Portfolio diversification in the sovereign credit swap markets

Andrea Consiglio *
Somayyeh Lotfi †
Stavros A. Zenios ‡

July 2016. Revised May 2017.

Published in *Annals of Operations Research*, online July 2017.
https://link.springer.com/article/10.1007/s10479-017-2565-5

Abstract

We develop models for portfolio diversification in the sovereign credit default swaps (CDS) markets and show that, despite literature findings that sovereign CDS spreads are affected by global factors, there is sufficient idiosyncratic risk to be diversified. However, we identify regime switching in the times series of CDS spreads, and the optimal diversified strategies can be regime dependent. The developed models trade off the CVaR risk measure against expected return, consistently with the statistical properties of spreads. We consider three investment strategies suited for different CDS market participants: for investors with long positions, speculators that hold uncovered long and short positions, and hedgers with covered long and short exposures. We use the models to illustrate that diversification pays in the CDS market. The models are also tested for active portfolio management in Eurozone core and periphery, and Central, Eastern and South-Eastern Europe (CESEE) countries, and the optimized portfolio results outperform the broad S&P/ISDA Eurozone Developed Nation Sovereign CDS index. The paper concludes by identifying open questions in developing integrated enterprise-wide risk management models using CDS.

Keywords: Credit derivatives; portfolio diversification; Eurozone crisis; CDS spreads; Conditional Value-at-Risk; regime switching.

*Department of Economics, Management and Statistics, University of Palermo, Palermo, IT. andrea.consiglio@unipa.it

†Department of Accounting and Finance, University of Cyprus, Nicosia, CY. lotfinoghabi–.somayyeh@ucy.ac.cy

‡Department of Accounting and Finance, University of Cyprus, Nicosia, CY, Norwegian School of Economics, and Wharton Financial Institutions Center, University of Pennsylvania, USA. zenios.stavros@ucy.ac.cy

1 Introduction

We take a portfolio view of sovereign credit default swaps (CDS), contributing to existing (and extensive) pricing literature the natural extension from individual CDS instruments to portfolios. Sovereign CDS are insurance contracts offering protection against default of a reference sovereign. They emerged in the 1990's as a credit derivative security in the sovereign debt market. Their *raison d'être* is to hedge and trade sovereign credit risks and they offer investors the opportunity to take a view purely on credit. They are used by sovereign debt investors to *hedge* credit events, whereas speculators take *naked* positions in these instruments —without buying the underlying asset— to bet on the credit risk of the reference entity. Arbitrageurs exploit price differences between the derivative and the underlying debt obligation(s) by taking offsetting positions in the two.

Following standardization of CDS contracts in 1998-1999 and successful execution in a few defaults —starting with Argentina in 2001— the market grew rapidly. Packer and Suthiphongchai (2003) discuss the early developments and Figure 1 illustrates the market growth since 2005 when BIS started publishing data, showing notional amounts and gross market value together with the number of dealers. Notional amounts provide a measure of market size, but gross market values reflect the scale of risk transfer in the market. We observe a significant increase in both the nominal amounts issued and the number of dealers in CDS from 2005 until mid-2013, with a subsequent decline to 2010 levels. Much smaller, and with smaller variation across time, are the gross amounts, indicating that the risk transfer function of CDS remains steady whereas the speculative function of the markets fluctuate.

CDS have been criticized for facilitating market manipulations in the eurozone crisis, and naked trading was banned by the German financial regulator in May 2010 and by the EU since November 2012. However, a European Commission report (Criado et al., 2010) found no apparent mis-pricing in the sovereign bond and CDS market. The empirical investigation of this report finds "no conclusive evidence that CDS markets increase funding costs for Member States". More recently IMF (2013) presented evidence that also refutes the criticism against their use and argues that CDS have contributed to the deepening and efficiency of the sovereign markets. A nuanced view on the role of CDS in the crisis is given by Stulz (2010) who writes "financial derivatives have clearly lost any presumption of innocence" but argues it would be misguided "to turn 180 degrees from a presumption of innocence to a presumption of guilt".

The CDS markets, the statistical properties of CDS spreads, spread returns and spread term structures, the price discovery mechanisms, and market spillovers, have been studied extensively. The lion's share of research goes to corporate CDS, but attention turned recently to the sovereign market as well. We do not review the extensive body of knowledge and refer readers to the survey and discussion on future prospects by Augustin et al. (2014, 2016), and the recent work on sovereign CDS by Fabozzi et al. (2016).

Conspicuously absent from the literature are studies of CDS in a portfolio context. This is where our paper makes a contribution. It provides practical models for CDS investors, establishes the validity of diversification in sovereign CDS markets, and validates the models during the eurozone crisis. A related contribution is Giesecke et al. (2014) that also study CDS portfolios using goal programming to address trading constraints faced by credit swap investors, and illustrate their impact on optimal portfolios. Their paper and ours make complementary contributions and pave the way for further research in integrated enterprise-wide risk management (Holmer and Zenios, 1995) to incorporate

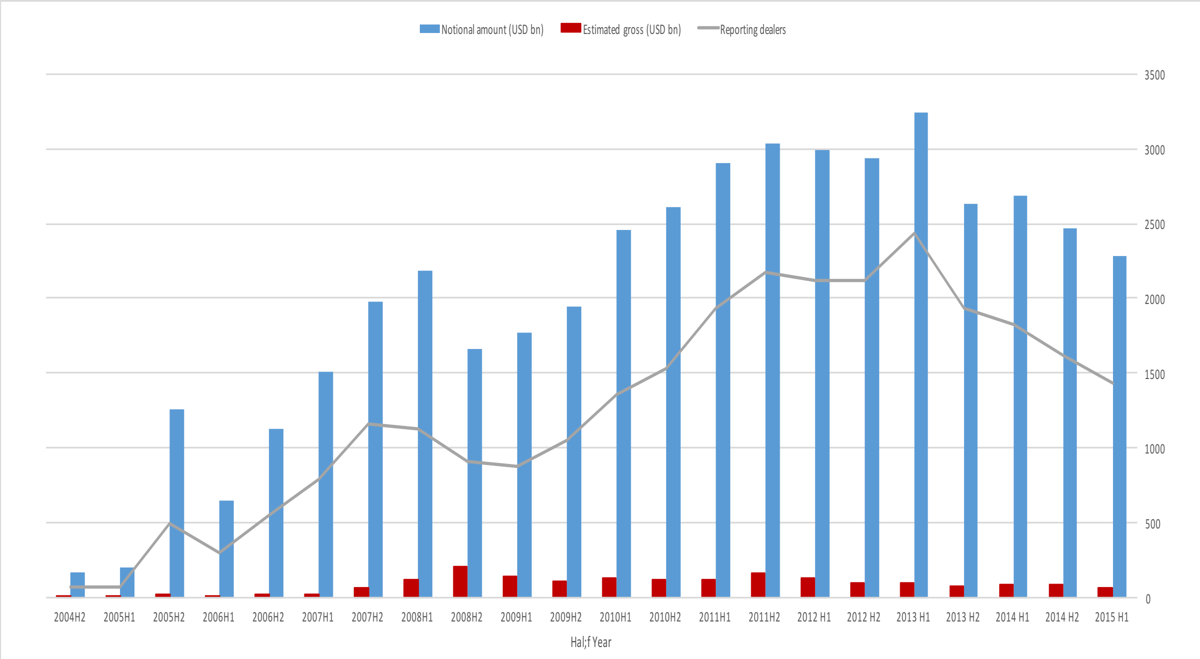


Figure 1: The growing market for sovereign credit default swaps.
(Source: Bank for International Settlement and authors' calculations.)

CDS positions with the underlying sovereign bonds in a diversified portfolio.

The motivation is coming from the following observations:

1. While CDS are typically bought to hedge against the default of a reference sovereign bond, enterprise risk management requires sovereign bond investors to consider the insurance needs of their whole portfolio. A silo approach to hedging, whereby CDS insurance is bought for each bond separately, leads to over-insurance when entities are negatively correlated. A portfolio approach is warranted.

2. A portfolio approach is also required for some aspects of EU regulation on CDS (European Union, 2012). The regulatory ban on naked positions does not apply if a CDS transaction serves to hedge a long position in a portfolio of debt instruments highly correlated with a reference sovereign bond. In this case the CDS holder is not hedging a specific sovereign entity but their own portfolio, and a CDS portfolio may be (most likely, it will be) a better hedge than a single contract.

3. Empirical research on sovereign CDS spread determinants finds considerable evidence that a significant fraction of the fluctuations in sovereign CDS spreads is determined by global factors, unrelated to a country's economy, see, e.g., Longstaff et al. (2011) (Augustin et al., 2014, Sec. 7.4). However, idiosyncratic risks remain — explaining 4% to 43% of CDS return variation depending on country and time scale— and hence a portfolio approach is useful in diversifying these risks. Our work provides normative models to do so, and the application to eurozone core and periphery, and CESEE countries shows that diversification pays.

4. Increased market liquidity, standardization of contracts and the shift from OTC deals to exchange trades, facilitated the interest in CDS portfolio management. Hedge funds made significant profits in the CDS markets. Napier Group, Saba and

Blue Mountain are funds quoted in Augustin et al. (2016) as benefiting from their CDS positions. Activist shareholder Carl Icahn announced in November 2014 that he owns CDS on high yield debt against the 5-year U.S. Treasury note and stated that "the risk-reward is great in that CDS" [1].

5. The development of CDS indices provides benchmarks for CDS investment strategies. See, for instance the Markit CDX family of tradeable CDS indices covering North America and emerging markets, and the S&P/ISDA CDS indices. Cobranding S&Ps CDS indices jointly with the International Swaps and Derivatives Association (ISDA) increases transparency and efficiency in the derivatives market. S&P and ISDA currently offer the *S&P/ISDA Eurozone Developed Nation Sovereign CDS Index*, among others, which we use later to benchmark model performance.

The models developed in this paper are building blocks for implementing the strategies of sovereign bond investors who buy CDS to hedge the credit risk of their portfolios, of speculators that seek to exploit perceived credit risk opportunities from deterioration (by going long) or improvement (by going short) of a sovereign's credit rating, and of dealers that both buy and sell CDS and wish to have a covered portfolio exposure. We consider CDS-only portfolios and discuss in the concluding section the important extension of incorporating the underlying sovereign bond(s) as well. The paper is organized as follows: Section 2 reports statistical analysis of the sovereign CDS spreads and identifies regime switching, Section 3 formulates models for hedgers, speculators, and dealers. Sections 4 and 5 report results with portfolio diversification and active portfolio management, respectively. Section 6 draws conclusions and discusses open questions.

2 Some empirical analysis of sovereign CDS markets

The choice of a model should be guided by the statistical properties of the market data. We analyze the most liquid 5-yr CDS spreads for a sample of European core and periphery countries, and CESEE countries, using daily observations from Datastream. For the analysis of individual countries we use all available data going back as far as December 2007 (the period examined is indicated on the x-axis of the figures for each country). Since not all countries offered CDS starting in 2007, we analyze common regimes over the period 8 October 2008 to 18 March 2016 during which there were CDS for all countries in our sample. This period starts with the sub-prime crisis in the USA, covers the beginning of the Eurozone crisis and goes well into its endgame. Greek CDS stopped trading on 22 February 2012 after a vertiginous ascent of its spread to 14912bp, and while we identify regime switching for Greek CDS, we exclude it from the portfolio experiments.

2.1 Regime switching

Given significant evidence that the determinants of CDS spreads and spread returns change with time (Alexander and Kaeck, 2008; Cont and Kan, 2011), we first search for regime switching and then calculate the moments in each regime. Other studies cited earlier (Augustin et al., 2014, Sec. 7.4) were searching for the factors that determine corporate CDS spreads. We are not concerned here with identifying specific factors

[1] See *REUTERS SUMMIT-Investors overpaying for yield after years of low rates, Thu. Nov. 20, 2014*, `http://www.reuters.com/article/investment-yearend-yield-idUSL2N0T82YH20141120`

for sovereign CDS spreads but, instead, with identifying discernible regimes without necessarily identifying the factors that drove regime switches. Hence, we consider regime switching in the level of CDS spreads with time. This analysis is sufficient for testing the main thesis of this paper that portfolio diversification pays and whether the benefits are regime dependent. One could consider different regime identification mechanisms, such as regime switching in spread returns. We could also consider regime switching not with time but with some underlying factor, such as market volatility, as we do in the next subsection. Identifying the common risk factors is a key input to risk management and here we test whether regimes are an important factor in CDS spreads and find that they are. We do not claim that we have the best way for identifying regime switching and this open question is discussed in the concluding section.

