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Credit Risk Decomposition for Asset Allocation

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Journal

THE CAPCO INSTITUTE JOURNAL OF FINANCIAL TRANSFORMATION

RISK

#43
05.2016

Journal

The Capco Institute Journal of Financial Transformation

Recipient of the Apex Award for Publication Excellence

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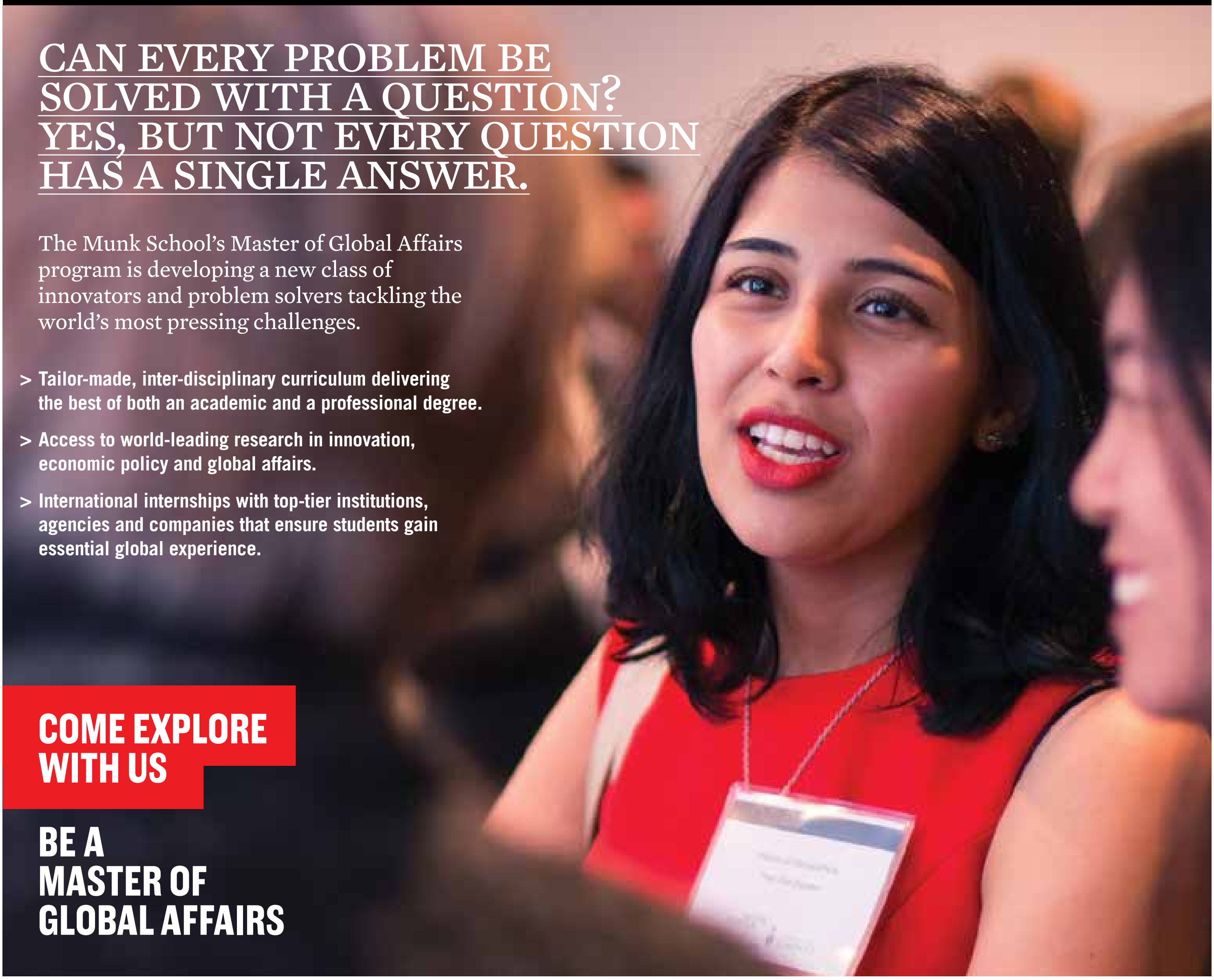

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Credit Risk Decomposition for Asset Allocation

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Abstract
We provide a methodology for credit risk analysis that can be embedded into a risk appetite framework. We analyze the information content in CDS spreads to estimate the systematic and idiosyncratic components of credit risk for CDS issuers in the industrial sector of Europe. Such decomposition should be an important tool for the evaluation of the diversification possibilities of credit portfolios or for the design of appropriate hedging strategies. It could be used by financial institutions to maintain their risk limits when taking their asset allocation decisions as well as by supervisors investigating potential systematic risk problems. The analysis could be extended to other sectors.

