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Modeling Corporate CDS Spreads Using Markov Switching Regressions

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Abstract: This paper investigates the determinants of the European iTraxx corporate CDS index considering a large set of explanatory variables within a Markov switching model framework. The influence of financial and economic variables on CDS spreads are compared using linear, two, three, and four-regime models in a sample post-subprime financial crisis up to the COVID-19 pandemic. Results indicate that four regimes are necessary to model the CDS spreads. The fourth regime was activated during the COVID-19 pandemic and in high volatility periods. Further, the effect of the covariates differs significantly across regimes. Brent and term structure factors became relevant after the outbreak of the COVID-19 pandemic.

Keywords: corporate CDS index; Markov switching; Bayesian econometrics

JEL Classification: C11; C24; G12

1 Introduction

The credit default swap (CDS) is the most used derivative in credit risk hedging. According to Vogel, Bannier, and Heidorn (2013), CDS spreads have become a valuable indicator of the creditworthiness of the reference entity, as well as a barometer of health for the broad credit markets since this information is generated from banks' trading and hedging activity. Indeed, an increase in CDS spreads can be interpreted as a higher demand for credit protection, as financial institutions perceive a higher risk of these loans. Moreover, credit ratings tend to be slow to change. Therefore, a deep understanding of the CDS spreads determinants is crucial for both policymakers interested in preserving the stability of the financial system and for financial insiders interested in managing credit and financial risks.

Although previous studies have analyzed the factors impacting CDS spreads under a constant and regime-switching parameter framework, this paper extends the literature on the CDS spread determinants in four directions and provides new evidence on the functioning of CDS markets. First, we update the (Alexander et al. 2008) analysis in a new time range, from the 2007–2009 crisis to the COVID-19 pandemic. Second, we extend the (Collin-Dufresne, Goldstein, and Martin 2001) analysis by applying a Markov switching regression model and allowing for non-linear behaviors in the CDS spreads. Third, we introduce a Bayesian Markov switching model, which naturally accounts for parameter uncertainty and makes inference more tractable. Fourth, we extend Yau and Holmes (2011) by applying different priors distributions that induce variable selection and parameter shrinkage towards a common mean effect across regimes.

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We provide evidence of four volatility regimes in the CDS time series: low, normal, high, and extreme volatility regimes. The extreme volatility regime is mainly, but not only, associated with the economic impact of the COVID-19 pandemic, extending evidence in (Gormsen and Koijen 2020) for European and US stock and bond market returns and in (Onali 2020) for VIX index, among others (Baker et al. 2020). compare the COVID-19 period to past diseases (Spanish flu and Ebola), finding that the COVID-19 pandemic has caused a stock market impact never seen before, with levels of volatility comparable to the ones of the 2007–2009 crisis. Our analysis confirms it for CDS spreads and captures the COVID-19 dynamics with a separate regime. Finally, the impact of covariates differs significantly across regimes, and a linear specification tends to over-select variables, causing possible misinterpretation of the relevance of macroeconomic variables.

The remainder of this work is organized as follows. Section 2 reviews the main literature on CDS determinants. Section 3 provides a description of the credit risk measures and of the CDS determinants used in the empirical analysis. Section 4 introduces the Makov-Switching regression (MSR) framework for modeling credit risk. Section 5 reports the estimation results. Section 7 concludes.

2 Literature on CDS Determinants

Multiple papers have studied the CDS market inefficiencies and the arbitrage opportunities employing statistical models, i.e. statistical arbitrage. The main findings in the CDS literature are that several CDS markets are not efficient and present significant autocorrelated dynamics and time-varying efficiency. Byström (2005) analyzes separately seven Europe iTraxx sub-indexes (i.e. industrials, autos, energy, TMT, consumers, senior financials, and sub-ordinated financials), finding positive autocorrelation and that some firm-specific information is embedded first in stock prices respect to CDS prices. Byström (2006), considering the same sub-indexes, tries to exploit this inefficiency by applying a simple trading strategy, which generates profits before considering transaction costs. In a similar way, Avino and Nneji (2014) consider the Financial Seniors and Non-Financials indexes. They build a trading strategy based on linear and non-linear prediction models and generate results similar to the ones in (Byström 2006). In addition, they find that return autocorrelation is significant only during low volatility periods, while in volatile ones, it ceases to exist. Senso et al. (2017) analyzes several sovereign CDS markets employing a permutation entropy approach in combination with an independence test, highlighting the fact that they have different degrees of time-varying efficiency and that efficiency also changes depending on the region to which the index refers.

The linkage between CDS and credit spreads has also been studied. Blanco, Brennan, and Marsh (2005) discover the evidence of cointegration for all the U.S. firms where CDS and bonds market-priced risk equally on average. Conversely, in Europe, there is little evidence of cointegration for the entities involved in the research. Nevertheless, the cointegration test partially failed due to possibly different contract specifications between Europe and the U.S. (i.e. cheapest-to-deliver option). In light of the reasons given above, a full understanding of CDS spread determinants is of interest to financial actors and policymakers. The former are interested in an efficient risk assessment, while the latter aim at the financial stability of the economic system. Moreover, CDS spreads have become a powerful price discovery tool (Blanco, Brennan, and Marsh 2005; Lee, Naranjo, and Velioglu 2018; Schreiber et al. 2012). Their findings are united by the fact that the CDS market leads stock and bond markets and equity market volatility.

There is a large literature on credit risk pricing, divided into structural and reduced-form models. If firm-specific information is used, the model considered is structural. On the other hand, reduced form models assume less detailed information about the firm, and the estimation of the model relies on market data (Jarrow and Protter 2004).

The first structural model, which has been extended in several different directions, is given by Merton (1974) (see also Black and Scholes 1973). The model assumes that the dynamics of a firm's value can be described using stochastic differential equations and finds that the risk premium depends on three variables: the firm's volatility, the present value of the financial leverage, and the risk-free rate (used in the calculus of the present value).

The structural approach has been criticized by (Collin-Dufresne, Goldstein, and Martin 2001), among others. The authors compare the explained variance by two multiple regression models, one estimated just considering firm-specific variables and the other adding macroeconomic factors. The result is that the second one outperforms the first one in terms of credit spread explained. Nevertheless, most variation is due to a common unknown systematic factor. Abid et al. (2006) estimate a multiple regression model finding that macroeconomic variables have greater explanatory power than firm-specific ones. Similar results are achieved by Fu, Li, and Molyneux (2020), Ericsson, Jacobs, and Oviedo (2009) and Blanco, Brennan, and Marsh (2005). In particular, this latter finds that macroeconomic variables, such as interest rates, term structure, equity market returns, and market volatility, have a larger and immediate impact on credit spreads. In contrast, CDS spreads are more sensitive to firm-specific variables. However, considering the long-run arbitrage-based equivalence, they are equally sensitive to macro and firm-specific factors. In any case, theoretical determinants, which are used in structural models, must be considered to analyze credit risk.

