers. We found a total of 135 Euro denominated bonds that mature before June 2012 but only 85 of them include reliable information on the CDS spreads and the asset swap spreads. Of these, 3 bonds have been discarded because the issued amount does not exceed 300 million Euros, another 4 bonds were discarded because they were not investment grade bonds during the whole sample period. The time to maturity was lower than twelve months by August 2007 for 4 bonds that were discarded, another 3 bonds were discarded because their asset swap spreads were persistently negative and, finally, 7 bonds were discarded because prices were too far from par. Thus, although we consider all the bonds issued by nonfinancial European companies to be employed in our study, the final number of bonds is 64 due to the imposed requirements.

ASPs are usually highly correlated with few exceptions (Carrefour I, Siemens, Technip, and Veolia Environ in Panel C1 and Carrefour II in Panel C2). Note that the average correlation increased in the crisis period. Finally, Panel D presents descriptive statistics for the basis for the first and second subperiods, respectively. We observe that, before the crisis, the average basis is negative for 17 of the 55 issues while it is negative for 20 of the 46 issues during the crisis. On average, the basis is lower and much more volatile in the second period which suggests that arbitrage strategies become riskier during the crisis. Panels E1 and E2 report the summary statistics of the CDS spreads for the four databases during the first and second subperiod, respectively. We find that all data sources are in agreement between them and the average of the relative differences between the CDS spreads of the four databases is similar before and after the crisis.

Table I: Descriptive Statistics

Panel A describes the rating and sector of the CDS and bond issuer. We report the rating at the end of the first subperiod, which spans from November 2005 to August 2007, and at the end of the second subperiod, which covers the subprime crisis and spans from August 2007 to June 2009. Panel B provides descriptive information on the bonds during the first and second subperiods. Panel C includes descriptive statistics for ASP, bond and CDS spreads and splits into two panels, Panel C1 and Panel C2, corresponding to the first and second subperiod. Panel D reports descriptive statistics for the basis, which is defined as the difference between ASP and CDS spreads, during the first and second subperiods. Panels E1 and E2 report the descriptive statistics of the CDS spreads for the four different databases in the first and second subperiod, respectively.

Panel A

Issuer	Rating	Sector
Akzo Nobel	A- / BBB+	Chemicals
Altadis	BBB / -	Beverages & Tobacco
Astrazeneca	- / AA-	Pharmaceuticals & Biotechnology
Auchan	- / A	Retail - Department Stores
BASF	- / A+	Chemicals
Bayer	- / A-	Chemicals
Belgacom	- / A+	Fixed-Line Telecommunication Svs.
BMW	A+ / A	Automobile
Bouygues	BBB+ / BBB+	Construction
British AM Tob.	BBB+ / BBB+	Beverages & Tobacco
Carrefour	A / A	Food & Drug Retailers
Casino G. P.	BBB- / BBB-	Food & Drug Retailers
Compass Group	BBB+ / -	Support Services
Edison	BBB+ / BBB+	Public Utilities
Enel	A- / A-	Public Utilities
Energias de Portugal	A- / A-	Electricity
E.ON	A+ / -	Utilities
France Telecom	A- / A-	Fixed-Line Telecommunication Svs.
Iberdrola	A / A-	Petrol and Power
Kingfisher	BBB- / BBB-	General Retailers
Louis Vuitton	BBB+ / BBB+	Other Textiles and Leather Goods
Philips	- / A-	Electronic & Electrical Equipment
PPR	BBB- / BBB-	Retailers - Multi Department
Reed Elsevier	A- / -	Media & Entertainment
Renault	BBB+ / -	Automobiles
Repsol YPF	BBB+ / BBB+	Petrol and Power
Reuters	A- / -	Publishing
Saint Gobain	BBB+ / BBB+	Building and Construction Materials
Scania	A- / -	Machinery and Engineering
Schneider	- / A-	Electrical Equipment
SES	BBB / BBB	Telecommunications
Siemens	AA- / A+	Industrial
Sodexho	BBB+ / -	Business Support Services
Stora Enso	BBB- / -	Forest Product & Paper
Technip	BBB / BBB	Oil - Services
Telecom Italia	BBB+ / BBB	Public Utilities
Telefonica	BBB+ / A-	Technology and Telecommunications
Telekom Austria	BBB+ / BBB+	Machinery, Transport and Technology
Teliasonera	- / A-	Telecommunications
Tesco	A / A-	Food & Drug Retailers
Thales	A- / A-	Defence
Thyssenkrupp	BBB+ / BBB-	Industrial
Union Fenosa	A- / A-	Petrol and Power
Veolia Environ.	BBB+ / -	Water
Vinci	BBB+ / -	Other Construction
Vivendi	BBB / -	Subscription Entertainment Networks
Vodafone	A- / -	Wireless Telecomunications Svs.
Volkswagen	A- / BBB+	Automobile
Volvo	A- / BBB+	Machinery & Engineering

Panel B

Issuer	Amount issued (millions of euros)	Coupon (%)	Nov 2005 - Aug 2007		Aug 2007 - June 2009	
			Obs.	Mean Price	Obs.	Mean Price
Akzo Nobel I	750	4.250	220	100.03	396	99.26
Akzo Nobel II	1,000	5.625	286	103.94	-	-
Altadis	600	4.250	330	100.32	-	-
Astrazeneca	750	4.625	-	-	157	100.68
Auchan	600	3.000	-	-	169	96.69
BASF	1,400	3.375	-	-	290	97.44
Bayer	2,000	6.000	-	-	347	104.55
Belgacom	775	4.125	-	-	38	98.06
BMW	750	3.875	295	98.63	393	98.00
Bouygues I	750	4.625	197	101.40	260	99.79
Bouyges II	1,000	5.875	221	104.64	-	-
British AM Tob. I	1,700	4.875	338	101.86	-	-
British AM Tob. II	1,000	4.375	232	99.61	300	98.92
Carrefour I	1,100	4.375	221	100.22	324	100.24
Carrefour II	1,000	6.125	314	107.15	324	103.45
Casino G. P. I	400	4.750	148	99.98	304	98.34
Casino G. P. II	500	5.250	195	102.18	304	100.59
Casino G. P. III	700	6.000	-	-	304	100.74
Compass Group	300	6.000	121	104.08	-	-
Edison	700	5.125	339	103.43	338	101.31
Enel	750	4.125	91	99.22	206	100.23
Energias de Portugal I	1,000	6.400	184	107.40	258	102.17
Energias de Portugal II	747	5.875	162	106.80	251	103.41
E.ON	4,250	5.750	200	104.44	-	-
France Telecom I	750	4.625	119	99.77	298	100.75
France Telecom II	1,000	4.375	100	98.48	298	99.49
France Telecom III	1,000	3.000	294	95.82	298	97.73
Iberdrola I	750	4.375	234	98.35	291	100.06
Iberdrola II	600	4.500	195	101.36	-	-
Kingfisher	500	4.500	270	100.11	146	95.27
Louis Vuitton I	600	4.625	251	100.85	368	100.25
Louis Vuitton II	750	5.000	352	102.69	369	100.93
Philips	750	6.125	-	-	237	104.46
PPR	800	5.250	289	102.71	339	98.71
Reed Elsevier	500	5.000	208	102.68	-	-
Renault	1,000	6.125	249	104.53	-	-
Repsol YPF	1,175	6.000	298	105.68	358	102.02
Reuters	500	4.625	229	101.23	-	-
Saint Gobain I	1,000	4.750	316	101.46	-	-
Saint Gobain II	1,100	4.250	261	99.03	384	97.11
Saint Gobain III	1,000	5.000	337	102.55	384	100.15
Scania	600	3.625	219	97.36	-	-
Schneider	900	3.125	-	-	110	96.11
SES	500	3.875	52	100.78	119	96.77
Siemens	2,000	5.750	72	105.55	228	103.86
Sodexho	1,000	5.875	350	104.09	-	-
Stora Enso	500	3.250	316	96.31	-	-
Technip	650	4.625	112	100.97	194	98.97
Telecom Italia I	750	4.500	300	99.88	299	98.35
Telecom Italia II	2,000	7.250	269	110.40	299	104.28
Telefonica	2,250	3.750	317	97.41	272	97.89
Telekom Austria	500	3.375	137	97.40	255	98.36
Teliasonera	500	3.625	-	-	383	95.65
Tesco I	750	4.750	347	102.18	276	100.85
Tesco II	500	3.875	303	98.67	286	98.74
Thales	500	4.375	111	100.17	298	99.95
Thyssenkrupp	750	5.000	235	101.73	358	100.52
Union Fenosa	500	5.000	317	103.00	288	100.92
Veolia Environ.	2,000	5.875	239	103.20	-	-
Vinci	1,025	5.875	158	104.73	-	-
Vivendi	630	3.625	97	97.85	-	-
Vodafone	1,900	5.125	311	100.22	-	-
Volkswagen	1,000	4.125	255	98.93	400	98.01
Volvo	300	5.375	324	103.79	327	99.86
Average	942	4.788	235	101.59	285	99.78

Panel C1

	CDS Premium (basis points)				Asset Swap Spread (b.p.)				Bond Spread (b.p.)				CDS vs AS
Issuer	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD	Corr
Akzo Nobel I	23.55	17.14	30.72	2.31	17.66	3.80	35.60	8.25	19.29	4.50	37.40	8.43	0.48
Akzo Nobel II	14.11	9.85	27.89	3.47	17.17	4.90	28.80	5.57	18.26	5.60	30.80	5.49	0.72
Altadis	16.83	8.59	35.00	6.36	20.91	9.90	37.50	5.84	23.49	12.30	39.50	5.66	0.33
BMW	12.10	6.61	23.86	4.77	10.49	2.10	18.70	3.69	12.03	4.30	20.60	3.80	0.72
Bouygues I	21.10	12.00	35.00	5.81	25.52	11.50	39.30	6.56	26.93	12.80	41.30	6.55	0.70
Bouygues II	20.24	11.94	33.60	6.35	15.80	4.00	28.10	5.33	16.91	6.10	29.70	5.08	0.79
British AM Tob. I	24.81	6.05	54.00	13.18	20.20	3.00	45.90	9.31	22.01	3.20	47.80	9.05	0.88
British AM Tob. II	24.89	13.12	40.00	6.96	32.99	16.19	54.10	8.86	35.03	20.00	57.00	9.01	0.90
Carrefour I	16.19	9.43	38.63	4.58	18.75	8.17	31.20	5.13	20.35	9.70	31.90	5.17	0.20
Carrefour II	12.87	6.80	28.05	3.51	7.45	1.20	22.80	3.90	8.30	1.20	23.20	3.87	0.61
Casino I	48.03	31.05	76.51	8.67	55.06	33.70	77.20	9.87	57.60	36.90	79.80	9.83	0.68
Casino II	45.02	22.31	122.71	24.22	49.67	17.30	126.10	25.99	51.29	19.30	128.20	25.78	0.95
Compass Group	22.99	10.80	83.29	15.59	31.36	4.53	94.00	18.18	32.42	6.20	93.40	17.70	0.94
Edison	16.90	6.52	30.40	5.30	23.93	10.20	32.80	5.71	24.97	10.80	34.10	5.53	0.76
Enel	15.51	8.98	38.05	5.73	13.50	2.40	29.84	6.61	14.93	4.00	30.30	6.95	0.71
Energias de Portugal I	12.30	6.37	23.65	4.92	12.11	1.80	19.60	3.18	19.93	2.20	19.90	3.02	0.47
Energias de Portugal II	14.80	8.46	28.00	4.93	16.72	3.24	24.20	3.49	17.41	5.00	24.00	3.07	0.54
E.ON	10.87	5.02	15.46	2.63	9.47	2.10	18.60	3.63	10.58	2.50	19.40	3.67	0.50
France Telecom I	21.25	14.56	39.39	4.31	25.22	18.80	44.01	4.75	27.45	21.00	48.50	5.34	0.73
France Telecom II	21.39	15.00	40.57	4.64	25.36	19.30	38.99	4.20	27.53	20.90	43.40	4.68	0.88
France Telecom III	25.15	10.68	50.03	10.18	17.46	4.10	30.00	6.82	19.68	6.50	32.70	7.28	0.81
Iberdrola I	16.63	6.82	27.97	5.00	16.78	3.30	28.70	5.39	19.48	5.40	30.10	5.23	0.65
Iberdrola II	11.70	6.00	18.40	3.09	10.77	2.50	17.00	2.47	12.30	7.50	19.90	2.49	0.36
Kingfisher	44.81	31.99	80.96	8.85	49.22	29.10	71.80	9.07	51.53	31.90	74.20	8.89	0.81
Louis Vuitton I	19.26	9.09	29.19	5.45	23.04	10.30	38.70	7.77	24.61	11.70	41.40	7.85	0.87
Louis Vuitton II	16.40	5.86	27.07	6.22	21.62	4.06	31.20	7.14	22.98	5.40	33.50	7.04	0.93
PPR	39.60	25.73	72.88	6.89	47.98	30.10	60.90	6.79	49.47	32.80	63.70	6.65	0.74
Reed Elsevier	13.83	8.67	28.18	4.03	12.57	4.80	21.10	3.25	14.84	8.00	23.50	2.87	0.48
Renault	16.85	5.05	30.80	6.69	22.29	5.00	43.90	9.10	23.15	6.07	45.40	9.02	0.93
Repsol YPF	21.08	9.69	36.24	7.15	26.49	10.40	37.90	7.73	27.17	13.02	38.50	7.26	0.80
Reuters	17.75	9.13	31.78	5.64	23.42	6.68	34.20	6.55	24.92	8.70	35.30	6.49	0.81
Saint Gobain I	18.10	10.13	31.77	4.64	17.36	6.30	28.30	5.19	18.84	7.30	29.80	5.29	0.65
Saint Gobain II	26.86	15.93	47.58	6.86	31.75	16.90	49.60	8.42	33.96	19.90	52.70	8.57	0.89
Saint Gobain III	22.78	11.65	38.06	7.23	26.75	9.60	39.00	8.15	28.07	11.80	40.40	7.93	0.81
Scania	24.69	10.31	41.00	8.58	23.53	8.60	38.20	7.46	25.79	10.20	41.30	7.66	0.53
SES	20.92	14.28	26.18	3.16	21.42	11.02	28.30	4.82	23.95	16.20	30.90	4.14	0.65
Siemens	12.08	9.35	17.00	1.58	9.60	4.94	13.50	1.81	10.61	6.60	14.40	1.63	-0.04
Sodexho	9.98	4.45	25.89	4.56	18.90	3.39	34.40	5.56	20.21	6.30	34.60	5.11	0.81
Stora Enso	38.10	21.18	88.19	13.38	40.27	21.30	62.30	12.15	43.66	24.60	64.80	12.66	0.91
Technip	24.55	15.79	34.93	3.61	33.84	20.60	41.40	4.17	35.57	21.90	45.10	4.29	0.17
Telecom Italia I	44.46	23.01	71.60	10.27	46.49	20.90	84.80	11.94	48.87	24.00	87.00	12.02	0.92
Telecom Italia II	45.95	24.40	75.40	10.85	45.34	22.00	64.30	10.64	44.46	23.70	62.80	9.65	0.87
Telefonica	33.40	16.46	59.20	8.87	36.77	17.70	57.90	9.32	39.55	20.20	60.10	9.59	0.93
Telekom Austria	24.04	9.55	64.27	12.71	25.57	11.32	51.60	9.61	28.00	11.70	55.20	9.95	0.94
Tesco I	9.45	4.06	21.63	4.81	12.09	1.70	24.60	5.06	13.35	2.50	25.90	5.03	0.52
Tesco II	10.38	5.00	22.95	4.36	14.46	2.30	29.30	5.99	16.10	3.30	30.60	6.17	0.77
Thales	13.98	9.31	19.08	3.19	18.63	6.74	27.40	5.39	20.21	8.60	28.70	5.35	0.74
Thyssenkrupp	35.04	17.12	68.64	12.85	36.92	9.80	75.90	18.28	38.63	12.10	78.70	18.30	0.96
Union Fenosa	20.74	7.29	38.08	7.63	25.07	7.86	36.10	6.47	26.28	9.00	35.50	6.29	0.89
Veolia Environ.	10.70	5.03	21.04	4.00	11.50	5.40	17.40	2.80	13.47	5.40	19.30	2.91	-0.05
Vinci	23.96	12.26	38.82	7.08	23.16	10.62	35.00	6.05	24.14	10.10	34.50	5.82	0.72
Vivendi	34.30	17.70	55.20	8.30	38.95	18.40	51.40	9.18	41.97	23.40	56.40	9.33	0.90
Vodafone	15.31	10.93	24.78	3.28	12.25	4.00	25.90	7.10	14.04	0.20	29.70	7.23	0.78
Volkswagen	21.21	10.82	37.60	6.33	23.61	6.97	37.60	8.11	25.52	7.50	40.40	8.30	0.77
Volvo	20.86	9.80	35.07	6.77	21.92	4.54	40.90	8.08	23.03	6.00	43.40	7.93	0.74
Average	22.19	11.91	41.50	6.77	24.31	9.84	41.05	7.31	26.09	11.60	42.92	7.27	0.70

Panel C2

	CDS Premium (basis points)				Asset Swap Spread (b.p.)				Bond Spread (b.p.)				CDS vs AS
Issuer	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD	Corr
Akzo Nobel I	65.19	13.58	172.60	42.68	72.45	3.17	254.30	69.83	73.77	0.30	304.70	72.63	0.91
Astrazeneca	51.12	16.53	170.83	32.64	40.94	16.31	169.50	25.25	40.61	15.10	154.70	23.51	0.77
Auchan	27.82	8.62	68.00	12.04	37.37	1.09	145.40	34.79	34.19	1.02	132.00	28.01	0.73
BASF	64.26	14.37	159.37	41.23	36.69	2.30	119.20	31.94	35.32	2.00	125.30	31.74	0.78
Bayer	64.72	20.42	137.87	27.24	87.10	27.43	202.70	40.64	84.96	26.50	286.20	40.75	0.85
Belgacom	40.88	18.18	89.92	17.06	46.44	14.00	103.90	15.58	47.95	11.80	102.10	16.03	0.57
BMW	144.24	12.83	537.50	143.93	99.04	1.10	479.00	102.82	101.42	1.30	515.40	106.08	0.86
Bouygues I	102.76	23.00	270.32	67.01	101.66	16.73	262.10	65.28	99.20	16.70	263.50	64.47	0.91
British AM Tob. II	67.14	19.16	173.66	32.03	107.03	27.40	293.10	60.43	109.13	25.30	298.20	61.14	0.72
Carrefour I	49.82	13.89	153.67	28.23	52.93	1.00	174.60	42.99	50.76	2.00	174.20	41.51	0.83
Carrefour II	47.49	11.14	159.47	31.39	30.89	2.81	116.30	19.42	31.18	2.40	137.40	24.21	0.28
Casino I	142.33	38.24	390.00	75.60	172.53	58.08	389.70	95.31	177.10	59.50	418.30	99.07	0.90
Casino II	130.09	26.59	390.00	81.10	111.67	19.89	284.90	61.22	115.18	17.90	292.90	69.88	0.53
Casino III	146.96	45.32	390.00	73.33	208.31	64.89	456.20	110.23	211.57	64.60	489.80	114.06	0.88
Edison	65.48	16.87	198.00	52.92	82.27	6.30	215.50	62.45	81.05	4.80	218.80	59.79	0.87
Enel	178.55	23.43	743.31	166.70	53.71	0.20	146.00	39.91	53.71	0.80	150.10	40.08	0.80
Energias de Portugal I	73.52	17.11	205.52	50.81	53.74	1.50	165.00	37.86	52.70	0.40	167.34	38.64	0.67
Energias de Portugal II	82.34	21.48	190.27	45.93	100.71	4.94	244.90	65.18	98.78	4.90	247.70	65.40	0.81
France Telecom I	64.58	21.74	121.87	26.03	74.94	23.70	193.10	38.64	72.99	3.30	187.00	37.58	0.67
France Telecom II	64.98	21.96	121.65	25.90	87.54	35.12	209.80	39.49	88.27	32.10	211.60	38.92	0.78
France Telecom III	59.48	17.98	122.00	26.99	50.08	5.80	195.00	32.83	49.27	6.00	189.50	30.67	0.66
Iberdrola I	92.62	13.12	295.50	57.70	75.65	0.91	211.00	56.40	74.15	1.50	218.30	55.43	0.90
Kingfisher	191.71	46.30	435.00	101.87	218.77	41.00	376.50	109.45	232.37	43.30	407.50	119.06	0.84
Louis Vuitton I	71.15	15.74	246.00	50.72	70.56	11.09	200.90	47.50	69.89	12.00	201.30	47.31	0.90
Louis Vuitton II	65.95	11.55	246.00	54.05	62.37	1.13	234.20	49.06	61.37	1.20	211.70	48.38	0.88
Philips	59.31	13.80	162.66	34.89	65.24	5.07	197.00	58.26	63.13	6.00	194.60	56.32	0.87
PPR	252.50	49.20	759.03	199.38	200.16	35.18	553.70	144.48	205.98	36.10	590.60	151.84	0.97
Repsol YPF	115.13	21.18	441.16	111.58	107.20	18.21	368.40	87.01	106.35	13.40	391.90	88.56	0.91
Saint Gobain II	177.26	25.63	555.63	134.35	158.10	38.24	458.10	111.38	162.70	41.10	496.70	115.75	0.92
Saint Gobain III	156.89	19.87	522.04	132.37	110.95	22.78	323.10	72.01	117.41	23.10	366.30	85.89	0.85
Schneider	68.66	17.59	199.78	42.03	70.63	12.64	252.60	34.20	73.11	11.70	232.50	34.13	0.85
SES	77.35	24.58	181.86	41.73	122.23	30.11	352.30	83.71	127.17	30.80	369.60	87.52	0.88
Siemens	76.03	13.98	238.85	56.55	62.58	3.00	175.60	47.26	61.59	3.00	171.40	46.51	0.77
Technip	98.66	16.83	302.73	80.09	109.91	24.42	303.50	83.61	114.41	18.50	314.90	89.36	0.76
Telecom Italia I	183.38	30.18	546.17	138.43	158.12	38.94	434.70	95.31	171.65	36.10	654.50	118.10	0.84
Telecom Italia II	184.89	30.95	540.33	136.07	216.49	38.01	536.70	148.10	215.13	36.50	552.30	149.77	0.97
Telefonica	97.99	25.54	247.69	54.96	102.31	31.61	276.10	56.25	103.94	32.80	278.00	56.46	0.90
Telekom Austria	59.18	13.71	142.58	30.07	93.66	12.43	326.80	62.25	99.57	9.40	321.90	64.89	0.68
Teliasonera	62.75	18.82	127.51	25.89	82.56	0.00	259.30	62.00	86.10	0.00	270.40	64.48	0.86
Tesco I	59.59	8.94	182.00	52.12	63.17	1.93	246.30	61.63	62.76	1.73	239.70	60.91	0.79
Tesco II	64.20	11.19	182.19	49.32	67.64	2.43	189.70	53.60	66.84	2.10	197.40	53.13	0.91
Thales	78.50	12.70	300.99	60.90	74.07	0.70	211.10	67.53	77.81	0.64	557.20	78.43	0.58
Thyssenkrupp	192.95	25.52	580.00	166.28	106.84	0.30	313.30	96.80	114.43	0.10	327.00	101.68	0.87
Union Fenosa	88.40	13.73	382.50	82.13	89.31	6.30	215.80	65.98	86.99	5.60	213.30	63.84	0.79
Volkswagen	132.69	18.92	360.02	91.15	119.99	17.44	352.20	94.58	123.23	17.70	363.40	96.96	0.89
Volvo	219.66	16.24	733.80	234.40	252.10	0.20	777.80	271.29	263.15	1.00	857.90	290.67	0.96
Average	101.33	20.40	301.69	72.17	99.32	15.82	281.89	69.82	101.09	14.87	305.81	72.38	0.81

Panel D

	Basis (b.p.) Nov. 2005 - Aug. 2007				Basis (b.p.) Aug. 2007 - June 2009			
Issuer	Mean	Min	Max	SD	Mean	Min	Max	SD
Akzo Nobel I	-5.89	-20.04	10.21	7.43	7.26	-53.23	117.83	35.69
Akzo Nobel II	3.06	-7.51	11.51	3.92	-	-	-	-
Altadis	3.57	-14.29	16.19	7.09	-	-	-	-
Astrazeneca	-	-	-	-	-10.19	-86.63	93.67	20.74
Auchan	-	-	-	-	9.55	-26.74	101.42	27.25
BASF	-	-	-	-	-27.57	-123.71	21.75	25.80
Bayer	-	-	-	-	22.37	-43.90	112.97	22.69
Belgacom	-	-	-	-	5.56	-25.12	30.95	15.18
BMW	-1.61	-15.77	8.49	3.31	-45.20	-356.80	273.54	76.37
Bouygues I	4.41	-7.42	13.43	4.87	-1.10	-58.90	101.42	28.11
Bouygues II	-4.43	-22.81	3.00	3.88	-	-	-	-
British AM Tob. I	-4.61	-26.30	10.90	6.65	-	-	-	-
British AM Tob. II	8.10	-7.18	15.10	4.04	47.36	-16.35	202.58	44.59
Carrefour I	2.56	-26.95	15.53	6.15	3.11	-50.27	120.18	25.26
Carrefour II	-5.42	-21.84	4.10	3.28	-16.60	-145.87	73.84	31.96
Casino G. P. I	7.04	-27.10	17.56	7.46	30.20	-55.30	170.01	42.99
Casino G. P. II	4.66	-27.15	16.25	7.98	-18.42	-315.10	112.15	71.18
Casino G. P. III	-	-	-	-	61.35	-31.73	218.98	57.14
Compass Group	8.37	-14.26	20.86	6.44	-	-	-	-
Edison	7.03	-15.85	15.74	3.84	16.79	-30.09	134.90	30.66
Enel	-2.01	-19.47	5.89	4.81	-124.83	-656.01	20.97	136.64
Energias de Portugal I	-0.18	-10.00	7.59	4.44	-9.78	-71.42	95.40	28.60
Energias de Portugal II	1.91	-14.88	9.05	4.22	28.37	-72.24	155.44	42.72
E.ON	-1.41	-9.36	9.08	3.24	-	-	-	-
France Telecom I	3.97	-6.25	14.46	3.36	10.36	-64.55	94.61	28.52
France Telecom II	3.97	-6.32	7.99	2.17	22.56	-38.73	110.98	25.33
France Telecom III	-7.68	-30.40	0.53	6.19	-9.41	-79.81	103.03	25.32
Iberdrola I	0.15	-11.47	12.10	4.40	-16.97	-110.50	57.54	25.66
Iberdrola II	-0.93	-8.61	6.31	3.18	-	-	-	-
Kingfisher	0.41	-43.52	10.18	5.55	27.06	-130.16	153.20	59.81
Louis Vuitton I	3.78	-16.28	13.70	4.03	-0.59	-86.30	82.79	22.17
Louis Vuitton II	3.22	-6.21	10.34	2.60	-3.58	-91.90	135.19	26.22
Philips	-	-	-	-	5.93	-51.09	109.81	32.95
PPR	8.38	-23.05	16.78	4.92	-52.34	-340.83	60.54	70.35
Reed Elsevier	-1.26	-11.96	5.94	3.77	-	-	-	-
Renault	5.43	-7.00	21.04	3.75	-	-	-	-
Repsol YPF	5.41	-11.79	17.12	4.77	-7.93	-173.30	110.67	47.86
Reuters	5.67	-8.30	15.08	3.85	-	-	-	-
Saint Gobain I	-0.74	-21.91	9.16	4.17	-	-	-	-
Saint Gobain II	4.89	-16.54	14.34	3.96	0.84	-122.94	161.76	44.82
Saint Gobain III	3.97	-16.68	14.70	4.79	-31.94	-267.54	101.73	55.43
Scania	-1.17	-19.60	14.03	7.88	-	-	-	-
Schneider	-	-	-	-	1.97	-49.42	86.03	21.94
SES	0.42	-9.91	5.59	3.70	44.88	-43.05	192.58	51.28
Siemens	-2.48	-10.89	2.56	2.45	-13.46	-188.60	40.29	35.99
Sodexho	8.92	-5.86	15.52	3.27	-	-	-	-
Stora Enso	2.17	-33.44	11.16	5.54	-	-	-	-
Technip	9.30	-12.92	19.33	5.03	11.24	-167.69	127.37	56.59
Telecom Italia I	2.03	-13.60	17.54	4.69	-25.26	-356.17	84.10	78.72
Telecom Italia II	-0.61	-11.77	18.98	5.54	31.59	-34.29	168.70	34.92
Telefonica	3.37	-15.80	12.72	3.51	4.31	-81.50	106.08	25.40
Telekom Austria	1.53	-17.34	8.82	5.03	34.48	-31.41	239.45	47.33
Teliasonera	-	-	-	-	32.49	-20.96	181.59	36.83
Tesco I	2.64	-10.02	12.06	4.86	3.59	-64.70	155.67	37.88
Tesco II	4.08	-12.61	13.15	3.81	3.43	-43.35	100.88	22.78
Thales	4.64	-9.70	13.73	3.74	-4.43	-296.49	73.78	59.07
Thyssenkrupp	1.87	-19.24	15.79	6.88	-72.11	-326.40	80.24	89.82
Union Fenosa	4.32	-7.49	10.88	3.53	12.91	-169.00	132.75	45.34
Veolia Environ	0.86	-9.87	9.87	4.97	-	-	-	-
Vinci	-0.80	-16.18	9.03	4.98	-	-	-	-
Vivendi	4.66	-6.54	18.36	4.06	-	-	-	-
Vodafone	-3.05	-15.04	7.93	4.97	-	-	-	-
Volkswagen	2.40	-27.12	11.22	5.14	-12.70	-151.92	180.09	43.70
Volvo	1.06	-17.49	13.48	5.48	32.44	-154.80	378.40	82.12
Average	2.00	-15.58	12.04	4.68	0.17	-129.50	125.39	43.43

Panel E1

	GFI CDS Premium (b.p.)				CMA CDS Premium (b.p.)				JPMorgan CDS Premium (b.p.)			
Issuer	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD
Akzo Nobel I	23.55	17.14	30.72	2.31	23.39	15.40	41.80	3.68	22.98	14.55	49.90	4.10
Akzo Nobel II	14.11	9.85	27.89	3.47	12.57	6.31	25.30	3.95	12.93	5.46	31.33	4.45
Altadis	16.83	8.59	35.00	6.36	14.17	5.20	34.42	4.22	-	-	-	-
BMW	12.10	6.61	23.86	4.77	11.98	6.28	26.11	4.80	11.66	5.11	26.82	4.92
Bouygues I	21.10	12.00	35.00	5.81	20.18	11.18	35.45	5.99	19.58	10.68	35.46	5.90
Bouygues II	20.24	11.94	33.60	6.35	20.01	11.45	33.15	6.02	19.22	10.38	35.14	6.01
British AM Tob. I	24.81	6.05	54.00	13.18	24.21	6.34	53.36	13.01	23.48	5.79	54.61	13.35
British AM Tob. II	24.89	13.12	40.00	6.96	24.38	14.51	38.73	6.18	23.96	12.12	36.72	6.48
Carrefour I	16.19	9.43	38.63	4.58	15.83	9.54	33.35	4.39	15.27	9.67	35.10	4.30
Carrefour II	12.87	6.80	28.05	3.51	12.67	6.80	23.20	3.54	12.84	6.82	30.78	3.97
Casino I	48.03	31.05	76.51	8.67	48.76	30.39	80.98	8.90	46.30	28.14	69.67	7.96
Casino II	45.02	22.31	122.71	24.22	44.97	20.26	122.98	24.35	42.33	16.81	124.43	25.45
Compass Group	22.99	10.80	83.29	15.59	24.05	11.19	80.48	14.62	22.33	9.88	80.93	14.86
Edison	16.90	6.52	30.40	5.30	15.94	6.36	28.38	5.04	15.91	5.64	28.87	5.32
Enel	15.51	8.98	38.05	5.73	15.32	9.39	36.99	5.36	14.64	8.40	33.27	5.42
Energias de Portugal I	12.30	6.37	23.65	4.92	11.37	4.43	20.87	4.36	11.59	4.96	22.70	4.97
Energias de Portugal II	14.80	8.46	28.00	4.93	14.26	7.40	27.50	4.83	14.57	8.69	26.22	4.08
E.ON	10.87	5.02	15.46	2.63	9.75	3.37	15.96	2.76	9.91	2.96	16.18	3.28
France Telecom I	21.25	14.56	39.39	4.31	21.90	15.73	43.61	4.48	20.85	14.60	40.45	4.17
France Telecom II	21.39	15.00	40.57	4.64	22.00	15.99	44.53	4.96	20.94	15.07	41.36	4.58
France Telecom III	25.15	10.68	50.03	10.18	25.12	11.05	49.58	9.84	24.51	10.29	49.29	10.18
Iberdrola I	16.63	6.82	27.97	5.00	16.06	8.17	27.87	4.74	16.56	7.84	27.81	4.92
Iberdrola II	11.70	6.00	18.40	3.09	10.57	6.05	18.89	3.00	10.58	4.48	20.39	3.61
Kingfisher	44.81	31.99	80.96	8.85	43.39	31.21	83.74	8.31	43.33	30.52	81.16	8.95
Louis Vuitton I	19.26	9.09	29.19	5.45	18.93	11.49	31.60	4.50	17.12	7.97	27.68	5.03
Louis Vuitton II	16.40	5.86	27.07	6.22	16.27	8.10	32.02	5.78	15.11	5.69	31.44	6.60
PPR	39.60	25.73	72.88	6.89	39.39	24.11	69.37	6.52	38.58	21.95	63.33	6.65
Reed Elsevier	13.83	8.67	28.18	4.03	8.92	5.61	24.61	3.09	7.59	3.52	29.28	3.28
Renault	16.85	5.05	30.80	6.69	17.20	6.85	29.85	5.34	15.68	6.05	29.27	5.54
Repsol YPF	21.08	9.69	36.24	7.15	20.81	10.14	40.99	7.03	21.25	9.52	43.77	8.16
Reuters	17.75	9.13	31.78	5.64	17.55	9.15	29.33	4.79	17.00	8.87	29.39	4.88
Saint Gobain I	18.10	10.13	31.77	4.64	15.87	8.34	28.59	5.21	14.90	4.29	32.66	5.90
Saint Gobain II	26.86	15.93	47.58	6.86	26.21	15.66	48.31	6.77	25.13	13.28	52.85	7.43
Saint Gobain III	22.78	11.65	38.06	7.23	21.62	11.09	34.22	6.83	20.51	8.15	40.03	7.68
Scania	24.69	10.31	41.00	8.58	23.90	11.11	40.50	7.78	22.46	9.94	38.53	7.71
SES	20.92	14.28	26.18	3.16	21.88	15.07	27.45	3.19	20.33	15.55	27.07	3.14
Siemens	12.08	9.35	17.00	1.58	11.26	8.50	16.07	1.82	10.98	7.49	16.46	1.97
Sodexho	9.98	4.45	25.89	4.56	10.05	4.51	23.83	3.86	-	-	-	-
Stora Enso	38.10	21.18	88.19	13.38	36.55	20.79	73.32	11.71	34.90	16.47	99.83	14.20
Technip	24.55	15.79	34.93	3.61	22.82	13.98	28.30	2.53	22.00	10.89	26.68	2.91
Telecom Italia I	44.46	23.01	71.60	10.27	44.17	23.29	70.06	10.02	44.06	22.81	70.80	10.03
Telecom Italia II	45.95	24.40	75.40	10.85	45.88	24.90	74.26	10.65	45.69	23.93	74.02	10.55
Telefonica	33.40	16.46	59.20	8.87	32.45	15.82	57.05	9.06	31.73	15.44	56.67	9.15
Telekom Austria	24.04	9.55	64.27	12.71	23.91	9.19	60.32	11.48	23.20	8.99	62.40	12.21
Tesco I	9.45	4.06	21.63	4.81	9.74	3.80	22.28	4.69	10.47	4.94	20.87	4.42
Tesco II	10.38	5.00	22.95	4.36	11.07	5.42	22.50	4.38	11.42	6.09	22.35	4.01
Thales	13.98	9.31	19.08	3.19	14.22	9.77	23.05	3.10	14.31	10.19	22.47	2.98
Thyssenkrupp	35.04	17.12	68.64	12.85	33.76	16.59	64.20	12.35	32.72	14.96	61.79	12.54
Union Fenosa	20.74	7.29	38.08	7.63	21.15	8.30	35.56	6.99	21.69	9.22	34.86	7.11
Veolia Environ.	10.70	5.03	21.04	4.00	8.74	3.67	20.35	3.35	8.78	3.12	21.94	3.55
Vinci	23.96	12.26	38.82	7.08	20.48	10.08	32.71	6.12	19.81	7.54	37.90	7.84
Vivendi	34.30	17.70	55.20	8.30	32.49	17.06	47.89	7.25	32.25	17.76	50.12	7.85
Vodafone	15.31	10.93	24.78	3.28	14.02	8.62	22.85	3.69	12.70	7.50	78.08	5.07
Volkswagen	21.21	10.82	37.60	6.33	21.47	11.37	37.23	6.27	20.96	10.77	41.23	6.47
Volvo	20.86	9.80	35.07	6.77	20.50	8.69	33.77	6.45	18.84	7.80	34.08	6.67
Average	22.53	12.11	41.91	6.82	21.92	11.80	40.97	6.52	21.29	10.75	42.95	6.84

Panel E2

	GFI CDS Premium (b.p.)				CMA CDS Premium (b.p.)				Reuters CDS Premium (b.p.)				JPMorgan CDS Premium (b.p.)			
Issuer	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD
Akzo Nobel I	65.19	13.58	172.60	42.68	68.28	13.97	179.18	46.97	68.86	13.58	189.58	48.77	66.15	12.70	200.50	43.36
Astrazeneca	51.12	16.53	170.83	32.64	43.85	14.94	151.87	35.36	47.78	16.53	162.13	38.51	-	-	-	-
Auchan	27.82	8.62	68.00	12.04	26.39	9.33	59.06	10.66	30.45	8.62	83.37	16.05	32.89	10.56	100.16	17.00
BASF	64.26	14.37	159.37	41.23	69.65	14.22	183.67	49.02	66.28	14.37	155.00	44.42	67.70	13.47	180.66	46.22
Bayer	64.72	20.42	137.87	27.24	67.40	20.19	151.83	31.81	65.77	20.42	145.00	30.04	67.58	18.65	177.00	34.73
Belgacom	40.88	18.18	89.92	17.06	40.88	18.18	89.92	17.06	38.84	18.18	93.43	16.79	-	-	-	-
BMW	144.24	12.83	537.50	143.93	147.89	14.47	537.88	144.01	148.77	0.01	607.12	148.52	147.68	11.87	558.53	145.91
Bouygues I	102.76	23.00	270.32	67.01	100.60	20.42	271.44	69.67	104.58	23.00	270.44	74.15	105.66	23.25	330.46	78.81
British AM Tob. II	67.14	19.16	173.66	32.03	67.65	19.96	175.64	33.76	67.84	19.16	197.07	37.61	69.46	18.40	195.15	36.91
Carrefour I	49.82	13.89	153.67	28.23	47.19	13.20	111.50	22.28	50.26	13.89	142.59	28.58	55.16	8.78	154.90	32.58
Carrefour II	47.49	11.14	159.47	31.39	41.78	9.30	99.42	24.55	46.64	11.14	150.45	32.30	52.18	7.52	166.25	34.73
Casino I	142.33	38.24	390.00	75.60	135.51	40.03	316.49	65.06	143.83	19.12	419.32	87.12	150.97	34.70	425.99	91.91
Casino II	130.09	26.59	390.00	81.10	112.60	26.61	267.23	60.19	135.61	26.59	450.48	98.85	137.72	21.87	438.15	102.39
Casino III	146.96	45.32	390.00	73.33	143.81	46.53	338.00	65.83	148.11	45.32	405.34	80.40	153.80	41.71	424.19	87.68
Edison	65.48	16.87	198.00	52.92	60.62	16.78	168.94	45.33	60.43	17.58	230.22	44.52	63.61	14.93	190.48	48.41
Enel	178.55	23.43	743.31	166.70	182.04	26.04	627.55	164.44	191.97	23.43	687.16	177.35	189.28	18.47	678.26	177.13
Energias de Portugal I	73.52	17.11	205.52	50.81	71.86	13.79	206.06	52.63	82.55	17.11	198.06	55.94	81.86	9.97	212.77	60.11
Energias de Portugal II	82.34	21.48	190.27	45.93	79.96	20.77	195.22	45.77	83.88	21.48	185.04	47.08	90.13	14.53	191.58	53.91
France Telecom I	64.58	21.74	121.87	26.03	67.44	20.45	126.01	27.44	66.41	21.74	124.21	27.23	68.28	18.48	129.98	29.45
France Telecom II	64.98	21.96	121.65	25.90	67.87	20.82	125.68	27.38	66.82	21.96	124.98	27.15	68.63	18.82	129.60	29.33
France Telecom III	59.48	17.98	122.00	26.99	59.21	14.99	123.47	27.92	58.61	17.98	124.98	27.74	60.56	14.42	131.52	29.89
Iberdrola I	92.62	13.12	295.50	57.70	94.08	15.55	222.38	58.51	95.11	13.12	279.93	64.98	99.38	14.87	288.35	68.69
Kingfisher	191.71	46.30	435.00	101.87	193.77	48.05	417.92	104.68	196.90	46.30	504.99	110.12	198.97	42.65	451.60	112.29
Louis Vuitton I	71.15	15.74	246.00	50.72	66.59	15.97	192.27	44.48	68.54	15.74	241.28	51.84	68.94	13.52	215.16	50.47
Louis Vuitton II	65.95	11.55	246.00	54.05	56.99	11.08	172.17	43.20	63.18	11.55	256.77	56.03	62.13	10.45	215.36	53.00
Philips	59.31	13.80	162.66	34.89	60.41	15.05	178.02	36.68	60.01	13.80	177.75	38.07	62.20	16.88	544.72	50.23
PPR	252.50	49.20	759.03	199.38	235.09	42.71	626.48	178.01	260.37	0.31	777.31	214.88	253.72	20.45	766.72	209.60
Repsol YPF	115.13	21.18	441.16	111.58	111.62	21.93	418.33	103.32	129.17	21.18	538.76	135.36	129.48	17.89	540.68	136.95
Saint Gobain II	177.26	25.63	555.63	134.35	177.34	26.74	598.69	135.17	178.87	25.63	542.81	139.96	184.10	24.75	716.99	150.31
Saint Gobain III	156.89	19.87	522.04	132.37	157.73	19.99	558.35	136.76	162.85	19.87	551.90	145.83	166.59	16.22	678.78	149.80
Schneider	68.66	17.59	199.78	42.03	59.11	16.01	190.79	36.62	59.73	17.59	224.02	48.43	66.01	18.25	205.27	45.13
SES	77.35	24.58	181.86	41.73	67.10	25.24	209.14	49.28	75.85	24.58	171.71	38.95	73.58	22.70	186.25	46.81
Siemens	76.03	13.98	238.85	56.55	76.03	15.31	221.31	52.55	75.30	13.98	237.34	53.11	76.17	14.24	243.46	54.22
Technip	98.66	16.83	302.73	80.09	104.16	18.73	337.98	85.92	104.66	16.83	331.48	82.84	118.05	9.19	359.02	89.82
Telecom Italia I	183.38	30.18	546.17	138.43	181.85	31.08	509.91	134.23	185.45	30.18	506.29	140.39	183.89	30.76	533.91	140.90
Telecom Italia II	184.89	30.95	540.33	136.07	183.87	32.87	502.01	131.94	187.16	30.95	503.61	137.81	186.49	33.07	532.19	138.95
Telefonica	97.99	25.54	247.69	54.96	93.37	28.53	203.95	46.64	94.97	25.54	228.13	49.22	98.27	25.26	258.90	53.15
Telekom Austria	59.18	13.71	142.58	30.07	67.44	14.34	194.68	41.74	63.00	13.71	160.78	34.63	69.16	14.41	206.46	44.21
Teliasonera	62.75	18.82	127.51	25.89	67.02	19.01	130.62	27.39	65.70	18.82	126.65	26.67	68.52	18.76	186.44	30.58
Tesco I	59.59	8.94	182.00	52.12	52.16	8.43	152.47	42.97	59.16	8.94	198.54	51.65	57.72	6.61	175.34	46.65
Tesco II	64.20	11.19	182.19	49.32	60.26	11.31	162.82	43.96	66.21	11.19	198.35	51.82	62.94	11.47	175.18	44.84
Thales	78.50	12.70	300.99	60.90	75.73	13.66	314.25	63.64	77.27	12.70	313.26	61.36	77.59	14.90	299.55	61.62
Thyssenkrupp	192.95	25.52	580.00	166.28	198.62	25.45	599.56	174.80	204.98	17.06	652.42	182.89	206.40	23.67	589.30	180.49
Union Fenosa	88.40	13.73	382.50	82.13	90.06	17.20	396.35	84.08	92.34	13.73	388.82	84.11	92.00	14.71	349.09	79.00
Volkswagen	132.69	18.92	360.02	91.15	143.18	18.38	418.14	104.23	142.96	5.87	415.92	104.38	140.31	15.61	429.68	103.28
Volvo	219.66	16.24	733.80	234.40	230.55	16.02	790.37	237.53	226.83	16.24	774.29	228.44	217.25	10.26	724.63	227.37
Average	103.84	20.53	309.48	74.32	102.77	20.69	295.07	73.02	106.46	18.23	322.58	78.81	107.94	18.06	338.39	80.66

2.7 Results

2.7.1 Long-run arbitrage test empirical results

Table II shows that most spreads are I(1). Only in four cases in the first subperiod, Carrefour II, Casino II, Compass Group, and Siemens, and in other two cases in the crisis period, Carrefour II and Schneider, credit spreads are I(0). Table II indicates that the long-run equivalence relation holds and the two markets move together in the long-run in 31 of the total 51 cases in the first period and in 37 of the total 44 cases in the second one.[23] The potential long-run arbitrage opportunities could be due to the presence of a cheapest-to-deliver option in the CDS price, the constraints in the bonds' short-sales or the existence of a liquidity premium, among other causes. These opportunities should be exploited by means of cash-and-carry arbitrage strategies, where either long or short positions in ASPs are needed.

[23] Norden and Weber (2004), Blanco, Brennan, and Marsh (2005), and Zhu (2006) find a long-run equivalence relation between CDS and bond spreads in 36 of 58 cases, in 26 of 33 cases, and in 15 of 24 cases, respectively. De Wit (2006) finds a long-run equivalence relation between CDS and ASP spreads in 88 of 144 cases.

Table II: Unit Root Test for Credit Spreads

Table II reports the results of the unit root test for the credit spreads and the basis. The first three columns contain the order of integration of the CDS premium, ASP spread and the basis for the period before the crisis. The last three column contain the order of integration of the CDS premium, ASP spread and the basis for the crisis period.

	November 2005 - August 2007			August 2007 - June 2009		
Issuer	CDS	ASP	Basis	CDS	ASP	Basis
Akzo Nobel I	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Akzo Nobel II	I(1)	I(1)	I(0)	-	-	-
Altadis	I(1)	I(1)	I(1)	-	-	-
Astrazeneca	-	-	-	I(1)	I(1)	I(0)
Auchan	-	-	-	I(1)	I(1)	I(0)
BASF	-	-	-	I(1)	I(1)	I(0)
Bayer	-	-	-	I(1)	I(1)	I(0)
Belgacom	-	-	-	I(1)	I(1)	I(0)
BMW	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Bouygues I	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Bouygues II	I(1)	I(1)	I(1)	-	-	-
British AM Tob. I	I(1)	I(1)	I(0)	-	-	-
British AM Tob. II	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
Carrefour I	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Carrefour II	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Casino I	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Casino II	I(0)	I(0)	I(0)	I(1)	I(1)	I(0)
Casino III	-	-	-	I(1)	I(1)	I(0)
Compass Group	I(0)	I(0)	I(0)	-	-	-
Edison	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Enel	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
Energias de Portugal I	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
Energias de Portugal II	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
E.ON	I(1)	I(1)	I(0)	-	-	-
France Telecom I	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
France Telecom II	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
France Telecom III	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Iberdrola I	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Iberdrola II	I(1)	I(1)	I(0)	-	-	-
Kingfisher	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Louis Vuitton I	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Louis Vuitton II	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Philips	-	-	-	I(1)	I(1)	I(0)
PPR	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Reed Elsevier	I(1)	I(1)	I(0)	-	-	-
Renault	I(1)	I(1)	I(1)	-	-	-
Repsol YPF	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Reuters	I(1)	I(1)	I(1)	-	-	-
Saint Gobain I	I(1)	I(1)	I(0)	-	-	-
Saint Gobain II	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Saint Gobain III	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Scania	I(1)	I(1)	I(1)	-	-	-
Schneider	-	-	-	I(0)	I(0)	I(0)
SES	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Siemens	I(0)	I(0)	I(0)	I(1)	I(1)	I(0)
Sodexho	I(1)	I(1)	I(1)	-	-	-
Stora Enso	I(1)	I(1)	I(1)	-	-	-
Technip	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Telecom Italia I	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Telecom Italia II	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Telefonica	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Telekom Austria	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
Teliasonera	-	-	-	I(1)	I(1)	I(1)
Tesco I	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Tesco II	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Thales	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Thyssenkrupp	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Union Fenosa	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Veolia Environ	I(1)	I(1)	I(0)	-	-	-
Vinci	I(1)	I(1)	I(0)	-	-	-
Vivendi	I(1)	I(1)	I(0)	-	-	-
Vodafone	I(1)	I(1)	I(1)	-	-	-
Volkswagen	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Volvo	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)

The previous analyses based on the CDS and bond spreads' long-run equivalence relation do not distinguish among the cases in which the investor needs either short or long positions in ASPs. Nevertheless, shorting ASPs is not always a feasible option and for this reason, we distinguish between both cases. We consider that a given strategy is based on an asset swap short sale (long position) whenever the sum of the discounted trading profits is significantly negative (positive). This sum is significantly negative in Akzo Nobel I, Bouygues II, Scania, Tesco I, and Vodafone in the first subperiod and in Enel, Energias de Portugal I, and Thyssenkrupp in the second subperiod. On the other hand, the sum of the discounted trading profits is significantly positive for the rest of the cases. It means that there are 15 potential long-run arbitrage opportunities based on long positions in ASPs in the first subperiod and 4 in the second one. However, if we attend to the cointegration test's results, there are 20 (7) long-run arbitrage opportunities before (during) the crisis although some of them cannot be exploited.