1 The authors acknowledge comments received from J.A. De Juan Herrero.
Financial support from Spanish Ministry of Education through grant ECO2015-67305-P, the PROMETEO 2013 Program of Comunidad Valenciana and from Banco de España through a Programa de Ayudas a la Investigacion grant is gratefully acknowledged. This article reflects the opinions of the authors, and not those of BBVA.

INTRODUCTION

The most widely used measures of credit risk use information on CDS spreads, which are forward-looking and reflect the market perception of the credit risk of the issuer. A firm with a large idiosyncratic component of credit risk could default with a minor impact on its sector or the economy, while the opposite will happen for a firm that has important sectorial or systematic components of risk. If the systematic component is important, the behavior of its CDS will tend to follow that of the market, leaving few possibilities for hedging a credit position on that firm. Hence, from the point of view of implementing the risk policy at a given financial institution, as well as evaluating the possibilities for hedging a credit portfolio, estimating the relevance of the systematic, sectoria,l and idiosyncratic components of risk for a given creditor is critical.

We propose a simple methodology for the estimation of these different components of credit risk. We use the information provided by a wide set of financial indicators to decompose the credit risk of each firm into systematic, sectorial, and idiosyncratic components. Such decomposition should be central to evaluating which firms have more potential to produce systematic risk problems. This information would clearly be essential for the policymakers responsible for supervision and regulation. It will also be extremely useful for companies, investors, hedgers, and speculators who are involved in the credit markets and in the pricing of credit, since it provides some insights on the possibilities of hedging the credit risk of a given position. Our analysis is based on the degree of commonality among CDS spreads across sectors, as well as on the correlation among CDS spreads of firms operating in a given sector. A principal component analysis of the mentioned set of financial indicators is used to characterize the systematic components of credit risk, while a principal component analysis of CDS spreads across firms in a given sector is used to characterize the sectorial component of credit risk in those firms. The idiosyncratic component is what is left after estimation of the systematic and sectorial components of credit risk.

An alternative methodology using the first component of sectorial indices of CDS spreads to identify the systematic component of credit risk yields a very similar decomposition. Further research should examine the relationship between our estimated risk components and certain characteristics of firms, such as the size of assets and liabilities, profit and loss, equity and bond prices, and market share. That would allow us to extend the risk evaluation results obtained in this paper for CDS issuers to any other firm.

LITERATURE REVIEW

Given the importance of the topic for researchers and for market regulators after the financial crisis, the recent literature on measuring systematic risk has been quite extensive. We briefly review in this section those we consider most relevant for our work.

Ericsson et al. (2009) analyzed the relationship between theoretical determinants of default risk, such as firm leverage, volatility, risk-free interest rate, and actual market premium, using the CDS on senior debt for the period 1999-2002. Using time series regressions, they found that these variables explain approximately 60% of the variations of CDS premia, while the R-squared for changes in default swap premia is approximately 23%. Tang and Yan (2013) used transactions data from 2002 to 2009, covering 861 North American corporates, to find that CDS spreads are mostly driven by fundamental variables such as firm volatility and leverage, market conditions, and investor risk aversion. Hence, even if actual default risk remains constant, CDS spreads may increase when investors become more pessimistic and more risk averse. A 1% increase in the VIX index, interpreted as a measure of market sentiment or investor risk aversion, is shown to be associated with about 1% increase in CDS spreads.

Some studies have used synthetic risk indicators, illustrating the existence of a strong degree of commonality in credit risk. Rodríguez-Moreno and Pena (2013) analyzed two groups of systematic risk measures when searching for the best systematic indicator over the January 2004-November 2009 sample period. The first group contained indicators related to the overall tension in the market, while the second group was made up of indicators related to the contributions of individual institutions to systematic risk. In a sample of 20 European banks and 13 U.S. banks they found that the first principal component of CDS spreads performed better than measures of market stress. For a sample of 150 European firms from January 2003 to July 2007, Berndt and Obreja (2010) showed that the first principal component of CDS returns explained less than 30% of the variation in weekly CDS returns, but that fraction surged to 50% during the crisis, from August 2007 to December 2008. The shift in the correlation structure of European equity returns was more modest when compared to CDS returns.