Zhang, Zhou, and Zhu (2009) analyze changes in single-name CDS spreads considering both jump risk effects and firm-specific variables, explaining an additional 14 %–18 % of spread variation. Kajurová (2014) analyzes the CDS spread determinants by applying linear regression models in the periods before, during, and after the subprime crisis. The explanatory power of the variables considered changes upon the economic conditions. Similarly, Annaert et al. (2013) apply a rolling linear regression analysis of the bank CDS spreads and find that the explanatory variables' sign changes given the economic conditions. The authors suggest that for efficient policy decisions, policymakers should not rely only on financial institutions' spreads to monitor their credit risk but also on liquidity and business cycle factors.

Extending the literature on the application of regime-switching models for macro-financial variables, Alexander et al. (2008) introduce a regime-dependent framework to analyze daily corporate CDS spread determinants of different CDS indexes, see also Ang and Bekaert (2002a,b). They apply a two-state MSR and find that the influence of theoretical determinants has a regime-dependent behavior and that the unknown systematic factor found in Collin-Dufresne, Goldstein, and Martin (2001) is due to the regime-specific behavior of CDS spreads.

Building on this, Riedel, Thuraisamy, and Wagner (2013) apply a Markov switching model to estimate the credit cycle and study the spread determinants in emerging sovereign debt markets daily. In their findings, credit spreads are characterized by a varying influence of the spread determinants. Ma et al. (2018) examine short-term sovereign CDS spreads considering country-specific and global variables, finding that the significance of the considered variables changes according to a regime-switching dynamic. Sabkha, de Peretti, and Hmaied (2019) analyze the non-linear relationship between oil shocks and sovereign CDS spreads. They find that during the high volatility regime, sovereign debt is sensitive to these shocks. Avino and Nneji (2014) compare Markov switching and linear models for predicting the CDS index changes. They found that linear models have better predictive power than non-linear models. Chan et al. (2014) study CDS spreads determinants in a Markov switching framework for investment-grade and high-yield companies. They use a large set of macroeconomic and firm-specific variables and find that the impact of monetary policy is significant in both tranquil and turbulent regimes. Guidolin, Melloni, and Pedio (2019) estimate a Markov switching vector error correction model and find evidence of non-linearities in the adjustment mechanism between corporate and CDS spreads.

Therefore, compared to the existing literature, this paper includes a larger set of determinants of the CDS spread, which are discussed in detail in the following section, it includes an updated period that includes the COVID-19 shock, and it allows for regime-dependent effects of the covariates in more than two regimes under different shrinkage priors.

3 European CDS Markets

3.1 Credit Risk Measures

A single-name credit default swap (CDS) is a contract in which two parties are involved. On the one hand, the protection buyer pays periodic fixed payments to the counterparty until the CDS expires due to a credit event or maturity. On the other hand, the protection seller, who receives the fixed payments and, as the credit event occurs, must buy the bonds owned by the counterparty at their face value. The fixed spread represents the compensation for the insurance in case of a credit event. Conversely, multi-name CDSs, which consider multiple entities, are contracts that include CDS indexes, basket products, and CDS tranches. In this case, the credit event of a single reference entity does not terminate the contract. So, a CDS is an insurance contract against the risk of default of the underlying reference entity. The total value of the bonds that can be sold is known as the notional principal, and the settlement can be physical if the protection buyer delivers the bonds to the protection seller, or cash settlement in which just the difference between the face value and the value of the bonds at the time of default is paid. A key aspect is the aforementioned credit event, usually defined as either bankruptcy or restructuring of debt.

Its origin dates back to the mid-90s. In 1994, Morgan created CDSs to reduce credit risk exposure extending its loan capability. The CDS was written with the European Bank of Reconstruction and Development (EBRD), and the deal aimed to allow the bank to offer a line of credit of USD 5 billion to Exxon, maintaining balance sheet flexibility (Vogel, Bannier, and Heidorn 2013). Over the years, CDSs have become more and more complex instruments and saw a steady increase in volumes and notional outstanding, reaching the peak of USD 60 trillion before the subprime crisis.

In 2008, the insurance giant AIG was one of the main CDS sellers. The use of those derivatives at that time was to concentrate risk rather than disperse it, pushing AIG on the brink of collapse as the subprime bubble burst (see for example Krishnamurthy 2010).

Given their primary role in the 2007–2009 crisis and the fact that they are traded only on over-the-counter (OTC) markets, causing a lack of transparency, has forced the regulator to standardize the market, introducing central counterparties (CCPs) to erase the counterparty risk (Aldasoro 2018). These changes were introduced for European markets in 2009 with the small-bang protocol, including two main features: the standardized coupon rates and the quoting conventions.

This paper focuses on the European iTraxx corporate index (labeled $\Delta iTraxx$ in Equations and Tables). Each considered index has a 5-year maturity because deemed as the most liquid in the market. The Markit iTraxx is a family of Asian, European, and Emerging Market credit default swap indexes. The iTraxx group was formed by the merger in 2004 of JP Morgan and Morgan Stanley Trac-X indexes and the ones created by Deutsche Bank, ABN Amro, and IBoxx (i.e. iBoxx CDS indexes). In November 2007, Markit acquired both CDX and iTraxx, and by 2011 Markit owned and managed most of the CDS indexes. They aim to transfer risk more efficiently rather than using multiple single-name CDSs. The Markit iTraxx Europe Main index[1] trades with maturities of 3, 5, 7, and 10 years. It is an equally-weighted index composed of the 125 most liquid listed companies, with a weight of 0.8 % for each constituent firm's CDS (icmagroup.org). Every six months the index is updated, rolling out the firms that either defaulted/merged or did not respect the liquidity parameter, and including new ones.[2]

3.2 Explanatory Variables

We review the explanatory variables to be used to predict the CDS spread. Several multi-factor analyses from a firm-specific (microeconomic) and market-specific (macroeconomic) perspective have been used to study the determinants of credit default swap (CDS) spreads. In this paper, we take a macro perspective since we work with aggregate indices. Table 1 lists a short selection of studies following a macro approach and the market-specific factors considered, skipping firm-specific variables.

In our analysis, the first three variables are derived from the theory related to structural models: the firm's debt-to-equity ratio, the firm's operation volatility, and the risk-free interest rate (Merton 1974). The proxy for the debt-to-equity component is represented by returns of three different equally-weighted portfolios composed of the stocks of the firms included in the iTraxx indexes (iTraxx Main index, iTraxx Financial Seniors index, and iTraxx Non-financials index). There are some cases in which stock price series are not available. To

1 Also known as "the Main".

2 On 21st September and 21st March of each year.

Table 1: List of relevant papers on CDS spread, including the type of econometric models and macroeconomic variables applied.