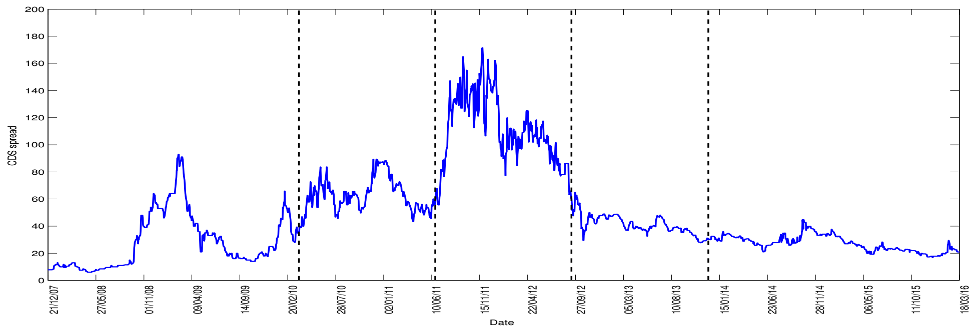
Using the test of Bai and Perron (1998) we identify regime changes for all countries in our sample. The Bai-Perron test identifies multiple breaks in linear regressions. Assuming a linear model, we identify the break points using the dynamic programming algorithm described in Bai and Perron (2003), as implemented in the free software system R. To avoid over-fitting we limit the maximum number of break points to five. Figures 2–3 show the regime breaks for core and periphery Eurozone countries. (Appendix A shows findings for CESEE and Baltic countries.) Confidence intervals for the regime switching range are small (see the discussion for the common regime switches for all countries in the next subsection). We observe that France, Italy, Portugal, Spain, and Cyprus are synchronized in their regime switching, whereas Germany, Ireland and Greece have idiosyncratic regime changes. For instance, only Germany has a regime switch associated with the onset of the subprime crisis and the collapse of Lehman Brothers in September 2008, while the eurozone crisis in spring 2010 signals regime switching for all countries. This finding hints that CDS portfolios could diversify idiosyncratic risks, motivating the portfolio optimization models of the next section.

The first four moments, and max and min values of CDS spread returns, for different regimes, are summarized in Appendix B. These estimates show that sovereign CDS spread returns are asymmetric with fat tails, an observation exemplified for corporate CDS by Cont and Kan (2011). This dictates the type of portfolio diversification model we use next, as the classical mean variance models do not apply. The estimates also reveal significant changes of the moments between regimes, implying that the optimal portfolios can be regime dependent.

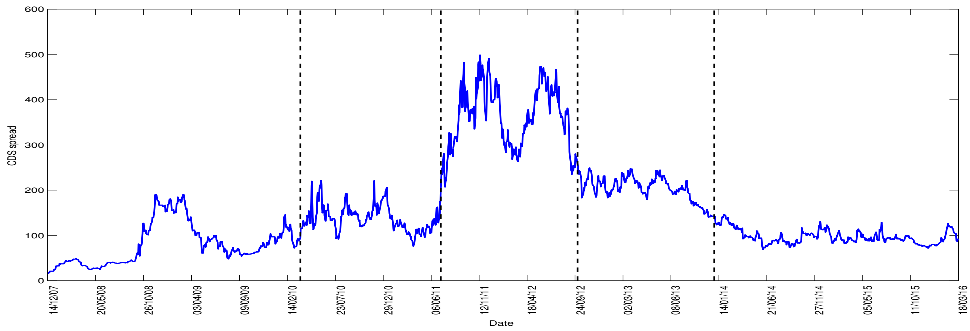
2.2 Common regime breaks

To test our portfolio management models we need to identify *common* regimes for all CDS series. An extension of the Bai-Perron test to multivariate regressions is Qu and Perron (2007) and we run the Bai-Qu-Perron test using GAUSS 16.0.3 on the series of Eurozone core, periphery and Baltic countries[2]. As common regressor we use the Euro Stoxx 50 Volatility Index (VSTOXX) since volatility is a key determinant of CDS spreads and VSTOXX is the most watched European volatility index. The test on the full set of eurozone core and periphery, and CESEE countries, would not converge, but we found various combinations of core, periphery and Baltic countries being stable when adding one more country. Hence, we use the regimes identified for core, periphery and the Baltics as applying to the whole set of countries. The results are given in Table 1 and moments

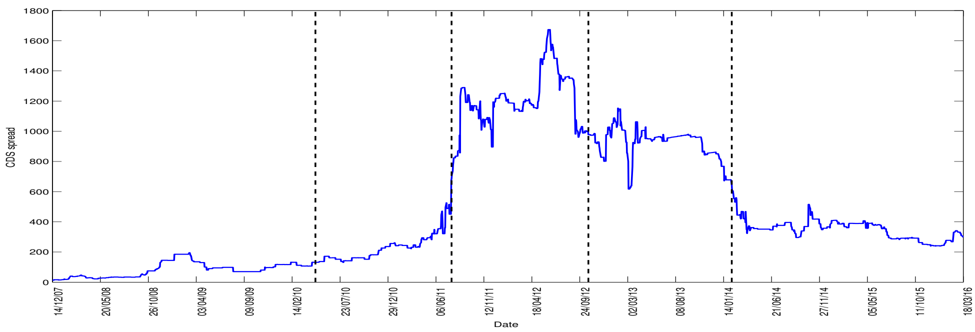
[2]The GAUSS code is available from Zhongjun Qu as "GAUSS code: Estimating and Testing Structural Changes in Multivariate Regressions at `http://people.bu.edu/qu/code.htm`



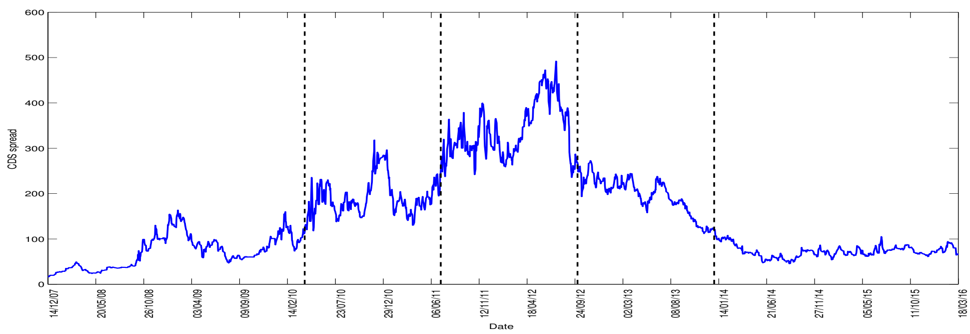
(a) France.



(b) Italy.

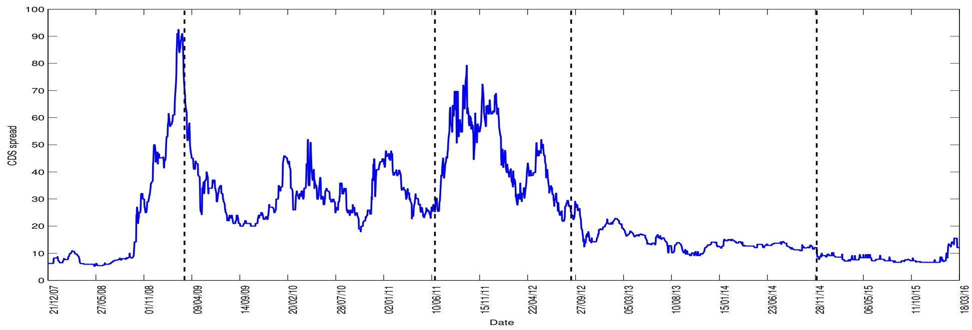


(c) Cyprus.

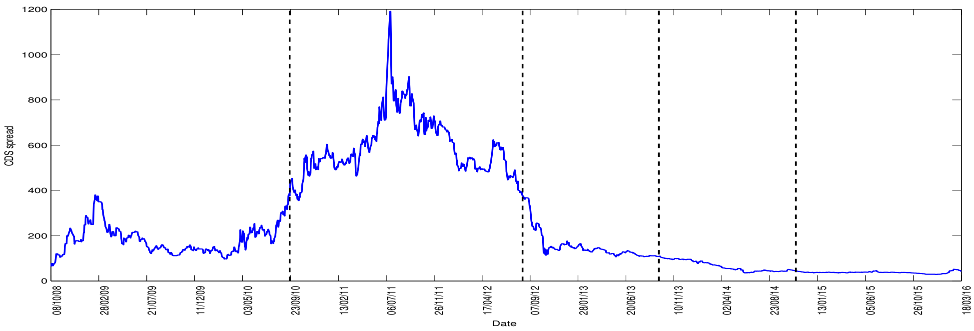


(d) Spain.

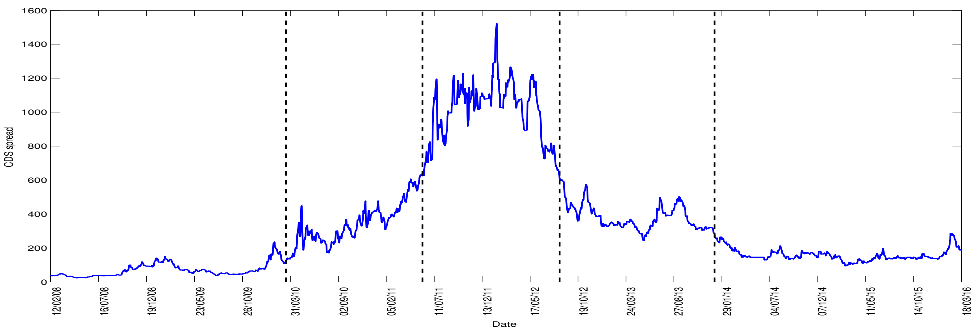
Figure 2: Regime switching identified separately for each one of these core and periphery countries appears synchronized. (Portugal is also synchronized, see Figure 3.)



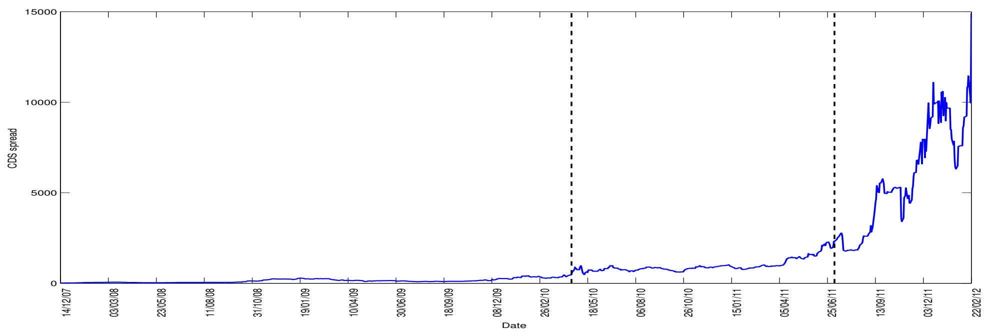
(a) Germany.



(b) Ireland.



(c) Portugal.



(d) Greece.

Figure 3: Regime switching identified separately for each one of these core and periphery countries appears idiosyncratic.

Variable tested	Regime switching date and confidence interval	Regime switching date and confidence interval
Spread level	25/11/2010	25/2/2013
	[24/11/2010, 26/11/2010]	[22/2/2013, 26/2/2013]
Spread return	22/6/2010	19/3/2013
	[14/6/2010, 30/6/2010]	[19/2/2013, 16/4/2013]

Table 1: Common regime switching dates using Bai-Qu-Perron test with VSTOXX as a common risk factor, and confidence intervals at the 95% level.

are tabulated in Appendix B, Tables 6–7. We also tested for regime switching in the spread returns, see Table 1. Regime switching of returns leads regime switching of spread level by five months at the start of the crisis. For the end of the crisis we can not reject the hypothesis that the regime switches were identical for spreads and spread returns.

In testing the portfolio optimization strategies we use regimes identified for spread levels that have tight confidence intervals of two to four days. These regimes coincide with phases of the eurozone crisis and we refer to them as *I. Turbulent*, *II. Crisis* and *III. Post crisis.*

3 The CVaR portfolio optimization models

Given the skewed and fat-tailed returns of CDS identified by Cont et al. (2010) for corporates, and from our own analysis above for sovereigns, we develop portfolio diversification models using CVaR optimization. CVaR optimization has its origins in the work of Rockafellar and Uryasev (2002, 2000) and its properties are well understood, see, e.g., (Zenios, 2007, sec. 5.5). We develop single-period CVaR optimization models. Returns are measured during the risk horizon by the log of spread changes, but do not account for collected premia or payments in the case of default. This is a reasonable approximation for short horizons or when dealing with sovereigns with very low probabilities of default (e.g, Germany), and extensions are discussed in Section 6.