The significant increase of funding costs during the crisis [see Elizalde and Doctor (2009)] makes difficult to accept that in the cases in which the basis is not stationary there are long-run arbitrage opportunities. However, these cases do reflect a persistent long-run deviation between the corresponding credit spreads. The decrease in long-run arbitrage opportunities is consistent with the increase in correlation across financial markets in crisis periods documented in many papers. Although Table II reports the results obtained from GFI data, the same results are obtained using the other data sources. We next analyze the potential arbitrage opportunities that could be exploited by means of long positions in both ASPs and CDSs based on the statistical arbitrage methodology.

2.7.2 Statistical arbitrage test empirical results

The increments in the discounted cumulative trading profits $\Delta v(t_i)$ are summarized in Table III. Panel A reports the profits obtained in the first subperiod while Panel B reports the profits during the crisis. We observe that the average value is around 72 Euros in the first period and 168 Euros in the second one. These profits present a high deal of variation: 79 and 403 Euros on average in the first and second period, respectively. The coefficient of variation for these profits during the crisis doubles the one obtained in the first period. The vast majority of the cases in which the average basis is negative also have a negative average of $\Delta v(t_i)$.

Table III: Descriptive Statistics for Incremental Cumulative Trading Profits

This table provides descriptive statistics for the increment in the discounted cumulative trading profits, which are obtained from the cash-and-carry arbitrage strategy and are denoted as Δv(t). Panel A reports the descriptive statistics corresponding to the period before crisis while Panel B reports the descriptive statistics corresponding to the crisis. * indicates long-run arbitrage opportunities according to Table II.

Panel A

Issuer	Sample Size	Min (€)	Max (€)	Median (€)	Mean (€)	S.D. (€)	Skewness	Kurtosis
Akzo Nobel I*	252	-263.31	127.31	-15.14	-28.12	89.85	-0.36	2.48
Akzo Nobel II	405	-117.31	314.56	124.47	124.77	87.34	-0.09	2.36
Altadis*	402	-36.73	541.64	220.79	225.94	126.69	0.13	2.47
BMW	343	-118.89	6.38	0.00	-18.63	33.93	-1.43	3.49
Bouygues I*	377	-85.84	378.81	108.99	111.47	100.66	0.20	2.33
Bouygues II*	414	-119.82	5.94	-0.18	-27.97	41.79	-0.98	2.20
British AM Tob. I	418	-224.29	136.07	-1.95	-25.35	75.36	-0.74	4.01
British AM Tob. II	299	49.11	637.32	236.93	258.20	125.55	0.74	2.92
Carrefour I	299	-210.59	342.67	123.07	127.35	70.13	-0.10	5.27
Carrefour II	443	-158.68	10.16	0.02	-20.31	42.58	-1.79	4.67
Casino I*	273	-236.88	531.98	148.18	147.37	124.15	0.22	2.54
Casino II	397	-167.80	554.81	121.12	131.37	127.81	0.70	2.98
Compass Group	405	-36.25	554.61	113.24	129.38	136.74	0.95	3.28
Edison*	404	-33.58	671.12	297.26	273.62	161.16	0.02	1.91
Enel	316	-233.54	122.46	-0.01	-3.99	48.76	-0.93	6.00
Energias de Portugal I	363	-110.53	3.70	-0.04	-25.28	36.30	-0.84	2.00
Energias de Portugal II	349	-127.60	68.35	-0.01	-16.09	44.16	-1.11	3.45
E.ON	410	-116.90	42.08	-0.90	-20.13	35.30	-0.98	3.02
France Telecom I*	146	-33.50	212.43	46.13	52.98	53.61	0.74	3.16
France Telecom II	122	-77.94	158.41	51.03	55.29	42.01	0.33	3.34
France Telecom III	440	-332.43	8.65	0.05	-14.86	67.25	-4.23	18.98
Iberdrola I	400	-84.76	8.87	-0.05	-19.38	30.28	-0.96	2.05
Iberdrola II	348	-107.16	4.15	-1.28	-30.11	33.61	-0.52	1.78
Kingfisher	400	-147.86	222.92	44.36	42.28	60.03	-0.21	3.94
Louis Vuitton I	287	-64.87	345.12	138.34	146.09	70.97	0.12	3.12
Louis Vuitton II	414	-35.14	352.81	119.32	121.76	84.66	0.32	2.43
PPR	353	-120.38	679.26	291.10	285.61	170.16	0.01	2.09
Reed Elsevier	387	-158.42	12.96	-12.63	-35.87	44.16	-0.84	2.38
Renault*	344	-26.46	483.63	188.59	187.04	94.12	0.06	2.80
Repsol YPF	410	-64.16	573.18	151.33	174.82	140.43	0.47	2.27
Reuters*	415	-79.56	523.83	109.21	127.21	111.02	0.70	2.85
Saint Gobain I	398	-326.44	132.47	0.05	2.09	60.54	-0.83	5.38
Saint Gobain II	310	-25.82	402.05	192.10	186.13	81.36	0.15	2.45
Saint Gobain III	452	-132.28	479.56	177.52	160.39	124.46	-0.03	1.95
Scania*	380	-209.71	7.99	0.04	-16.79	49.86	-2.73	8.86
SES*	367	-118.50	93.99	0.00	8.54	24.59	0.19	6.97
Siemens	274	-122.21	24.30	0.00	-10.11	23.42	-2.81	11.59
Sodexho*	403	-0.43	776.56	369.08	357.99	192.90	0.01	1.96
Stora Enso*	449	-147.99	318.71	107.43	104.74	90.16	-0.03	1.97
Technip*	311	-6.32	512.24	137.88	143.40	131.97	0.76	2.89
Telecom Italia I	397	-168.95	67.73	-4.11	-14.96	41.02	-1.31	6.40
Telecom Italia II	338	-327.23	248.78	-8.94	-17.73	90.59	-0.54	3.84
Telefonica*	394	-161.50	351.80	119.98	116.38	96.16	0.11	2.46
Telekom Austria	407	-216.61	10.43	0.04	-23.45	55.39	-2.20	6.49
Tesco I*	411	-124.89	9.89	0.00	-22.96	40.64	-1.27	2.86
Tesco II*	358	-0.04	388.22	187.28	177.83	89.68	0.03	2.07
Thales*	260	-64.51	308.67	72.56	75.33	68.35	0.92	3.83
Thyssenkrupp*	355	-177.82	371.69	117.90	114.70	103.87	0.12	2.35
Union Fenosa	409	-144.62	365.64	107.83	119.61	104.52	0.13	2.04
Veolia Environ	424	-123.08	6.13	-36.26	-36.83	38.85	-0.36	1.62
Vinci	431	-248.46	87.01	-0.02	-18.57	53.56	-1.77	7.32
Vivendi	414	-63.05	299.16	25.82	54.13	71.76	1.20	3.89
Vodafone*	384	-169.58	121.65	-9.99	-24.64	61.25	-0.39	2.45
Volkswagen	310	-232.47	295.36	108.34	109.53	74.00	-0.45	3.95
Volvo	412	-121.11	136.63	-19.39	-24.37	38.92	-0.44	3.46
Average	365	-129.38	262.78	77.21	71.94	78.52	-0.40	3.77

Panel B

Issuer	Sample Size	Min (€)	Max (€)	Median (€)	Mean (€)	S.D. (€)	Skewness	Kurtosis
Akzo Nobel I	480	-312.96	38.05	0.01	-21.73	66.99	-2.87	7.00
Astrazeneca	415	-506.96	187.62	19.78	-33.32	161.45	-0.96	0.10
Auchan	472	-635.74	1373.19	11.49	115.85	381.50	1.54	2.24
BASF	480	-223.42	20.64	-0.01	-17.54	51.05	-2.83	6.88
Bayer	480	-269.88	2987.31	459.25	627.79	582.89	1.16	1.11
Belgacom	480	-308.50	390.79	0.21	36.99	120.29	0.58	2.01
BMW	480	-331.21	25.63	-0.16	-24.83	67.34	-2.75	7.01
Bouygues I	480	-1367.03	1392.84	62.97	57.50	383.58	0.04	2.19
British AM Tob. II*	480	-121.11	5192.88	777.32	1211.50	1176.86	1.19	0.62
Carrefour I	480	-233.06	22.32	-0.36	-24.08	55.41	-2.19	3.62
Carrefour II	463	-203.87	28.80	-1.04	-33.02	62.00	-1.44	0.30
Casino G. P. I	480	-694.12	2827.54	99.17	296.95	603.76	1.76	3.57
Casino G. P. II	442	-1493.23	834.44	-0.25	-93.64	401.82	-0.81	0.94
Casino G. P. III	480	-295.07	4439.21	575.94	921.33	995.94	1.36	1.22
Edison	480	-753.78	3190.80	291.44	536.99	693.19	1.40	1.54
Enel*	480	-404.82	22.50	-0.05	-24.41	83.35	-3.33	9.83
Energias de Portugal I*	312	-327.60	243.70	-0.12	-34.30	93.76	-1.14	2.37
Energias de Portugal II	480	-282.72	27.18	-0.09	-25.69	72.00	-2.56	4.94
France Telecom I	480	-938.23	508.55	0.42	-89.40	316.69	-0.52	-0.64
France Telecom II	480	-622.14	2641.78	357.34	514.26	540.29	1.27	1.39
France Telecom III	480	-239.45	25.13	-0.82	-30.18	62.72	-1.95	2.49
Iberdrola I	480	-252.78	39.22	-0.32	-27.42	64.19	-2.19	3.51
Kingfisher	324	-1425.17	3383.41	77.86	329.24	797.85	0.89	1.49
Louis Vuitton I	480	-1616.56	1107.59	90.56	-36.30	546.18	-0.82	0.43
Louis Vuitton II	445	-1025.47	593.97	29.03	-56.82	362.17	-0.60	-0.32
Philips	480	-572.69	200.56	0.03	-11.42	130.34	-1.89	5.82
PPR	480	-1089.23	344.26	35.50	-10.88	264.10	-1.83	3.68
Repsol YPF	451	-3134.09	2119.35	151.50	97.05	861.39	-1.20	2.68
Saint Gobain II	480	-2070.10	2296.55	141.71	75.26	634.94	0.08	1.27
Saint Gobain III	435	-1617.87	783.78	36.35	-98.24	485.71	-0.88	0.07
Schneider	480	-617.60	1017.40	27.88	50.62	254.37	-0.28	0.36
SES*	480	-522.90	4192.00	264.83	479.69	702.76	2.25	5.92
Siemens	480	-243.25	22.16	-0.07	-23.48	64.81	-2.40	3.92
Technip	480	-1727.33	3282.13	324.61	346.18	649.37	-0.42	1.81
Telecom Italia I	480	-4577.43	1531.38	121.73	-265.17	1253.56	-1.61	1.88
Telecom Italia II	480	-811.16	4560.67	591.18	783.26	812.20	1.37	2.22
Telefonica	480	-1127.02	2126.51	195.86	227.94	391.27	0.84	3.03
Telekom Austria*	372	-589.60	3955.00	272.20	503.60	743.14	2.50	6.50
Teliasonera*	480	-60.45	5151.41	900.01	1257.90	1127.19	1.28	0.97
Tesco I	433	-1568.02	2058.54	25.06	153.66	542.60	1.60	3.20
Tesco II	480	-732.93	1390.59	43.92	119.07	377.67	1.17	1.67
Thales	480	-185.89	21.57	-0.42	-22.50	45.84	-1.85	2.15
Thyssenkrupp*	480	-429.46	57.17	-0.25	-26.40	67.95	-3.56	15.27
Union Fenosa	480	-247.97	60.78	-0.58	-28.10	61.62	-1.70	1.94
Volkswagen	480	-205.68	44.81	-0.62	-25.05	49.73	-1.91	3.04
Volvo	371	-648.70	556.50	76.04	58.94	256.32	-0.31	-0.17
Average	462	-818.79	1463.44	131.65	167.77	402.61	-0.53	2.89

The Panels A and B of Table IV show the results for the analysis of statistical arbitrage under the UM model during the first and second subperiods, respectively. The sign of parameter μ for every company in Panel A is in line with the sign of the mean incremental cumulative trading profits collected in Panel A of Table III with few exceptions (British AM Tob. I and Enel). The unconstrained mean specification is not rejected in most of the cases as the *t-statistic* associated with the parameter θ reveals. We find 16 statistical arbitrage opportunities at 5% confidence level during the period before the crisis. We find that eight of these cases are also long-run arbitrage opportunities. However, the existence of statistical arbitrage is strongly rejected for cases such as Akzo Nobel I, Bouygues II, Scania, Stora Enso, Telefonica, Thales, Thyssenkrupp, Tesco I, and Vodafone where supposedly there are long-run arbitrage opportunities (the basis is not stationary). During the crisis period there are eight statistical arbitrage opportunities and among them, we find the four long-run arbitrage opportunities based on long positions in ASPs. As in the first subperiod, the existence of statistical arbitrage is strongly rejected for some cases in which supposedly there exist long-run arbitrage opportunities (the basis is not stationary) that should be exploited by shorting ASPs such as Enel, Energias de Portugal I, and Thyssenkrupp. Thus, the results obtained using our procedure are different to the ones obtained using the long-run arbitrage test. The reason is that if we employ the cointegration methodology, we are ignoring (i) bonds or ASPs short sales restrictions and (ii) the real risk incurred to obtain arbitrage profits. However, the statistical arbitrage methodology overcomes these two problems. The results obtained with the other data sources (Reuters, CMA, and JPMorgan) are similar to the ones reported in Table IV.[24] The last column in Panels A and B of Table IV show the results using JTTW's test. In fact, we find that both HJTW and JTTW tests offer similar results. A total of 27 arbitrage opportunities at 5% confidence level are found during the first subperiod and 11 during the second one. As expected and given the simulation's results, our test seems to be more conservative than JTTW. The differences between both tests are due mainly to the estimators and the corresponding *p-values* associated with restrictions R_1^c and R_2^c which are defined in Subsection 4.3.[25] The UM model usually presents smaller Akaike Information Criteria (AIC) and Schwarz Information Criteria (SC) than the CM model, suggesting that the former is the most appropriate model. For this reason, we only report the results obtained for the UM model. Comparing Panels A and B of Table III, we observe that the average of the incremental trading profits, $\Delta v(t)$, is noticeably higher during the subprime crisis. This could lead to the appearance of more statistical arbitrage opportunities if that deviation between the ASPs and CDSs spreads persists over time. However, the volatility in credit spreads has also increased considerably during the crisis which makes that the variance of the incremental trading profits also increases and as a consequence, it could even lead to the non-rejection of the restriction R_2^c.

[24] In the period before the crisis, we find an additional statistical arbitrage opportunity using the CMA and the J. P. Morgan databases: Stora Enso. In the crisis period, we find that Edison (Telecom Italia II) does not represent a statistical arbitrage opportunity in the Reuters and CMA databases (Reuters and J.P. Morgan databases) but it does in the J. P. Morgan database (CMA database).

[25] Our test does not reject the absence of statistical arbitrage in some cases in which the mean parameter μ is not significantly different to zero at the 5% level (France Telecom I, Kingfisher, SES, and Vivendi in the first subperiod, and Casino I and Union Fenosa in the second one). With respect to restriction R_2^c, our test does not find that the rate of growth of the mean, θ, is significantly higher than the rate of growth of the variance, λ, for Akzo Nobel II, Thyssenkrupp, and Volkswagen in the period before the crisis and for Volvo in the crisis period. Indeed, in all these cases, the *t-statistic* associated with the difference of the QML parameters $\theta - \lambda$, which is part of the restriction R_2^c in Subsection 4.3, is not significantly higher than zero at a significance level of 5%. Restriction R_2^c ensures that the variance of the incremental trading profits, given a potential drop in them, converges to zero. Note that it corroborates the results obtained when we compare the Type I errors of both tests focused on restriction R_2^c.

Table IV: Statistical Arbitrage Test for Unconstrained Mean (UM) model

Under the UM model, the process for the increment in the discounted cumulative trading profits is defined as $\Delta v_i = \mu i^{\theta} + i^{\lambda} z_i$. Panel A reports the statistical test results obtained for the period before crisis (November 2005 - August 2007) while Panel B reports the results obtained during the crisis (August 2007 - June 2009). The first four columns of each panel include the estimated parameters. The next four columns report the *t-statistic* of the corresponding parameter. The nineth column of each panel shows whether statistical arbitrage (SA) opportunities exist or not. The tenth column of each panel presents the *p-value* associated to the absence of SA. The last column reports the existence or absence of SA under JTTW test. In boldface are the statistical arbitrage opportunities detected by our test. The symbols ***, **, and * denote that the null hypothesis (absence of SA opportunities) is rejected at 1, 5, and 10%, respectively.

Panel A

Issuer	Parameters				t-stat					SA	
	μ	σ	θ	λ	μ	σ	θ	λ	SA	p-value	SA (JTTW)
Akzo Nobel I	$-2\mathrm{x}10^{-3}$	67.55	2.05	0.02	-0.59	5.05	6.53	0.50	No	0.59	No
Akzo Nobel II	14.18	11.46	0.42	0.38	5.05	4.64	11.01	8.98	No	0.35	Yes***
Altadis	**12.48**	**13.82**	**0.56**	**0.38**	**6.24**	**5.06**	**18.45**	**9.83**	**Yes****	**0.04**	**Yes*****
BMW	-59.66	37.89	-0.25	-0.03	-2.76	4.98	-3.00	-0.63	No	1.00	No
Bouygues I	1.52	32.67	0.83	0.18	2.59	5.57	11.84	4.97	Yes*	0.06	Yes***
Bouygues II	-82.59	40.11	-0.22	0.01	-3.63	4.81	-3.66	0.14	No	1.00	No
British AM Tob. I	98.68	90.79	-1.62	-0.03	1.16	4.86	-1.89	-0.67	No	1.00	No
British AM Tob. II	**54.86**	**40.32**	**0.32**	**0.19**	**4.90**	**5.38**	**7.75**	**4.97**	**Yes****	**0.04**	**Yes*****
Carrefour I	39.84	6.03	0.25	0.48	13.48	6.01	14.26	13.91	No	0.92	No
Carrefour II	-71.84	53.33	-0.26	-0.05	-2.66	5.40	-3.18	-1.32	No	1.00	No
Casino I	**7.71**	**27.83**	**0.61**	**0.28**	**2.79**	**4.74**	**8.58**	**6.36**	**Yes****	**0.02**	**Yes*****
Casino II	**3.32**	**28.60**	**0.70**	**0.26**	**2.22**	**7.01**	**8.57**	**9.44**	**Yes*****	**0.00**	**Yes*****
Compass Group	**3.37**	**52.32**	**0.70**	**0.17**	**1.88**	**7.16**	**7.25**	**6.15**	**Yes****	**0.04**	**Yes*****
Edison	**2.71**	**12.80**	**0.87**	**0.34**	**6.56**	**6.52**	**31.78**	**11.30**	**Yes*****	**0.00**	**Yes*****
Enel	0.00	14.79	4.42	0.23	0.00	3.62	53.93	8.23	No	0.86	No
Energias de Portugal I	-74.31	36.63	-0.23	-0.01	-3.59	4.86	-3.61	-0.12	No	1.00	No
Energias de Portugal II	-68.21	47.46	-0.31	-0.02	-2.49	5.34	-3.23	-0.45	No	1.00	No
E.ON	-37.51	40.50	-0.13	-0.03	-2.33	5.62	-1.44	-0.82	No	1.00	No
France Telecom I	0.27	11.86	1.22	0.28	1.45	5.48	8.24	6.44	No	0.10	Yes***
France Telecom II	11.14	5.03	0.40	0.49	4.89	3.71	7.47	7.14	No	0.50	No
France Telecom III	-330.98	73.33	-0.81	-0.03	-4.25	5.26	-4.86	-0.67	No	1.00	No
Iberdrola I	-58.25	33.35	-0.23	-0.02	-3.63	5.15	-3.79	-0.59	No	1.00	No
Iberdrola II	-57.61	27.08	-0.15	0.04	-4.51	4.43	-3.16	0.76	No	1.00	No
Kingfisher	1.57	27.82	0.63	0.14	1.35	5.38	4.70	3.88	Yes*	0.08	Yes***
Louis Vuitton I	**57.60**	**50.72**	**0.20**	**0.06**	**4.70**	**4.99**	**4.52**	**1.37**	**Yes****	**0.04**	**Yes*****
Louis Vuitton II	**1.18**	**26.05**	**0.87**	**0.15**	**3.17**	**6.33**	**15.57**	**4.98**	**Yes****	**0.05**	**Yes*****
PPR	**3.94**	**20.21**	**0.83**	**0.29**	**5.51**	**5.50**	**24.84**	**8.07**	**Yes*****	**0.00**	**Yes*****
Reed Elsevier	-48.31	54.90	-0.06	-0.05	-3.20	5.28	-0.97	-1.19	No	1.00	No
Renault	**11.75**	**19.38**	**0.55**	**0.24**	**6.37**	**5.19**	**18.38**	**6.14**	**Yes****	**0.02**	**Yes*****
Repsol YPF	**0.71**	**13.99**	**1.03**	**0.36**	**3.15**	**7.49**	**18.27**	**14.02**	**Yes****	**0.02**	**Yes*****
Reuters	**0.52**	**8.99**	**1.03**	**0.41**	**2.56**	**7.21**	**14.79**	**15.39**	**Yes****	**0.04**	**Yes*****
Saint Gobain I	4.36	8.76	-1.46	0.36	0.52	6.30	-0.92	11.75	No	1.00	No
Saint Gobain II	**46.42**	**20.30**	**0.28**	**0.23**	**7.81**	**6.01**	**10.89**	**7.03**	**Yes****	**0.05**	**Yes****
Saint Gobain III	0.49	15.38	1.07	0.30	3.41	5.51	20.87	8.72	No	0.13	Yes***
Scania	-68.78	75.84	-0.29	-0.09	-1.86	5.46	-2.50	-2.44	No	1.00	No
SES	0.22	4.49	0.71	0.32	0.88	6.87	3.37	11.28	No	0.10	Yes***
Siemens	-0.43	5.99	0.65	0.28	-0.82	4.81	2.69	6.34	No	0.95	No
Sodexho	**6.52**	**41.16**	**0.76**	**0.15**	**6.64**	**6.53**	**28.16**	**5.16**	**Yes****	**0.03**	**Yes*****
Stora Enso	0.29	9.84	1.08	0.35	2.68	5.36	16.63	9.88	No	0.17	Yes***
Technip	**16.92**	**39.30**	**0.43**	**0.23**	**2.78**	**5.09**	**6.13**	**5.75**	**Yes****	**0.02**	**Yes*****
Telecom Italia I	-4.47	14.91	0.24	0.20	-1.37	4.45	1.67	4.45	No	1.00	No
Telecom Italia II	$-3\mathrm{x}10^{-4}$	32.82	2.17	0.19	-0.41	5.46	4.97	5.15	No	0.58	No
Telefonica	0.36	10.71	1.09	0.35	2.91	5.54	17.72	9.76	No	0.17	Yes***
Telekom Austria	-43.98	70.42	-0.13	-0.05	-1.63	5.86	-1.02	-1.47	No	1.00	No
Tesco I	-78.92	40.38	-0.26	$-1\mathrm{x}10^{-3}$	-3.37	5.29	-3.81	-0.03	No	1.00	No
Tesco II	**6.96**	**22.14**	**0.63**	**0.16**	**6.85**	**6.74**	**23.46**	**5.39**	**Yes*****	**0.00**	**Yes*****
Thales	48.80	26.02	0.09	0.20	4.06	4.67	1.67	4.39	No	0.63	No
Thyssenkrupp	18.67	17.40	0.36	0.35	4.18	4.45	7.61	7.69	No	0.53	No
Union Fenosa	0.55	19.32	1.01	0.26	2.74	6.79	15.69	9.12	No	0.24	Yes***
Veolia Environ.	-39.40	44.15	-0.01	-0.03	-3.60	5.59	-0.25	-0.74	No	1.00	No
Vinci	-0.42	8.50	0.71	0.35	-0.92	5.03	3.60	9.00	No	0.94	No
Vivendi	0.94	9.68	0.77	0.36	1.58	6.58	6.66	12.37	No	0.11	Yes***
Vodafone	$-2\mathrm{x}10^{-7}$	2.18	3.44	0.60	-0.49	3.92	9.70	11.81	No	0.47	No
Volkswagen	17.07	17.09	0.38	0.27	4.66	6.74	8.81	9.00	No	0.11	Yes***
Volvo	-6.68	40.84	0.25	-0.01	-1.94	5.89	2.68	-0.38	No	1.00	No

Panel B

Issuer	Parameters				t-stat				SA	SA	SA (JTTW)
	μ	σ	θ	λ	μ	σ	θ	λ	SA	p-value	
Akzo Nobel I	-238.73	67.18	-0.53	-0.01	-3.89	5.38	-6.08	-0.15	No	1.00	No
Astrazeneca	-0.25	82.09	0.93	0.13	-0.44	5.26	2.32	3.48	No	0.67	No
Auchan	-157.36	14.62	-1.17	0.58	-10.74	8.06	-3.69	25.18	No	1.00	No
BASF	-76.46	65.90	-0.30	-0.05	-1.99	6.12	-2.71	-1.68	No	1.00	No
Bayer	**4.12**	**17.32**	**0.92**	**0.58**	**2.55**	**5.18**	**13.09**	**15.83**	**Yes****	**0.04**	**Yes*****
Belgacom	4.65	11.35	0.40	0.44	1.72	3.94	3.58	9.06	No	0.53	No
BMW	-198.15	71.26	-0.44	-0.01	-3.35	5.47	-5.33	-0.43	No	1.00	No
Bouygues I	10.91	21.76	0.36	0.51	1.88	7.04	3.53	19.21	No	0.65	No
British AM Tob. II	**0.69**	**11.45**	**1.35**	**0.74**	**2.59**	**8.38**	**20.07**	**33.28**	**Yes****	**0.03**	**Yes*****
Carrefour I	-70.70	69.77	-0.21	-0.05	-2.09	5.97	-2.17	-1.46	No	1.00	No
Carrefour II	-91.26	69.85	-0.20	-0.02	-2.48	5.60	-2.41	-0.73	No	1.00	No
Casino I	0.15	10.45	1.45	0.75	0.92	7.30	7.74	29.21	No	0.16	Yes**
Casino II	0.00	4.06	2.65	0.41	-0.34	5.93	5.42	12.82	No	0.67	No
Casino III	**1.08**	**21.69**	**1.22**	**0.64**	**2.05**	**7.23**	**14.37**	**24.51**	**Yes****	**0.05**	**Yes*****
Edison	**1.36**	**32.40**	**1.09**	**0.52**	**1.83**	**8.14**	**11.38**	**22.79**	**Yes****	**0.05**	**Yes*****
Enel	-82.74	116.84	-0.24	-0.07	-1.42	6.40	-1.67	-2.28	No	1.00	No
Energias de Portugal I	-66.19	98.89	-0.12	-0.01	-1.75	5.64	-1.08	-0.35	No	1.00	No
Energias de Portugal II	-82.64	96.30	-0.23	-0.06	-1.72	6.28	-2.03	-1.93	No	1.00	No
France Telecom I	72.24	43.58	-0.38	0.37	2.36	5.35	-2.51	10.51	No	1.00	No
France Telecom II	23.22	15.56	0.57	0.61	4.01	5.63	11.74	18.07	No	0.55	No
France Telecom III	-104.98	74.34	-0.25	-0.04	-2.50	5.73	-2.92	-1.06	No	1.00	No
Iberdrola I	-89.98	78.76	-0.24	-0.04	-2.14	5.80	-2.42	-1.27	No	1.00	No
Kingfisher	0.00	15.45	2.30	0.74	0.25	5.86	3.14	21.39	No	0.46	No
Louis Vuitton I	-11.53	16.33	-0.94	0.63	-0.76	5.99	-1.05	19.99	No	1.00	No
Louis Vuitton II	-176.41	23.14	-0.79	0.51	-8.16	5.18	-4.74	13.82	No	1.00	No
Philips	-80.45	82.09	-0.43	0.09	-1.39	5.25	-2.15	2.42	No	1.00	No
PPR	-135.61	79.49	-0.57	0.22	-2.20	6.17	-2.64	7.30	No	1.00	No
Repsol YPF	3.90	11.75	0.68	0.75	1.73	8.53	6.28	34.31	No	0.44	No
Saint Gobain II	29.38	16.66	0.32	0.65	3.73	6.11	5.31	21.15	No	0.93	No
Saint Gobain III	0.00	52.84	2.12	0.40	-0.31	5.68	3.95	12.07	No	1.00	No
Schneider	11.01	18.70	0.32	0.48	1.82	4.50	2.87	11.39	No	0.64	No
SES	**0.26**	**2.86**	**1.36**	**0.94**	**2.18**	**6.67**	**13.82**	**33.24**	**Yes****	**0.05**	**Yes*****
Siemens	-166.11	71.49	-0.41	-0.02	-2.97	5.55	-4.70	-0.66	No	1.00	No
Technip	3.82	3.54	0.85	0.93	3.76	5.34	16.54	26.17	No	0.80	No
Telecom Italia I	72.40	9.96	0.07	0.85	8.74	8.02	1.07	36.51	No	1.00	No
Telecom Italia II	**16.25**	**21.86**	**0.71**	**0.56**	**3.39**	**6.55**	**13.01**	**21.43**	**Yes****	**0.05**	**Yes*****
Telefonica	24.20	13.19	0.42	0.60	4.56	7.18	9.36	22.94	No	0.76	No
Telekom Austria	**0.21**	**2.23**	**1.47**	**1.04**	**2.11**	**7.49**	**17.59**	**41.54**	**Yes****	**0.05**	**Yes*****
Teliasonera	**7.01**	**9.26**	**0.92**	**0.70**	**6.60**	**24.42**	**69.97**	**7.44**	**Yes****	**0.04**	**Yes*****
Tesco I	-128.68	5.52	-0.24	0.81	-25.52	6.76	-6.23	29.18	No	1.00	No
Tesco II	-108.21	15.23	-0.48	0.58	-8.25	6.99	-5.20	21.55	No	1.00	No
Thales	-32.44	49.43	-0.07	-0.01	-2.06	5.81	-0.76	-0.46	No	1.00	No
Thyssenkrupp	-69.91	86.34	-0.19	-0.05	-1.83	5.92	-1.73	-1.49	No	1.00	No
Union Fenosa	0.40	33.52	1.29	0.53	1.35	7.03	10.09	19.71	No	0.12	Yes***
Volkswagen	-83.03	56.11	-0.24	-0.03	-2.80	5.85	-3.16	-0.79	No	1.00	No
Volvo	10.22	62.75	0.30	0.27	1.18	5.96	2.16	8.57	No	0.25	Yes**

Table V shows the profits, the total investment, the returns, the probability of a loss, the Fisher's skewness of the payments when these are below the percentile 33% and a performance ratio of the arbitrage opportunities. As one of the statistical arbitrage conditions states that investors are only concerned about the variance of a potential decrease in wealth, we avoid penalizing positive profit deviations from their expected values, since investors benefit from these deviations. For this reason, as a performance measure ratio we show a modified version of the symmetric downside risk Sharpe ratio in Ziemba (2005). This performance ratio is defined as the ratio between the total profits and the corresponding semi-standard deviation of payments.[26] To take into account the downside risk in the payments and more specifically, the downside risk in the losses or lower payments, we employ the skewness of the payments below the percentile 33% given that the investors could be averse to negative skewness. In Figure 1 we show Fisher's skewness as defined above to clarify the economic difference between our test and JTTW's test. Before the crisis and using our test, all statistical arbitrage opportunities have positive skewness except in one case (-0.04). On the other hand, the arbitrage opportunities discarded by our test but accepted by JTTW's test all have negative skewness ranging from ($-0.08, -2.36$). During the crisis and using our test, all statistical arbitrage opportunities have positive skewness except in one case (-0.05).

[26] The semivariance of payments is calculated as:

$$\sigma_-^2 = \frac{\sum_{i=1}^{n} (payment_i - \overline{payment}^*)_-^2}{n-1}$$

where $payment_i$ represents the payment at time i, $\overline{payment}^*$ refers to the payment in the 30th percentile and n defines the number of observations. The summatory is applied whenever the payment is below $\overline{payment}^*$. The modified version of the Ziemba ratio is defined as:

$$S_- = \frac{Total\ Profits}{\sqrt{2}\sigma_-}.$$

On the other hand, the arbitrage opportunities discarded by our test but accepted by JTTW's test all have negative skewness ranging from $(-1.45, -2.24)$. Therefore, as explained in Section 5 there is a relevant economic difference between JTTW's test and ours. Arbitrageurs engaging in arbitrage opportunities detected by JTTW's test (but not detected by our test) are exposed inadvertently to significant downside risk that is even more extreme during the crisis period.

Figure 1: Fisher's skewness of the payments below the percentile 33%

This figure shows the Fisher's skewness of the payments when these are below the percentile 33%. Figure 1.1 shows the Fisher's skewness for the arbitrage opportunities detected by our test and by JTTW's test before the crisis. Figure 1.2 shows the Fisher's skewness for the arbitrage opportunities detected by our test and by JTTW's test during the crisis.

Figure 1.1

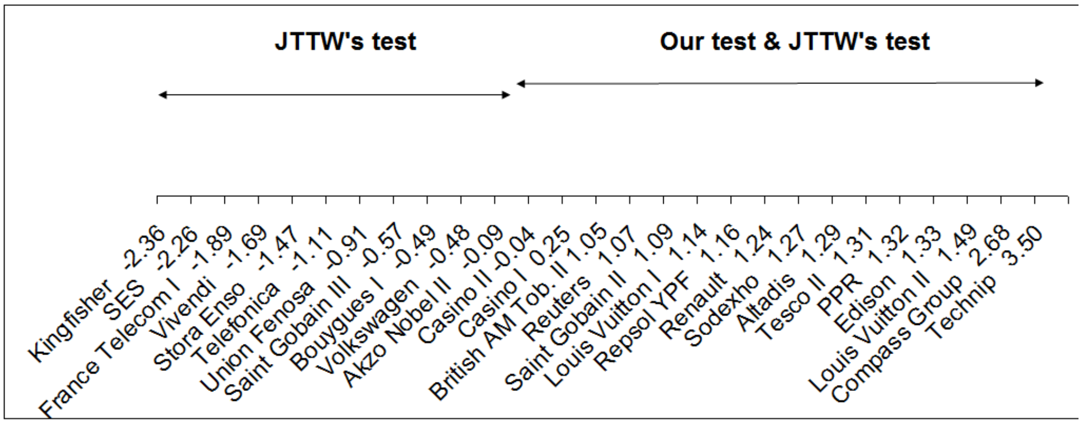
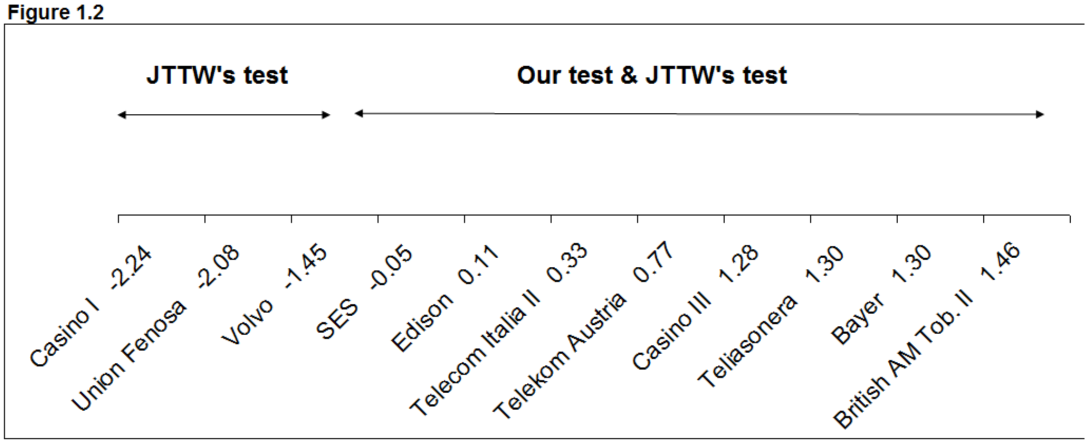


Figure 1.2



In Table V we show that the number of investment days presents a high deal of variation. In fact, we observe that in some cases this number is even below ten. The reason is that in those cases, the investment strategy stops because the total expected future losses exceed €25,000.[27] Regarding the profits and the performance measures

[27] As the stop rule imposed to the strategy leads to a low number of investment days in some of the cases in which the existence of statistical arbitrage is rejected, we extend the analysis by excluding this stop rule and find similar results (see Section 8). In this case the number of investment days coincides with the number of observations reported in the Panel B of Table I whenever the trading strategy does not stop due to other reasons. Note also that the cases in which the investment strategy stops due to the high expected future losses, correspond to potential statistical arbitrage opportunities using inverse positions based on short sales of ASPs.

obtained during the period before the crisis which are reported in Panel A of Table V, it should be noted that the only attractive opportunities compared to the ones where our test finds statistical arbitrage are: Saint Gobain III and Vivendi. However, the probability of loss in Saint Gobain III is around 10%, while in Vivendi investments take place on only 23% of the total potential trading days, respectively, and so total profits are low. On the other hand, we find statistical arbitrage opportunities under both HJTW and JTTW methodologies which correspond to cases with either a high probability of a loss or a poor performance or both, such as Bouygues I, France Telecom I, Kingfisher, SES, Stora Enso, Union Fenosa, or Volkswagen. These are rejected under our test. According to the profits and performance measures corresponding to the crisis period which are reported in Panel B, we observe that the only attractive opportunities that our test does not detect are France Telecom II and Union Fenosa. However, France Telecom II does not fulfill the restriction R_2^c and in Union Fenosa the mean parameter μ is not significantly higher than 0 and moreover the number of days with losses is around 24% of the total. HJTW and JTTW tests consider as statistical arbitrage opportunities Casino I, Union Fenosa, and Volvo. In these cases we observe a high probability of a loss and a poor performance compared with the statistical arbitrage opportunities detected by our test which, on the other hand, seem to be the most profitable opportunities according to all the performance measures of Table V.

Table V: Profits and Performance Measures

Table V reports the profits and performance measures corresponding to the different cases under study. This table splits into two panels. Panel A refers to the period before the crisis (November 2005 - August 2007) while Panel B corresponds to the crisis period (August 2007 - June 2009). The first column of each panel reports the total profits in Euros. The second column of each panel shows the number of investment days while the third one shows the total investment in ASPs or CDSs, which is calculated as the number of investment days multiplied by the nominal of each purchase (500,000 Euros). The fourth column includes the returns in basis points obtained as the ratio between the first and the third columns. The fifth column reports the probability of a loss, which is defined as the ratio between the number of days with losses and the total number of investment days. The sixth column reports the Fisher's skewness of the payments obtained by the investor when these payments are below the percentile 33% (pctl 33). The symbol denotes that the skewness of the payments below the percentile 33% is significantly positive at 5% level. The last column includes a modification of the symmetric downside-risk Sharpe ratio in Ziemba (2005), which is obtained as the ratio between the total profits and the corresponding semivariance of the payments. In boldface are the statistical arbitrage opportunities deteced by our test.

Panel A

Issuer	Total Profits	Number of investment days	Total investment in AS/CDSs	Returns per AS/CDS invest. (b.p.)	Days with losses (%)	Skewness (pctl 33 of payments)	Modified Ziemba Ratio
Akzo Nobel I	-7,089	152	76,000,000	-0.93	0.49	-1.22	-117.71
Akzo Nobel II	50,534	344	172,000,000	2.94	0.06	-0.09	871.42
Altadis	**90,829**	**300**	**150,000,000**	**6.06**	**0.00**	**1.29***	**1274.58**
BMW	-6,391	15	7,500,000	-8.52	1.00	-1.11	-114.33
Bouygues I	42,025	197	98,500,000	4.27	0.11	-0.49	880.47
Bouygues II	-11,578	21	10,500,000	-11.03	1.00	-1.05	-234.42
British AM Tob. I	-10,595	42	21,000,000	-5.05	0.76	-1.45	-140.05
British AM Tob. II	**77,202**	**232**	**116,000,000**	**6.66**	**0.00**	**1.05***	**2632.81**
Carrefour I	38,077	221	110,500,000	3.45	0.04	-0.08	809.54
Carrefour II	-8,996	13	6,500,000	-13.84	1.00	-1.13	-131.55
Casino I	**40,231**	**148**	**74,000,000**	**5.44**	**0.05**	**0.25**	**1173.74**
Casino II	**52,153**	**196**	**98,000,000**	**5.32**	**0.08**	**-0.04**	**1293.27**
Compass Group	**52,398**	**121**	**60,500,000**	**8.66**	**0.01**	**2.68***	**24460.91**
Edison	**110,543**	**339**	**169,500,000**	**6.52**	**0.00**	**1.33***	**1610.33**
Enel	-1,263	91	45,500,000	-0.28	0.58	-1.68	-21.70
Energias de Portugal I	-9,176	21	10,500,000	-8.74	1.00	-1.07	-474.67
Energias de Portugal II	-5,615	37	18,500,000	-3.04	0.62	-1.32	-106.64
E.ON	-8,255	43	21,500,000	-3.84	0.70	-1.20	-251.67
France Telecom I	7,735	119	59,500,000	1.30	0.09	-1.89	597.31
France Telecom II	6,745	100	50,000,000	1.35	0.01	-0.74	268.70
France Telecom III	-6,537	3	1,500,000	-43.58	1.00	-1.08	-65.60
Iberdrola I	-7,752	19	9,500,000	-8.16	1.00	-1.05	-439.92
Iberdrola II	-9,596	28	14,000,000	-6.85	1.00	-1.08	-615.27
Kingfisher	16,911	270	135,000,000	1.25	0.19	-2.36	396.31
Louis Vuitton I	**41,928**	**251**	**125,500,000**	**3.34**	**0.01**	**1.14***	**975.46**
Louis Vuitton II	**50,408**	**345**	**172,500,000**	**2.92**	**0.03**	**1.49***	**1127.47**
PPR	**100,819**	**289**	**144,500,000**	**6.98**	**0.02**	**1.32***	**1117.27**
Reed Elsevier	-13,883	36	18,000,000	-7.71	0.97	-1.11	-414.19
Renault	**64,342**	**249**	**124,500,000**	**5.17**	**0.01**	**1.24***	**1058.43**
Repsol YPF	**71,678**	**298**	**149,000,000**	**4.81**	**0.04**	**1.16***	**1665.42**
Reuters	**52,793**	**229**	**114,500,000**	**4.61**	**0.02**	**1.07***	**1684.79**
Saint Gobain I	833	312	156,000,000	0.05	0.51	-1.92	15.86
Saint Gobain II	**57,699**	**261**	**130,500,000**	**4.42**	**0.00**	**1.09***	**1818.04**
Saint Gobain III	72,495	348	174,000,000	4.17	0.09	-0.57	1402.95
Scania	-6,382	7	3,500,000	-18.23	1.00	-1.11	-84.03
SES	3,134	52	26,000,000	1.21	0.35	-2.26	179.61
Siemens	-2,771	36	18,000,000	-1.54	0.83	-1.89	-83.01
Sodexho	**144,270**	**350**	**175,000,000**	**8.24**	**0.00**	**1.27***	**1386.46**
Stora Enso	47,029	250	125,000,000	3.76	0.13	-1.47	1136.87
Technip	**44,597**	**112**	**56,000,000**	**7.96**	**0.00**	**3.50***	**1339.04**
Telecom Italia I	-5,940	63	31,500,000	-1.89	0.70	-1.65	-138.85
Telecom Italia II	-5,993	197	98,500,000	-0.61	0.56	-1.47	-77.62
Telefonica	45,854	317	158,500,000	2.89	0.09	-1.11	1015.34
Telekom Austria	-9,545	11	5,500,000	-17.35	1.00	-1.18	-109.26
Tesco I	-9,439	150	75,000,000	-1.26	1.00	-1.07	-139.61
Tesco II	**63,664**	**250**	**125,000,000**	**5.09**	**0.00**	**1.31***	**1070.41**
Thales	19,586	110	55,000,000	3.56	0.05	-0.77	738.67
Thyssenkrupp	40,719	235	117,500,000	3.47	0.10	-1.90	820.77
Union Fenosa	48,922	250	125,000,000	3.91	0.13	-0.91	1036.56
Veolia Environ.	-15,617	34	17,000,000	-9.19	1.00	-1.06	-727.89
Vinci	-8,006	53	26,500,000	-3.02	0.66	-1.67	-110.11
Vivendi	22,408	97	48,500,000	4.62	0.08	-1.69	2131.29
Vodafone	-9,462	233	116,500,000	-0.81	0.52	-1.16	-198.53
Volkswagen	33,954	256	128,000,000	2.65	0.05	-0.48	681.39
Volvo	-10,040	71	35,500,000	-2.83	0.69	-1.20	-320.31

Panel B

Issuer	Total Profits	Number of investment days	Total investment in AS/CDSs	Returns per AS/CDS invest. (b.p.)	Days with losses (%)	Skewness (pctl 33 of payments)	Modified Ziemba Ratio
Akzo Nobel I	-10,431	6	3,000,000	-34.77	1.000	-1.11	-101.75
Astrazeneca	-13,828	81	40,500,000	-3.41	0.407	-1.31	-99.34
Auchan	54,683	169	84,500,000	6.47	0.373	-1.70	305.36
BASF	-8,417	7	3,500,000	-24.05	1.000	-1.17	-107.18
Bayer	**301,341**	**347**	**173,500,000**	**17.37**	**0.032**	**1.30***	**2000.15**
Belgacom	17,754	38	19,000,000	9.34	0.289	-1.54	212.54
BMW	-11,920	8	4,000,000	-29.80	1.000	-1.22	-114.36
Bouygues I	27,598	260	130,000,000	2.12	0.377	-1.83	86.12
British AM Tob. II	**581,521**	**300**	**150,000,000**	**38.77**	**0.017**	**1.46***	**2386.71**
Carrefour I	-11,560	11	5,500,000	-21.02	1.000	-1.21	-130.99
Carrefour II	-15,850	13	6,500,000	-24.38	1.000	-1.05	-156.35
Casino G. P. I	177,187	200	100,000,000	17.72	0.230	-2.24	1065.67
Casino G. P. II	-18,947	190	95,000,000	-1.99	0.453	-1.46	-122.91
Casino G. P. III	**442,238**	**231**	**115,500,000**	**38.29**	**0.056**	**1.28***	**2584.89**
Edison	**257,755**	**338**	**169,000,000**	**15.25**	**0.080**	**0.11**	**1780.05**
Enel	-11,719	5	2,500,000	-46.87	1.000	-1.13	-92.62
Energias de Portugal I	-16,025	20	10,000,000	-16.02	0.750	-1.27	-126.52
Energias de Portugal II	-12,331	7	3,500,000	-35.23	1.000	-1.09	-111.00
France Telecom I	-17,910	154	77,000,000	-2.33	0.442	-1.19	-211.82
France Telecom II	246,844	298	149,000,000	16.57	0.108	-0.27	1626.87
France Telecom III	-14,488	13	6,500,000	-22.29	1.000	-1.22	-143.50
Iberdrola I	-13,160	10	5,000,000	-26.32	1.000	-1.16	-129.91
Kingfisher	106,675	146	73,000,000	14.61	0.267	-1.77	233.51
Louis Vuitton I	-17,424	282	141,000,000	-1.24	0.379	-1.43	-33.23
Louis Vuitton II	-17,272	243	121,500,000	-1.42	0.449	-1.28	-103.31
Philips	-5,484	44	22,000,000	-2.49	0.455	-1.96	-33.04
PPR	-5,221	116	58,000,000	-0.90	0.379	-1.85	-15.63
Repsol YPF	46,583	358	179,000,000	2.60	0.310	-1.95	49.07
Saint Gobain II	36,126	384	192,000,000	1.88	0.393	-1.56	71.12
Saint Gobain III	-17,957	202	101,000,000	-1.78	0.361	-1.31	-107.86
Schneider	24,296	110	55,000,000	4.42	0.364	-1.47	101.75
SES	**230,252**	**119**	**59,500,000**	**38.70**	**0.091**	**-0.05**	**2721.04**
Siemens	-11,270	7	3,500,000	-32.20	1.000	-1.04	-112.62
Technip	166,168	194	97,000,000	17.13	0.144	-2.17	328.26
Telecom Italia I	-19,283	205	102,500,000	-1.88	0.341	-1.53	-75.31
Telecom Italia II	**375,964**	**299**	**149,500,000**	**25.15**	**0.057**	**0.33***	**1549.79**
Telefonica	109,413	272	136,000,000	8.05	0.235	-2.53	438.23
Telekom Austria	**366,608**	**250**	**125,000,000**	**29.33**	**0.056**	**0.77***	**3242.14**
Teliasonera	**479,520**	**250**	**125,000,000**	**38.36**	**0.007**	**1.30***	**2186.69**
Tesco I	73,755	276	138,000,000	5.34	0.453	-2.30	308.19
Tesco II	57,154	250	125,000,000	4.57	0.408	-1.56	294.27
Thales	-10,800	15	7,500,000	-14.40	0.933	-1.23	-145.61
Thyssenkrupp	-12,673	12	6,000,000	-21.12	1.000	-1.81	-118.63
Union Fenosa	240,685	250	125,000,000	19.25	0.236	-2.08	965.01
Volkswagen	-12,026	15	7,500,000	-16.03	1.000	-1.31	-149.18
Volvo	23,846	150	75,000,000	3.18	0.373	-1.45	116.86

The previous results are concentrated on the income from the basis itself and ignore any of the funding costs involved in entering the trade. Although during the period prior to the crisis, funding costs are probably very low, the situation changes after the summer of 2007 and funding costs increases significantly. Funding costs are a function of the investor credit quality and of the credit quality of the underlying instrument (e.g. investment grade vs. high yield). Elizalde and Doctor (2009) denote investors who have access to cheap credit as "banks" and investors who are required to pay higher levels of funding as "hedge funds". Elizalde and Doctor (2009) estimations for the "banks" and "hedge funds" costs of funding long risk positions in bonds for a typical investment grade bond are: 6 / 25 b.p. in July 2008, 51 / 101 b.p. in October 2008 and 14 / 44 b.p. in July 2009. On the other hand, the funding costs before August 2007 were negligible for the "banks".