Paper	Model	Variables
Collin-Dufresne, Goldstein, and Martin (2001)	Linear	Interest rate level (10 y yield) and slope (10 y – 2 y yields), volatility index, implied volatility jumps, bond market liquidity, small-big and high-low equity market factors
Alexander and Kaeck (2008)	2-regimes Markov switching	Equity market returns, volatility index, first and second principal components of the term structure of yields
Avramov, Jostova, and Philipov (2007)	Linear	Equity return momentum, volatility index, price-to-book ratio, interest rate level (5 y yield) and slope (5 y – 3 m yields), financial leverage, Fama and French factors: HML, SMB and MKT
Zhang, Zhou, and Zhu (2009)	Linear	Equity market returns, volatility index, interest rate level (3 m yield) and slope (10 y – 3 m yields)
Ericsson, Jacobs, and Oviedo (2009)	Linear	Default swap spreads, volatility index, firm leverage, interest rate level (10 y yield)
Sabhka et al. (2019)	FIAPARCH and SETAR	Equity market returns, volatility index, government bond yields, and debt, Inflation, consumer confidence index, oil prices, oil volatility
Galil et al. (2014)	Linear	Interest rate level (5 y yield) and slope (10 y – 2 y yields), equity market returns, volatility index, Fama and French factors: HML, SMB, and MKT, Pastor and Stambaugh liquidity factor, industrial production, unexpected inflation, corporate spread (Baa-Aaa rates)

solve that problem, we drop them from the dataset, decreasing the number of stocks included in that portfolio (Δ*StockMain*, Δ*StockNon-financials*, Δ*StockFinancialSeniors*). The single firm's volatility is proxied by aggregate volatility. Hence, we include the VStoxx index, composed of the implied volatility of options with Euro Stoxx 50 as the underlying asset (ΔV). As a risk-free rate, we use the Euro swap rates with maturities from 1 to 30 years and compute the first two factors – level and slope – from the principal component analysis (PCA) applied to the different assets ($PC1$, $PC2$).

Following Byström (2006), Byström et al. (2005) and Avino and Nneji (2014), we also consider the lagged value of the iTraxx spreads. As suggested by Annaert et al. (2013) and Collin-Dufresne, Goldstein, and Martin (2001), we also include liquidity and macroeconomic indicators. As liquidity, we follow Collin-Dufresne, Goldstein, and Martin (2001) and apply the difference between the 10-year Euro swap rate and the 10-year Bund yield (Δliq). The first macroeconomic indicator is Brent oil returns (Δ*Brent*). Oil shocks are a common macroeconomic indicator analysts use to assess the economy's health. Sabkha, de Peretti, and Hmaied (2019) find that in high volatility regimes, sovereign credit volatility becomes highly sensitive to these shocks. The second macroeconomic variable is the Baltic Dry Index (Δ*BDI*), which is a measure of economic activity available at a daily frequency. The index was created in 1985 and is measured by the intersection between the demand for shipping capacity and the supply of dry bulk carriers. It refers mainly to the shipping of dry raw materials (steel, concrete, food, and so on), so it does not consider oil across oceans. It is seen by financial analysts as an efficient indicator of economic activity. Lin, Chang, and Hsiao (2019) analyze the BDI spillover effects, finding that the BDI drives movements of equity, commodity, and currency markets.

Table 2: Summary statistics. The second column reports the sample means; the third one the standard deviations; the fourth and fifth skewness and kurtosis; the last two ones the minimum and maximum values of each series.

Variables	Mean	St dev	Skew	Kurt	Min	Max
ΔiTraxx main	−0.015	2.505	0.801	21.81	−21.32	25.24
ΔiTraxx non-financials	−0.011	2.103	2.676	46.89	−15.27	29.95
ΔiTraxx financial seniors	−0.024	3.137	0.776	23.50	−32.07	31.05
ΔVstoxx	0.007	1.804	1.130	16.83	−11.90	17.76
ΔStock main (%)	0.021	1.161	−1.172	19.59	−13.19	9.020
ΔStock non-financials (%)	0.006	1.094	−1.604	22.93	−13.60	7.710
ΔStock financial seniors (%)	0.010	1.592	−0.881	17.08	−15.65	12.52
Δliq	0.000	0.016	−0.333	8.262	−0.100	0.090
ΔBrent (%)	−0.018	2.587	−0.298	18.07	−24.40	21.02
ΔBDI	−0.012	32.37	0.736	12.68	−194.0	281.0
$\Delta PC1$	−0.070	0.164	0.430	5.664	−0.680	0.910
$\Delta PC2$	0.000	0.030	0.531	9.862	−0.170	0.280

We use daily observations between the 22nd of November 2013 and the 1st of September 2020 for a total of 1704 observations. The dependent and independent variables are considered in differential terms to obtain stationary time series.[3]

Before the estimation results, some preliminary statistics are calculated and collected in Table 2. All variables, except interest rate ones, have high volatility, kurtosis, and skewness measures, which differ from the Normal distribution references. Minimum and maximum values are also spread over large intervals. These stylized facts call for the use of nonlinear and heteroscedastic models.

4 A Bayesian Markov-Switching Model for CDS

We propose a Markov switching model to deal with the European CDS. We extend the linear regression approach in Alexander et al. (2008) by adding more variables and assuming the relationship varies across regimes dynamically over time.

4.1 A Markov-Switching Regression Model

Let y_t, $t = 1, \dots, T$ be a sequence of observations for a CDS measure (dependent variable) and $\mathbf{x}_t = (x_{1t}, x_{2t}, \dots, x_{nt})'$, the observations for the set of n covariates discussed in the previous section. We consider the following time-varying regression model.

$$y_t = \beta_0(s_t) + \beta_1(s_t)x_{1t} + \cdots + \beta_n(s_t)x_{nt} + \varepsilon_t, \quad \varepsilon_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2(s_t)) \tag{1}$$

where $\beta_0\,(s_t)$ is the time-varying intercept; $\beta_j\,(s_t)$, $l = 1, \dots, n$, the time-varying coefficients and $\sigma^2\,(s_t)$ the time-varying volatility. We assume the parameters are driven by a hidden Markov-chain process s_t, with K-states and constant transition probabilities $\mathbb{P}(s_t = j|s_{t-1} = i) = p_{ij}$, with $i, j \in \{1, \dots, K\}$.

Let us introduce the allocation variable $\xi_{kt} = \mathbb{I}(s_t = k)$ indicating the regime to which the current observation y_t belongs to, where $\mathbb{I}(x)$ is the indicator function that takes value 1 if $x = 0$, and 0 otherwise. We assume the time-varying parameters are.

3 Data are downloaded from Bloomberg, investing.com, and stoxx.com.

$$\beta_j(s_t) = \sum_{k=1}^{K} \xi_{kt}\beta_{jk}, \quad j = 0,\dots,n, \qquad \sigma^2(s_t) = \sum_{k=1}^{K} \xi_{kt}\sigma_k^2. \tag{2}$$

Define $\mathbf{z}_t' = \boldsymbol{\xi}_t' \otimes (1, \mathbf{x}_t')$ with $\boldsymbol{\xi}_t = (\xi_{1t},\dots,\xi_{Kt})'$, $\mathbf{x}_t = (x_{1t},\dots,x_{nt})'$, and $\beta = (\beta_1',\dots,\beta_K')'$ with $\beta_k = (\beta_{0k}, \beta_{1k},\dots,\beta_{nk})$. The allocation variables are used to write the random-coefficient regression model in equation (1) as a linear regression model.

$$y_t = \mathbf{z}_t'\beta + \varepsilon_t, \quad \varepsilon_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \gamma_t),$$

with heteroskedastic effects $\gamma_t = \boldsymbol{\xi}_t'\boldsymbol{\sigma}^2$ with $\boldsymbol{\sigma}^2 = (\sigma_1^2,\dots,\sigma_K^2)'$ (Frühwirth-Schnatter 2006).