Bhansali et al. (2008) used a three-jump model to carry out a decomposition of CDS spreads among systematic risk, sector risk, and idiosyncratic risk as we attempt to do in this paper, although their methodological approach is quite different.

DECOMPOSITION OF RISK IN SPECIFIC SECTORS: SYSTEMATIC, SECTORIAL, AND IDIOSYNCRATIC RISKS

For asset allocation purposes, it is central to have some knowledge of the nature of risk involved in a given credit position. We aim to measure the degree to which firms in a given sector are subject to systematic, as well as to sectorial, risk and determine the relevance of idiosyncratic risk.

We consider systematic risk events as those that have an influence across the global credit markets. Consequently, our approach to decompose risk is based on the use of a set of financial factors, which we split into two groups. The initial set of seven credit market indicators include: Markit iTraxx Europe Index, Markit iTraxx Europe HiVol Index, Markit CDX North American Investment Grade Index, Markit CDX North American Investment Grade Index High Yield, 3-month ATM iTraxx Europe Index Option, 3-month ATM CDX North American Investment Grade Index Option, iTraxx Japan IG. A second set of 21 indicators include: the 3-month EURIBOR interest rate, the 3-month EONIA Index, the Euro liquidity premium, measured by the absolute difference between 3-month EURIBOR and 3-month EONIA, both in euros, the 1-, 5- and 10-year Euro swap rates, the 3-month/ 5-year ATM Euro swaption, the VSTOXX index, the 5-year German government yield, the 3-month USD LIBOR interest rate, the 3-month USD overnight index, the USD liquidity premium, measured by the absolute difference between 3-month LIBOR and the 3-month USD overnight index, the 1-, 5- and 10-year USD swap rate, the 3-month/5-year ATM USD swaption rate, the VIX index, the 5-year US Treasury Rate, the EUR/USD FX spot rate, the EUR/USD 3-month ATM option, the 5-year JPY swap rate. Data were obtained from Bloomberg.[2]

We determine common risk factors among CDS spreads from the different sectors using the principal component methodology to the covariance matrix of weekly returns on CDSs. Two principal components of the subset of credit market variables and three principal components of the subset of other financial indicators explain more than 98% of the fluctuations in each group of indicators.

Sectorial risk events are those that impact all of the firms in a given sector, with no major implications elsewhere. For a given sector, a principal component will contain some features common across firms in the sector, possibly combined with some elements of systematic risk.

European industrial sector

Our sample contains CDS spreads for 30 issuers in the European industrial sector, with daily quoted prices for the 2006-2012 period. There is important commonality among the time evolution of these spreads, but there are also significant risk components that are specific to each issuer in the sector. The first principal component of the time series for the 30 CDS spreads is an approximate average of CDS prices across the sector, with all the firms entering with a similar load in its definition. It has a linear correlation coefficient with the iTraxx Index of 0.72, and it explains 64.4% of the joint fluctuation in the set of spreads. We would need to consider at least six principal components to explain more than 80% of the volatility in the vector of CDS prices. Firms like Rentokil Initial 1927 Plc, Heidelberg Cement AG, Invensys plc, Alstom, and Siemens AG have a significant presence in defining the successive principal components. Hence, the first intrasector principal component can be safely used as an indicator of sectorial risk, since most of what it is unable to explain is due to idiosyncratic risk that is captured by further principal components, which we do not use.

Column 2 in Table 1 shows the adjusted R-squared from a regression of CDS spreads on the first two principal components of credit indicators plus the first three principal components of non-credit indicators. These R-squared statistics, between 0.22 and 0.57, can be interpreted as an estimate of the size of the systematic risk component for each firm. They are very close to the R-squared statistics obtained by explaining CDS spreads with just the two first principal components obtained from credit market indicators.[3] To be conservative, we have chosen to maintain the two sets of principal components in these projections to obtain the R-squared values shown in column 2.