We find that if the annualized average funding cost associated to each investment during the period before the crisis is greater than 2 b.p. the statistical arbitrage opportunities disappear in British AM Tob. II, Louis Vuitton I and II, Repsol YPF, Reuters, Saint Gobain II, and Technip. When they are greater than 3 b.p., the same is true for Altadis, Casino I and II, and Compass Group. Ditto for 4 b.p. in Edison and Renault; and in PRR and Tesco II for 5 b.p.. Finally, the statistical arbitrage opportunity found in Sodexho remains until costs exceed 7 b.p..[28] We conclude that for a highly rated investor (bank), statistical arbitrage opportunities are profitable even after the use of funding costs given that they are negligible before the crisis and that the underlying

[28] We are considering average constant funding costs for the corresponding period although it is likely that an investor would have to renew their funding at regular intervals and so would be somewhat exposed to changes in the levels of funding. To have a better perspective of these average costs, the average ASP, bond, and CDS spread during the period before the crisis is around 25 b.p. and, so, a cost of 3 b.p. is around 12% of the credit spread.

instruments are investment grade bonds.

We find that if the annualized average funding cost associated to each investment during the crisis is greater than 1 b.p., the statistical arbitrage opportunities disappear in SES, Telecom Italia II, and Telekom Austria. When they are greater than 2 b.p., the same is true for Casino III and Edison. Ditto for 3 b.p. in Bayer, British AM. Tob. II, and Teliasonera. According to the funding costs of the long risk positions estimated by Elizalde and Doctor (2009), we conclude that no statistical arbitrage opportunity remains during the crisis neither for "banks" nor for "hedge funds" investors.

In addition to funding costs, the trading costs probably increased during the crisis. This increase reinforces the absence of statistical arbitrage opportunities during the crisis but it could also affect to the statistical arbitrages that were found before the crisis. We employ the quote-level data to answer this question and add the trading costs, which are measured by means of the bid-ask spread, to the strategy's profits. We find that the number of statistical arbitrage opportunities decreases to nine: Altadis, British AM Tob. II, Compass Group, Edison, PRR, Renault, Saint Gobain II, Sodexho, and Tesco II.

Although shorting a corporate bond or ASP is not always a feasible option, we also apply the statistical arbitrage test to the strategy based on short positions both in Portfolio I and Portfolio II for the whole sample of entities. We find three additional statistical arbitrage opportunities during the period before the crisis (Carrefour II, British AM Tob. I, and France Telecom III). The number of statistical arbitrage opportunities increases to eight during the crisis (Astrazeneca, BASF, Enel, France Telecom III, Iberdrola I, PPR, Thyssenkrupp, and Volkswagen). It shows that there exists a noticeable difference between both subperiods. Nevertheless, during the crisis the ASPs short sales are less feasible and most costly than under a normal regime. It could prevent investors to exploit potential arbitrage opportunities and then, deviations from the equivalence relation between ASPs and CDSs spreads could persist over time.

During periods of financial distress, the cash-and-carry strategy based on ASPs and CDSs is not completely riskless due to a higher risk of default, to a liquidity premium derived from the uncertainty about ASPs and CDSs' liquidity, to market segmentation, to funding risk which could affect ASPs and to counterparty risk in CDSs. The influence of the previous aspects could cause that credit spreads depart farther from the no-arbitrage relation. We find persistent deviations between credit spreads, based on either long or short risk positions, in 34.8% of the cases during the crisis.

Finally, we test how asset swaps, bonds and CDSs characteristics influence the existence of statistical arbitrage. We employ a Probit regression model with heteroskedasticity robust standard errors for the total 101 cases studied in both subperiods, using as dependent variable a dummy variable that equals one if there is a statistical arbitrage opportunity, ignoring funding and trading costs, and zero otherwise. To control and test the effect of the crisis, we create a dummy variable equal to one if a given case corresponds to the crisis period. As the coefficients in the Probit model are difficult to interpret, we compute the marginal effects that indicate the change in the probability of statistical arbitrage for a marginal change in the independent continuous variable or for a discrete change in the independent dummy variable. Results are shown in Table VI. The statistical arbitrage opportunities seem to be more frequent when the asset swaps packages contain relatively low-rated bonds. Thus, the higher the issuer risk, the more frequent are the persistent deviations between CDSs and ASPs spreads. Moreover, apparent long-run arbitrage opportunities are related with statistical ones. Thus, a long-run arbitrage opportunity is also a statistical arbitrage one with a probability around 28.5%. The bond coupon has a non-significant effect. Finally, the crisis dummy has a non-significant effect on statistical arbitrage. According to these results, there is one salient factor that determines the existence of statistical arbitrage: the issuer's risk. The higher the issuer's risk, the more valuable are potential factors that could cause deviations between the ASP and CDS spreads: counterparty risk, liquidity, funding costs, and CTD among others. Crouch and Marsh (2005) suggest that as the credit risk rises, the arbitrage forces holding the two levels together begin to weaken. Yu (2006) also finds that speculative obligors produce a higher mean excess return and Sharpe ratio than investment grade obligors for capital structure arbitrage strategies, which relate equity and CDS markets.

Table VI: Determinants of Statistical Arbitrage Opportunities

This table presents the effects of the potential determinants of statistical arbitrage opportunities. The results are estimated by a Probit model with heteroskedasticity robust standard errors. The sample is formed by 101 cases/bonds from two different periods, 55 cases correspond to the period before crisis and 46 of them to the crisis period. The dependent variable is a dummy variable that equals 1 if there is a statistical arbitrage opportunity and 0 otherwise. The potential determinants of statistical arbitrage considered are: *Rating* is a discrete variable with values between 1 and 7, such that 1 corresponds to rating BBB- and 7 to rating AA-, the rest of the values correspond to the intermediate ratings; *Bond coupon*; *Existence of long-run arbitrage opportunities* that refers to a dummy variable equals to one if there exists a long run arbitrage opportunity; *Crisis* which is a dummy variable with value equals to one when the observation corresponds to the crisis period. The first column reports the estimated coefficients. The second column presents the heteroskedasticity-robust standard errors. The third column reports the coefficient *p-value* and last column reports the marginal effect.

	Coefficient	Robust Std. Err.	P-value	Marginal Effect
Rating	-0.375	0.120	0.002	-0.097
Bond coupon	0.220	0.183	0.229	0.057
Existence of long-run arbitrage opportunities	0.935	0.337	0.006	0.285
Crisis	-0.357	0.340	0.295	-0.091
Constant	-0.763	1.055	0.469	
Pseudo R-squared	0.201			
Number of observations	101			
Wald chi2(4 df)	23.220			
Prob > chi2	0.000			

Liquidity could be other salient factor that affects statistical arbitrage. However, as Nashikkar and Subrahmanyam (2007) state, while liquidity is easy to define in theoretical terms, its empirical measurement in an accurate and reliable manner is quite difficult, except in markets that are relatively very liquid. Credit markets are not the most liquid ones and moreover, we find that the potential liquidity proxies are correlated with the issuer rating and bond coupon. We have employed several liquidity measures in the Probit regression but they are not significant with high *p-values* which suggests a potential relation between credit quality and liquidity and so, the liquidity effect could be implicit in the issuer rating or the coupon bond.[29]

Finally, we evaluate the effect of additional factors which have been traditionally considered as determinants of deviations between CDSs and ASPs or bonds:

[29]We have employed as liquidity proxies: the logarithm of the bond issued amount, the number of issued bonds by the underlying company, the bond time-to-maturity (in years), the bond age (in years), the average relative bid-ask spread for the bonds and CDSs, and the number of 5-year CDS missing trading prices during the corresponding period. The last CDS liquidity measure presents more missing trading prices during the crisis.

Funding costs: We find that funding costs have a highly significant effect given that they impede the existence of statistical arbitrage opportunities during the crisis. During this period, there are noticeable deviations from the parity relation but the increase in funding costs makes the apparent arbitrage opportunities non profitable. Thus, these deviations could persist over time given that the arbitrageurs cannot exploit them. This novel fact, regarding the credit derivatives markets, is formally shown in this paper for the first time as far as we know.

ASP short sales restrictions: Other factor that could cause deviations between credit spreads is the relative ease of shorting credit risk in the CDS market compared to the underlying cash market. However, contrary to the long-run arbitrage test, our test is not affected by these restrictions given that the arbitrage strategy is based on ASP and CDS long positions.

Bond price close/far to/from par: The ASP spread is a fair indicator for the CDS spread when the bond price is close to par. However, as the bond price deviates from par the ASP spread's role as a fair indicator worsens. Moreover, when the bond is priced at a discount, buying the ASP could be more attractive than buying the CDS and it suggests that the ASP spread should be greater than the CDS spread. Although we focus on the cases in which the bond price is relatively close to par, we include a proxy that is defined as the difference between the average price during the corresponding period and the par value. We find that this proxy is not significant, suggesting that the statistical arbitrages found by our test are not affected by how far the bond price is away from par. This fact implies that, in all cases, the asset swap is an appropriate indicator for the CDS spread and thus the arbitrage opportunities detected are evidence of persistent mispricings.

Cheapest-to-deliver (CTD) option: The CTD option in the CDS contract could also cause deviations between the credit spreads. Blanco, Brennan, and Marsh (2005) suggest that the violations in the long-run equivalence relation are possibly due to a wider range of deliverable debt obligations. We repeat the Probit analysis using as a proxy for the CTD the total number of bonds issued by the underlying company. This variable is not significant at any standard confidence level.[30]

2.8 Robustness tests and extensions

In this section, we perform some robustness tests and extensions. First, we analyze the effect on results of a periodic liquidation of positions every quarter. Then, we test how the results are affected by increasing the number of trading days without attending to liquidity restrictions and employing quotes instead of transaction prices. We also repeat the analysis by allowing the standard deviation parameter to evolve as a GARCH process. Finally, we study whether a change in the limit of acceptable losses, which had been set at 25,000 Euros, has any influence on the previous results. We comment the results under the model that best fits the data according to AIC and SC.

[30] The existence of counterparty risk could be a factor impacting potential statistical arbitrages. As counterparty risk is difficult to measure and involve many additional issues we left this topic for future research. It should be pointed out that the new practice derived from the Standardized North American Contract (SNAC) could lead to a fall in counterparty risk due to the margin requirements that this contract implies. If the counterparty risk is the main factor that determines the existence of persistent deviations between credit spreads, the deviations should be partly mitigated after the arrival of the SNAC.

2.8.1 Closing positions

The investor positions were not closed in the previous analysis since future losses are perfectly known at the current moment if no default occurs. CDSs transfer credit risk from one party to another and it is possible that the investors only want exposure to risk for a limited period of time. These investors could liquidate their positions at a given price if there is an adequate level of liquidity in this OTC market. Thus, we analyze the same strategy but closing, at the end of every quarter, any investment made during that quarter under the assumption that both CDSs and ASPs positions can be closed at the same time.[31] Positions are closed whenever the basis $(s_t^A - \overline{s}_t)$ is negative to avoid closing positions at dates when an important and certain loss would take place. If the basis is positive at a given date, the positions will be closed on the first subsequent date when it is negative. However, if investors close a high number of positions at a given date, it would lead to a large payment a quarter after that date which is derived from the closed positions. It affects the mean and variance growth rates. Ignoring funding and trading costs, the number of arbitrage opportunities decreases to seven during the period before the crisis (Bouygues I, Louis Vuitton II, Renault, Sodexho, Stora Enso, Technip, and Tesco II) and increases to nine during the crisis period (British AM. Tob. II, Casino III, Edison, Kingfisher, Repsol, SES, Telekom Austria, Teliasonera, and Union Fenosa). If we repeat the analysis closing the positions every 45 days instead of every quarter, we find that the number of statistical arbitrage opportunities before the crisis increases to 18 (the 16 opportunities reported in Panel A of Table IV plus Bouygues I

[31] Note that it is easier to get into credit derivatives contracts than it is to get out of them. The CDSs' maturity is set at a given horizon and the investor can take the other side of the nearest maturity contract and build a book of offsetting positions, or try to sell the current contract.

and Stora Enso). Nevertheless, we find the same nine opportunities during the crisis.

2.8.2 Trading days and CDS prices analysis

The investment strategy is implemented whenever there is an adequate grade of liquidity according to the information on transaction prices. However, we repeat the analysis ignoring this restriction and assume that the investments are implemented every day. For this aim, we employ quotes from CMA, Reuters, J.P. Morgan, and the Fenics curve from GFI. In the first subperiod, we find the same statistical arbitrage opportunities that are reported in Panel A of Table IV and other five additional opportunities. The additional opportunities are common to CMA, J.P. Morgan, and Fenics (GFI) databases: Bouygues I, Saint Gobain III, Stora Enso, Telefonica, and Vivendi. In the crisis period and ignoring funding and trading costs, we find two statistical arbitrage opportunities less, for the four databases, than the ones reported in Panel B of Table IV: Edison and Telecom Italia II.

2.8.3 Trade size analysis

We employ CDSs with a notional equal to €500,000 and assume that the strategy stops if the total investment in a given bond exceeds 25% of the bond's issued amount or if the total expected future losses exceed €25,000. The reason for using this notional is to guarantee a substantial number of investments to test the existence of persistent anomalies in credit markets. However, as in some execution platforms for CDSs the minimum trade size is of €1 million, we repeat the analysis employing CDSs of this notional value and increasing the barrier of losses to €50,000. In the first subperiod we find one additional statistical arbitrage opportunity: Bouygues I. In the crisis period and ignoring funding and trading costs, we find an additional statistical arbitrage opportunity: Union Fenosa.

2.8.4 Nonconstant variance parameter

Although the standard deviation parameter of the profits process, σ, was assumed to be constant, it could evolve as a GARCH process. We have repeated the analysis by letting the standard deviation parameter evolve as a GARCH. Results do not change significantly.

2.8.5 Limit of losses analysis

The barrier of 25,000 Euros for the total expected losses which determine the point at which the strategy stops could seem to be an arbitrary limit. For this reason, we repeated the test with barriers of 10,000 and 50,000 Euros and with no barrier under both UM and CM models. Results confirm that a barrier of 10,000 Euros seems too low given that it could lead to stopping the strategy prematurely. However, a barrier of 50,000 Euros leads to the same results as using a limit of 25,000 Euros for both subperiods. Finally, if the strategy does not stop, independently of the investor's losses, we only find one additional statistical arbitrage opportunity for Tesco I under the CM model in the first subperiod and none under the UM model. As the preferred model for Tesco I is UM, we conclude that the last alternative does not lead to additional statistical arbitrage opportunities and moreover its use would involve a high risk.

2.9 Conclusions

The ongoing financial crisis and its possible consequences for the regulation of financial markets makes the study of the possible persistent mispricing in credit derivatives markets a topic of salient relevance.

We make five contributions to this important topic. First, we present a new test of statistical arbitrage allowing for more general structure in the innovations and which has lower Type I error and selects arbitrage opportunities with lower downside risk than existing alternatives. Second, we apply the new test to a specific segment of the credit derivatives markets: CDS and ASP. We also apply cointegration techniques to the same problem. Our third contribution relates to the appropriate way of testing for arbitrage opportunities. We focus our analysis to test the cases in which long positions in CDSs and ASPs are needed. Fourth, we employ four different databases to show that during the period before the subprime crisis, in 27% of the cases there are long-run arbitrage opportunities and in 29% there are statistical arbitrage opportunities. On the other hand, during the crisis we find 9% of cases of long-run arbitrage and 17% of statistical arbitrage. In this second period, we find a higher correlation between credit spreads and a higher volatility in the basis and the credit spreads. We show that arbitrageurs engaging in arbitrage opportunities detected by the previous alternatives (but not detected by our test) are exposed unwittingly to significant downside risk that is even more extreme during the crisis period. This is an economically relevant difference between JTTW's test and our test besides its better statistical properties. After considering funding and trading costs, we find statistical arbitrage opportunities in 16% of the cases before the crisis but never during the crisis. Nevertheless, the persistent deviations between credit spreads, based on either long or short risk positions, are very frequent during the crisis. Fifth, we show that statistical arbitrage opportunities seem to be more frequent when the ASPs contain relatively low-rated bonds.

In summary, the paper's main empirical findings are: first, before the crisis some persistent mispricings are found. Specifically, CDS spreads are too low in comparison with asset swap spreads. This fact puts into question the efficiency of this segment of the CDS market. Second, once the crisis started, the increase in funding costs makes the apparent arbitrage opportunities non profitable. This novel fact, regarding the credit derivatives markets, is formally shown in this paper for the first time as far as we know. Looking forward, we expect more definite evidence on other arbitrage strategies as well as in other market segments. The new test and the procedure (long positions only) of this paper can also be applied to other financial markets.

CHAPTER 3

THE EFFECT OF LIQUIDITY ON THE PRICE DISCOVERY PROCESS IN CREDIT DERIVATIVES MARKETS IN TIMES OF FINANCIAL DISTRESS

3.1 Introduction

The purpose of this chapter is to analyze the role of liquidity in the price discovery process. Specifically, we focus on the credit derivatives markets in the context of the subprime crisis. Liquidity is defined in terms of the relative number of participants in a given market, i. e. the number of agents operating in one market relative to the number of participants in another market. Our results suggest that this is the main factor that determines the leadership of the price discovery process between the two markets. We present a theoretical model that helps to understand how the process of price discovery works in the asset swap, bond and CDS markets. Then we present an empirical application with data from 2005 to 2009 that confirms the theoretical model's insights.

The importance of liquidity in the corporate bond market is not a new topic. Collin-Dufresne et al. (2001), Perraudin and Taylor (2003), Elton et al. (2001), Delianedis and Geske (2002) and Chen et al. (2007) among others find that liquidity is an additional factor to credit risk which is present in credit spreads. Longstaff et al. (2005) and Tang and Yan (2007) also support the presence of a liquidity premium in CDS spreads. Tang and Yan (2007) find that both liquidity level and liquidity risk[1] are significant factors in determining CDS spreads. De Jong and Driessen (2006) show that not only liquidity in a given market affects credit spreads but there are also liquidity risk and liquidity spillover effects from the treasury bonds and equity markets, effects.

According to Yan and Zivot (2007) an efficient price discovery process is characterized by the fast adjustment of market prices from the old equilibrium to the new equilibrium with the arrival of new information. The new equilibrium is achieved by means of the interactions of buyers and sellers. Thus, the financial instrument price's that contributes more and newer information to the price discovery process should be the one with the highest number of informed market participants. Assuming that in a given market the higher the overall number of market participants, the higher the number of informed agents and given that the overall number of market participants is a measure of market liquidity, we state that liquidity is the common element in price discovery analyses that determines which market reveals information more efficiently. The price discovery analysis has been applied to a wide number of financial instruments such as stocks, commodities and credit markets among others. Working (1948), Stein (1961) and Garbade and Silver (1983) (GS henceforth) can be considered among the pioneers on this topic. GS posit a formal model to analyze the process of price discovery and show empirically that this process is led by the markets where the number of participants is higher, in their case the futures market in comparison with the spot market.

[1]Acharya and Schaefer (2006) posit that liquidity risk can be defined as unpredictable changes in transaction costs and in liquidity. These adverse liquidity shocks, systematic or idiosyncratic, are mainly due to high and negative changes in financial products' returns and reduce the amount of capital available to financial intermediaries which lowers the ability of their trading desk to provide liquidity.

More recently, a number of analyses that study price discovery on the basis of either Hasbrouck's (1995) or Gonzalo and Granger's (1995) (GG henceforth) methodologies have appeared. Both methodologies are supported by an empirical test based on a VAR with an Error Correction Term model. In one of these applications to the commodities market, Figuerola-Ferretti and Gonzalo (2008) (FFG henceforth) develop an econometric approach in order to match the theoretical model of GS (1983) and the econometric methodology of GG based on the permanent-transitory decomposition. They find that the prices of futures on non-ferrous metals are "information dominant" with respect to the spot prices in the most liquid futures markets.

The applications of the price discovery methodology to credit derivatives markets are relatively new, if we compare them with the applications to the futures and spot markets, due to the recent development of CDS market.[2] These applications analyze the efficiency of both CDS and bond markets in terms of price discovery. Blanco et al. (2005) and Zhu (2006) use American and European corporate bonds and CDSs and obtain that the CDS market reflects the information more accurately and quickly than the bond market. The same results are found in Baba and Inada (2007) who repeat the same analysis for subordinated CDS and subordinated bond spreads of Japanese mega-banks. In other analyses of price discovery based on emerging markets sovereign bonds and CDS, Ammer and Cai (2007) find that bond spreads lead CDS premiums more often than has been found for investment-grade corporate credits.[3] Based on

[2] The value of CDSs outstanding at the end of 2004, 2005 and 2006 was $8.42, $17.1 and $34.4 trillion, respectively. The CDS market exploded over the past decade to more than $45 trillion in mid-2007 and more than $62 trillion in the second half of the same year, according to the ISDA. The size of the CDS market in mid-2007 is roughly twice the size of the U.S. stock market (which is valued at about $22 trillion) and far exceeds the $7.1 trillion mortgage market and $4.4 trillion U.S. treasuries market. However, the notional amount outstanding decreased to $38.6 trillion at the end of 2008.

[3] The main reason is the existence of a higher cheapest-to-deliver option due to the higher risk of

iTraxx companies, Dötz (2007) finds that both markets make net contributions to price discovery, with the CDS market dominating slightly the bond market.[4] In general terms, liquidity and credit risk factors are considered as the main determinants of the role of leadership in credit markets.

The analysis of price discovery is extended in Norden and Weber (2004), Forte and Peña (2009) and Coudert and Gex (2008) to the stock market. All of them find that the stock market leads the CDS and bond markets while there is a leading role of the CDS market with respect to the bond market.[5]

However, a formal theoretical model that analyzes the process of price discovery in credit derivatives markets is still lacking. We fill this gap presenting a theoretical model based on the participation of different market players and match this model with GG's econometric methodology by means of FFG's econometric approach. Our model is an extension of GS model allowing for the simultaneous participation of agents in different markets. This is our first contribution.

Moreover, we find another gap in the price discovery literature in credit markets, namely, no analysis of the price discovery process between Asset Swap Packages (ASPs) and CDSs has been carried out up to now.[6] Price discovery in credit markets has focused

borrowers and also to liquidity reasons given that the higher the number of bonds issued, which they use as a liquidity measure, the more difficult is that CDSs leads price discovery.

[4] According to Dötz (2007), the relatively large contribution of the CDS market to price discovery is not necessarily tantamount to general and lasting improvement in the processing of information; the turbulence in the credit markets in spring 2005 was apparently handled much better by the bond market than by the CDS market. The weaknesses of the CDSs are likely to consist in the relatively high concentration and homogeneousness of its market players, whose herding behavior, particularly in times of crisis, can strain liquidity, amplify market volatility and hamper price discovery.

[5] Chan-Lau and Kim (2004) relate the same three financial instruments but for emerging market sovereign issuers. In most countries they do not find any equilibrium price relationship between equity and bond markets and in terms of price discovery it is difficult to conclude that one particular market dominates the price discovery process.

[6] As far as we know, the relationship between ASP and CDS has only been treated in De Wit (2006). However, the perspective adopted in De Wit (2006) is based on the long-run equilibrium that should exist, and which the author finds, between ASP and CDS, ignoring the price discovery process.

on bond and CDS spreads. We analyze the price discovery process between ASPs and CDSs in the time period from 2005 to 2009 and find that the leadership, in terms of price discovery, between ASPs and CDSs is very sensitive to the appearance of the subprime crisis. During the period before the crisis, the CDSs appear clearly as the more efficient market in 87.5% of the cases. During the crisis, ASP spreads reveal more efficiently credit risk than before up to the point that in 71.88% of the cases ASP spreads lead CDS spreads in the price discovery process. This is our second contribution.

De Wit (2006), Felsenheimer (2004) and Francis et al. (2003) among others suggest that ASP spreads should be a more accurate measure of credit risk than bond spreads. Actually, according to Schonbucher (2003), ASPs are liquid instruments and it is even easier to trade an ASP than the underlying defaultable bond alone. We give support to this idea by means of our empirical price discovery analysis for asset swap and bond spreads up to the point that according to GS (1983) terms, we find that the bond market is a "pure satellite" of the asset swap market. This finding is our third contribution.

To summarize, our analysis and results are significant contributions to an important contemporary issue in the discipline of Financial Institutions and Markets research for the following reasons. First, we present a simple theoretical model which helps to understand the process of price discovery in credit derivatives markets in the context of the recent financial crisis. Second, our empirical results may be of special interest for market regulators and investors because they provide a number of insights into the relative reliability of market-based credit risk measures. Given the fact of the relatively low liquidity of CDS market in comparison with bonds and ASPs, our results cast doubts on the representativeness of market prices quoted in the CDS market in periods of financial distress as the current crisis. The key implication of this result is that inferences on the creditworthiness of a given firm based solely in CDS spreads in periods of high market turbulence and low liquidity are bound to be misleading. Third, given that we find that, in all cases, the ASP spread reflects credit risk more efficiently than the bond spread our results suggest that it is more appropiate to use the ASP spread as a credit risk indicator instead of the bond spread.

This chapter is divided into four sections, in Section 2 we describe the price discovery model and the hypotheses to test. Section 3 describes the data. Section 4 presents the price discovery results. Section 5 concludes.

3.2 Price Discovery Model

First of all, we report a brief definition of the two credit derivatives employed in this paper. A CDS is a traded insurance contract which provides protection against credit risk until the occurrence of a credit event or the maturity date of the contract, whichever is first, in exchange for periodic premium payments (the CDS premium or CDS spread) and/or an upfront payment. In the event of default CDSs are settled in one of two ways: by physical settlement or by cash settlement. A buyer of CDS protection on a single name makes regular payments of the CDS' full running spread to the protection seller. The CDS contract that we analyze is unfunded and so investors do not make an up-front payment (ignoring dealer margins and transaction costs). Thus, the traded CDS premium or the market CDS spread is an at-market annuity premium rate $\overline{s}$ such that the market value of the CDS is zero at origination.

An ASP contains a defaultable coupon bond with coupon $\bar{c}$ and an interest-rate swap (IRS) that swaps the bond's coupon (fixed leg) into Euribor plus the asset swap spread rate s^A (floating leg). The asset swap's fixed leg represents the buyer's periodic fixed rate payments, while its floating leg represents the seller's payment. The asset swap spread is chosen so that the value of the whole package is the par value of the defaultable bond and for this reason it is also known as a par to par swap. The Interest Rate Swap (IRS) included in the asset-swap package has zero cost and so the asset swap's cost is equal to the price of the defaultable bond included in the package. As the asset swap spread valuation is obtained using the bond's face value (FV), an up-front payment must be added to the bond's price at the investment period t to ensure that the value of the whole package is FV. The asset swap spread is computed by setting the present value of all cash flows equal to zero and the up-front payment represents the net present value of the swap.

The goal of the price discovery model is to analyze the dynamics and interaction between CDS and ASP spreads in an equilibrium non-arbitrage model.[7] The procedure is based on the behaviour of market participants in the corresponding market place. We adapt and extend to the credit derivatives markets, the model of price discovery developed in GS and focus in the case where the arbitrageurs present a finite elasticity demand/supply of arbitrage services. We modify the model of price discovery developed in GS by considering five different types of market participants instead of three. Each agent that participates in the market place can be classified into one of the following groups:

i) The first group is formed by arbitrageurs. Whenever there exists an adequate

[7] Although we develop the case of CDS and ASP prices, the model can also be applied to study the interaction between CDS and bond spreads or between ASP and bond spreads.

grade of liquidity they try to exploit possible discrepancies among CDS and ASP prices. Thus, they invest whenever a security is trading above/below the "correct price".[8]

ii) Agents that only take positions in the asset swap market. They can be understood either as long-run investors such as portfolio managers that feel attracted by asset swap characteristics or as investors that must hold any capital requirement. Examples of these agents are insurance firms or pension funds that invest in bonds or asset swaps as a "buy and hold" strategy.

iii) Agents that only participate in the CDS market either as protection sellers or buyers. For instance, the CDO issuer usually enters the CDS market as a protection seller.[9] These participants in the CDS market can also be understood in most cases as speculators.[10] Some examples of these agents are hedge funds that benefit from CDSs leverage effect, contrary to the ASPs or bonds, whose buyers incur in an outlay at the investment date.

iv) Agents that participate in both financial markets as market makers. According to Acharya et al. (2007), most of the financial institutions that make markets in corporate bonds are also the liquidity providers in other related segments of the fixed-income markets, specifically in credit markets such as CDSs and CLOs or CDOs. This type of agents can also be considered as financial intermediaries who manage portfolios for

[8] A popular arbitrage strategy employed by hedge funds in credit derivatives markets defines the correct price from a long-term equilibrium price based on the cointegration methodology. The arbitrageur is betting only that the spread between the two cointegrated assets will narrow, which can be understood as a permanent adjustment process towards an economic equilibrium.

[9] As Dötz (2007) state, the market for synthetic CDO products, which as opposed to cash CDS products are not backed by bonds or loans but by CDSs, presents some advantages such as the better availability of CDSs relative to bonds or loans and the heavy demand among investors for unfunded supersenior tranches.

[10] We may also find protection sellers who hedge their positions, again, in the CDS market or individuals that participate in the CDS market in order to hedge their exposures to other institutions that are not due to debt positions.

different customers or simply as investors in credit markets. We consider that these individuals take a given position in one market or the other, attending to their reservations prices for the corresponding market.

v) Agents that use the CDS market to hedge their positions in corporate debt. These agents buy bonds or asset swaps that at the same time are hedged by means of CDSs.[11] They employ CDSs to hedge their bond or ASP positions contrary to the individuals in group iii) who do not have any underlying bond or ASP.

GS, as well as FFG, consider three types of agents and two markets in such a way that the only individuals that operate in both markets are the arbitrageurs. We offer a more general model that includes participants that operate in both markets and hedgers. It means that both markets are not only linked by arbitrageurs as in GS but by the two additional groups of individuals. This aspect is of special relevance for understanding price discovery in credit markets given that price setters in the CDS market are frequently the same as in bonds or asset swap markets and the link is not only given by the arbitrageurs.

3.2.1 Arbitrageur's demand

The procedure employed by arbitrageurs to exploit potential mispricings between CDSs and ASPs is based on a cash-and-carry strategy. This strategy is equivalent to the one employed in Chapter 2 to study the existence of statistical arbitrage opportunities in CDS and ASP markets. The arbitrageur strategy is constructed from the following portfolios depending on if asset swap spread is above (below) CDS spread:

[11] We include this type of agents in order to make the model more comprehensive given that the nature of CDSs is to provide insurance. In fact, CDSs are usually used to manage the credit risk.

Portfolio I

- Long (short) position in a CDS with an annual full running premium equal to $\bar{s}$ which is paid (received) quarterly.

Portfolio II

- Long (short) position in an ASP whose cost is equal to the bond's par value. The investor pays to (receives from) the counterparty the bond's coupon at the coupon dates in exchange for receiving (paying) every quarter the 3-month Euribor rate ($E_{3m,t}$) plus the asset swap spread (s_t^A). The quarterly payments dates coincide with the CDS premium payment dates.[12]

- Loan (deposit) with a principal equal to the bond's face value at 3-month Euribor.[13] Interest payment dates coincide with both CDS premium and asset swap floating leg payment dates.

Portfolio II is equivalent to a synthetic short (long) position in a CDS and so, there should be an equivalence relationship between CDS and asset swap spreads. Otherwise, arbitrage opportunities may appear.[14]

At origination, the cost of both portfolios is zero, and so the net payoff is also zero. A quarter after origination and every subsequent quarter, in case of no default,

[12] As CDSs are OTC instruments, it is possible to buy a CDS contract whose maturity coincides with the bond's maturity and whose premium payments timing is agreed by the parties. As the bond's maturity date approaches, the use of CDSs with a 5-year constant maturity would lead to overhedging, given that the maturity dates of CDSs and asset swaps do not coincide. The consequence is that the investor will pay a CDS spread above the one needed to be fully hedged. Thus, we take advantage of the range of CDSs maturities to fit a CDS curve using a Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) algorithm that allows us to match asset swap and CDS maturities. This method is also used in Levin et al. (2005).

[13] In order to proceed in this way we assume that the investor can borrow money at Euribor flat.

[14] If $s_t^A - \bar{s}_t > 0$, then a profitable arbitrage opportunity exists. The investor should take long positions in both CDS and ASP and borrow the required quantity of money in order to finance the investment at 3 months Euribor. If $s_t^A - \bar{s}_t < 0$, the inverse strategy will lead to an arbitrage opportunity.

a combination of long positions on both the CDS and ASP leads to a net payment for the investor equal to the difference between ASP and CDS spreads, $s_t^A - \overline{s}_t$,[15] both of them converted into quarterly terms using an "actual/360" day count convention.[16] This difference is known as the basis.

However, in case of default, the investor's net payment differs from the basis. On the one hand, the IRS included into the ASP remains alive after default, and it should be serviced or unwound at market value. On the other hand, the CDS accrued premium as well as loan's accrued interests must be paid. Moreover, not only the underlying bond but a given number of bonds, even cheaper than the underlying, can be delivered which gives the holder of a CDS a cheapest-to-deliver (CTD) bond option. Then, the net payment is different from the basis.

In order to find the non-arbitrage equilibrium condition the following assumptions must be imposed:

A1. No limitations on short sales of the ASP.[17]

A2. No limitations on borrowing and no restrictions on participating in the ASPs and CDSs market (market segmentation does not affect the arbitrageur).

A3. No tax effects.

A4. No additional costs except the ones required to fund an ASP position.

Arbitrageurs can be identified as hedge fund investors whose demand takes place after identifying securities that are trading above/below the correct price. Among the

[15] A combination of short positions on both the CDS and ASP leads to a net payment for the investor equal to the difference between CDS and ASP spreads, $\overline{s}_t - s_t^A$.

[16] The net payoff is also zero at coupon payment dates while at bond's maturity, as in every quarterly payment, the net payoff is equal to the basis.

[17] Assumption A1 is necessary to reach a two-sided bound on the CDS rate and to guarantee that the equivalence relationship holds.

strategies employed to exploit arbitrage opportunities in fixed-income markets hedge funds employ merger arbitrage, fixed-income arbitrage, capital structure arbitrage, volatility arbitrage or what is known, from our point of view erroneously, as statistical arbitrage that is based on the cointegration methodology proposed by Engle and Granger (1987).[18] Of the above strategies the one employed to exploit transitory mispricings in CDS and ASP spreads is the one based on the cointegration methodology. The idea is that, given two cointegrated assets, an investor can profit by buying one cointegrated asset and selling the other in case of transitory mispricings. The investor is betting that the spread between the two cointegrated assets will narrow given the cointegration's adjustment process towards an economic equilibrium. Thus, if the ASP spread is too high relative to the long term equilibrium, arbitrageurs will take long positions both in CDSs and ASPs. This long-term no-arbitrage equilibrium condition is also known as the equivalence or parity relationship between ASP and CDS spreads. Thus, we define the arbitrageurs demand on the basis of the following long-run equivalence relationship:

$$s_t^A = \beta_2 \bar{s}_t + \beta_3 \tag{3.1}$$

According to Blanco, Brennan and Marsch's (2005) terminology, β_2 includes nontransient factors besides credit risk.[19] The parameter β_3 includes factors or imperfections that generate a constant difference between both spreads such as institutional factors

[18] An example of a statistical arbitrage analysis in credit derivatives markets according to the technique and concept introduced Hogan et al. (2004) can be found in Chapter 2.

[19] Cossin and Lu (2005) state that the liquidity premium, the CTD option and the market segmentation explain the pricing differences between bonds and CDS. The effect of the CTD option is more important as default risk increases.

causing differences in funding or transaction costs, or other costs in general.

The demand of arbitrageurs will depend on the grade to which the equivalence relationship holds and on their elasticity of demand which is denoted as H:

$$H(\beta_2 \bar{s}_t + \beta_3 - s_t^A), \quad H > 0 \tag{3.2}$$

We assume that there exist an unspecified number of arbitrageurs and β_2 is allowed to be different from 1.[20][21] The possibility of a default means that the cash-and-carry strategy, which is based on long positions in the CDS and short positions in the synthetic CDS or vice versa, is not completely riskless. In case of default, the investor's net payment differs from the basis and the arbitrageur could even incur in losses which means that the strategy is not exempt of risk. Another argument that reinforces the idea that the strategy is not riskless is that the CDS and the synthetic CDS are not exactly the same asset and thus their prices can change in a different way at a given time period. Moreover, although we assume that there are no restrictions on corporate bond and ASP short sales, these may appear in real world.[22] These restrictions make it difficult to exploit arbitrage opportunities whenever short sales are needed and this fact limits the

[20] In their analysis of price discovery in commodity markets, FFG introduce for the first time a price discovery analysis based on a VAR with Error Correction Term that allows a cointegrating vector $(1, -\beta_2)$ different from $(1, -1)$.

[21] If the two markets price credit risk equally in the long run, then their prices should be cointegrated with cointegrating vector $[1, -1, c]$, suggesting a stationary basis.

[22] Shorting a corporate bond or an ASP with a required maturity, even years, is not an easy task. The short sale of bonds or ASPs could be done via a repurchase agreement (repo) but as Blanco et al. (2005) explain, it is impossible to borrow a bond via a repo. The reason is that repo market for corporate bonds is illiquid and even if it is possible to short a bond via a repo, the tenor of the agreement would be short. Schonbucher (2003) states that this limitation could be solved by issuing credit-linked notes linked to the corresponding bond and selling them to the investors in the asset swap market. This alternative presents other limitations given that the issuance of credit-linked notes takes time and implies high fixed cost. This fact implies that deviations in the equivalence relationship might not imply arbitrage opportunities whenever an asset swap short sale is needed. Thus, in some cases traders are not able to exploit price differentials when the CDS premium is higher than the asset swap spread and as Blanco et al. (2005) suggest, this asymmetry may affect significantly the dynamic adjustment of credit spreads. The restrictions on short-sales could be even more severe in periods of financial distress.

arbitrageurs demand. Moreover, there could be constraints in the short-run availability of arbitrage capital or restrictions to market participation. For this reason it seems more realistic to assume that H is finite. GS also consider as more realistic a finite value for H in the commodities markets.

3.2.2 Demand schedule of market participants

The behaviour of the other agents in the market place is defined according to their demand schedules. Thus, the demand schedule for the j^{th} participant who deals only in ASP market is:

$$E_{j,t} - A^{ASP}(R_{j,t}^{ASP} - s_t^A), \quad A^{ASP} > 0, j = 1, ...N_{ASP} \tag{3.3}$$

where according to GS notation we define $E_{j,t}$ as the ASP endowment of the j^{th} participant immediately prior to period t, N_{ASP} is the number of participants who deal only in the asset swap market. Let $R_{j,t}^{ASP}$ be the reservation price at which participant j^{th} is willing to hold the endowments of ASPs $E_{j,t}$ while A^{ASP} represents the elasticity of demand which is assumed to be the same for the N_{ASP} participants. $A^{ASP}(R_{j,t}^{ASP} - s_t^A)$ represents the variation in the endowments prior to period t, $E_{j,t}$. An increase in the asset swap spread means an increase in the ASP buyers' returns as these are given by the sum of the floating rate and the asset swap spread. It leads to an increase in the ASP endowments prior to period $t+1$, $E_{j,t+1}$, whenever $R_{j,t}^{ASP} < s_t^A$. It is the reservation price with respect to the ASP spread what defines an investor as ASP seller or buyer.

The demand schedule for the participants who deal only in the CDS market is:

$$E_{i,t} - A^{CDS}(\overline{s}_t - R_{i,t}^{CDS}), \quad A^{CDS} > 0, i = 1, ...N_{CDS} \tag{3.4}$$

where $E_{i,t}$ is the CDS endowment of the i^{th} participant immediately prior to period t, N_{CDS} is the number of participants who deal only in the CDS market, $R_{i,t}^{CDS}$ is the reservation price at which participant i^{th} is willing to hold the endowments of CDSs $E_{j,t}$ while A^{CDS} represents the elasticity of demand which is the same for the N_{CDS} participants. The individuals that operate only in the CDS market are buyers or sellers depending on their reservation prices. These individuals can be considered as speculators that bet about the probability of default. The individuals with $\overline{s}_t > R_{i,t}^{CDS}$ will be net suppliers of CDSs or protection sellers as they benefit from the periodic payments that receive and implicitly find that at that price they are willing to bet about the non-default.[23] As $\overline{s}_t > R_{i,t}^{CDS}$, the CDS endowments of these individuals decrease with respect to those immediately prior to period t. This supply of CDSs could be absorbed for instance by an individual i_2^{th} for whom that price of risk is such that $\overline{s}_t < R_{i_2,t}^{CDS}$ or by the debt hedgers or by the other individuals that participate in both markets at the same time. The individuals with $\overline{s}_t < R_{i_2,t}^{CDS}$ are net demanders of CDSs or net demanders of protection who bet about the underlying company default.

The demand schedule of individuals that participate in both financial markets as market makers is defined from the reservation price in the corresponding market such that the endowments of ASPs are not conditioned by the endowments of CDSs. The ASPs and CDSs' demand schedule of these agents is:

[23] These individual interpret that $R_{i,t}^{CDS}$ is the CDS price given its probability of default. As the market price $\overline{s}_t$ is above the reservation price, the investor is interested in selling protection in exchange of $\overline{s}_t$.

$$E_{k,t}^{B,ASP} - A^{B,ASP}(R_{k,t}^{B,ASP} - s_t^A), \quad A^{B,ASP} > 0, k = 1, ...N_{BOTH} \tag{3.5}$$

$$E_{k,t}^{B,CDS} - A^{B,CDS}(\bar{s}_t - R_{k,t}^{B,CDS}), \quad A^{B,CDS} > 0, k = 1, ...N_{BOTH} \tag{3.6}$$

where the notation in equations (3.5) and (3.6) is equivalent to the one employed in equations (3.3) and (3.4).

The demand schedule of hedgers is conditioned by their positions in ASPs. We assume that the positions in ASPs of these agents are completely hedged. Thus, the endowments and demand of CDSs are independent of the CDSs premium and they are equal to the endowments and demand of ASPs. The endowments of ASPs increase as the ASP spread increases:

$$E_{h,t}^{H,ASP} - A^{H,ASP}(R_{h,t}^{H,ASP} - s_t^A), \quad A^{H,ASP} > 0, h = 1, ...N_H \tag{3.7}$$

Notation for equation (3.7) is equivalent to the one in equations (3.3) and (3.5) and it represents the debt hedgers demand schedule for both ASPs and CDSs.

3.2.3 Clearing market conditions

Using all the above demand schedules for the five types of individuals, we set the clearing market conditions for both markets.[24]

The ASP market will clear at the value of s_t^A that solves the supply/demand equation:

[24] Note that the total endowments can increase exogenously from period t to period $t+1$, for instance, by means of CDS or bond issuances.

$$\sum_{j=1}^{N_{ASP}} E_{j,t} + \sum_{k=1}^{N_{BOTH}} E_{k,t}^{B,ASP} + \sum_{k=1}^{N_H} E_{h,t}^{H,ASP} =$$
$$= \sum_{j=1}^{N_{ASP}} \left[E_{j,t} - A^{ASP}(R_{j,t}^{ASP} - s_t^A)\right] + \sum_{k=1}^{N_{BOTH}} \left[E_{k,t}^{B,ASP} - A^{B,ASP}(R_{k,t}^{B,ASP} - s_t^A)\right] +$$
$$+ \sum_{h=1}^{N_H} \left[E_{h,t}^{H,ASP} - A^{H,ASP}(R_{h,t}^{H,ASP} - s_t^A)\right] - H(\beta_2 \overline{s}_t + \beta_3 - s_t^A) \quad (3.8)$$

The CDS market will clear at the value of $\overline{s}_t$ that solves the supply/demand equation:

$$\sum_{i=1}^{N_{CDS}} E_{i,t} + \sum_{k=1}^{N_{BOTH}} E_{k,t}^{B,CDS} + \sum_{h=1}^{N_H} E_{h,t}^{H,ASP} =$$
$$= \sum_{i=1}^{N_{CDS}} \left[E_{i,t} - A^{CDS}(\overline{s}_t - R_{i,t}^{CDS})\right] + \sum_{k=1}^{N_{BOTH}} \left[E_{k,t}^{B,CDS} - A^{B,CDS}(\overline{s}_t - R_{k,t}^{B,CDS})\right] +$$
$$+ \sum_{h=1}^{N_H} \left[E_{h,t}^{H,ASP} - A^{H,ASP}(R_{h,t}^{H,ASP} - s_t^A)\right] - H(\beta_2 \overline{s}_t + \beta_3 - s_t^A) \quad (3.9)$$

We solve the previous equations in order to find the CDS and ASP prices that clear both markets. For this purpose and as in GS, we assume that the mean reservation price for the N_{CDS} individuals in the CDS market is $R_t^{CDS} = N_{CDS}^{-1} \sum_{i=1}^{N_{CDS}} R_{i,t}^{CDS}$ and for the N_{ASP} individuals in the ASP market it is given by $R_t^{ASP} = N_{ASP}^{-1} \sum_{j=1}^{N_{ASP}} R_{j,t}^{ASP}$. For the individuals that are present in both markets we have that the mean reservation prices are $R_t^{B,CDS} = N_{BOTH}^{-1} \sum_{k=1}^{N_{BOTH}} R_{k,t}^{B,CDS}$ and $R_t^{B,ASP} = N_{BOTH}^{-1} \sum_{k=1}^{N_{BOTH}} R_{k,t}^{B,ASP}$ as well as for the hedgers the reservation price is defined as $R_t^{H,ASP} = N_H^{-1} \sum_{h=1}^{N_H} R_{h,t}^{H,ASP}$. As in GS we assume that the elasticities are the same for all market participants in ASP and CDS markets ($A^{ASP} = A^{B,ASP} = A^{CDS} = A^{B,CDS} = A^{H,ASP}$).[25] Solving equations (3.8)

[25]The idea is that under the assumptions employed when defining the arbitrageurs demand, the fact

and (3.9) for s_t^A and $\bar{s}_t$ as a function of the mean reservation prices, we obtain:[26]

$$s_t^A = \frac{C + H\beta_2 F + A(N_{CDS} + N_{BOTH})(N_H R_t^{H,ASP} + N_{BOTH} R_t^{B,ASP} + N_{ASP} R_t^{ASP})}{B} \tag{3.10}$$

$$\begin{aligned}\bar{s}_t \quad = \quad & \frac{-D + HF + A\left\{(N_{CDS}(N_H + N_{BOTH} + N_{ASP})R_t^{CDS} + \right.}{B} \\ & \frac{+N_H\left[N_{BOTH}(-R_t^{H,ASP} + R_t^{B,ASP} + R_t^{B,CDS}) + \right.}{B} \\ & \frac{\left. +N_{ASP}(-R_t^{H,ASP} + R_t^{ASP})\right] + N_{BOTH}(N_{BOTH} + N_{ASP})R_t^{B,CDS} \left.\right\}}{B}\end{aligned} \tag{3.11}$$

where the grouped elements that appear in equations (3.10) and (3.11) are defined as:

$$\begin{aligned} B &= A(N_{CDS} + N_{BOTH})(N_H + N_{BOTH} + N_{ASP}) + \qquad (3.12.a) \\ & \quad + H(N_{CDS} + N_{BOTH} + \beta_2 N_{BOTH} + \beta_2 N_{ASP}) \\ C &= H\beta_3(N_{CDS} + N_{BOTH}) \qquad (3.12.b) \\ D &= H\beta_3(N_{ASP} + N_{BOTH}) \qquad (3.12.c) \\ F &= N_{CDS} R_t^{CDS} + N_{BOTH}(R_t^{B,ASP} + R_t^{B,CDS}) + N_{ASP} R_t^{ASP} \qquad (3.12.d) \end{aligned}$$

In order to derive the dynamic price relationship, the model in equations (3.10) and (3.11) must be characterized with a description of the evolution of the reservation prices. Immediately after the market clearing in period $t-1$, a given market participant

that the ASP spread is a good indicator, although not perfect, of the CDS spread and given that both spreads are prices of the credit risk of a given firm, it seems reasonable to assume that the elasticities are similar.