The inference for latent variable models is a difficult task since the likelihood function is not tractable. Thus, we choose a Bayesian inference approach that allows us to make more accessible the inference task thanks to data augmentation (see Tanner et al. 1987) and Monte Carlo simulation methods. Another advantage of the Bayesian approach is that it naturally accounts for parameter uncertainty in the analysis. In our data-augmentation framework, the joint posterior distribution of parameters and latent variables given the observations is

$$\pi(\boldsymbol{\theta}, \boldsymbol{\xi}_{1:T} | \mathbf{y}_{1:T}) \propto \prod_{t=1}^{T} (2\pi\gamma_t)^{-\frac{1}{2}} \exp\left\{ -\frac{(y_t - \mathbf{z}_t'\beta)^2}{2\gamma_t} \right\} \prod_{k=1}^{K}\prod_{j=1}^{K} p_{jk}^{\xi_{jt-1}\xi_{kt}} \pi(\boldsymbol{\theta}). \tag{3}$$

4.2 Prior Specification

The description of the model is completed by specifying the prior distributions $\pi(\boldsymbol{\theta})$ for the parameters $\boldsymbol{\theta} = (\beta', \boldsymbol{\sigma}^{2\prime}, \mathbf{p})'$ where $\mathbf{p} = (\mathbf{p}_{1\cdot},\dots,\mathbf{p}_{K\cdot})'$, $\mathbf{p}_{k\cdot} = (p_{k1},\dots,p_{kK})$. For all the regime-specific volatilities σ_k^2 and transition probabilities $\mathbf{p}_{k\cdot}$ we assume Gamma and Dirichlet prior distributions, respectively, that are

$$\sigma_k^2 \overset{i.i.d.}{\sim} \mathcal{IG}(a,b)\mathbb{I}_{\mathcal{A}}(\sigma_k^2), \quad k = 1,\dots,K$$

$$\mathbf{p}_{k\cdot} \overset{i.i.d.}{\sim} \mathcal{D}(\delta_1,\dots,\delta_K), \quad k = 1,\dots,K.$$

The set of regime-identification constrains $\mathcal{A} = \{\boldsymbol{\sigma}^2 \in \mathbb{R}_+^K,\ s.t.\ \sigma_1^2 < \sigma_2^2 < \dots < \sigma_K^2\}$ allows us to interpret the first and Kth state of the chain as low and high volatility states, respectively.

In the case of the regression coefficients β_k, the main model assumes a Normal distribution

$$\beta \sim \mathcal{N}_{K(n+1)}(\boldsymbol{\nu}_\beta, \Upsilon_\beta), \tag{4}$$

where the hyperparameters $\boldsymbol{\nu}_\beta$ and Υ_β refer to the prior mean and variance–covariance matrix, respectively. In this paper, we also consider alternative priors, Laplace and Horseshoe prior, to induce variable selection (1 level prior), and shrinkage toward a common mean (2 level priors).

The different priors are presented in Table 3. The Normal prior with only 1-level is equivalent to (4), where the hyperparameters are assumed to be fixed. Under this prior structure, the same level of ridge shrinkage is applied to all the coefficients in all states. On the other hand, different prior variances are allowed under the Laplace (Bayesian LASSO) and the Horseshoe prior with 1-level, which induces a variable selection shrinkage across explanatory variables and states. In other words, these two prior distributions are characterized by a higher density close to zero and thicker tails, which *a priori* corresponds to the case of only a few relevant coefficients (Carvalho, Polson, and Scott 2010; Park et al. 2008). The global shrinkage is governed by the parameter λ^2, whose prior is inverse gamma (Gamma distribution $\mathcal{G}(r,\delta)$ with expected value $r\delta$) for the Horseshoe (Laplace) case.

In the third column of Table 7, the same prior distributions are considered, but with 2 levels extending Yau and Holmes (2011) to Markov-switching models. In particular, the prior mean $\boldsymbol{\nu}$ is not fixed anymore, but a vector to be estimated, which can be interpreted as the average effect of the explanatory variables across states,

Table 3: Alternative prior distributions for the regression coefficients.

Prior	1-Level prior	2-Level prior
Normal	(*ii*) $\boldsymbol{v}_\beta$ and Υ_β are fixed. (*ii*) $\boldsymbol{v}_\beta = \mathbf{0}$.	(i') Υ_β is fixed. (ii') $\boldsymbol{v}_\beta = \left(\mathbf{1}'_K \otimes \boldsymbol{\alpha}'\right)'$, where $\boldsymbol{\alpha} = (\alpha_0, \ldots, \alpha_n)'$. (iii') $\boldsymbol{\alpha} \sim \mathcal{N}_{n+1}(\mathbf{0}, R)$, where R is fixed.
Laplace	(*i*) $\boldsymbol{v}_\beta$ is fixed. $\boldsymbol{v}_\beta = \mathbf{0}$. (*ii*) $\Upsilon_\beta = \text{diag}(\omega_{01}, \omega_{21}, \ldots, \omega_{n1}, \omega_{02}, \ldots, \omega_{nK})$. (*iii*) $\omega_{pk} \mid \lambda^2 \overset{i.i.d.}{\sim} \mathcal{G}(1, 2/\lambda^2)$. (iv) $\lambda^2 \sim \mathcal{G}(r, \delta)$.	(i') $\Upsilon_\beta = \text{diag}(\omega_{01}, \omega_{21}, \ldots, \omega_{n1}, \omega_{02}, \ldots, \omega_{nK})$. (ii') $\omega_{pk} \mid \lambda^2 \overset{i.i.d.}{\sim} \mathcal{G}\left(1, 2/\lambda_p^2\right)$. (iii') $\lambda_p^2 \overset{i.i.d.}{\sim} \mathcal{G}(r, \delta)$. (iv') $\boldsymbol{v}_\beta = \left(\mathbf{1}'_K \otimes \boldsymbol{\alpha}'\right)'$, where $\boldsymbol{\alpha} = (\alpha_0, \ldots, \alpha_n)'$. (v') $\boldsymbol{\alpha} \sim \mathcal{N}_{n+1}(\mathbf{0}, R)$, where R is fixed.
Horseshoe	(*i*) $\boldsymbol{v}_\beta$ is fixed. $\boldsymbol{v}_\beta = \mathbf{0}$. (*ii*) $\Upsilon_\beta = \text{diag}(\omega_{01}, \omega_{21}, \ldots, \omega_{n1}, \omega_{02}, \ldots, \omega_{nK})$. (*iii*) $\omega_{pk} = \lambda^2 \tau_{pk}$. (iv) $\tau_{pk} \mid \eta_{qr} \overset{i.i.d.}{\sim} \mathcal{IG}(1/2, 1/\eta_{pk})$; $\eta_{pk} \overset{i.i.d.}{\sim} \mathcal{IG}(1/2, 1)$. (v) $\lambda^2 \sim \mathcal{IG}(1/2, 1/\xi)$; $\xi \sim \mathcal{IG}(1/2, 1)$.	(i') $\Upsilon_\beta = \text{diag}(\omega_{01}, \omega_{21}, \ldots, \omega_{n1}, \omega_{02}, \ldots, \omega_{nK})$. (ii') $\omega_{pk} = \lambda^2 \tau_{pk}$. (iii') $\tau_{pk} \mid \eta_{qr} \overset{i.i.d.}{\sim} \mathcal{IG}(1/2, 1/\eta_{pk})$; $\eta_{pk} \overset{i.i.d.}{\sim} \mathcal{IG}(1/2, 1)$. (iv') $\lambda_p^2 \sim \mathcal{IG}(1/2, 1/\xi_p)$; $\xi_p \overset{i.i.d.}{\sim} \mathcal{IG}(1/2, 1)$. (v') $\boldsymbol{v}_\beta = \left(\mathbf{1}'_K \otimes \boldsymbol{\alpha}'\right)'$, where $\boldsymbol{\alpha} = (\alpha_0, \ldots, \alpha_n)'$. (vi') $\boldsymbol{\alpha} \sim \mathcal{N}_{n+1}(\mathbf{0}, R)$, where R is fixed.

