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Decomposing European CDS Returns*

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Abstract. Nearly half of the variation in European CDS returns is captured by a novel factor that mimics economic catastrophe risk. During the financial crisis of 2007–8, this factor became more important relative to other sources of risk, leading to a shift in the correlation structure of CDS returns. Using equivalent CDS and equity portfolios, we show that while crucial for explaining temporal and cross-sectional variation in CDS returns, the factor plays a lesser role for equity. This is likely due to the limited sensitivity of the equity value at default to whether the event is of systemic or idiosyncratic nature.

JEL Classification: G12, G13, G15

1. Introduction

What started as a financial sector crisis in Europe in August 2007 has since spread throughout the economy. S&P reports a total of 34 corporate defaults involving 31.8 billion euros of outstanding debt for 2008 alone, resulting in a 2008 default rate of 4.5 percent, three times higher than that for 2007. Ensuing investor anxiety about widespread defaults has brought an important issue sharply into focus–to what extent are European credit markets exposed to systemic shocks? Although much attention, both in the past and the present, has been paid to U.S. markets, the empirical evidence for Europe remains sparse.[1] Yet the problems resulting from a

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[1] The existing literature does not measure European credit market returns directly, and only few papers focus on explaining changes in credit spreads. Boss and Scheicher (2002), Van Landschoot (2004), Annaert et al. (2006), Alexander and Kaeck (2008) and Castagnetti and Rossi (2008) analyze the explanatory power of variables that should in theory determine European credit spread changes,

systemic credit crisis are just as far-reaching for Europe, and may pose an even greater difficulty resolving given that European monetary policy is supported not by one but by many different fiscal and tax regimes answering to different political regimes.

Our sample tracks all public European firms with an active credit default swap (CDS) market over the six-year period from January 2003 to December 2008. A default swap is an insurance contract that allows investors to sell protection against the event that the underlying company defaults. Returns on a CDS can easily be constructed and reward for the exposure to the company's default risk. Analyzing the correlation structure of weekly CDS returns, we show that prior to August 2007 European credit markets exhibited a moderate amount of comovement, with the first principal component of standardized CDS returns explaining about 40% of the variation. When the sample is extended until December 2008, the picture changes dramatically. The first principal component now captures an impressive 53% of the total variation. This indicates a shift in the correlation structure of CDS returns with the onset of the recent financial crisis, and raises a number of important questions: What drives the commonality in European CDS returns? Why did the comovements become more pronounced during the recent financial crisis? Is the shift in the correlation structure reflected in equity markets as well? Answering these three questions is the main contribution of our paper.

To understand the source of commonality in CDS returns, we examine the weight vector associated with the first principal component. At a first glance, it suggests a roughly equal weighting for most of the European firms in our sample. But closer inspection reveals that large firms of high credit quality and low equity volatility tend to have larger weights, and that small firms of low credit quality and high equity volatility play a less important role. This is an important observation since it allows us to focus on the type of risk priced in a specific subset of firms. Large, high-credit-quality and low-volatility firms usually are expected to fulfill the payments they promise to their debt holders except in the worst economic states.[2] In other words, the risk profile of investing in default swaps of such firms is closely related to that of insuring economic catastrophe risk.[3]

often in a similar fashion to the studies by Collin-Dufresne et al. (2001) and Ericsson et al. (2009) for the U.S. market. A number of papers aim at explaining the *level* of European credit spreads (as opposed to changes in spreads or credit market returns), including Annaert et al. (2000), Kiesel et al. (2003), Blanco et al. (2005), Abid and Naifar (2006), Byström (2006), Düllmann and Sosinska (2007), Byström (2008) and Karlson and Willebrand (2008).

[2] The default of a large investment-grade company can also be a firm-specific event, as witnessed by headline-making accounting scandals both in Europe (Parmalat) and the U.S. (Enron, WorldCom).

[3] The term "economic catastrophe risk" is derived from Coval et al. (2009), who denote bonds that default only under severe economic conditions as economic catastrophe bonds. An alternative terminology would be that of economywide or systemic default risk (see, for example, Bhansali et al. (2008) and Longstaff and Rajan (2008)).

The pricing of economic catastrophe risk became possible with the creation of structured credit products that pool a large number of default swaps into portfolios and tranche them into prioritized cash flow claims. A typical tranching scheme for the resulting synthetic collateralized debt obligations prioritizes losses of the underlying collateral pool so that the senior claims suffer losses only after the junior and mezzanine tranches have been exhausted. The most widely traded CDS index for European credit protection is the iTraxx Europe, composed of the 125 most liquidly traded investment-grade default swaps. Market participants can invest in a number of tranches, with the safest being the super-senior tranche that covers the twelfth to twenty-second loss percentile on the underlying portfolio. Bhansali et al. (2008) argue that spreads for this super-senior tranche can be interpreted as the market price for bearing economic catastrophe risk. This is intuitive since super-senior tranche investors incur losses only if a shock occurs that trickers the nearly simultaneous default of a large number of firms in the economy.

We therefore rely on the price information in the super-senior tranche spreads of the iTraxx Europe index to construct a return-based factor, FCR, that mimics economic catastrophe risk. We adapt Breeden et al. (1989) to construct FCR as the portfolio of CDS returns maximally correlated with (negative) super-senior tranche spread changes. FCR by itself explains about 46% of the variation in weekly CDS returns. This is not surprising given that it has a staggering correlation of 96% with their first principal component. The correlation between FCR and equity and reference bond market systematic factors is modest at best, ranging between −0.43 and 0.46. The latter include the market factor, MKT, as measured by the weekly excess return on the MSCI Europe index, and TERM, computed as the spread between the weekly return on the ten-year Euribor bond and the one-week Euribor rate. In addition, we construct the Fama and French (1993) SMB and HML factors for Europe, as well as a factor that mimics aggregate volatility risk, FVDX, based on Ang et al. (2006). Even after controlling for these five factors, CDS return residuals exhibit a large first principal component that still accounts for 45% of the variation. In that sense, previously established systematic risk factors are not sufficient to capture the common time series variation in CDS returns.[4] FCR, however, explains about 26% of the variation in these 5-factor CDS return residuals, and its correlation with their first principal component remains high at 78%.

To further decompose CDS returns, we also study their second principal component. It explains a much smaller fraction of the variation (about 8%), and places positive weight on firms with high credit spreads and high equity volatility, and negative weight on firms with low credit spreads and low equity volatility. Since the weights in both the first and the second principal component sort on credit

[4] These results for European credit markets are qualitatively in line with the observations made by Collin-Dufresne et al. (2001) for the U.S. corporate bond market.

quality and volatility, albeit to different degrees, CDS return factors constructed as long-short strategies after sorting on these characteristics are likely to be correlated with FCR. As an alternative, we rank firms on deviations of equity returns from normality. The resulting factor is nearly orthogonal to FCR, and is closely associated with the second principal component, even after controlling for MKT, TERM, SMB, HML and FVDX. A regression of CDS returns on the five equity and reference bond market factors, FCR and this additional factor yields an average adjusted R^2 of 54%, but only FCR is statistically significant. A one basis point increase in FCR leads to an average increase of 4.8 basis points in weekly CDS returns. The return residuals no longer exhibit any clear signs of commonality.

A cross-sectional analysis is performed by constructing CDS rating portfolios. We show that average portfolio returns line up nicely with the FCR-factor loadings, supporting the notion that FCR is a priced risk factor in European credit markets. The risk premium for FCR is estimated to be negative and significant at -1.1 basis points per week, or about -0.6% annually. We complete the investigation of the first question–what drives the commonality in CDS returns–by addressing the fact that we construct FCR using the same set of firms on which we run factor regressions. Since we include all public European firms for which CDS data are available, the set-up of our analysis is no different than the construction and testing of risk factors usually performed for equity markets. A caveat, however, may be the smaller size of the (liquid) default swap market. As a robustness check, we verify that the economic catastrophe risk mimicking factor does indeed have similar explanatory power in broader fixed-income markets by repeating the analysis for Markit iBoxx EUR corporate bond portfolios.

After identifying innovations to economic catastrophe risk as an integral common component of European CDS returns, we investigate their role in light of the recent financial crisis. We find that prior to August 2007, FCR by itself explained less than 30% of the variation in weekly CDS returns, but that this fraction surged to 50% during the crisis. We show that the increase in FCR's explanatory power is due to a large increase in the volatility of economic catastrophe risk innovations starting in August 2007, not just relative to other risk factors but also in comparison to idiosyncratic CDS return components. There is less support for the notion that credit market investors readjusted the sensitivity of their positions to innovations in economic catastrophe risk.

Given the important role FCR plays for CDS and corporate bond markets, a natural question to ask is whether it has any explanatory power for equity markets as well. We argue that innovations in economic catastrophe risk have a larger effect on assets whose payoff structure at default is closely tied to the economic states in which the event occurs. Since this is the case for corporate debt more so than for equity, it is not surprising that FCR by itself explains only 10% of the variation in weekly equity returns. As a result, the shift in the correlation structure of European equity returns is more modest when compared to CDS returns. The first principal component of equity returns explained about 33% of the variation prior to August 2007, and 44% during the crisis. This increase can largely be attributed to an increase in market-factor volatility.

The explanatory power of FCR for the cross-section of equity returns is also limited. We construct equity-equivalent portfolios that match the set of firms and weighting scheme in the CDS rating portfolios. Although FCR loadings generally do line up with average equity portfolio returns, they are mostly insignificant. Similar results are obtained when equity portfolios are formed by matching the constituents and weighting scheme of the Markit iBoxx corporate bond portfolios, reinforcing the notion that the economic catastrophe risk mimicking factor plays a less important role for equity markets.

The remainder of this paper is organized as follows. Section 2 describes how CDS returns are calculated and analyzes their correlation structure. We interpret the sources of commonality in CDS returns in Section 3. Section 4 presents the results of our factor regression analysis, explains the shift in the correlation structure of CDS returns and extends the analysis to include equity returns. Section 5 concludes.

2. CDS Returns and Their Correlation Structure

We begin our empirical analysis by constructing CDS returns and analyzing their correlation structure in the context of a principal components analysis.

2.1 CREDIT DEFAULT SWAPS AND DATA

Credit default swaps are single-name over-the-counter credit derivatives that provide default insurance. The payoff to the buyer of protection covers losses up to the notional value in the event of a default by the reference entity. Default events are triggered by bankruptcy, failure to pay, or a debt-restructuring event. The buyer of protection pays a quarterly premium, quoted as an annualized percentage of the notional value, and in return receives the payoff from the seller of protection should a credit event occur. Fueled by participation from commercial banks, insurance companies, and hedge funds, the size of the international CDS market has soared well above the value of the underlying debt that it insures, reaching more than $62 trillion in notional amount outstanding by the end of 2007 as reported by the International Swaps and Derivatives Association. Although the single-name CDS market has fared better than widely anticipated during the recent financial crisis, the credit boom came to a halt with a 37% decline in notional amount outstanding to $39 trillion at the end of 2008.

For our analysis, we rely on default swap spreads instead of corporate bond yield spreads as the primary source for prices of default risk because the former are less confounded by illiquidity, taxes and various market microstructure effects that are known to have a marked effect on corporate bond yield spreads.[5] In particular, we use default swap spreads for five-year CDS contracts with modified-modified restructuring for Euro-denominated senior unsecured debt. Berndt et al. (2007) document that the majority of European default swaps are transacted according to the modified-modified restructuring clause. The data are provided by Bloomberg. It contains all available bid and ask quotes, from January 2003 until December 2008. The bid and ask quotes are composite end-of-day quotes, calculated as the average of all contributor spreads received during the previous 24 hours. When there are five or more contributed spreads, the highest and lowest prices are excluded. We only consider firms that are domiciled in Europe. We eliminate stale quotes and all firms with less than 26 weeks (six months) of data. In addition, we require firms to be listed both in the Compustat Global database as well as in Worldscope (accessed via Datastream), in order to link prices to firm characteristics.

This leaves us with a final sample of default swap rates for 150 firms from 17 European countries. Descriptive statistics by country are provided in Table I. It shows that the median firm in our sample has an average credit spread of 56 basis points.[6] The distribution of median long-term S&P credit ratings is centered around medium credit quality: less than 1% of the firms in our sample have a median rating of AAA, 11% have a median rating of AA, 37% of A, 40% of BBB, 9% of BB and 2% of B. The top panel of Figure 1 shows the weekly time series of average CDS rates. Average credit spreads for Europe were fairly flat until the third quarter of 2007, when they started to increase in response to the credit crunch. They peaked at over 440 basis points in December 2008.

2.2 CDS RETURNS

The main difficulty in constructing CDS returns is that there is no time series data on actual transaction prices for a specific default swap contract. Reported instead are at-market spreads for newly issued default swap contracts with constant maturity.

To translate these spreads into returns, consider a portfolio that combines a long position in a T-year par defaultable bond issued by firm i and a short position in a T-year par riskless bond.[7] It may be thought of as a 100% leveraged position in the

[5] Recent papers that analyze the contribution of non-credit factors to corporate bond yields include Longstaff et al. (2005), Ericsson and Renault (2006) and Zhou (2007).

[6] Data are collected starting in 2003. Since the construction of some of the risk factors in our study requires an initial set-up period of up to 18 months, all summary statistics and empirical results are reported for the period from July 2004 to December 2008.

[7] We thank our referee for pointing us in this direction.

Table I. Descriptive Statistics

This table presents summary statistics for the average level of CDS spreads (columns one through three), average weekly excess returns on CDS (columns four through six), average weekly excess returns on equity (columns seven through nine), and the number of firms (last column) for the 17 European countries represented in our sample. For each country, the first row shows the summary statistics for the set of firms for which both CDS and equity data are available during our sample period from July 2004 to December 2008, whereas the second row reports figures using all firms with equity data for that country. All rates are reported in basis points. The last two rows of the table show the summary statistics across all firms in our sample. There are a total of 150 European firms for which both CDS and equity data are available, and there are 4216 firms with equity data.