[26] The objective of this paper is not related with the literature of credit risk pricing and so, equations (3.10) and (3.11) are not pricing equations of credit risk, such as the ones defined from the probability of default and recovery rates, but simply the ASP and CDS prices that clear both markets.

in CDSs is willing to hold an amount $E_{i,t}$ or $E_{k,t}^{B,CDS}$, depending on the investor's type, at price $\overline{s}_{t-1}$. A given participant in the ASP market is willing to hold an amount $E_{j,t}$, $E_{k,t}^{B,ASP}$ or $E_{h,t}^{H,ASP}$, depending on the investor's type, at price s_{t-1}^{A}. It implies that the corresponding reservation prices after that clearing are $\overline{s}_{t-1}$ and s_{t-1}^{A} for participants in CDS and ASP markets respectively. Thus, the reservation prices behave according to the following process:

$$
\begin{aligned}
R_{i,t}^{CDS} &= \overline{s}_{t-1} + v_t + w_{i,t}^{CDS}, \quad i = 1, ...N_{CDS} && (3.13.a)\\
R_{j,t}^{ASP} &= s_{t-1}^{A} + v_t + w_{j,t}^{ASP}, \quad j = 1, ...N_{ASP} && (3.13.b)\\
R_{k,t}^{B,CDS} &= \overline{s}_{t-1} + v_t + w_{k,t}^{B,CDS}, \quad k = 1, ...N_{BOTH} && (3.13.c)\\
R_{k,t}^{B,ASP} &= s_{t-1}^{A} + v_t + w_{k,t}^{B,ASP}, \quad k = 1, ...N_{BOTH} && (3.13.d)\\
R_{h,t}^{H,ASP} &= s_{t-1}^{A} + v_t + w_{h,t}^{H,ASP}, \quad h = 1, ...N_{H} && (3.13.e)
\end{aligned}
$$

such that:

$$
\begin{aligned}
cov(v_t, w_{l,t}) &= 0, \ \forall l && (3.13.f)\\
cov(w_{e,t}, w_{l,t}) &= 0, \ \forall l \neq e. && (3.13.g)
\end{aligned}
$$

where v_t is a white noise with finite variance that is a common component for all participants and $w_{i,t}, w_{j,t}, w_{k,t}$ and $w_{h,t}$ are also white noises with finite variance that represent the idiosyncratic component for participants i, j, k and h, respectively.

As GS state, the price change for the above individuals, for instance $R_{i,t}^{CDS} - \overline{s}_{t-1}$ for the individuals that operate only in the CDS market, 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 quantity $E_{i,t}$ of the CDS. The price changes have a component common to all participants (v_t) and a component idiosyncratic to the ith participant ($w_{i,t}$). Thus, the mean reservation price can be also expressed as:

$$R_t^{CDS} = \bar{s}_{t-1} + v_t + w_t^{CDS} \tag{3.14.a}$$

$$R_t^{ASP} = s_{t-1}^{A} + v_t + w_t^{ASP} \tag{3.14.b}$$

$$R_t^{B,CDS} = \bar{s}_{t-1} + v_t + w_t^{B,CDS} \tag{3.14.c}$$

$$R_t^{B,ASP} = s_{t-1}^{A} + v_t + w_t^{B,ASP} \tag{3.14.d}$$

$$R_t^{H,ASP} = s_{t-1}^{A} + v_t + w_t^{H,ASP} \tag{3.14.e}$$

where $w_t^{CDS} = \frac{\sum_{i=1}^{N_{CDS}} w_{i,t}^{CDS}}{N_{CDS}}$, $w_t^{ASP} = \frac{\sum_{j=1}^{N_{ASP}} w_{j,t}^{ASP}}{N_{ASP}}$, $w_t^{B,CDS} = \frac{\sum_{k=1}^{N_{BOTH}} w_{k,t}^{B,CDS}}{N_{BOTH}}$, $w_t^{B,ASP} = \frac{\sum_{k=1}^{N_{BOTH}} w_{k,t}^{B,ASP}}{N_{BOTH}}$ and $w_t^{H,ASP} = \frac{\sum_{h=1}^{N_H} w_{h,t}^{H,ASP}}{N_H}$. We substitute the expressions (3.14) into the equations (3.10) and (3.11) and obtain the following equation (see Appendix A.1):

$$\begin{pmatrix} \Delta s_t^A \\ \Delta \bar{s}_t \end{pmatrix} = \frac{H}{B} \begin{bmatrix} -(N_{BOTH} + N_{CDS}) \\ (N_{BOTH} + N_{ASP}) \end{bmatrix} (1, -\beta_2, -\beta_3) \begin{pmatrix} s_{t-1}^A \\ \bar{s}_{t-1} \\ 1 \end{pmatrix} + \begin{pmatrix} u_t^{ASP} \\ u_t^{CDS} \end{pmatrix} \tag{3.15}$$

where $u_t = \begin{pmatrix} u_t^{ASP} & u_t^{CDS} \end{pmatrix}$ is a vector white noise with $E(u_t) = 0$ and $Var(u_t) = \Omega > 0$. In u_t we include both the common components and the participants' noises.[27]

[27] We do not report the whole expression of u_t in order to save space and also, because of the assumptions on residuals they are not going to appear in our analysis.

The model in equation (3.15) can be changed into a VECM model by subtracting vector of prices $(s_t^A, \bar{s}_t)'$ from both sides:

Although GS provide the first step for understanding price discovery, current analyses are based on either Hasbrouck's (1995) or Gonzalo and Granger's (1995) methodologies. Contrary to GS, the last two approaches are based on a VAR with an Error Correction Term model. As in FFG, we pretend to match GS and GG methodology from the use of a VECM specification. Equation (3.15) can be extended, with lags of vector $\left(\Delta s_t^A, \Delta \bar{s}_t\right)'$, and represented according to a VECM specification:

$$\Delta X_t = \alpha\beta' X_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-i} + u_t \tag{3.16}$$

where $X_t = (s_t^A, \bar{s}_t)'$ and u_t is a white noise vector. According to expression (3.15), $\alpha' = \left(-\frac{H}{B}(N_{BOTH} + N_{CDS}), \frac{H}{B}(N_{BOTH} + N_{ASP})\right)$ and $\beta' = (1, -\beta_2)$.

In this paper we adopt GG's methodology and thus, their permanent-transitory (PT) component decomposition to measure market contribution to price discovery (see Appendix A.2). We find that the percentages of price discovery of ASP and CDS markets can be defined from the GG price discovery metrics that we denote as GG_1 and GG_2, respectively:

$$GG_1 = \frac{\alpha_2}{-\alpha_1 + \alpha_2} \text{ and } GG_2 = \frac{-\alpha_1}{-\alpha_1 + \alpha_2} \tag{3.17}$$

Or equivalently:

$$GG_1 = \frac{N_{BOTH} + N_{ASP}}{2N_{BOTH} + N_{ASP} + N_{CDS}} \text{ and } GG_2 = \frac{N_{BOTH} + N_{CDS}}{2N_{BOTH} + N_{ASP} + N_{CDS}} \tag{3.18}$$

Note that the number of hedgers are not relevant to define the price discovery metrics and as a consequence in the price discovery process.[28] Note also that although the theoretical model's liquidity variable is defined as the number of market participants in a given market relative to other market, this metric can be easily related with other commonly employed liquidity measures like the number of contracts or the volume in a given market relative to the other.

3.2.4 Hypothesis

According to the price discovery metric in equation (3.18), the interaction between both markets due to the market players that operate jointly in CDS and ASP markets is of crucial importance. The subprime crisis has affected liquidity in credit derivatives markets and as a consequence the five types of market players. The subprime crisis leads to a decrease in CDS liquidity. The high counterparty risk in the CDS market jointly with, as Dötz (2007) suggests, the relatively high concentration and the homogeneousness of its often leveraged market players has affected the CDS market severely.[29] According to the International Financial Services London (IFSL) Research (2009a), centralized clearing and voluntary termination of contacts has contributed to a 39% drop in notional amounts outstanding of CDS from \$62 trillion at end-2007 to \$38 trillion at end-2008, according to the ISDA (see Panel A of Figure 1).[30] However, as the IFSL

[28] Although hedgers are not important in the price discovery process, they must be included in the model because these individuals really participate in credit markets and we need them in order to make the model more comprehensive.

[29] This concentration seems to be common in the OTC derivatives markets and is increasing through time. According to the IFSL Research (2009a), the OTC derivatives markets in UK became even more concentrated between 2004 and 2007, with the share of the largest 10 institutions rising from 79% to 81%. In 1995 the share of the top ten had been 52%. In the US, the share of the largest 10 institutions was over 90% of turnover. Moreover, according to the BIS, the market share of major players seems to be even larger in Europe than it is for the total global market.

[30] This decline in trading during the second half of 2008 reflects a combination of significantly reduced risk appetite, expectations of stable low interest rates in major markets and lower hedge fund activity.

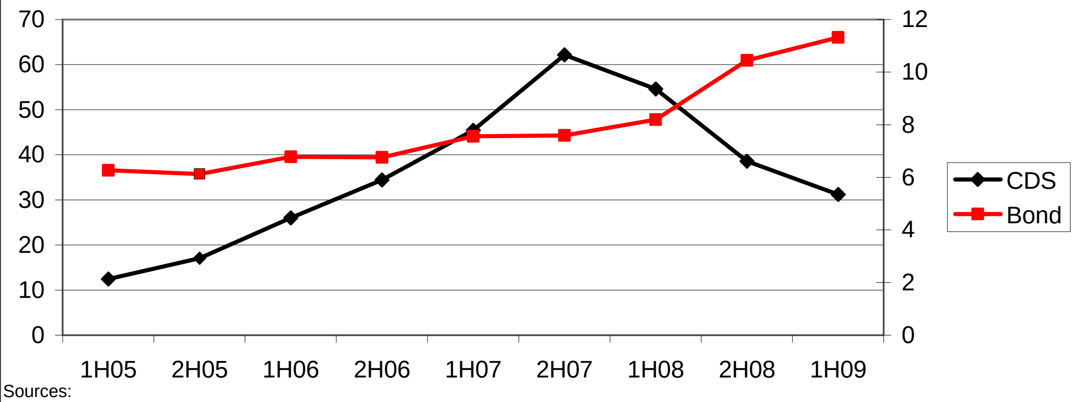
Research (2009b) states, the fall in liquidity during the subprime crisis has increased the importance of bond markets as a source of finance for companies and governments. The issuance of corporate bonds increased to record levels towards the end of 2008 and the first quarter of 2009, particularly in Europe.[31] With respect to the bond trading activity, IFSL Research (2009b) reports that the trading of bonds on exchanges increased by a quarter in 2008 to over 19$ trillion (see Panel A of Figure 1).

Exchange rate movements may also have affected to this decline. Most institutions report their positions in US dollars and the euro and the pound sterling depreciated by 30% and 12%, respectively, against the US dollar between June and December 2008.

[31] During the first quarter of 2009, issuance of investment grade corporate bonds in Europe totalled a record €140bn, well above quarterly levels of less than €50bn seen in recent years. It is motivated, among other reasons, by the use of bond markets for funding and the government guarantees to aid to the bond issuance. IFSL Research (2009b) reports that the amounts outstanding on the global bond market, which includes bonds, notes and money market instruments, increased 6% in 2008 to $83 trillion.

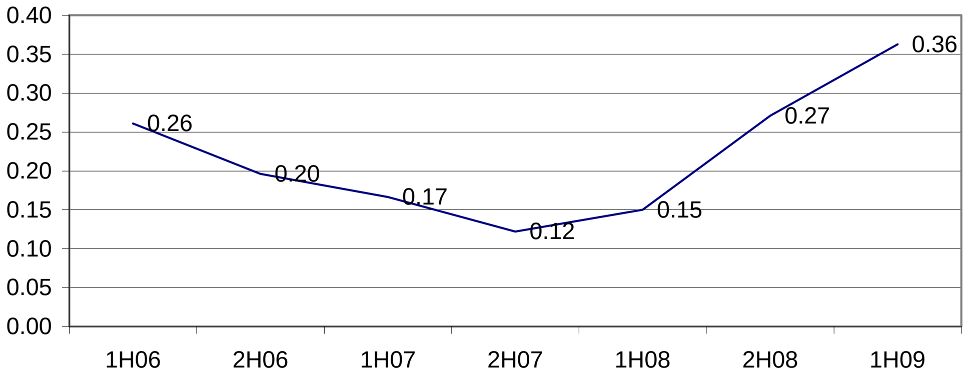
Figure 1: Credit Default Swap Notional Amount Outstanding and Bond Trading on Exchanges

Panel A: CDS Amount Outstanding and Bond Trading (in USD trillion)



Sources:
CDS Notional Amount Outstanding: International Swaps and Derivatives Association (ISDA)
Bond Trading on Exchanges: World Federation of Exchanges

Panel B: Ratio of Bond Trading and CDS Amount Outstanding (in percentage)



Source:
CDS Notional Amount Outstanding: International Swaps and Derivatives Association (ISDA)
Bond Trading on Exchanges: World Federation of Exchanges

This figure reports the CDS notional amount outstanding and the bond trading in exchanges. Panel A shows the CDS amount outstanding and the bond trading in USD trillion. Both amounts have a semi-annual frequency. The first observation for both series corresponds to the first half of year 2005 while the last observation corresponds to the first half of year 2009. The CDS notional amount outstanding is labeled in the left axis while the bond trading on exchanges is labeled in the right axis. Panel B reports the ratio of the bond trading in exchanges and the CDS notional amount outstanding. The ratio has a semi-annual frequency. The first observation corresponds to the first half of year 2005 while the last observation corresponds to the first half of year 2009.

Our first aim is to analyze whether in periods when liquidity is especially low, CDSs maintain their role as the main determinant in the price discovery process. To test this statement we analyze price discovery for two subperiods which correspond to the periods before and after the subprime crisis such that the break point is set at July 2007. Given previous published evidence,[32] we expect that before the crisis, CDSs lead the price discovery process or at least, if the role of participants in both markets is highly influential (N_{BOTH} is high), the price discovery measure of equation (3.18) should be close to 0.5.[33] According to our model, the leadership of CDSs' market can be explained by its higher liquidity (number of participants). The buy-and-hold strategy employed by the ASP or bond investors contrary to the active behaviour of CDS investors, in part due to the leverage associated with a CDSs purchase, could lead to a higher market activity in the CDS market than in the bond market before the subprime crisis.

Hypothesis 1: Under scenarios with high liquidity, the CDS market should lead the ASP market in the price discovery process.

The reason is that the number of participants in the CDS market is high relative to the number of players in the ASP market ($N_{CDS} > N_{ASP}$). In addition to the previous hypothesis, when the number of individuals who operate in both markets is high (N_{BOTH} is high), the CDS market should reveal information as efficiently as the ASP market.

According to Acharya and Schaefer (2006) and Acharya et al. (2007), in periods with low liquidity one should expect that market makers, who at the same time are price

[32] See for instance Norden and Weber (2004), Blanco et al. (2005), Zhu (2006), Baba and Inada (2007), Dötz (2007), Forte and Peña (2009) and Coudert and Gex (2008).

[33] In a limit case, if N_{BOTH} tends to infinity, the price discovery is equal to 0.5.

setters in both credit markets, are financially constrained and thus their participation in both markets will decrease. In terms of our model notation is equivalent to say that $N_{BOTH} \longrightarrow 0$ and the new percentages of price discovery would change into a measure similar to the one introduced in GS and employed by FFG:

$$\frac{N_{ASP}}{N_{ASP}+N_{CDS}} \text{ and } \frac{N_{CDS}}{N_{ASP}+N_{CDS}} \tag{3.19}$$

According to the IFSL Research (2009a and 2009b) reports, the attraction of bonds, and implicitly ASPs, as an investment has increased since the start of the credit crisis and large institutional, as well as retail, investors increased their holdings due to the losses on equity markets and due to the bonds and ASPs high returns as yields during 2008.[34] On the other hand, there is a drop in both the notional amounts outstanding and the number of participants in the CDS market.[35] Thus, if the crisis has affected activity in the CDS more severely than in the ASP market, we expect the ASPs to reveal information faster and more adequately than before the crisis, up to the point that ASPs could lead the process of price discovery in some cases.[36]

Hypothesis 2: Under scenarios with low liquidity leading to a generalized reduction in market participation in credit derivatives markets, the relative position of the ASP market as information provider improves with respect to the one observed under

[34] Allocation to bonds from high-net-worth individuals increased form 27% to 29% during 2008 with equities seeing the largest decline in their share of portfolio allocation.

[35] The nominal of CDSs with respect to ASP contracts serves to show how in periods of financial distress it is much more difficult to participate in CDS than in ASP markets. The standard bond's faced value is €1,000 while the CDS typical notional amount is €10-20 million for investment grade credits and €2-5 million for high yield credits.

[36] Ammer and Cai (2007) state that the main reason to support that bond spreads lead CDS premiums is the existence of a higher cheapest-to-deliver option and for liquidity reasons. In particular they employ as a liquidity measure the number of bonds outstanding by a given firm and find that the higher the number of bonds the less likely it is that CDSs will lead price discovery. Under illiquid scenarios, the CTD option embedded in CDS becomes more valuable and the liquidity premium to bear liquidity risk increases.

high liquid scenarios.

Finally, we analyze the process of price discovery between ASP and bond spreads.

Hypothesis 3: The ASP market always (before and after the subprime crisis) leads the price discovery process with respect to the bond market.

3.3 Data

Our database contains daily data on Eurobonds and ASPs denominated in Euros and issued by non-financial companies that are collected from Reuters and on CDSs also denominated in Euros and issued by the same non-financial companies that are obtained from GFI.

GFI is a major inter-dealer broker (IDB) specializing in the trading of credit derivatives. GFI data contain single-name CDSs market prices for 1, 2, 3, 4 and 5 years maturities. These prices correspond to actual trades, or firm bids and offers where capital is actually committed and so they are not consensus or indications. Thus, these prices are an accurate indication of where the CDS markets traded and closed for a given day. For some companies and for some maturities, especially two and four years, the data availability is scarce and in these cases we employ mid-price quotes from a credit curve also reported by GFI to fill the missing data.[37] GFI data have also been used by Hull, Predescu, and White (2004), Predescu (2006), Saita (2006), Nashikkar

[37] The GFI FENICS® Credit curves are calculated each hour for over 1900 reference entities. The calculation of the curves gives preference to real trades and quoted mid points where available, and in their absence will calculate a running point level using the John Hull and Alan White methodology to ensure a credit curve always exists for each reference entity. This curve is a good approximation for CDSs at any maturity as several error analyses reveal. The median of the absolute difference in basis points between five years CDS premiums as defined from credit curve and the actual quotes or transaction prices for the period between April 2001 and May 2002, is equal to 1.16, 2.01 and 3.82 basis points for AAA/AA, A and BBB ratings for a total of 2,659, 9,585 and 8,170 companies respectively. Moreover, market CDS spread could be different from what we are assuming to be the true CDS spread by as much as 3.725 bps. on average.

and Subrahmanyam (2007), Fulop and Lescourret (2007) or Nashikkar, Subrahmanyam and Mahanti (2009) among others.

For each bond there is information on both bid and ask prices, the swap spread, the asset swap spread, the sector of the entity and its geographical location, the currency, the seniority, the rating history (Fitch, S&P and Moody's ratings), the issuance date and the amount issued, the coupon and coupon dates and the maturity. We use bonds whose maturity at the investment dates is lower than five years. Several bonds issued by the same company may be used whenever they satisfy all the required criteria. The reason is that although CDS spread quotes refer to the issuer and not to an individual bond, asset swap spreads are quoted for individual bonds. Due to liquidity considerations, bonds with time to maturity equal to or less than twelve months in the date corresponding to their last observation are excluded. Moreover, our sample contains fixed-rate senior unsecured Euro denominated bonds whose issued quantity exceeds 300 million Euros.[38] Other requirements imposed on bonds to be included in the sample are: i) straight bonds , ii) neither callable nor convertible, iii) with rating history available, iv) with constant coupons and with a fixed frequency, v) without a sinking fund, vi) without options, vii) without an odd frequency of coupon payments, viii) no government bonds and ix) no inflation-indexed bonds. We cross-check the data on bonds with the equivalent data obtained from Datastream. Due to liquidity restrictions, investments are restricted to periods where there are 5-year CDS data on either actual trades or bids and offers where capital is committed.

The data spans from November 1st, 2005 to June 29th, 2009. However, we split

[38] This limit is set in order to avoid the selection of bonds with a small volume which could require higher transaction costs due to their reduced liquidity.

the data into two subperiods to take into account the possible effects of the ongoing financial crisis. We estimate the breakpoints for each series of CDSs by means of the algorithm described in Bai and Perron (2003) for simultaneous estimation of multiple breakpoints. The ideas behind this implementation are described in Zeileis et al. (2003). The breakpoint is, on average, the 17th July 2007. For this reason, the first subperiod covers the period from November 1st, 2005 to July 16th, 2007 while the second one spans from July 17th, 2007 to June 29th, 2009.[39] The final sample consists of 38 non-financial companies and 50 ASPs and bonds.[40] Table 1 presents information about all issuers, asset swaps, bonds and CDSs for the full sample. According to Panel B we observe a great deal of variation both in the amount issued and in the sample size. The last column shows how far bonds are from par. Panel C1 and Panel C2 include the CDS spread, the asset swap spread, the bond spread and the bases descriptive statistics before and during crisis, respectively.

[39] The first subperiod does not show any episode of significant market turbulence. This subperiod starts after the episode of GM and Ford downgrades to "junk category" which reduced market liquidity and ends with the beginning of the subprime crisis. The subprime crisis implies an illiquid regime for ASP, bond and CDS markets.

[40] Our initial sample was 285 corporate bond issuers. We found a total of 116 Euro denominated bonds that mature before February 2012 but only 67 of them include information on 5-year bid/ask CDS spreads, asset swap spreads and Fenics Curve for at least 90 trading days. Of these, two bonds have been discarded because the issued amount does not exceed 150 millions of Euros, another four bonds were discarded because they were not investment grade bonds throughout the whole sample period. Another four bonds were discarded because their asset swap spreads were persistently negative and, finally, seven bonds were discarded because prices were too far from par.

Table I: Descriptive Statistics

This table reports several descriptive statistics and includes different panels. Panel A describes the rating and sector of the CDS and bond issuer. We report the rating at the end of the first subperiod, which spans from November 2005 to July 2007, and at the end of the second subperiod, which covers the subprime crisis and spans from July 2007 to June 2009. Panel B provides descriptive statistics for bonds. Panel C includes descriptive statistics (in basis points) for the ASP spread; the bond spread; the CDS spread; and the bases, which are obtained as the difference between the ASP and the CDS spreads and as the difference between the bond and the CDS spreads, before the crisis (Panel C1) and during the crisis (Panel C2).

Panel A

Issuer	Rating	Sector
Akzo Nobel	A- / BBB+	Chemicals
BMW	A+ / A	Automobile
Bouygues	BBB+ / BBB+	Construction
British AM Tob.	BBB+ / BBB+	Beverages & Tobacco
Carrefour	A / A	Food & Drug Retailers
Casino G. P.	BBB- / BBB-	Food & Drug Retailers
Compass Group	BBB+ / BBB+	Support Services
Edison	BBB+ / BBB+	Public Utilities
Enel	A- / A-	Public Utilities
Energias de Portugal	A- / A-	Electricity
E.ON	A / A+	Utilities
France Telecom	A- / A-	Fixed-Line Telecommunication Svs.
Iberdrola	A / A-	Petrol and Power
Kingfisher	BBB- / BBB-	General Retailers
Koninklijke KPN	BBB+ / BBB+	Telecommunication Services
Louis Vuitton	BBB+ / BBB+	Other Textiles and Leather Goods
PPR	BBB- / BBB-	Retailers - Multi Department
Renault	BBB+ / BBB+	Automobiles
Repsol YPF	BBB+ / BBB+	Petrol and Power
Reuters	BBB+ / A-	Publishing
Saint Gobain	A- / BBB+	Building and Construction Materials
Scania	A- / A-	Machinery and Engineering
Siemens	AA- / A+	Industrial
Sodexho	BBB+ / BBB+	Business Support Services
Stora Enso	BBB- / BBB-	Forest Product & Paper
Technip	BBB / BBB	Oil - Services
Telecom Italia	BBB+ / BBB	Public Utilities
Telefonica	BBB+ / A-	Technology and Telecommunications
Telekom Austria	BBB+ / BBB+	Machinery, Transport and Technology
Tesco	A / A-	Food & Drug Retailers
Thales	A- / A-	Defence
Thyssenkrupp	BBB+ / BBB-	Industrial
Union Fenosa	A- / A-	Petrol and Power
Vinci	BBB+ / BBB+	Other Construction
Vivendi	BBB / BBB	Subscription Entertainment Networks
Vodafone	A- / A-	Wireless Telecomunications Svs.
Volkswagen	A- / BBB+	Automobile
Volvo	A- / BBB+	Machinery & Engineering

Panel B

Issuer	Amount issued (millions of euros)	Coupon (%)	Nov. 2005 - July 2007		July 2007 - June 2009	
			Obs.	Avg Price	Obs.	Avg Price
Akzo I	750	4.250	264	99.99	411	99.20
Akzo II	1,000	5.625	386	103.76	287	101.13
BMW	750	3.875	329	98.80	403	97.98
Bouygues I	750	4.625	346	101.33	275	99.71
Bouyges II	1,000	5.875	384	104.48	289	101.30
British AM Tob. I	1,700	4.875	406	101.88	285	100.08
British AM Tob. II	1,000	4.375	280	99.69	315	98.98
Carrefour I	1,100	4.375	278	100.28	334	100.21
Carrefour II	1,000	6.125	392	107.07	334	103.44
Casino G. P. I	400	4.750	249	100.14	316	98.24
Casino G. P. II	500	5.250	385	102.38	318	100.57
Compass Group	300	6.000	398	104.35	273	101.46
Edison Spa	700	5.125	377	103.43	347	101.29
Enel	750	4.125	298	99.60	221	100.29
Energia de Portugal I	1,000	6.400	391	106.75	273	102.22
Energia de Portugal II	747	5.875	337	106.47	266	103.40
E.ON	4,250	5.750	392	104.51	263	101.33
France Telecom	2,500	7.000	383	108.44	289	103.79
Iberdrola I	750	4.375	382	100.82	306	100.00
Iberdrola II	600	4.500	377	101.21	287	99.91
Kingfisher	500	4.500	383	100.14	161	95.17
Koninklijke KPN	1,425	4.500	253	99.27	402	98.66
Louis Vuitton I	600	4.625	261	101.01	373	100.31
Louis Vuitton II	750	5.000	419	102.93	376	100.99
PPR	800	5.250	328	102.64	354	98.66
Renault	1,000	6.125	322	104.53	290	101.66
Repsol YPF	1,175	6.000	388	105.83	371	101.99
Reuters	500	4.625	396	101.59	286	99.66
Saint Gobain I	1,000	4.750	378	101.65	290	99.88
Saint Gobain II	1,100	4.250	289	99.25	399	97.22
Saint Gobain III	1,000	5.000	376	102.52	399	100.27
Scania	600	3.625	361	97.49	290	96.30
Siemens	2,000	5.750	267	106.11	243	103.96
Sodexho	1,000	5.875	378	104.18	285	101.07
Stora Enso	500	3.250	384	96.34	290	94.64
Technip	650	4.625	291	100.78	209	98.91
Telecom Italia I	750	4.500	386	100.20	314	98.33
Telecom Italia II	2,000	7.250	320	110.62	314	104.40
Telefonica	2,250	3.750	375	97.55	287	97.85
Telekom Austria	500	3.375	389	97.51	270	98.33
Tesco I	750	4.750	400	102.26	291	100.95
Tesco II	500	3.875	339	98.70	301	98.69
Thales	500	4.375	251	100.23	313	99.95
Thyssenkrupp	750	5.000	335	101.97	370	100.51
Union Fenosa	500	5.000	395	103.04	303	100.92
Vinci	1,025	5.875	375	104.60	285	101.36
Vivendi	630	3.625	398	97.73	256	96.81
Vodafone	1,900	5.125	374	100.52	273	99.41
Volkswagen	1,000	4.125	290	99.07	405	97.97
Volvo	300	5.375	395	103.83	342	99.86
Average	990.04	4.94	350.60	101.99	308.68	99.98

Panel C1

	CDS spread		ASP spread (ASS)		Bond spread (BS)		Basis ASS - CDS	Basis BS - CDS
Issuer	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	Mean
Akzo I	22.99	2.68	16.27	8.36	17.82	8.62	-6.72	-5.17
Akzo II	13.46	3.91	15.31	5.63	16.54	5.28	1.84	3.08
BMW	11.80	4.68	10.57	3.51	12.10	3.63	-1.24	0.30
Bouygues I	20.09	5.67	24.52	6.89	26.00	6.85	4.42	5.90
Bouygues II	18.94	6.02	14.97	5.08	16.03	4.83	-3.96	-2.91
British AM Tob. I	23.77	13.22	19.68	8.84	21.41	8.53	-4.09	-2.36
British AM Tob. II	23.75	6.73	32.26	8.42	34.27	8.57	8.51	10.52
Carrefour I	15.63	4.29	18.72	5.40	20.30	5.45	3.09	4.68
Carrefour II	12.51	3.30	7.48	4.30	8.33	4.26	-5.03	-4.18
Casino I	47.94	8.57	56.73	11.40	59.28	11.28	8.79	11.34
Casino II	47.73	24.70	54.23	26.19	55.86	26.12	6.49	8.13
Compass Group	26.32	18.28	35.19	19.90	36.13	19.37	8.87	9.82
Edison Spa	15.88	3.07	18.67	5.17	19.98	5.31	2.80	4.10
Enel	13.82	3.46	12.65	6.27	14.12	6.39	-1.17	0.29
Energia de Portugal I	11.01	4.78	10.85	4.00	11.77	3.75	-0.16	0.75
Energia de Portugal II	13.68	4.85	16.25	3.58	17.03	3.18	2.57	3.36
E.ON	10.46	2.76	9.32	3.91	10.55	3.77	-1.15	0.09
France Telecom	20.42	8.34	19.67	7.97	20.06	7.34	-0.75	-0.36
Iberdrola I	16.49	5.07	17.55	5.34	19.11	5.21	1.06	2.62
Iberdrola II	11.29	3.16	10.25	3.44	11.69	3.36	-1.05	0.40
Kingfisher	47.86	8.68	48.81	9.50	51.10	9.35	0.95	3.24
Koninklijke KPN	47.32	10.42	53.02	12.48	55.78	12.65	5.70	8.45
Louis Vuitton I	19.34	5.38	23.77	7.71	25.31	7.78	4.42	5.96
Louis Vuitton II	18.63	6.41	22.04	6.89	23.29	6.67	3.40	4.65
PPR	43.62	6.20	49.93	7.14	51.16	7.00	6.31	7.54
Renault	16.03	6.64	21.45	8.72	22.33	8.58	5.41	6.30
Repsol YPF	21.07	6.80	27.16	7.37	27.81	6.92	6.09	6.74
Reuters	19.04	5.66	25.79	5.63	27.20	5.53	6.76	8.16
Saint Gobain I	17.95	4.37	17.75	5.00	19.18	5.08	-0.19	1.23
Saint Gobain II	26.14	5.95	31.77	8.04	33.90	8.16	5.63	7.77
Saint Gobain III	21.64	6.22	26.83	7.74	28.14	7.60	5.19	6.50
Scania	24.83	8.49	24.59	7.06	26.80	7.34	-0.23	1.97
Siemens	12.21	1.59	10.25	1.75	11.19	1.65	-1.96	-1.02
Sodexho	10.17	4.97	19.38	5.60	20.63	5.18	9.22	10.47
Stora Enso	36.02	11.22	37.94	11.12	41.21	11.66	1.92	5.19
Technip	24.41	3.47	33.08	5.14	34.86	5.14	8.67	10.45
Telecom Italia I	45.57	10.80	47.86	12.81	50.22	12.81	2.29	4.65
Telecom Italia II	46.73	11.68	45.54	11.04	44.69	9.91	-1.19	-2.04
Telefonica	34.22	9.86	37.60	9.87	40.36	10.07	3.38	6.14
Telekom Austria	27.04	14.98	27.56	10.47	30.09	10.92	0.52	3.05
Tesco I	9.35	4.93	11.85	4.81	13.12	4.81	2.51	3.78
Tesco II	10.15	4.47	14.47	5.93	16.08	6.14	4.32	5.93
Thales	13.62	3.03	18.66	4.64	20.21	4.71	5.04	6.60
Thyssenkrupp	38.83	12.98	41.02	18.66	42.67	18.70	2.19	3.84
Union Fenosa	20.10	8.35	24.49	6.98	25.61	6.72	4.39	5.51
Vinci	22.62	6.89	22.48	5.72	23.40	5.56	-0.14	0.77
Vivendi	37.86	8.46	42.65	10.12	45.21	9.35	4.79	7.36
Vodafone	15.93	3.80	13.33	7.18	15.03	7.32	-2.60	-0.90
Volkswagen	21.66	5.81	24.25	7.61	26.16	7.83	2.59	4.50
Volvo	20.32	6.88	21.69	7.73	22.80	7.59	1.37	2.48
Average	23.37	7.06	25.76	7.88	27.28	7.80	2.40	3.91

Panel C2

	CDS spread		ASP spread (ASS)		Bond spread (BS)		Basis ASS - CDS	Basis BS - CDS
Issuer	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	Mean
Akzo I	22.91	13.77	15.77	13.08	15.23	13.39	-7.14	-7.67
Akzo II	65.35	43.04	71.75	70.25	73.09	73.10	6.39	7.73
BMW	143.30	145.26	97.84	103.52	100.27	106.85	-45.46	-43.03
Bouygues I	102.37	67.46	101.73	65.78	99.32	64.96	-0.63	-3.05
Bouygues II	46.74	20.56	28.48	13.32	26.13	13.78	-18.26	-20.61
British AM Tob. I	21.75	13.04	27.88	13.73	26.59	15.03	6.13	4.84
British AM Tob. II	59.05	28.23	107.48	61.30	109.66	62.00	48.43	50.61
Carrefour I	49.78	28.57	52.85	43.52	50.35	42.18	3.07	0.57
Carrefour II	47.36	31.76	30.36	19.34	28.90	26.65	-17.00	-18.46
Casino I	142.42	76.61	172.68	96.59	177.36	100.39	30.26	34.94
Casino II	129.82	82.17	111.39	62.01	127.01	86.35	-18.43	-2.81
Compass Group	28.22	11.57	28.99	14.97	26.73	15.02	0.76	-1.49
Edison Spa	64.67	53.41	81.73	63.20	80.56	60.52	17.06	15.89
Enel	181.47	169.90	53.62	40.81	53.68	40.98	-127.85	-127.79
Energia de Portugal I	63.18	31.30	50.25	33.62	70.44	84.02	-12.92	7.26
Energia de Portugal II	72.19	34.54	101.37	66.28	99.56	66.46	29.18	27.37
E.ON	29.97	15.03	23.24	11.17	20.90	10.61	-6.73	-9.07
France Telecom	41.24	20.63	36.15	14.59	33.65	13.16	-5.09	-7.59
Iberdrola I	91.91	58.70	75.33	57.46	73.77	56.47	-16.57	-18.13
Iberdrola II	56.21	17.04	22.62	8.08	21.11	7.63	-33.59	-35.09
Kingfisher	191.71	101.87	218.77	109.45	232.37	119.06	27.06	40.66
Koninklijke KPN	72.67	28.30	113.49	55.43	118.28	59.64	40.82	45.61
Louis Vuitton I	71.18	51.35	70.48	48.09	69.81	47.89	-0.70	-1.37
Louis Vuitton II	65.82	54.71	62.18	49.64	60.81	48.82	-3.63	-5.00
PPR	251.15	200.92	200.10	145.78	206.13	153.20	-51.05	-45.02
Renault	58.74	40.11	34.95	13.50	32.73	13.39	-23.79	-26.02
Repsol YPF	115.08	112.21	107.03	87.49	106.07	89.01	-8.06	-9.02
Reuters	25.21	5.80	31.72	14.25	32.18	14.14	6.51	6.97
Saint Gobain I	71.05	44.75	36.41	13.34	35.05	13.62	-34.64	-36.00
Saint Gobain II	157.12	105.03	158.11	112.11	162.77	116.51	0.99	5.64
Saint Gobain III	142.68	102.03	110.63	72.43	117.04	86.39	-32.06	-25.64
Scania	53.84	22.69	52.89	17.10	55.32	17.84	-0.96	1.47
Siemens	75.68	56.84	62.26	47.49	61.29	46.75	-13.42	-14.39
Sodexho	20.22	11.43	37.02	15.13	34.54	16.24	16.81	14.33
Stora Enso	151.65	99.48	130.83	53.31	138.58	56.83	-20.82	-13.06
Technip	98.15	80.35	109.03	83.60	113.56	89.44	10.88	15.41
Telecom Italia I	183.94	140.76	157.81	96.93	171.91	120.12	-26.14	-12.03
Telecom Italia II	185.40	138.37	216.94	150.62	215.83	152.30	31.54	30.44
Telefonica	97.65	55.63	103.07	56.78	104.85	56.91	5.42	7.21
Telekom Austria	58.36	30.30	94.18	63.32	99.73	66.06	35.82	41.36
Tesco I	58.86	52.31	63.37	62.18	36.48	60.87	4.51	-22.37
Tesco II	63.58	49.52	67.35	54.03	66.59	53.57	3.77	3.01
Thales	78.65	61.84	72.49	67.95	76.33	79.17	-6.16	-2.32
Thyssenkrupp	173.81	157.73	104.64	96.12	112.44	105.46	-69.17	-61.37
Union Fenosa	72.71	69.03	87.48	65.76	85.18	63.58	14.77	12.47
Vinci	51.93	29.75	41.63	17.90	39.68	18.21	-10.30	-12.25
Vivendi	62.87	27.14	80.13	38.10	82.10	39.92	17.26	19.24
Vodafone	39.41	14.36	25.67	11.42	23.75	11.67	-13.74	-15.65
Volkswagen	131.18	91.80	118.90	95.54	122.20	97.98	-12.28	-8.98
Volvo	215.51	235.82	244.23	269.96	254.70	290.16	28.72	39.19
Average	91.11	64.70	86.11	59.15	87.65	63.29	-5.01	-3.46

3.4 Price Discovery Results

We analyze the price discovery process in two different contexts. On the one hand, before July 2007 there exists a scenario of high liquidity where the number of market participants is higher than in the second period, which represents the illiquid scenario.

The process of price discovery is analyzed from an equilibrium model based on an Error Correction Model and the long-run equilibrium condition is based on the existence of cointegration between credit spreads. Econometric details on the model estimation of the VECM defined in equation (3.16) can be found in Juselius (2006).

Before the price discovery analysis, we firstly verify the series stationarity by means of a Ng-Perron unit root test. Table 2 shows that credit spreads are I(1) for the two periods considered in 46 of the total 50 cases which correspond to 50 different ASPs and bonds.

Table 2: Unit Root Test for Credit Spreads

This table reports the unit root tests for CDS, ASP and bond spreads in two different periods. The first column is divided in two sub-columns that present the order of integration of the CDS premium for the period before the crisis (November 2005 - July 2007) and the crisis (July 2007 - June 2009), respectively. The second column is divided into other two columns that present the order of integration for the ASP spreads for the same two periods. The last column reports the order of integration for the bond spreads for the same periods. The cases where all the credit spreads are not integrated of order one in the two periods are in bold.

	CDS		ASP		Bond	
Issuer	First Period	Second Period	First Period	Second Period	First Period	Second Period
Akzo I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Akzo II	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
BMW	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Bouygues I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Bouygues II	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
British AM Tob. I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
British AM Tob. II	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Carrefour I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Carrefour II	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Casino I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Casino II	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Compass Group	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Edison Spa	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Enel	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Energia de Portugal I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Energia de Portugal II	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
E.ON	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
France Telecom	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Iberdrola I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Iberdrola II	**I(1)**	**I(1)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**
Kingfisher	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Koninklijke KPN	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Louis Vuitton I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Louis Vuitton II	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
PPR	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Renault	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Repsol YPF	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Reuters	**I(0)**	**I(1)**	**I(1)**	**I(1)**	**I(1)**	**I(1)**
Saint Gobain I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Saint Gobain II	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Saint Gobain III	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Scania	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Siemens	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
Sodexho	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Stora Enso	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Technip	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Telecom Italia I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Telecom Italia II	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Telefonica	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Telekom Austria	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Tesco I	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Tesco II	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Thales	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
Thyssenkrupp	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Union Fenosa	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Vinci	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Vivendi	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Vodafone	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Volkswagen	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Volvo	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)

In Panel A of Table 3 we report Johansen (1991) cointegration test results for each reference entity whenever the CDS and ASP spreads are I(1) in the two periods. In 32 of the total 46 cases we find cointegration between ASP and CDS spreads. We find cointegration between bond and CDS spreads in the same 32 cases.[41] The number of cointegration relationships that we find is similar to one obtained in previous analyses. Norden and Weber (2004), Blanco, Brennan, and Marsh (2005) and Zhu (2006) find cointegration relationships between CDS and bond spreads in 36 of 58 cases, in 26 of 33 cases and in 15 of 24 cases, respectively. De Wit (2006) finds cointegration relationships between CDS and ASP spreads in 88 of 144 cases. With respect to ASP and bond spreads we find evidence of cointegration between them for all the 46 cases.[42] We then test why there is no cointegration between the ASP and CDS market. To achieve this, we run a Probit regression with heteroskedasticity robust standard errors for the total 92 cases studied in both subperiods, using as dependent variable a dummy variable that equals 1 if there is cointegration and 0 otherwise. In order to control and test the effect of the crisis, we create a dummy variable equal to one if a given case corresponds to the crisis period. Results are shown in Panel B of Table 3. The cointegration seems to be more frequent in bonds/ASPs and with a high coupon rate and with a long time to maturity. The results suggest that the riskier the underlying bond or the longer the time to maturity, the more similar are the credit spreads in the long run. The first result is consistent with the increase in correlation across financial markets as the risk increases. The second result suggests that the deviations among credit spreads are higher

[41] We do not report these results because they are similar to the ones presented in Table 3. However, these results are available upon request.
[42] Cointegration test detailed results for ASP and bond spreads are avaiable upon request.

close to the bond maturity. The rating; the basis, which is defined as the difference between the ASP and CDS spreads; and the crisis dummy have a non-significant effect on cointegration.

Table 3: Cointegration Tests based on CDS and ASP spreads

This table reports the results obtained in the cointegration analyses applied to the CDSs and the ASPs spreads. The first two columns in Panel A of Table 3 report Johansen trace test statistics for the number of cointegrating relations between the CDSs and the ASPs spreads for the period before the subprime crisis (November 2005 - July 2007). The last two columns in Panel A of Table 3 report the same statistics for the crisis period (July 2007 - June 2009).
A constant is included in the long-run relation if it is significantly different from zero. The number of lags in the vector autoregression is optimized using the AIC and attending to the autocorrelation LM residual test such that there is no autocorrelation at an adequate lag order. The superscripts ***, ** or * denotes the rejection of the null at the 1, 5 or 10% level (in bold the cases where we do not find evidence of cointegration between credit spreads for the two periods).
In Panel B of Table 3 we test why there is no cointegration between the ASP and CDS market. The results are estimated by a Probit model with heteroskedasticity robust standard errors. The sample is formed by 92 cases/bonds studied in both subperiods, using as dependent variable a dummy variable that equals 1 if there is cointegration and 0 otherwise. The potential determinants of cointegration considered are: *Bond coupon*; *Logarithm of the time to maturity* which is measured in days from the beginning of the corresponding period; *Rating* is a discrete variable with values between 1 and 7, such that 1 corresponds to rating BBB- and 7 to rating AA-, the rest of the values correspond to the intermediate *ratings; Logarithm of the bond amount issued (in Euros); Basis* defined as the difference between the ASP and CDS spreads; *Crisis* which is a dummy variable with value equals to one when the observation corresponds to the crisis period. The first column reports the estimated coefficients. The second column presents the heteroskedasticity-robust standard errors. The third column reports the coefficient p-value and last column reports the marginal effect.

Panel A

Issuer	November 2005 - July 2007		July 2007 - June 2009	
	None	At most 1	None	At most 1
Akzo I	13.93**	0.36	16.81**	1.99
Akzo II	20.42***	3.98	13.02**	3.24
BMW	14.88**	3.75	28.87***	3.01
Bouygues I	13.74**	2.77	18.07**	2.04
Bouygues II	19.98**	4.47	20.01**	5.89
British AM Tob. I	**21.14****	**2.30**	**6.40**	**2.38**
British AM Tob. II	**21.84****	**8.10**	**7.46**	**2.72**
Carrefour I	13.70**	0.11	13.58**	0.58
Carrefour II	20.05**	6.12	13.03**	0.48
Casino I	26.90***	4.00	22.29**	1.86
Casino II	20.18**	2.41	24.92***	3.34
Compass Group	49.43***	5.41	17.13**	3.03
Edison Spa	13.21**	3.56	20.75**	2.38
Enel	**21.83****	**1.64**	**10.79**	**1.97**
Energia de Portugal I	**22.80****	**8.42**	**6.88**	**2.70**
Energia de Portugal II	17.44***	3.23	12.60**	0.00
E.ON	15.36**	1.67	24.11**	2.18
France Telecom	**16.40**	**3.82**	**8.17**	**2.13**
Iberdrola I	14.19**	2.90	22.41**	2.55
Kingfisher	42.19***	6.21	21.78**	3.11
Koninklijke KPN	13.22**	3.57	23.32**	4.13
Louis Vuitton I	17.30**	0.60	21.26**	2.36
Louis Vuitton II	15.16**	2.43	32.78***	2.79
PPR	17.85**	1.34	21.80**	2.03
Renault	15.57**	0.93	15.46**	1.97
Repsol YPF	13.74**	1.70	26.70***	2.38
Saint Gobain I	**21.67****	**6.45**	**9.67**	**2.24**
Saint Gobain II	12.67**	3.04	16.47**	1.59
Saint Gobain III	20.77**	4.78	20.77***	0.01
Scania	**7.33**	**2.82**	**20.302****	**2.41**
Sodexho	17.36**	3.50	13.06**	0.01
Stora Enso	**15.60**	**4.20**	**11.69**	**4.50**
Technip	**12.01**	**1.60**	**21.47****	**2.93**
Telecom Italia I	23.71**	1.69	25.43***	2.62
Telecom Italia II	12.98**	0.60	20.10**	2.32
Telefonica	16.41**	1.75	20.10**	2.78
Telekom Austria	**19.99****	**9.14**	**12.43**	**3.65**
Tesco I	**11.42**	**3.41**	**24.48****	**2.70**
Tesco II	27.13***	3.65	21.25**	2.33
Thyssenkrupp	19.18**	1.82	16.93**	0.16
Union Fenosa	19.67**	6.01	13.23**	0.10
Vinci	**14.26****	**2.62**	**5.70**	**0.53**
Vivendi	**12.58**	**1.15**	**7.76**	**3.26**
Vodafone	21.00**	3.56	17.95***	0.21
Volkswagen	**10.31**	**3.27**	**22.94****	**2.78**
Volvo	17.17**	3.76	12.54**	0.06

Panel B

Explanatory Variable	Coefficient	Robust Std. Err.	P-value	Marginal Effect
Bond Coupon	0.855	0.261	0.001	0.188
Rating	1.596	0.796	0.045	0.350
Logarithm of the bond amount issued	0.057	0.128	0.655	0.013
Basis (ASP spread - CDS spread)	0.005	0.007	0.495	0.001
Crisis dummy	0.441	0.536	0.411	0.097
Constant	-14.954	6.623	0.024	
R-squared	0.191			
Number of observations	92			
Wald chi2(6 df)	13.5			
Prob > chi2	0.019			

The analysis of price discovery is based on the VECM specification presented in equations (3.15) and (3.16) and it is applied to the 32 cases where we find a long-run equilibrium behavior of the credit spreads series. The vector α in equation (3.16) represents the coefficients that determine the market contribution to price discovery. We conclude that a given market leads the process of price discovery whenever its corresponding price discovery metric ($GG_i \ for \ i = 1, 2$) is higher than 0.5. Both markets reveal information in an equally efficient way whenever the price discovery metrics are close to 0.5 for both markets ($0.45 < GG_i < 0.55 \ for \ i = 1, 2$). The GG_i price discovery metric is defined such that it has a lower bound of 0 and an upper bound of 1 in order to be consistent with the definition in equation (3.18) and the meaning of this metric.

3.4.1 The leadership of the CDS market before the crisis

Panel A of Table 4 shows that during the period before the crisis, Hypothesis 1 is confirmed and the CDSs appear clearly as the more efficient market in 87.5% of the cases (28 cases). According to our model, the role of price discovery leadership comes from the relative number of market participants in the CDS with respect to the ASP market. An implication of the above results is that the market activity in Euro-denominated corporate bonds and ASPs is more limited than in CDS markets. A possible explanation is that the former are often held by investors until maturity which affects in a negative sense during periods of high liquidity their role as information providers. The ASP market reflects credit risk more efficiently in the remaining four cases. In eight cases we observe that the CDS market reveals information as efficiently as the ASP market (GG_1 is between 0.45 and 0.55). According to equation (3.18), the last eight cases where both markets reveal information in an equally efficient way could be explained by a higher market participation of the agents who operate in both markets (N_{BOTH} is high). On average, we find that the CDS market leads the ASP market during the period before the crisis as the value of 0.227 for the corresponding GG average metric reveals. The 95% confidence interval for the average GG metric is 0.151 to 0.302, where even the upper limit implies that the CDS market leads the ASP market. The minimum GG metric is 0, which means that the CDS market reveals all the information, while the maximum is 0.55.

Table 4: Contributions to Price Discovery (CDS vs ASP)

This table reports the price discovery analysis results. Panel A reports the contributions to price discovery of CDS and ASP spreads ($\boxed{s_t^A \text{ and } \bar{s}_{t-j}}$ during the period before the subprime crisis. Panel B presents the contribution of the previous spreads during the crisis. The measures of price discovery are based on the following system of two equations:

$$\boxed{\begin{aligned}\Delta s_t^A &= \alpha_1(s_{t-1}^A - \beta_3 - \beta_2 \bar{s}_{t-1}) + \sum_{j=1}^{p} \delta_{1,j} \Delta s_{t-j}^A + \sum_{j=1}^{p} \eta_{1,j} \Delta \bar{s}_{t-j} + u_{1,t} \\ \Delta \bar{s}_t &= \alpha_2(s_{t-1}^A - \beta_3 - \beta_2 \bar{s}_{t-1}) + \sum_{j=1}^{p} \delta_{2,j} \Delta s_{t-j}^A + \sum_{j=1}^{p} \eta_{2,j} \Delta \bar{s}_{t-j} + u_{2,t}\end{aligned}}$$

The values of coefficients α_1, α_2, β_1 and β_2[‡] and the *t-statistics* of coefficients αs are reported in Panels A and B. The columns are named by the coefficients themselves. The last three columns in Panels A and B report the price discovery measure attributed to the ASP (PD_1), the price discovery measure attributed to the CDS (PD_2) and the percentage of price discovery attributed to the ASP market (GG_1) which is equivalent to the Gonzalo and Granger price discovery metric attributed to the ASP market for a parameter β_2 equal to 1. The ASP market leads the process of price discovery whenever GG_1 is higher than 0.5. However, when GG_1 is below a value of 0.5, the CDS market leads the process of price discovery. The last rows in Panels A and B show the average coefficient or metric and the corresponding lower limit (LL) and upper limit (UL) for their 95% confidence interval. Panel C reports the results for the cases where credit spreads are I(1) but cointegration is rejected. For these cases we test price discovery by means of a Granger causality test from a VAR in first differences for the same three periods. Columns (1) and (2) report the results for the period before the crisis and the crisis period, respectively. The null hypothesis Ho: A states that CDS does not cause ASP while null hypothesis Ho: B states that ASP does not cause CDS. For each test we report the *Chi-Square* statistic and the corresponding *p-value*. In the second sub-row for each issuer, we show the sum of the significant coefficients of lagged CDS and ASP spreads as an additional test of price discovery.