The subscript p stands for the explanatory variable $p \in \{0, \ldots, n\}$ and k the regime k in $k \in \{1, \ldots, K\}$..

$\boldsymbol{\alpha}$. The prior distribution on $\boldsymbol{\alpha}$ is assumed to be normal. As in 1-level, Laplace and Horseshoe prior allow for different shrinkage levels, but in this case, towards the average effect across states. Therefore, while, in the first column, the coefficients are shrunk toward zero identifying the most significant explanatory marginal effects, the second column prior structures aim at identifying coefficients deviating more from $\boldsymbol{\alpha}$ and potentially leading the heterogeneity between states. It is important to notice that in 2-level priors, there is no global shrinkage parameter but a shrinkage by explanatory variable, $\lambda_p^2,\ \ p = 0, \ldots, n$.

4.3 Posterior Approximation

Samples from the joint posterior distribution of the parameters and the allocation variables are obtained by sampling iteratively from the full conditional distributions of $\beta, \boldsymbol{\sigma}^2, \mathbf{p}_{k\cdot}$ and $\boldsymbol{\xi}_{1:T}$. The full conditional distribution of β is the following Gaussian distribution.

$$f(\beta | \mathbf{y}_{1:T}, \boldsymbol{\xi}_{1:T}, \boldsymbol{\sigma^2}, \mathbf{p}) \propto \mathcal{N}_{(n+1)K}(\bar{\boldsymbol{\mu}}_\beta, \bar{\Upsilon}_\beta),$$

where $\bar{\boldsymbol{\mu}}_\beta = \bar{\Upsilon}_\beta \left(\sum_{t=1}^T \mathbf{z}_t \gamma_t^{-1} y_t + \Upsilon_\beta^{-1} \boldsymbol{v}_\beta \right)$ and $\bar{\Upsilon}_\beta = \left(\sum_{t=1}^T \mathbf{z}_t \gamma_t^{-1} \mathbf{z}'_t + \Upsilon_\beta^{-1} \right)^{-1}$. This also applies for the alternative priors in Table 3, see Appendix A for the additional steps of these priors. The full conditional distribution of $\boldsymbol{\sigma}^2$ is a product of gamma distribution truncated on the set of identifying restrictions

$$f(\boldsymbol{\sigma}^2 | \mathbf{y}_{1:T}, \boldsymbol{\xi}_{1:T}, \beta, \mathbf{p}) \propto \prod_{k=1}^K \mathcal{G}a(\bar{a}_k/2, \bar{b}_k/2) \mathbb{I}_{\mathcal{A}}(\boldsymbol{\sigma}^2) \tag{5}$$

where $u_t = y_t - \beta_{0k} - \mathbf{x}'_t \beta_k$, $\bar{a}_k = a_k + T_k/2$ and $\bar{b}_k = b_k + \sum_{t \in \mathcal{T}_k} u_{kt}^2/2$ with $T_k = \text{Card}(\mathcal{T}_k)$. The transition probabilities $\mathbf{p}_{k\cdot}$ has the following Dirichlet full conditional distribution,

$$f(\mathbf{p}_{k\cdot} | \mathbf{y}_{1:T}, \xi_{1:T}, \beta, \boldsymbol{\sigma}^2, \mathbf{p}_{-k}) \propto \mathcal{D}(\delta_1 + N_{k1}, \ldots, \delta_K + N_{kK}),$$

where $\mathbf{p}_{-k} = (\mathbf{p}_{1\cdot}, \ldots, \mathbf{p}_{k-1\cdot}, \mathbf{p}_{k+1\cdot}, \ldots, \mathbf{p}_{K\cdot})'$ and $N_{kj} = \sum_{t=1}^T \mathbb{I}(s_t - j) \mathbb{I}(s_{t-1} - k)$ counts the number of transitions of the chain from the state k to the state j.

The joint posterior distribution of the hidden Markov process is obtained by iterating the prediction and updating steps for $t = 1, \ldots, T$,

$$p(\xi_t = \iota_j | \mathbf{y}_{1:t-1}, \xi_{1:t-1}) = \sum_{i=1}^{K} p(\xi_t = \iota_j | \xi_{t-1} = \iota_i) p(\xi_{t-1} = \iota_i | \mathbf{y}_{1:t-1}) \tag{6}$$

$$p(\xi_t | \mathbf{y}_{1:t}, \xi_{1:t}) \propto p(\xi_t | \mathbf{y}_{1:t-1}) p(y_t | \mathbf{x}_t, \xi_t), \tag{7}$$

and evaluating the smoothing probabilities $t = T, T - 1, \ldots, 1$,

$$p(\xi_t = \iota_j | \mathbf{y}_{1:T}) \propto \sum_{i=1}^{K} p(\xi_t = \iota_j | \xi_{t+1} = \iota_i, \mathbf{y}_{1:t}) p(\xi_{t+1} = \iota_i | \mathbf{y}_{1:T}), \tag{8}$$

where $p(\xi_t = \iota_j | \xi_{t-1} = \iota_i) = p_{ij}$, with ι_m the mth column of the identity matrix and $p\,(y_t | \mathbf{x}_t, \xi_t)$ is the density of y_t given $s_t = k$, that is the density $\mathcal{N}\left(\beta_k' \mathbf{x}_t, \sigma_k^2\right)$ evaluated at y_t (see Hamilton 1994, ch. 22). The smoothing probabilities are used in the forward-filtering backward sampling (FFBS) algorithm to sample jointly the allocation variables (see Frühwirth-Schnatter 2006, ch. 11–13).