	CDS spreads			CDS returns			Equity returns			
	Min	Med	Max	Min	Med	Max	Min	Med	Max	Firms
Austria	54.73	54.73	54.73	−0.86	−0.86	−0.86	−33.30	−33.30	−33.30	1
							−143.60	11.49	108.38	92
Belgium	35.68	35.68	35.68	−2.32	−2.32	−2.32	−8.64	−8.64	−8.64	1
							−121.17	7.53	172.21	125
Denmark	102.25	130.32	158.40	−8.46	−6.40	−4.34	8.57	25.09	41.61	2
							−185.73	3.66	384.39	176
Finland	29.75	110.53	598.96	−33.87	−6.06	−1.69	−75.06	−6.09	36.88	6
							−157.80	1.99	96.87	124
France	20.41	69.71	415.48	−66.04	−4.29	−0.31	−267.12	−8.34	81.28	35
							−235.46	2.91	270.96	687
Germany	26.56	49.59	552.98	−102.87	−3.09	−0.68	−311.16	−2.19	66.80	28
							−262.54	7.17	231.13	791
Greece	56.03	56.03	56.03	−2.20	−2.20	−2.20	7.98	7.98	7.98	1
							−176.08	9.94	124.71	107
Ireland	215.93	215.93	215.93	−20.20	−20.20	−20.20	−431.61	−431.61	−431.61	1
							−195.98	−10.92	171.15	41
Italy	12.48	35.19	599.19	−87.85	−3.30	0.64	−298.87	−5.42	47.23	13
							−143.74	−5.92	217.09	304
Luxembg	95.52	95.52	95.52	−13.65	−13.65	−13.65	−61.34	−61.34	−61.34	1
							−15.02	19.48	75.87	11
Netherlds	19.73	46.97	124.97	−17.87	−1.96	−0.44	−70.07	0.68	42.76	10
							−290.54	5.37	143.87	167
Norway	42.72	253.07	463.42	−27.97	−15.22	−2.47	−101.73	−47.80	6.13	2
							−173.96	11.37	267.55	174
Portugal	32.76	35.46	84.30	−2.30	−1.78	−1.37	−24.65	−7.91	14.37	4
							−68.72	6.36	130.17	41
Spain	41.39	52.58	151.34	−9.05	−3.42	−0.89	−12.63	25.42	50.96	7
							−461.27	5.97	196.40	156
Sweden	43.77	57.72	475.07	−12.90	−4.42	−1.18	−21.44	−1.23	16.47	9
							−191.07	2.34	352.10	273
Switzerld	16.63	71.13	115.53	−12.19	−3.00	0.40	−30.48	−9.75	44.07	9
							−438.90	10.61	116.72	227
UK	20.33	53.00	302.87	−22.85	−3.21	5.66	−77.47	−0.02	91.42	20
							−463.86	−35.81	185.02	720
All	12.48	55.77	599.19	−102.87	−3.31	5.66	−431.61	−2.68	91.42	150
							−463.86	0.86	384.39	4216

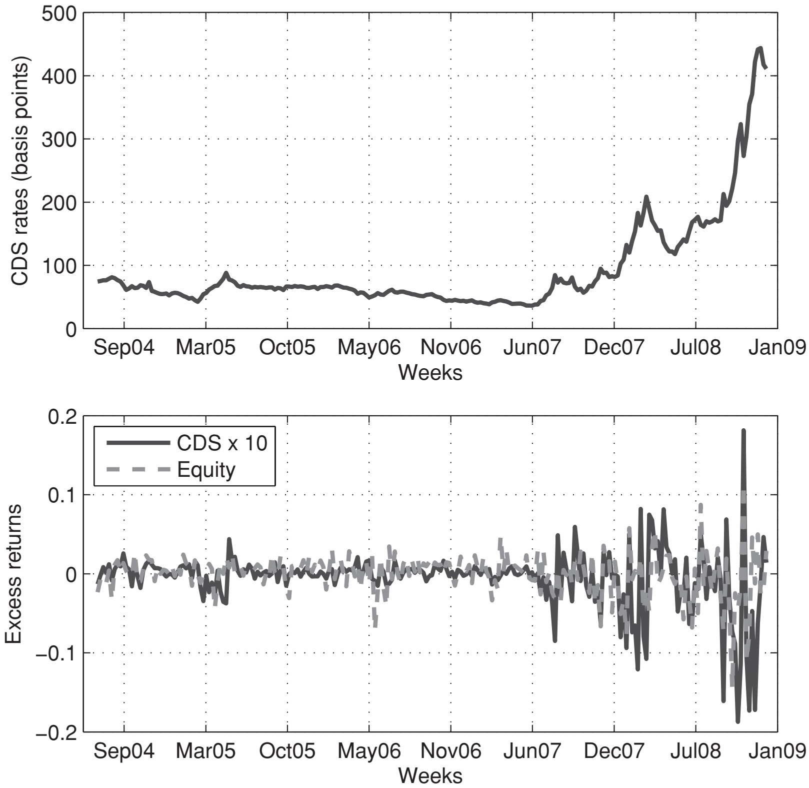

Figure 1. Time Series of CDS Rates, CDS Returns and Equity Returns
The first panel of this figure shows the weekly time series of average CDS rates for the 150 firms for which both CDS and equity data are available. The second panel plots the average weekly excess returns on CDS (solid line) and equity (dashed line) across the same set of firms. The sample period is July 2004 to December 2008.

risky bond. To a close approximation, it generates cash-flows that are the same as those from selling protection on firm i via a T-year CDS contract with a nominal value of par.[8]

The initial value of both the CDS contract and the long-short bond position is zero. Over a short time interval, the change in the value of the CDS contract to the investor, ΔV_{CDS}, is therefore equal to the change in value of the long-short bond position. Hence,

$$\Delta V_{\mathrm{CDS}} = \Delta P_D - \Delta P_{RF}, \tag{1}$$

[8] This replication ignores the effect that, in the event of a default, it is not guaranteed that the fixed-rate Treasury bond will be selling at par.

where ΔP_D and ΔP_{RF} denote changes in the value of the risky and risk-free bond. Dividing each side by par, the excess return on the defaultable bond, r_D^e, is given as

$$r_D^e = \Delta V_{\text{CDS}}. \tag{2}$$

In other words, the rate of return on the defaultable bond is equal to the rate of return on the riskless bond plus the change in value of the CDS contract divided by par. We refer to r_D^e as CDS-implied excess return on defaultable debt, or simply as CDS *return*.[9]

Over a short interval, the change in the value of the CDS contract to the investor is equal to minus the change in the CDS rate, $-\Delta\text{CDS}$, multiplied by the value of a defaultable T-year annuity, $A(T)$. To be specific,

$$\Delta V_{\text{CDS}} = -\Delta\text{CDS}\, A(T), \tag{3}$$

where

$$A(T) = \frac{1}{4}\sum_{j=1}^{4T} \delta(j/4)\, q(j/4). \tag{4}$$

Here, $\delta(s)$ denotes the risk-free discount factor for s years out, and $q(s)$ is the risk-neutral survival probability of firm i over the next s years.[10] The discount factors $\delta(s)$ are fitted from Datastream Euro zero curves that are constructed relative to the Euro Interbank Offered Rate (Euribor).

To obtain estimates for $q(s)$, we assume a constant risk-neutral default intensity λ for firm i.[11] The survival probabilities then simplify to

$$q(s;\lambda) = e^{-\lambda s}, \tag{5}$$

which allows us to express the annuity factor $A(T)$ as a function of λ. As a consequence, λ can be computed directly from observed CDS rates by solving the equation

$$\text{CDS}\, A(T;\lambda) = L \sum_{j=1}^{4T} \delta(j/4)\, \left[q((j-1)/4;\lambda) - q(j/4;\lambda)\right]. \tag{6}$$

Here, L denotes the risk-neutral expected fraction of notional lost in the event of default. For our analysis, we assume that it is constant at 60%. The right-hand side

[9] These are realized excess returns. If default occurs over the small time increment, then ΔP_D is equal to minus the fraction of notional lost in default. None of the 150 firms in our sample defaulted.

[10] Equation (4) assumes risk-neutral independence between interest rates and the default time, a standard assumption in the CDS modeling and valuation literature. We have verified that the role of risk-neutral correlation between interest rates and default risk is negligible for our return calculations.

[11] This simplifying assumption represents a tradeoff between a loss of generality on the one side and a potentially incorrect measurement of λ due to model misspecification errors on the other.

of (6) approximates the value of the protection-seller leg at initiation of the default swap contract, whereas CDS $A(T)$ equals the value of the protection-buyer leg. Equality holds since at-market CDS rates are set so that both of these values agree. Using (5) to simplify (6) yields $\mathrm{CDS}/4 = L\,(e^{\lambda/4} - 1)$, or

$$\lambda = 4 \log \left(1 + \frac{\mathrm{CDS}}{4\,L} \right). \tag{7}$$

We compute r_D^e using weekly (Wednesday) CDS rates to optimally mitigate the tradeoff between market microstructure effects of high-frequency quotes and the statistical power of our empirical tests. The bottom panel of Figure 1 shows the time series of average weekly CDS returns. Returns stayed relatively flat throughout the first three years of our sample.[12] They were significantly more volatile in the second half of 2007 and in 2008. We find especially large negative returns at the beginning of the financial crisis (August 2007), the first quarter of 2008, and between September and December 2008. The plot also shows the time series of average weekly excess returns on equity for the same set of firms. A comparison of the two return series highlights the fact that they generally move in the same direction, and that CDS returns are often much smaller in absolute values than equity returns.

2.3 THE CORRELATION STRUCTURE OF CDS RETURNS

To gain initial insights into the correlation structure of European CDS returns we perform a simple principal components analysis. The top panel of Table II reports summary statistics for the principal components analysis on the correlation matrix of weekly CDS returns. The results indicate that there is a significant amount of commonality in the variation of CDS spreads across European firms. The first principal component (PC1) captures 53% of the variation in the correlation matrix. In comparison, the second principal component plays a much smaller role, capturing about 8% of the variation. The first three principal components collectively explain nearly two-thirds of the variation.

Interpretation of the First Principal Component

At a first glance, the histogram of the weight vector associated with the first principal component (not shown) suggests a roughly equal weighting for most of the European firms in our sample. But closer inspection reveals that low-credit-spread firms tend to have larger weights, and that firms with high credit spreads play a less important role in forming the first principal component. This is evident

[12] An exception is May 2005, when medium- and low-rated European credit spreads widened in response to the downgrading of General Motors and Ford in the U.S.

Table II. Principal Components Analysis

This table reports the individual and cumulative variance explained by the first three principal components of the correlation matrix of weekly excess returns on CDS for the 150 firms for which both CDS and equity data are available (first two columns), weekly excess returns on equity for the same set of firms (middle two columns), and weekly excess returns on equity for all 4216 firms in the 17 European countries represented in our sample (last two columns). Results are shown for the full sample period from July 2004 to December 2008 (top panel) and two subsamples: July 2004 to July 2007 (middle panel) and August 2007 to December 2008 (bottom panel). For each panel, we report results for raw returns, 1-factor return residuals after controlling for MKT, and 5-factor return residuals after controlling for MKT, TERM, SMB, HML and FVDX.

CDS returns		Equity returns (matched sample)		Equity returns (all firms)	
Individual	Cumulative	Individual	Cumulative	Individual	Cumulative
		July 2004–December 2008			
		Raw returns			
0.53	0.53	0.41	0.41	0.18	0.18
0.08	0.61	0.05	0.46	0.02	0.20
0.05	0.66	0.03	0.49	0.02	0.21
		1-factor return residuals			
0.47	0.47	0.11	0.11	0.06	0.06
0.09	0.56	0.05	0.17	0.02	0.09
0.05	0.60	0.04	0.21	0.02	0.11
		5-factor return residuals			
0.45	0.45	0.09	0.09	0.03	0.03
0.09	0.54	0.06	0.15	0.02	0.05
0.05	0.59	0.04	0.19	0.02	0.07
		July 2004–July 2007			
		Raw returns			
0.40	0.40	0.33	0.33	0.11	0.11
0.06	0.45	0.03	0.36	0.01	0.12
0.04	0.49	0.03	0.38	0.01	0.14
		1-factor return residuals			
0.38	0.38	0.05	0.05	0.04	0.04
0.06	0.44	0.04	0.09	0.01	0.05
0.04	0.48	0.04	0.12	0.01	0.07
		5-factor return residuals			
0.36	0.36	0.05	0.05	0.02	0.02
0.06	0.42	0.04	0.09	0.01	0.03
0.04	0.46	0.04	0.13	0.01	0.05
		August 2007–December 2008			
		Raw returns			
0.55	0.55	0.44	0.44	0.22	0.22
0.08	0.63	0.07	0.51	0.03	0.25
0.05	0.68	0.04	0.55	0.03	0.28
		1-factor return residuals			
0.48	0.48	0.15	0.15	0.09	0.09
0.09	0.57	0.07	0.23	0.04	0.14
0.05	0.62	0.06	0.28	0.04	0.17
		5-factor return residuals			
0.47	0.47	0.12	0.12	0.05	0.05
0.10	0.57	0.09	0.21	0.05	0.10
0.05	0.63	0.05	0.27	0.04	0.14

Table III. Interpretation of Principal Components

The top panel of this table reports average firm characteristics for tercile portfolios sorted on the firm's weight in the first principal component of weekly CDS returns. For each portfolio, we show the average weight (wgt, in percent), the average CDS rate (rate, in basis points), the average firm-specific elasticity measure (β_E, in percent), and the average historical relative CDS bid-ask spread (BA). The average idiosyncratic equity volatility (V, in percent), absolute skewness (|S|) and kurtosis (K), and the average Andersen-Darling test statistic for deviations of equity returns from normality (AD) are also reported, as well as average firm size (Sz, in billions), book leverage (Lev), Altman's Z-score (Z) and Ohlson's O-score (O). The last two columns show the average correlation between CDS returns and negative super-senior tranche spread changes for the iTraxx Europe ($\rho_{\Delta ST}$) and average coefficients from regressing CDS returns on these negative super-senior tranche spread changes after controlling for MKT ($\Delta\beta_{ST}$). We report similar results for the second and third principal components. The bottom panel shows the same set of results for 5-factor CDS return residuals after controlling for MKT, TERM, SMB, HML and FVDX. The sample includes the 150 firms for which both CDS and equity data are available, and covers the period from July 2004 to December 2008.