Panel A: Contributions to Price Discovery (CDS vs ASP) before the crisis

Issuer	α_1	t-stat	α_2	t-stat	β_3	β_2	PD_1	PD_2	GG_1
Akzo I	-0.037	-2.607	-0.005	-0.619	0.000	0.580	-0.146	1.085	0.000
Akzo II	-0.075	-3.786	0.004	0.600	0.000	1.152	0.050	0.942	0.050
BMW	-0.085	-3.023	-0.015	-1.547	0.000	0.771	-0.198	1.153	0.000
Bouygues I	-0.015	-1.340	0.016	2.964	0.000	1.382	0.425	0.413	0.507
Bouygues II	-0.034	-1.169	0.041	3.410	0.133	0.864	0.594	0.487	0.550
Carrefour I	-0.058	-2.4462	-0.015	-1.079	0.000	1.128	-0.374	1.422	0.000
Carrefour II	-0.101	-3.418	0.008	0.527	-10.492	1.461	0.069	0.899	0.072
Casino I	-0.089	-4.310	-0.034	-1.354	1.837	1.213	-0.709	1.859	0.000
Casino II	-0.050	-2.634	0.013	0.662	3.205	1.048	0.200	0.791	0.202
Compass Group	-0.094	-5.141	0.008	0.561	29.194	0.631	0.084	0.947	0.081
Edison Spa	-0.018	-1.145	0.022	2.688	0.000	1.543	0.422	0.350	0.547
Energia de Portugal II	-0.021	-1.159	0.023	3.616	0.000	1.316	0.448	0.410	0.522
E.ON	-0.092	-3.307	0.011	1.255	0.000	0.920	0.109	0.900	0.108
Iberdrola I	-0.054	-2.661	0.019	2.171	0.000	1.096	0.250	0.726	0.256
Kingfisher	-0.163	-6.045	0.006	0.184	-3.706	1.077	0.033	0.964	0.033
Koninklijke KPN	-0.074	-1.858	0.073	2.351	0.000	1.129	0.468	0.472	0.498
Louis Vuitton I	-0.116	-3.405	0.032	2.032	-2.542	1.357	0.201	0.728	0.216
Louis Vuitton II	-0.094	-3.535	0.007	0.501	0.000	1.107	0.071	0.921	0.072
PPR	-0.036	-3.495	0.024	2.017	-13.492	1.658	0.318	0.473	0.402
Renault	-0.112	-2.707	0.075	3.864	0.000	1.353	0.352	0.524	0.402
Repsol YPF	-0.064	-3.438	0.002	0.153	0.000	1.229	0.023	0.971	0.023
Saint Gobain II	-0.078	-2.914	0.013	0.734	0.000	1.189	0.142	0.831	0.146
Saint Gobain III	-0.045	-2.9105	0.019	2.039	-7.708	1.614	0.255	0.588	0.303
Sodexho	-0.038	-1.372	0.033	2.668	6.973	1.257	0.413	0.481	0.462
Telecom Italia I	-0.103	-3.296	0.062	2.386	-7.878	1.221	0.346	0.577	0.375
Telecom Italia II	-0.056	-2.323	0.055	2.297	0.000	0.972	0.503	0.511	0.496
Telefonica	-0.063	-2.287	0.055	2.526	1.246	1.063	0.454	0.518	0.467
Tesco II	-0.056	-2.987	-0.031	-3.259	4.779	0.906	-1.095	1.992	0.000
Thyssenkrupp	-0.071	-3.099	0.054	2.260	-14.014	1.465	0.360	0.473	0.432
Union Fenosa	-0.073	-2.780	0.003	0.248	5.833	0.942	0.037	0.965	0.037
Vodafone	-0.056	-2.301	-0.010	-1.238	-9.632	1.443	-0.241	1.348	0.000
Volvo	-0.070	-3.369	-0.003	-0.306	-7.900	1.460	-0.042	1.062	0.000
Average	-0.068	-2.883	0.018	1.104	-0.755	1.173	0.119	0.837	0.227
95% Conf. Interval LL	-0.080		0.008		-3.457	1.077			0.151
UL	-0.057		0.028		1.947	1.270			0.302

‡ The paremeters βs that we report in Panel A of Table 4 are significant at 5% level in all the cases that we study.

3.4.2 The leadership of the ASP and bond markets during the crisis

Panel B of Table 4 reports the results for the subprime crisis period. Comparing Panels A and B of Table 4 we observe that during the crisis, ASP spreads reveal more efficiently credit risk than before. This result is consistent with Hypothesis 2 up to the point that in 71.88% of the cases (23 cases), ASP spreads lead CDS spreads in the price discovery process. The CDS market reflects credit risk more efficiently in the remaining nine cases. Thus, the ASPs' predominant position as information providers during the crisis is in line with the evidence reported in the IFSL Research (2009a and 2009b) about CDS and bond notional amounts outstanding and trading activity. Dötz (2007) states that the turbulence in the credit markets in spring 2005 was apparently handled much better by the bond market than by the CDS market. The role of ASP as information providers improves with respect to the one observed before the crisis in 84.4% of the cases (27 cases). This role only worsens in five cases which could be explained by a drop in the ASPs' liquidity that even exceeds the drop in CDS liquidity. On average, we find that the ASP market leads the CDS market during the crisis as the value of 0.554 for the corresponding GG average metric reveals. The 95% confidence interval for the average GG metric is 0.461 to 0.647. The minimum GG metric is 0.005, which means that the CDS market reveals almost all the information, while the maximum is 0.954, which means that the ASP market reveals almost all the information. The range for this metric is wider than in the period before crisis which may be related with a decrease in the presence of the agents that operate in both markets. This idea is reinforced because in Panel B of Table we do not find any GG metric close to 0.5 ($0.45 < GG < 0.55$). Comparing results before and during the crisis, the ASP spreads reveal credit risk more efficiently during than before the crisis given that the average GG measure during the crisis (0.554 with a standard deviation of 0.258) is almost 2.5 times the one observed before the crisis (0.227 with a standard deviation of 0.209). We then test whether pre and during-crisis GG measures are different. The average difference (0.327) is significantly greater than zero with asymptotic t-statistic equal to 5.3 ($p - value \approx 0$). Also, using a test of means we obtain that the average GG measure during the crisis is higher than the average GG measure before the crisis with asymptotic t-statistic equal to 2.7 ($p - value \approx 0.005$). Panels A and B of Figure 1 help to understand these results given that there is one main determinant of price discovery that we are considering in this paper: liquidity. We realize that there is no generally held definition of liquidity. Many other measures have been suggested in the literature. In fact there is a close relationship between many of the measures and actual transactions costs, and the assumption that liquidity proxies measure liquidity seems to be granted, see Goyenko, Holden and Trzcinka (2008). The analysis of price discovery is extended to the case where the informational efficiency of CDS spreads are compared to bond spreads. Results are similar to the ones presented for CDS and ASP spreads and Hypotheses 1 and 2 also hold.[43]

Other factors that may influence the price discovery process across markets are the cheapest-to-deliver option embedded in the CDS, a potential illiquidity premium and the existence of a high counterparty risk in the CDS. Regarding the first two factors, Ammer and Cai (2007) find that the main reason supporting the price leadership of bond spreads with respect to CDS premiums is the existence of a higher cheapest-to-deliver

[43] Results of this analysis are available upon request.

option and the illiquidity. Actually, these two factors as well as the counterparty risk are assumed to be more influential during the current subprime crisis and it is precisely in this period when we find that both ASP and bond markets reflect the information more efficiently that the CDS market.

Panel B: Contributions to Price Discovery (CDS vs ASP) during the crisis

Issuer	α_1	t-stat	α_2	t-stat	β_3	β_2	PD_1	PD_2	GG_1
Akzo I	-0.068	-2.878	0.021	2.063	-33.021	1.616	0.204	0.670	0.233
Akzo II	-0.011	-0.374	0.020	2.009	0.000	0.785	0.757	0.406	0.651
BMW	-0.045	-1.527	0.069	4.390	0.000	0.667	0.757	0.495	0.605
Bouygues I	-0.011	-0.369	0.065	3.346	-3.965	1.029	0.831	0.145	0.852
Bouygues II	-0.030	-1.267	0.058	2.893	3.483	0.513	0.964	0.506	0.656
Carrefour I	-0.018	-0.8861	0.034	2.832	0.000	1.169	0.585	0.316	0.649
Carrefour II	-0.036	-1.258	0.061	3.089	0.000	0.562	0.867	0.512	0.629
Casino I	-0.022	-1.401	0.068	3.717	-20.117	1.354	0.595	0.194	0.754
Casino II	-0.048	-3.912	0.002	0.154	24.198	0.755	0.041	0.969	0.041
Compass Group	-0.102	-2.142	0.029	2.072	-0.647	1.043	0.220	0.770	0.222
Edison Spa	-0.027	-1.264	0.049	3.454	6.619	1.112	0.603	0.330	0.646
Energia de Portugal II	-0.080	-3.072	0.016	1.219	0.000	1.508	0.153	0.769	0.166
E.ON	-0.015	-0.604	0.025	2.340	5.165	0.586	0.840	0.507	0.623
Iberdrola I	-0.037	-1.364	0.101	4.096	-19.347	1.010	0.726	0.267	0.732
Kingfisher	-0.126	-3.339	0.068	1.682	45.657	1.029	0.348	0.642	0.351
Koninklijke KPN	-0.066	-2.676	0.014	1.340	-31.071	1.643	0.153	0.749	0.169
Louis Vuitton I	-0.046	-2.065	0.078	3.466	2.706	0.949	0.647	0.386	0.626
Louis Vuitton II	-0.054	-2.055	0.082	4.315	4.995	0.857	0.658	0.437	0.601
PPR	-0.059	-2.339	0.127	2.980	16.282	0.718	0.844	0.394	0.682
Renault	-0.062	-1.110	0.132	3.068	10.265	0.594	0.938	0.443	0.679
Repsol YPF	-0.010	-0.384	0.126	4.919	13.871	0.800	1.142	0.087	0.929
Saint Gobain II	-0.027	-1.841	0.039	2.576	-17.603	1.109	0.558	0.381	0.594
Saint Gobain III	-0.115	-4.3677	0.021	1.001	0.000	0.764	0.160	0.878	0.154
Sodexho	-0.017	-0.592	0.053	3.527	0.000	2.239	0.392	0.123	0.761
Telecom Italia I	-0.115	-4.569	0.001	0.021	45.865	0.636	0.005	0.997	0.005
Telecom Italia II	-0.071	-1.702	0.088	2.562	13.265	1.104	0.522	0.424	0.552
Telefonica	-0.030	-0.898	0.082	2.975	-4.623	1.073	0.692	0.257	0.729
Tesco II	-0.004	-0.159	0.087	4.140	-5.743	1.073	0.892	0.043	0.954
Thyssenkrupp	-0.030	-1.571	0.043	2.156	2.880	0.527	0.823	0.567	0.592
Union Fenosa	-0.007	-0.478	0.077	3.583	0.000	1.025	0.894	0.083	0.915
Vodafone	-0.031	-0.8451	0.043	2.118	0.000	0.672	0.723	0.516	0.584
Volvo	-0.068	-1.898	0.045	2.581	0.000	1.229	0.364	0.552	0.397
Average	-0.047	-1.725	0.057	2.709	1.847	0.992	0.591	0.463	0.554
95% Conf. Interval LL	-0.059		0.044		-4.209	0.855			0.461
UL	-0.035		0.070		7.903	1.129			0.647

‡ The paremeters βs that we report in Panel B of Table 4 are significant at 5% level in all the cases that we study.

For the cases where credit spreads are I(1) but the existence of cointegration is rejected, the VECM representation is not valid. In Panel C of Table 4, we report the price discovery analysis results on the basis of a Granger causality test for a VAR in first differences and for the three same periods. According to the *p-value* of the *chi-square* statistics of the Granger causality test and the sum of the coefficients on lagged spreads which are significantly different from zero, we conclude that in the first subperiod, CDS prices Granger-cause ASP spreads for five of the fourteen cases, we find causation in the opposite direction in two cases, bidirectional causation in one case and no causation in the remaining six cases. In the second subperiod, we find that ASP spreads Granger-cause CDS prices in three of the fourteen cases, we find causation in the opposite direction in one case, bidirectional causation in five cases and no causation in the remaining five cases. The sum of the significant coefficients on lagged CDS and ASP spreads confirm the results of the Granger causality test.

Panel C: Granger Causality Test (CDS vs ASP) for the cases where credit spreads are I(1) but not cointegrated

Issuer	(1) Before the crisis				(2) During the crisis			
	Ho: A		Ho: B		Ho: A		Ho: B	
	Chi-Sq.	P-val.	Chi-Sq.	P-val.	Chi-Sq.	P-val.	Chi-Sq.	P-val.
British AM Tob. I	6.480	0.091	3.404	0.334	3.443	0.487	5.249	0.263
		0.000	0.000			0.000	0.000	
British AM Tob. II	30.905	0.000	0.997	0.910	27.563	0.004	17.947	0.083
		0.877	0.000			0.716	0.219	
Enel	3.953	0.267	0.724	0.867	46.197	0.000	15.946	0.026
		0.000	0.000			0.218	0.551	
Energia de Portugal I	4.081	0.666	5.932	0.431	7.669	0.467	9.697	0.287
		0.000	0.000			0.000	0.000	
France Telecom	4.352	0.739	42.776	0.000	20.061	0.003	20.280	0.003
		0.000	0.928			0.502	0.322	
Saint Gobain I	26.891	0.000	10.845	0.093	0.641	0.726	0.310	0.856
		0.143	0.000			0.000	0.000	
Scania	5.735	0.220	2.867	0.580	11.848	0.065	26.600	0.000
		0.000	0.000			0.340	0.408	
Stora Enso	25.350	0.000	15.567	0.004	25.350	0.000	15.567	0.004
		0.456	0.287			0.456	0.287	
Technip	2.993	0.810	24.707	0.000	18.557	0.017	24.856	0.002
		0.000	0.208			0.439	0.431	
Telekom Austria	25.155	0.000	8.057	0.090	9.168	0.164	15.916	0.014
		0.388	0.111			0.000	0.080	
Tesco I	0.671	0.715	0.738	0.692	13.255	0.210	29.309	0.001
		0.000	0.000			0.000	0.524	
Vinci	1.994	0.737	4.7309	0.316	1.723	0.423	2.406	0.300
		0.000	0.000			0.000	0.000	
Vivendi	13.740	0.001	0.985	0.611	5.489	0.483	6.797	0.340
		0.227	0.000			0.000	0.000	
Volkswagen	7.149	0.028	3.390	0.184	25.216	0.003	26.216	0.002
		0.275	0.000			0.264	0.289	

As a robustness test and to overcome the shortcoming that the precision of our estimates cannot be assessed analytically, we use the bootstrap method for cointegrated systems developed by Li and Maddala (1997). We choose to bootstrap from the estimated residuals of the VECM in order not to distort the dynamic structure of our model. Using estimated parameters and initial values, we create a new set of system variables (with the same number of observations as in the original data) by drawing observations randomly with replacement from the innovations. Based upon the generated data, the common trend relationship and the subsequent price discovery measures are re-estimated. This process is then repeated 1,000 times and the standard errors are calculated from the empirical distribution. Finally, we test whether the corresponding GG metric is significantly higher than 0.5 before and during the crisis for both markets. To test these hypotheses, we construct a t-statistic using the bootstrapped standard errors. Results are reported in Table 5. Before the crisis the CDS spreads lead, in most cases, the price discovery process with respect to the ASP spreads. During the crisis, the roles are reversed being the ASP spreads the leaders in the price discovery process.[44]

[44] The *t-statistics* presented in Table 5 are obtained using the GG metrics reported in Table 4. Moreover, we employ the average GG metric obtained accross the 1,000 bootstrap repetitions and obtain similar results.

Table 5: Bootstrap Estimation of the Significance Level of the Price Discovery Metrics

In this table we present the estimates of the *t-statistics* which are employed to test whether a given GG metric is significantly higher than 0.5 before and during the crisis for the CDS and the ASP markets, respectively. These hypotheses are tested by means of *t-statistics* which are constructed using the bootstrapped standard errors. Columns (2) and (3) report the results obtained when we test if the GG metrics for the CDS market, Column (1), are higher than 0.5 before the crisis. Columns (5) and (6) report the results obtained when we test if the GG metrics for the ASP market, Column (4), are higher metrics for the ASP market, Column (4), are higher than 0.5 during the crisis. Columns (1) and (4) are extracted from Panels A and B of Table 4.

Issuer	GG(CDS)	t-stat	p-val	GG(ASP)	t-stat	p-val
Akzo I	1.000	369.499	0.000	0.233	-29.107	1.000
Akzo II	0.950	29.214	0.000	0.651	12.216	0.000
BMW	1.000	62.696	0.000	0.605	6.407	0.000
Bouygues I	0.493	-0.689	0.755	0.852	17.237	0.000
Bouygues II	0.450	-4.255	1.000	0.656	7.960	0.000
Carrefour I	1.000	158.322	0.000	0.649	24.527	0.000
Carrefour II	0.928	63.718	0.000	0.629	16.713	0.000
Casino I	1.000	159.017	0.000	0.754	14.534	0.000
Casino II	0.798	27.359	0.000	0.041	-67.913	1.000
Compass Group	0.919	51.098	0.000	0.222	-41.068	1.000
Edison Spa	0.453	-4.647	1.000	0.646	10.407	0.000
Energia de Portugal II	0.478	-2.390	0.991	0.166	-27.630	1.000
E.ON	0.892	198.328	0.000	0.623	8.809	0.000
Iberdrola I	0.744	29.706	0.000	0.732	12.883	0.000
Kingfisher	0.967	47.427	0.000	0.351	-13.782	1.000
Koninklijke KPN	0.502	0.080	0.468	0.169	-41.129	1.000
Louis Vuitton I	0.784	61.625	0.000	0.626	6.382	0.000
Louis Vuitton II	0.928	44.549	0.000	0.601	7.035	0.000
PPR	0.598	17.425	0.000	0.682	15.184	0.000
Renault	0.598	12.688	0.000	0.679	10.335	0.000
Repsol YPF	0.977	42.715	0.000	0.929	29.679	0.000
Saint Gobain II	0.854	21.746	0.000	0.594	2.104	0.018
Saint Gobain III	0.697	23.907	0.000	0.154	-42.130	1.000
Sodexho	0.538	4.207	0.000	0.761	27.442	0.000
Telecom Italia I	0.625	16.017	0.000	0.005	-52.782	1.000
Telecom Italia II	0.504	0.727	0.234	0.552	0.078	0.469
Telefonica	0.533	2.817	0.002	0.729	17.927	0.000
Tesco II	1.000	119.058	0.000	0.954	33.782	0.000
Thyssenkrupp	0.568	9.903	0.000	0.592	6.755	0.000
Union Fenosa	0.963	32.525	0.000	0.915	24.949	0.000
Vodafone	1.000	89.653	0.000	0.584	6.705	0.000
Volvo	1.000	93.904	0.000	0.397	-10.677	1.000

3.4.3 Comparing the informational efficiency of the ASP and bond spreads

In Table 6 we show that Hypothesis 3, which states that the ASP market reflects credit risk more efficiently than the bond market, is consistent with the empirical evidence for the two periods of time analyzed. This result confirms empirically for the first time, at least to our knowledge, that the ASP spread is a better measure for credit risk than bond spreads are. Only in two of a total of 46 cases in the first subperiod, do bond spreads lead ASP spreads. This occurs in two cases in the second subperiod. The reason that explains these results may be a higher relative liquidity in the ASP market, which means that the number of market participants in the ASP market (liquidity) is greater than the number of players in the bond market.

Table 6: Contributions to Price Discovery (bond vs ASP)

This table reports the contributions to price discovery of bond and ASP spreads ($\boxed{bs_t \text{ and } s_t^A}$. The first column presents the contribution of ASP spreads with respect to bond spreads during the period before the crisis. A value equal to or higher to 0.5 indicates that ASP markets lead bond markets in the process of price discovery while a value equal to or higher than 1 indicates that negligible information about credit risk is reported by bond spreads relative to the one reported by ASP spreads. The second column reports the same information for the crisis period. As in Table 4, the measures of price discovery are based on the following system of two equations:

$$\boxed{\begin{aligned} \Delta s_t^A &= \alpha_1(s_{t-1}^A - \beta_3 - \beta_2 bs_{t-1}) + \sum_{j=1}^{p} \delta_{1,j} \Delta s_{t-j}^A + \sum_{j=1}^{p} \eta_{1,j} \Delta bs_{t-j} + u_{1,t} \\ \Delta bs_t &= \alpha_2(s_{t-1}^A - \beta_3 - \beta_2 bs_{t-1}) + \sum_{j=1}^{p} \delta_{2,j} \Delta s_{t-j}^A + \sum_{j=1}^{p} \eta_{2,j} \Delta bs_{t-j} + u_{2,t} \end{aligned}}$$

We directly report the Gonzalo and Granger metric ($GG_{1)}$ that is obtained as the ratio between the price discovery measure attributed to the ASP (PD_1) and the sum of PD_1 and PD_2 where PD_2 is the price discovery measure attributed to the bond. This ratio indicates the percentage of price discovery attributed to the ASP.

Issuer		Nov. 05 - July 07 GG_1 metric	July 07 - June 09 GG_1 metric
Akzo I		0.696	1.000
Akzo II		0.640	0.801
BMW		0.705	1.000
Bouygues I		0.634	1.000
Bouygues II		1.000	0.683
British AM Tob. I		1.000	1.000
British AM Tob. II		1.000	1.000
Carrefour I		0.607	0.856
Carrefour II		0.346	1.000
Casino I		0.732	1.000
Casino II		1.000	0.787
Compass Group		0.800	0.653
Edison Spa		1.000	1.000
Enel		0.701	0.619
Energia de Portugal I		0.985	0.967
Energia de Portugal II		1.000	0.694
E.ON		0.622	1.000
France Telecom		0.670	1.000
Iberdrola I		0.635	1.000
Kingfisher		0.842	1.000
Koninklijke KPN		0.730	0.737
Louis Vuitton I		0.864	0.980
Louis Vuitton II		1.000	0.869
PPR		1.000	1.000
Renault		0.614	0.254
Repsol YPF		1.000	1.000
Saint Gobain I		0.874	0.427
Saint Gobain II		1.000	1.000
Saint Gobain III		0.653	0.839
Scania		0.712	1.000
Sodexho		0.843	1.000
Stora Enso		0.603	1.000
Technip		1.000	0.825
Telecom Italia I		0.556	0.832
Telecom Italia II		0.844	1.000
Telefonica		0.745	1.000
Telekom Austria		0.708	1.000
Tesco II		0.556	0.949
Thyssenkrupp		0.723	0.915
Union Fenosa		0.565	1.000
Vinci		0.750	1.000
Vivendi		0.883	1.000
Vodafone		0.488	0.525
Volkswagen		0.983	1.000
Volvo		0.622	1.000
Average		0.781	0.893
95% Confidence Interval	LL	0.729	0.841
	UL	0.833	0.945

3.5 Conclusions

We find that liquidity does affect the price discovery process in credit derivatives markets. We make three contributions to the literature. Firstly, we offer a theoretical model for testing price discovery in credit derivatives markets that allows for simultaneous agent participation in different markets. Secondly, we analyze the price discovery process between ASPs and CDSs and find that the leadership, in terms of price discovery, between ASPs and CDSs is very sensitive to the appearance of the subprime crisis. Before the crisis CDSs market leads ASP market but during the crisis ASP market leads CDS market. Thirdly, to our knowledge, this is the first price discovery analysis based on the ASP and bond markets. We find, according to GS terms, that the bond market is a "pure satellite" of the asset swap market. Thus, the ASP spread is a more accurate measure of credit risk than the bond spread. For this reason, it seems more appropriate to use the ASP spread as an alternative or as a complement to the CDS rather than the bond spread.

Finally, we highlight the four main policy implications that emerge from our study and which could be of special interest for investors and regulators alike. First, we find that during the crisis the ASP market reveals credit risk more efficiently that the CDS market. Reasons explaining this finding include the cheapest-to-deliver option embedded in the CDS spread, the liquidity premium and the counterparty risk in CDSs.[45] The

[45] Amato and Remolona (2003) state that when it turns out to be very costly to undertake transactions in a given instrument, the investors must be compensated for it. This compensation is reinforced in the presence of uncertainty about the liquidity (or illiquidity) of an ASP, bond or CDS at a given time, and thus the investors could require a premium to bear this risk. This liquidity premium has been proved to exist both in CDS and bond markets. Longstaff et al. (2005) and Tang and Yan (2007) among others support the presence of a liquidity premium in CDS spreads. Collin-Dufresne et al. (2001), Perraudin and Taylor (2003), Elton et al. (2001), Delianedis and Geske (2002) and Chen et al. (2007) among others find that liquidity is an additional factor to credit risk which is present in bond spreads.

key implication of this result is that inferences on the creditworthiness of a given firm based solely in CDS spreads in periods of high market turbulence and low liquidity are bound to be misleading. Second, we find that the ASP spread leads the price discovery process of credit risk more efficiently than the bond spread, before and during the crisis. For this reason, it is more appropriate to use the ASP spread as an alternative or as a complement to the CDS spread as a measure of credit risk rather than the bond spread. However, most of the existing literature has focused primarily on the bond and CDS spreads ignoring the role of the ASP spread as a credit risk indicator. Third, our theoretical model and empirical results highlight the importance of the agents that operate in both markets (N_{BOTH}) in order to provide stability to the credit markets. The arbitrageurs also play a special role in these markets given that their demands are defined in terms of a long-run equivalence or adjustment which could reduce deviations from the equilibrium prices. Fourth, the debt hedgers do not play any apparent role in the price discovery process if they are fully hedged. However, when they only hedge a given proportion of the total investment in ASPs or bonds, they also contribute to the price discovery process.

CHAPTER 4

THE EFFECT OF THE CURRENT FINANCIAL CRISIS ON THE INTERNAL AND EXTERNAL INTEGRATION OF THE EUROPEAN CORPORATE CREDIT MARKETS

4.1 Introduction

We present empirical evidence suggesting that the current financial crisis affects both the degree of internal market integration of three individual corporate credit markets: Corporate Bonds (Bonds), Asset Swaps Packages (ASP) and corporate Credit Default Swaps (CDS) and the degree of market integration among them. Market-specific liquidity factors as well as global risks factors are significant elements leading changes in internal and external market integration.

In this chapter we define market integration in terms of the correlation structures estimated between two credit spreads innovations obtained after subtracting from the credit spreads the effect of the fundamentals of the underlying entities. We find that credit spread changes are largely driven by innovations. To capture the characteristics of time-varying correlations we employ the Dynamic Conditional Correlation (DCC-GARCH) model of Engle (2002), which is particularly well suited to examine correlation dynamics among assets. The higher the innovation's correlation, the stronger is the market integration. We test both the internal or intra-market integration (within a given market) and the external or inter-market integration (between two given markets). Our measure of internal market integration is based on the correlation between an individual (firm-specific) credit spread innovation, and the corresponding average market credit spread innovations. Similarly, our measure of external market integration is based on the DCCs between the two individual credit spreads innovations of the same firm but in different markets.

The DCC models have been employed to study the integration or co-movement among different financial markets and among different economic areas as in Kim, Lucey and Wu (2005), Cappiello, Engle and Sheppard (2006), Li and Zou (2008), or Savva, Osborn and Gill (2009) among others. Kim, Lucey and Wu (2005) examine the integration of European government bond markets using daily returns over the 1998-2003 time period. Cappiello, Engle and Sheppard (2006) analyze the behaviour of international equities and government bonds. Li and Zou (2008) investigate the impacts of policy and information shocks on the correlation of China's T-bond and stock returns. Other examples of studies based on the stock and bond markets' integration are: Kim, Moshirian and Wu (2005), Kim, Moshirian and Wu (2006), Panchenko and Wu (2009) and Yang, Zhou and Wang (2009) among others. Savva, Osborn and Gill (2009) investigate the transmission of price and volatility spillovers across the New York, London, Frankfurt and Paris stock markets.[1]

[1] Other extensions of the DCC models have been employed to study financial integration. Aslanidis, Dungey and Savva (2009) employ a single VAR model by embedding Smooth Transition Conditional Correlation (STCC) models with fat tails, spillovers, volatility clustering, and asymmetric volatility effects (GJRGARCH). By means of this VARGJRGARCH-STCC-t specification they measure the stock market integration between the three largest new EU members (Hungary, the Czech Republic and Poland) and the Euro-zone. Cai, Chou and Li (2009) use the Double Smooth Transition Conditional Correlation with Conditional Auto Regressive Range (DSTCC-CARR) model to investigate the dynamic correlations among six international stock market indices and their relationship to inflation fluctuation and market volatility.

In related research, Acharya and Schaefer (2006) and Acharya et al. (2007) analyze the existence of correlation risk in credit markets in the context of the Ford and GM downgrades in May 2005 and find an excess co-movement in the overall fixed-income securities. Coudert and Gex (2008) study the variations in the correlation between CDS premium around the episode of Ford and GM downgrades by using different measures such as the DCC-GARCH model. They find a significant increase in CDS premium correlations between firms during the previous episode which can be interpreted as a contagion effect. The current financial crisis represents an illiquid scenario even more severe than the one analyzed by Coudert and Gex (2008) focused on the Ford and GM downgrade context.

In this chapter we contribute to the literature by investigating the changes in internal and external integration over time in fifty firms quoted in three European financial markets. Unlike a number of previous studies, we do not restrict ourselves to few particular aggregate market indexes. The reason for taking a broader perspective is to provide an insight into the integration process of financial markets at the micro level rather than simply a narrower integration within or among overall markets.

The underlying motivation for the research stems from the current discussion on the relative reliability of credit spreads provided by the different markets for credit risk (Dötz, 2007 , Forte and Peña, 2009), which deserves further empirical testing. Beyond that, the research findings presented here have important implications for investors, which are concerned by the proper degree of portfolio diversification, and regulators in an international context, in the sense that a tendency towards stronger (weaker) convergence of credit spreads provides for a more (less) stable environment for financial decisions.

Our main findings are as follows. Credit spread changes are largely driven by firm-specific innovations and to a much lesser extent by changes in fundamentals. Internal market integration increases during the crisis for CDSs but decreases for Bonds and ASPs. External market integration decreases during the crisis between the CDS and the other two markets. Both facts suggest that the CDS market tends to follow its own way to a considerable extent in times of financial distress. This finding combined with the fact of the relatively low liquidity of CDS market in comparison with Bonds and ASP casts some doubts on the representativeness of market prices quoted in this market. The degree of internal and external integration is significantly affected by liquidity and global risk factors.

The remainder of the chapter is organised as follows: Section 2 explains the underlying principles of the test procedures employed. Section 3 describes the data set and clarifies the choice of periods analysed, while Section 4 presents and discusses the statistical results. In Section 5 we present several robustness tests. Finally, Section 6 summarises and sets out the main conclusions of the study and the economic implications.

4.2 Methodology

It is a generally accepted idea that the current financial crisis leads to a decrease in corporate CDS liquidity. The high counterparty risk in the CDS market jointly with, as Dötz (2007) suggests, the relatively high concentration and the homogeneousness of its often leveraged market players has affected the CDS market severely. The International

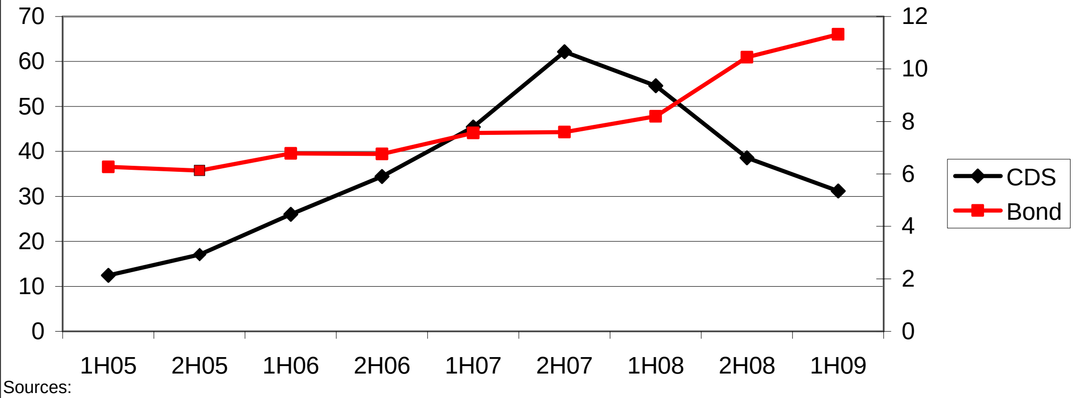
Financial Services London (IFSL) Research (2009a) states that centralized clearing and voluntary termination of contacts has contributed to a 39% drop in notional amounts outstanding of CDS from $62 trillion at end-2007 to $38 trillion at end-2008, according to the ISDA statistics (see Panel A of Figure 1).[2] However, as the IFSL Research (2009b) states, the fall in liquidity during the subprime crisis has increased the importance of bond markets as a source of finance for companies and governments. The issuance of corporate bonds increased to record levels towards the end of 2008 and the first quarter of 2009, particularly in Europe.[3] IFSL Research (2009b) reports that the amounts outstanding on the global bond market, which includes bonds, notes and money market instruments, increased 6% in 2008 to $83 trillion. With respect to the bond trading activity, IFSL Research (2009b) reports that over $1 trillion was traded daily on the US bond market in 2008, up 1% on the previous year. Moreover, the trading of bonds on exchanges increased by a quarter in 2008 to over 19$ trillion (see Panel A of Figure 1).

[2]This decline in trading during the second half of 2008 reflects a combination of significantly reduced risk appetite, expectations of stable low interest rates in major markets and lower hedge fund activity. Exchange rate movements may also have affected to this decline. Most institutions report their positions in US dollars and the euro and the pound sterling depreciated by 30% and 12%, respectively, against the US dollar between June and December 2008.

[3]During the first quarter of 2009, issuance of investment grade corporate bonds in Europe totalled a record €140bn, well above quarterly levels of less than €50bn seen in recent years. It is motivated, among other reasons, by the use of bond markets for funding and the generalized government guarantees aiming to encourage the bond issuance.

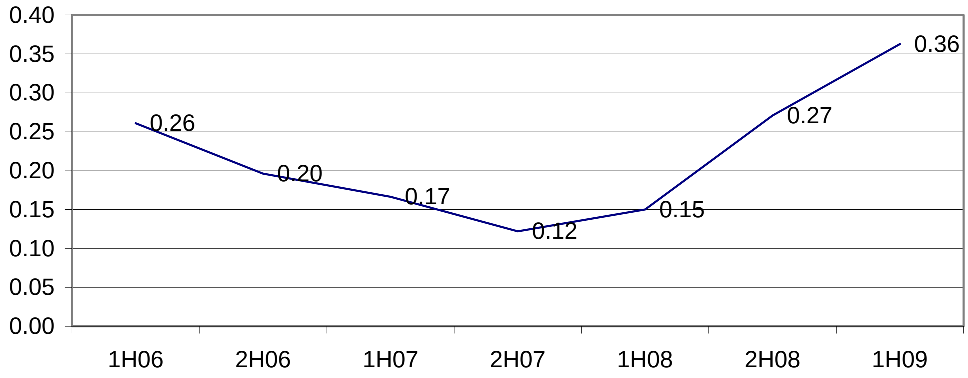
Figure 1: Credit Default Swap Notional Amount Outstanding and Bond Trading on Exchanges

Panel A: CDS Amount Outstanding and Bond Trading (in USD trillion)



Sources:
CDS Notional Amount Outstanding: International Swaps and Derivatives Association (ISDA)
Bond Trading on Exchanges: World Federation of Exchanges

Panel B: Ratio of Bond Trading and CDS Amount Outstanding (in percentage)



Source:
CDS Notional Amount Outstanding: International Swaps and Derivatives Association (ISDA)
Bond Trading on Exchanges: World Federation of Exchanges

This figure reports the CDS notional amount outstanding and the bond trading in exchanges. Panel A shows the CDS amount outstanding and the bond trading in USD trillion. Both amounts have a semi-annual frequency. The first observation for both series corresponds to the first half of year 2005 while the last observation corresponds to the first half of year 2009. The CDS notional amount outstanding is labeled in the left axis while the bond trading on exchanges is labeled in the right axis. Panel B reports the ratio of the bond trading in exchanges and the CDS notional amount outstanding. The ratio has a semi-annual frequency. The first observation corresponds to the first half of year 2005 while the last observation corresponds to the first half of year 2009.

In Chapter 3, we employ a sample of 50 ASPs/Bonds and find that before the current crisis, the ASP spreads, in most cases, reveal credit risk as efficiently as the CDS spreads suggesting the existence of a high number of individuals operating in both markets. During the crisis, they find that the relative position of the ASP market as an information provider has improved with respect to its role before the crisis, revealing information on credit risk faster and more accurately than the CDS market.[4] Overall the above results indicate a decrease in the number of the individuals operating in both markets. This follows from the fact that the number of cases where both markets reveal credit risk in an equally efficient way has declined during the crisis.

Acharya and Schaefer (2006) and Acharya et al. (2007) suggest that, in low-liquidity periods, market makers, who are price setters in both credit markets, are financially constrained and thus their participation in both markets will decrease. Although trading in ASP and Bond markets is predominantly institutional, there is also retail investment. However, there are no retail participants in the CDS market. Thus, the market participants in ASP and bond markets are more numerous and heterogeneous. On the other hand, given the results in Acharya et al. (2007) and in Coudert and Gex (2008) during the episode of Ford and GM downgrades, we should expect high correlation among CDS innovations (internal market integration) due to the special characteristics of the market's participants.

[4]According to IFSL Research (2009a and 2009b), the attraction of bonds, and implicitly ASPs, as an investment has increased since the start of the credit crisis and large institutional, as well as retail, investors increased their holdings due to the losses on equity markets and due to the bonds and ASPs high returns during 2008. On the other hand, there is a drop in both the notional amounts outstanding and the number of participants in the CDS market. The nominal of CDSs with respect to ASP contracts suggests that in periods of financial distress it is more difficult to participate in CDS than in ASP markets. The standard bond's face value is €1,000 while the CDS typical notional amount is €10-20 million for investment grade credits and €2-5 million for high yield credits.

Given that changes in fundamentals should have affected in a similar way all credit spreads in fixed-income markets, we subtract the component of CDS, ASP and bond spreads related to changes in fundamentals before analyzing internal and external integration. We follow Acharya et al. (2007), and the econometric methodology developed in Acharya and Johnson (2007). Thus, we do not employ CDS, ASP or bond spread changes but rather innovations to test co-movement between fixed-income markets. The innovations are the residuals obtained from a non-linear equation derived from a structural model of credit risk such as Merton (1974) in which we regress the credit spread (CDS spread, ASP spread, Bond spread) percentage changes on a constant, the contemporaneous and five lags of the stock return, the product of that return and the inverse credit spread level (CDS spread level, ASP spread level, Bond spread level), five lags of the credit spread percentage changes (CDS spread percentage changes, ASP spread percentage changes, Bond spread percentage changes), the 3-month risk-free rate ($3MRF$) and the 10-year risk free rate ($10YRF$):

$$\begin{aligned} CS(i)\ return_t \quad = \quad & \alpha+\sum_{k=0}^{5}\left[\beta_{t-k}+\gamma_{t-k}/(CS(i)\ level_t)\right](Stock\ return_{t-k})+ \\ & +\sum_{k=1}^{5}\delta_{t-k}(CS(i)\ return_{t-k})+3MRF_t+10YRF_t+\varepsilon_{it}\ for\ i=1,2,3. \end{aligned} \tag{4.1}$$

where $CS(1)$, $CS(2)$ and $CS(3)$ represent the CDS, ASP and Bond spreads, respectively, and ε_{1t}, ε_{2t} and ε_{3t} are the innovations for the CDS, ASP and Bond spread returns, respectively. We assume that a given pair of innovations $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ follows a Normal distribution such that $\varepsilon_t \mid I_{t-1} \sim N(0, H_t)$.

In order to study the external integration between CDS and ASP markets (we use this pair of credit markets to illustrate the methodology), or any other pair of markets, we obtain the dynamic correlations between the innovations by means of the DCC-GARCH model (Dynamic Conditional Correlation GARCH) of Engle and Sheppard (2001) and Engle (2002). This methodology allows us to analyze the evolution over time of the second moments and to detect any regime shifts or responses to shocks and also to distinguish the different behaviour of shocks before and during the crisis period.

Company by company, we estimate the residuals ε_{1t} and ε_{2t} and form pairs by firm in order to estimate bivariate DDC-GARCH models and the series of DCCs between ASPs and CDSs.[5] The multivariate conditional covariance matrix can be written as:

$$H_t = D_t^{1/2} V_t D_t^{1/2} \tag{4.2}$$

where D_t is a $2x2$ diagonal matrix formed by conditional variances from univariate GARCH models with $h_{ii,t}$ on the ith diagonal, and V_t is a matrix that contains the conditional correlations of the pair-wise residuals. The variance-covariance matrices are expanded into individual equations as:

$$h_{ii,t} = c_i + a_i h_{ii,t-1} + b_i \varepsilon^2_{i,t-1}, \quad i = 1, 2. \tag{4.3.a}$$

$$h_{ij,t} = \rho_{ij,t} \sqrt{h_{ii,t}} \sqrt{h_{jj,t}}, \quad i, j = 1, 2 \text{ and } i \neq j. \tag{4.3.b}$$

where $h_{ii,t}$ and $h_{ij,t}$ are, respectively, the conditional variance and conditional covariance with $i, j = 1, 2$ and $i \neq j$. The conditional correlation coefficient $\rho_{ij,t}$ is obtained as:

[5] In total, we have 50 series of DCCs given that in some cases we have several ASPs by firm.

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}, \qquad i, j = 1, 2 \text{ and } i \neq j. \tag{4.4}$$

where the conditional covariance $q_{ij,t}$ between the standardized residuals $\eta_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{ii,t}}}$ and $\eta_{j,t} = \frac{\varepsilon_{j,t}}{\sqrt{h_{jj,t}}}$ can be expressed in a mean reverting process given by:

$$q_{ij,t} = \overline{\rho}_{ij}(1 - \alpha - \beta) + \alpha \eta_{i,t-1} \eta_{j,t-1} + \beta q_{ij,t-1}, \qquad i, j = 1, 2 \text{ and } i \neq j. \tag{4.5}$$

with $\alpha + \beta < 1$ and $\alpha, \beta > 0$ and $\overline{\rho}_{ij}$ is the unconditional correlation between ε_{1t} and ε_{2t} The mean of $q_{ij,t}$ is $\overline{\rho}_{ij}$ and the variance is unity.

Engle and Sheppard (2001) and Engle (2002) state that the DCC model was designed to allow for two-stage estimation, where in the first stage univariate GARCH models are estimated for each innovations series and, in the second stage, the standardized innovations are used to estimate the parameters of the dynamic correlation model.

We repeat the same procedure for the CDS and Bond (ASP and Bond) markets and form pairs to estimate the DCCs between the CDS and Bond innovations (ASP and Bond innovations) for each firm.

In order to study the internal integration, for instance using the CDS market, we employ the CDS innovations for a given name and the average innovations of the rest of the firms to form pairs of residuals and then, we estimate a bivariate DCC-GARCH model for each pair. We use the same procedure to estimate DCCs with ASP innovations and also with Bond innovations.

When the credit spreads innovations are highly correlated, they will tend to move together on the up side or on the down side. Conversely, when the innovations are lowly correlated, they will often diverge. The higher the correlation, the larger the credit spread innovations co-movement within or between markets and the greater the market integration. As the financial crisis has had a significant impact on the credit markets, we wish to establish whether the correlations between them have changed over the sample period, suggesting increasing or decreasing financial integration.

4.3 Data

Our database contains daily data on Eurobonds and ASPs denominated in Euros and issued by non-financial companies that are collected from Reuters and on CDSs also denominated in Euros and issued by the same non-financial companies that are obtained from GFI.

GFI data contain single-name CDSs market prices for 1, 2, 3, 4 and 5 years maturities. These prices correspond to actual trades, or firm bids and offers where capital is actually committed and so they are not consensus or indications. For some companies and for some maturities, especially two and four years, the data availability is scarce and in these cases we employ mid-price quotes from a credit curve also reported by GFI to fill the missing data.

For each bond there is information on both bid and ask prices, the swap spread, the asset swap spread, the sector of the entity and its geographical location, the currency, the seniority, the rating history (Fitch, S&P and Moody's ratings), the issuance date and the amount issued, the coupon and coupon dates and the maturity. We use bonds whose maturity at the investment dates is lower than five years. Several bonds issued by the same company may be used whenever they satisfy all the required criteria. The reason is that although CDS spread quotes are referred to the issuer and not to an individual bond, asset swap spreads are quoted for individual bonds. Due to liquidity considerations, bonds with time to maturity equal to or less than twelve months in the date corresponding to their last observation are excluded. Moreover, our sample contains fixed-rate senior unsecured Euro denominated bonds whose issued quantity exceeds 300 million Euros to avoid the selection of bonds with a small volume and a reduced liquidity. Due to liquidity restrictions, investments are restricted to periods when there are 5-year CDS data on either actual trades or bids and offers where capital is committed.

The data spans from November 1st, 2005 to 9th September 2008. The sample consists of 38 non-financial companies and 50 ASPs and bonds.[6]

Table 1 presents information about all issuers, asset swaps, bonds and CDSs. According to Panel B we observe a great deal of variation both in the amount issued and in the sample size. The last column shows how far bonds are from par. Panel C includes CDS, asset swap and bond spread descriptive statistics. On average, CDS spread seems to be more volatile than the ASP and bond spreads.

[6] Our initial sample was 285 corporate bond issuers. We found a total of 116 Euro denominated bonds that mature before February 2012 but only 67 of them include enough information on 5-year bid/ask CDS spreads, asset swap spreads and Fenics Curve. Of these, two bonds have been discarded because the issued amount does not exceed 300 millions of Euros, another four bonds were discarded because they were not investment grade bonds throughout the whole sample period. Another four bonds were discarded because their asset swap spreads were persistently negative and, finally, seven bonds were discarded because prices were too far from par.

Table 1: Descriptive Statistics

This table reports several descriptive statistics and includes different panels. Panel A describes the rating and sector of the CDS and bond issuer. Panel B provides descriptive statistics for bonds. Panel C includes descriptive statistics (in basis points) for the ASP spread; the bond spread and the CDS spread.