5 Empirical Analysis

5.1 Preliminary Analysis

As an initial step of our analysis, we update the linear regression model of Alexander et al. (2008) with the enlarged set of variables described in the previous section and the updated sample from October 2011 to April 2020. We apply Bayesian inference with weak diffuse priors. We compute the marginal likelihood and compare it to the MSRs. However, since we use weak diffuse priors, the results are qualitatively similar to OLS estimation.

The first row of Table 4 reports the estimates of the linear regression. Seven over eight regressors differ significantly from zero, and only the Baltic index does not. Precisely, the VStoxx index has a positive sign, as theory suggests: higher uncertainty increases CDS spreads. The equity index is also significant with the predicted sign as in Collin-Dufresne, Goldstein, and Martin (2001) and Alexander et al. (2008). Therefore, upside movements in stock returns cause a downside movement in CDS spreads. Oil shocks have been studied only considering sovereign CDS spreads, revealing their significance in explaining sovereign CDS changes during turmoil periods (Sabkha, de Peretti, and Hmaied 2019). They can be seen as a world economic health indicator, and we find that they also have a relevant explanatory power for corporate CDS spreads, affecting them negatively. Changes in corporate bond liquidity are significant. During the time considered, several monetary policies have been undertaken by the ECB to tackle both the impact of the sovereign debt crisis (i.e. APP) and the Coronavirus impact. Such policies have pushed the interest rates below 0 %, and this may be influenced by the investors' risk-aversion, reallocating their investments toward stock markets.

The first principal component extracted from the Euro swap curve impacts the corporate CDS spreads significantly and with the expected sign, meaning that upward shifts of the term structure imply a decrease in CDS spreads. The result is consistent with the evidence provided by Alexander et al. (2008). The second principal component is also significant, as opposed to the original analysis of Alexander et al. (2008). Therefore, changes in the yield curve's slope positively affect CDS spreads. The sensitivity of CDS spreads to changes in interest rates can also be seen empirically as in Figure 1 pagina §. In fact, after the announcement of each TLTRO, that is policy actions to invert the slope, it follows a decline in the iTraxx main index. Finally, the first lag has a negative impact on CDS spreads.

To end this section, following Alexander et al. (2008), we apply a rolling Chow test to check the parameter's stability. Results indicate strong instability in the estimated parameters, and we interpret this as evidence of a non-linear relationship. Therefore, in the next section, the regression model will be extended by considering non-linearities and a regime-dependent behavior of CDS spreads.

Table 4: Estimation results for iTraxx Main.

s_t	β_0	$\Delta iTraxx_{t-1}$	ΔV_t	$\Delta Stock_t$	Δliq_t	$\Delta Brent_t$	ΔBDI_t	$PC1_t$	$PC2_t$	σ^2	ML	DIC
Panel A: Linear regression model												
1	0.007	**−0.066**	**0.120**	**−1.393**	**6.379**	**−0.055**	0.007	**−0.006**	**0.031**	2.614	−3236.5	6495.2
Panel B: Markov switching regression model: 2-regimes												
1	−0.045	0.024	**0.298**	**−0.951**	2.022	−0.006	0.006	**−0.004**	0.008	0.955	−2810.0	5640.2
2	0.225	**−0.140**	−0.036	**−1.810**	0.077	−0.105	−0.015	−0.015	0.076	12.353		
Panel C: Markov switching regression model: 3-regimes												
1	−0.049	0.020	**0.310**	**−0.936**	1.811	−0.008	0.006	−0.003	0.009	0.923	−2789.5	5593.7
2	1.819	−0.792	0.947	−0.104	0.021	0.101	**1.540**	0.075	−0.044	1.491		
3	0.118	−0.073	−0.089	**−1.773**	0.494	−0.044	−0.084	**−0.034**	0.039	8.423		
Panel D: Markov switching regression model: 4-regimes												
1	**−0.063**	0.017	**0.339**	**−0.876**	1.635	−0.009	−0.002	−0.002	0.013	0.830	−2761.9	5540.0
2	0.596	0.270	**3.559**	−0.741	−0.015	−0.109	2.355	−0.032	**−1.478**	1.076		
3	**2.732**	−0.168	0.741	−0.671	−0.028	**1.535**	0.340	0.083	**1.428**	1.679		
4	0.104	−0.063	−0.107	**−1.744**	0.824	−0.024	0.001	**−0.033**	−0.005	4.429		
Panel E: Markov switching regression model: 4-regimes, subsample 2013–2019												
1	**−0.121**	−0.026	0.163	**−0.761**	0.462	−0.006	−0.025	−0.033	0.002	0.424	−2379.0	4764.0
2	−0.032	0.008	**0.365**	**−1.121**	1.425	−0.025	0.007	−0.003	0.004	1.074		
3	1.309	1.294	1.026	−0.607	0.015	1.015	1.223	0.024	0.893	1.728		
4	0.397	−0.104	0.086	**−1.745**	0.370	−0.047	0.004	−0.023	0.008	6.698		

Estimation results for the linear regression model ($s_t = 1$); the MS k-regimes ($s_t = k$ for the kth regime) applied to the iTraxx main. Bold numbers indicate zero is not included in the 95 % credible interval. The column ML reports the (log) marginal likelihood for the different specifications and the column DIC gives the Deviance information criterion. The last panel repeats the analysis for the sub-sample 2013–2019.

5.2 Markov-Switching Regression Analysis of the CDS Spreads Determinants

Table 4 reports the estimates of the Markov switching models with 2, 3, and 4 regimes. Compared to the linear model, zero is included in the 95 % credible intervals in several parameter posteriors suggesting that only a few covariates are relevant. In several cases, signs of the coefficients differ across regimes. VStoxx has a positive sign in the first regime and a negative sign in the second regime in the model with two regimes or a negative in the third regime of the 3-regime model and the fourth regime of the 4-regime model. Similar sign changes can be observed for the Brent, BDI, and the two PC variables. In the case of liquidity, it is not significant in any of the regimes or models. Therefore, the Markov-switching models reduce the explanatory variables' contribution drastically, and instability plays a more important role.

Before continuing the analysis of parameter values and regime outputs, we compare the four specifications to see which shall be preferred. The last two columns in Table 4 show that the 4-regimes specification has the highest (log) marginal likelihood value and the lowest Deviance information criterion (DIC).[4] The marginal likelihood is based on a recursive approximation of the complete likelihood using the Hamilton filter as in Kadhem, Hewson, and Kaimi (2016)). The DIC penalizes complex models based on the estimation of the number of parameters. Despite this, our larger model is preferred. The difference is sizeable with the linear model, and the

4 Considering the hierarchical priors, such as 2-level Laplace and Horseshoe, and the number of latent variables, such as the state indicators and prior variances of the coefficients, Celeux et al. (2006), Kadhem, Hewson, and Kaimi (2016) suggest the DIC for model selection.