100 wgt	rate	100 β_E	BA	100 V	|S|	K	AD	Sz	Lev	Z	O	$\rho_{\Delta ST}$	$\beta_{\Delta ST}$
						CDS *returns*							
						First principal component							
7.71	115	1.19	0.14	1.75	0.53	5.84	1.40	30	0.51	1.4	−4.6	0.49	2.97
9.77	73	1.30	0.12	1.65	0.52	5.55	1.23	34	0.53	1.5	−4.5	0.65	2.85
10.79	53	0.93	0.13	1.53	0.53	5.88	1.22	42	0.46	1.4	−4.9	0.71	2.45
						Second principal component							
−11.36	46	0.83	0.15	1.53	0.50	5.54	1.28	43	0.61	1.4	−4.8	0.67	2.84
1.06	74	1.04	0.13	1.60	0.60	6.34	1.42	28	0.43	1.6	−4.8	0.61	2.48
9.57	117	1.52	0.11	1.78	0.48	5.37	1.14	36	0.46	1.3	−4.6	0.58	2.94
						Third principal component							
−11.04	63	0.89	0.15	1.59	0.51	5.58	1.23	36	0.43	1.6	−5.1	0.55	2.23
0.36	88	1.31	0.14	1.67	0.51	5.49	1.25	40	0.55	1.5	−4.6	0.66	3.01
9.56	86	1.21	0.10	1.66	0.57	6.20	1.36	30	0.52	1.3	−4.4	0.65	3.00
						5-factor CDS return residuals							
						First principal component							
7.33	129	1.43	0.13	1.82	0.57	6.01	1.38	27	0.53	1.2	−4.3	0.50	3.18
9.69	63	1.18	0.13	1.61	0.49	5.50	1.30	38	0.51	1.7	−4.9	0.65	2.78
11.08	49	0.84	0.13	1.50	0.53	5.77	1.17	41	0.47	1.4	−4.9	0.70	2.32
						Second principal component							
−11.12	43	0.96	0.15	1.55	0.48	5.34	1.22	44	0.59	1.6	−5.1	0.68	2.71
0.82	76	0.92	0.13	1.59	0.62	6.59	1.48	28	0.44	1.5	−4.7	0.59	2.54
9.98	118	1.53	0.11	1.77	0.48	5.32	1.14	36	0.47	1.3	−4.5	0.59	3.01
						Third principal component							
−11.12	60	1.00	0.15	1.62	0.48	5.29	1.22	28	0.55	1.5	−4.7	0.61	2.74
−0.07	66	0.87	0.14	1.63	0.50	5.70	1.20	50	0.47	1.7	−5.0	0.63	2.43
10.28	112	1.55	0.10	1.66	0.61	6.27	1.42	29	0.48	1.2	−4.4	0.62	3.09

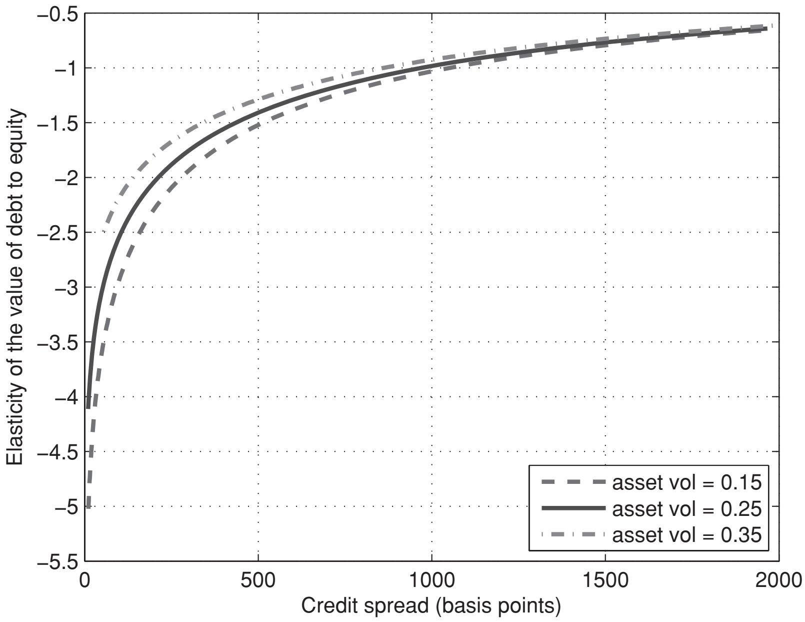

Figure 2. Elasticity of the Value of Debt to Equity
This figure plots the elasticity of the value of debt to equity, $(\partial D/D)/(\partial E/E)$, under the Merton (1974) model. We consider zero-coupon debt with a face value of 100 that matures in five years, with the risk-free interest rate set to 4%. Three values for asset volatility are used: 15%, 25% and 35%. The firm's asset value is varied in order to generate different debt and equity values. The elasticity is plotted against credit spreads for different asset values.

from the top panel of Table III, where we partition the 150 firms in our sample into terciles according to their weights in the first principal component. For each tercile, we report both the average weight (across firms) and the average CDS rate (across firms and weeks). As the former increases from 0.08 to 0.11, average credit spreads fall by more than 50%, from 115 to 53 basis points.

CDS rates may not only represent compensation for default risk, but also for liquidity risk (see, for example, Yan and Tang (2007) and Bongaerts et al. (2008)). We therefore compute alternative firm characteristics that are designed to capture default and liquidity risk separately. For the former, we will rely on intuition from the Merton (1974) model. Figure 2 shows that under the Merton model, the elasticity of the value of debt to equity, $(\partial D/D)/(\partial E/E)$, is a strictly increasing function of the firm's credit spread, conditional on asset volatility.[13] Schaefer and

[13] This is consistent with Schaefer and Strebulaev (2008) who show that the elasticity is equal to $(1/E_V - 1)E/D$, where E_V is the partial derivative of equity to firm value. Acharya and Johnson (2007) document a roughly linear relationship between the elasticity of credit spreads with respect to stock prices and the inverse level of the credit spread for the Merton model.

Strebulaev (2008) show that empirical estimates of this elasticity are not significantly different than those obtained from a simulation that assumes that the Merton model holds. Their evidence, together with the relationship displayed in Figure 2, suggests a close link between the estimated elasticity of the value of debt to equity and the Merton-model-implied credit spread of a firm. Schaefer and Strebulaev (2008) estimate the elasticity by regressing excess returns on corporate debt, r_D^e, on the excess return on the issuing firm's equity, r_E^e, and ten-year riskless bonds. In our applications, we measure r_D^e as CDS returns, as derived in Section 2.2. A preliminary analysis of the data reveals that the loadings on the riskless bond returns are mostly insignificant, and that maturity effects as described in Schaefer and Strebulaev (2008) are less of a concern in our setting since each CDS quote is effectively a new five-year par-coupon credit spread on the underlying firm. We therefore run firm-by-firm regressions

$$r_D^e(t) = \beta_0 + \beta_E\, r_E^e(t) + \varepsilon(t). \tag{8}$$

The coefficient of interest is β_E. It can be interpreted as a firm-specific elasticity measure, a characteristic that is closely related to default risk as predicted by the Merton model.[14] As β_E increases, Merton-model-implied credit spreads increase, conditional on asset volatility. For each firm and week in our sample, β_E is estimated from (8) using daily CDS and equity returns over the preceding six months. Table III shows that firms with the highest weight in the first principal component have the lowest elasticity measure, and hence the lowest default risk under the Merton model (holding asset volatility constant).

To measure liquidity risk at the firm level, we follow Yan and Tang (2007) and, at week t, compute the average of the daily percentage CDS bid-ask spreads over the past month, BA(t). The results in Table III indicate that the average, across firms and time, of these historical percentage bid-ask spreads are fairly flat across terciles, suggesting that the PC1-weights are somewhat less sensitive to firm-specific liquidity risk.

To further explore the interpretation of the first principal component of CDS returns, we consider a number of equity-return-based firm characteristics and accounting measures related to the financial health of a firm. As to the former, each week t we compute the idiosyncratic historical equity volatility, V(t), skewness, S(t), and kurtosis, K(t), using daily equity return data for the past six months. Table III shows that while firms with higher PC1-weights are substantially less volatile, their skewness and kurtosis measures have less explanatory power. In

[14] An alternative measure of firm-specific default risk in the Merton framework is the *distance to default* used, for example, in Vassalou and Xing (2004). Since accounting data for European firms are available only on an annual basis, the vast majority of the temporal variation in the distance to default would stem from changes in the firm's stock prices, ignoring the information content of credit spread changes.

addition to these higher-order moments of the equity return distribution, we construct the Anderson and Darling (1952) test statistic, AD, to directly measure the deviation of equity returns from normality. We have

$$AD = -\left(T + \sum_{t=1}^{T} \frac{2t-1}{T} \left[\log \Phi(y_t) + \log\left(1 - \Phi(y_{T-t+1})\right)\right]\right) \times \left(1 + \frac{0.75}{T} + \frac{2.25}{T^2}\right), \tag{9}$$

where $\{y_1 < \ldots < y_T\}$ are the sorted excess returns on equity, $\{r_E^e(t)\}_{t=1}^T$, and Φ denotes the normal cumulative distribution function. The higher AD, the further away the distribution is from normality. If it exceeds 0.752, the hypothesis of normality is rejected at the 5% confidence level. Stephens (1974) shows that AD is one of the best tests in detecting departures from normality. We compute AD using daily equity return data for the past six months and find that low PC1-weights are associated with large AD values.

The accounting measures include firm size (market value of equity), book leverage, and two measures of financial distress: the Altman (1968) Z-score and the Ohlson (1980) O-score.[15] Table III shows that firms with the highest PC1-weights are significantly larger, less levered and have the lowest default probability as measured by the O-score.[16]

In summary, we find that firms with high weights in the first principal component of CDS returns are usually large firms of high credit quality and low equity volatility. This is an important observation since it allows us to focus on the type of risk priced in this specific subset of firms. Large, high-credit-quality and low-volatility firms usually are expected to honor their outstanding debt except in the worst economic states. In other words, the risk profile of investing in default swaps of such firms is closely related to that of insuring economic catastrophe risk. Motivated by this observation, we compute firm-by-firm correlations between CDS returns and negative iTraxx Europe super-senior tranche spread changes. The portfolio averages of these sample correlations for each tercile are reported in the second to last column of Table III. The results clearly show that CDS returns of firms with higher PC1-weights are closer aligned with changes in the prices of economic catastrophe risk insurance than are firms with lower PC1-weights. This insight

[15] The accounting data are from Worldscope (via Datastream), and available on an annual basis. We use the last available figures to fill in weekly observations, without introducing any forward-looking bias. The lower a company's Z-score, or the higher its O-score, the higher its probability of bankruptcy.
[16] In our setting, Altman's Z-score has no explanatory power. For the U.S. market, Dichev (1998) finds that the O-score predicts CRSP delistings better than Altman's Z-score, and asset pricing studies on distress risk have since focused on the former (Griffin and Lemmon (2002)).

offers a unique point of departure for constructing a novel risk factor that is closely aligned with the first principal component of CDS returns.

Interpretation of the Second Principal Component

The results in Table III show that the second principal component of CDS returns (PC2) assigns positive weight to firms with high credit spreads, high default probability (as implied by the Merton model and as predicted by the O-score), and high equity volatility, and negative weight to firms with low credit spreads, low default risk and low equity volatility. It could thus be viewed as a portfolio that is long in low-credit-quality, high volatility firms and short in high-credit-quality, low volatility firms. The third principal component also appears to resemble a long-short position between firms that are riskier, with equity returns further away from normality, and firms that are less risky with return distributions closer to normality, but the pattern is less clear.

Since the weights in both the first and the second principal components sort on credit quality, albeit to different degrees, return factors constructed as long-short strategies after sorting on a firm's riskiness (or closely related measures) are likely to be correlated with PC1. But by construction, PC2 is uncorrelated to PC1. To better isolate the second principal component, it is therefore important to consider characteristics that are fairly equally distributed across firms' PC1-weights, but show a stronger pattern when sorted on PC2-weights. Table III reveals equity skewness and kurtosis as attractive candidates.

5-Factor CDS Return Residuals

We repeat the principal components analysis of CDS returns after controlling for five equity and reference bond market systematic factors. These include the market factor, MKT, as measured by the weekly excess return on the MSCI Europe index and a reference bond market factor, TERM, computed as the spread between the weekly returns on the ten-year Euribor bond and the one-week Euribor rate. The MSCI Europe index is a market capitalization index that is designed to measure equity performance in Europe. It consists of roughly 600 stocks from the same countries as the ones listed in Table I, with the exception of Luxembourg. Excess returns are computed relative to the one-week Euribor rate. All data are available from Datastream.

In addition, we construct weekly Fama-French SMB and HML factors for Europe, as well as a factor mimicking aggregate volatility risk, FVDX. For the construction of these factors, we use all available equity data for the 17 European countries in our study (see Table I). They consist of all twelve members of the Eurozone as of the beginning of our sample, plus Denmark, Greece, Norway, Sweden, Switzerland and the U.K. For non-Euro countries, stock prices are converted to Euro using

Datastream exchange rates. For a firm to enter this extended equity sample, it has to be listed in Compustat Global as well as in Worldscope. There are a total of 4216 firms, including the 150 firms with CDS data described in Section 2.1. The equity data are downloaded from Datastream in form of a return index for individual equities (data item RI), with dividends reinvested to purchase additional units of equity. Summary statistics are provided in Table I.

In constructing SMB and HML, we closely follow Fama and French (1993), but with weekly data and portfolio formation dates at the end of each year. FVDX is constructed similar to the aggregate volatility factor for the U.S. market in Ang et al. (2006), but without using forward-looking information. For each firm i, we first run the regression

$$r_E^{e,i}(t) = \beta_0 + \beta^i_{\mathrm{MKT}}\mathrm{MKT}(t) + \beta^i_{\Delta\mathrm{VDAX}}\Delta\mathrm{VDAX}(t) + \varepsilon^i(t), \tag{10}$$

where ΔVDAX(t) denotes the changes in the volatility DAX index, an indicator of future volatility in the DAX index. To construct a set of base assets that are sufficiently disperse in exposure to aggregate volatility innovations, we then sort firms into quintiles based on their $\beta^i_{\Delta\mathrm{VDAX}}$ coefficient, estimated over the past six months using regression (10) with daily data. Within each quintile portfolio, we value weight the stocks over the next six months. We link the returns across time to form one series of post-ranking returns for each quintile portfolio. We create the mimicking factor FVDX to track innovations in VDAX by estimating the vector of coefficients b_X in the regression

$$\Delta\mathrm{VDAX}(t) = b_0 + b_X' X(t) + \eta(t), \tag{11}$$

where $X(t)$ represents the vector of returns on the base assets. The return on the portfolio, $b_X' X(t)$, is the factor FVDX that mimics innovations in market volatility. We run the regression in (11) at a daily frequency every six months, using all data available up to that point. We then use the b_X estimate to compute FVDX over the *next* six months.

The sample correlation between the factor FVDX and ΔVDAX is 63%. We find that FVDX is strongly negatively correlated with the market factor (-0.94), reflecting the fact that when volatility increases, market returns are low. The sample correlations between FVDX and TERM, SMB and HML are -0.25, 0.72 and -0.12, respectively.

The top panel of Table II shows that even after controlling for equity and reference bond market factors, CDS return residuals still exhibit an important first principal component that accounts for 45% of the variation. The importance of the second principal component remains largely unchanged, and the first three principal components still account for nearly 60% of the variation. As a result, the large common component of CDS returns cannot be explained by previously established systematic risk factors. Although some of the commonality can be attributed to common sensitivity to the market factor, the majority of it is left unexplained. This is consistent with the evidence in Collin-Dufresne et al. (2001) for the U.S. corporate bond market.

Similarly, after controlling for the five factors MKT, TERM, SMB, HML and FVDX, the results in Table III remain largely unchanged, with even better sorting results for the elasticity measure, β_E, and book leverage.

3. Sources of Commonality in CDS Returns

In this section, we construct several novel CDS and equity-return-based risk factors, including a factor that mimics economic catastrophe risk.