The expected value of the α-tail[3] of the distribution of portfolio loss X, $\text{CVaR}_\alpha(X)$, and its minimization formula are given in the following theorem:

Theorem 3.1 ***Fundamental minimization formula*** (Rockafellar and Uryasev, 2002) *As a function of $\gamma \in \mathbb{R}$, the auxiliary function*

$$F_\alpha(X,\gamma) = \gamma + \frac{1}{1-\alpha}\mathbb{E}\left\{\max\left\{X-\gamma, 0\right\}\right\}$$

is finite and convex, with

$$\text{CVaR}_\alpha(X) = \min_{\gamma\in\mathbb{R}} F_\alpha(X,\gamma).$$

Consider an investor operating in a market with n risky assets with rates of return denoted by random vector ξ. For an investment vector $x \in \mathbb{R}^n$ of proportional notional allocations to the risky assets, the loss is given by the function $f(x,\xi) = -x^\top\xi$. When dealing with portfolio optimization, loss is a function of the portfolio x and we write the

[3] $\alpha \in (0,1]$ and all numerical experiments in this paper are carried out for $\alpha = 0.95$.

auxiliary function and CVaR as functions of x. From Theorem 3.1 we have:

$$\text{CVaR}_\alpha(x) = \min_{\gamma \in \mathbb{R}} F_\alpha(x, \gamma), \tag{1}$$

where

$$F_\alpha(x, \gamma) = \gamma + \frac{1}{1-\alpha} \mathbb{E}\{\max\{f(x, \xi) - \gamma, 0\}\}.$$

A model for selecting a portfolio with minimum CVaR and a target expected return is:

$$\begin{aligned} \min_{\gamma \in \mathbb{R}, x \in \mathbb{X}} \quad & F_\alpha(x, \gamma) \\ s.t. \quad & \mu^\top x \geq \bar{\mu}. \end{aligned} \tag{2}$$

$\mathbb{X}$ is the constraint set on the investment variables which specifies feasible portfolios depending on the investment strategy, μ is a vector of mean returns of risky assets, and $\bar{\mu} \in \mathbb{R}$ is the target expected return. γ is the Value-at-Risk of the loss function corresponding to the minimal CVaR.

From historical data we generate an $S \times n$ matrix R of S scenarios of returns for the n risky assets —Steps 0 in Section 5— and estimate μ as the n-vector of mean returns of R. From (2) we formulate CVaR optimization models for three investment strategies:

1. Long exposures (`L`). This strategy uses CDS as they were originally intended to hedge credit risk, but never, so far, employed in a portfolio context.

2. Uncovered long and short exposures (`LS`). This strategy is followed by speculators that seek to exploit credit risk opportunities from deterioration (by going long) or improvement (by going short) of a sovereign's rating.

3. Covered long and short exposures (`NZ`). This is the strategy of dealers that both buy and sell CDS but do not wish to be uncovered. This is a "net zero" position with no cash outflow.

The notion of covered and uncovered exposures is context dependent. Typically a short CDS position is covered if the investor has borrowed the underlying bond, or has entered into an agreement to borrow the bond, or has an arrangement that guarantees the bond can be made available. In the world of dealers an exposure is covered if there are as many long positions as there are short, and this is how we use the term here.

3.1 Long exposures

The constraint set on the investment variables in the simplest model stipulates only that all variables are non-negative (i.e., no short sales allowed) with a normalization constraint that asset allocations add up to an initial endowment of 1:

$$\mathbb{X}_L = \{x \in \mathbb{R}^n \mid x \geq 0, \sum_{i=1}^{n} x_i = 1\}. \tag{3}$$

The CVaR portfolio optimization model is given by

$$\begin{aligned} \min_{x \in \mathbb{X}_L,\, u \in \mathbb{R}^S,\, \gamma \in \mathbb{R}} \quad & \gamma + \frac{1}{S(1-\alpha)} e^\top u \\ s.t. \quad & \\ & -Rx - u - e\gamma \leq 0 \\ & \mu^\top x \geq \bar{\mu} \\ & u \geq 0, \end{aligned} \tag{4}$$

where e is a vector of all 1 and u is a dummy variable that transforms the argument of the minimization problem (1) from a discontinuous function with a max operator to a system of linear equations and inequalities as in Krokhmal et al. (2002) —for explanations see (Zenios, 2007, sec. 5.5)— to obtain a linear programming problem.

3.2 Uncovered long and short exposures

We introduce non-negative variables x^+ and x^- to represent long and short positions, respectively. An initial endowment of 1 is invested in long positions, but the long positions can be augmented from capital raised from short sales. We set an (arbitrary) limit that no single short position can be higher than our original endowment, but overall there is no guarantee that the aggregate short positions will not be significantly higher that the original endowment. The difference between the original endowment and the aggregate short position (if negative) is a proxy for the margin requirement for the investor to sell CDS protection. The constraint set on the investment variables is given by

$$\mathbb{X}_{LS} = \{x \in \mathbb{R}^n \mid x = x^+ - x^-,\, 0 \leq x^+ \leq 1,\, 0 \leq x^- \leq 1,\, \sum_{i=1}^{n} (x_i^+ - x_i^-) = 1\}. \tag{5}$$

The CVaR portfolio optimization model is formulated as:

$$\begin{aligned} \min_{x \in \mathbb{X}_{LS},\, u \in \mathbb{R}^S,\, \gamma \in \mathbb{R}} \quad & \gamma + \frac{1}{S(1-\alpha)} e^\top u \\ s.t. \quad & \\ & -Rx^+ + Rx^- - u - e\gamma \leq 0 \\ & \mu^\top x^+ - \mu^\top x^- \geq \bar{\mu} \\ & u \geq 0. \end{aligned} \tag{6}$$

3.3 Covered long and short exposures

We impose now a constraint that total short exposure is equal to total long exposure, so that we have a position with net zero cash outflow. The endowment of 1 unit is considered as collateral. The constraint set is given by

$$\mathbb{X}_{NZ} = \{x \in \mathbb{R}^n \mid x = x^+ - x^-,\, 0 \leq x^+ \leq 1,\, 0 \leq x^- \leq 1,\, \sum_{i=1}^{n} x_i^+ = 1,\, \sum_{i=1}^{n} x_i^- = 1\}. \tag{7}$$

The portfolio optimization model is obtained by substituting $\mathbb{X}_{LS}$ in model (6) by $\mathbb{X}_{NZ}$.

3.4 Notes on implementation

Some details on model implementation and testing are in order.

1. The models minimize the CVaR of portfolio return subject to meeting or exceeding a target $\bar{\mu}$ on expected return $\mu^\top x$. Varying the target we trace an efficient frontier trading off risk (CVaR) vs. reward (expected return), both measured in percentages. We report CVaR with a minus sign since it measures losses.

2. The models can incorporate linearly proportional transaction costs (Zenios, 2007, pp. 80–81), and numerical experiments are carried out with transaction cost 0.5%.

3. To carry out testing consistently with the models, whereby defaults are not modeled, Greece was excluded since it defaulted during the testing period.

4 Portfolio diversification

The models are now employed to develop frontiers for the three investment strategies. The S scenarios of returns are taken as the realizations of historical data observed during the time period of interest. We develop efficient frontiers for the whole period and for each one of the regimes separately.

4.1 Diversification pays

Figure 4 shows efficient frontiers for the whole time period October 2008–March 2016 with the three investment strategies. The following observations support the argument that diversification pays:

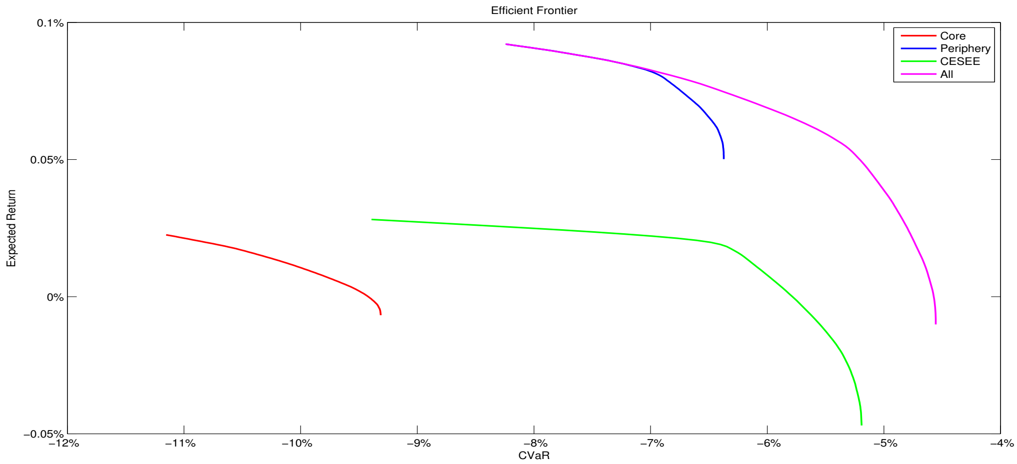
1. None of the frontiers are flat over the whole range of target expected returns, with the sole exception of the frontier including all countries using the `LS` strategy. Hence, there are trade-offs between risk and rewards in the CDS market.

2. We note Pareto improvements in the efficient frontiers when diversifying from core to CESEE and/or periphery countries. Hence, investors benefited by diversifying their portfolios from core to the riskier periphery and CESEE countries.

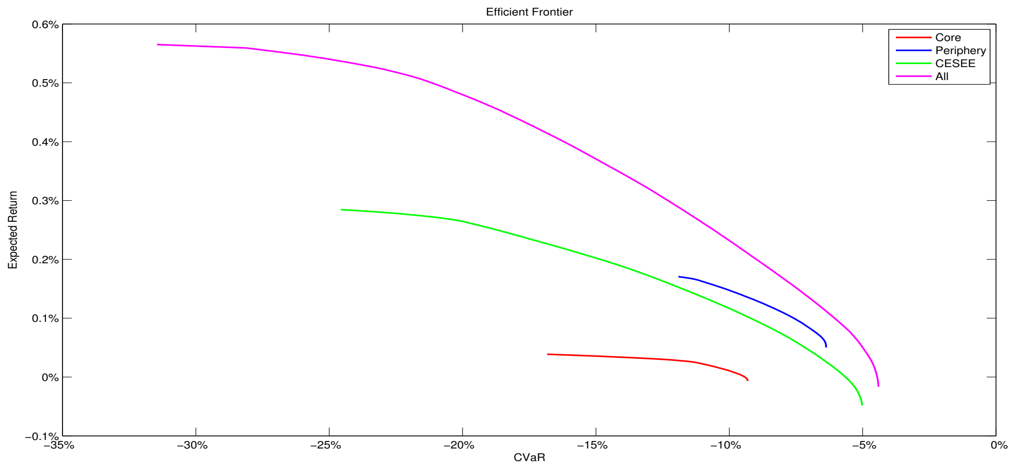
3. Pareto improvements are more pronounced when considering all countries together. This is particularly noticeable when using strategies `LS` and `NZ`, see Figure 4(b) and 4(c), further supporting diversification across regions.

Drawing the efficient frontiers for the different strategies together in Figure 5 we observe that (as expected) strategy `L` is the least efficient, whereas `LS` achieves the highest expected return but at higher risk. Strategy `NZ` dominates the other two at low risk levels, but limits the high expected return associated with high downside potential of the `LS` position. We also demonstrate that there exists a zero risk position with the `NZ` strategy.

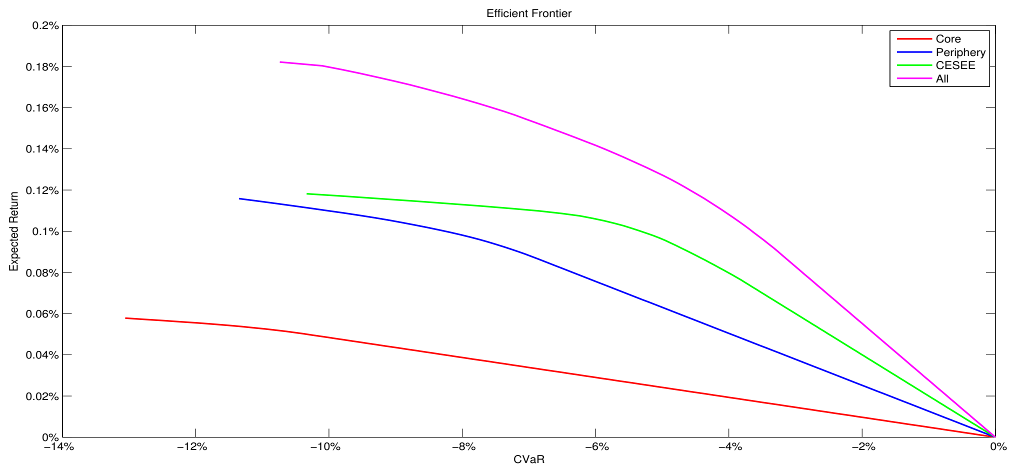
The results show that diversification consistently pays. However, the relative positions of the frontiers may change with the regimes and we explore this issue next.



(a) Long exposures



(b) Uncovered long and short exposures



(c) Covered long and short exposures

Figure 4: Efficient frontiers with different investment strategies over the whole period October 2008 to March 2016 showing the benefits of geographical diversification of CDS portfolios for all strategies.