To estimate a sectorial component of risk, we use the first principal component of CDS spreads for the 30 issuers as a sectorial credit risk factor. Column 3 shows the R-squared statistics from regressions of CDS changes on this risk factor, with values of between 0.29 and 0.79. They show a higher explanatory power than the credit and financial risk indicators taken together. Furthermore, when we put together all these factors in the regressions in column 4, the explanatory power is barely higher than the one obtained by the sectorial risk factor alone. Obviously, this factor reflects some sectorial implications, besides capturing some influences from the global credit markets. To segregate the implications of each component, we take in column 5 the difference between the numerical R-squared values of columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, what remains unexplained by the regression on credit and financial risk factors and the sectorial

2 The 3-month ATM iTraxx Europe Index Option and the 3-month ATM CDX North American Investment Grade Index Option are provided by JP Morgan.

3 The R-squared from regressions of CDS spreads on the credit indicators fall between 0.21 and 0.57, while the R-squared from regressions on the rest of the financial indicators are lower, between 0.05 and 0.27. For reasons of space, these regressions are not shown in the table.

(1) Issuer	(2) Systematic risk	(3) Sectorial PC	(4) Joint regression	(5) Sectorial risk	(6) Idiosyncratic risk
AB Volvo	**57.20%**	73.70%	74.20%	17.00%	25.80%
Cie de St Gobain	**56.90%**	78.40%	78.80%	21.90%	21.20%
Holcim Ltd	**56.70%**	79.30%	79.80%	23.10%	20.20%
Rolls-Royce Plc	**54.90%**	71.00%	73.80%	18.90%	26.20%
Lafarge	**54.70%**	79.10%	79.80%	25.10%	20.20%
Scania Ab	**54.60%**	70.80%	71.40%	16.80%	28.60%
Thales	**52.20%**	77.90%	80.00%	27.80%	20.00%
Finmeccanica S.p.A	**51.70%**	66.50%	68.30%	16.60%	31.70%
Vinci	**51.50%**	73.90%	74.50%	22.90%	25.50%
Volvo Treas AB	**51.00%**	69.20%	70.20%	19.20%	29.80%
Adecco S A	**48.40%**	68.60%	69.10%	20.70%	30.90%
BAE Systems PLC	**48.00%**	71.80%	72.10%	24.10%	27.90%
Deutsche Lufthansa AG	**47.20%**	66.00%	65.80%	18.70%	34.20%
Deutsche Post AG	**44.60%**	58.90%	59.80%	15.20%	40.20%
Eurpopean Aero Defence & Space Co Eads N V	**44.50%**	70.30%	70.80%	26.30%	29.20%
Rexam plc	**44.20%**	67.10%	67.00%	22.80%	33.00%
Metso Corp	**43.40%**	62.10%	63.00%	19.60%	37.00%
HeidelbergCement AG	**42.90%**	58.40%	59.90%	17.00%	40.10%
Societe Air France	**42.10%**	63.80%	63.80%	21.70%	36.30%
Assa Abloy Ab	**41.20%**	62.90%	63.00%	21.80%	37.00%
Alstom	**40.70%**	62.30%	62.10%	21.50%	37.90%
Securitas AB	40.60%	57.40%	59.20%	18.60%	**40.80%**
Siemens AG	39.80%	57.50%	60.10%	20.30%	**39.90%**
Atlas Copco AB	39.30%	59.20%	58.90%	19.60%	**41.10%**
Brit Airways plc	36.40%	53.40%	55.10%	18.70%	**44.90%**
Schneider Electric SA	36.40%	55.80%	55.70%	19.40%	**44.30%**
Smiths Group Plc	30.20%	51.00%	51.40%	21.20%	**48.60%**
Ab Skf	27.90%	45.20%	45.80%	17.90%	**54.20%**
Rentokil Initial 1927 Plc	23.00%	29.30%	30.90%	7.80%	**69.10%**
Invensys plc	21.80%	37.80%	39.30%	17.50%	**60.80%**

Note: Column1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on two first principal components of credit indicators and the three first principal components of non-credit financial indicators. Column 3 shows the adjusted R-squared from a regression on the first principal component of the European industrial CDS spreads in the sample. Column 4 shows the adjusted R-squared from a regression on the set of explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, column 6 displays the size of idiosyncratic risk, computed as 1 minus the adjusted R-squared in column 4. Bold figures indicate the most important factor in the risk decomposition for each CDS issuer. All regressions are estimated in weekly changes of the mentioned variables.