3.1 A FACTOR MIMICKING ECONOMIC CATASTROPHE RISK

In Section 2.3 we discovered that the first principal component of CDS returns is more robustly estimated by firms whose CDS returns are more closely aligned with changes in economic catastrophe risk insurance premia, as measured by the super-senior tranche spreads of the iTraxx Europe index. We therefore rely on the price information contained in these tranche spreads to construct a return-based factor that mimics economic catastrophe risk, called FCR.[17] Following Breeden et al. (1989), we construct it as the portfolio of asset returns maximally correlated with realized negative innovations in super-senior tranche spreads. We impose the negative sign since investors profit when tranche spreads decrease. That is, we create FCR by estimating the coefficient vector b_X in the regression

$$-\Delta ST(t) = b_0 + b_X' X(t) + \eta(t), \tag{12}$$

where $\Delta\mathrm{ST}(t)$ denotes changes in the super-senior tranche spreads of the iTraxx Europe index, and $X(t)$ represents the vector of returns on some base assets. The return on the portfolio, $b_X' X(t)$, is the factor FCR that mimics innovations in economic catastrophe risk. To obtain a set of base assets $X(t)$ that are sufficiently disperse in exposure to economic catastrophe risk innovations, we first sort firms into n equally sized portfolios based on their $\beta^i_{\Delta ST}$ coefficient in the firm-by-firm regressions

$$r_X^{e,i}(t) = \beta_0 + \beta^i_{\mathrm{MKT}}\mathrm{MKT}(t) - \beta^i_{\Delta ST}\Delta ST(t) + \varepsilon^i(t). \tag{13}$$

[17] Changes in super-senior tranche spreads cannot directly be interpreted as holding returns on catastrophe risk. To obtain such a measure directly from the tranche spreads, we would also need to know the timing of future cash flows that investors may expect. Estimating the latter requires not only CDS data on all index constituents but also an assumption regarding their correlation structure.

To create $X(t)$, for each portfolio we weight the asset returns over the next six months, and then link the returns across time to form one series of post-ranking returns.

In principal, we could use either default swaps or equity in Equation (13) to form the base assets $X(t)$, or a combination of both. We motivate our choice using a simple example of a levered firm with its outstanding debt due one period from today. At the end of that period, the firm either pays off its financial debt and continues to operate, an idiosyncratic credit shock causes the firm to default, or an economic catastrophe occurs that causes this and many other firms to default. If the firm defaults, all equity value is wiped out and bond holders recover only a fraction of their investment. Now suppose that just prior to today, investors observe a surprise increase in economic catastrophe risk through a sudden surge in super-senior tranche spreads. We distinguish between three scenarios: probability is shifted from non-default states to the catastrophic event (Scenario 1), probability is shifted from idiosyncratic credit events to the catastrophic scenario, leaving the firm's overall default risk unchanged (Scenario 2), and a decrease in the expected debt recovery value associated with a catastrophic event (Scenario 3).

Innovations to economic catastrophe risk are likely to involve a combination of these three scenarios. Independent of the type of news, however, the shock will lead to a downward adjustment in bond prices and hence lower realized bond returns as long as the payoff to bond holders in the event of an economic catastrophe is sufficiently small in comparison to that in non-default states and idiosyncratic default states. Equity values, on the other hand, do not change when the likelihood of default is shifted from idiosyncratic to systemic events (Scenario 2), or when debt recovery values at default change (Scenario 3). This is because of the limited sensitivity of equity value at default to whether the causing credit event is of systemic or idiosyncratic nature, and to the recovery value to debt holders. The only time current equity values change in response to a surprise increase in economic catastrophe risk is when states that were previously considered non-default states are now treated as catastrophic event times (Scenario 1). In such a scenario, we may observe a downward adjustment in equity value, depending on the financial health of the firm. The decrease in equity value will be larger for firms where the expiring debt accounts only for a small portion of the balance sheet, and smaller for highly levered firms, which introduces an additional layer of heterogeneity across firms when compared to the response in bond prices.[18] In summary, this motivating

[18] In Scenario 1, the latter mainly depends on debt recovery values associated with a catastrophic event which can be thought of as uniformly small across firms.

example suggests that FCR is more robustly estimated when CDS returns are used in (13).[19]

We run the regressions in (13) every six months, using weekly CDS returns for the 150 firms described in Table I. To insure a sufficient number of firms in each portfolio, we set *n* equal to three. When computing post-ranking returns, the portfolios are equally weighted, as is the norm for CDS index calculations. The regression in Equation (12) is run at a weekly frequency every six months, using all data available up to that point. The sample correlation between FCR and $-\Delta ST$ is 75%.

One hurdle to overcome is the fact that iTraxx Europe index tranche spread data become available only in September 2006. To impute values prior to that point, we use the individual CDS spread data for the firms in our sample and compute model-implied super-senior tranche spreads for the European credit market. We mimic the setup of the iTraxx Europe (i.e., index formation in March and September of each year, super-senior tranche attachment and detachment points of 12% and 22%, etc.) and use the standard copula-based approach, well reviewed in Gibson (2004), to value index tranches. The correlation parameter is set to match the first available value of the iTraxx Europe super-senior tranche, and is calibrated to be about 0.45. We have verified that variations in tranche correlations prior to September 2006 do not change our results qualitatively. They are also robust to restricting the sample period to September 2006 onwards.

Return Distribution and Risk Characteristics

To further investigate if firms with different sensitivities to negative super-senior tranche spread innovations, $\beta_{\Delta ST}$ as defined in Equation (13), are indeed able to generate any widespread distribution of CDS returns, we compute the average post-ranking returns of each tercile portfolio formed above. The results are reported in Table IV, together with the 5-factor alphas from regressing the portfolio returns on MKT, TERM, SMB, HML and FVDX. They reveal a wide distribution of average weekly excess returns and alphas, ranging from -3.5 and -3.7 basis points for the low-sensitivity tercile to -8.1 and -7.5 basis points for the high-sensitivity tercile. All alpha estimates are significantly different from zero. The negative signs reflect the extraordinary losses incurred in European credit markets during the recent crisis.

These results support the notion that the economic catastrophe risk mimicking factor FCR is likely to capture a large portion of the common variation in CDS returns. Indeed, Table V shows it has a staggering correlation of 0.96 with their first principal component, which is reflected in the time series plots in Figure 3.

[19] The example is of course only a simplification of reality and cannot accommodate all variables. Nevertheless, it provides us with a clear directive on how to choose the base assets. Further details are provided in an online supplement available at www2.wu-wien.ac.at/rof/supmat.html.

Table IV. Risk Characteristics

This table reports descriptive statistics for tercile portfolios sorted on different firm-specific risk characteristics. The first panel analyzes portfolios sorted on the sensitivity of CDS returns to negative super-senior tranche spread changes for the iTraxx Europe. The first row corresponds to the firms with the lowest sensitivity, the last row to the ones with the highest. Portfolios are formed every six months, and are equally weighted. For each portfolio, we report the average weekly CDS return and the associated 5-factor alpha estimate after controlling for MKT, TERM, SMB, HML and FVDX (α_5), both in basis points. Similar statistics are provided when equity excess returns are used for the same portfolios of firms (columns three and four). We append "*" to the alpha estimates to indicate statistical significance, based on Newey-West t-statistics with 13 lags (3 months). We also show the average (across weeks) of the average CDS rates (rate, in basis points), firm-specific elasticity measures (β_E, in percent), historical relative CDS bid-ask spreads (BA), idiosyncratic equity volatility (V, in percent), absolute skewness ($|S|$) and kurtosis (K), Andersen-Darling test statistic for deviations of equity returns from normality (AD), firm size (Sz, in billions), Altman's Z-score (Z) and Ohlson's O-score (O). Panels two through seven report similar results for portfolios sorted on the firm-specific sensitivity of CDS returns to equity returns, historical relative CDS bid-ask spreads, idiosyncratic equity volatility, absolute skewness and kurtosis, and deviations of equity returns from normality. The sample includes the 150 firms for which both CDS and equity data are available, and covers the period from July 2004 to December 2008.

CDS		Equity		Risk Characteristics									
E r^e	α_5	E r^e	α_5	rate	100 β_E	BA	100 V	$\lvert S\rvert$	K	AD	Sz	Z	O
Sensitivity of CDS returns to negative super-senior tranche spread changes													
−3.55	−3.74*	−0.20	−1.32	49	0.67	0.19	1.55	0.50	5.48	1.22	45	1.8	−4.6
−4.71	−4.83*	1.07	−3.06	57	0.88	0.12	1.59	0.54	5.94	1.32	31	1.3	−4.3
−8.11	−7.48*	−9.19	−19.15*	163	2.17	0.08	1.88	0.61	6.34	1.51	21	1.2	−3.8
Sensitivity of CDS returns to equity returns													
−3.19	−3.40*	2.78	−2.45	52	0.21	0.15	1.54	0.56	6.07	1.38	37	1.5	−4.3
−4.51	−4.24*	−3.28	−6.79	54	0.91	0.15	1.61	0.52	5.78	1.32	38	1.5	−4.4
−8.84	−8.67*	−8.05	−14.91	165	2.57	0.09	1.86	0.57	5.95	1.36	22	1.2	−3.8
Historical relative CDS bid-ask spreads													
−8.00	−7.41*	−11.48	−18.58	166	2.13	0.07	1.86	0.65	6.50	1.53	22	1.2	−3.8
−5.02	−5.21*	6.08	0.00	69	1.03	0.11	1.65	0.54	5.91	1.26	33	1.4	−4.3
−3.67	−3.73*	−3.75	−6.17	41	0.65	0.20	1.53	0.46	5.33	1.22	41	1.8	−4.6
Idiosyncratic equity volatility													
−4.45	−4.62*	6.10	4.39	55	0.98	0.16	1.30	0.52	5.84	1.40	35	1.4	−4.3
−4.31	−4.02*	−5.65	−11.08*	64	1.06	0.13	1.59	0.49	5.44	1.22	30	1.3	−4.2
−7.84	−7.70*	−9.54	−18.72*	155	1.70	0.10	2.13	0.64	6.58	1.47	31	1.4	−4.0
Absolute idiosyncratic equity skewness													
−5.88	−5.74*	−4.10	−10.96*	89	1.36	0.13	1.63	0.41	5.11	1.09	30	1.4	−4.2
−5.50	−5.30*	−3.86	−6.66	81	1.10	0.13	1.66	0.45	5.15	1.11	32	1.4	−4.2
−5.38	−5.42*	−2.03	−8.74	107	1.31	0.12	1.75	0.81	7.62	1.88	34	1.4	−4.1
Idiosyncratic equity kurtosis													
−6.52	−5.84*	−4.11	−5.92	83	1.25	0.14	1.63	0.41	4.80	0.94	33	1.4	−4.3
−4.86	−5.06*	−4.09	−11.43*	90	1.20	0.13	1.66	0.45	5.20	1.15	31	1.4	−4.1
−5.38	−5.56*	−1.65	−8.84	104	1.32	0.11	1.75	0.80	7.89	2.00	32	1.4	−4.1
Deviation of equity returns from normality													
−6.32	−5.81*	−5.52	−7.76	77	1.14	0.14	1.63	0.41	4.94	0.88	37	1.4	−4.3
−5.05	−5.44*	−2.09	−8.80	86	1.26	0.12	1.66	0.48	5.25	1.11	31	1.4	−4.2
−5.32	−5.16*	−1.75	−9.17	114	1.37	0.11	1.76	0.78	7.76	2.13	26	1.3	−4.0

Table V. Correlation Matrix

This table presents the pairwise correlation coefficients for the risk factors used in our study. MKT denotes the weekly excess return on the MSCI Europe index and TERM is the spread between weekly returns on the ten-year Euribor bond and the one-week Euribor rate. SMB, HML, FVDX, FV-E, FS-E, FK-E and FAD-E are equity-return-based factors that we construct using data for all 4216 firms in the 17 European countries represented in our sample. SMB and HML are the Fama-French factors constructed for Europe, FVDX is the aggregate volatility risk mimicking factor based on Ang et al. (2006), and FV-E, FS-E, FK-E and FAD-E are long-short strategies formed on idiosyncratic equity volatility, absolute skewness and kurtosis, and on the Andersen-Darling test statistic for deviations of equity returns from normality. The remaining factors are CDS-return-based factors that we construct using data for the 150 firms for which both CDS and equity data are available. FCR is the economic catastrophe risk mimicking factor. FE and FBA are long-short strategies formed on the firm-specific sensitivity of CDS returns to equity returns and on historical relative CDS bid-ask spreads. FV, FS, FK and FAD are the CDS counterparts to FV-E, FS-E, FK-E and FAD-E. PC1, PC2 and PC1-E denote the first and second principal components of CDS returns and the first principal component of equity excess returns. Appending “5” identifies the principal components for 5-factor return residuals. The sample period is July 2004 to December 2008.

	MKT	TERM	SMB	HML	FVDX	FV-E	FS-E	FK-E	FAD-E	FCR	FE	FBA	FV	FS	FK	FAD
MKT	1.00															
TERM	0.28	1.00														
SMB	−0.74	−0.16	1.00													
HML	0.22	0.05	−0.18	1.00												
FVDX	−0.94	−0.25	0.72	−0.12	1.00											
FV-E	0.52	0.18	−0.33	0.18	−0.61	1.00										
FS-E	−0.33	−0.08	0.39	0.18	0.38	−0.27	1.00									
FK-E	−0.47	−0.17	0.48	−0.02	0.50	−0.36	0.79	1.00								
FAD-E	−0.87	−0.26	0.82	−0.14	0.87	−0.54	0.46	0.57	1.00							
FCR	0.46	0.21	−0.23	0.36	−0.43	0.50	−0.07	−0.15	−0.37	1.00						
FE	0.60	0.24	−0.38	0.29	−0.56	0.45	−0.23	−0.28	−0.52	0.84	1.00					
FBA	−0.57	−0.28	0.37	−0.25	0.54	−0.46	0.21	0.25	0.50	−0.77	−0.94	1.00				
FV	0.61	0.21	−0.40	0.21	−0.56	0.45	−0.21	−0.25	−0.53	0.69	0.87	−0.89	1.00			
FS	0.13	−0.07	−0.06	0.12	−0.09	0.14	0.18	−0.01	−0.04	0.13	0.03	−0.07	0.20	1.00		
FK	−0.08	−0.23	0.08	−0.10	0.08	−0.15	0.18	0.12	0.14	−0.27	−0.29	0.25	−0.10	0.70	1.00	
FAD	0.04	−0.11	0.02	−0.03	−0.01	−0.09	0.14	0.06	0.05	0.00	−0.04	0.05	0.07	0.72	0.88	1.00
PC1	0.50	0.25	−0.27	0.33	−0.47	0.48	−0.07	−0.16	−0.41	0.96	0.84	−0.81	0.71	0.21	−0.14	0.13
PC1-5	0.00	0.00	0.00	0.00	0.00	0.20	0.01	0.06	−0.01	0.78	0.59	−0.57	0.46	0.16	−0.09	0.14
PC2	0.06	0.10	0.05	0.04	−0.08	0.09	−0.07	−0.01	−0.05	0.10	0.31	−0.34	0.27	−0.43	−0.61	−0.71
PC2-5	0.00	0.01	0.00	0.00	0.00	0.04	−0.09	−0.01	−0.04	0.10	0.30	−0.33	0.27	−0.43	−0.63	−0.73
PC1-E	0.98	0.26	−0.71	0.28	−0.95	0.59	−0.29	−0.45	−0.87	0.48	0.60	−0.57	0.60	0.13	−0.10	0.00
PC1-E5	0.00	0.00	0.00	−0.01	0.00	−0.29	−0.02	0.04	0.09	−0.11	−0.05	0.07	−0.07	−0.06	0.06	0.03