Panel A

Issuer	Rating	Sector
Akzo Nobel	A-	Chemicals
BMW	A+	Automobile
Bouygues	BBB+	Construction
British AM Tob.	BBB+	Beverages & Tobacco
Carrefour	A	Food & Drug Retailers
Casino G. P.	BBB-	Food & Drug Retailers
Compass Group	BBB+	Support Services
Edison	BBB+	Public Utilities
Enel	A-	Public Utilities
Energias de Portugal	A-	Electricity
E.ON	A+	Utilities
France Telecom	A-	Fixed-Line Telecommunication Svs.
Iberdrola	A	Petrol and Power
Kingfisher	BBB-	General Retailers
Koninklijke KPN	BBB+	Telecommunication Services
Louis Vuitton	BBB+	Other Textiles and Leather Goods
PPR	BBB-	Retailers - Multi Department
Renault	BBB+	Automobiles
Repsol YPF	BBB+	Petrol and Power
Reuters	A-	Publishing
Saint Gobain	BBB+	Building and Construction Materials
Scania	A-	Machinery and Engineering
Siemens	A+	Industrial
Sodexho	BBB+	Business Support Services
Stora Enso	BBB-	Forest Product & Paper
Technip	BBB	Oil - Services
Telecom Italia	BBB	Public Utilities
Telefonica	BBB+	Technology and Telecommunications
Telekom Austria	BBB+	Machinery, Transport and Technology
Tesco	A-	Food & Drug Retailers
Thales	A-	Defence
Thyssenkrupp	BBB	Industrial
Union Fenosa	A-	Petrol and Power
Vinci	BBB+	Other Construction
Vivendi	BBB	Subscription Entertainment Networks
Vodafone	A-	Wireless Telecomunications Svs.
Volkswagen	A-	Automobile
Volvo	A-	Machinery & Engineering

Panel B

Issuer	Amount issued (millions of euros)	Observations	Coupon (%)	Price		
				Mean	Max	Min
Akzo I	750	545	4.250	99.35	101.36	96.56
Akzo II	1,000	674	5.625	102.63	106.95	100.22
BMW	750	617	3.875	98.26	100.02	96.00
Bouygues I	750	645	4.625	100.31	104.04	97.04
Bouyges II	1,000	674	5.875	103.11	107.98	100.28
British AM Tob. I	1,700	692	4.875	101.14	104.58	99.60
British AM Tob. II	1,000	571	4.375	98.66	101.07	95.17
Carrefour I	1,100	554	4.375	99.69	101.96	96.94
Carrefour II	1,000	672	6.125	105.40	111.76	101.09
Casino G. P. I	400	544	4.750	98.93	101.36	95.34
Casino G. P. II	500	677	5.250	101.45	103.98	98.42
Compass Group	300	672	6.000	103.17	106.59	100.60
Edison Spa	700	699	5.125	102.25	106.90	98.71
Enel	750	587	4.125	99.01	101.03	96.75
Energia de Portugal I	1,000	682	6.400	105.05	111.13	100.96
Energia de Portugal II	747	617	5.875	104.82	108.90	100.07
E.ON	4,250	657	5.750	103.23	108.34	100.25
France Telecom	2,500	679	7.000	106.44	112.71	101.82
Iberdrola I	750	674	4.375	100.09	103.68	97.34
Iberdrola II	600	665	4.500	100.65	103.65	99.34
Kingfisher	500	648	4.500	98.24	102.31	91.44
Koninklijke KPN	1,425	545	4.500	98.39	100.55	95.42
Louis Vuitton I	600	556	4.625	100.14	102.43	97.28
Louis Vuitton II	750	702	5.000	101.94	106.32	98.89
PPR	800	547	5.250	101.53	104.58	97.48
Renault	1,000	545	6.125	103.52	106.70	100.83
Repsol YPF	1,175	673	6.000	104.20	109.67	99.96
Reuters	500	683	4.625	100.78	105.38	97.40
Saint Gobain I	1,000	665	4.750	100.86	104.10	98.96
Saint Gobain II	1,100	581	4.250	98.10	100.61	94.17
Saint Gobain III	1,000	653	5.000	101.30	105.27	98.33
Scania	600	652	3.625	96.96	99.98	94.61
Siemens	2,000	577	5.750	104.52	108.22	100.37
Sodexho	1,000	664	5.875	102.83	107.15	100.14
Stora Enso	500	675	3.250	95.61	97.74	92.38
Technip	650	582	4.625	99.61	102.54	95.36
Telecom Italia I	750	678	4.500	99.12	108.60	94.66
Telecom Italia II	2,000	612	7.250	108.02	113.22	102.24
Telefonica	2,250	666	3.750	97.00	99.34	94.67
Telekom Austria	500	681	3.375	97.37	99.15	96.27
Tesco I	750	660	4.750	101.42	105.95	98.75
Tesco II	500	631	3.875	98.20	100.15	95.70
Thales	500	539	4.375	99.35	101.76	96.10
Thyssenkrupp	750	610	5.000	101.22	103.06	98.07
Union Fenosa	500	687	5.000	101.90	107.03	98.28
Vinci	1,025	661	5.875	103.21	108.21	100.08
Vivendi	630	600	3.625	97.45	100.45	94.83
Vodafone	1,900	648	5.125	100.05	102.48	98.90
Volkswagen	1,000	581	4.125	98.35	100.33	95.61
Volvo	300	685	5.375	102.61	107.76	99.56
Average	990.04	633.68	4.94	100.95	104.58	97.78

Panel C

	CDS Premium (basis points)				Asset Swap Spread (b.p.)				Bond Spread (b.p.)			
Issuer	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD
Akzo I	30.74	13.57	82.09	13.58	21.20	0.70	51.90	10.43	22.20	0.30	54.90	10.63
Akzo II	17.44	6.35	50.05	10.51	15.49	-12.70	49.40	10.87	15.01	-14.30	46.40	11.04
BMW	28.40	6.61	116.66	24.19	17.36	1.30	55.09	10.88	18.50	2.20	58.60	10.86
Bouygues I	33.81	12.00	129.35	21.92	36.39	9.40	79.65	17.40	37.85	11.80	83.50	17.53
Bouygues II	30.73	11.92	119.90	19.61	20.63	0.56	56.97	11.20	20.35	-1.80	94.00	10.86
British AM Tob. I	22.97	6.04	54.00	13.25	22.95	0.25	60.12	11.43	23.66	0.20	77.00	12.02
British AM Tob. II	34.78	13.12	136.64	21.11	52.30	16.90	138.07	29.46	54.70	20.00	144.90	30.34
Carrefour I	23.46	9.43	66.62	11.16	21.46	3.98	50.92	8.30	22.55	0.30	53.70	8.37
Carrefour II	18.43	6.80	52.73	9.41	13.93	0.20	49.36	10.50	13.88	0.40	48.50	9.84
Casino I	70.04	31.03	172.11	31.97	79.54	33.70	163.90	30.89	82.73	36.90	172.10	31.91
Casino II	57.81	22.31	140.94	29.40	61.60	15.72	126.10	26.29	62.60	16.70	128.20	26.02
Compass Group	26.96	9.44	83.29	15.81	32.41	0.70	104.50	18.25	34.04	0.20	103.60	18.28
Edison Spa	23.64	6.51	62.42	11.50	31.26	10.20	59.83	10.47	32.09	3.20	81.60	14.97
Enel	38.89	7.97	144.44	31.67	17.90	-9.00	62.80	10.35	18.89	-4.30	64.20	10.47
Energia de Portugal I	20.10	5.27	64.08	13.46	14.69	-33.18	55.31	14.59	14.13	-40.80	50.60	13.92
Energia de Portugal II	24.40	6.81	71.25	14.61	28.31	0.32	66.19	17.05	28.77	0.80	67.70	16.72
E.ON	18.20	4.98	68.90	13.56	14.91	0.30	54.77	10.30	14.70	0.60	51.10	8.89
France Telecom	29.36	7.64	89.00	18.02	26.74	0.81	68.30	13.85	25.86	1.60	64.70	12.18
Iberdrola I	30.73	6.82	125.48	23.13	22.86	0.91	57.80	10.37	23.89	0.80	58.70	10.05
Iberdrola II	24.76	5.99	106.92	21.06	9.81	0.50	37.09	7.09	9.59	0.60	33.10	9.61
Kingfisher	99.64	31.55	438.26	89.68	110.45	29.10	377.00	103.71	117.27	31.70	407.50	112.10
Koninklijke KPN	56.39	25.16	159.51	23.96	68.86	29.50	173.13	28.29	71.87	33.30	180.40	29.28
Louis Vuitton I	31.20	9.09	110.42	18.20	31.85	10.30	65.21	13.11	33.00	11.10	67.20	13.04
Louis Vuitton II	25.27	5.86	85.36	13.85	26.36	1.74	67.37	10.98	26.71	0.20	66.20	10.39
PPR	64.08	24.73	233.49	44.39	69.38	34.77	187.50	38.00	70.99	36.10	193.50	39.11
Renault	25.24	5.05	95.85	19.94	26.24	5.00	73.80	13.00	25.56	3.30	71.20	11.89
Repsol YPF	31.42	9.69	99.91	17.92	37.74	8.37	98.80	19.30	37.67	9.20	93.10	18.29
Reuters	18.78	9.06	35.72	5.72	28.25	0.67	66.40	10.54	29.27	1.40	66.90	10.33
Saint Gobain I	40.57	10.13	184.47	39.38	25.70	0.33	68.10	13.30	26.02	0.70	67.50	12.64
Saint Gobain II	60.46	15.93	220.00	51.61	58.75	16.90	181.60	35.57	61.70	19.90	192.90	36.81
Saint Gobain III	47.46	11.65	199.16	44.62	42.10	9.60	123.10	23.54	42.82	11.80	124.90	22.80
Scania	37.65	10.24	119.40	21.78	37.06	8.60	81.29	18.87	39.38	10.20	86.90	19.32
Siemens	28.80	9.34	96.52	21.05	22.90	1.66	58.94	14.60	23.52	1.40	60.60	14.42
Sodexho	14.38	4.32	41.93	9.69	26.85	3.39	73.08	13.85	26.45	0.20	69.90	12.20
Stora Enso	84.78	20.37	339.33	87.13	77.72	21.30	276.70	58.21	82.91	24.60	298.00	61.41
Technip	33.37	14.80	83.60	15.76	52.75	18.80	143.34	30.83	54.91	21.10	149.10	31.93
Telecom Italia I	62.34	23.01	205.15	35.48	66.94	20.90	238.20	36.77	68.90	24.00	256.40	38.71
Telecom Italia II	66.30	24.40	212.75	38.90	74.66	22.00	252.27	47.02	73.79	23.70	258.70	47.34
Telefonica	46.56	16.46	153.25	25.46	50.08	17.70	118.12	21.70	52.98	20.20	126.00	22.39
Telekom Austria	29.81	9.66	67.53	14.63	35.19	3.75	87.74	17.46	36.63	5.50	93.10	16.92
Tesco I	15.28	4.06	43.58	9.76	16.36	1.50	66.20	9.29	16.61	0.80	63.40	8.47
Tesco II	18.28	5.00	55.74	11.64	20.65	0.63	55.00	10.49	21.81	0.50	52.90	10.30
Thales	24.63	9.27	82.04	15.53	19.85	1.89	74.88	17.97	31.20	3.70	79.80	18.26
Thyssenkrupp	53.64	17.12	160.77	31.24	43.08	0.20	96.05	19.81	44.36	0.10	95.50	20.28
Union Fenosa	25.26	7.29	58.21	12.16	32.43	6.30	84.39	15.92	33.32	5.60	85.70	15.71
Vinci	34.56	12.26	124.42	24.39	30.66	6.61	76.00	15.39	30.50	4.50	104.70	14.95
Vivendi	43.13	15.74	113.02	21.71	54.18	21.14	127.50	30.43	56.96	22.50	130.30	31.40
Vodafone	25.74	10.90	68.50	15.09	18.44	0.40	56.84	11.00	18.61	0.10	56.00	10.31
Volkswagen	44.61	10.82	170.39	34.28	35.74	6.97	83.20	17.31	37.49	7.50	86.80	17.58
Volvo	28.65	9.73	90.95	15.64	29.38	4.54	69.32	14.73	29.43	6.00	68.40	13.46
Average	36.48	11.87	121.72	23.99	36.65	7.12	100.98	20.42	37.97	7.53	105.81	20.73

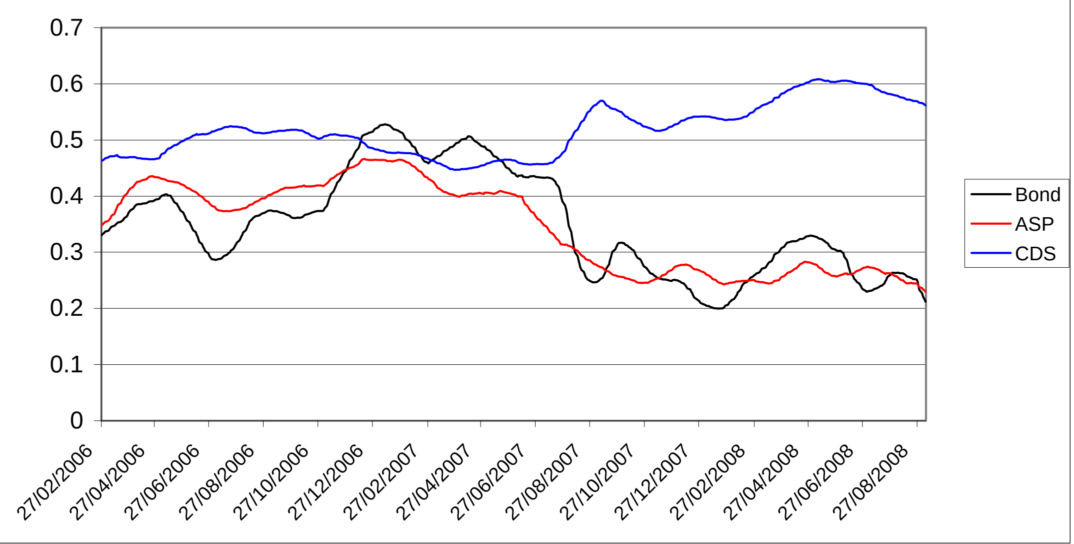
4.4 Results

The average R^2 obtained in the estimations of equation (4.1) for the CDS, Bond and ASP spreads percentage changes are: 11% (CDS), 12% (Bond) and 13% (ASP). It suggests that credit spread changes are largely driven by innovations and to a much lesser extent by changes in fundamentals. Figure 2 reports the 30-day moving average of the average intramarket DCCs over time for CDS, ASP and bond innovations. The DCCs shown are the average of the fifty individual DCCs obtained for each firm/bond in the sample. The average DCCs in CDSs innovations before the crisis are lower than after (0.4850 vs. 0.5544) being the opposite for ASPs (0.4114 vs. 0.2640) and Bonds (0.4087 vs. 0.2733). In the pre-crisis period internal integration tends to be slightly higher in the CDS market than in the two other markets which had similar levels on internal market integration. However during the crisis internal integration increased even more in the CDS market but decreased substantially in ASP and Bonds markets.[7][8] One reason justifying the increase in internal CDS market integration in the crisis period is the concentration of some players in the CDS market. The “extinction” of a portion of individuals operating in various markets jointly with the heterogeneity and the disperse distribution of the remaining market players in ASP and Bond markets could be the causes behind the trend towards fragmentation observed in these markets.

[7] In order to calculate the average DCCs before and during the crisis we first estimate the breakpoints for each series of DCCs for the CDSs, ASPs and bonds' innovations by means of the algorithm described in Bai and Perron (2003) for simultaneous estimation of multiple breakpoints. See also Zeileis et al. (2003). We find that the breakpoint for the DCCs series of CDSs (ASPs and Bonds) is the 25th July 2007 (12th June 2007 and 13th July 2007, respectively). We consider the dates after the minimum of the three previous dates (12th June 2007) as the crisis period and split the sample period in two subsamples at this point.

[8] The individual DCCs for these three combinations of innovations are available upon request. We also calculate the average correlations between credit spreads and find the same behaviour as in the DCC correlations between innovations. The average correlation between CDS spreads before the crisis are lower than after (0.84 vs. 0.90) and the opposite is true for ASP spreads (0.84 vs. 0.73) and Bond spreads (0.83 vs. 0.72).

Figure 2: DCCs for bond, ASP and CDS innovations



This figure reports the 30-day moving average of DCCs for Bond, ASP and CDS innovations. The DCCs for the Bond (ASP and CDS) innovations are obtained by averaging over the 50 firms the DCCs obtained between each individual issuer's Bond (ASP and CDS) innovations and the overall Bond (ASP and CDS) innovations.

Figure 3 reports the 30-day moving average of the average inter-market (external) DCCs. In the pre-crisis period the external integration between ASP and Bonds is high (average 0.64) and increases slightly (average 0.67) during the crisis.[9] On the other hand the external integration of CDS and ASP (Bonds) shows a more complex pattern. Before the crisis the degree of external integration of CDS/ASP and CDS/Bond was similar. There is noticeable fall, coinciding with the beginning of the subprime crisis, in the degree of external integration both of CDS/ASP and CDS/Bond. At some points in 2007 the coefficients are even negative reaching a minimum of -0.045 in mid-november 2007. After that point there is a very volatile period with ups and downs and negative

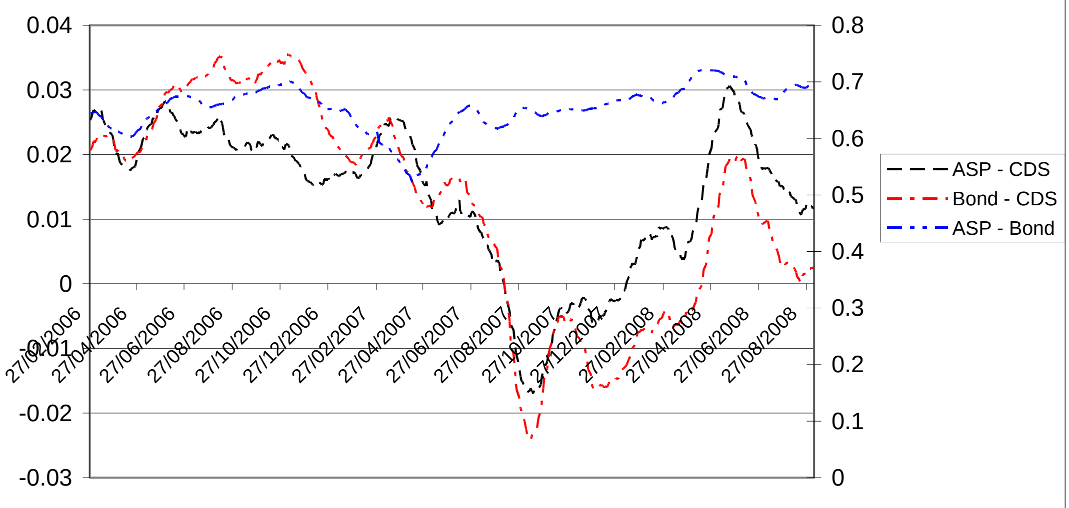
[9]The average correlation between ASP and Bond spreads during the crisis is slightly higher than before the crisis (0.98 vs. 0.97).

values near the Lehman Brothers bankruptcy. The average DCCs between ASP and CDS (Bond and CDS) before and during the crisis are 0.0203 and 0.0059 (0.0247 and -0.0023), respectively.[10] The overall impression is that the CDS market had, at the most acute crisis moments, a noticeable decrease in its external integration and then a very volatile behaviour ensued.[11] Reasons justifying the high volatility in external CDS-ASP and CDS-Bond market integration in the crisis period are related with the diminishing number of participants in that market as discussed before and also to the drastic change in liquidity in the CDS market (see Panels A and B of Figure 1). The European Central Bank report (2009) states that part of the break between the CDS and the cash bond market in the subprime crisis has resulted from the role that counterparty risk plays in pricing of CDSs and the role that funding risk plays in the pricing of cash bonds.

[10] The individual DCCs for these two combinations of innovations are available upon request. The average correlations between credit spreads are also calculated and reflect the same behaviour as the DCCs between innovations. The average correlation between ASP and CDS spreads before the crisis are higher than after it (0.79 vs. 0.52) and the same is true for the correlations between Bond and CDS spreads (0.78 vs. 0.52).

[11] The CDS's crisis-related decrease in external integration, as measured by the DCCs, can be caused by decreases in covariance and/or increases in each market's volatility. We find that the major source of change are the covariance that change sign (from positive to negative) during the most acute crisis period.

Figure 3: DCCs for ASP-CDS, Bond-CDS and ASP-Bond innovations



This figure reports the 30-day moving average of DCCs between ASP and CDS innovations, Bond and CDS innovations, and ASP and bond innovations. The DCCs between the ASP and CDS (between the Bond and CDS and between the ASP and Bond) innovations are obtained by averaging over the 50 issuers, the DCCs obtained between each issuer's ASP and CDS (Bond and CDS, and ASP and Bond) innovations. The average DCCs between ASP and CDS innovations and between Bond and CDS innovations are labeled in the left axis while the average DCCs between ASP and bond innovations are labeled in the right axis.

We now analyze the determinants of the DCCs, or in other words, the determinants of the internal and external market integration or co-movement among credit markets. For this aim, we group the panels by bond/firm in such a way that we have, at most, fifty groups which form a global unbalanced panel and estimate the effect of the potential determinants by means of an OLS regression with correlated panels corrected standard errors (PCSEs) and which are robust to heteroskedasticity and contemporaneous correlation across panels.[12] We employ the Fisher's transformation for the DCCs to ensure that they are defined in the range of all real numbers:

[12] Each element in the covariance matrix of the disturbances is computed with all available observations that are common to the two panels contributing to the covariance, thus if an observation has missing data, we do not exclude the rest of observations for that time period when estimating the covariance matrix.

$$\widetilde{DCC} = \frac{1}{2}\log\left(\frac{1+DCC}{1-DCC}\right) \tag{4.6}$$

Then, we regress the daily $\widetilde{DCCs}$ obtained for each of the 50 cases on three groups of potential determinants of these DCCs:[13]

Liquidity: We employ illiquidity measures in bond and CDS markets by means of the bid-ask spread. As we do not have any illiquidity measure for the ASPs, we proxy it by means of the bid-ask spread of the underlying bond in the ASP.[14] When we analyze the internal integration, we employ the illiquidity measure in the corresponding market as an explanatory variable or a potential determinant of the DCCs' pattern. When we study the external integration, we employ a relative illiquidity measure which is obtained by dividing the bid-ask spreads of the two markets. In the special case of external integration between ASP and Bond markets we employ the illiquidity measure (bid-ask) in the bond market.

Company information: We summarize the company information by means of the rating. As the firms that form the sample are investment grade and their ratings are between the interval with the lower limit in BBB- and the upper limit in A+, we assign values from 1 to 6 such that the value 1 is assigned to the lower rating and the value 6 is assigned to rating A+.

Market Risk factor: We measure the risk that affects the European firms that form the sample by means of the logarithm of the implied volatility index for the German

[13] We have tested for potential problems of multicollinearity and find that the maximum correlation between the explanatory variables is close to 0.3 for the correlation between the measure of bond or CDS illiquidity and the logarithm of the VDAX index. The table of correlations is available upon request.

[14] The ASP consists of a corporate bond and an IRS but the IRS is a very liquid instrument and thus, we focus on the importance of the bond illiquidity measure.

Futures and Options Exchange (VDAX) which is based on DAX index options.[15] Moreover, and to test the possible impact of punctual influential events during the crisis, we use a dummy variable equal to one the day before the influential event, the day corresponding to the influential event and the day after it.[16]

Table 2 reports the results for the determinants of the external integration between the ASP and CDS markets, between the bond and CDS markets, and between the ASP and bond markets. Column (1) shows the results obtained using the DCCs between the ASPs and CDSs innovations as the dependent variable while Columns (2) reports the results for the regression where the dependent variable is the DCCs between the Bonds and CDSs innovations. In both columns, we find that as the CDS/Bond relative illiquidity measure increases, the external integration or co-movement between the CDS/ASP and CDS/Bond markets decreases. Or in other words, as the CDS market becomes more illiquid relative to the Bond market, the DCCs between the ASP and CDS innovations and between the Bond and CDS innovations decrease. Thus, the relative illiquidity measure could explain the change in the trend of DCCs that occur coinciding with the beginning of the crisis. The reason is that the liquidity in the CDS market relative to the ASP/Bond market has decreased during the crisis as can be observed in Panel B of Figure 1.[17] Although all the firms that form the sample are investment grade, we find that the DCCs are lower for the firms with a high rating. With respect to the market risk factors, we find that the higher the market risk, the lower is the external

[15] We employ the VDAX Index instead of the VIX Index to capture the risk that affects the European firms because the correlation between the Eurostoxx 50 and the VDAX is higher in absolute terms ($|-0.32|$) than the correlation between Eurostoxx 50 and the VIX ($|-0.15|$).

[16] A list of the influential events is in Appendix B.

[17] In Chapter 3, we find that the ASP/Bond market reveals credit risk more efficiently than the CDS market during the crisis.

integration. This is consistent with Figure 3. Of course, risk has increased considerably during the subprime crisis and as occurs with the bond illiquidity, these signs could also reflect the change of trend of DCCs in Figure 3 around the summer of 2007. Finally, in Column (3) we report the results for the regression where the dependent variable is the DCCs between the ASPs and Bonds innovations. The bond illiquidity measure has a positive and significant effect on the dependent variable. It seems that, on average, both markets are more integrated in periods of low liquidity as the current financial crisis. We find that the market risk factors (VDAX Index and dummy for influential events) have a positive and significant effect on the DCCs. The coefficient of the firm's credit quality has the same sign that in Columns (1) and (2) although it has a higher and more significant effect.

Table 2: Determinants of the Financial Integration Process between ASPs and CDSs, between bonds and CDSs and between ASPs and bonds

This table reports the determinants of the shock transmission process between credit markets. Column (1) shows the results obtained after using the Fisher's transformed DCCs between the ASPs and CDSs daily innovations as the dependent variable. Column (2) reports the results for the regression where the dependent variable is the Fisher's transformed DCCs between the bonds and CDSs daily innovations. Column (3) shows the results obtained after using the Fisher's transformed DCCs between the ASPs and bonds daily innovations as the dependent variable. We group the panels by bond/firm in such a way that we have, at most, 50 groups which form a global unbalanced panel. We estimate the coefficients of the determinants of the shock transmission process by means of an OLS regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity and contemporaneous correlation across panels. The results presented in each column, (1), (2) and (3), correspond to the estimated coefficient (first sub-column) and the *t-statistic* (second subcolumn).

		(1)		(2)		(3)	
		Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
CDS/Bond relative illiquidity measure		-0.1351	-3.46	-0.1773	-4.06		
Bond illiquidity (bid-ask)						0.6437	23.50
Company rating		-0.0078	-22.30	-0.0077	-24.30	-0.0549	-49.37
Dummy for influential events		-0.0127	-8.59	-0.0168	-9.13	0.0240	2.35
VDAX Index (in logs)		-0.0201	-7.59	-0.0396	-12.26	0.0485	2.69
Constant		0.1036	13.26	0.1579	16.90	0.7810	15.26
R-squared		0.025		0.035		0.078	
Observations		23614		23614		28366	
Number of groups		50		50		50	
Obs. per group	Minimum	189		189		414	
	Average	472		472		567	
	Maximum	587		587		605	
Wald chi2 (10 df)		710.99		1028.75		2995.53	
Prob. > chi2		0		0		0	
Condition Index		7.11		7.11		7.85	

Table 3 reports the results for the determinants of the internal integration in the CDS, ASP and Bond markets. Column (1) shows the results for the CDS market while Columns (2) and (3) report the results for the ASP and Bond markets, respectively. These columns confirm the different behavior of the CDS market compared to ASPs/bonds markets during the illiquid scenario that we are analyzing. The integration within the CDS market increases with the illiquidity in the CDS market. Nevertheless, the integration within both Bond and ASP markets is negatively related to the illiquidity in the Bond market. The company rating also presents a different influence. A low rating increases (decreases) the DCCs in the CDS market (ASP or bond market). The coefficients on the dummy for influential events and the VDAX Index present different signs for the CDS on the one hand, and the ASP and Bond spreads on the other. It suggest that the market risk levels inherent to the subprime crisis have the expected effect on CDS markets, an increase in the shocks correlation, and also on ASP and bond markets, a decrease in the shocks correlation.

Table 3: Determinants of the Financial Integration Process between CDSs, ASPs and bonds innovations themselves

This table shows the determinants of the shock transmission process between credit markets. Column (1) shows the results obtained after using the Fisher's transformed DCCs between the CDSs daily innovations themselves as the dependent variable, while Columns (2) and (3) report the results for the regressions where the dependent variables are the Fisher's transformed DCCs between ASP daily innovations themselves and bond daily innovations themselves, respectively. We group the panels by bond/firm such that we have, at most, fifty groups which form a global unbalanced panel. We estimate the coefficients of the determinants of the shock transmission process by means of an OLS regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity and contemporaneous correlation across panels. The results presented in each column, (1), (2) and (3), correspond to the estimated coefficient (first sub-column) and the *t-statistic* (second subcolumn).

		(1)		(2)		(3)	
		Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
CDS illiquidity (bid-ask)		0.2645	7.34				
Bond illiquidity (bid-ask)				-0.2091	-16.69	-0.1083	-5.34
Company rating		-0.0121	-15.69	0.0378	62.39	0.0232	32.40
Dummy for influential events		0.0225	3.43	-0.0545	-7.87	-0.0450	-3.79
VDAX Index (in logs)		0.1721	14.73	-0.2598	-21.25	-0.3232	-15.79
Constant		0.1161	3.52	1.0425	29.93	1.2715	21.78
R-squared		0.103		0.245		0.130	
Observations		23650		28366		28366	
Number of groups		50		50		50	
Obs. per group	Minimum	189		414		414	
	Average	473		567		567	
	Maximum	587		605		605	
Wald chi2 (10 df)		744.18		5050.33		1477.44	
Prob. > chi2		0		0		0	
Condition Index		8.00		7.85		7.85	

4.5 Robustness Tests

We repeat the analysis of the DCCs determinants under other regression models. First, we estimate the effect of the potential determinants by means of an OLS regression with bond/ASP fixed effects. Of course, the rating variable cannot be used in this regression as it is constant for each bond/ASP along time. The results are consistent with the ones reported in Tables 2 and 3. Second, we estimate the effect of the potential determinants by means of a Prais-Winsten regression with correlated panels, corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation within panels. The correlation within panels is treated as a first-order autocorrelation AR(1) and the coefficient of this process common to all the panels. The data for some bonds/ASPs/CDSs form an unbalanced panel with missing observations not only at the beginning of the series but also in the middle of the series. Thus, we substitute the missing observations by interpolating linearly the corresponding variable such that at the end we only have missing values at the beginning of the series and there are no missing values once we include the first realization of the series. We find that the results are consistent with respect to the ones reported in Tables 2 and 3.

We employ the VDAX Index in our analysis instead of the VIX Index to capture the risk that affects the European firms because the correlation between the Eurostoxx 50 and the VDAX is higher in absolute terms ($|-0.32|$) than the correlation between Eurostoxx 50 and the VIX ($|-0.15|$). However, we repeat the analysis using the VIX and a systemic risk measure [Interbank Rate (BBA LIBOR) minus Interest Rate Swaps (Overnight Swap)] to proxy the risk factor and results do not change significantly with respect to the ones obtained when we use the VDAX Index. Finally, besides the CDS and bond bid-ask spreads we employ two additional liquidity proxies. We use the CDS notional amount outstanding (in USD trillion) and the value of bond trading (in USD trillion). Both series are shown in Figure 1. These variables have semi-annual frequency. We obtain similar results to the ones reported in Tables 2 and 3.

4.6 Conclusions

This paper uses the information on credit risk for fifty firms using the prices in CDS, ASP and Bonds from November 1st, 2005 to 9th September 2008 to study the market's internal and external integration. To do this, we first compute the innovations using a non-linear equation derived from a Merton-based structural model of credit risk and then we estimate a DCC-GARCH model and evaluate its results. We find that credit spread changes are largely driven by firm-specific innovations and to a much lesser extent by changes in fundamentals. Internal market integration increases during the crisis for CDSs but decreases for Bonds and ASPs. External market integration decreases during the crisis between the CDS and the other two markets. The degree of internal and external integration is significantly affected by liquidity and global risk factors.

The results provide a number of insights into the important issue of the relative reliability of market-based credit risk measures. In particular we find that the CDS market tends to follow its own way to a considerable extent in times of financial distress. These results have a number of important economic implications. For example, they suggest that a substantial portion of the changes in corporate credit risk is not related with changes in economic fundamentals and may not be diversifiable. This has clear implications for portfolio choice and the cost of corporate debt capital. Furthermore and given the fact of the relatively low liquidity of CDS market in comparison with Bonds and ASP, our results cast some doubts on the representativeness of market prices quoted in the CDS market.

CHAPTER 5

TOWARDS A COMMON EUROPEAN MONETARY UNION RISK FREE RATE

5.1 Introduction

We present a tentative estimate of a new financial variable: the common risk free rate of interest for the European Monetary Union (EMU) members. We show how to estimate it for a given set of countries and discuss its uses for monetary policy management and its implication for financial markets' integration. The results suggest that this common rate, in all cases, could imply savings in borrowing costs for all the countries involved.

The possibility of a common European bond has attracted the interest of the financial press and is receiving increased attention from policy makers.[1] There are potential wider benefits for the Eurozone as well as specific benefits for market agents such as issuers, dealers, and investors. A large common bond issue could have benefits even for countries with low credit risk (Germany, France), as it could rival American's treasuries market for liquidity. Moreover a single issuer would make EMU bonds more attractive to investors in large foreign-exchange reserves (China, Japan) and enhance the euro's standing as a reserve currency, as well as lowering borrowing costs for all countries that took part in it.[2] On the other hand, some arguments against it have been raised focu-

[1] EPDA(2008,2009).

[2] Additional technical advantages such as minimizing the possibilities of "squeezes" are discussed in

sing on the possible increase in moral hazard as well as the technical and institutional difficulties of managing a common bond issuance. However, as far as we know, there is no published quantification of a common risk free rate, nor a detailed comparison with other possible alternatives is available. This chapter addresses both questions.

A common risk free rate could be used as a benchmark for measuring the benefits from financial market integration in the EMU. We conjecture and provide some evidence that our estimate of this rate would be close to what a common EMU-based single bond would yield for a specified maturity. We can then compare actual rates offered by the different EMU countries with sovereign bonds with this common rate. This allows us to compute the savings in terms of financing costs per year for the different EMU members. Given the common risk free rate measure we conjecture, our results suggest that there would be savings in borrowing costs for all EMU countries involved. Of course, there are many institutional design features that must be resolved (seniority, amount relative to total debt issues, guarantee fund, etc.) before such a common bond can be launched. But our paper provides a first insight into one central issue, namely, what should be the required compensation a given country X should pay to the actual issuer (let's assume that the issuer is the ECB or other EMU-wide agency) to be allowed to share a given issue of EMU-based single bonds. We argue that this compensation should be the Credit Default Swap (CDS) spread on X's sovereign bonds. The benefits for country X in using the common bond (instead of the sovereign bond) will be the enhanced rating and liquidity the common bond would provide plus additional premiums for country X's macro fundamentals.

Pagano and Von Thadden (2004).

Motivated by a simple theoretical portfolio selection model, we first analyze the determinants of EMU sovereign yield spreads and find significant effects of the credit quality, macro, correlation, and liquidity variables. Robustness tests with different data frequencies, benchmarks, liquidity and risk variables, cross section regressions, balanced panels and maturities confirm the initial results.

We define the 'Hedged Yield' of the sovereign debt of a country as the difference of actual yield and the corresponding CDS spread. Based on these hedged yields we build one estimate of the common risk free rate and show that this common rate would imply savings in borrowing costs for all the countries involved.

The remainder of the chapter is organized as follows: Section 1 reviews some current literature on the subject; Section 2 introduces a theoretical model that allows us to determine the main components of the sovereign bond yields. Section 3 describes the data. Section 4 discusses the empirical results and presents some robustness tests. Section 5 introduces the construction of the common risk free rate. Section 6 discusses some policy implications and Section 7 offers some concluding remarks and proposes future lines of research.

5.2 Related Literature on EMU Sovereign Bond spreads

Since the formation of the European Monetary Union (EMU henceforth) the topic of the determinants of the sovereign bonds' yield spreads within the EMU has been the subject of intense and increasing research. Researchers have tried to find out which are the factors that explain the differences between sovereign yields in the EMU countries, but so far no clear consensus has emerged. Codogno, Favero and Misale

(2003) find that for most EMU countries only international risk factors have explanatory power while liquidity factors play a smaller role. Amira (2004) finds that sovereign yields increase with maturity, issue size and gross fees and decrease with credit rating. Geyer, Kossmeier and Pichler (2004) report that EMU government bond spreads are related to common factors whereas they do not find evidence for a significant impact of macroeconomic or liquidity related variables. Bernoth, von Hagen and Schuknecht (2006) report that global risk factors as well as idiosyncratic macroeconomic factors affect yield spreads, whereas liquidity plays a marginal role. Gomez-Puig (2008) finds that idiosyncratic factors (credit risk and liquidity) mostly drive yield differentials but systemic risk factors play only a marginal role. Favero, Pagano and Von Thadden (2008) find that one aggregate risk factor is consistently priced, that liquidity differentials are priced for a subset of countries, and that the interaction of liquidity differentials with the risk factor is consistently priced. In all these papers the benchmark for comparing the yield spreads is based on the German 10-year bund or German zero coupon curves. Beber, Brandt and Kavajecz (2009), however, use as benchmark the Euro-swap curve and show that the bulk of yield spread is explained by differences in credit quality as measured by the CDS, whereas liquidity plays a nontrivial role especially for low credit risk countries and in times of high market uncertainty. In summary, most papers suggest that credit quality-related factors, common business cycle factors (international or EMU), and, to a lower extent, liquidity-related factors are critical drivers of sovereign yield differentials.

The selection of the appropriate benchmark reference, however, has not received extensive attention in the literature. The most common view associates the benchmark bond with the lowest yield. If that were all that mattered for benchmark status, then the German market would provide, on average, the benchmark at all maturities. Analysts who take this view accept that the appropriate criterion for benchmark status is that this is the security against which others are priced, and they simply assume that the security with lowest yield takes that role. A plausible alternative, however, is to interpret benchmark to mean the most liquid security, which is therefore most capable of providing a reference point for the market. But the Italian market, not the German, is easily the most liquid for short-dated bonds;[3] and perhaps the French is most liquid at medium maturities.[4] Dunne, Moore and Portes (2002) consider in detail the meaning of the term "benchmark" bond. They investigate two possible criteria, using Granger-causality and cointegration tests. They find rather different results with the two methods, reflecting their different temporal focus. But with neither of them do they find the unambiguous benchmark status for German securities that would come from a simple focus on the securities with the lowest yield at a given maturity. They suggest looking for benchmark portfolios rather than a single benchmark security. This may be particularly appropriate in this partially integrated market and it is the approach we take in this paper. We take the benchmark to be a weighted average of the total gross debt at nominal value issued by the general governments of the different EMU members.

[3] Most of the trading for 10-year German bonds occurs on the futures market; this market is then more liquid and deeper than the cash market.

[4] Favero, et al. (2008) set the French bond as the benchmark for the five-year maturity. This choice is supported by the evidence in Dunne, Moore and Portes (2002) and by the fact that traders view the French bond as the most liquid for that maturity.

5.3 Theoretical Model

The model we use to motivate the explanatory variables employed in the empirical part of the paper is an extension of the portfolio model of bond yield differentials developed in Bernoth et al (2006). Consider a domestic (benchmark) investor allocating a fraction θ_t (θ_t^*) of his real wealth w_t (w_t^*) to a domestic D (benchmark F) security and a fraction $1 - \theta_t$ ($1 - \theta_t^*$) to a benchmark (domestic) security. Assume that both the domestic and benchmark securities are subject to default risk. The default process is assumed to follow a correlated bivariate Bernoulli process (x_t, x_t^*), with domestic (benchmark) default probability $1 - P_t$ ($1 - P_t^*$). In the event of default the investor receives a fraction τ_t (τ_t^*) of his gross domestic (benchmark) payment, $\tau_t \in [0, 1+r)$ ($\tau_t^* \in [0, 1+r^*)$) where r (r^*) is the interest rate on the domestic (benchmark) bond. There are proportional transaction costs l_t (l_t^*) decreasing with domestic (benchmark) market liquidity. To simplify the presentation the coefficient of risk aversion ρ is assumed to be the same for both investors. Let S_t be the total supply of bond issued by the domestic government and assuming that the market clears, market equilibrium requires that:

$$S_t = \widehat{\theta}_t w_t + \widehat{\theta}_t^* w_t^* \tag{5.1}$$

where the first term in the right hand side denotes the optimal amount of domestic bonds held by the domestic investor and the second term denotes the optimal amount of domestic bonds held by the benchmark investor. Assuming that the investors maximize a one period mean-variance utility function it is possible to solve for the interest rate differential between the two economies (details of the model can be found in Appendix C.1):

$$\begin{aligned}
r_t - r_t^* &= (l_t - l_t^*) + S_t \frac{\rho}{2} Var\left[(1 + r_t - \tau_t)\, x_t - (1 + r_t^* - \tau_t^*)\, x_t^*\right] - \\
&\quad - \frac{\rho}{2}(w_t + w_t^*) \left[(1 + r_t^* - \tau_t^*)^2 P_t^* (1 - P_t^*)\right] + \\
&\quad + \frac{\rho}{2}(w_t + w_t^*) \left[(1 + r_t - \tau_t)(1 + r_t^* - \tau_t^*)\, Cov(x_t, x_t^*)\right] + \\
&\quad + (1 + r_t - \tau_t)(1 - P_t) - (1 + r_t^* - \tau_t^*)(1 - P_t^*)
\end{aligned} \tag{5.2}$$

Defining

$k = (1 + r_t - \tau_t)$

$k^* = (1 + r_t^* - \tau_t^*)$

The model can then be written:

$$\begin{aligned}
r_t - r_t^* &= kE\left[1 - x_t\right] - k^* E\left[1 - x_t^*\right] + (l_t - l_t^*) + \\
&\quad + A_1 S_t Var\left[k x_t - k^* x_t^*\right] + A_2 \left(k k^* Cov\left[x_t, x_t^*\right] - (k^*)^2 Var\left[x_t^*\right]\right)
\end{aligned} \tag{5.3}$$

where

$A_1 = \frac{\rho}{2}$

$A_2 = A_1 \left[w_t + w_t^*\right]$

Equation (5.3) decomposes the yield spread into four components. The first two terms are the *default risk premium* which is related with individual (country-specific) default probabilities. The higher is the domestic (benchmark) country-specific default probability the higher (lower) is the spread. Also, the riskier the domestic bond is in comparison with the benchmark, the greater will be the premium. Overall the effect of increases in the default risk premium will tend to increase yield spreads.[5] The third term on the right hand side is the *liquidity premium*. The less liquid the domestic bond is in comparison with the benchmark' liquidity, the greater will be this premium. The fourth term depends on the total debt S_t (which we later proxy with macro factors like budget and trade balances), the volatility of the differences in the default processes, and their interaction. The last term in the equation is a measure of *covariance risk* in excess of the volatility of the benchmark's default risk.

To test this model empirically we need to specify proxies for the components in equation (5.3). We use the CDS spreads as a proxy of the default risk premium as suggested in Beber et al. (2009).[6] As a measure of liquidity we use the bond's daily turnover volume; the difference between the domestic and benchmark economy serves to estimate the liquidity premium.[7] We also include two macro measures directly related with the total supply of bond issued by the domestic government and the health of the trade sector: total debt over GDP and net trade balance over GDP, both of them in deviations from the benchmark. Also, we use the interaction between the total debt over GDP and the volatility of the differences between the domestic and benchmark yields as a measure of both the total supply of debt and its relative risk.[8] Since the

[5] In the domestic (benchmark) cases the default risk premium decreases (increases) with an increase in the recovery rates in case of default τ_t (τ_t^*).

[6] To deal with possible endogeneity problems we use the one day-lagged CDS spread.

[7] We realize that there is no generally held definition of liquidity. Many other measures have been suggested in the literature. In fact there is a close relationship between many of the measures and actual transactions costs, and the assumption that liquidity proxies measure liquidity seems to be granted, see Goyenko, Holden and Trzcinka (2008). Moreover, volume and other liquidity measures are usually employed in policy analysis, see European Central Bank (2009). In Section 4.2.4 we perform some robustness tests with respect to different specifications of the liquidity variable.

[8] The volatility of the differences between the domestic and benchmark yields accounts for the differences in the default processes.

overall investor's risk attitude is not observable we proxy the global risk aversion with the Chicago Board Options Exchange Volatility Index VIX.[9] Finally, the correlation between the domestic bond yield and the benchmark bond yield is used as a proxy for country-specific covariance risk.[10]

Recent work by Favero et al. (2009) and Berber et al. (2009) suggests that liquidity factors tend to be more important in uncertain times and that liquidity and credit risk potentially interact. We include in the regressions a proxy for that interaction variable between liquidity and credit risk using the product of liquidity times CDS spread to incorporate the effect of time-varying uncertainty.[11] This interaction also allows us to capture the differential effects across countries of flight-to-safety and/or flight-to-liquidity. We also include a crisis dummy variable to take into account possible changes in the intercept before and during crisis.

5.4 Data

The data consists of daily sovereign yields with maturities of 3, 5, 7, and 10 years for eleven EMU countries from January, 1 2004 to February 27, 2009. From August 9, 2007 to February 27, 2009, the period during the ongoing financial crisis, a crisis dummy is added to some of the estimations. Appendix C.2 provides additional details about the

[9] The VIX is often used as a proxy for investor's attitude toward risk and appears to explain movements of the bond spreads in recent years, see Hartelius et al. (2008) and Pan and Singleton (2007).

[10] This approximation is consistent with assuming that the volatility of both rates are similar and then the last term in (3) reduces to $[(k/k^*)Corr(x, x^*) - 1]$ and the expected sign for our proxy is positive.

[11] The liquidity measure employed to construct the interaction term is the Bid-Ask spread to make sure that both credit and liquidity variables move in the same direction. Thus, the higher the illiquidity or the credit risk, the higher is the interaction term. We also employ this liquidity measure to avoid multicollinearity problems. These problems are derived from the use of the turnover volume variable to control for interaction effects given that the correlation between the CDS spread lagged one period and the interaction term obtained from the turnover volume and the CDS spread lagged one period is 0.9.

definition, sources, and timing of the data used in the study.[12] Table 1 reports the total gross government debt outstanding at the end of the year for the eleven EMU members for the period 2003-2008. Summarizing the most salient features in Table 1, the three largest EMU bond issuers are Germany (25%), Italy (25%) and France (21%) and the smallest are Austria (2.7%), Portugal (1.6%) and Ireland (1.1%).

Table 1: General Government Gross Debt

This table reports the total gross government debt outstanding at the end of the year for eleven EMU members for the period 2003-2008 in billions (milliards) of Euros. It also reports the proportion of the total debt outstanding by each of the EMU members.

		2003	2004	2005	2006	2007	2008
Austria:	Amount outs.	**150.7**	**155.8**	**159.5**	**161**	**176.4**	**193.2**
	% of the total	2.78%	2.75%	2.75%	2.73%	2.76%	2.77%
Belgium:	Amount outs.	**273.2**	**278.6**	**279.7**	**281.2**	**308.7**	**325.7**
	% of the total	5.04%	4.91%	4.82%	4.77%	4.83%	4.68%
Finland:	Amount outs.	**67.24**	**65.05**	**65.54**	**63.03**	**62.14**	**71.61**
	% of the total	1.24%	1.15%	1.13%	1.07%	0.97%	1.03%
France:	Amount outs.	**1076.9**	**1145.4**	**1149.9**	**1208.8**	**1327.1**	**1531.6**
	% of the total	19.87%	20.20%	19.83%	20.50%	20.78%	21.99%
Germany:	Amount outs.	**1451.1**	**1521.9**	**1569**	**1576.6**	**1641.8**	**1752.7**
	% of the total	26.77%	26.83%	27.05%	26.74%	25.71%	25.17%
Greece:	Amount outs.	**183.2**	**195.3**	**204.4**	**216.4**	**237.2**	**254.1**
	% of the total	3.38%	3.44%	3.52%	3.67%	3.71%	3.65%
Ireland:	Amount outs.	**43.9**	**44.6**	**44.2**	**47.6**	**80.3**	**102.1**
	% of the total	0.81%	0.79%	0.76%	0.81%	1.26%	1.47%
Italy:	Amount outs.	**1444.6**	**1512.8**	**1582**	**1599**	**1663.6**	**1732.1**
	% of the total	26.65%	26.67%	27.28%	27.12%	26.05%	24.87%
Netherlands:	Amount outs.	**257.6**	**266.1**	**255.9**	**258.8**	**346.2**	**332.2**
	% of the total	4.75%	4.69%	4.41%	4.39%	5.42%	4.77%
Portugal:	Amount outs.	**84**	**94.8**	**100.5**	**103.7**	**110.4**	**123.4**
	% of the total	1.55%	1.67%	1.73%	1.76%	1.73%	1.77%
Spain:	Amount outs.	**388.4**	**391**	**389.4**	**380.7**	**432.5**	**545.4**
	% of the total	7.16%	6.89%	6.71%	6.46%	6.77%	7.83%
Total:	Amount outs.	**5420.84**	**5671.35**	**5800.04**	**5896.83**	**6386.34**	**6964.11**
	% of the total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Source: Ameco Database. Economic and Financial Affairs, European Commission.

In all cases the yields increase and the volatilities decrease with maturity. In general, average trading volume decreased during the crisis[13] suggesting that transaction costs increased across the board in the crisis period as well as CDS spreads and yield volatilities.[14] There is also evidence of an overall worsening of the trade balance across

[12] Detailed descriptive statistics for all the variables and countries are available on request. We report some of the important descriptive statistics below.

[13] There are slight increases in Belgium, Ireland and the Netherlands.

[14] It is interesting to note that some countries viewed by the market as having very little average sovereign risk (CDS spread around 2 basis points) before the crisis, like Germany, Austria, Belgium,

countries after the crisis started[15] as well as a decrease of the ratio of debt to GDP.[16]

For the 3, 5, 7, and 10 year sovereign yields the lowest averages are 3.30, 3.51, 3.70 and 3.91 respectively for Germany; the highest averages are 3.56, 3.82, 4.02, and 4.28 for Greece. Both the standard deviations and the minimum and maximum values indicate that there can be significant time-series variation in the sovereign yields. For example, 3-year yield for Italy ranges from 2.29 to 5.02 during the sample period.

Average daily trading volume (in millions of Euros) also presents wide variation ranging from the high volumes for Germany (16,813) and Italy (11,772) to the low volumes for Finland (239) and Ireland (130).

Average CDS rates vary substantially across countries. The lowest average in the whole sample is 8.41 basis points for Germany; the highest average is 40.25 basis points for Greece.[17] The macro factors also vary widely across countries. For instance the country with highest average Debt/GDP ratio is Italy (104%) and the lowest Ireland (27%) and the country with worse average trade balance is Greece (-6.5%) and the best one is Ireland (+5.6%). Regarding the average interaction debt factor, which measures not only the total debt outstanding but also its risk with respect to the benchmark, varies between 10 for Greece and 2 for Ireland, increasing markedly once the crisis starts to 16 and 4 respectively.[18] With respect to the liquidity/credit risk interaction factor, it varies between 0.1 basis points for Germany and 2.9 basis points for

France, or The Netherlands, were penalized in different ways once the crisis unfolds, being Germany (16 b.p.) and France (20 b.p.) viewed as the safest, then The Netherlands (25 b.p.) and finally Belgium (33 b.p.) and Austria (37 b.p.). However all countries experienced, in specific days, very high CDS premium, for instance Germany (91.8 b.p.), France (96 b.p.) or Austria (272 b.p.).

[15] The only exception being Italy whose (negative) external balance does not change.

[16] Portugal is the only exception with a ratio of 63% after the crisis in comparison with 61% before it.

[17] Both the standard deviations and the minimum and maximum values indicate that there can also be significant time-series variation in the sovereign CDS premium. For example, the cost of credit protection for Ireland ranges from 2.80 to 395.80 basis points during the sample period.

[18] Similar increases are also observed in all other countries.