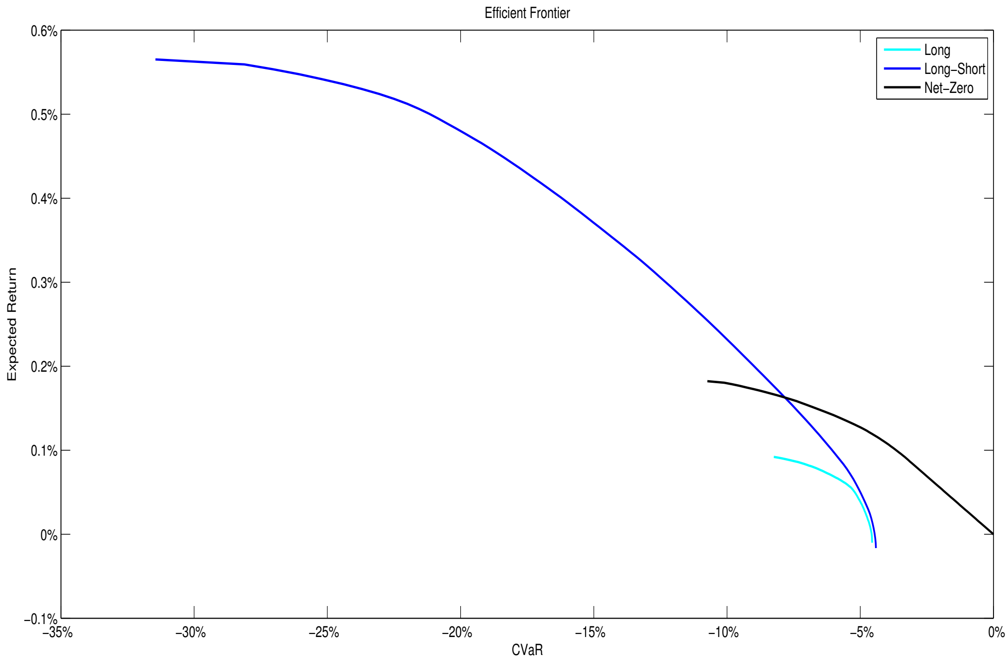


Figure 5: Comparing the efficient frontiers of the different investment strategies over the whole period October 2008 to March 2016 shows the relative merits of each strategy: the `L` strategy is dominated whereas `LS` and `NZ` perform better when going from higher to lower risk appetite, respectively.

4.2 Diversification is regime dependent

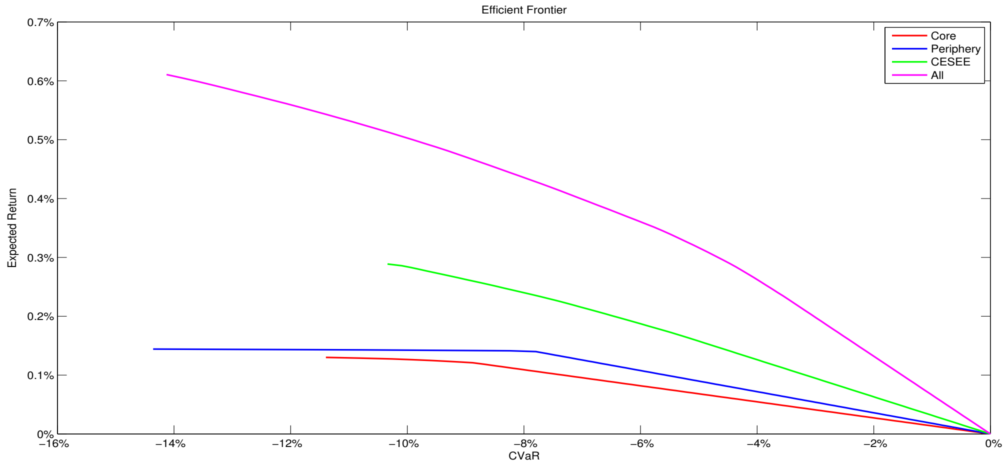
To study the effect of regime switching on portfolio diversification we develop efficient frontiers for each regime separately. Figure 6 illustrates changes in the relative position of the frontiers for each country group with the regimes, when using the `NZ` strategy. (Similar results are shown in Appendix C for strategies `L` and `LS`.) Figure 7 illustrates the relative position of the frontiers obtained using different strategies for all countries under the different regimes. The following observations can be made from these results:

1. Diversification pays consistently in all regimes, see Figure 6, and this is a robustness test of the "diversification pays" thesis of the previous subsection.

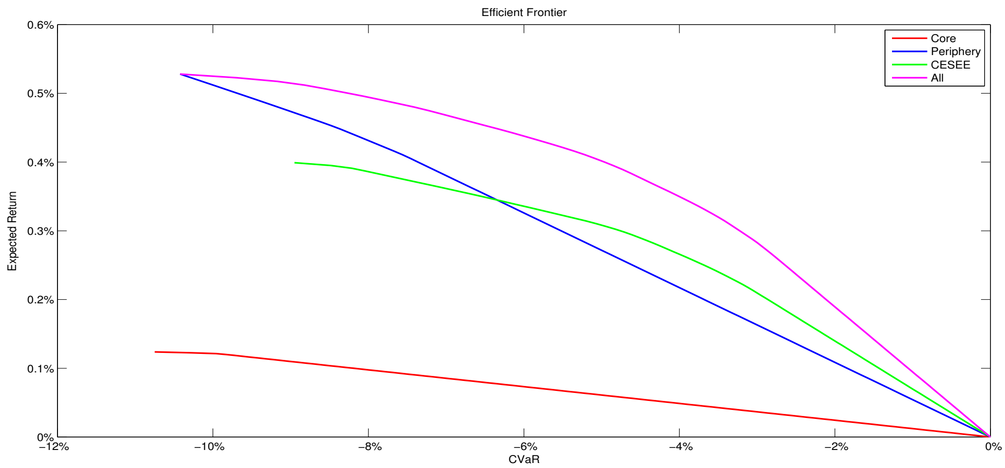
2. The relative performance of the three strategies remains unaltered among regimes, see Figure 7. The observation that `NZ` dominates at low risk levels, but `LS` dominates are high risk is robust to regime changes.

3. The relative efficiency of portfolios in the different country groups changes with the regimes. For instance, the results of Figure 6(a) show that before the crisis it paid to diversify from the core to CESEE and/or periphery countries, with a small advantage of CESEE over periphery. The relative advantage of CESEE over periphery is blurred during the crisis, Figure 6(b), and the CESEE countries clearly dominate post-crisis, Figure 6(c).

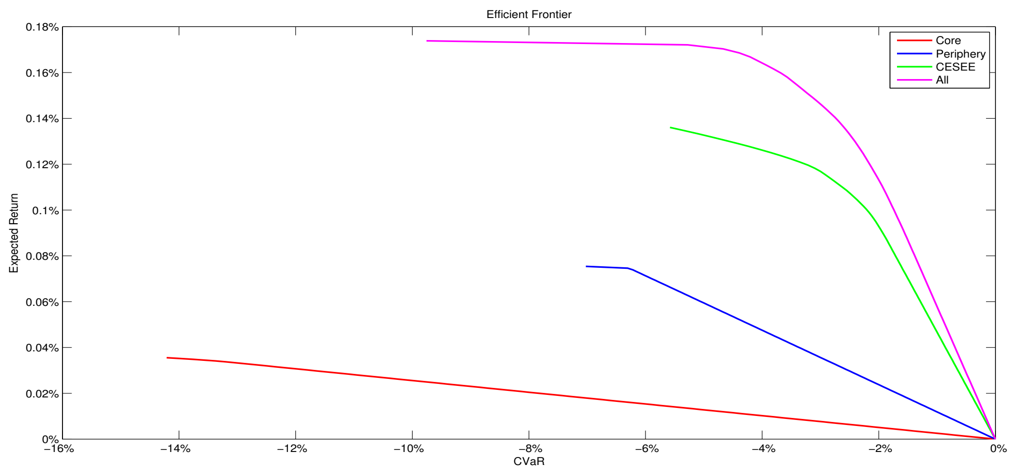
The main conclusion from these observations is that diversification pays for all strategies and in all regimes. Also the relative merits of the `LS` and `NZ` strategies are robust to regime changes. However, the regimes change the diversified portfolio. Therefore expectations about the regimes should be included in the diversification models, and this issue is addressed in the concluding section.



(a) Regime I. Turbulent

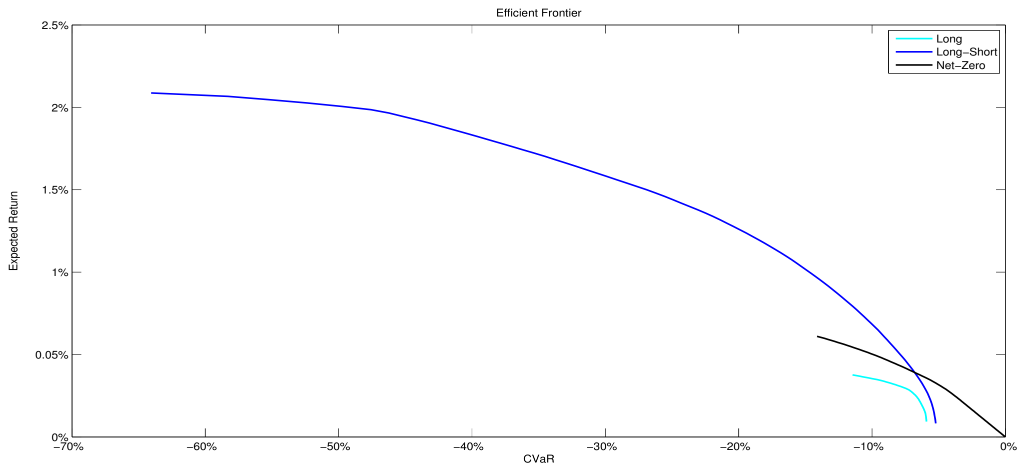


(b) Regime II. Crisis

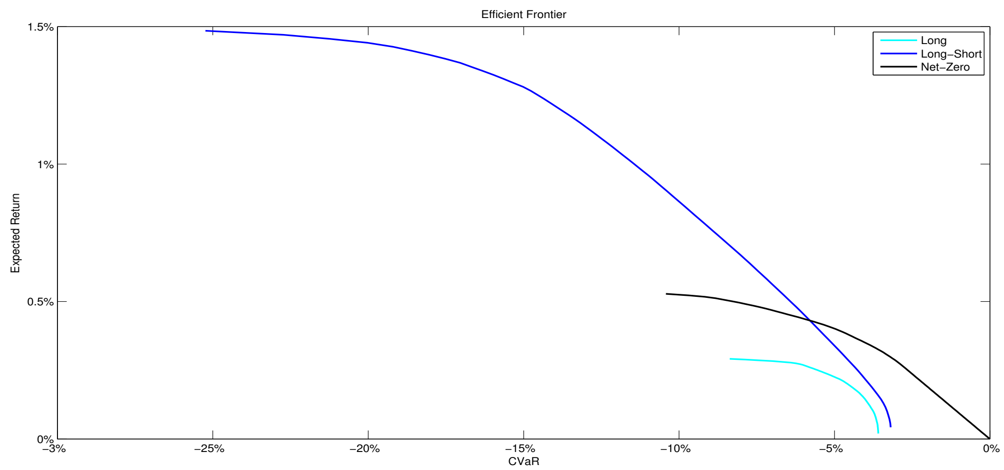


(c) Regime III. Post crisis

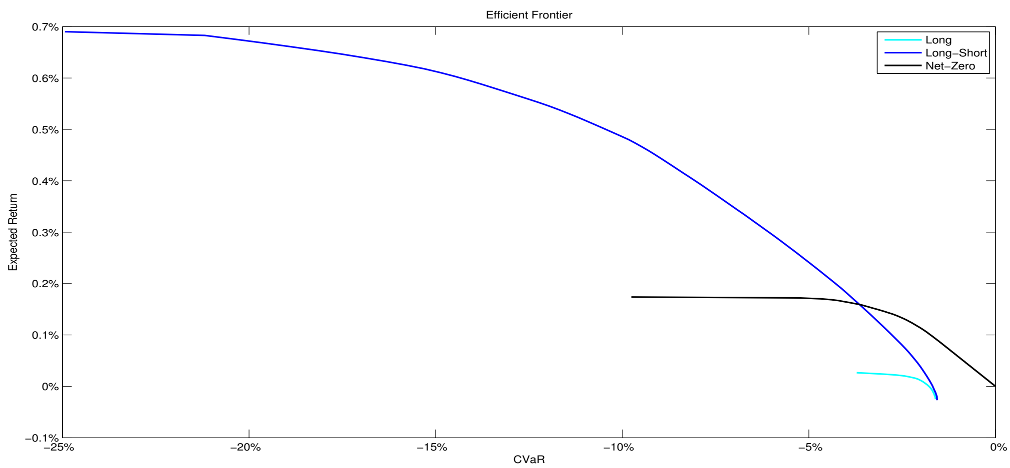
Figure 6: Regime dependent relative position of efficient frontiers for each country group using strategy `NZ`.