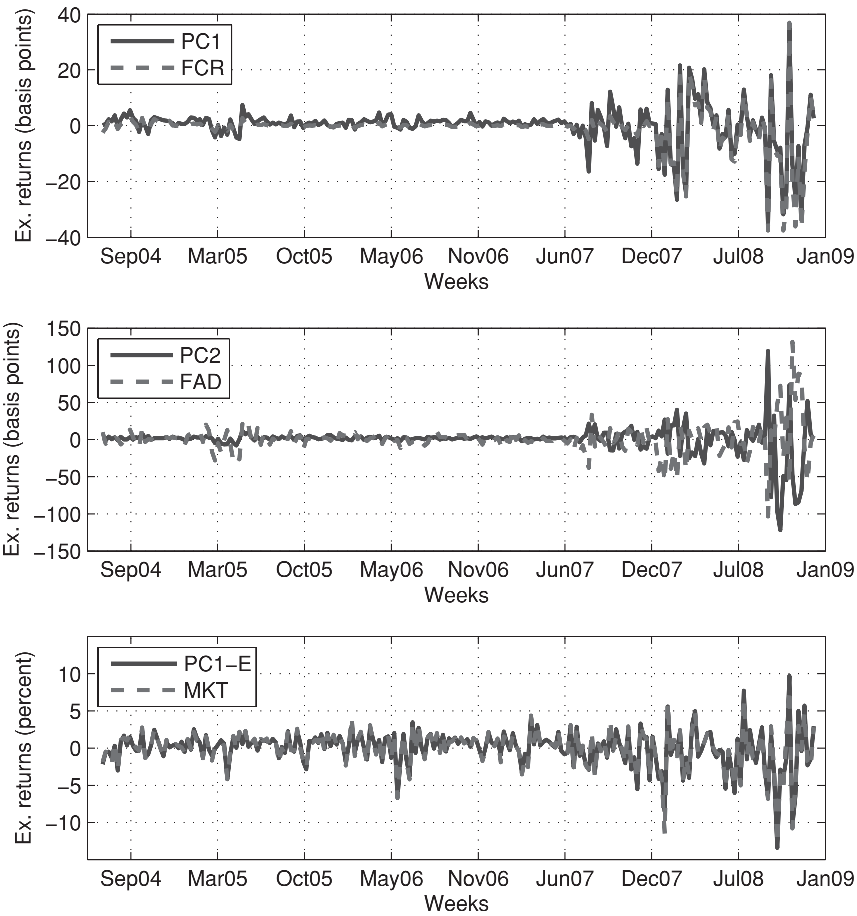

Figure 3. Principal Components of CDS and Equity Returns
The top panel of this figure plots the first principal component of CDS returns (PC1) and the economic catastrophe risk mimicking factor (FCR), whereas the middle panel shows the second principal component of CDS returns (PC2) and the risk factor formed on the Andersen-Darling test statistic for deviations of equity returns from normality (FAD). The bottom panel plots the first principal component of equity excess returns for the same set of firms (PC1-E) and the MKT factor. In all three panels, the principal components are rescaled to have the same variance as the second factor plotted. The sample includes the 150 firms for which both CDS and equity data are available, and covers the period from July 2004 to December 2008.

Moreover, FCR is still highly correlated (0.78) with the first principal component of the 5-factor CDS return residuals.

Table IV also shows the average (across weeks) of average CDS rates and firm characteristics for each portfolio. Low-$\beta_{\Delta ST}$ firms are characterized as large firms with high credit quality (low spreads, low bankruptcy probabilities predicted by the Merton model, Z and O-score), high percentage bid-ask spreads, low equity volatility, skewness, kurtosis and deviations from normality. This is in line with the results in Table III.[20]

3.2 ALTERNATIVE RISK FACTORS

To capture the variation in the second principal component of CDS returns, we construct an array of alternative factors associated with the risk characteristics identified in Table III.

CDS-Return-Based Factors

Let Y denote a firm characteristic such as β_E, V, |S|, K, AD, or BA. At the end of each six-month period, we sort firms into terciles according to their current value $Y(t)$. For each tercile, we compute equally weighted CDS returns over the next six months. We link the returns across time to form one series of post-ranking returns for each tercile portfolio. The CDS-return-based factor associated with characteristic Y, FY (or FE in the case of β_E), is defined as the portfolio that is long in large-Y firms and short in small-Y firms. No forward-looking information is used in the construction of the FY factors.

Table V shows the pairwise correlation coefficients for these additional factors. Not surprisingly, the default risk factor FE is highly correlated with the idiosyncratic equity volatility factor FV (0.87) and with the CDS liquidity factor FBA (-0.94). The negative correlation with FBA reflects the fact that, on average across firms, the correlation between a firm's CDS rate and its historical relative bid-ask spread is negative (-0.44 for our sample). FE, FBA and FV are also the factors most closely related to FCR, and hence the first principal component of CDS returns. The correlations with the second principal component, on the other hand, are strongest for FAD at -0.71 (also see Figure 3), and remain strong at -0.73 after controlling for MKT, TERM, SMB, HML and FVDX. Figure 4 shows that deviations of equity returns from normality, as measured by AD, are higher when skewness and kurtosis are more pronounced. They exhibit a somewhat weaker, if any, association with the other risk or volatility measures. Skewness and kurtosis already emerged as candidate characteristics for capturing PC2 in the preliminary analysis in Table III. Together with the evidence in Figure 4, this explains not only why FS, FK and FAD are all closely related, but also why they are at least moderately successful in replicating the second principal component of CDS returns.

[20] Ignoring, for a moment, the market factor, $\beta_{\Delta ST}$ increases as correlations between CDS returns and $-\Delta ST$ increase and/or as the CDS return volatility increases. In Table III we find that overall, $\beta_{\Delta ST}$ increases as a firm's weight in the first principal component of CDS return decreases, mainly due to substantially higher CDS return volatility for more risky firms.

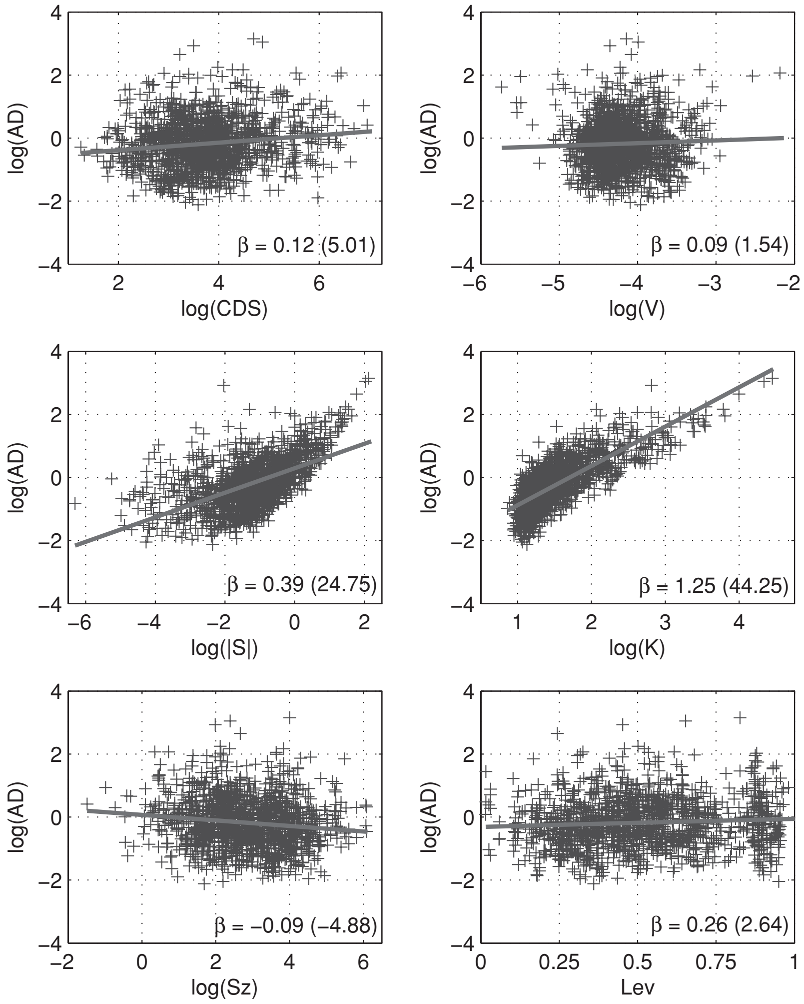

Figure 4. Distribution of the AD Measure
This figure shows scatter plots of the logarithm of the Andersen-Darling test statistic for deviations of equity returns from normality (AD) versus the logarithm of credit spreads (CDS), idiosyncratic equity volatility (V), absolute skewness (|S|) and kurtosis (K), firm size (Sz) and book leverage (Lev), across bi-annual portfolio formation dates and the 150 firms for which both CDS and equity data are available. For each plot, we also show the fitted linear regression line, as well as the estimate and t-statistic (in parentheses) for the slope coefficient, β. The sample period is July 2004 to December 2008.

Return Distribution and Risk Characteristics

For each firm characteristic underlying these alternative factors, Table IV reports the average post-ranking returns and 5-factor alphas for the associated tercile portfolios. The sensitivity of CDS returns to equity returns, historical percentage bid-ask spreads and idiosyncratic equity volatility all generate a fairly wide range of average weekly CDS returns and alphas. Along these three dimensions, firms are still sorted by some of the firm characteristics in columns five through fourteen of the table, but the associations are less strong compared to the portfolios formed on the sensitivity of CDS returns to super-senior tranche spread changes. The fact that sorting on the BA measure lines up firms in the opposite direction is intuitive given the negative correlation between credit spreads and percentage bid-ask spreads.

When sorted on absolute skewness, kurtosis or the AD measure, the tercile portfolios exhibit much less variation in average post-ranking returns and 5-factor alphas. It suggests that factors sorted on these firm characteristics, although correlated with the second principal component of CDS returns, are less likely to explain a large portion of the cross-sectional distribution.

Equity-Return-Based Factors

When possible, we also construct equity-return-based factors associated with the characteristics Y. This allows us to directly compare the explanatory power of risk factors constructed by forming CDS return portfolios to those based on equity return portfolios, a notion that to our knowledge has been absent from the literature. To be consistent with the construction of the equity market factors SMB, HML and FVDX in Section 2.3, we use data for all 4216 firms in the 17 European countries described in Table I. The factors are denoted by FY-E. Construction proceeds exactly as for FY described above, except that we form quintiles (utilizing the larger number of firms) and value weight equity returns within each portfolio (as in Section 2.3).

This approach is feasible for all firm characteristics that do no rely on CDS data, that is, V, S, K, and AD. Table V shows that FV-E has a moderate positive correlation of 0.45 with FV, and that it is positively correlated with the market factor (in market downturns, high-V returns are lower than low-V returns). As suggested by the evidence in Figure 4, FS-E, FK-E and FAD-E are fairly closely aligned, with pairwise correlations between 0.46 and 0.79. Interestingly, these three factors show very little comovement with their credit market equivalents (correlations range between 0.05 and 0.18), highlighting potential differences in the information content of CDS and equity markets. Somewhat surprisingly, perhaps, they have a negative sample correlation with FV-E and the market factor, implying, for example, that in the recent market downturn, high-AD firms suffered less than low-AD firms. Figure 4, however, shows no significant association between the AD measure and idiosyncratic equity volatility. In that sense, the correlation results for FAD-E (and FS-E, FK-E) are not in contradiction to those for FV-E. On the contrary, given the negative and significant relationship between AD and firm size, our findings are in line with the negative correlation between SMB and the market factor for Europe.

While the correlations of the FY-E factors with the first principal component of CDS returns are generally of moderate size (up to 0.48 in absolute values), their associations with the second principal component are limited.

3.3 FACTOR RISK PREMIA AND SHARPE RATIOS

During our sample period, the risk premium on the market factor is −3.3 basis points per week, or −1.7% annually. The negative sign is due to the market-wide losses incurred during the recent financial crisis. Indeed, prior to August 2007, the risk premium was positive and significant at 31.5 basis points per week, or 16.4% annually. These results are reported in Table VI. In comparison, the weekly risk premium on the S&P 500 index is −15 basis points (11 basis points prior to the crisis, −69 basis points from August 2007 to December 2008). Sharpe ratios, based on weekly data, were 0.19 for Europe and 0.08 for the U.S. between July 2004 and July 2007, and fairly similar at −0.21 for Europe and −0.20 for the U.S. during the first 17 months of the financial crisis. The risk premia for TERM, SMB, HML and FVDX are −18, 14, −4 and −11 basis points per week, respectively.

The construction of the economic catastrophe risk factor did not use any forward looking information, which allows us to treat FCR as a tradable factor and, following Lewellen et al. (2008), estimate its risk premium as the average excess return on the factor. Table VI reports that sample average as negative and significant at −1.1 basis points per week, or −0.6% annually. While nearly zero prior to August 2007, it has plunged to a significant −3.4 basis points per week, or −1.8% annually, since then. This sudden shift is reflected in a drop of FCR's Sharpe ratio from the pre-crisis (0.05) to the crisis (−0.26) years.

The alternative CDS-return-based factors FE, FBA and FV behave fairly similar to FCR (with reverse signs for FBA), but the risk premia for FS, FK and FAD show different patterns. They amount to only a few basis points throughout the sample period, even during the financial crisis. Their Sharpe ratios are positive and vary between 0.04 and 0.06, with slightly higher numbers since August 2007. Risk premia on the alternative equity-return-based risk factors are generally positive, both before and during the crisis. The only exception is FV-E, where weekly risk premia change from 55 basis points prior to August 2007 to −47 basis points between August 2007 and December 2008.

4. Regression Analysis

Next we analyze the explanatory power of the risk factors constructed in Section 3.

Table VI. Factor Risk Premia, Sharpe Ratios and Explanatory Power

This table presents the average (row 1, in percent, "*" indicates statistical significance), standard deviation (row 2, in percent) and Sharpe ratio (row 3) for the risk factors used in our study, as well as for weekly excess returns on the S&P 500 index. Results are shown for the full sample period from July 2004 to December 2008 (top panel) and two subsamples: July 2004 to July 2007 (middle panel) and August 2007 to December 2008 (bottom panel). For each panel, we also report the average adjusted R^2 from regressing CDS returns (rows four and five) and equity excess returns (rows six and seven) on a single risk factor, using data for the 150 firms for which both CDS and equity data are available. Appending "5" indicates that the regression uses 5-factor return residuals after controlling for MKT, TERM, SMB, HML and FVDX in place of raw returns.