Greece, increasing substantially during the crisis to 0.4 and 7.9 basis points, respectively. The low magnitude associated to the liquidity/credit risk interaction is due to the low magnitude of the bid-ask spread (i.e.: the average bid-ask spread is 6.7 basis points for Greece). Finally, the average correlation between the domestic 10-year government yield and the benchmark is highest for Germany (0.98) and lowest for Austria (0.87) decreasing in all countries during the crisis period, with France being the highest (0.96) and Greece the lowest (0.76). This decrease in the correlations could reflect a decrease in the degree of integration in the sovereign bond market of the EMU area in time periods of financial distress.[19]

5.5 Empirical Results

Having established the factors to be used as explanatory variables for the sovereign yields spreads (as suggested by the theoretical model), we now turn our attention to examine the economic and statistical significance of the variables in explaining both the cross-section as well as the time series of yields spreads. We group the data by country (11 countries) and maturity (3, 5, 7 and 10 years) totaling 44 groups which form an unbalanced panel.[20]

Average correlations among dependent and explanatory variables are presented in Table 2.[21] As expected, sovereign yields spreads are positively related to CDSs lagged by one day. This is consistent with our theoretical model's prediction that increases

[19] Analyses of financial integration in the Euro Area sovereign bond market can be found in Adam et al. (2002), Adjaouté and Danthine (2003) Baele et al. (2004) and Schulz and Wolff (2008) among others. They conclude that despite the great convergence between yields, yield differentials have not disappeared completely under EMU and so, European sovereign bonds are still not perfect substitutes.

[20] The panel is unbalanced because we do not have information on some variables from the beginning of the sample. However, there are no missing values once we include the first realization of the series.

[21] All the variables, with the exception of the measure of global risk, the correlation between the domestic Government and benchmark yields, and the crisis dummy are in deviations from the benchmark.

in default risk premiums are associated with increases in yield spreads. The negative correlation between yield spreads and the liquidity variable is in agreement with the theoretical prediction that the less liquid the domestic bond market is in comparison with the benchmark' liquidity, the greater will be the yield spread. The positive correlations for the Debt/GDP, Interaction variable and global risk suggest that as they each increase, sovereign yield spreads increase. The high and positive correlation between the liquidity/credit risk interaction variable and the sovereign yield spread suggests that there is an additional interactive effect in addition to the individual effect of these two variables. The negative correlation for the Trade balance variable suggests that trade deficit increase government yield spreads. Overall, the signs are in agreement with the ones suggested by the theoretical model. Our main objective, however, is to examine the joint effect of these explanatory variables on the yield spreads.

Table 2: Correlation between explanatory variables

This table reports the correlation between the dependent and explanatory variables employed in equations (4), (5) and (6). Gov. Yield refers to the difference between the domestic Government yield and the benchmark yield. CDS(-1) refers to the difference between the domestic and benchmark CDS spreads (in percentage) lagged one day. Liquidity represents the deviation of the logarithm of the domestic total bond daily turnover volume, in millions of Euros, from the log of the benchmark total bond daily turnover volume. Debt/GDP refers to the difference between the domestic and benchmark total gross debt outstanding at the end of the year divided by the corresponding GDP at that moment. Inter. (Debt) is an interaction term that represents the product of Debt/GDP and the standard deviation of the domestic yield minus the benchmark yield. Trade Balance/GDP refers to the deviation of the domestic net trade balance at the end of every month divided by the GDP from the benchmark equivalent measure. Global Risk is a measure of the overall risk which is obtained from the Chicago Board Options Exchange Volatility Index (VIX) and it is a measure of the implied volatility of S&P 500 index options. Corr(dom. & bnchmk y.) is the monthly correlation between the domestic Government bond yield and the EMU benchmark bond yield. Yield - CDS refers to the deviation of the domestic Government yield minus the CDS spread for the same maturity from the benchmark equivalent measure. Inter. Liq. (Bid-Ask) - CDS(-1) represents the difference (in percentage) between two interaction terms referred to the domestic country and the benchmark, respectively. The first interaction term is referred to the domestic country and represents the product of a liquidity premium or trading costs, which are measured by means of the bid-ask spread, and the CDS spread lagged one day while the second interaction term represents the benchmark equivalent measure. Crisis Dummy represents a variable which is equal to one during the crisis and zero otherwise. Gov. Yield is employed as dependent variable in equations (5.4) and (5.5). The dependent variable in equation (5.6) is the Government yield minus the CDS spread for the same maturity but this variable is not in deviations from the benchmark as the Yield - CDS variable that appears in this table.

Observations = 44062	Gov. Yield	CDS(-1)	Liquidity	Debt/GDP	Inter. (Debt)	Trade Bal./GDP	Global Risk	Corr(dom&bchmk)	Yield - CDS	Inter. Liq-Risk	Crisis
Gov. Yield											
CDS(-1)	0.849										
Liquidity	-0.014	-0.073									
Debt/GDP	0.290	0.142	0.600								
Inter. (Debt)	0.608	0.535	-0.016	0.180							
Trade Bal./GDP	-0.275	-0.144	-0.210	-0.476	-0.170						
Global Risk: log(VIX)	0.224	0.192	0.024	-0.045	0.540	0.011					
Corr(dom. & bnchmk y.)	-0.398	-0.481	0.241	0.137	-0.725	-0.045	-0.333				
Yield - CDS	0.311	-0.219	0.073	0.245	0.169	-0.208	0.053	0.115			
Inter. Liq. (Bid-Ask) - CDS(-1)	0.697	0.764	-0.062	0.146	0.584	-0.151	0.319	-0.453	-0.082		
Crisis Dummy	0.153	0.135	0.032	-0.059	0.404	-0.008	0.801	-0.216	0.011	0.213	

5.5.1 Unbalanced Panel Regression

We regress the difference between the sovereign yield in EMU country i and the benchmark portfolio yield onto differences in country i's credit quality, liquidity and macro measures from their respective cross-sectional weighted averages (or benchmark values) and onto global risk and interaction measures. We employ a Prais-Winsten regression with correlated panels, corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation within panels. The correlation within panels is treated as a first-order autocorrelation AR(1) and the coefficient of this process common[22] to all the panels.[23] Our panel regression model is described by the equation:

$$r_{i,t} - r^*_{i,t} = \alpha + \sum_{k=1}^{K} \beta_k \left(X_{k,i,t} - X_{k,BNCH,t} \right) + \sum_{j=1}^{M} \gamma_j D_{j,t} + \chi Y_{i,t} + \delta Z_t + \psi C_{i,t} + \varphi H_{i,t} + \varepsilon_{i,t} \tag{5.4}$$

where the dependent variable is the spread between the government bond's yield of country i, $r_{i,t}$ at four different maturities (3,5,7,and 10 years) and the benchmark yield $r^*_{i,t}$, at the same maturities. The benchmark yields are obtained as the weighted average of the Government yields of the EMU countries in the sample for the corresponding maturity (3, 5, 7, and 10 years). The weights are proportional to the portion of debt outstanding by each country with respect to the total amount outstanding by all these countries and change annually.[24] The $X_{k,i,t}$ are credit risk, liquidity and macro explanatory variables (CDS_{t-1}, Volume, Total debt/GDP, Net Trade Balance/GDP) and

[22] Better fit, as measured by the Schwarz Information Criteria, is obtained using an AR(1) autocorrelation structure common to all panels instead of a panel-specific AR(1) autocorrelation structure.

[23] Each element in the covariance matrix of the disturbances is computed with all available observations that are common to the two panels contributing to the covariance.

[24] To gain a better perspective of the dependent variable, it is worth mentioning that its maximum (minimum) average value is equal to 21.5 (-8.9) basis points for Greece (Germany).

$X_{k,BNCH,t}$ are their respective weighted averages over the eleven countries, obtained using the same procedure employed to build the benchmark yield.[25] Notice that we specify the credit, liquidity and macro variables as differences from their cross-sectional weighted averages (or benchmark value). This approach stresses the fact that credit risk; liquidity and macro variables are relative concepts. The $D_{j,t}$ are dummy variables to take into account the maturity effect in bond yields (3,5, and 7 years) as well as the crisis dummy that is equal to zero before August 9, 2007 and one afterwards. The $Y_{i,t}$ is the interaction term of total debt/GDP of country i times the volatility of the difference between domestic yield and benchmark yield. The Z_t is the global risk factor measured as the log of the VIX index and $C_{i,t}$ is the correlation between the country i yield (for its corresponding maturity) and the benchmark's yield. Finally, $H_{i,t}$ is the difference (in percentage) between two interaction terms referred to the country i and the benchmark, respectively. The first interaction term is referred to the country i and represents the product of a liquidity premium or trading costs, which are measured by means of the bid-ask spread, and the CDS spread lagged one day while the second interaction term represents the benchmark equivalent measure.

The results of the panel regressions are reported in Table 3. Column 1 gives the results without the crisis dummy, and Column 2 with the crisis dummy. The explanatory power of the regressions, reflected in their adjusted R^2, is 19.9% and 19.4%, respectively. Consistent with intuition as well as with our theoretical model and the previous literature, the CDS lagged one period has a strong positive impact on sovereign yield spread which indicates that a lower credit quality increases the yield spread. The li-

[25] Notice that the CDS variable is different for different maturities, whereas the other variables are the same for all maturities.

quidity differential is also significant. The negative coefficient suggests that higher than average liquidity is associated with lower yield spreads. The two macro factors (relative to GDP) and the global risk factor have also a positive and significant impact in the sovereign yield spread. The effect of the term measuring the interaction of total debt relative to GDP and the standard deviation of the domestic yield minus the benchmark yield is positive and significant. Recall that this variable measures both the total supply of debt and its relative risk against the benchmark. Therefore the economic meaning of this variable is that, for a given debt level, an increase in the volatility of the difference of the domestic yield and benchmark yield increases yield spreads. The more the two rates grow apart the higher the effect on yield spreads. This could be the case in a situation where a given country's spreads tends to diverge from the benchmark behavior and then the market penalizes this divergence demanding higher yield spreads. If two countries present the same divergence from the benchmark yield behavior, the penalization is higher for the country with the higher level of debt relative to GDP. The correlation between the domestic bond yield and the benchmark bond yield has positive effect as expected (see footnote 10).

The crisis dummy is positive and significant as well as the liquidity/credit risk interaction variable. This result suggests that there is a constant deviation between the domestic and benchmark yields which increases during the crisis. Moreover, the significant effect of the liquidity/credit risk interaction variable is consistent with the idea that liquidity factors tend to be more important in uncertain times and that liquidity and credit risk interact. Finally the maturity dummy variables coefficients reflect the decreasing premium for longer maturities.[26] Overall, these results provide strong support for the theoretical model and for all the proxy explanatory variables chosen. The inclusion of the crisis dummy, though significantly positive, does not affect materially the size and significance of the other explanatory variables.

[26]We repeated the regression in Table 3 using weights proportional to the debt outstanding by each EMU member in the Prais-Winsten regression and results do not change significantly. These results are available upon request.

Table 3: Determinants of the deviations between the Government Yield and the Benchmark Yield

This table reports the results of the unbalanced panel regressions. The dependent variable is the deviations between the Government yields and the Benchmark yields which are obtained as the weighted average of the Governments yields of the different European Monetary Union countries in the sample. The weights are proportional to the portion of debt outstanding by each of the EMU countries with respect to the total amount outstanding by all these countries. Our database is formed by eleven EMU countries and spans from January 2004 to February 2009. All the variables (dependent and explanatory) except the measure of global risk, the measure of correlation between the domestic Government and benchmark yields and the crisis dummy are presented in deviations from the value of the same variable for the benchmark. We group the panels by country and maturity (3, 5, 7 and 10 years) such that we have, at most, 44 groups which form an overall unbalanced panel. We estimate the coefficients of the determinants of deviations between yields by means of a Prais-Winsten regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation within panels. The correlation within panels is treated as a first-order autocorrelation AR(1) and the coefficient of this process common to all the panels. Each element in the covariance matrix of the disturbances is computed with all available observations that are common to the two panels contributing to the covariance. Column (1) reports the results which are obtained without using the crisis dummy as an explanatory variable and Column (2) reports the results using the crisis dummy as explanatory variable. The results presented correspond to the estimated coefficient and the *t-statistic* (between brackets).

		(1)	(2)
CDS(-1)		0.522	0.519
		(34.68)	(34.19)
Log (Total bond daily turnover volume)		-0.011	-0.011
		(-5.85)	(-5.92)
Total debt issued divided by GDP		0.144	0.148
		(12.11)	(12.29)
Interaction of total debt divided by GDP and the standard deviation of the domestic yield minus the benchmark yield		1.234	1.187
		(12.60)	(11.88)
Net Trade Balance divided by GDP		-49.049	-48.639
		(-6.39)	(-6.27)
Global risk measure: log(VIX index)		0.013	0.011
		(4.80)	(3.63)
Correlation between domestic Government yield and EMU benchmark Government Yield		0.076	0.073
		(4.51)	(4.28)
Interaction of liquidity (bid-ask spread) and CDS(-1)		0.165	0.161
		(2.57)	(2.50)
Dummy for the 3-year yield		0.013	0.013
		(3.98)	(3.93)
Dummy for the 5-year yield		0.012	0.012
		(4.27)	(4.22)
Dummy for the 7-year yield		0.005	0.005
		(2.21)	(2.16)
Crisis dummy			0.011
			(2.58)
Constant		-0.135	-0.127
		(-7.29)	(-6.75)
Autorregressive (AR(1)) coefficient		0.900	0.901
R-squared		0.199	0.194
Observations		47904	47904
Number of groups		44	44
Observations per group	Minimum	202	202
	Average	1089	1089
	Maximum	1294	1294
Wald chi2 (10 df)		2835.130	2791.910
Prob. > chi2		0	0
Condition Index		20.190	27.160

Since there is a potential endogeneity between a country's sovereign yields and its CDS rates, in the panel regression results reported in Table 3 we have used a one period (day) lag in the CDS explanatory variable. This is a standard procedure to deal with potential endogeneity. To further address this issue, we have run an identical panel regression but omitting the deviation of the domestic CDS spread from the benchmark and the deviation of the domestic interaction between the CDS and bid-ask spreads from the benchmark corresponding interaction. These results are reported in Table 4 without and with the crisis dummy (Column 1 and Column 2, respectively). As can be seen from this table the results are qualitatively very similar to those in Table 3, confirming the significance of the other explanatory variables and suggesting that endogeneity is not a serious issue in our case. As expected, the explanatory power of the panel regressions is lower given that we are omitting two powerful explanatory variables: the CDS spread lagged one period and the interaction liquidity/credit risk.

Table 4: Determinants of the deviations between the Government Yield and the Benchmark Yield without including CDSs

This table reports the results of the unbalanced panel regression excluding the CDS variable, that is, the variables employed in this table are the same as in Table 3 with the exception of the deviation of the domestic CDS spread from the benchmark and the deviation of the domestic interaction between the CDS and bid-ask spreads from the benchmark corresponding interaction which are now excluded. All the variables (dependent and explanatory) except the measure of global risk, the measure of correlation between the domestic Government and benchmark yields and the crisis dummy are presented in deviations from the value of the same variable for the benchmark. We group the panels by country and maturity (3, 5, 7 and 10 years) such that we have, at most, 44 groups which form an overall unbalanced panel. We estimate the coefficients of the determinants of deviations between yields by means of a Prais-Winsten regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation within panels. The correlation within panels is treated as a first-order autocorrelation AR(1) and the coefficient of this process common to all the panels. Each element in the covariance matrix of the disturbances is computed with all available observations that are common to the two panels contributing to the covariance. Column (1) reports the results obtained excluding the CDS(-1) variable, the interaction of liquidity and CDS(-1) variable and the crisis dummy. Column (2) reports the results obtained excluding both the CDS(-1) and the interaction of liquidity and CDS(-1) variables. The results presented correspond to the estimated coefficient and the *t-statistic* (between brackets).

		(1)	(2)
Log (Total bond daily turnover volume)		-0.014	-0.015
		(-4.53)	(-4.64)
Total debt issued divided by GDP		0.221	0.228
		(8.89)	(9.16)
Interaction of total debt divided by GDP and the standard deviation of the domestic yield minus the benchmark yield		0.882	0.839
		(8.10)	(7.69)
Net Trade Balance divided by GDP		-42.481	-41.766
		(-3.36)	(-3.31)
Global risk measure: log(VIX index)		0.014	0.012
		(4.79)	(3.89)
Correlation between domestic Government yield and EMU benchmark Government Yield		0.032	0.030
		(1.78)	(1.65)
Dummy for the 3-year yield		0.014	0.014
		(2.07)	(2.07)
Dummy for the 5-year yield		0.013	0.013
		(2.41)	(2.40)
Dummy for the 7-year yield		0.006	0.006
		(1.31)	(1.30)
Crisis dummy			0.028
			(5.08)
Constant		-0.074	-0.073
		(-3.55)	(-3.53)
Autorregressive (AR(1)) coefficient		0.952	0.952
R-squared		0.014	0.015
Observations		47904	47904
Number of groups		44	44
Observations per group	Minimum	202	202
	Average	1089	1089
	Maximum	1294	1294
Wald chi2 (10 df)		245.420	281.150
Prob. > chi2		0	0
Condition Index		20.840	28.160

Finally, we analyze the effect of the cross-sectional dispersion between countries in the explanatory variables on the dependent variable. For this aim, we first calculate the standard deviation of each explanatory variable across countries at each date t. Then, we compute the average of these standard deviations for all dates and finally multiply this average by the corresponding coefficient (see Table 3). In Table 5 we report the results of this sensitivity analysis of the determinants of the yield spreads. Specifically, we report the magnitude of the change, in basis points, of the dependent variable given a change equal to the average of the standard deviations across countries of a given explanatory variable over all dates.[27] We focus on the cross-sectional dimension of the panel and employ the time-series dimension to calculate the average effect across time.[28] This allows us to evaluate how the different macro or risk factors of the countries under study affect the yield spreads.

The largest effect on yield spreads is caused by deviations between the countries' CDSs spreads (4.78 b.p.). The variable with the second strongest effect is the total debt issued relative to GDP. The average change in the dependent variable is 3.57 b.p. The next most influential variables are liquidity and the net trade balance over GDP, albeit with lower order of magnitude, whereas the other variables have lower effects. Note that the sensitivities are practically unaffected by the inclusion of the crisis dummy.

[27] The standard deviation of the following variables: CDS spread (lagged one day); interaction of total debt divided by GDP and the standard deviation of the difference between domestic and benchmark yields; correlation between domestic Government yield and benchmark yield; and liquidity/credit risk interaction variable are calculated for the five year's maturity.

[28] We repeat the sensitivity analysis focused on the time-series dimension of the panel. By means of this analysis, we estimate the change in the dependent variable after a change of one standard deviation in a given explanatory variable across time and countries. Results are in line with the ones in Table 5 but are not reported in this paper given that our aim is to focus on how the differences between countries affect the deviations in the yield spreads and so, we focus in the cross-section dimension.

Table 5: Sensitivity Analysis of the Determinants of the deviations between the Government Yield and the Benchmark Yield

This table provides the sensitivity analysis of the determinants of the deviations between the Government yields and the Benchmark yields. All the variables (dependent and explanatory) excepting the correlation between the domestic and benchmark yields are presented in deviations from the value of the variable for the benchmark. Column (1) reports the results which are obtained without using the crisis dummy as an explanatory variable and Column (2) reports the results using the crisis dummy as explanatory variable. Each column reports the response, in basis points, of the dependent variable (deviation of the domestic Government yield from the benchmark yield) to a change equal to the average of the standard deviations of a given explanatory variable across countries over all dates. For this aim, we first calculate the standard deviation of each explanatory variable across countries at each date *t* . Then, we compute the average of these standard deviations for all the dates *t* and finally, we multiply this average by the corresponding coefficient (see Table 3). The standard deviation of variables: CDS spread (lagged one period); interaction of total debt divided by GDP and yield S.D.; correlation between Gov. yield and benchmark yield; and interaction of liquidity and CDS spread (lagged one period) are presented for a maturity of five years.

	(1)	(2)
CDS (lagged one period) spread	4.78	4.75
Total bond daily turnover volume	-1.70	-1.74
Total debt issued divided by GDP	3.57	3.67
Interation of total debt divided by GDP and the yield S.D.	1.27	1.22
Net Trade Balance divided by GDP	-1.74	-1.72
Correlation between Gov. yield and benchmark yield	0.45	0.43
Interaction of liquidity (bid-ask spread) and CDS(-1)	0.18	0.17

5.5.2 Robustness Tests

In this section, we report the results of several checks on the basic results. The robustness tests consider cross-section regressions, changes in the benchmark, using balance panel regressions and alternative liquidity measures, employing alternative data frequencies and analysing maturity by maturity. In all cases the results are robust to the alternative specifications.

5.5.2.1 Cross Section Regressions

As a first robustness test we run a cross-section regression every day and then we test for the significance of the time series of coefficients, see Fama and Macbeth (1973). Equation (5.5) details our cross-section regression model:

$$
\begin{aligned}
r_{i,t} - r^*_{i,t} &= \alpha_t + \sum_{k=1}^{K} \beta_{k,t} \left(X_{k,i,t} - X_{k,BNCH,t} \right) + \sum_{j=1}^{M} \gamma_{j,t} D_{j,t} + \chi_t Y_{i,t} + \varphi_t H_{i,t} + \varepsilon_{i,t} \\
i &= 1, ..., 44 \quad t = 1, ..., 1294 \qquad (5.5)
\end{aligned}
$$

where the dependent variable is the spread between the government bond's yield of country i (i=1,. . . ,11) $r_{i,t}$ at four different maturities (3,5,7,and 10 years) and the benchmark yield $r^*_{i,t}$, at the same maturities. The benchmark yields are obtained as the weighted average of the Government yields of the EMU countries in the sample for the corresponding maturity (3, 5, 7, and 10 years). The weights are proportional to the portion of debt outstanding by each country with respect to the total amount outstanding by all these countries. The $X_{k,i,t}$ are credit risk, liquidity and macro explanatory variables (CDS_{t-1}, Volume, Total debt/GDP, Trade Balance/GDP) and $X_{k,BNCH,t}$ are their respective weighted averages over the eleven countries. Notice that we specify the credit, liquidity and macro variables as differences from their cross-sectional weighted averages. This approach stresses that credit risk, liquidity, and macro stance are relative concepts. The $D_{j,t}$ are dummy variables to take into account the maturity effect in bond yields (3, 5, and 7 years). The $Y_{i,t}$ is the interaction term of total debt relative to GDP times the volatility of the difference between domestic yield and benchmark yield.[29] Finally, $H_{i,t}$ is the difference (in percentage) between two interaction terms referred to the country i and the benchmark respectively. The first interaction term is referred to the country i and represents the product of a liquidity premium or trading costs, which are measured

[29] Note that in equation (5.5) we do not employ the VIX index, the crisis dummy and the correlation between the domestic and the benchmark yields. The reason is because both the VIX index and the crisis dummy are the same for all the countries and maturities. We exclude the correlation variable because it causes multicollinearity problems.

by means of the bid-ask spread, and the CDS spread lagged one day while the second interaction term represents the benchmark equivalent measure.

In order to estimate the cross-sectional effects of the above variables, we run a cross-sectional regression by OLS for every date in the sample (1294 in total) and compute the average coefficient for the whole sample. Petersen (2009) states that the Fama-MacBeth standard errors are biased in exactly the same way as the OLS estimates and the magnitude of the bias is a function of the serial correlation of both the independent variable and the residual within a cluster and the number of time periods per firm (or cluster). Thus, we must adjust the standard errors for the autocorrelation of the estimated slope coefficients.[30] We employ the Fama-MacBeth methodology with Newey-West standard errors.[31]

The results of the cross section regressions are reported in Table 6. Column 1 gives the estimated coefficients, Column 2 the corrected t-statistics, Column 3 the proportion of coefficients with the right sign, Column 4 the change in the dependent variable given a change of one standard deviation in the explanatory variable and the last Column the explained variance by each explanatory variable (in percentage). The average R2 of the cross-sectional regression is 73%. The magnitude of the regression coefficient suggests that a one standard deviation increase in the CDS above the weighted average is associated with an average increase in the sovereign yield spread of 6.8 b.p.[32] This

[30] As Petersen (2009) states, when there is only a time effect, the correlation of the estimated slope coefficients across years is zero and the standard errors estimated by the Fama-MacBeth are unbiased.

[31] In order to find an unbiased t-statistic, we regress the estimated coefficients on a constant using the Newey-West adjustment to control for serial correlation. This methodology is also employed in Davydenko and Strebulaev (2007).

[32] To gain a better understanding of the effects of the explanatory variables on the dependent variable, it is worth noting that the maximum (minimum) average value by country for the deviation between the Government yield and the benchmark yield is equal to 21.5 (-8.9) basis points for Greece (Germany).

is the most economically significant effect found for the explanatory variables. The two macro factors (relative to GDP) have a significant impact in the sovereign yield spread. One standard deviation increase in the total debt and the net trade balance, both above the weighted average, is associated with an average increase in the sovereign yield spread of 1.8 b.p. and a decrease of 1.6 b.p. respectively.

The effect of the term measuring the interaction of total debt and the standard deviation of the domestic yield minus the benchmark yield is positive and significant. One standard deviation increase in this variable is associated with an average increase in the sovereign yield spread of 1.7 b.p.

With respect to the liquidity differential variable the negative coefficient suggests that higher than weighted average liquidity is associated with lower yield spreads. The economic impact of the liquidity differential is the lowest of all the explanatory variables in the analysis. One standard deviation increase in liquidity above the average is associated with an average change in the sovereign yield spread of -1.1 basis points. The liquidity/credit risk interaction factor is significant but its effect is only of 0.5 b.p. Finally the dummy variables coefficients reflect the decreasing premium for longer maturities.

Overall the results of the cross sectional regressions are consistent with the ones given by the unbalanced panel regression reported in Section 4.1 indicating that the main results of the analysis are robust to different specifications of the regressions. The sensitivity analysis' results for the cross-sectional regression are also similar to those reported in Table 5 for the panel regressions.

Table 6: Determinants of the deviations between the Government Yield and the Benchmark Yield (Cross Section Analysis)

This table reports the results of the cross-sectional regressions. All the variables (dependent and explanatory) are presented in deviations from the benchmark. We run a cross-sectional regression by OLS for every date (1294) in the sample and calculate the average coefficient for the 1294 regressions which is reported in the first column. We find that the estimated slope coefficients present autocorrelation and for this reason, in the second column we report the t-statistic obtained from the Newey-West adjusted standard errors. These errors are obtained after regressing with Newey-West standard errors adjustment the loadings on each factor, which are shown in the first column, on a constant. The intercept that was included at the first stage is not reported. The third column reports the portion of cross-sectional regressions where the sign of the coefficient is the same as the expected sign. The fourth column shows the change in the dependent variable after a change in the explanatory variable equal to one standard deviation. Last column reports the portion of variance in the dependent variable explained by the corresponding explanatory variable. This proportion is calculated after multiplying the coefficient by the ratio of the standard deviations of the independent variable and the dependent variable. We report the results obtained using all the explanatory variables in Table 3 excluding the global risk, the crisis dummy and the correlation between domestic and EMU benchmark Government yields.

	Coefficient	Corrected t-stat	Right Sign (%)	1 S.D. change	Explained var. (%)
CDS spread lagged one period	0.861	15.21	0.808	0.068	0.256
Log (Total bond daily bond turnover volume)	-0.009	-5.98	0.566	-0.011	0.002
Total debt issued divided by GDP	0.075	10.49	0.658	0.018	0.009
Interaction of total debt divided by GDP and the standard deviation of the domestic yield minus the benchmark yield	1.884	29.730	0.727	0.017	0.024
Net Trade Balance divided by GDP	-46.220	-9.09	0.320	-0.016	0.015
Dummy for the 3-year yield	0.019	15.02	0.737	0.008	0.014
Dummy for the 5-year yield	0.016	13.29	0.688	0.007	0.007
Dummy for the 7-year yield	0.008	10.84	0.667	0.004	0.002
Interaction of liquidity (bid-ask spread) and CDS(-1)	1.916	4.800	0.505	0.005	0.009
Constant	-0.030	-21.25	0.264		
Average R-squared	0.736				
Cross-Sections with Condition Matrix Above 30	66				

5.5.2.2 Changing the Benchmark

We next address the issue of how robust are our results to the choice of benchmark. In particular, as is common in the literature, we use the German bond as a benchmark.

Table 7 presents the results of estimating the panel regression equation (5.4) using two different benchmarks. Besides the benchmark used in this study, which is obtained from the relative weights calculated from the total debt outstanding by each country over the total amount in the EMU, we present the results obtained using the German bond as the benchmark. As can be seen from Table 7, our main results are not very sensitive to the choice of benchmark.[33]

[33] As a potential benchmark we have also analyzed the Euro Swap rate. In fact, Beber, Brandt and Kavajecz (2009) use the Euro swap curve. When we use the Euro Swap rate as the benchmark and, contrary to our base case, the interaction between the debt and the standard deviation of the difference between the domestic and benchmark yields is not significant. Also the coefficient of the crisis dummy is now negative. Therefore, during the crisis, the Euro Swap rate was on average higher than the sovereign yields and this fact casts doubts on its adequacy as a benchmark.

Table 7: Determinants of the deviations between the Government Yield and the Benchmark Yield for different benchmarks

This table reports the results of the unbalanced panel regressions using an alternative benchmark: the German bond yield. All the variables (dependent and explanatory) except the measure of global risk, the measure of correlation between the domestic Government and benchmark yields and the crisis dummy are presented in deviations from the value of the variable for the benchmark. We group the panels by country and maturity (3, 5, 7 and 10 years) such that we have, at most, 44 groups which form an overall unbalanced panel. We estimate the coefficients of the determinants of deviations between yields by means of a Prais-Winsten regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation within panels. The correlation within panels is treated as a first-order autocorrelation AR(1) and the coefficient of this process common to all the panels. Each element in the covariance matrix of the disturbances is computed with all available observations that are common to the two panels contributing to the covariance. Column (1) reports the results for the benchmark employed in Table 3 and it is equivalent to the second column of that table. The results in Column (2) are obtained by using the values of Germany as the benchmark. The results presented correspond to the estimated coefficient and the *t-statistic* (between brackets).

		(1)	(2)
CDS(-1)		0.519	0.439
		(34.19)	(22.31)
Log (Total bond daily turnover volume)		-0.011	-0.004
		(-5.92)	(-1.36)
Total debt issued divided by GDP		0.148	0.099
		(12.29)	(4.37)
Interaction of total debt divided by GDP and the standard deviation of the domestic yield minus the benchmark yield		1.187	0.011
		(11.88)	(8.61)
Net Trade Balance divided by GDP		-48.639	-40.154
		(-6.27)	(-3.26)
Global risk measure: log(VIX index)		0.011	0.034
		(3.63)	(3.78)
Correlation between domestic Government yield and EMU benchmark Government Yield		0.073	0.025
		(4.28)	(1.07)
Interaction of liquidity (bid-ask spread) and CDS(-1)		0.161	0.358
		(2.50)	(4.68)
Crisis dummy		0.013	0.120
		(3.93)	(7.70)
Dummy for the 3-year yield		0.012	-0.026
		(4.22)	(-2.33)
Dummy for the 5-year yield		0.005	-0.009
		(2.16)	(-1.24)
Dummy for the 7-year yield		0.011	-0.006
		(2.58)	(-1.08)
Constant		-0.127	-0.052
		(-6.75)	(-1.46)
Autorregressive (AR(1)) coefficient		0.901	0.943
R-squared		0.194	0.107
Observations		47904	47904
Number of groups		44	44
Observations per group	Minimum	202	202
	Average	1089	1089
	Maximum	1294	1294
Wald chi2 (10 df)		2791.910	1344.340

5.5.2.3 Balanced Panel

To be able to use as much of the data as possible and deal with missing observations the panel regressions estimated in this paper have been unbalanced. In this section we look at the robustness of our results to the use of a balanced panel.

Table 8 presents the results of fitting equation (5.4) to a balanced panel data formed by ten of the eleven countries, and ranging from March 2006 to February 2009.[34] The estimation is done by means of Generalized Least Squares (GLS). The GLS procedure allows estimation in the presence of AR(1) autocorrelation within panels and cross-sectional correlation and heteroskedasticity across panels. Even though the data used in this regression is somewhat different, the results obtained are similar to those obtained for the unbalanced panel. In fact, the magnitude and significance of the explanatory variables provides stronger support for the specification used.

[34] We exclude Finland and the observations before the 27th of March, 2006 in order to have a balanced panel. The reason is that for some countries, the CDSs series present missing values before that date. In the case of Finland there are only 202 observations on CDSs.

Table 8: Determinants of the deviations between the Government Yield and the Benchmark Yield using a balanced panel

This table reports the results of the balanced panel regressions. The data includes only ten of the eleven EMU countries and spans the period from March 2006 to February 2009. In order to have a balanced panel, Finland and the observations before the 27th of March are excluded. All the variables (dependent and explanatory) except the measure of global risk, the measure of correlation between the domestic Government and benchmark yields and the crisis dummy are presented in deviations from the value of the variable for the benchmark. We group the panels by country and maturity (3, 5, 7, and 10 years) such that we have, at most 40 groups which form a balanced panel. The estimation is done using Generalized Least Squares. The GLS procedure that we employ allows estimation in the presence of AR(1) autocorrelation within panels and cross-sectional correlation and heteroskedasticity across panels. Column (1) reports the results for the whole sample without using the crisis dummy as an explanatory variable and Column (2) reports the results using the crisis dummy as explanatory variable. The results presented correspond to the estimated coefficient and the t-statistic (between brackets).

	(1)	(2)
CDS(-1)	0.416	0.416
	(40.12)	(40.03)
Log (Total bond daily turnover volume)	-0.013	-0.013
	(-8.00)	(-8.07)
Total debt issued divided by GDP	0.207	0.208
	(20.46)	(20.50)
Interaction of total debt divided by GDP and the standard deviation of the domestic yield minus the benchmark yield	0.245	0.235
	(13.40)	(12.94)
Net Trade Balance divided by GDP	-38.713	-38.536
	(-6.44)	(-6.39)
Global risk measure: log(VIX index)	0.006	0.005
	(7.06)	(5.22)
Correlation between domestic Government yield and EMU benchmark Government Yield	0.011	0.010
	(3.83)	(3.70)
Interaction of liquidity (bid-ask spread) and CDS(-1)	0.258	0.246
	(5.78)	(5.48)
Dummy for the 3-year yield	0.003	0.003
	(6.90)	(6.98)
Dummy for the 5-year yield	0.004	0.004
	(11.99)	(12.05)
Dummy for the 7-year yield	0.001	0.000
	(2.66)	(2.58)
Crisis dummy		0.006
		(3.96)
Constant	-0.033	-0.032
	(-8.33)	(-7.90)
Autorregressive (AR(1)) coefficient	0.896	0.897
Log likelihood	105576	105600
Observations	35040	35040
Number of groups	40.00	40
Time periods	876.00	876
Wald chi2 (10 df)	4343.320	4359.290
Prob. > chi2	0	0
Condition Index	19.260	26.380

5.5.2.4 Liquidity and risk measures

We also analyze the robustness of our results to alternative specifications of the liquidity measure. Table 9 presents the results of fitting model (4) to the full sample using three alternative liquidity measures: total daily turnover volume, bid-ask spreads and average daily turnover volume.[35] In all cases the liquidity coefficients have the expected signs and they are significant. The results for the other variables do not change materially. As the volume and the bid-ask spread are different liquidity measures and they affect yields in the opposite direction, the coefficients' order of magnitude cannot be directly compared. However, looking at a standardized measure such as the t-statistic we observe that all the liquidity measures have a similar effect. Note that in the Column (2) the interaction of the liquidity and the CDS spread is not significant given that the individual effect of the liquidity variable (bid-ask spread) seems to be more important than the interaction term. This fact gives support to our approach of using a specific liquidity variable (turnover volume) and an interaction variable (liquidity-risk) defined from the bid-ask spread.

[35] This average volume is calculated as the ratio between the total daily turnover volume and the number of bonds issued by the corresponding country.

Table 9: Determinants of the deviations between the Government Yield and the Benchmark Yield using different liquidity measures

This table reports the results of the unbalanced panel regression using alternative liquidity measures. Column (1) reports the results obtained using as liquidity proxy the total daily turnover volume, Column (2) reports the results obtained using the bid-ask spread (b.p.) as the liquidity measure and Column (3) shows the results obtained using as a proxy for liquidity the average daily turnover volume. This average volume is calculated as the ratio between the total daily turnover volume and the number of bonds issued by the corresponding country. The results presented correspond to the estimated coefficient and the t-statistic (between brackets). We estimate the coefficients of the determinants of deviations between yields by means of a Prais-Winsten regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation within panels. The correlation within panels is treated as a first-order autocorrelation AR(1) and the coefficient of this process common to all the panels. Each element in the covariance matrix of the disturbances is computed with all available observations that are common to the two panels contributing to the covariance.

		(1)	(2)	(3)
CDS(-1)		0.519	0.537	0.519
		(34.19)	(35.21)	(34.09)
Liquidity		-0.011	0.256	-0.012
		(-5.92)	(3.60)	(-4.77)
Total debt issued divided by GDP		0.148	0.099	0.135
		(12.29)	(8.85)	(11.38)
Interaction of total debt divided by GDP and the standard deviation of the domestic yield minus the benchmark yield		1.187	1.236	1.176
		(11.88)	(12.36)	(11.77)
Net Trade Balance divided by GDP		-48.639	-51.846	-49.791
		(-6.27)	(-6.79)	(-6.37)
Global risk measure: log(VIX index)		0.011	0.010	0.011
		(3.63)	(3.39)	(3.63)
Correlation between domestic Government yield and EMU benchmark Government Yield		0.073	0.073	0.070
		(4.28)	(4.31)	(4.14)
Interaction of liquidity (bid-ask spread) and CDS(-1)		0.161	0.047	0.162
		(2.50)	(0.64)	(2.52)
Dummy for the 3-year yield		0.013	0.014	0.013
		(3.93)	(4.00)	(3.90)
Dummy for the 5-year yield		0.012	0.012	0.012
		(4.22)	(4.30)	(4.19)
Dummy for the 7-year yield		0.005	0.005	0.005
		(2.16)	(2.25)	(2.16)
Crisis dummy		0.011	0.007	0.011
		(2.58)	(1.74)	(2.60)
Constant		-0.127	-0.116	-0.121
		(-6.75)	(-6.22)	(-6.44)
Autorregressive (AR(1)) coefficient		0.901	0.899	0.902
R-squared		0.194	0.199	0.191
Observations		47904	47904	47904
Number of groups		44	44	44
Observations per group	Minimum	202	202	202
	Average	1089	1089	1089
	Maximum	1294	1294	1294
Wald chi2 (10 df)		2791.910	2834.750	2729.960
Prob. > chi2		0	0	0
Condition Index		27.16	26.32	27.07

As the liquidity proxies change with maturity and given that what matters to investors is the liquidity of a particular segment of the yield curve and not the overall liquidity of the sovereign bond market, we repeat the analysis using alternative liquidity measures with the corresponding maturity (3, 5, 7 or 10 years). The results obtained under this modification are shown in Table 10 and they do not change with respect to Table 9.

Table 10: Determinants of the deviations between the Government Yield and the Benchmark Yield using different liquidity measures with the corresponding maturity

This table reports the results of the unbalanced panel regression using alternative liquidity measures with the corresponding maturity (3, 5, 7 or 10 years). This table is similar to Table 10 but the liquidity variables are defined for different maturities. Column (1) reports the results which are obtained using as liquidity proxy the total daily turnover volume, Column (2) reports the results which are obtained using the bid-ask spread as the liquidity measure and Column (3) shows the results obtained using as a proxy for liquidity the average daily turnover volume. This average volume is calculated as the ratio between the total daily turnover volume and the number of bonds issued by the corresponding country. The results presented correspond to the estimated coefficient and the *t-statistic* (between brackets). We estimate the coefficients of the determinants of deviations between yields by means of a Prais-Winsten regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation within panels. The correlation within panels is treated as a first-order autocorrelation AR(1) and the coefficient of this process common to all the panels. Each element in the covariance matrix of the disturbances is computed with all available observations that are common to the two panels contributing to the covariance.

		(1)	(2)	(3)
CDS(-1)		0.530	0.533	0.530
		(35.38)	(31.76)	(35.32)
Liquidity		-0.007	0.089	-0.007
		(-5.65)	(4.59)	(-4.87)
Total debt issued divided by GDP		0.137	0.108	0.128
		(11.84)	(9.51)	(11.23)
Interaction of total debt divided by GDP and the standard deviation of the domestic yield minus the benchmark yield		1.220	1.235	1.217
		(11.62)	(11.75)	(11.59)
Net Trade Balance divided by GDP		-53.750	-56.165	-55.223
		(-6.63)	(-6.92)	(-6.79)
Global risk measure: log(VIX index)		0.011	0.010	0.011
		(3.61)	(3.36)	(3.59)
Correlation between domestic Government yield and EMU benchmark Government Yield		0.083	0.083	0.082
		(4.52)	(4.52)	(4.45)
Interaction of liquidity (bid-ask spread) and CDS(-1)		0.093	0.117	0.092
		(5.21)	(1.64)	(5.19)
Dummy for the 3-year yield		0.013	0.013	0.012
		(3.42)	(3.67)	(3.23)
Dummy for the 5-year yield		0.010	0.013	0.009
		(3.77)	(4.85)	(3.26)
Dummy for the 7-year yield		0.003	0.006	0.002
		(1.40)	(2.75)	(0.77)
Crisis dummy		0.009	0.007	0.009
		(2.18)	(1.69)	(2.13)
Constant		-0.130	-0.124	-0.126
		(-6.56)	(-6.25)	(-6.31)
Autorregressive (AR(1)) coefficient		0.901	0.901	0.901
R-squared		0.193	0.193	0.191
Observations		45256	45055	45248
Number of groups		44	43	44
Observations per group	Minimum	202	202	202
	Average	1029	1048	1028
	Maximum	1294	1294	1294
Wald chi2 (10 df)		2546.960	2499.170	2516.500
Prob. > chi2		0	0	0
Condition Index		19.83	26.50	26.93

A similar concern can be applied to the use of the CDS spread. The price of risk changes with maturity and what matters to investors is the price of the risk for the maturity they are willing to hedge and not only the 5-year maturity. For this reason, we repeat the analysis using both the CDS lagged one period and the interaction of the liquidity (bid-ask spread) and CDS lagged one period variables with the corresponding maturity (3, 5, 7 or 10 years). As one can observe in Table 11 we obtain similar results as in Table 3.

We report and comment the main results of the paper based on Table 3 given that using the CDS spread lagged one period for the 5-year maturity and the liquidity measure for the overall maturities, we have a higher number of observations and we can homogenize the risk and liquidity effects.

Finally, besides the logarithm of the VIX Index we try different proxies for the global risk factor due to the great variety of variables that have been traditionally employed to proxy this factor. For instance, we employ: logarithm of the VDAX Index, square of the MSCI returns, iTraxx Europe (European CDS Index), difference between 10-year AAA US corporate yield and 10-year US Government bonds yield, difference between 10-year BBB US corporate yield and 10-year US Government bonds yield, difference between 10-year BBB US corporate yield and 10-year AAA US corporate yield. We find that their effects are positive in all cases and the standardizations of the coefficients from the t-statistics are very similar among them. Moreover, the coefficients of the remaining variables remain unchanged.[36]

[36] These results are available upon request.

Table 11: Determinants of the deviations between the Government Yield and the Benchmark Yield using the CDSs with the corresponding maturity

This table reports the results of the unbalanced panel regression using the CDS(-1) and the Interaction of liquidity (bid-ask spread) and CDS(-1) variables with the corresponding maturity (3, 5, 7 or 10 years). This table is similar to Table 3 but the CDS(-1) and the Interaction of liquidity and CDS(-1) variables are defined for the different CDS maturities. Column (1) reports the results which are obtained using the crisis dummy as explanatory variable. Column (2) reports the results without using the crisis dummy as an explanatory variable. The results presented correspond to the estimated coefficient and the *t-statistic* (between brackets). We estimate the coefficients of the determinants of deviations between yields by means of a Prais-Winsten regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation within panels. The correlation within panels is treated as a first-order autocorrelation AR(1) and the coefficient of this process common to all the panels. Each element in the covariance matrix of the disturbances is computed with all available observations that are common to the two panels contributing to the covariance.

		(1)	(2)
CDS(-1)		0.209	0.210
		(26.16)	(26.20)
Liquidity		-0.019	-0.019
		(-9.34)	(-9.25)
Total debt issued divided by GDP		0.192	0.189
		(16.51)	(16.30)
Interaction of total debt divided by GDP and the standard deviation of the domestic yield minus the benchmark yield		1.754	1.786
		(17.25)	(17.91)
Net Trade Balance divided by GDP		-50.754	-51.035
		(-6.85)	(-6.89)
Global risk measure: log(VIX index)		0.011	0.014
		(3.37)	(4.59)
Correlation between domestic Government yield and EMU benchmark Government Yield		0.066	0.068
		(3.63)	(3.77)
Interaction of liquidity (bid-ask spread) and CDS(-1)		0.954	0.958
		(16.10)	(16.19)
Dummy for the 3-year yield		0.010	0.010
		(3.04)	(3.04)
Dummy for the 5-year yield		0.009	0.009
		(3.41)	(3.33)
Dummy for the 7-year yield		0.005	0.005
		(2.23)	(2.25)
Crisis dummy		0.009	
		(2.13)	
Constant		-0.133	-0.140
		(-6.69)	(-7.19)
Autorregressive (AR(1)) coefficient		0.884	0.884
R-squared		0	0
Observations		44055	44055
Number of groups		44	44
Observations per group	Minimum	202	202
	Average	1001	1001
	Maximum	1293	1293
Wald chi2 (10 df)		2801.440	2763.790
Prob. > chi2		0	0
Condition Index		26.68	19.87

5.5.2.5 Data frequency

Some macro series (Gross Debt outstanding) have annual frequency; other series (GDP) have quarterly frequency while others (Net Trade Balance) have monthly frequency. In fact these are the data frequencies employed in Curto et al. (2008) or Codogno et al. (2003) among others. As an additional robustness test we analyze the regression in equation (5.4) using data with a monthly and quarterly frequency. In both cases the number of observations decreases substantially with respect to the case where we use daily frequency. However, results are in line with the ones obtained using a daily data and are available on request. Overall the above outcomes suggest that our main findings are not sensitive to the data's time frequency.[37]

5.5.2.6 Maturity Analysis

The effect of credit or macro risk is likely to have a differential effect on bonds with a different maturity. In equations (5.4) and (5.5) we only incorporate a level effect by means of the dummies for the different maturities. As an additional robustness test, we include the effect of the different maturities by regressing the yield spread on the explanatory variables for individual maturities. Results are shown in Table 12.

We observe that the macro variables (total debt divided by GDP and net trade balance divided by GDP) have a stronger effect on the longer maturities. The liquidity, the interaction liquidity/risk, the interaction of the debt and the standard deviation

[37] Gomez-Puig (2007) transforms the macro variables employed in her analysis into variables with a daily frequency. For this transformation, she extrapolates the corresponding variable assuming a daily constant rate of increase. We find that the results obtained after extrapolating the macro variables, assuming a constant rate of increase between two different values of the corresponding variable, are equivalent to the ones obtained in Table 3. These results and the ones commented in Subsection 4.2.5 are available upon request.

of the difference between the domestic and benchmark yields as well as the correlation between the domestic and benchmark yields have a stronger effect on the shorter maturities. The effect of the crisis dummy is only significant for the 7 and 10 year maturities. Finally, the domestic (CDS lagged one period) and the global risk factors do not follow a clear pattern along the different maturities but they seem to have a more significant effect on the 5 and 7 year maturities. The interaction liquidity/risk is significant for all the maturities but the 7-year maturity. Overall, however, these results are in line with the results presented in Table 3.

Table 12: Determinants of the deviations between the Government Yield and the Benchmark Yield by maturity

This table reports the results of the unbalanced panel regressions. The dependent variable is the deviations between the Government yields and the Benchmark yields which are obtained as the weighted average of the Governments yields of the different European Monetary Union countries in the sample. The weights are proportional to the portion of debt outstanding by each of the EMU countries with respect to the total amount outstanding by all these countries. Our database is formed by eleven EMU countries and spans from January 2004 to February 2009. All the variables (dependent and explanatory) except the measure of global risk, the measure of correlation between the domestic Government and benchmark yields and the crisis dummy are presented in deviations from the value of the same variable for the benchmark. We group the panels by country such that we have, at most, 11 groups for each maturity which form an overall unbalanced panel. We estimate the coefficients of the determinants of deviations between yields by means of a Prais-Winsten regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation within panels. The correlation within panels is treated as a first-order autocorrelation AR(1) and the coefficient of this process common to all the panels. Each element in the covariance matrix of the disturbances is computed with all available observations that are common to the two panels contributing to the covariance. Columns (1), (2), (3) and (4) report the results for the 3, 5, 7 and 10 years maturities, respectively. The results presented correspond to the estimated coefficient and the *t-statistic* (between brackets).