(a) Regime I. Turbulent



(b) Regime II. Crisis



(c) Regime III. Post crisis

Figure 7: The relative positions of efficient frontiers using different investment strategies are robust to regime switching.

5 Active portfolio management

Testing was so far carried out in a static setting whereby a diversified portfolio was created and held throughout the investment period. In practice, diversified portfolios are revised as new information arrives and the models are now tested using active portfolio management. Testing proceeds as follows:

Step 0. Use the first 500 days of data from 8 October 2008 to 8 September 2010 (call this date t) to generate the scenario return matrix R.

Step 1. Run the CVaR models and choose a portfolio from the efficient frontier.

Step 2. Move the clock to $t+1$, and record the ex post portfolio return from t to $t+1$.

Step 3. Update the scenario return matrix by adding the observed market returns from t to $t+1$ and removing the oldest observation, and return to Step 1.

This active management strategy is repeated for 1442 daily steps from 9 September 2010 to 18 March 2016. This five-year period covers the Eurozone crisis with the three regimes identified in Section 2. Instead of reporting returns for each period we equivalently report cumulative wealth starting with an initial endowment of 100. We pick portfolios on the efficient frontier with increasing risk appetite: (1) the portfolio that minimizes CVaR, with expected return denoted by R_{min}, (2) the portfolio with target expected return half-way between R_{min} and the maximum expected return R_{max}, denoted by R_{mid}, (3) the portfolio with target expected return $\frac{1}{2}(R_{mid} + R_{max})$, (4) the portfolio that maximizes expected return R_{max}. As a benchmark we use the S&P/ISDA Eurozone Developed Nation Sovereign CDS index, illustrated in Figure 8. Results with active portfolio management using the three investment strategies are shown in Figure 9. Also shown as a reference is the cumulative wealth of an investment in the risk-free rate taken to be the yield of AAA-rated 3-month sovereigns.

Several observations are drawn from these figures:

1. All strategies can deliver overall positive returns for the whole period. Investors with average risk appetite (target expected return R_{mid}) achieved overall annualized return of 5.65% (strategy `L`) and 10.35% (strategy `NZ`). Using strategy `LS` with the same level of risk appetite generates loses -5.56%. However, if the risk appetite is set higher, consistently with the `LS` strategy, by increasing the expected target return to $\frac{1}{2}(R_{mid} + R_{max})$, then return turns positive 5.22%. These results compare favorably with the annualized return of 0% for the benchmark AAA-rated bond and -13.54% of the index.

2. Investment strategies `L` and `LS` have volatile returns (`LS` more than `L`).

3. Increasing the risk appetite by setting target expected return to $\frac{1}{2}(R_{mid} + R_{max})$, from R_{min}, improves the performance of actively managed portfolios. However, the situation deteriorates as risk appetite increases further by setting the target at R_{max}. Hence, neither too little (R_{min}) nor too much (R_{max}) risk serves best the investor. This exemplifies the need for risk management models carefully calibrated to CDS spread dynamics.

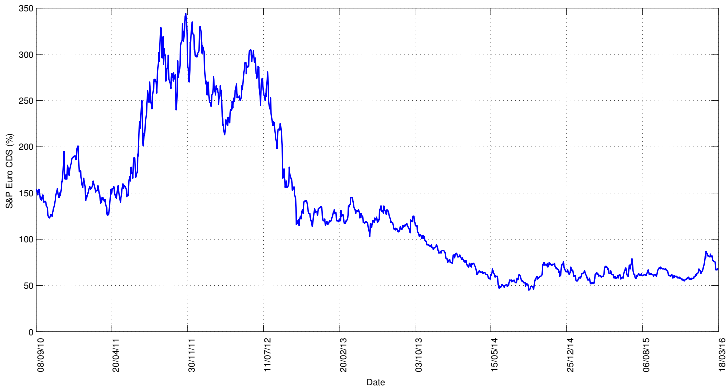


Figure 8: The S&P/ISDA Eurozone Developed Nation Sovereign CDS index.

4. Strategy NZ performs uniformly well. It generates less volatile returns than the other two strategies and rides smoothly past the big up- and down-swings of the crisis. For medium risk appetite this strategy achieves returns of 10.35% to 18.17%. It is only when ignoring totally the CVaR risk criterion by setting expected return to R_{max} that this strategy ends up very close to zero cumulative return and eventually registers loss of -6.88% at the end of the testing period.

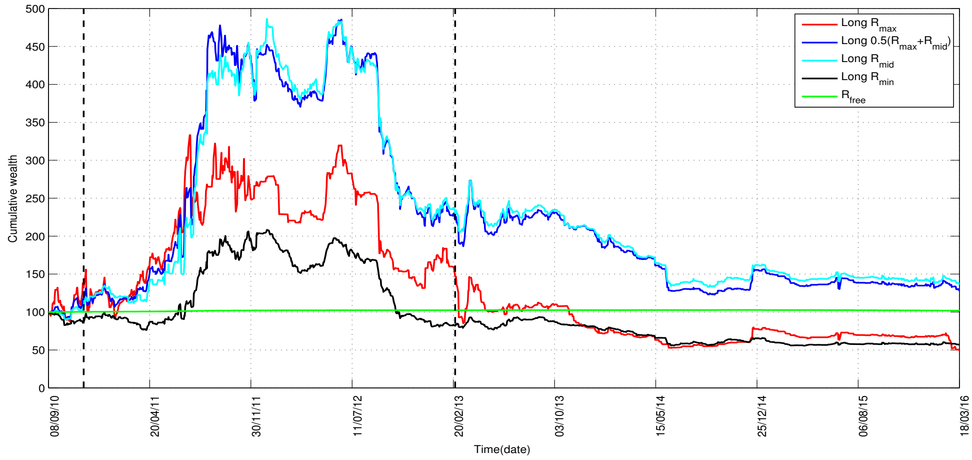
5. The models generate overall well diversified portfolios. Counting the number of assets in each portfolio at each point in time we have the following averages over the testing period, rounded to the nearest integer:

Strategy L	6 assets (ranging from 4 to 10)
Strategy LS	8 assets (ranging from 5 to 12)
Strategy NZ	15 assets (ranging from 10 to 18)

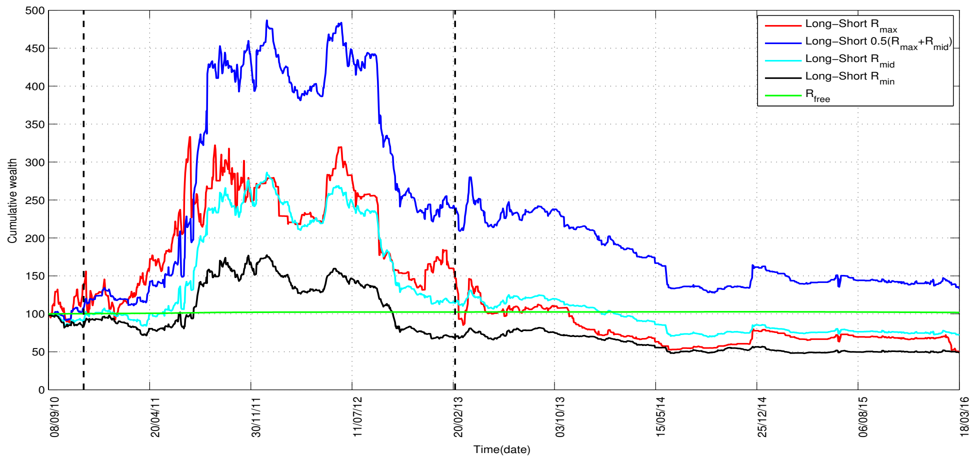
The average Gini coefficient of asset holdings is 0.5 for all strategies, which indicates balanced distribution of holdings among the selected assets. With 18 available assets we consider portfolios of 6 to 15 assets, on average, as well diversified. For strategy L there were trading days when the model selected portfolios with 4 to 5 assets. These portfolios can not be considered well-diversified but they occur very rarely —for about a dozen trading days during the five years. Ad hoc constraints can be added to ensure a minimum number of assets in the portfolio, but since they are rarely needed they will not alter materially model performance.

Since returns are volatile it is not sufficient to look at the total return, even if it is positive and higher than the index. Hence, we compute the Sharpe ratio for each strategy and compare it with the Sharpe ratio of the index. We compute the ratio suggested by Sharpe (1994) and the ratio that penalizes only downside risk (Ziemba, 2005). Sharpe ratios are reported on an annual basis and are consistent with the daily ratios that we also computed but do not report. The Sharpe ratios in Table 2 confirm the relative merits of the different strategies and the significant out-performance of the optimized strategies over the index.

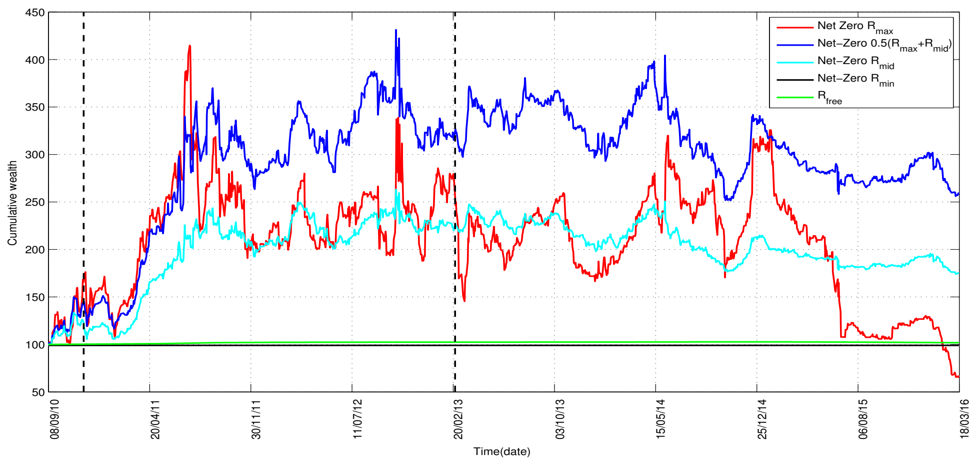
We also tested active portfolio management with weekly portfolio rebalancing (we thank a referee for suggesting this test). Sharpe ratios using the NZ strategy with weekly revisions are given in Table 2 and they are uniformly better than the Sharpe ratios of the



(a) Long exposures



(b) Uncovered long and short exposures



(c) Covered long and short exposures

Figure 9: Wealth accumulation with active portfolio management of sovereign CDS over the period September 2010 to March 2016.

Strategy and rebalancing frequency	Sharpe ratio (Sharpe, 1994)	Sharpe ratio (Ziemba, 2005)
Long positions (L), daily		
Target expected return R_{min}	-0.055	-0.068
Target expected return R_{mid}	0.275	0.445
Target expected return $\frac{1}{2}(R_{mid} + R_{max})$	0.275	0.451
Target expected return R_{max}	0.091	0.121
Uncovered Long-Short positions (LS), daily		
Target expected return R_{min}	-0.186	-0.220
Target expected return R_{mid}	0.106	0.147
Target expected return $\frac{1}{2}(R_{mid} + R_{max})$	0.276	0.446
Target expected return R_{max}	0.091	0.121
Covered Long-Short positions (NZ), daily		
Target expected return R_{min}	-0.503	-0.428
Target expected return R_{mid}	0.306	0.518
Target expected return $\frac{1}{2}(R_{mid} + R_{max})$	0.355	0.603
Target expected return R_{max}	0.112	0.159
Covered Long-Short positions (NZ), weekly		
Target expected return R_{min}	-0.440	-0.428
Target expected return R_{mid}	0.457	0.871
Target expected return $\frac{1}{2}(R_{mid} + R_{max})$	0.428	0.809
Target expected return R_{max}	0.134	0.185
S&P/ISDA Eurozone Developed CDS Index	-0.304	-0.355

Table 2: Sharpe ratios for active management using the three portfolio optimization strategies and for the S&P/ISDA Eurozone Developed Nation Sovereign CDS index.

daily rebalanced strategy. This improvement can be explained by the reduction in transaction costs with lesones frequent weekly rebalancing. However, it is not clear beforehand if a daily or weekly (or monthly) revision is the most effective. In dynamic multi-period stochastic programming models for asset allocation the portfolio rebalancing is carried out as frequently as optimally necessary (Mulvey and Vladimirou, 1992; Zenios et al., 1998), but in a single-period model the length of the time period has to be determined a priori and there is no good way for doing so.