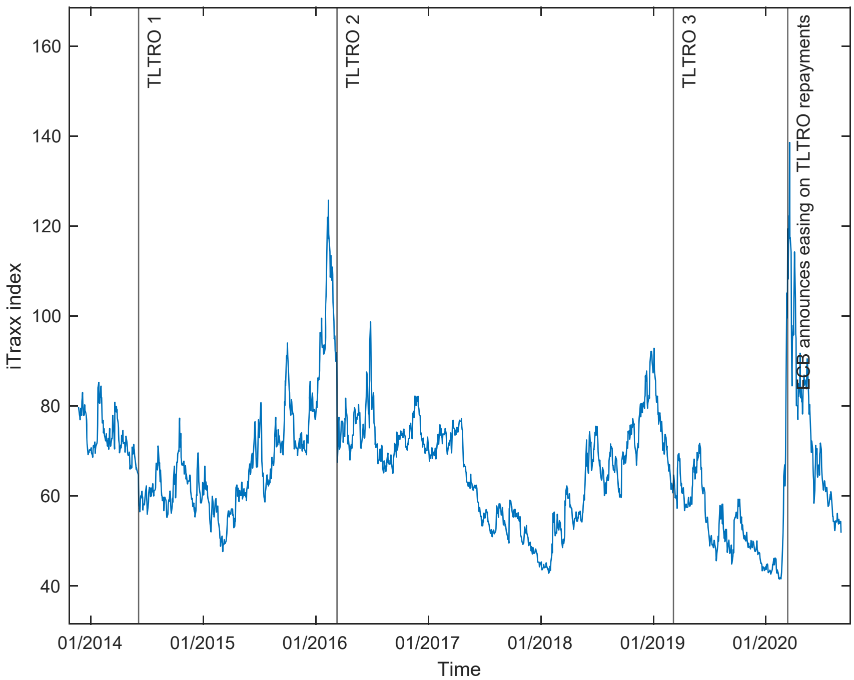

Figure 1: This figure represents the corporate iTraxx main index reaction to ECB announcements. In particular, from left to right, TLTRO 1, TLTRO 2, TLTRO 3, and the more recent announcement of policies to tackle the COVID-19 pandemic recession (ecb.europa.eu).

values of the 2 and 3-regimes models are also inferior. Therefore, we describe results for the Markov switching 4-regimes model and refer to Figures 6, 7, 8 and 9 in Appendix B.1 for results on the 2 and 3-regimes models.

Returning to parameter estimates, implied volatility and stock prices are significant with the expected sign in regime 1, the regime with lower volatility (the mean posterior estimate of σ^2 is equal to 0.830 which is lower than the value of 2.614 for the linear regression model). In the second regime, the one with moderate volatility (the estimate of σ^2 is equal to 1.076), the implied volatility, and the term structure slope are significant. Both posterior mean values are higher than in the linear regression model and the other two regimes. In the third regime, the one with moderate-high volatility (the estimate of σ^2 is equal to 1.679), the Brent and the term structure slope have a significant positive impact. In the fourth regime, stock and the level of the slope curve are significant, both with a negative coefficient.

No covariate is consistently significant in all four regimes. The implied volatility is relevant only during periods of low uncertainty (regimes 1 and 2) with a positive coefficient, while stock prices are significant in the extreme scenarios of high and low volatility, in both cases having a negative effect on CDS spreads. The effect of the slope of the term structure (PC2) is only significant in two of the four regimes (regimes 2 and 3), but also with different signs (negative and positive, respectively). Hence, these results indicate that macroeconomic variables can explain part of the CDS spread variations, as suggested by Annaert et al. (2013), Collin-Dufresne, Goldstein, and Martin (2001), but more importantly, monitoring the changes in regimes is essential to have a better understanding of the role of each of these indicators, given that regime transitions can even imply a change in the relationship with CDS spreads.

Volatility estimates in regimes 1, 2, and three are lower than the ones for the linear regression model, whereas the estimate in the fourth regime is almost twice as large. See also Figure 2 for the full posterior distribution.

Figure 3 shows the estimated hidden states (top) and the log-volatility process (bottom). The first regime with lower volatility is the most probable over time, in particular in the years 2017–2018. The other three regimes are less persistent, given that they capture exceptional events. In some cases, the second regime anticipates or follows the third regime. The COVID-19 pandemic is mainly associated with the fourth regime, and also other

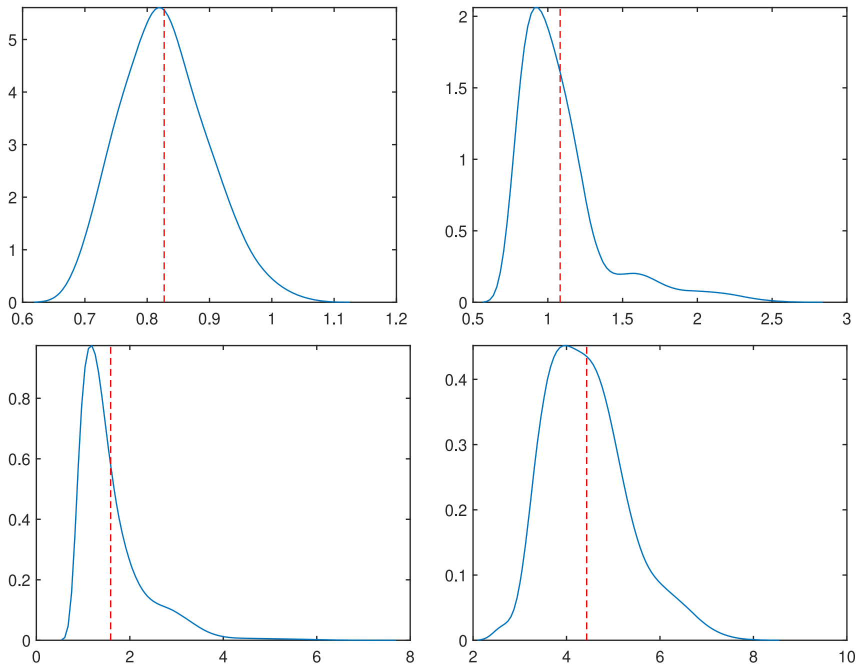

Figure 2: Estimates of the regime-specific variance σ_k^2 (dashed lines) and their posterior distributions (solid lines) in the 4-regimes model fitted to Δ*iTraxx*. From top-left to bottom-right, the posterior distribution in regimes from 1 to 4.

periods, such as the beginning of 2016, Volatility estimates in regimes 1, 2, and three are lower than the ones for the linear regression model, whereas the estimate in the fourth regime is almost characterized by high volatility in the series. So, the fourth regime is necessary to fit the extremely high volatility that few significant regressors cannot capture alone. The red line in the bottom plot reports the estimated conditional volatility in the 4-regime model, that is $\widehat{V(y_t|s_t,\theta)}$, which is constant within each regime. The Bayesian approach allows for incorporating the parameter uncertainty and the explanatory variables in the volatility process. Comparing the conditional volatility with the integrated volatility processes $\widehat{V(y_t)}$ (bottom, black line), we find that explanatory variables have an important role in explaining the volatility changes within each regime.