Table 1 – European industrial issuer CDS spread decomposition

factor can be naturally interpreted as the size of the idiosyncratic component of risk. This way, we have a decomposition of CDS risk in systematic risk (column 2), sector-specific risk (column 5) and firm-specific risk (column 6), adding up to +100%. Firms in Table 1 are ranked by the size of their systematic components of risk. Firms with a high idiosyncratic component of risk should be preferred by financial institutions, since they offer better prospects for build a well-diversified credit portfolio. On the other hand, it would also be unwise to take a credit position in a few firms with large idiosyncratic risk components.

Sectorial risk oscillates between 8% and 28%, while the idiosyncratic component of risk ranges from 20% and 69%. In most issuers (27 out of 30), the idiosyncratic component is below 50% of total risk. Bold figures in the table denote the most important component for each single issuer. For 21 of the 30 issuers, global risk factors are the most important components of CDS risk, while firm-specific factors are the most important component for the other nine issuers. In our estimates, sector-specific components were never the most important source of fluctuations. Using median values, the systematic component of risk for the European industrial sector is 44% of total risk, sectorial risk is 20%, and the idiosyncratic component amounts to 35%.[4]

An alternative decomposition of risk

To develop an alternative method of decomposing risk, we initially select a set of 5-year CDSs trading as senior unsecured debt, SNRFOR, with 1825 daily observations on approximately 2500 issuers, from the eleven industries and the thirteen geographical areas.[5]

We then construct CDS indices for each sector by taking the median CDS spread traded each day in that sector across all regions. To reduce the possibility of excessive noise due to low trading, we aggregate over time, taking weekly averages of sectorial indices. Finally, we compute logarithmic changes of weekly CDS spreads, obtaining a total of 365 weekly observations for each sector index over the 2006-2012 period. We used this data to characterize common risk factors among CDS spreads from the different sectors using the principal component methodology. The first principal component, by itself, explains 68% of the fluctuations in the set of eleven sectorial indices, indicating that there is strong commonality among the sectors. This is a higher percentage than the one estimated by Berndt and Obreja (2010) for European firms during the 2003 to 2008 period, but it is very close to the average explanatory power estimated by Chen and Härdle (2012) for the pre- (58.7%) and post-crisis periods (72.3%).

Since the first principal component explains more than two thirds of the fluctuations in the whole set of CDS issues from all sectors and geographical areas, it can naturally be interpreted as representing a global risk factor, capturing the systematic elements of risk. Hence, an alternative decomposition to the one we used earlier would estimate the relevance of systematic risk by the adjusted R-squared of CDS spreads for each firm on the global risk factor. The first intra-sector principal component adds some sector-specific information to the global risk factor, and we take the difference between their joint explanatory powers and that of the global risk factor alone as an estimate of the relevance of sectorial risk. The residual in that joint regression is an estimate of the idiosyncratic component of risk; its relevance being estimated as 1 minus the R-squared in such regression.

Surprisingly, estimates of risk components by both procedures are quite similar. The rank correlation coefficient between the estimated relevance of systematic risk by both approaches is 0.78, with a linear correlation coefficient of 0.86. The similarity between the estimated relevance of idiosyncratic components is still higher, with a rank correlation coefficient and a linear correlation coefficient of 0.99.

An analysis of the estimated idiosyncratic components of credit risk[6]

The estimated idiosyncratic component of CDS risk turns out to be quite large in many firms, which might be due to the fact that our estimated idiosyncratic component could still contain some systematic risk elements. To test for the effectiveness of our methodology we examine whether our estimates of the idiosyncratic component of credit risk have the appropriate features.

A first test consists of examining the possibility of diversification. If idiosyncratic components are relatively important, then a well-diversified portfolio should be much easier to hedge than positions on individual assets. In the European industrial sector, hedging positions on CDS from an individual firm using a contrary position on iTraxx leads to a significant decline in variance,[7] with a median reduction of 14.1%. On the other hand, for the equally weighted portfolio we would achieve a reduction in variance of 30.0%. The fact that the hedge is much more successful for the equally weighted portfolio than hedging a position in any single firm in the sector suggests that idiosyncratic components of credit risk are indeed important.