	S&P	MKT	TERM	SMB	HML	FVDX	FV-E	FS-E	FK-E	FAD-E	FCR	FE	FBA	FV	FS	FK	FAD
								July 2004–December 2008									
mean	−0.15	−0.03	−0.18*	0.14	−0.04	−0.11	0.22	0.12	0.13	0.15	−0.01*	−0.06*	0.04	−0.03	0.00	0.01	0.01
std	2.28	2.55	0.96	1.40	0.82	2.34	3.59	1.43	1.40	2.07	0.08	0.40	0.41	0.30	0.13	0.20	0.20
SR	−0.07	−0.01	−0.18	0.10	−0.05	−0.05	0.06	0.09	0.09	0.07	−0.14	−0.14	0.11	−0.11	0.04	0.06	0.05
CDS	–	0.14	0.03	0.05	0.05	0.12	0.11	0.01	0.02	0.10	0.46	0.37	0.35	0.28	0.05	0.05	0.06
CDS5	–	–	–	–	–	–	0.02	0.00	0.00	0.00	0.26	0.16	0.16	0.11	0.04	0.05	0.06
Eq	–	0.36	0.03	0.20	0.04	0.35	0.15	0.03	0.08	0.29	0.10	0.14	0.13	0.14	0.01	0.01	0.00
Eq5	–	–	–	–	–	–	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01
								July 2004–July 2007									
mean	0.11	0.32*	−0.11	0.22*	0.04	−0.47*	0.55*	0.05	0.06	0.07	0.00	0.00	−0.01	0.01	0.00	0.00	0.00
std	1.27	1.64	0.76	0.97	0.51	1.69	2.17	0.99	0.88	1.28	0.01	0.17	0.24	0.19	0.07	0.09	0.08
SR	0.08	0.19	−0.15	0.22	0.07	−0.28	0.25	0.05	0.07	0.05	0.05	0.00	−0.03	0.03	0.01	0.01	0.04
CDS	–	0.04	0.01	0.00	0.00	0.03	0.01	0.00	0.00	0.01	0.29	0.26	0.29	0.25	0.08	0.14	0.17
CDS5	–	–	–	–	–	–	0.00	0.00	0.00	0.00	0.20	0.17	0.19	0.16	0.05	0.10	0.12
Eq	–	0.30	0.01	0.15	0.02	0.27	0.02	0.03	0.05	0.18	0.03	0.05	0.05	0.05	0.01	0.01	0.02
Eq5	–	–	–	–	–	–	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
								August 2007–December 2008									
mean	−0.69	−0.77	−0.30*	−0.02	−0.21	0.63	−0.47	0.27	0.27	0.32	−0.03*	−0.17*	0.15*	−0.12*	0.01	0.03	0.02
std	3.54	3.73	1.29	2.02	1.22	3.20	5.46	2.07	2.12	3.15	0.13	0.66	0.61	0.45	0.22	0.32	0.34
SR	−0.20	−0.21	−0.24	−0.01	−0.17	0.20	−0.09	0.13	0.13	0.10	−0.26	−0.26	0.24	−0.26	0.06	0.11	0.07
CDS	–	0.17	0.05	0.08	0.07	0.16	0.15	0.00	0.02	0.13	0.50	0.41	0.40	0.32	0.04	0.05	0.05
CDS5	–	–	–	–	–	–	0.00	−0.01	−0.01	−0.01	0.27	0.16	0.18	0.11	0.04	0.05	0.06
Eq	–	0.40	0.04	0.26	0.09	0.40	0.22	0.03	0.09	0.36	0.12	0.17	0.16	0.19	0.01	0.01	0.00
Eq5	–	–	–	–	–	–	0.01	0.00	0.00	−0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01

4.1 THE DETERMINANTS OF CDS RETURNS

The results in Table VII show that the five equity and reference bond market factors MKT, TERM, SMB, HML and FVDX have limited explanatory power for CDS returns. For the average European firm, they explain less than 20% of the variation in terms of adjusted R^2. Much of this explanatory power stems from the market factor. While the MKT betas, by themselves, are significantly different from zero, using all five factors in the regression renders each of them insignificant due to collinearity. Adding additional equity-return-based factors such as FV-E, FK-E, FS-E and FAD-E to the regression does not improve matters much. The adjusted R^2 for the average firm is raised only slightly to 22%, and the dominant role of the first principal component of the return residuals persists. Our results complement those in Collin-Dufresne et al. (2001) and others, in that we show that even this enlarged set of equity and reference bond market factors is unable to adequately capture the common time series variation in CDS returns.

Results change dramatically when the economic catastrophe risk mimicking factor, FCR, is taken into consideration. Table VIII reveals that the average adjusted R^2 from regressing firm-specific CDS returns on FCR is 0.46. For the average firm, the FCR coefficient is positive and statistically significant. A one basis point increase in the mimicking factor returns leads to a 5.3 basis point increase in CDS returns. After controlling for FCR, the first principal component accounts for only 17% of the variation in the return residuals, down from 44% when all equity market factors and TERM are used. PC1 is now much less dominant when compared to higher-order principal components. This highlights the fact that a single credit market factor that mimics economic catastrophe risk innovations, FCR, is able to explain most of the commonality in the temporal pattern of CDS returns. Considering the alternative CDS-return-based factors constructed in Section 3.2 individually, only FE, FBA and FV make a comparable contribution towards explaining CDS returns (see Table VI). But none of them is as successful as FCR.

Controlling for the market factor, or any of the other equity or reference bond market factors, only yields small improvements. The average adjusted R^2 from regressing CDS returns on MKT, TERM, SMB, HML, FVDX and FCR is 0.49. The market factor coefficient is still positive for the average firm, but rather small and not significant.

Given the high correlation between FAD and the second principal component of CDS returns, it is not surprising that adding FAD as a covariate increases the adjusted coefficient of determination from 0.49 to 0.54. The estimate of the FAD beta is positive and of moderate size, although also not statistically significant. A ten basis point increase in FAD leads to a 1.1 basis point increase in CDS returns, on average. Return residuals no longer exhibit a dominant first principal component and indicate that common variation in European CDS returns, to a large extent,

Table VII. Factor Regressions using Equity-Return-Based Risk Factors

This table presents the results from the firm-by-firm regressions of weekly excess returns on CDS (left panel) and equity (right panel) on equity-return-based risk factors and TERM. The first and second columns in each panel show summary statistics for firm-specific regressions of returns on MKT and FVDX, respectively. In column three, we regress on MKT, TERM, SMB, HML and FVDX, and in the last column four additional factors (FV-E, FS-E, FK-E and FAD-E) are considered. We report the average of the estimated regression coefficients, the average Newey-West t-statistics with 13 lags (in parentheses), as well as the percentage of firms for which the coefficient estimate has the opposite sign from that of the average estimate (in brackets). For each set of regressions, the average adjusted R^2 is shown, together with the fraction of total variation explained by each of the first three principal components of the return residuals' correlation matrix. The sample includes the 150 firms for which both CDS and equity data are available, and covers the period from July 2004 to December 2008.

	CDS returns				Equity returns (matched sample)			
100 α	−0.053	−0.065	−0.055	−0.057	−0.011	−0.157	−0.067	−0.077
	(−1.254)	(−1.518)	(−1.184)	(−1.283)	(0.175)	(−0.604)	(−0.139)	(−0.190)
	[0.042]	[0.028]	[0.056]	[0.042]	[0.535]	[0.278]	[0.444]	[0.424]
MKT	0.082		0.066	0.092	1.033		0.539	0.542
	(4.014)		(1.403)	(1.939)	(8.824)		(1.841)	(1.856)
	[0.014]		[0.118]	[0.049]	[0.000]		[0.146]	[0.174]
TERM			0.037	0.036			−0.013	−0.029
			(0.982)	(0.851)			(−0.151)	(−0.195)
			[0.201]	[0.229]			[0.465]	[0.458]
SMB			0.062	0.047			0.109	0.165
			(1.127)	(0.738)			(0.349)	(0.358)
			[0.188]	[0.264]			[0.424]	[0.403]
HML			0.107	0.092			0.434	0.378
			(1.569)	(1.415)			(0.821)	(0.884)
			[0.056]	[0.042]			[0.375]	[0.368]
FVDX		−0.085	−0.035	0.019		−1.114	−0.590	−0.431
		(−3.791)	(−0.674)	(0.258)		(−8.908)	(−1.185)	(−0.935)
		[0.014]	[0.306]	[0.417]		[0.000]	[0.236]	[0.257]
FV-E				0.029				0.049
				(1.798)				(0.310)
				[0.063]				[0.438]
FS-E				−0.034				0.079
				(−0.377)				(0.290)
				[0.354]				[0.417]
FK-E				0.048				0.056
				(0.823)				(0.146)
				[0.201]				[0.465]
FAD-E				−0.001				−0.207
				(−0.018)				(−0.515)
				[0.563]				[0.340]
adj. R^2	0.14	0.12	0.19	0.22	0.36	0.35	0.40	0.42
PC1	0.47	0.48	0.45	0.44	0.11	0.11	0.09	0.09
PC2	0.09	0.09	0.09	0.10	0.05	0.05	0.06	0.05
PC3	0.05	0.05	0.05	0.05	0.04	0.05	0.04	0.04

Table VIII. Factor Regressions using CDS-Return-Based Risk Factors

This table presents the results from the firm-by-firm regressions of weekly excess returns on CDS (top panel) and equity (bottom panel) on CDS-return-based risk factors. The first and second columns in each panel show summary statistics for firm-specific regressions of returns on FCR, and on FCR after controlling for MKT, TERM, SMB, HML and FVDX. The next six columns consider one additional factor FX each, where FX is either FE, FBA, FV, FS, FK or FAD, and the last column includes all six of these additional factors. We report the average of the estimated regression coefficients (except for TERM, SMB, HML and FVDX, and FX in the last column), the average Newey-West t-statistics with 13 lags (in parentheses), as well as the percentage of firms for which the coefficient estimate has the opposite sign from that of the average estimate (in brackets). For each set of regressions, the average adjusted R^2 is shown, together with the fraction of total variation explained by each of the first three principal components of the return residuals' correlation matrix. The sample includes the 150 firms for which both CDS and equity data are available, and covers the period from July 2004 to December 2008.

FX:			FE	FBA	FV	FS	FK	FAD	All
					CDS returns				
100 α	−0.004	−0.007	−0.003	−0.007	−0.003	−0.007	−0.006	−0.008	−0.003
	(0.208)	(0.177)	(0.242)	(0.148)	(0.231)	(0.162)	(0.227)	(0.158)	(0.109)
	[0.611]	[0.583]	[0.604]	[0.576]	[0.576]	[0.569]	[0.576]	[0.569]	[0.583]
MKT	–	0.021	0.005	0.013	−0.003	0.020	0.018	0.017	0.001
		(0.227)	(0.086)	(0.112)	(−0.049)	(0.134)	(0.105)	(0.036)	(0.057)
		[0.382]	[0.438]	[0.417]	[0.500]	[0.410]	[0.403]	[0.451]	[0.451]
FCR	5.268	4.946	3.406	3.479	3.834	4.896	4.946	4.833	3.343
	(7.068)	(6.830)	(3.720)	(4.242)	(4.928)	(7.839)	(7.826)	(7.909)	(4.590)
	[0.007]	[0.007]	[0.063]	[0.063]	[0.042]	[0.007]	[0.007]	[0.007]	[0.063]
FX	–	–	0.344	−0.322	0.354	0.068	0.105	0.112	–
			(0.644)	(−0.974)	(0.835)	(0.997)	(1.354)	(1.281)	
			[0.472]	[0.361]	[0.403]	[0.319]	[0.306]	[0.278]	
adj. R^2	0.46	0.49	0.52	0.53	0.52	0.52	0.54	0.54	0.62
PC1	0.17	0.17	0.17	0.18	0.18	0.15	0.14	0.13	0.13
PC2	0.12	0.11	0.10	0.09	0.10	0.11	0.11	0.11	0.10
PC3	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.09
					Equity returns (matched sample)				
100 α	0.137	−0.053	−0.054	−0.052	−0.048	−0.051	−0.056	−0.051	−0.061
	(0.738)	(−0.145)	(−0.146)	(−0.142)	(−0.133)	(−0.143)	(−0.150)	(−0.134)	(−0.196)
	[0.243]	[0.410]	[0.396]	[0.417]	[0.410]	[0.424]	[0.417]	[0.403]	[0.368]
MKT	–	0.530	0.534	0.530	0.513	0.537	0.543	0.547	0.542
		(1.816)	(1.801)	(1.807)	(1.767)	(1.830)	(1.845)	(1.868)	(1.910)
		[0.139]	[0.160]	[0.139]	[0.181]	[0.146]	[0.146]	[0.139]	[0.174]
FCR	19.389	1.010	0.836	−0.447	−0.188	0.825	0.371	0.965	0.083
	(3.376)	(−0.041)	(0.028)	(−0.093)	(−0.155)	(−0.015)	(−0.069)	(0.008)	(0.049)
	[0.007]	[0.528]	[0.514]	[0.451]	[0.465]	[0.514]	[0.563]	[0.521]	[0.507]
FX	–	–	−0.024	−0.197	0.251	−0.174	−0.310	−0.338	–
			(−0.014)	(−0.171)	(0.140)	(−0.186)	(−0.345)	(−0.386)	
			[0.507]	[0.444]	[0.451]	[0.493]	[0.451]	[0.389]	
adj. R^2	0.10	0.41	0.41	0.41	0.41	0.41	0.41	0.42	0.43
PC1	0.36	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.10
PC2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05
PC3	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05

has been accounted for. Similar results are obtained for FS and FK. Including all alternative CDS-return-based factors in the regression yields an average adjusted coefficient of determination of 0.62.

Cross-Sectional Analysis

Having established the explanatory power of FCR for the time series of CDS returns, we now perform a cross-sectional analysis. Using the 150 European firms with CDS data, we form five rating portfolios (AA, A, BBB, BB and B). Every six months we assign each firm to one of these portfolios, based on its current long-term S&P credit rating. For each portfolio, we weight CDS returns equally over the next six months, and then link the portfolio returns across time. Next, we regress the portfolio return series on FCR, while controlling for the five equity and reference bond market factors. The results are reported in the left panel of Table IX. We find that the FCR loadings are all positive and significant, and increase as credit quality deteriorates (except for BB). Given the negative risk premia for FCR in Table V, average excess returns on the rating portfolios line up nicely with the FCR-factor loadings, supporting the notion that FCR is a priced risk factor in European CDS markets.

The cross-sectional results for FE and FV are similar to those for FCR, in that the loadings are all positive and significant, and generally increase as credit quality deteriorates. The same applies to FBA, although with reversed signs due to its negative correlation with FCR. Note, however, that the time series fit for these alternative factors is not as good as that for FCR, especially for the AA and A portfolios. Interestingly, for the factors related to higher moments of equity return distributions, FS, FK and FAD, the beta coefficients exhibit a U-shape across the credit spectrum of firms. But they are not statistically different from zero.

Robustness Check using Corporate Bond Returns

Finally, we address the fact that we have formed and tested the CDS-return-based factors on the same set of 150 firms. Since this set represents the universe of public European firms with an active CDS market during our sample period, the set-up of our analysis is no different than testing the performance of SMB, HML or FVDX on equity data. The only caveat may be the smaller size of the (liquid) CDS market. To verify that the CDS market factors have similar explanatory power for broader fixed-income markets, we repeat the analysis in Table IX for a set of alternative test assets. Specifically, we collect data on Markit iBoxx EUR corporate bond indices. These indices are based on a much larger set of firms, of which our sample of 150 active-CDS-market firms is likely to constitute a smaller subset. Data are available from the Markit index website at www.indexco.com.