6 Conclusions and open questions

The paper modeled CDS portfolio problems using optimization of a risk measure (CVaR) to capture the empirically observed characteristics of CDS spread returns. Three portfolio strategies were modeled and tested empirically using long positions, long and short positions, and covered long and short positions. Empirical analysis of CDS spreads going back before the start of the global financial crisis of 2008 reveals that they are subject to regime switching and the models were tested separately for each regime and for all regimes together.

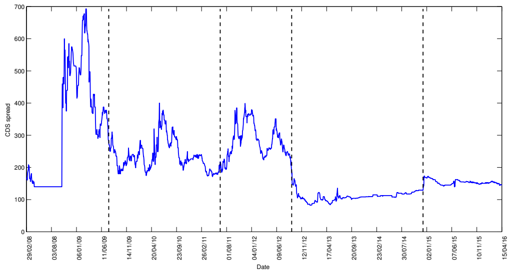
Testing was carried out over the highly volatile period that covers the eurozone crisis and using data from eurozone core and periphery, and CESEE countries. One set of tests used a static approach for building diversified portfolios and tracing the efficient frontier. Results uniformly show that diversification pays. While the precise type of diversification may be regime dependent, the observation that diversification pays is robust across regimes and for all three portfolio strategies. A second set of tests used the models for active CDS portfolio management. Results establish that the model-selected portfolios outperform, ex post, the broad market index. Investors' risk appetite has an impact on results, but except for extremely conservative or extremely risky choices, the diversified portfolios consistently dominate.

While the paper contributes several innovations on an important problem, it also identifies questions for further research. First, an extension of great practical significance is to incorporate the underlying sovereign bond(s) in the models. CDS are often used to hedge default risk of an underlying sovereign bond portfolio, and CDS and bond portfolios should be integrated (Holmer and Zenios, 1995). The models can incorporate bonds as one more asset class, but additional work is needed to generate scenarios of CDS returns that are consistent with the bond returns. To do so we need to capture the correlations between bond yields and CDS spreads. Second, the models do not account for collected premia or payments in the case of default. This highlights the major limitation of our models, which are single-period. In the single period context we can not explicitly model events other than changes in CDS spread returns. To the extent that returns capture credit and liquidity risk, the models work fine. But if there is a liquidity break, like with some eurozone crisis countries, the model has no direct way of dealing with it. A multi-period extension using stochastic programming could deal with default. Allowing for the eventuality of default also allows us to consider situations arising during crises whereby lack of liquidity in the markets renders these instruments ineffective for hedging. This is a topic for future research for which we have precedence in the literature for modeling defaults on credit derivatives (Schönbucher, 2003) and the multi-period stochastic programming model with default for corporate bonds (Jobst et al., 2006). Third, it is natural to introduce regime switching in the scenarios of the optimization models. Our models treat all scenarios the same and there is no explicit modeling of regime-switching. Since the models of this paper are scenario-based they can incorporate regime scenarios as well. However, generating such scenarios is difficult, given the limited history of regime switching observations. There is a long history of modeling regime switching in financial times series starting with the seminal work of Hamilton (1994), and a model for regime switching in CDS spreads is given in Consiglio et al. (2016). Diversification with regime switching is better represented with multi-period models to capture regime persistence, and this is another promising direction for future research.

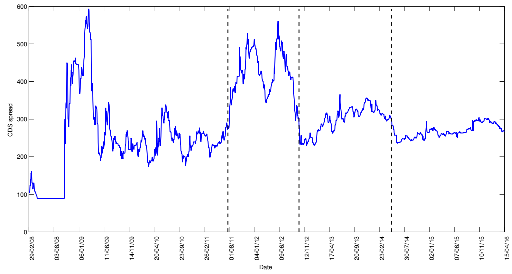
Acknowledgements

Stavros Zenios is holder of a Marie Sklodowska-Curie fellowship funded from the European Union Horizon 2020 research and innovation programme under grant agreement No 655092. The authors benefited from the comments of two anonymous referees and participants at the Macro seminars at the Finance Department of the Wharton School.

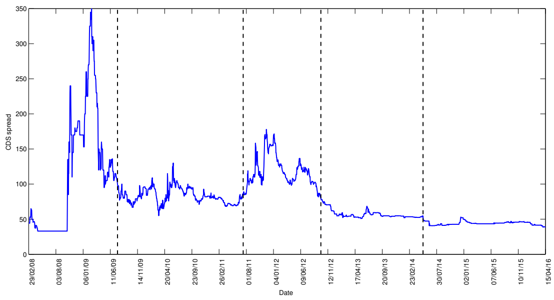
A Appendix: Regime switching in the CDS spread levels of CESEE and Baltic countries



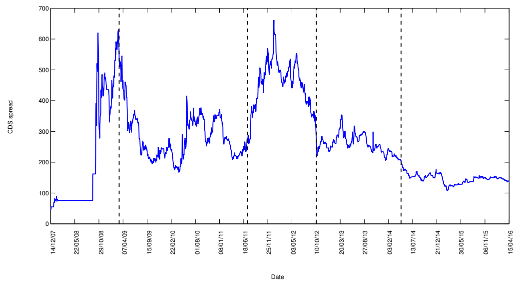
(a) Bulgaria.



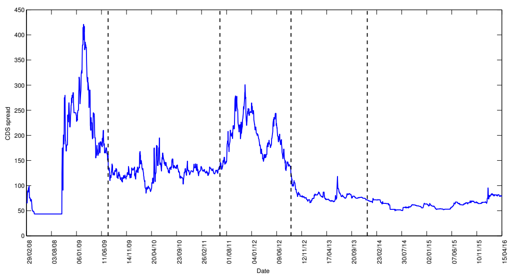
(b) Croatia.



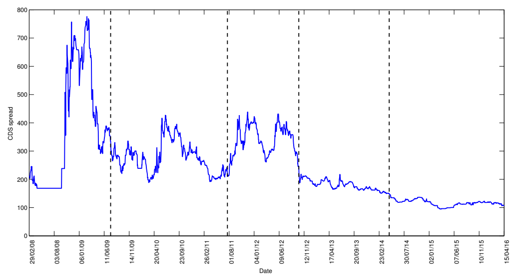
(c) Czech Republic.



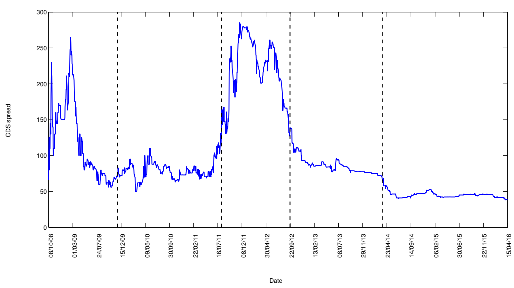
(d) Hungary.



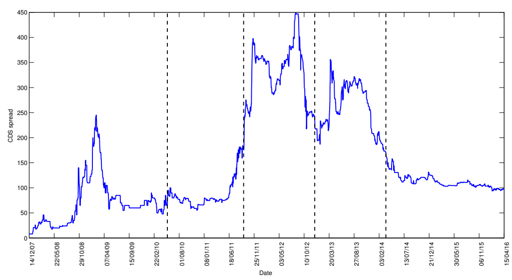
(e) Poland.



(f) Romania.

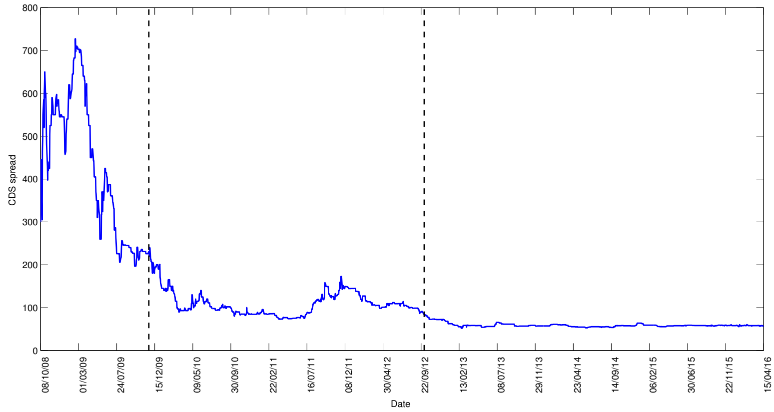


(g) Slovakia.

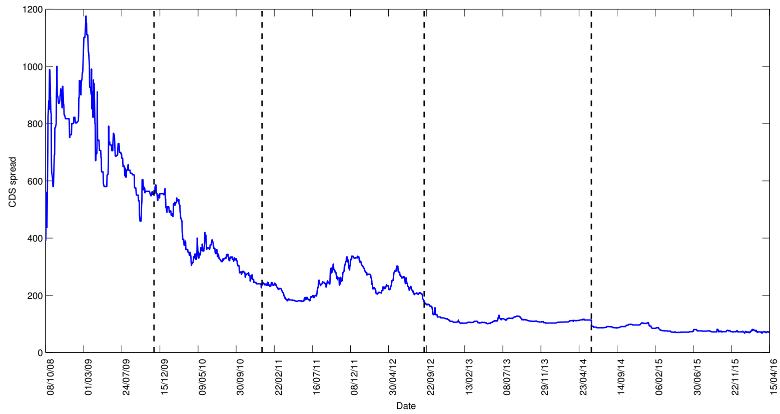


(h) Slovenia.

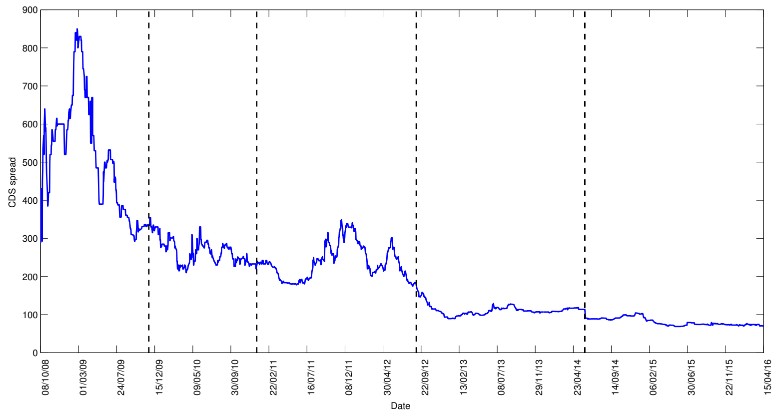
Figure 10: Regime switching appears synchronized for these CESEE countries.



(a) Estonia.



(b) Latvia.



(c) Lithuania.

Figure 11: Regime switching appears idiosyncratic for the Baltic countries.

B Appendix: CDS spread moments of all country groups under different regimes

Country-Regime	Mean	SD	Skewness	Kurtosis	Max	Min
France						
21/12/07–26/03/10	0.25	5.72	0.98	11.20	37.47	-21.85
29/03/10–21/06/11	0.15	4.87	-0.04	5.64	18.44	-20.53
22/06/11–13/09/12	0.03	6.22	-0.01	4.46	19.18	-23.08
14/09/12–09/12/13	-0.21	3.49	-1.06	16.86	17.14	-23.39
10/12/13–18/03/16	-0.07	4.01	0.47	10.55	25.36	-18.49
Germany						
21/12/07–13/03/09	0.78	5.48	2.82	28.86	52.48	-17.44
16/03/09–20/06/11	-0.18	5.48	-0.57	10.58	24.92	-37.14
21/06/11–12/09/12	-0.02	6.24	0.54	6.26	31.87	-21.04
13/09/12–02/12/14	-0.13	3.95	-0.23	12.16	23.12	-23.12
03/12/14–18/03/16	-0.00	6.31	-0.02	7.39	25.76	-25.07
Italy						
14/12/07–29/03/10	0.29	5.01	0.02	13.95	33.86	-37.12
30/03/10–07/07/11	0.18	6.51	-0.84	10.39	20.97	-45.20
08/07/11–02/10/12	0.13	4.94	0.34	5.55	22.20	-16.27
03/10/12–27/12/13	-0.19	2.91	0.38	8.20	15.68	-14.68
30/12/13–18/03/16	-0.08	3.67	0.38	7.98	23.39	-16.15
Ireland						
08/10/08–20/09/10	0.34	5.41	0.20	8.32	25.37	-33.11
21/09/10–15/08/12	-0.00	3.08	-0.26	6.08	13.11	-13.47
16/08/12–26/09/13	-0.43	3.93	-1.11	15.49	17.48	-22.15
27/09/13–07/11/14	-0.30	2.19	-2.64	21.33	6.13	-18.08
10/11/14–18/03/16	-0.01	1.69	1.57	13.96	11.43	-7.12
Cyprus						
14/12/07–30/04/10	0.37	4.40	0.51	22.11	26.24	-33.65
03/05/10–27/07/11	0.51	4.55	3.41	32.69	40.68	-20.91
28/07/11–22/10/12	0.12	3.72	2.90	49.28	36.27	-27.07
23/10/12–07/02/14	-0.11	3.00	-0.49	31.65	19.79	-26.14
10/02/14–18/03/16	-0.15	3.19	1.28	44.46	33.46	-29.74
Portugal						
12/02/08–16/03/10	0.20	4.61	0.28	5.62	17.70	-17.65
17/03/10–02/06/11	0.54	6.59	-2.28	24.99	27.42	-59.00
03/06/11–20/08/12	-0.00	4.09	0.37	7.65	21.28	-17.61
21/08/12–03/01/14	-0.22	2.85	0.86	11.45	18.95	-11.79
06/01/14–18/03/16	-0.08	3.84	0.62	6.07	17.32	-14.28
Spain						
14/12/07–12/04/10	0.32	5.17	0.10	10.34	33.85	-30.13
13/04/10–07/07/11	0.24	6.26	-0.63	10.17	28.26	-41.75
08/07/11–02/10/12	0.04	4.83	0.03	5.92	21.66	-19.35
03/10/12–27/12/13	-0.24	2.94	-0.01	6.89	11.79	-15.28
30/12/13–18/03/16	-0.11	3.97	0.54	8.26	25.10	-18.41
Greece						
14/12/07–20/04/10	0.54	4.45	0.33	9.03	24.54	-23.65
21/04/10–06/07/11	0.51	5.20	-2.51	37.50	22.26	-52.20
07/07/11–22/02/12	0.89	8.05	-0.41	6.73	26.78	-37.83

Table 3: CDS spread return moment estimates during each regime for eurozone core and periphery countries.