A second test considers whether the hedging possibilities increase with the size of the idiosyncratic component of risk. This is clearly the case: the reduction in variance from hedging the portfolios made up of the 5 or 10 firms with the highest idiosyncratic components of risk is of 62% and 65%, respectively, while the reduction in variance from hedging a portfolio of the 5 or 10 firms with the lowest idiosyncratic components of risk is 43% and 54%, respectively. Hence, hedging efficiency is clearly higher for portfolios made up of firms with high idiosyncratic risk. Among portfolios with low idiosyncratic risk, a sufficient hedging efficiency would require considering portfolios made up of a larger number of firms.

4 Being median values they may not add up exactly to 100%.

5 We use Markit industry levels, which considers eleven industries: basic materials, consumer goods, consumer services, energy, financials, health care, industrials, technology, telecommunication services, utilities, and government. Government is another category considered by Markit but not included in the Industry Classification Benchmark. Finally, Markit considers thirteen different regions: Africa, Asia, Caribbean, Eastern Europe, Europe, India, Latin America, Middle East, North America, Oceania, Offshore, Pacific, and Supranational.

6 Since both approaches lead to similar decompositions of credit risk, we just interpret the results obtained with the use of 28 financial indicators to estimate the systematic component of credit risk.

7 We consider a least-squares hedge, with the hedge ratio being the negative of the estimated slope in a regression of the CDS spread for a given issuer on the iTraxx index.

(1) Issuer	(2) Systematic risk	(3) Sectorial PC	(4) Joint regression	(5) Sectorial risk	(6) Idiosyncratic risk
AB Volvo	**59.60%**	73.70%	73.70%	14.10%	26.30%
Cie de St Gobain	**66.00%**	78.40%	78.30%	12.30%	21.70%
Holcim Ltd	**65.20%**	79.30%	79.20%	14.10%	20.80%
Rolls-Royce Plc	**52.60%**	71.00%	72.10%	19.50%	27.90%
Lafarge	**67.70%**	79.10%	79.10%	11.40%	20.90%
Scania Ab	**60.70%**	70.80%	70.80%	10.10%	29.30%
THALES	**62.90%**	77.90%	78.00%	15.00%	22.10%
Finmeccanica S.p.A	**52.60%**	66.50%	66.70%	14.10%	33.30%
Vinci	**59.50%**	73.90%	74.00%	14.50%	26.00%
Volvo Treas AB	**58.70%**	69.20%	69.10%	10.40%	30.90%
Adecco S A	**58.90%**	68.60%	68.60%	9.70%	31.40%
BAE Systems PLC	**57.00%**	71.80%	71.90%	14.90%	28.10%
Deutsche Lufthansa AG	**53.30%**	66.00%	66.00%	12.70%	34.00%
Deutsche Post AG	**48.70%**	58.90%	58.80%	10.10%	41.20%
European Aero Defence & Space Co Eads N V	**57.10%**	70.30%	70.30%	13.20%	29.70%
Rexam plc	**58.70%**	67.10%	67.20%	8.50%	32.80%
Metso Corp	**56.50%**	62.10%	62.60%	6.20%	37.40%
HeidelbergCement AG	**46.70%**	58.40%	58.40%	11.70%	41.60%
Societe Air France	**53.80%**	63.80%	63.70%	9.80%	36.30%
Assa Abloy Ab	**59.20%**	62.90%	64.00%	4.80%	36.00%
Alstom	**51.60%**	62.30%	62.20%	10.60%	37.80%
Securitas AB	**49.00%**	57.40%	57.30%	8.40%	42.70%
Siemens AG	**53.50%**	57.50%	58.30%	4.80%	41.70%
Atlas Copco AB	**58.20%**	59.20%	61.30%	3.10%	38.70%
British Airways plc	**47.60%**	53.40%	53.60%	5.90%	46.40%
Schneider Electric SA	**50.00%**	55.80%	56.10%	6.10%	43.90%
Smiths Group Plc	41.30%	51.00%	51.00%	9.70%	**49.00%**
Ab Skf	45.30%	45.20%	47.20%	1.80%	**52.80%**
Rentokil Initial 1927 Plc	24.10%	29.30%	29.10%	5.10%	**70.90%**
Invensys plc	29.10%	37.80%	37.90%	8.80%	**62.10%**

Note: Column1 shows the company name from Markit database. Column 2 displays the adjusted R-squared from a regression on the global risk factor, which is estimated as the first principal component of sectorial CDS indices. Column 3 shows the adjusted R-squared from a regression on the first principal component of the European industrial CDS spreads in the sample. Column 4 shows the adjusted R-squared from a regression on the explanatory variables in the two previous regressions. Column 5 displays the difference between the numerical R-squared values in columns 4 and 2 as an estimate of the relevance of sectorial risk. Finally, column 6 displays the size of idiosyncratic risk, computed as 1 minus the adjusted R-squared in column 4. Bold figures indicate the most important factors in the risk decomposition for each CDS issuer. All regressions are estimated using weekly changes of the mentioned variables.