Table IX. Matched CDS and Equity Rating Portfolios

This table presents the results from regressing weekly excess returns on portfolios sorted on rating on MKT, TERM, SMB, HML and FVDX, plus a single CDS-return-based risk factor: the economic catastrophe risk factor FCR (top panel), risk factors formed on the firm-specific sensitivity of CDS returns to equity returns (FE, second panel) and historical relative CDS bid-ask spreads (FBA, third panel), and risk factors formed on idiosyncratic equity volatility (FV), absolute skewness (FS), kurtosis (FK) and the Andersen-Darling test statistic for deviations of equity returns from normality (FAD) in the remaining panels. For each portfolio, we report the alpha estimate, the beta estimate for the CDS-return-based risk factor, and the adjusted R^2. Newey-West t-statistics with 13 lags are shown in parentheses. Portfolios are formed every six months, and are equally weighted. The first five columns use CDS returns to compute the portfolio returns, and the last five columns use equity returns for the same sets of firms. The sample includes the 150 firms for which both CDS and equity data are available, and covers the period from July 2004 to December 2008.

	CDS returns					Equity returns (matched sample)				
	AA	A	BBB	BB	B	AA	A	BBB	BB	B
100 E r^e	−0.03	−0.03	−0.08	−0.04	−0.18	−0.03	0.04	−0.09	0.12	−0.76
						FCR				
100 α	0.00	0.00	−0.01	0.00	−0.11	0.05	0.03	−0.15	0.00	−0.69
	(−0.01)	(0.60)	(−0.68)	(0.10)	(−2.11)	(0.65)	(0.83)	(−2.44)	(−0.01)	(−2.40)
β	2.77	3.27	6.08	5.13	8.56	1.16	0.75	1.47	−1.34	6.39
	(5.79)	(17.97)	(21.17)	(20.84)	(10.88)	(0.69)	(0.94)	(1.34)	(−0.75)	(1.29)
adj. R^2	0.72	0.92	0.87	0.73	0.64	0.92	0.96	0.90	0.75	0.53
						FE				
100 α	−0.01	−0.01	−0.01	0.00	−0.11	0.03	0.03	−0.15	−0.04	−0.75
	(−0.77)	(−0.58)	(−0.57)	(0.17)	(−1.68)	(0.43)	(0.84)	(−2.41)	(−0.36)	(−2.62)
β	0.38	0.50	1.27	1.09	1.78	−0.12	0.15	0.26	−1.05	0.14
	(4.24)	(6.51)	(21.49)	(10.88)	(6.50)	(−0.49)	(1.20)	(1.21)	(−3.03)	(0.16)
adj. R^2	0.48	0.64	0.90	0.77	0.65	0.92	0.96	0.90	0.76	0.53
						FBA				
100 α	−0.02	−0.02	−0.03	−0.01	−0.14	0.04	0.03	−0.15	−0.01	−0.74
	(−1.37)	(−1.22)	(−1.77)	(−0.67)	(−2.12)	(0.55)	(0.85)	(−2.50)	(−0.13)	(−2.59)
β	−0.28	−0.45	−1.16	−1.07	−1.63	−0.13	−0.18	−0.28	0.78	−0.63
	(−3.81)	(−6.18)	(−8.41)	(−14.18)	(−10.31)	(−0.65)	(−1.35)	(−1.25)	(1.97)	(−0.69)
adj. R^2	0.40	0.60	0.85	0.79	0.63	0.92	0.96	0.90	0.76	0.53
						FV				
100 α	−0.02	−0.02	−0.03	−0.01	−0.14	0.04	0.03	−0.15	−0.01	−0.78
	(−1.47)	(−1.34)	(−1.58)	(−0.50)	(−2.03)	(0.51)	(0.86)	(−2.49)	(−0.10)	(−2.83)
β	0.36	0.51	1.36	1.42	2.21	0.05	0.17	0.38	−0.83	−0.57
	(4.25)	(4.92)	(7.29)	(15.34)	(7.56)	(0.16)	(1.21)	(1.33)	(−1.59)	(−0.59)
adj. R^2	0.38	0.49	0.71	0.75	0.62	0.92	0.96	0.90	0.75	0.53
						FS				
100 α	−0.03	−0.03	−0.07	−0.06	−0.21	0.03	0.02	−0.16	0.01	−0.76
	(−2.02)	(−2.04)	(−2.44)	(−1.66)	(−2.74)	(0.48)	(0.73)	(−2.89)	(0.11)	(−2.92)
β	0.44	0.24	0.09	0.45	0.68	1.90	−0.57	−0.05	0.78	−0.15
	(1.13)	(0.61)	(0.12)	(0.72)	(0.63)	(2.49)	(−3.37)	(−0.16)	(0.71)	(−0.08)
adj. R^2	0.32	0.30	0.36	0.35	0.40	0.92	0.96	0.90	0.75	0.53

Table IX. (Continued)

	CDS returns					Equity returns (matched sample)				
	AA	A	BBB	BB	B	AA	A	BBB	BB	B
					FK					
100 α	−0.03	−0.03	−0.07	−0.05	−0.20	0.04	0.02	−0.16	0.01	−0.76
	(−2.08)	(−2.10)	(−2.51)	(−1.67)	(−2.79)	(0.48)	(0.69)	(−2.76)	(0.10)	(−2.79)
β	0.13	−0.11	−0.60	−0.20	−0.17	0.41	−0.67	−0.44	1.05	−2.56
	(0.62)	(−0.45)	(−1.14)	(−0.39)	(−0.22)	(1.41)	(−6.85)	(−1.61)	(1.82)	(−1.62)
adj. R^2	0.28	0.29	0.41	0.34	0.39	0.92	0.96	0.90	0.75	0.53
					FAD					
100 α	−0.03	−0.03	−0.07	−0.05	−0.21	0.04	0.02	−0.16	0.01	−0.74
	(−2.16)	(−2.19)	(−2.52)	(−1.72)	(−2.84)	(0.46)	(0.77)	(−2.72)	(0.09)	(−2.68)
β	0.41	0.15	−0.10	0.12	0.31	0.42	−0.50	−0.46	0.70	−3.87
	(1.80)	(0.59)	(−0.19)	(0.26)	(0.37)	(1.20)	(−4.68)	(−1.98)	(0.95)	(−2.26)
adj. R^2	0.37	0.30	0.36	0.34	0.39	0.92	0.96	0.90	0.75	0.54

As of December 2008, the benchmark iBoxx EUR index consisted of 1058 investment-grade Euro-denominated bonds issued by more than 400 firms. About 72% of the issuers were domiciled in one of the 17 European countries in Table I, with the majority of the remaining names being U.S. issuers. The broadest high yield (HY) iBoxx EUR index (the unconstrained cum crossover HY index) consisted of 192 bonds from more than 150 issuers, 68% of which were European. Indeed, all major bond market indices for Europe contain some fraction of Euro-denominated bonds issued by non-European firms.

We analyze three investment-grade subindices (AA, A and BBB) as well as the HY index. Based on total return index data, where all coupon payments are reinvested, we compute weekly excess returns relative to the one-week Euribor rate. Table X reveals that the FCR loadings increase as credit quality decreases. They are positive and significant for the medium and low-credit-quality bond portfolios. As in Table IX, average rating portfolio returns line up nicely with the FCR-factor loadings, lending support to the notion that FCR is a priced risk factor in broader European fixed-income markets. The cross-sectional results for FE, FBA and FV are similar to those for FCR, with reversed signs for FBA. While there is no clear pattern for FS-factor loadings, the FK and FAD betas decrease as credit quality deteriorates and, given their positive risk premia, do line up with average portfolio returns. But in light of the results in Table IX, it comes as no surprise that FS, FK and FAD betas are generally not significant, and hence not well-equipped to explain cross-sectional variation in corporate bond returns.

Table X. Matched Bond and Equity Rating Portfolios

This table presents the results from regressing weekly excess returns on portfolios sorted on rating on MKT, TERM, SMB, HML and FVDX, plus a single CDS-return-based risk factor: the economic catastrophe risk factor FCR (top panel), risk factors formed on the firm-specific sensitivity of CDS returns to equity returns (FE, second panel) and historical relative CDS bid-ask spreads (FBA, third panel), and risk factors formed on idiosyncratic equity volatility (FV), absolute skewness (FS), kurtosis (FK) and the Andersen-Darling test statistic for deviations of equity returns from normality (FAD) in the remaining panels. For each portfolio, we report the alpha estimate, the beta estimate for the CDS-return-based risk factor, and the adjusted R^2. Newey-West t-statistics with 13 lags are shown in parentheses. Portfolios are formed every month, and are capitalization weighted. The first four columns are for the Markit iBoxx EUR corporate bond portfolios, and the last four columns use equity returns for the matched sets of firms. The sample period is July 2004 to December 2008.

	iBoxx EUR returns				Equity returns (matched sample)			
	AA	A	BBB	HY	AA	A	BBB	HY
100 E r^e	−0.02	−0.06	−0.06	−0.15	−0.11	−0.02	0.06	−0.25
					FCR			
100 α	−0.10	−0.13	−0.11	−0.15	0.05	0.02	0.01	−0.32
	(−3.31)	(−2.89)	(−3.04)	(−1.71)	(0.53)	(0.41)	(0.23)	(−2.64)
β	0.32	1.13	1.61	6.42	6.79	2.94	−1.99	4.03
	(0.92)	(2.72)	(4.74)	(6.89)	(1.69)	(1.43)	(−1.79)	(2.54)
adj. R^2	0.64	0.54	0.48	0.53	0.90	0.95	0.93	0.81
					FE			
100 α	−0.10	−0.13	−0.11	−0.14	0.03	0.01	0.01	−0.34
	(−3.26)	(−2.76)	(−2.98)	(−1.55)	(0.37)	(0.34)	(0.30)	(−2.86)
β	−0.06	0.15	0.39	1.47	1.07	0.51	−0.37	0.40
	(−0.71)	(2.28)	(4.62)	(11.72)	(2.81)	(2.09)	(−2.41)	(0.93)
adj. R^2	0.64	0.53	0.49	0.58	0.90	0.95	0.93	0.81
					FBA			
100 α	−0.10	−0.14	−0.11	−0.17	0.01	0.00	0.02	−0.36
	(−3.19)	(−2.81)	(−3.05)	(−1.81)	(0.11)	(0.08)	(0.51)	(−2.98)
β	0.00	−0.17	−0.47	−1.41	−1.02	−0.49	0.28	−0.16
	(0.00)	(−3.30)	(−5.71)	(−8.19)	(−2.01)	(−1.77)	(1.61)	(−0.41)
adj. R^2	0.64	0.53	0.53	0.57	0.90	0.95	0.92	0.81
					FV			
100 α	−0.10	−0.14	−0.11	−0.17	0.00	0.00	0.02	−0.37
	(−3.39)	(−2.96)	(−3.27)	(−1.76)	(0.06)	(−0.01)	(0.53)	(−3.23)
β	−0.12	0.21	0.61	1.81	1.18	0.51	−0.29	−0.26
	(−1.44)	(3.62)	(3.25)	(7.27)	(3.43)	(1.39)	(−1.43)	(−0.39)
adj. R^2	0.65	0.53	0.52	0.55	0.90	0.94	0.92	0.81
					FS			
100 α	−0.10	−0.14	−0.13	−0.23	−0.03	−0.02	0.03	−0.36
	(−3.41)	(−3.00)	(−3.33)	(−2.02)	(−0.48)	(−0.45)	(0.72)	(−2.85)
β	0.19	0.26	0.15	0.52	0.72	−0.04	−0.36	−0.70
	(0.89)	(0.80)	(0.94)	(0.98)	(0.81)	(−0.09)	(−0.76)	(−1.15)
adj. R^2	0.65	0.53	0.43	0.39	0.89	0.94	0.92	0.81

Table X. (Continued)

	iBoxx EUR returns				Equity returns (matched sample)			
	AA	A	BBB	HY	AA	A	BBB	HY
					FK			
100 α	−0.10	−0.14	−0.13	−0.22	−0.03	−0.01	0.03	−0.36
	(−3.30)	(−3.01)	(−3.33)	(−2.10)	(−0.38)	(−0.41)	(0.73)	(−2.92)
β	−0.06	−0.14	−0.38	−0.61	−1.36	−0.60	0.07	−0.07
	(−0.38)	(−0.70)	(−1.84)	(−1.17)	(−3.04)	(−4.05)	(0.36)	(−0.12)
adj. R^2	0.64	0.52	0.45	0.40	0.90	0.94	0.92	0.81
					FAD			
100 α	−0.10	−0.14	−0.12	−0.22	−0.03	−0.01	0.03	−0.37
	(−3.25)	(−2.99)	(−3.42)	(−2.12)	(−0.40)	(−0.43)	(0.74)	(−3.08)
β	−0.06	−0.14	−0.53	−0.54	−0.63	−0.18	−0.23	0.77
	(−0.35)	(−0.66)	(−2.13)	(−0.91)	(−1.19)	(−0.86)	(−0.92)	(1.29)
adj. R^2	0.64	0.52	0.48	0.40	0.89	0.94	0.92	0.81

4.2 A SHIFT IN THE CORRELATION STRUCTURE OF CDS RETURNS

The recent financial crisis has brought the notion of economic catastrophe risk insurance sharply into focus. Since our sample period covers both the years leading up to the monumental credit crunch of 2007–8, and the crisis itself, we are in a unique position to investigate potential structural shifts in European credit markets. Table II reveals that prior to August 2007, the first principal component of CDS returns explained about 40% of the variation. Since the onset of the financial crisis, that fraction has increased dramatically to 55%. This shift in the correlation structure is not only observed for raw CDS returns, but also for CDS return residuals after controlling for the MKT factor, or even all five equity and reference bond market factors.

So why did CDS return comovements become more pronounced during the financial crisis? To offer economic insights, we rely on the fact that the economic catastrophe risk mimicking factor, FCR, is a close match for PC1. Table VI reports that prior to August 2007, FCR explained about 29% of the CDS return variation for the average firm in our sample. Since then, that fraction has soared to 50%. For 5-factor CDS return residuals, the results are still dramatic. While FCR explained 20% of the variation pre-crisis, that fraction increased to 27% during the crisis. This highlights the fact that comovement in CDS returns became more pronounced during the financial crisis, and closer aligned with innovations in economic catastrophe risk premia. The increase in FCR's explanatory power could be due to one of two reasons: credit market investors may have readjusted the sensitivity of their positions to economic catastrophes risk starting August 2007, and/or the importance of FCR relative to other risk factors and/or idiosyncratic CDS return components increased during the recent crisis.

To explore these alternative explanations, we perform firm-by-firm regressions of CDS returns on MKT, TERM, SMB, HML, FVDX and FCR, both before the crisis and from August 2007 to December 2008.[21] We find that pre-crisis, the FCR beta estimates ranged from 0.49 to 90.41, with an average of 12.83. They were significant for the majority of firms. During the crisis, similar results were obtained, although often with substantially *smaller* FCR betas. From August 2007 to December 2008, FCR beta estimates were between 0.10 and 22.22, with an average of 4.46. This observation reveals that the increase in comovement in credit markets during the crisis cannot simply be explained by investors readjusting their sensitivity to economic catastrophe risk innovations.