Country-Regime	**Mean**	**SD**	**Skewness**	**Kurtosis**	**Max**	**Min**
Bulgaria						
29/02/08–24/07/09	0.15	5.70	6.45	84.09	74.45	-21.19
27/07/09–22/06/11	-0.07	3.69	0.76	14.52	29.19	-22.31
23/06/11–10/09/12	-0.02	3.02	-0.18	6.61	11.92	-15.45
11/09/12–09/12/14	-0.07	2.22	-0.36	29.36	17.34	-20.94
10/12/14–15/04/16	0.03	1.63	3.65	53.57	17.54	-9.73
Croatia						
29/02/08–22/07/11	0.11	4.94	6.28	116.34	87.50	-24.89
25/07/11–10/10/12	0.03	2.46	1.14	11.18	17.06	-7.46
11/10/12–12/05/14	-0.00	1.69	-1.31	17.24	8.33	-13.54
13/05/14–15/04/16	-0.02	1.16	-0.26	19.70	8.38	-8.00
Czech Republic						
29/02/08–22/07/09	0.23	8.05	1.85	26.80	68.94	-46.26
23/07/09–14/07/11	-0.04	4.13	0.13	17.54	30.23	-31.85
15/07/11–02/10/12	-0.02	3.61	1.11	12.90	21.74	-17.92
03/10/12–12/05/14	-0.09	1.43	0.21	17.35	9.61	-8.36
13/05/14–15/04/16	-0.07	1.35	0.21	47.75	13.97	-12.41
Hungary						
14/12/07–12/03/09	0.78	6.77	5.54	56.67	75.62	-20.06
13/03/09–13/07/11	-0.12	3.63	0.85	15.06	27.25	-24.05
14/07/11–11/10/12	0.02	2.77	0.04	4.60	10.59	-9.47
12/10/12–25/04/14	-0.08	2.61	0.69	43.84	26.01	-23.29
28/04/14–15/04/16	-0.08	1.46	0.17	8.94	7.61	-5.93
Poland						
29/02/08–22/07/09	0.25	8.64	4.52	74.83	105.40	-65.39
23/07/09–20/06/11	-0.03	4.29	-0.71	14.20	24.54	-33.65
21/06/11–06/09/12	-0.04	3.46	-0.21	4.89	10.77	-13.58
07/09/12–26/12/13	-0.16	2.64	1.79	21.19	20.72	-13.09
27/12/13–15/04/16	0.01	1.93	-1.39	43.89	16.27	-21.26
Romania						
29/02/08–21/07/09	0.13	5.57	2.13	25.53	39.67	-33.93
22/07/09–21/07/11	-0.08	3.23	0.15	12.75	22.53	-22.29
22/07/11–09/10/12	0.03	2.72	0.37	5.85	11.39	-9.11
10/10/12–25/04/14	-0.12	1.61	-0.06	22.63	12.27	-11.91
28/04/14–15/04/16	-0.07	1.15	-0.44	11.91	6.54	-5.82
Slovakia						
08/10/08–20/11/09	0.02	7.77	0.48	14.47	46.05	-44.63
23/11/09–05/08/11	0.11	4.78	0.14	10.92	24.85	-28.77
08/08/11–20/09/12	0.03	4.34	0.88	12.33	27.57	-19.60
21/09/12–26/03/14	-0.16	1.66	-1.69	31.64	9.30	-14.45
27/03/14–15/04/16	-0.11	1.43	-2.40	26.66	7.35	-13.56
Slovenia						
14/12/07–17/05/10	0.33	7.11	1.17	17.37	55.96	-36.10
18/05/10–16/09/11	0.29	3.82	1.19	10.51	20.76	-11.78
19/09/11–17/12/12	0.10	2.99	0.12	13.94	14.47	-18.83
18/12/12–18/03/14	-0.11	2.49	1.11	13.84	14.38	-11.03
19/03/14–15/04/16	-0.11	1.49	0.10	13.96	8.76	-8.33

Table 4: CDS spread return moment estimates during each regime for CESEE countries.

Country-Regime	Mean	SD	Skewness	Kurtosis	Max	Min
Estonia						
08/10/08–20/11/09	-0.10	5.84	1.56	18.12	42.17	-28.39
23/11/09–03/10/12	-0.13	3.25	-0.02	12.59	20.07	-19.31
04/10/12–15/04/16	-0.04	1.16	0.02	27.38	9.41	-8.92
Latvia						
08/10/08–20/11/09	0.12	5.46	0.34	10.86	30.50	-24.67
23/11/09–06/01/11	-0.29	2.64	-0.43	7.72	12.22	-14.11
07/01/11–12/09/12	-0.06	2.27	0.73	8.05	11.35	-10.42
13/09/12–06/06/14	-0.10	1.57	-2.61	42.88	10.63	-17.02
09/06/14–15/04/16	-0.10	1.88	-2.90	44.89	11.68	-21.62
Lithuania						
08/10/08–20/11/09	0.05	5.73	0.98	24.55	43.08	-38.53
23/11/09–06/01/11	-0.13	3.38	-0.28	9.18	15.68	-18.23
07/01/11–03/09/12	-0.05	2.28	0.10	7.10	10.80	-10.11
04/09/12–05/06/14	-0.10	1.40	-0.27	17.50	10.65	-8.88
06/06/14–15/04/16	-0.10	1.59	-5.67	96.75	9.53	-23.02

Table 5: CDS spread return moment estimates during each regime for the Baltic countries.

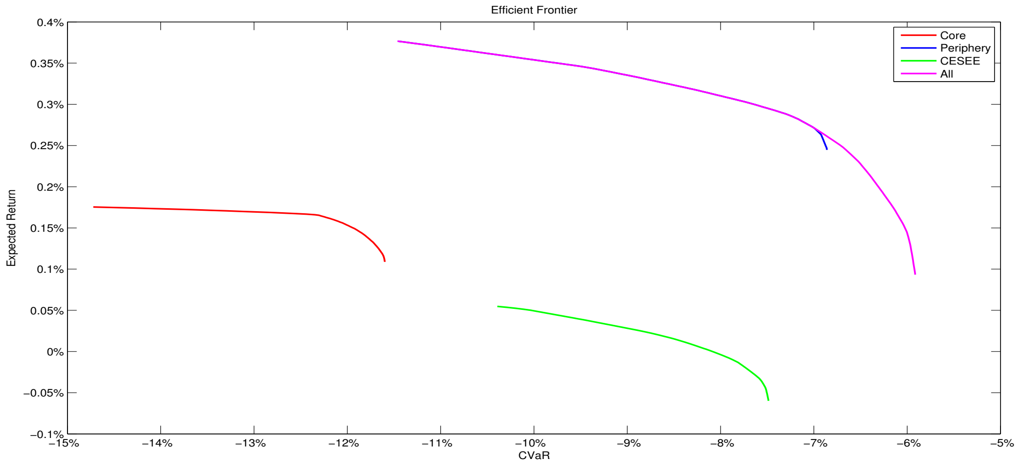
Country-Regime	Mean	SD	Skewness	Kurtosis	Max	Min
Regime I. Turbulent						
France	0.16	5.58	0.46	7.77	36.10	-21.51
Germany	0.05	5.26	-0.26	7.69	24.92	-28.86
Italy	0.18	6.16	-0.63	13.03	33.86	-45.20
Ireland	0.38	5.32	0.19	8.26	25.37	-33.11
Cyprus	0.23	3.85	0.48	34.32	26.24	-33.65
Portugal	0.33	6.15	-1.44	19.61	27.42	-59.00
Spain	0.24	6.30	-0.30	10.01	33.85	-41.75
Regime II. Crisis						
France	-0.08	5.44	-0.07	6.06	19.18	-23.39
Germany	-0.07	5.91	-0.03	8.72	31.87	-37.14
Italy	0.05	4.96	0.17	5.28	22.20	-21.37
Ireland	-0.24	3.68	-0.86	12.08	17.48	-22.15
Cyprus	0.29	4.28	3.16	37.75	40.68	-27.07
Portugal	-0.03	3.88	-0.02	7.99	21.28	-21.00
Spain	-0.02	4.68	-0.14	5.57	21.66	-19.35
Regime III. Post-crisis						
France	-0.10	3.64	0.48	11.86	25.36	-18.49
Germany	-0.07	4.96	0.01	10.79	25.76	-25.07
Italy	-0.10	3.40	0.52	8.75	23.39	-16.15
Ireland	-0.14	1.88	-1.06	19.65	11.43	-18.08
Cyprus	-0.15	3.13	0.45	42.14	33.46	-29.74
Portugal	-0.07	3.58	0.77	7.36	18.95	-14.28
Spain	-0.15	3.66	0.59	8.79	25.10	-18.41

Table 6: CDS spread return statistics for eurozone core and periphery countries under the common regimes.

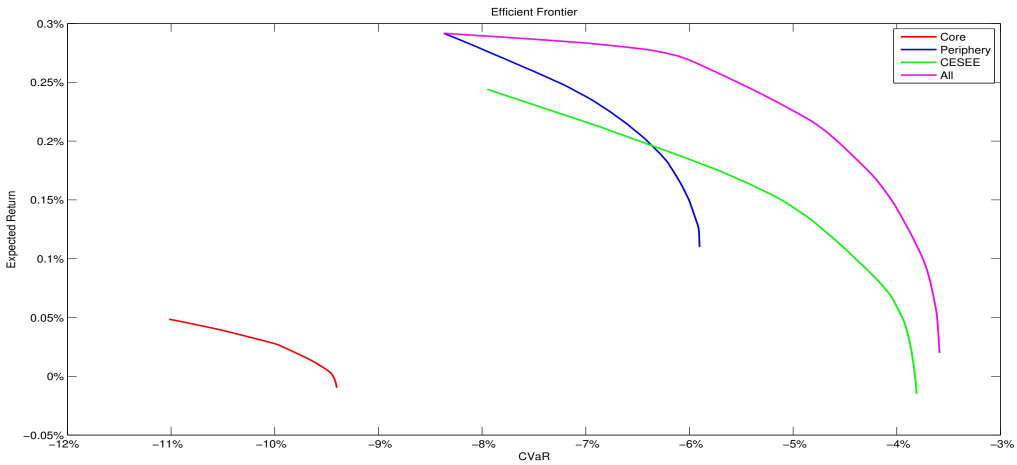
Country-Regime	Mean	SD	Skewness	Kurtosis	Max	Min
Regime I. Turbulent						
Bulgaria	-0.06	4.60	0.86	12.07	30.41	-22.31
Croatia	0.00	4.63	0.08	10.01	23.24	-24.89
Czech Republic	0.04	6.76	0.24	17.99	46.81	-46.26
Hungary	0.05	5.07	1.86	21.29	46.23	-24.05
Poland	-0.01	6.42	-0.87	32.07	53.24	-65.39
Romania	-0.02	4.81	0.98	22.80	39.67	-33.93
Slovakia	-0.01	6.53	0.41	17.21	46.05	-44.63
Slovenia	-0.00	6.14	1.30	22.23	55.96	-36.10
Estonia	-0.23	5.05	1.22	18.58	42.17	-28.39
Latvia	-0.07	4.38	0.39	14.33	30.50	-24.67
Lithuania	-0.04	4.80	0.86	27.50	43.08	-38.53
Regime II. Crisis						
Bulgaria	-0.10	2.91	-0.62	10.42	11.92	-20.94
Croatia	0.05	2.37	0.30	10.85	17.06	-13.54
Czech Republic	-0.07	2.97	1.17	16.19	21.74	-17.92
Hungary	-0.01	2.58	-0.02	5.68	10.59	-11.66
Poland	-0.06	3.03	-0.14	6.07	10.77	-13.58
Romania	-0.08	2.50	0.05	7.09	11.39	-11.91
Slovakia	0.05	4.19	0.70	10.62	27.57	-19.60
Slovenia	0.24	3.37	0.65	10.91	17.75	-18.83
Estonia	-0.08	2.60	0.60	19.60	20.07	-19.31
Latvia	-0.15	2.31	-0.09	12.40	11.35	-17.02
Lithuania	-0.14	2.19	-0.11	7.50	10.80	-10.11
Regime III. Post-crisis						
Bulgaria	0.03	1.73	2.91	42.79	17.54	-10.47
Croatia	-0.00	1.30	0.17	15.09	8.38	-8.00
Czech Republic	-0.03	1.33	0.48	39.93	13.97	-12.41
Hungary	-0.09	2.02	1.05	60.05	26.01	-23.29
Poland	-0.01	2.19	0.77	36.19	20.72	-21.26
Romania	-0.06	1.25	1.27	20.71	12.27	-5.82
Slovakia	-0.09	1.36	-1.40	30.05	9.30	-13.56
Slovenia	-0.11	1.83	1.00	17.66	14.38	-11.03
Estonia	0.01	1.07	1.60	31.29	9.41	-7.33
Latvia	-0.05	1.57	-3.10	57.57	11.68	-21.62
Lithuania	-0.04	1.45	-4.08	88.89	10.65	-23.02

Table 7: CDS spread return statistics for CESEE and Baltic countries under the common regimes.