Table 2 – European industrial issuer CDS spread decomposition using GRF as the systematic explanatory variable

The last test is based on the fact that the estimated idiosyncratic components turn out to be essentially uncorrelated across firms, which is a necessary condition for the interpretation we give to this component. There are 30 issuers in the European industrial sector, implying 435 pairwise correlations between idiosyncratic components, with a low median correlation of -0.05. Ninety percent of them are in absolute value below 0.23. These are all low levels that justify an interpretation of our estimated idiosyncratic components as being firm-specific in nature.

Taken together, the possibilities for hedging the risk of a well-diversified sectorial portfolio, the higher efficiency in hedging portfolios made up of firms with the highest idiosyncratic components of risk, and the low pairwise correlations across firms in the European industrial sector, suggest that our estimates of such components are appropriate.

However, a question remains: what is causing the large idiosyncratic component of risk? A possible conjecture would be that the large idiosyncratic components of risk could be just a reflection of the low liquidity in some issues. To examine the validity of this assumption, we could relate the size of the estimated idiosyncratic risk component with either the number of contributors giving price to the 5-year CDS, the quality rating of the data provided by Markit, or the volatility of CDS spreads. In the latter case, the argument would be that illiquid CDSs would often repeat price in the Markit database, the time series of CDS spreads then having a relatively low variance. Hence, we would expect a negative correlation between the size of the idiosyncratic component of risk and the volatility of CDS spreads. That correlation between the size of the idiosyncratic risk component and the annual volatility of CDS weekly changes among European industrial issuers is equal to -0.30. Hence, the large size of the idiosyncratic risk component for some issuers could in part be due to the low liquidity of their CDS spreads.

CONCLUSIONS

A central component of a risk appetite framework at financial institutions would be a mechanism to decompose asset risk into systematic, sectorial and idiosyncratic components. We use a large set of 28 credit and non-credit financial indicators to estimate the systematic component of credit risk. A regression model to explain CDS spreads on five principal components summarizing the commonality in these indicators provides an estimate of the market perception of systematic risk for each firm. Next, we use a principal component of CDS spreads across firms in the sector to estimate the relevance of the sectorial component of credit risk. The idiosyncratic component of risk is the remaining CDS spreads for a given firm after extracting the systematic and sectorial components of risk. An alternative decomposition using the first principal component for sectorial CDS indices to estimate systematic risk yields a similar decomposition of credit risk.

This evaluation of the relevance of risk components has obvious implications for the asset allocation strategy by a given financial institution that wants to diversify its credit portfolio in that sector. When designing their credit policy, financial institutions should avoid firms with a large systematic risk component in favor of those with larger idiosyncratic risk components, always trying to form sufficiently diversified portfolios, thereby maintaining their risk limits when taking their asset allocation decisions.

We have provided some evidence that the estimated idiosyncratic components are due in part to lack of liquidity. We have also shown evidence suggesting that portfolios made up of firms with higher idiosyncratic components are easier to hedge, contrary to what happens with portfolios made up of firms with lower idiosyncratic risk components. By and large, the estimated idiosyncratic risk components turn out to be uncorrelated across firms in the sector.

By evaluating the firms with the most potential to produce systematic risk problems, our analysis should also be considered to be crucial for supervisors and regulators. Even though we restrict our analysis to CDS issuers, further research should attempt to relate our estimated risk components to firms' characteristics such as size of assets and liabilities, profit and loss, the leverage ratio, the EBITDA, bond prices, market share, or the market value of equity. This is an open question that would allow for extending the evaluation of credit risk components for CDS issuers to any other firm, even if it is not a CDS issuer. A further issue would consider the dynamics of defaults, analyzing how the stand alone default of a given issuer might affect other companies in its sector. Characterizing the interconnection between CDS issuers [as in Kanno (2016)] would provide us with information to identify the firms that play a central role in their network, thereby allowing for a more efficient coverage of credit risks at financial institutions.

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