Indeed, the driving factor seems to be a surge in FCR's volatility. The results in Table VI reveal that it increased more than ten-fold, from 1 basis point pre-crisis to 13 basis points during the crisis. Although the other risk factors saw increases in volatility as well, the effect was less pronounced since volatility at most tripled. The idiosyncratic risk, as measured by the volatility of the residuals from regressing firm-specific CDS returns on the five equity and reference bond market factors, plus FCR, increased four-fold from 15 basis points pre-crisis to 60 basis points during the crisis, on average across firms. Although dramatic, the relative increase in idiosyncratic risk was less steep than that in FCR's volatility. In summary, the shift in the correlation structure is largely due to the economic catastrophe risk factor becoming more important, not just relative to other risk factors, but also relative to the idiosyncratic CDS return components.

4.3 THE ROLE OF FCR IN EQUITY MARKETS

Given the important role FCR plays for CDS and corporate bond markets, a natural question to ask is whether it has any explanatory power for equity markets as well. To facilitate a direct comparison between CDS and equity markets, we perform time series and cross-sectional tests using equity data for the 150 firms in our CDS sample.

We first analyze the correlation structure of weekly returns on equity, in excess of the one-week Euribor rate, using principal components analysis on the correlation matrix. Columns three and four of Table II show that the fraction of variation explained by the first principal component is lower for equity returns (41%) than for CDS returns (53%) on the same set of firms. The same holds true for the fraction of variation explained by the first three principal components (less than

[21] A single regression that uses dummy variables to estimate different betas for the pre-crisis and crisis years is misspecified. The residual variance is substantially higher during the latter period.

50% for equity returns compared to 66% for CDS returns). In that sense, equity returns exhibit less commonality than CDS returns. After controlling for the MKT factor, the first principal component of the equity return residuals captures only 11% of the variation. This suggests a close association between the first principal component of equity returns, PC1-E, and the market factor. Indeed, Table V reports that PC1-E is almost perfectly correlated with the MKT factor (0.98, also see Figure 3). Once TERM, SMB, HML and FVDX are added as additional controls, the correlation structure of the equity return residuals no longer exhibits a prominent first principal component. In contrast to the CDS market, it appears that the five equity and reference bond market systematic factors are, to a large extent, able to capture the common time series variation in European equity returns.

As a robustness check, we also report the results for the set of all 4216 European firms for which equity data are available in columns five and six of Table II. They confirm the notion that after controlling for the MKT factor, equity return residuals show a very limited amount of comovement, with the first, second and third principal components explaining 6%, 2% and 2% of the variation. After controlling for all five equity and reference bond market factors, these fractions are even lower at 3%, 2% and 2%.

This initial evidence suggests that after controlling for previously established systematic risk factors, there is less room for FCR to play as dominant a role in equity markets as in credit markets. Instead, the vast majority of the commonality in equity returns is explained by the MKT factor. The results in Table VII show that regressing equity returns on the MKT factor yields an adjusted R^2 of about 0.36 for the average firm in our sample, substantially higher than the 0.14 value obtained for CDS returns on the same set of firms. The average market beta is highly statistically significant and close to one. The latter is especially reassuring given that the set of 150 firms for which both CDS and equity data are available only represents a small set when compared to the number of firms (about 600) entering the MSCI Europe market portfolio. The adjusted R^2 increases to 0.40 when TERM, SMB, HML and FVDX are added as controls.

In comparison, the bottom panel of Table VIII reveals that the average adjusted R^2 from regressing firm-specific equity returns on FCR is only 0.10. After controlling for FCR, the first principal component still accounts for 36% of the variation in the equity return residuals and is dominant when compared to other higher-order principal components. These results are in stark contrast to the ones obtained for CDS markets and confirm that FCR's contribution to explaining common time series variation in equity markets is limited. Indeed, Table V shows that FCR has only a moderate correlation of 0.48 with the first principal component of equity returns, and that it is even less correlated (-0.11) with the first principal component of the 5-factor equity return residuals. Not surprisingly, adding MKT, TERM, SMB, HML and FVDX to FCR improves the time series fit and diminishes the importance of the first principal component in the return residuals. The average adjusted R^2 increases to 0.41. The market factor coefficient is 0.53 and no longer close to one, due to the high collinearity between MKT and FVDX. The FCR beta is still positive, on average, but no longer statistically significant.

Cross-Sectional Analysis

In addition to the time series properties, we also investigate the explanatory power of FCR for the cross-section of equity returns. To see if the base assets used to construct FCR generate any widespread distribution of equity returns, we compute the average post-ranking excess returns on equity for the tercile portfolios formed on the sensitivity of firm-specific CDS returns to negative super-senior tranche spread innovations, $\beta_{\Delta ST}$, as described in Section 3.1. The results are reported in Table IV, together with the 5-factor alphas from regressing the equity portfolio returns on MKT, TERM, SMB, HML and FVDX. Contrary to CDS returns, equity returns for the equivalent portfolios with the same proportions do not line up with $\beta_{\Delta ST}$. Instead, they are higher for medium-$\beta_{\Delta ST}$ firms and lower for low-$\beta_{\Delta ST}$ and high-$\beta_{\Delta ST}$ firms. This hump-shaped structure disappears, however, after controlling for the five equity and reference bond market factors. The 5-factor alpha decreases from -1.3 basis points per week for low-$\beta_{\Delta ST}$ firms to -19.2 basis points for high-$\beta_{\Delta ST}$ firms. In contrast to CDS return portfolios, the alpha estimates are no longer significantly different from zero, except for the high-$\beta_{\Delta ST}$ tercile. These results suggest that FCR may have some, albeit limited, ability to explain cross-sectional differences in equity returns, especially for risky firms.

To offer further evidence along these lines we construct an alternative set of equity portfolios. To be specific, for each firm in a given CDS rating portfolio in Table IX we take that issuer's equity and construct the equity-equivalent portfolio with the same proportions. We find that average equity portfolio returns do not line up along the rating scale. This is in line with the findings for the U.S. market in Dichev (1998), Griffin and Lemmon (2002), Vassalou and Xing (2004), Garlappi et al. (2006), Campbell et al. (2008), and, most recently, Avramov et al. (2009). But regressing portfolio returns on MKT, TERM, SMB, HML, FVDX and FCR reveals that equity portfolios with higher loadings on FCR have lower average returns. Given the negative risk premium for FCR during our sample period (see Table VI), this implies that for portfolios sorted on rating, average equity portfolio returns do indeed line up with their FCR-factor loadings. But the loadings themselves are not statistically significant, which prevents us from concluding that FCR is a priced risk factor in European equity markets.

As a robustness check, we also construct equity portfolios equivalent to the Markit iBoxx corporate bond portfolios in Table X. Markit iBoxx bond portfolios are rebalanced at the end of each month, and the index constituents can be downloaded from the Markit index website. To form equity-equivalent portfolios for the AA, A and BBB subindices, as well as the HY index, at the end of each month we identify their constituents for the following month. We match bonds to issuers and use the equity of the European issuers to compute equity portfolio returns.[22] We mimic the capitalization-based weighting scheme for the bond portfolios by aggregating the outstanding notional across all bonds for a particular issuer, and use that aggregate notional amount as the issuer-specific portfolio weight. Results are reported in the right panel of Table X. Again, FCR loadings do not line up along the rating scale, but average equity portfolio returns generally decrease as FCR loadings increase. Overall, the results for equity-equivalent corporate bond portfolios support our findings for equity-equivalent CDS portfolios. For high-yield firms, we even estimate the FCR beta to be positive and significant.

Alternative Risk Factors

The additional explanatory power of alternative risk factors is generally limited. Table VII shows that adding FV-E, FK-E, FS-E and FAD-E to the equity return regressions improves the fit only somewhat. The average adjusted R^2 is raised to 42%. None of the added regression coefficients is significant, largely due to collinearity effects. In Table VIII, we find that adding alternative CDS-return-based factors offers very little improvement of the time series fit for equity returns.

For the cross-section, the preliminary analysis in Table IV shows that average equity returns, as well as 5-factor alphas, tend to decrease as the sensitivity of CDS returns to equity returns and idiosyncratic equity volatility increase. No clear trend is visible for portfolios sorted on historical relative CDS bid-ask spreads. The pattern of average equity returns reverses for equity skewness, kurtosis and deviations from normality. Nevertheless, Table IX shows that the cross-sectional results for alternative CDS-return-based risk factors are generally disappointing, in that loadings are often insignificant and no clear relations with average portfolio returns emerge. This is confirmed in Table X, where equity-equivalent portfolios for the Markit iBoxx rating indices are analyzed.

In summary, we document that equity markets show less comovement and more idiosyncratic risk when compared to CDS markets during our sample period from July 2004 to December 2008. Almost all of the time series comovement that is observed can be captured by the MKT factor or, by close association, the factor mimicking aggregate volatility risk, FVDX. In a regression setting, the explanatory power of FCR is limited. In the cross-section, we do find some evidence that higher

[22] Since not all index members are domiciled in Europe, the resulting equity portfolios use a subset of the firms represented in the associated bond indices. The coverage ratio is decreased further since not all issuers are listed in Compustat Global and Worldscope. We are able to identify 164 public European firms in the investment-grade indices and 55 in the HY index.

FCR loadings correspond to lower average portfolio returns. The loadings, however, are generally not statistically significant, with the exception of the HY equity portfolio in Table X. The results are consistent with our argument in Section 3.1 that systemic credit risk innovations are less precisely identified in equity markets than in credit or corporate bond markets. The explanatory power of alternative CDS and equity-return-based factors is limited.

4.4 A SHIFT IN THE CORRELATION STRUCTURE OF EQUITY RETURNS?

Table II reveals that prior to August 2007, the first principal component of equity returns, for the matched sample of firms, explained about 33% of the variation. Since the onset of the financial crisis, that fraction has increased to 44%. As for CDS markets, this points to a shift in the correlation structure of equity returns, although to a somewhat less severe one. In Section 4.2 we attribute the shift in CDS return correlations to the economic catastrophe risk factor FCR becoming more important relative to other sources of risk. Table VI shows that FCR explained about 3% of the equity return variation pre-crisis, and 12% during the crisis. But for 5-factor equity return residuals, the effects are less pronounced: FCR explained less than 1% of the variation both prior to and since August 2007. This highlights the fact that while comovements in equity returns did become more pronounced during the financial crisis, after controlling for the five equity and reference bond market factors, FCR no longer plays an important role in explaining this shift.

To offer further evidence, we repeat the regression analysis in Section 4.2 using equity returns. For each firm for which both CDS and equity data are available, we run firm-by-firm regressions of equity returns on MKT, TERM, SMB, HML, FVDX, plus FCR, both before the crisis and from August 2007 to December 2008. The results reveal that neither before nor during the crisis the loading on FCR was significant for the average firm in our sample. In comparison, the MKT beta was positive and significant for the majority of the firms prior to the crisis, and still positive although somewhat smaller during the crisis. These observations reveal that the increase in equity return comovements during the crisis cannot simple be explained by investors readjusting their sensitivity to economic catastrophes risk, or market risk in general. Rather, the underlying driver seems to be the increase in MKT volatility. The results in Table VI reveal that, on average, MKT volatility more than doubled, from 1.6% pre-crisis to 3.7% during the crisis. In comparison, the idiosyncratic risk, as measured by the average volatility of the return residuals, increased less steeply from 2.4% to 4.1%. In summary, the shift in the correlation structure of equity returns is somewhat more moderate than that in CDS returns, and mainly due to the MKT factor becoming more volatile relative to idiosyncratic return components.

5. Conclusion

This paper investigates the sources of common variation in European CDS returns. We find that the first principal component of CDS returns explains more than half of the variation in the correlation matrix. Even after controlling for the usual equity and reference bond market systematic factors, that fraction remains high at 45%. Sorting firms on their weight in the first principal component reveals that it is more robustly estimated by the CDS returns on large firms of high credit quality and low equity volatility, and less so by small firms of low credit quality and high equity volatility. This is an important insight that allows us to focus on the type of risk priced in the former subset of firms, which we argue is closely related to that of insuring economic catastrophe risk. So motivated, we use CDS return data to construct a risk factor, called FCR, that mimics economic catastrophe risk innovations. The latter are measured by (negative) changes in super-senior tranche spreads of the iTraxx Europe index. Our first main contribution is to reveal the close association between FCR and the first principal component of CDS returns–the correlation coefficient is 0.96. After controlling for FCR, the dominance of the first principal component in the return residuals is largely reduced. For the average firm, FCR by itself explains nearly half of the variation in CDS returns. Using CDS and corporate bond portfolios sorted on ratings, we show that FCR loadings line up nicely with average excess returns, suggesting that FCR is priced in European credit and fixed-income markets. During our sample period from July 2004 to December 2008, FCR carried a negative risk premia of -0.6% annually, with the negative sign being due to the large losses incurred in European credit markets during the recent financial crisis.

The monumental credit crunch of 2007–8 has brought the notion of economic catastrophe risk insurance sharply into focus. Since August 2007, European credit markets have experienced a dramatic surge in the uncertainty regarding economic catastrophe risk, with FCR volatility increasing more than ten-fold from the pre-crisis to the crisis years. The increase in volatility was much steeper for FCR than for other sources of risk, including idiosyncratic CDS return components. It led to FCR becoming a more important risk factor, which, in turn, contributed to a shift in the correlation structure of CDS returns. This insight summarizes the second contribution of the paper. Indeed, while CDS returns exhibited a moderate amount of correlation prior to August 2007, since then the fraction of variation explained by the first principal component has surged to 55%. An important implication is that the risk profile of credit portfolios has changed dramatically over the last few years. Credit modeling tools that were built prior to the crisis were likely to underestimate actual correlation effects in European credit markets during times of severe stresses, and hence likely to fail when they were needed the most.

Given the dominant role FCR plays for European CDS markets, our third contribution is to show that it plays a less important role for equity markets, and to offer economic intuition for this result. Indeed, we find that the vast majority of comovement in equity returns is explained by the market factor, which captures about 36% of the time series variation for the average firm in our sample. In comparison, the average adjusted R^2 from regressing firm-specific equity returns on FCR is only 0.10. After controlling for FCR, the first principal component of equity return residuals still accounts for 36% of the variation, and is dominant when compared to other higher-order principal components. These results are in stark contrast to the ones obtained for CDS markets and suggest that FCR's contribution to explaining common time series variation in equity markets is limited. A cross-sectional analysis based on equity-equivalent rating portfolios reveals that FCR loadings generally do line up with average excess returns on equity, and we even find some support for significantly higher loadings for risker firms. But overall, results are less strong when compared to credit markets. The more modest shift in the correlation structure of equity returns during the financial crisis can be explained by an increase in market-factor volatility, and less so by FCR becoming more important. Instead of interpreting these differences as evidence of market disintegration, we argue that FCR plays a less important role for equity markets due to the limited sensitivity of the value of equity at default to whether the credit event is of systemic or idiosyncratic nature.

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