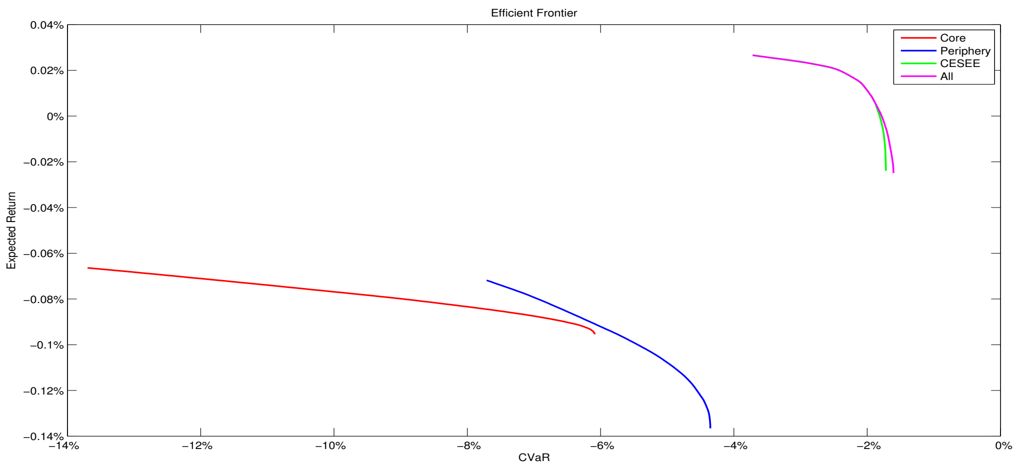
C Appendix: Efficient frontiers under different regimes



(a) Regime I. Turbulent

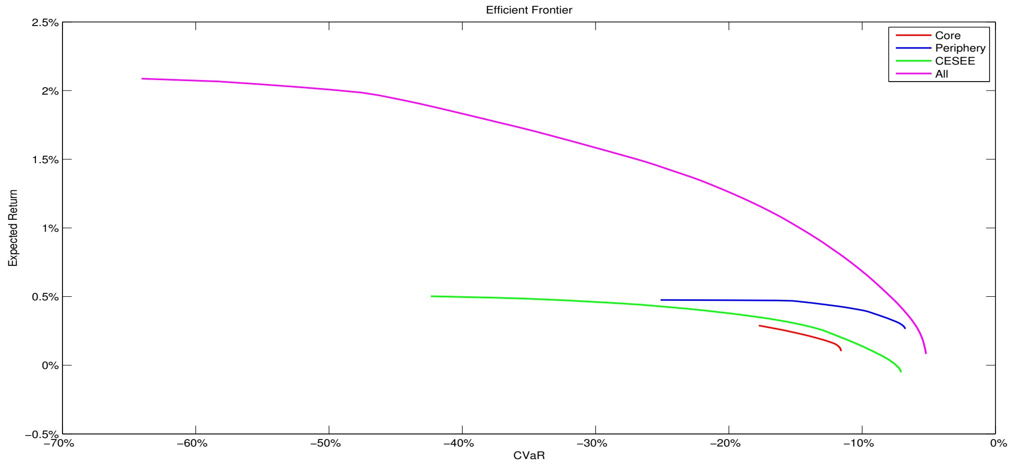


(b) Regime II. Crisis

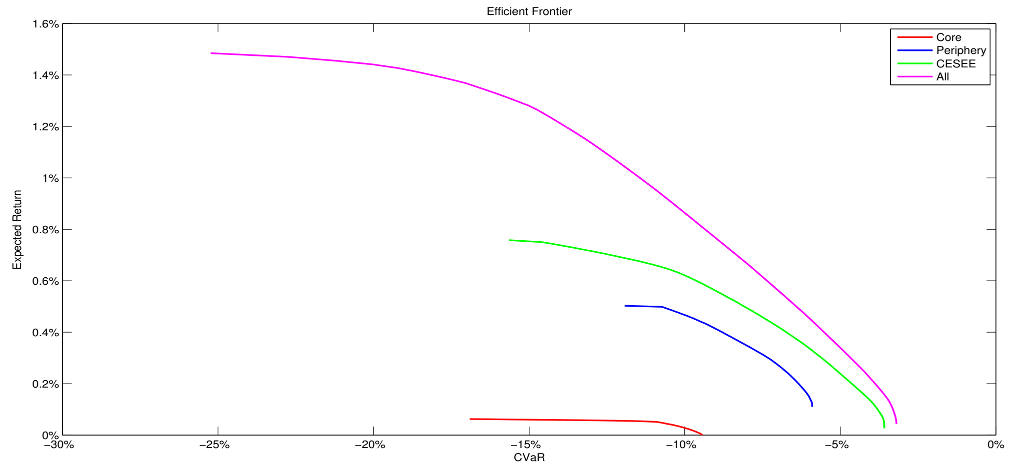


(c) Regime III. Post crisis

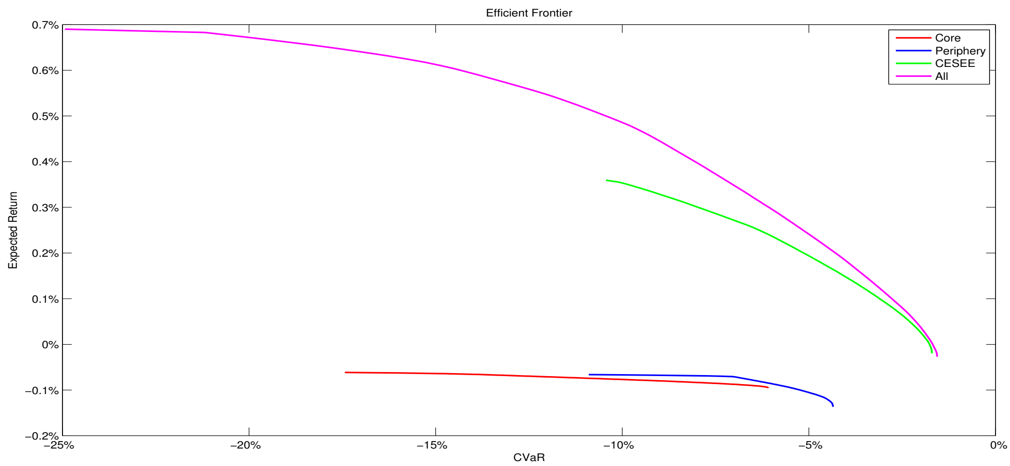
Figure 12: The relative position of efficient frontiers for each country group using strategy L is regime dependent.



(a) Regime I. Turbulent



(b) Regime II. Crisis



(c) Regime III. Post crisis

Figure 13: The relative position of efficient frontiers for each country group using strategy LS is regime dependent.

References

C. Alexander and A. Kaeck. Regime dependent determinants of credit default swap spreads. *Journal of Banking and Finance*, 32(6):1008–1021, 2008.

P. Augustin, M.G. Subrahmanyam, D. Y. Tang, and S. Q. Wang. Credit default swaps: a survey. *Foundations and Trends in Finance*, 9(1–2):1–196, 2014.

P. Augustin, M.G. Subrahmanyam, D. Y. Tang, and S. Q. Wang. Credit default swaps: Past, present, and future. *Annual Review of Financial Economics*, 8:175–196, 2016.

J. Bai and P. Perron. Evaluating and testing linear models with multiple structural changes. *Econometrica*, 66(1):47–78, 1998.

J. Bai and P. Perron. Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1):1–22, 2003.

A. Consiglio, M. Tumminello, and S.A. Zenios. Pricing sovereign contingent convertible debt. Working Paper 16-05, The Wharton Financial Institutions Center, University of Pennsylvania, Philadelphia. Available at `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2813427`, 2016.

R. Cont and Y-H. Kan. Statistical modeling of credit default swap portfolios. Available at SSRN: `http://ssrn.com/abstract=1771862`, April 2011.

R. Cont, R. Deguest, and G. Scandolo. Robustness and sensitivity analysis of risk measurement procedures. *Quantitative Finance*, 10(6):593–606, 2010.

S. Criado, L. Degabriel, M. Lewandowska, S. Linden, and P. Ritter. Sovereign CDS report. Official report DG COMP, DG ECFIN and DG MARKT, European Commission, Brussels, 2010.

European Union. Regulation (EU) of the European Parliament and the Council on short selling and certain aspects of credit default swaps. Regulation EU 236/2012, Offical Journal of the European Union, 2012.

F. Fabozzi, R. Giacometti, and N. Tsuchida. Factor decomposition of the eurozone sovereign CDS spreads. *Journal of International Money and Finance*, 65:1–23, July 2016.

K. Giesecke, B. Kim, K. Kim, and G. Tsoukalas. Optimal credit swap portfolios. *Management Science*, 60(9):2291–2307, 2014.

J.D. Hamilton. *Time Series Analysis*. Princeton University Press, Princeton, NJ, 1994.

M.R. Holmer and S.A. Zenios. The productivity of financial intermediation and the technology of financial product management. *Operations Research*, 43(6):970–982, 1995.

IMF. *A New Look at the Role of Sovereign Credit Default Swaps*, volume Global Financial Stability Report, chapter 2, pages 57–92. International Monetary Fund, Washington, DC., April 2013.

N. Jobst, G. Mitra, and S.A. Zenios. Integrating market and credit risk: A simulation and optimization perspective. *Journal of Banking and Finance*, 30:717–742, 2006.

P. Krokhmal, J. Palmquist, and S. Uryasev. Portfolio optimization with conditional Value-At-Risk objective and constraints. *Journal of Risk*, 4(2):11–27, Winter 2002.

F.A. Longstaff, J. Pan, L.H. Pedersen, and K.J. Singleton. How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics*, 3:75–103, April 2011.

J.M. Mulvey and H. Vladimirou. Stochastic network programming for financial planning problems. *Management Science*, 38(11):1642–1664, 1992.

F. Packer and C. Suthiphongchai. Sovereign credit default swaps. *BIS Quarterly Review*, pages 79–88, December 2003.

Z. Qu and P. Perron. Estimating and testing structural changes in multivariate regressions. *Econometrica*, 75:459–502, March 2007.

R. Rockafellar and S. Uryasev. Conditional Value-at-Risk for general loss distributions. *Journal of Banking and Finance*, 26:1443–1471, 2002.

R.T. Rockafellar and S. Uryasev. Optimization of conditional Value–at–Risk. *Journal of Risk*, 2(3):21–41, 2000.

P. Schönbucher. *Credit Derivatives Pricing Models: Models, Pricing and Implementation.* Wiley Finance, New York, NY, 2003.

W.F. Sharpe. The Sharpe ratio. *The Journal of Portfolio Management*, 21(1):49–58, 1994.

R. Stulz. Credit default swaps and the credit crisis. *Journal of Economic Perspectives*, 24(1):73–92, 2010.

S.A. Zenios. *Practical Financial Optimization. Decision making for financial engineers.* Blackwell-Wiley Finance, Malden, MA, 2007.

S.A. Zenios, M.R. Holmer, R. McKendall, and C. Vassiadou-Zeniou. Dynamic models for fixed-income portfolio management under uncertainty. *Journal of Economic Dynamics and Control*, 22(10):1517–1541, 1998.

W. T. Ziemba. The symmetric downside risk Sharpe ratio. *Journal of Portfolio Management*, 32(1):108–122, 2005.