		(1)	(2)	(3)	(4)
CDS(-1)		0.479	0.541	0.585	0.497
		(19.13)	(28.87)	(38.08)	(30.51)
Log (Total bond daily turnover volume)		-0.013	-0.012	-0.010	-0.010
		(-4.79)	(-5.06)	(-4.91)	(-4.46)
Total debt issued divided by GDP		0.082	0.117	0.166	0.223
		(5.30)	(7.90)	(13.05)	(13.38)
Interaction of total debt divided by GDP and the standard deviation of the domestic yield minus the benchmark yield		1.717	1.310	1.097	0.688
		(10.99)	(10.24)	(9.20)	(5.41)
Net Trade Balance divided by GDP		-31.024	-34.535	-40.182	-86.617
		(-2.83)	(-3.59)	(-5.10)	(-9.34)
Global risk measure: log(VIX index)		0.008	0.012	0.014	0.009
		(1.79)	(3.19)	(3.90)	(2.55)
Correlation between domestic Government yield and EMU benchmark Government Yield		0.119	0.121	0.082	-0.017
		(3.90)	(4.88)	(3.86)	(-0.79)
Interaction of liquidity (bid-ask spread) and CDS(-1)		0.268	0.198	-0.026	0.189
		(2.51)	(2.51)	(-0.38)	(2.69)
Crisis dummy		-0.009	0.009	0.015	0.024
		(-1.46)	(1.64)	(3.12)	(4.84)
Constant		-0.157	-0.168	-0.135	-0.027
		(-4.95)	(-6.30)	(-5.83)	(-1.18)
Autorregressive (AR(1)) coefficient		0.893	0.904	0.894	0.901
R-squared		0.163	0.208	0.272	0.205
Observations		11976	11976	11976	11976
Number of groups		11	11	11	11
Observations per group	Minimum	202	202	202	202
	Average	1089	1089	1089	1089
	Maximum	1294	1294	1294	1294
Wald chi2 (10 df)		1754.280	2039.130	2910.910	2487.630
Prob. > chi2		0	0	0	0
Condition Index		24.510	25.790	25.940	25.370

5.6 Computing Common Risk Free Rates

The results in the previous section motivate the following question. What should be the yield of a common eurozone bond, free, at least to some extent, from the effect of the risk factors (credit, liquidity, macro, correlation) that influence the yield of individual sovereign bonds? The existence of a common European bond would imply the existence of a common European interest rate.[38] In this section, we attempt to provide a measure for this rate and discuss the hypothetical benefits that it would yield. A common risk free rate could produce benefits for every EMU country because of the enhanced rating and liquidity of the common bond and from the reduction of the effects associated with macro fundamentals.

It seems reasonable to suggest that to be allowed to profit from the reduction in borrowing costs this common rate would provide, each EMU country interested in participating in an issue of common bonds should compensate the bond issuer for the specific country's credit risk. As a starting point for this analysis we suggest that the CDSs on its sovereign bonds is the best proxy publicly available to measure the country risk and so, the CDS spreads represent the compensation that a given country should pay in order to be allowed to participate in the issuance of common bonds. In what follows we refer to the 'Hedged Yield' of the sovereign debt of a country as the difference of actual yield and the corresponding CDS spread.

Our proposed measure, which we call Common Risk-Free Rate (CRFR), is the Hedged Yield free of liquidity, correlation and macro risk effects.[39] The reasons why

[38] As Galati and Tsatsaronis (2001) remark, the most vivid illustration of the shortcomings of the Government bond market is the absence of a single established reference yield curve for the new currency.

[39] The impact of these effects is estimated by means of a Prais-Winsten regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation

we think CRFR would be free to a considerable extent of those effects are as follows. Regarding liquidity our model implies that CRFR will not be affected by individual bond's liquidity variables. One can argue that a specific liquidity factor related with the common bond may appear in due course but our view is that this variable will have small effects. Liquidity is valuable for market participants, and especially in times of market stress, the most liquid bonds have tended to command a considerable price premium. Previous studies of liquidity and liquidity premia in government bond markets, based mainly on data from the U.S. Treasury market and also from European sovereign bonds such as ECB (2010), have identified pronounced liquidity differences across government securities, being the benchmark bonds (and we assume that the common bond will have a fair chance to be the benchmark) the most favoured. Regarding the net trade balance over GDP, it should be remembered that about 70% of the total trade of EMU countries is within the European Union and therefore the aggregate value of this variable (due to offsetting positions) is bound to be small. Finally, and with respect to total debt over GDP, our model implies that CRFR will not be affected by individual bond's total debt. It can be argued that the aggregate debt ratio of the EMU countries could have some effect on CRFR.[40] We test this possibility below and the variable is not significant.

The CRFR is computed using the following steps:

a) We run the following Prais-Winsten regression:

across panels and serial autocorrelation.

[40] Given the evidence in Krishnamurthy, and Vissing-Jørgensen (2007), we should expect that when the stock of total debt over GDP is low, the marginal convenience valuation of sovereign debt is high. Investors bid up the price of Treasuries relative to other securities, such as corporate bonds, causing the yield on Treasuries to fall further below corporate bond rate. The opposite applies when the stock of debt is high.

$$r_{i,t} - CDS_{i,t} = \alpha + \sum_{k=1}^{K} \beta_k X_{k,i,t} + \sum_{j=1}^{M} \gamma_j D_{j,t} + \chi Y_{i,t} + \delta Z_t + \psi C_{i,t} + \varepsilon_{i,t} \quad i = 1, ..., 44 \quad (5.6)$$

where the dependent variable is the Hedged Yield of country i ($i = 1, \ldots, 11$) at four different maturities (3, 5, 7 and 10 years). The $X_{k,i,t}$ are liquidity and macro explanatory variables (Volume, Total debt/GDP, Trade Balance/GDP) of country i. The $D_{j,t}$ are dummy variables to take into account the maturity effect in bond yields (3,5, and 7 years) and the crisis dummy. The $Y_{i,t}$ is the interaction term of total debt relative to GDP times the volatility of the difference between domestic yield and benchmark yield. The Z_t is the global risk factor measured as the logarithm of VIX. The $C_{i,t}$ is the correlation between the country i yield (for its corresponding maturity) and the benchmark's yield.

This regression is similar to the one in equation (5.4) with the exception that the dependent variable is the hedged yield and the liquidity and macro variables are not deviations from the benchmark. Table C1 in Appendix C.3 contains the results for the estimation of equation (5.6).

b) We define the Common Risk Free Rate (CRFR) at time t for the corresponding maturity according to:

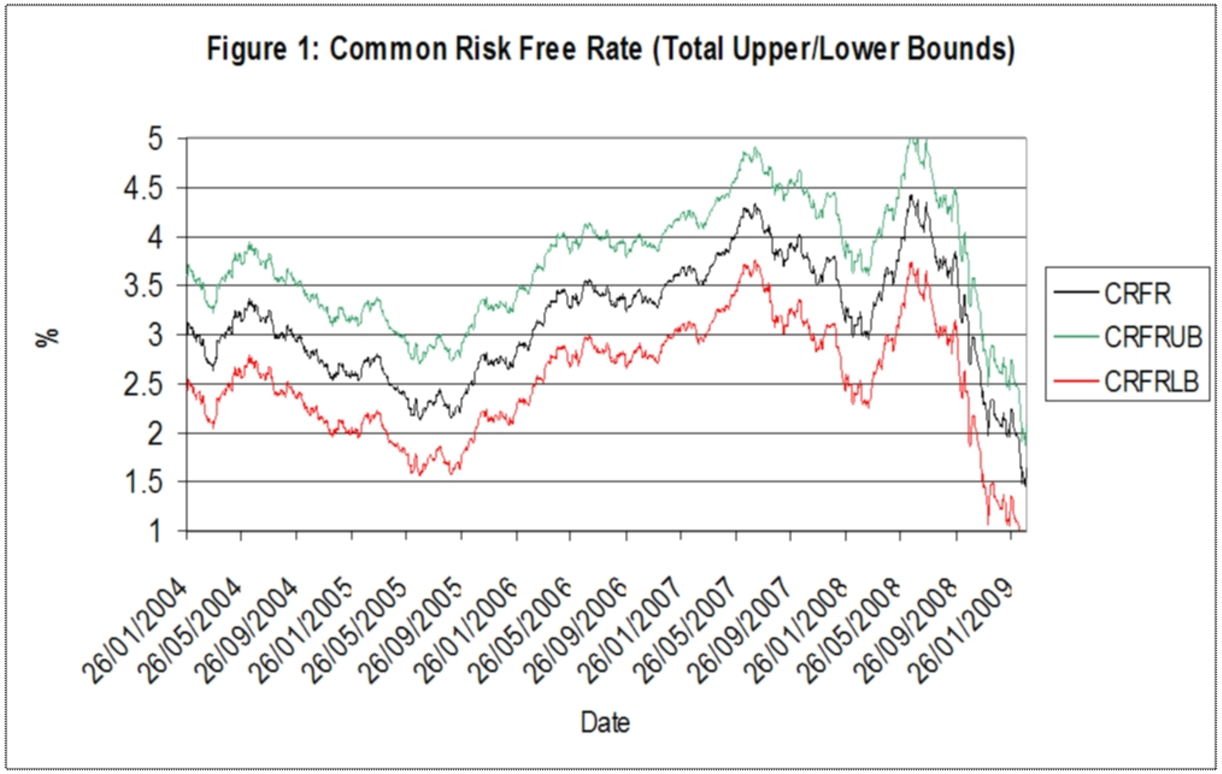
$$CRFR_t = \widehat{\alpha} + \widehat{\gamma}_j + \widehat{\delta} Z_t + \overline{\widehat{\varepsilon}}_t \qquad j = 1, 2, 3, 4. \qquad (5.7)$$

where the parameter $\widehat{\alpha}$ is the estimated constant, $\widehat{\gamma}_j$ is the estimate of the dummy parameters for the maturities of 3, 5 and 7 years and for the crisis dummy, respectively,

$\widehat{\delta}$ is the estimate of the logarithm of VIX parameter, and $\overline{\overline{\widehat{\varepsilon}}}_t$ is the average cross-sectional residual among the eleven EMU countries at time t. The parameter $\widehat{\alpha}$ gives the average common hedged risk free rate without the effect of the other variables, $\widehat{\gamma}_j$ gives the term structure and the changes in the intercept before and during crisis, $\widehat{\delta}$ gives the global risk effect and $\overline{\overline{\widehat{\varepsilon}}}_t$ gives the time series variation in interest rates. The benefits for a given country in using the common bond will be the enhanced rating and liquidity the common bond would provide plus additional premiums for country's macro fundamentals. On the other hand the common risk free rate is not unfettered of the influence of the crisis and global risk factor's influence. Additionally, we test whether total EMU debt over GDP has any explanatory power for CRFR and the regression coefficient is small and not significant.

As the measure proposed here comes from an estimated model, (equation (5.6) above) the estimate is vulnerable to sampling and model specification error. To address this point we construct 95% confidence bands around the estimates using 95% upper and lower limits of the estimated parameters (i.e 2.5% in each direction).

In Figure 1 we show the estimated 5-year common risk free rate in the EMU area (CRFR) and the confidence bands around the CRFR. The CRFR average value is 3.13% while the average values for the upper and the lower bands are 3.74% and 2.53%, respectively.



The figure shows the estimated 5-year common risk free rate in the EMU area (CRFR) and the confidence bands around the CRFR. The common rate measure (CRFR) is obtained as the sum of an intercept on the hedge yields, a maturity adjustment, a crisis constant adjustment, the effect of the VIX Index on the hedge yields, and a residual after controlling for liquidity and macroeconomic variables using a Prais-Winsten regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation. To estimate the lower (CRFRLB) and upper (CRFRUB) confidence bands, we employ the estimated lower and upper confidence limits of the 95% confidence interval for each parameter involved in the estimation of the CRFR.

5.7 Policy Implications: Savings in Borrowing Costs

The measure previously defined can be used to estimate the possible savings in borrowing costs from the issuance of common bonds in the EMU. The procedure could work as follows. We obtain these savings for a given country and maturity every day by subtracting from the corresponding yield the CDS spread and the estimate of the common risk free rate for 3-year, 5-year, 7-year, and 10-year maturities. The results are reported in Panel A on Table 13. In Panel B we report the average annual savings using the information on all EMU countries Euro-denominated sovereign bonds issued during the sample period (2004 – 2009) and with a maturity equal or lower than 11 years at the issuance date.[41] These average annual savings are computed as the bond's coupon minus the CRFR minus the corresponding CDS spread for every bond in our sample. The CRFR and CDS are the ones observed at the moment of bond's issuance. Note that the savings reported in both panels are largely similar. The average savings in borrowing costs are positive irrespective of the country and maturity. According to Panel A, the country that, on average, gets the biggest decrease in financing costs is Finland while Ireland is the one getting the smallest decrease.[42][43] Finland does not appear in Panel B due to the lack of observations to calculate the savings. In Panel B,

[41] We have estimated the Common Risk Free Rate for the 3, 5, 7 and 10 years maturities. Thus, in the cases in which we have a bond with a time-to-maturity different to the estimated CRFR maturities, we employ a Piecewise Cubic Hermite Interpolation Polynomial (PCHIP) algorithm to obtain the corresponding term. The same procedure is used whenever we do not have information on a CDS with a given maturity.

[42] For some maturities, the savings for Finland are higher than for Greece. However, we have only 202 observations for Finland in comparison with the almost 900 observations for Greece.

[43] The low decrease in financing costs for Ireland can be explained from the definition of the cost of financing. This cost is defined from (i) the CDS spread to be paid to participate in the issuance of common bonds and (ii) the common risk free rate. Thus, the difference between the hedge yield (Yield – CDS) and the CRFR represents the savings in terms of borrowing costs. However, the lowest hedge yield is the one corresponding to Ireland due to the high CDS spread and to the fact that the Irish yield is not so high relative to other countries' yields.

the country that, on average, gets the biggest decrease in financing costs is Portugal while Ireland is, again, the one getting the smallest decrease. Countries above (below) the average in Panel A are Belgium, Finland, Greece, and Portugal (Austria, Germany, Ireland, Spain, and Netherlands) whereas France and Italy are close to the average. These results are tentative and subject to measurement error (see Figure 1), but they give some idea about the possible savings involved in a common bond. As an additional test, we also compute the CRFR adding the (non-significant) effect of the total EMU debt over GDP to the ones reported in equation (5.7). The CRFR increases on average by 8.6 b.p. and the average total saving are 24.7. Again, average savings are positive for all countries.

Adjaouté and Danthine (2003) argue that a unified market is Pareto superior to a fragmented market given that yields will be lower in the former. As Adjaouté and Danthine (2003) point out, the pricing differences between yields reflect a failure of integration and imply costs to the euro-area Treasuries. They estimate that at the debt levels in the euro area in 2000 the annual cost may be as high as €5 billion which could be saved with a common bond.[44] They consider that the integration could occur simply by the establishment of a centralized agency in charge of issuing debt on behalf of the euro area's governments.[45] However, they do not give additional details about how to achieve this integration and how to estimate the common rates derived from

[44] Adjaouté and Danthine (2003) estimate this amount by multiplying the outstanding debt of the Euro area minus Germany in 2000 (2,470 billion) by the average difference of the yields with respect to German yield which is employed as the benchmark (20 basis points).

[45] Such a proposal was made in 1999 with a view of harmonizing the maturity structures, delivering a true and single benchmark curve and helping reduce the cost that some member states have to pay to primary dealers in order to promote their debt outside the country (Favero et al., 2000). Adjaouté and Danthine (2003) proposal was met with considerable skepticism, because such a set-up implies some collective responsibility for national debts, which runs contrary to the Maastricht Treaty but they also argue that the debate on the establishment of a multilateral agency should be reopened.

the centralized debt issuance. According to our estimations of the common risk free rate, the average savings could be higher than in Adjaouté and Danthine (2003). Our estimations suggest that the average annual savings for the EMU in the period that spans from September 2005 to February 2009 might be around €19.52 billion with the Common Risk Free Rate.[46] Moreover, the average annual savings for the EMU obtained from the Euro-denominated sovereign bonds issued during the sample period (2004 – 2009) and with a maturity equal or lower than 11 years at the issuance date are roughly €1.1 billion. As Favero and Von Thadden (2004) state, the possibility of joint bond issuance by euro-area countries has been repeatedly considered because of its ability to exploit fully the liquidity benefits, among others, of a unified market. They also suggest that this scheme has been discarded because it would generate an implicit debt guarantee by some countries in favour of others. Our tentative evidence, based on hedged yields, suggests that a common bond market with a common yield would reap liquidity benefits for all countries involved.

An additional question is how the system could work in practice. We suggest that an EMU-wide agency (ECB for instance) issues the bonds and distributes the money to participant countries. Participant members would pay to the agency their CDS spreads, common bond's coupons and repay the principal at maturity. Additionally they would post the corresponding amount on sovereign euro bonds as guaranty,[47] possibly subject

[46] The annual average savings are obtained by multiplying the annual average debt outstanding in the EMU during the period 2003-2008 by the average annual profits in terms of yields for the period 2004-2009 (see Panel A of Table 6). The average yield value is obtained as the average of the four different maturities.

[47] It may be argued that the common euro bond would be subject to currency risk because, if the ECB is in charge, and given that it cannot tax participant countries, then the ECB may need to print Euros to pay the debt. Therefore our CRFR measure would be a downward biased measure of the "true" risk free rate. However to quantify this specific effect is beyond the scope of this paper and is left for future research.

to margin calls to minimize moral hazard.

5.8 Summary and Conclusions

In this paper we study the determinants of EMU sovereign bonds yields and then present an estimation of the hypothetical risk free rate that a common bond would yield. To model the determinants of yield spreads we first propose a theoretical portfolio selection model to motivate the variable selection. Then for the period 2004 to 2009 we fit an unbalanced panel model, using as a benchmark a weighted average of the total gross debt issued by the governments of the different EMU members. We find that credit quality, macro, correlation, and liquidity variables have a significant effects on EMU sovereign yield spreads. Robustness tests with different data frequency, benchmarks, liquidity and risk variables, cross section regressions, balanced panel and maturities analyses confirm the initial results.

Motivated by these results we try to answer the following question: What should be the yield of a common eurozone bond, free, at least to some extent, from the effect of the risk factors (credit, liquidity, macro, correlation) that influence the yield of individual sovereign bonds? We present an estimation of this hypothetical common risk free rate and show that average savings in borrowing costs for all EMU countries are positive irrespective of the maturity of the common risk free rate measure employed.

We realize that there are many complex institutional design features that must be resolved before an actual common bond issue for the eurozone could be a reality, but our paper provides a first insight into one central issue. Namely, what should be the required compensation a given country should pay to the formal issuer to be allowed to share a given issue of EMU-based single bonds. We argue that this compensation should be the CDS spread on a given country sovereign bonds. The benefits for a given country in using the common bond (instead of the sovereign) will be the enhanced rating and liquidity the common bond would provide plus additional premiums for country macro fundamentals.

Our results may be interpreted as tentative evidence in favour of the hypothesis that a common bond and a common risk free rate in the EMU could produce substantial savings in borrowing costs for all the countries involved. Looking forward, we expect more conclusive evidence on other common risk free rate measures as well as in other market segments. The procedures of this paper can also be applied to other sovereign bonds and common currency areas as well as rates on state bonds for states in the USA or other federal states.

CHAPTER 6

GENERAL CONCLUSIONS, CONTRIBUTIONS AND LINES FOR FURTHER RESEARCH

In this thesis, I study the interaction of Credit Derivatives and Fixed Income Markets from three different perspectives: arbitrage (Chapter 2), price discovery (Chapter 3) and financial integration (Chapter 4). Moreover, I also focus on the European Monetary Union (EMU) sovereign bond market and analyze the potential arrival of a common risk free rate for the EMU and the advantages derived from it (Chapter 5).

Our main conclusions are as follows:

a) First, using a new statistical arbitrage test we find evidence in favour of the hypothesis that before the crisis some persistent mispricings can be found in the corporate credit derivatives markets. This result puts into question the efficiency of these markets. However once the crisis started, noticeable deviations from the parity relation appeared although the increase in funding costs makes the apparent arbitrage opportunities non profitable.

b) Second, using a novel approach combining theoretical models and sophisticated econometric specifications, we find that the price discovery process in these credit markets is very sensitive to the appearance of the subprime crisis. Before the crisis the CDS market leads both Bond and ASP markets. During crisis the ASP market leads both CDS and Bond markets.

c) Third, using rigorous empirical analysis, we find that the internal market integration increases during the crisis for CDSs but decreases for Bonds and ASPs. External market integration decreases during the crisis between the CDS and the other two markets. This is consistent with results in a) and b) above in the sense that during the crisis period the CDS market tends to become detached from the other two markets. These facts cast serious doubts on the reliability of the price signals coming from the corporate CDS market in crisis time periods.

d) Fourth, we estimate the yield of a hypothetical common Euro zone bond, free, at least to some extent, from the effect of the risk factors (credit, liquidity, macro, correlation) that influence the yield of individual sovereign bonds. We show that average savings in borrowing costs for all EMU countries are positive irrespective of the maturity of the common risk free rate measure employed. Our contributions are both on the theoretical and empirical streams of the financial literature.

Lines for further research can be summarized as follows:

In Chapter 2, we expect more definite evidence on other arbitrage strategies as well as in other market segments. The new test and the procedure (long positions only) of this paper can also be applied to other financial markets. In future research, we also expect to test the effect of the new rules for standardization in the CDS market. These rules were introduced in the form of the Standardized North American Contract (SNAC).

There are two open questions in Chapter 3 that will be treated in further research.

The first question is based on how the fact that information on a given single name CDS is mainly revealed by speculators could affect to other financial instruments (stocks or options) of the same underlying firm. The second question is related with the demand elasticity's estimation for the different market participants that we consider in our model and its sensitivity to the arrival of the subprime crisis.

In Chapter 4, we expect more definite evidence on the financial integration's process and on the effect of the financial crisis and the market players' characteristics regarding other market segments. Moreover, we pretend to extend this analysis to study not only the degree of market integration but also the contagion effect among these credit markets and also among additional financial markets.

In Chapter 5, we expect more conclusive evidence on other common risk free rate measures as well as in other market segments. The procedures of this paper can also be applied to other sovereign bonds and common currency areas as well as rates on state bonds for states in the USA or other federal states.

Summing up, the analysis of the potential interactions among credit markets in any of the four perspectives treated in this thesis is a topic of salient relevance. Additional research on these topics is need before proceeding to develop and regulate these markets. The subprime crisis offers and interesting scenario to test the robustness of the different alternatives which may be considered for this purpose. An effective and fair regulation on credit markets seems of special relevance given that as Greenspan states "Credit default swaps are becoming the most important instrument I've seen in decades".[1] This

[1] Speaking at the Bond Market Association, in New York, New York, May 18, 2006, quoted in Caroline Salas, Derivatives, Not Bonds, Show What Pimco, TIAA-CREF Really Think, Bloomberg.com (May 31, 2006).

regulation will determine if this importance has a positive effect or a negative effect, as it was observed in the current crisis, on financial stability.

CHAPTER 7

APPENDICES

7.1 Appendix A.1 (Chapter 3)

In order to obtain an expression for the credit spreads we substitute the expressions (3.14) into the equations (3.10) and (3.11) and obtain the following equation:

$$\begin{pmatrix} s_t^A \\ \bar{s}_t \end{pmatrix} = \frac{H\beta_3}{B} \begin{bmatrix} (N_{BOTH} + N_{CDS}) \\ -(N_{BOTH} + N_{ASP}) \end{bmatrix} + Q \begin{pmatrix} s_{t-1}^A \\ \bar{s}_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^{ASP} \\ u_t^{CDS} \end{pmatrix} \tag{A1.1}$$

where $u_t = \begin{pmatrix} u_t^{ASP} & u_t^{CDS} \end{pmatrix}$ is a vector white noise with $E(u_t) = 0$ and $Var(u_t) = \Omega > 0$. In u_t we include both the common components and the participants' noises.[1] The model in equation (3.15) can be changed into a VECM model by subtracting vector of prices $(s_t^A, \bar{s}_t)'$ from both sides:

$$\begin{pmatrix} \Delta s_t^A \\ \Delta \bar{s}_t \end{pmatrix} = \frac{H\beta_3}{B} \begin{bmatrix} (N_{BOTH} + N_{CDS}) \\ -(N_{BOTH} + N_{ASP}) \end{bmatrix} + (Q - I) \begin{pmatrix} s_{t-1}^A \\ \bar{s}_{t-1} \end{pmatrix} + \begin{pmatrix} u_t^{ASP} \\ u_t^{CDS} \end{pmatrix} \tag{A1.2}$$

with

$$Q - I = \frac{1}{B} \begin{bmatrix} -H(N_{BOTH} + N_{CDS}) & H\beta_2(N_{BOTH} + N_{CDS}) \\ H(N_{BOTH} + N_{ASP}) & -H\beta_2(N_{BOTH} + N_{ASP}) \end{bmatrix} \tag{A1.3}$$

[1] We do not report the whole expression of u_t in order to save space and also, because of the assumptions on residuals they are not going to appear in our analysis.

The previous expression can be transformed into the following final expression (equation (3.15)):

$$\begin{pmatrix} \Delta s_t^A \\ \\ \Delta \overline{s}_t \end{pmatrix} = \frac{H}{B} \begin{bmatrix} -(N_{BOTH} + N_{CDS}) \\ \\ (N_{BOTH} + N_{ASP}) \end{bmatrix} (1, -\beta_2, -\beta_3) \begin{pmatrix} s_{t-1}^A \\ \\ \overline{s}_{t-1} \\ \\ 1 \end{pmatrix} + \begin{pmatrix} u_t^{ASP} \\ \\ u_t^{CDS} \end{pmatrix} \tag{A1.4}$$

7.2 Appendix A.2 (Chapter 3)

In this paper we adopt GG's methodology and thus, their permanent-transitory (PT) component decomposition to measure market contribution to price discovery. GG PT decomposition has the following form:

$$X_t = A_1 f_t + A_2 z_t \tag{A2.1}$$

where f_t is the permanent component, z_t is the transitory component, and A_1 and A_2 are loading matrices. The components f_t and z_t are linear combinations of X_t such that $f_t \sim I(1)$, $z_t \sim I(0)$, z_t does not Granger cause f_t in the long run and:

$$f_t \quad = \quad \gamma' X_t \tag{A2.2.a}$$

$$A_1 \quad = \quad \beta_\perp (\alpha'_\perp \beta_\perp)^{-1} \text{ and } \gamma = (\alpha'_\perp \beta_\perp)^{-1} \alpha'_\perp \tag{A2.2.b}$$

where $\alpha_\perp$ and $\beta_\perp$ are 2×1 vectors such that $\alpha'_\perp \alpha = 0$ and $\beta'_\perp \beta = 0$ or equivalently:

$$\alpha_{1,\perp} = \frac{H}{B}(N_{BOTH} + N_{ASP}) \tag{A2.3.a}$$

$$\alpha_{2,\perp} = \frac{H}{B}(N_{BOTH} + N_{CDS}) \tag{A2.3.b}$$

while $\beta_{\perp} = (\beta_2, 1)$. Taking all these things together we have that:

$$\gamma' = \begin{bmatrix} \frac{(N_{BOTH}+N_{ASP})}{\beta_2(N_{BOTH}+N_{ASP})+(N_{BOTH}+N_{CDS})}, \\ , \frac{(N_{BOTH}+N_{CDS})}{\beta_2(N_{BOTH}+N_{ASP})+(N_{BOTH}+N_{CDS})} \end{bmatrix} \tag{A2.4}$$

and the permanent component f_t is defined as:

$$\begin{aligned} &\frac{N_{BOTH}+N_{ASP}}{\beta_2(N_{BOTH}+N_{ASP})+(N_{BOTH}+N_{CDS})} s_t^A + \\ &+ \frac{N_{BOTH}+N_{CDS}}{\beta_2(N_{BOTH}+N_{ASP})+(N_{BOTH}+N_{CDS})} \bar{s}_t \end{aligned} \tag{A2.5}$$

where the factor that multiplies s_t^A represents the price discovery measure attributed to the ASP (PD_1) and the factor that multiplies $\bar{s}_t$ represents the price discovery measure attributed to the CDS (PD_2). The ratio γ in equation (A2.4) that is obtained from the orthogonal vector to α, which is denoted as $\alpha_{\perp}$ (see equations (A2.3.a and A2.3.b)), can be understood as the relative number of market participants in a given market with respect to the other.

The percentage of price discovery attributable to ASP and CDS markets can also be defined as:

$$\frac{PD_1}{PD_1 + PD_2} = GG_1 \text{ and } \frac{PD_2}{PD_1 + PD_2} = GG_2 \tag{A2.6}$$

where GG_1 and GG_2 represent the GG price discovery metrics for the ASP and the CDS markets, respectively.

These metrics can be defined equivalently as:

$$GG_1 = \frac{\alpha_2}{-\alpha_1 + \alpha_2} \text{ and } GG_2 = \frac{-\alpha_1}{-\alpha_1 + \alpha_2} \tag{A2.7}$$

After substituting we obtain:

$$GG_1 = \frac{N_{BOTH} + N_{ASP}}{2N_{BOTH} + N_{ASP} + N_{CDS}} \text{ and } GG_2 = \frac{N_{BOTH} + N_{CDS}}{2N_{BOTH} + N_{ASP} + N_{CDS}} \tag{A2.8}$$

In order to be consistent with our model we investigate price discovery based on the metrics that when transformed into relative terms are equivalent to the GG approach's metrics of equation (A2.6). If $\beta_2 = 1$ and agents operate only in one market ($N_{BOTH} = 0$), both PD_1 and PD_2 measures for the permanent component are the same as the ones introduced in GS (1983) and after employed in FFG.[2] In previous papers where price discovery is analyzed for credit derivatives markets we find that there are two important facts that have been ignored, (i) the fact that β_2 can be different from 1.[3] Thus, a cointegrating vector between credit spreads different from $(1, -1)$ can be theoretically supported by our price discovery model given that the standard requirement that $\beta_2 = 1$ may be very restrictive. And (ii), a significant amount of market participants in these credit markets, at least in periods with a sufficient degree of liquidity, are represented

[2] Under these assumptions our permanent component could be defined as: $\frac{N_{ASP}}{N_{ASP}+N_{CDS}} s_t^A + \frac{N_{CDS}}{N_{ASP}+N_{CDS}} \bar{s}_t$

[3] According to our data and to Table III in Blanco et al. (2005), Table 5 in Ammer and Cai (2007), Table 7 in Cossin and Lu (2005) and Table G1-A in Coudert and Gex (2008), it can be observed that in a vast majority of cases $\beta_2 \neq 1$, which invalidates the metrics of price discovery in all the analyses where it is assumed and imposed that $\beta_2 = 1$.

by N_{BOTH}. To the best of our knowledge both facts have been not taken into account in the extant literature.

7.3 Appendix B (Chapter 4)

This is the list of the concrete influential events during the crisis that we consider to construct the corresponding dummy variable:

June 20: Bear Stearns hedge funds involved in securities backed by subprime loans near shutting down.

August 1: Bear Stearns was hit by a legal claim stemming from the meltdown of two of its hedge funds, sending its shares, already under pressure from woes at a third fund, to a 19-month low.

August 6: American Home Mortgage Investment Corporation (AHMI) files Chapter 11 bankruptcy. Two days before AHMI had laid off nearly ninety percent of its 7,000 employees. A German government-led bailout of IKB Deutsche Industriebank results in state-owned KfW assuming up to €1 billion in expected possible losses. Bear Stearns fires their co-president, Warren Spector. National City Home Equity, a unit of National City of Cleveland, stopped taking applications for new home-equity loans and lines of credit.

August 7: Numerous quantitative long/short equity hedge funds suddenly begin experiencing unprecedented losses as a result of what is believed to be liquidations by some managers eager to access cash during the liquidity crisis.

August 8: Mortgage Guaranty Insurance Corporation announces it will discontinue its purchase of Radian Group after suffering a billion-dollar loss of its investment in

Credit-Based Asset Servicing and Securitization.

August 9: French investment bank BNP Paribas suspends three investment funds that invested in subprime mortgage debt, due to a "complete evaporation of liquidity" in the market.

August 10: HomeBanc files for Chapter 11. Stock market downturn.

August 14: Sentinel Management Group suspends redemptions for investors and sells off \$312 million worth of assets; three days later Sentinel files for Chapter 11 bankruptcy protection. US and European stock indices continue to fall.

August 15: The stock of Countrywide Financial falls around 13% on the New York Stock Exchange after Countrywide says foreclosures and mortgage delinquencies have risen to their highest levels since early 2002.

August 16: Countrywide Financial Corporation narrowly avoids bankruptcy by taking out an emergency loan of \$11 billion from a group of banks.

August23: First Magnus Financial files for Chapter 11 bankruptcy protection.

August 26: Landesbank Baden-Württemberg (LBBW), the German public sector bank, agrees to buy Sachsen Landesbank for €250 million. Sachsen LB is the second German bank that needed to be bailed out.

August 31: Ameriquest, once the largest subprime lender in the U.S., goes out of business.

September 5: Stock market downturn due to the bad US economic data in USA.

September 11: Victoria Mortgages which has a portfolio of 440 million Euros declares that they have insufficient funds.

September 13: The Bank of England extends emergency funding to Northern

Rock. The move came after investors withdrew support of Northern Rock amid worries that the institution could face short term difficulties in raising the needed capital in the wholesale market.

September 17: Stock market downturn

September 21: Bear Stearns announces a 61% drop in earnings from the same quarter in 2006.

September 29: Affected by the spiraling mortgage and credit crises, Internet banking pioneer NetBank goes bankrupt.

October 1: the Swiss bank UBS announces that it lost US$690 million in the third quarter. Citigroup announces a 60% drop in earnings from the same quarter last year.

October 5: Merrill Lynch announces a US$5.5 billion loss as a consequence of the subprime crisis, which is revised to $8.4 billion.

October 24: The sum of US$5.5 billion loss announced by Merril Lynch on October 5 is revised to $8.4 billion, a sum that credit rating firm Standard & Poor's called "startling".

October 30: Merrill Lynch (ML) CEO, Stan O'Neal, resigns after an announcement that ML would write down around $7.9 billion ($3.4 billion more than ML had predicted just three weeks earlier) debt.

November 4: Citigroup CEO, Chuck Prince, resigns after an announcement that Citigroup may have to write down up to $11 billion in bad debt.

November 21: Freddie Mac announces a $2 billion loss in mortgage defaults and credit losses. Shares in Freddie Mac dropped 28.7% and Fannie Mae dropped 24.8% upon the announcement.

November 23: Two French banks pledge $1.5 billion to bailout French bond insurer CIFG.

December 5: Fannie Mae faces capital problems because of the deteriorating US housing market.

December 19: Morgan Stanley announces $9.4 billion in write downs from subprime losses.

December 20: Bear Stearns reports its first quarterly loss in its 84-year history of $854 million.

January 15: Stock market downturn.

January 21: Stock market downturn.

February 28: AIG announces a $5.2 billion loss for the fourth quarter of 2007, the second consecutive quarter of losses. The largest portion of losses came from AIG write-downs of $11.12 billion (pretax) concerning their revaluation of a large credit default swap portfolio.

March 3: UK's largest bank, HSBC, reports a $17.2 billion loss on write downs of its US mortgage portfolio.

March 10: Rumors start to appear on Wall Street that Bear Stearns could have liquidity problems. Investors believe rumors as financial stocks drop in value.

March 16: Bear Stearns is acquired for $2 a share by JPMorgan Chase in a fire sale avoiding bankruptcy. The deal is backed by the Federal Reserve, providing up to $30B to cover possible Bear Stearn losses.

March 17: Stock market downturn.

April 1: UBS announces it will write down $19 billion in the first quarter on its

US holdings.

April 8: The International Monetary Fund new estimate on credit crunch losses is projected upwards to $945 billion.

April 17: Merrill Lynch reveals first quarter losses of $1.96 billion and plans to cut 4,000 jobs worldwide.

April 18: Citigroup reports a $5.11 billion loss in the first quarter of 2008 off of a $12 billion write down on subprime mortgage loans and other risky assets. The largest US bank also announced it would cut 9,000 more jobs.

May 9: AIG reports 1st quarter earnings results as a net loss of $7.81 billion. One of the principle factors of this loss was a 1st quarter write down of $9.11 billion on the revaluation of their credit default swap portfolio.

July 8: Shares in Fannie Mae and Freddie Mac plunged around 20% as investors sell off their shares.

July 11: Indymac Bank, a subsidiary of Independent National Mortgage Corporation (Indymac), is placed into the receivership of the FDIC by the Office of Thrift Supervision. It was the fourth-largest bank failure in United States history, and the second-largest failure of a regulated thrift.

July 13: Investor speculation on the Freddie Mac and Fannie Mae bailout worsen the situation.

July 17: Major banks and financial institutions had borrowed and invested heavily in mortgage backed securities and reported losses of approximately $435 billion.

July 31: Deutsche Bank reveals more write downs bringing the total so far to $7.8 billion for this year. Without figuring in the write downs, Deutsche corporate banking and securities division would have an income 16% less than the second quarter of last year.

August 7: AIG shares drop 19.1%, its biggest daily drop in 39 years, after announcement of a higher than expected $5.4 billion loss for the second quarter. This loss was blamed on AIG's exposure to large subprime write downs.

7.4 Appendix C.1 (Chapter 5)

We consider a domestic (benchmark) investor allocating a fraction θ_t (θ_t^*) of his real wealth w_t (w_t^*) to a domestic D (benchmark, F) security and a fraction $1-\theta_t$ ($1-\theta_t^*$) to a benchmark (domestic) security. We assume that both the domestic and benchmark securities are subject to default risk. The default process is assumed to follow a correlated bivariate Bernoulli process (x_t, x_t^*), with domestic (benchmark) default probability $1-P_t$ ($1-P_t^*$). In the event of default the investor receives a fraction τ_t (τ_t^*) of his gross domestic (benchmark) payment, $\tau_t \in [0, 1+r)$ ($\tau_t^* \in [0, 1+r^*)$) where r (r^*) is the interest rate on the domestic (benchmark) bond. There are proportional transaction costs l_t (l_t^*) decreasing with domestic (benchmark) market liquidity. The coefficient of risk aversion ρ is the same for both investors. The utility function of both the domestic and foreign investors depends positively on the expected real wealth, and negatively on its variance . The domestic investor maximizes the following mean-variance utility function:

$$E_t\left[w_{t+1}\right] - \frac{\rho}{2} Var_t\left[w_{t+1}\right] \tag{C.1}$$

where according to the previous notation, the expected wealth and variance of wealth are, respectively:

$$
\begin{aligned}
E_t\left[w_{t+1}\right] &= \left(1+r_t\right)\theta_t w_t P_t + \tau_t \theta_t w_t (1-P_t) - \theta_t w_t l_t + \\
&\quad + \left(1+r_t^*\right)(1-\theta_t) w_t P_t^* + \tau_t^* (1-\theta_t) w_t (1-P_t^*) - (1-\theta_t) w_t l_t^*
\end{aligned}
\tag{C.2}
$$

$$
\begin{aligned}
Var_t\left[w_{t+1}\right] &= \left(1+r_t-\tau_t\right)^2 \theta_t^2 w_t^2 P_t (1-P_t) + \left(1+r_t^*-\tau_t^*\right)^2 (1-\theta_t)^2 w_t^2 P_t^* (1-P_t^*) + \\
&\quad + 2 w_t^2 \theta_t (1-\theta_t)\left(1+r_t-\tau_t\right)\left(1+r_t^*-\tau_t^*\right) Cov(x_t, x_t^*)
\end{aligned}
$$

The domestic investor maximizes his corresponding utility function to obtain the optimal fraction of his wealth to allocate to the domestic bond, $\widehat{\theta}_t$:

$$
\widehat{\theta}_t = \frac{\left(1+r_t\right)P_t + \tau_t(1-P_t) - l_t - \left(1+r_t^*\right)P_t^* - \tau_t^*(1-P_t^*) + l_t^* +}{\rho w_t \left[\left(1+r_t-\tau_t\right)^2 P_t(1-P_t) + \left(1+r_t^*-\tau_t^*\right)^2 P_t^*(1-P_t^*) - \right.}
\frac{+\rho w_t \left(1+r_t^*-\tau_t^*\right)^2 P_t^*(1-P_t^*) - \rho w_t \left(1+r_t-\tau_t\right)\left(1+r_t^*-\tau_t^*\right) Cov(x_t, x_t^*)}{\left. -2\left(1+r_t-\tau_t\right)\left(1+r_t^*-\tau_t^*\right) Cov(x_t, x_t^*)\right]}
\tag{C.3}
$$

The foreign investor maximizes his corresponding mean-variance utility function:

$$
E_t\left[w_{t+1}^*\right] - \frac{\rho}{2} Var_t\left[w_{t+1}^*\right] \tag{C.4}
$$

The foreign investor's expected wealth and variance of wealth are the following:

$$
\begin{aligned}
E_t\left[w_{t+1}^*\right] &= (1+r_t)\,\theta_t^* w_t^* P_t + \tau_t \theta_t^* w_t^* (1-P_t) - \theta_t^* w_t^* l_t + \\
&\quad + (1+r_t^*)\,(1-\theta_t^*) w_t^* P_t^* + \tau_t^* (1-\theta_t^*) w_t^* (1-P_t^*) - (1-\theta_t^*) w_t^* l_t^*
\end{aligned}
\tag{C.5}
$$

$$
\begin{aligned}
Var_t\left[w_{t+1}^*\right] &= (1+r_t-\tau_t)^2\,\theta_t^{*2} w_t^{*2} P_t(1-P_t) + (1+r_t^*-\tau_t^*)^2\,(1-\theta_t^*)^2 w_t^{*2} P_t^*(1-P_t^*) + \\
&\quad + 2 w_t^{*2} \theta_t^* (1-\theta_t^*)\,(1+r_t-\tau_t)\,(1+r_t^*-\tau_t^*)\,Cov(x_t, x_t^*)
\end{aligned}
$$

The foreign investor maximizes his utility function to obtain the optimal fraction of his wealth to allocate to the domestic bond, $\widehat{\theta}_t^*$:

$$
\widehat{\theta}_t^* = \frac{(1+r_t)\,P_t + \tau_t(1-P_t) - l_t - (1+r_t^*)\,P_t^* - \tau_t^*(1-P_t^*) + l_t^* +}{\rho w_t^*\left[(1+r_t-\tau_t)^2\,P_t(1-P_t) + (1+r_t^*-\tau_t^*)^2\,P_t^*(1-P_t^*) -\right.}
\tag{C.6}
$$

$$
\frac{+\rho w_t^*\,(1+r_t^*-\tau_t^*)^2\,P_t^*(1-P_t^*) - \rho w_t^*\,(1+r_t-\tau_t)\,(1+r_t^*-\tau_t^*)\,Cov(x_t, x_t^*)}{\left. -2\,(1+r_t-\tau_t)\,(1+r_t^*-\tau_t^*)\,Cov(x_t, x_t^*)\right]}
$$

After imposing market clearing equation (5.1) and rearranging terms we get the final expression:

$$
\begin{aligned}
r_t - r_t^* &= (l_t - l_t^*) + S_t \frac{\rho}{2} Var\left[(1+r_t-\tau_t)\,x_t - (1+r_t^*-\tau_t^*)\,x_t^*\right] - \\
&\quad - \frac{\rho}{2}(w_t + w_t^*)\left[(1+r_t^*-\tau_t^*)^2\,P_t^*(1-P_t^*)\right] + \\
&\quad + \frac{\rho}{2}(w_t + w_t^*)\left[(1+r_t-\tau_t)\,(1+r_t^*-\tau_t^*)\,Cov(x_t, x_t^*)\right] + \\
&\quad + (1+r_t-\tau_t)\,(1-P_t) - (1+r_t^*-\tau_t^*)\,(1-P_t^*)
\end{aligned}
\tag{C.7}
$$

7.5 Appendix C.2 (Chapter 5)

This appendix provides additional details about the definition, sources, and timing of the data used in the study:[4]

1. Sovereign Yields Spreads. 3, 5, 7 and 10 years daily sovereign yields are obtained from Datastream. These yields are computed using "on the run" (benchmark) 3, 5, 7 and 10-year bonds at every moment of time. The dependent variable in equation (5.4) is defined as the difference between the domestic sovereign yield and the benchmark yield. The benchmark yield is defined as the weighted average of the EMU Government yields. The weights are proportional to the portion of debt outstanding by each of the EMU countries with respect to the total amount outstanding in the EMU. The general governments gross debt data employed to form the weights are reported in Table 1 and are obtained from the AMECO database.

2. Liquidity (total bond daily turnover volume). Liquidity is proxied by the total daily turnover volume reported in Datastream. The total turnover volume is obtained as the sum of the turnover volumes of all the sovereign bonds issued by a given country. This volume is reported in terms of monthly information on the average daily turnover volume per bond during a given month by Datastream. The turnover volume for the total number of bonds issued by a given Government derives from trades entered into TRAX. In equation (5.4), we employ the deviation of the logarithm of the domestic total bond daily turnover volume, in million of Euros, from the log of the benchmark total bond daily turnover volume, in million of Euros. We also employ the average

[4] For yearly, quarterly and monthly data we use end of previous year (quarter or month) data. For instance, in the case of the Debt/GDP variable which has yearly frequency, we use the value at the end of 2004 for the whole year 2005. Thus, we are assuming that investors at any time in 2005 know the value of Debt/GDP variable at the end of 2004 but do not know its 2005 end-of-year value.

daily turnover volume which is calculated as the ratio between the total daily turnover volume and the number of bonds issued by the corresponding country.

3. CDS. The daily CDS spreads in the study are obtained from the Datastream system. These CDS spreads are midmarket indicative prices for three, five, seven and ten year CDS contracts. In all cases, the CDS contract references the sovereign (as opposed to a central bank or some other entity). For all countries CDSs are Euro-denominated. CDSs quotes are given in basis points. In equation (5.4) the explanatory variable referent to CDSs is obtained as the difference between the domestic and benchmark (weighted average) CDS spreads lagged one day, in percentages.

4. Debt/GDP. This variable is the ratio between the general Government gross debt at nominal value and the GDP, obtained from Ecowin. As the frequency of the gross debt is annual, the frequency of this ratio is also annual. In equation (5.4), we employ the difference between the domestic and benchmark Debt/GDP ratios as explanatory variable.

5. Interact.(Debt). This variable is an interaction term representing the product of Debt/GDP and the monthly standard deviation of the domestic yield minus the benchmark yield. This variable has monthly frequency.

6. Trade Balance/GDP. This variable is the ratio between the net trade balances at the end of every month divided by the GDP. The net trade balance data as well as GDP data are obtained from Ecowin. The frequency of this ratio is monthly. The explanatory variable of equation (5.4) is obtained as the deviation of the domestic Trade Balance/GDP ratio from the benchmark equivalent ratio.

7. VIX (Global risk). This variable represents the overall global risk and it is proxied by the Chicago Board Options Exchange Volatility Index (VIX) (it is a measure of the implied volatility of S&P 500 index options). VIX is obtained from the Reuters system. We take the logarithm of VIX when we employ it as an explanatory variable. VIX has daily frequency.

8. Corr (domestic, benchmark). This variable is the monthly correlation between the domestic Government bond yield and the EMU benchmark bond yield. This correlation is calculated for the 3, 5, 7 and 10 years maturities. The frequency of this variable is monthly.

9. Yield − CDS. This variable is the difference between the Government yield minus the CDS spread for the same maturity (3, 5, 7 and 10 years). This variable is employed as the dependent variable in equation (5.6) and has daily frequency.

10. Crisis dummy. This variable is a dummy variable which is equal to zero before August 9, 2007 and one afterwards.

11. Interaction of liquidity (bid-ask spread) and CDS lagged one period. This variable represents the difference (in percentage) between two interaction terms referred to the domestic country and the benchmark, respectively. The first interaction term is referred to the domestic country and represents the product of a liquidity premium or trading costs, which are measured by means of the bid-ask spread (in percentage) for the overall maturities, and the CDS spread (in percentage) for the 5-year maturity lagged one day while the second interaction term represents the benchmark equivalent measure. The daily bid-ask spreads are obtained from the Bloomberg system.

7.6 Appendix C.3 (Chapter 5)

In this appendix we show the results for the estimation of the determinants of the Government hedge yield.

Table C1: Determinants of the Government Hedge Yield

The table reports the results of the unbalanced panel regressions where the dependent variable is the country hedged yield. All the variables (dependent and explanatory) except the measure of global risk, the crisis dummy and the measure of correlation between the domestic Government and benchmark yields are presented in deviations from the value of the variable for the benchmark. We group the panels by country and maturity (3, 5, 7 and 10 years) such that we have, at most, 44 groups which form a global unbalanced panel. We estimate the coefficients of the determinants of deviations between yields by means of a Prais-Winsten regression with correlated panels corrected standard errors (PCSEs) and robust to heteroskedasticity, contemporaneous correlation across panels and serial autocorrelation within panels. The correlation within panels is treated as a first-order autocorrelation AR(1) and the coefficient of this process common to all the panels. Each element in the covariance matrix of the disturbances is computed with all available observations that are common to the two panels contributing to the covariance. Column (1) reports the results which are obtained without using the interaction of liquidity and CDS(-1) and the crisis dummy as explanatory variables and Column (2) reports the results without using the interaction of liquidity and CDS(-1) as explanatory variable but using the crisis dummy. The results presented correspond to the estimated coefficient and the *t-statistic* (between brackets).

Log (Total bond daily turnover volume)		0.005 (0.54)	0.004 (0.44)
Total debt issued divided by GDP		0.009 (2.48)	0.004 (2.40)
Interaction of total debt divided by GDP and the standard deviation of the domestic yield minus the benchmark yield		0.0002 (0.11)	0.0001 (0.05)
Net Trade Balance divided by GDP		0.114 (0.39)	0.130 (0.45)
Global risk measure: log(VIX index)		-0.087 (-4.99)	-0.089 (-5.00)
Correlation between domestic Government yield and EMU benchmark Government Yield		-0.004 (-0.17)	-0.11×10^{-3} (-0.00)
Dummy for the 3-year yield		-0.731 (-4.76)	-0.603 (-7.70)
Dummy for the 5-year yield		-0.457 (-3.26)	-0.408 (-6.35)
Dummy for the 7-year yield		-0.242 (-2.66)	-0.210 (-4.86)
Crisis dummy			-0.044 (-1.14)
Constant		3.266 (9.99)	3.676 (20.19)
Autorregressive (AR(1)) coefficient		0.993	0.991
R-squared		0.038	0.066
Observations		44062	44062
Number of groups		44	44
Observations per group	Minimum	202	202
	Average	1001	1001
	Maximum	1294	1294
Wald chi2 (10 df)		53.300	90.060
Prob. > chi2		0	0
Condition Index		22.220	24.580

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