Finally, we investigate the impact of the COVID-19 pandemic by ending the data in December 2019 and dropping the pandemic period from the sample. Our results confirm the best model is the 4-regime MSR (see Panel E of Table 4). The results confirm that stock returns and volatility are significant, whereas Brent and term structure factors become relevant only when including the pandemic sample period.

5.3 Sensitivity to Alternative Prior Specifications

Alternative priors are applied to the regression coefficients to identify the most important determinants of the CDS main index and those covariates effects that significantly differ across regimes. However, also the variance parameters have an essential role in the regime heterogeneity. This is evidenced by Table 5 where two special cases of Model (1) are considered: (a) $\beta_{p1} = \ldots = \beta_{pK}$ for $p = 0, \ldots, n$ (MSR, only variance), and (b) $\sigma_1^2 = \ldots = \sigma_K^2$ (MSR, only coefficients). Both special cases perform better than the Linear Regression Model (LRM), indicating that the two of them contribute to the regime heterogeneity, particularly the former. Indeed, the constant coefficients under case (b), still differ from LRM (see Table 8).

The most important coefficients are identified using Laplace and Horseshoe prior with 1 and 2 levels in Table 7. Under these two priors with 1-level, the most significant determinants are the positive effect of the VStoxx index (ΔV_t) during periods of low volatility (regimes 1 and 2) and the equity index ($\Delta Stock_t$), which consistently decrease CDS spreads in all regimes. Compared to Table 4, $\Delta Brent_t$, ΔBDI_t and $PC2_t$ are not relevant anymore. During periods of high volatility (regime 3), the proxy of risk-free rate, $PC1$, becomes relevant, having a negative

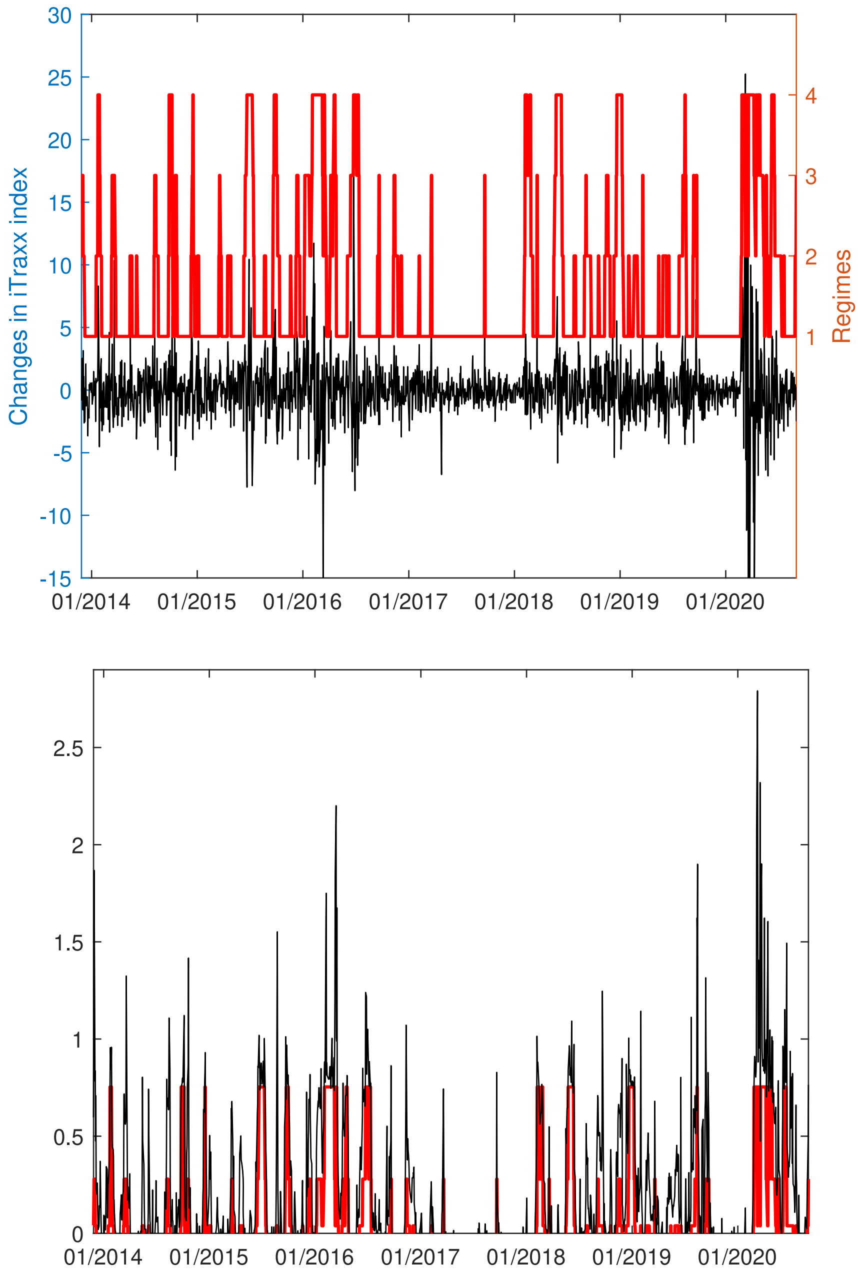

Figure 3: Top: Time series of the $\Delta iTraxx$ (black solid) and the estimated maximum a posteriori (MAP) hidden regime by date for the 4-regime model (red stepwise). Bottom: Unconditional (black line) and conditional (red line) log-volatility process.

Table 5: Comparison between MSR special cases.

Case	ML	DIC
LRM	−3236.5	6495.2
MSR	−2761.9	5540.0
MSR (only variance)	−2768.6	5555.2
MSR (only coefficients)	−2839.3	5702.0

The MSRs assume 4-regimes applied to the iTraxx main. The column ML reports the (log) marginal likelihood for the different specifications and the column DIC gives the Deviance information criterion.

effect. In the case of 2-level priors, the estimates of the prior variances of the coefficients Υ_β in Table 9 indicate that the factors that differ the most between regimes are the liquidity Δliq_t in regime three and equity $\Delta Stock_t$ in regime 1.

Table 6: Estimation results.

S_t	β_0	$\Delta iTraxx_{t-1}$	ΔV_t	$\Delta Stock_t$	Δliq_t	$\Delta Brent_t$	ΔBDI_t	$PC1_t$	$PC2_t$	σ^2	ML	DIC
						iTraxx non-financials						
						Panel A: Linear regression model						
1	−0.019	**0.080**	**0.462**	**−0.456**	**9.064**	**−0.107**	−0.008	**−0.011**	**0.049**	2.610	−3235.2	6496.6
						Panel B: Markov switching regression model: 2-regimes						
1	**−0.063**	**0.206**	**0.423**	**−0.074**	**2.370**	**−0.023**	−0.009	**−0.004**	0.015	0.434	−2417.6	4855.7
2	0.102	0.062	**0.427**	**−0.724**	0.312	**−0.160**	−0.015	**−0.041**	0.102	10.666		
						Panel C: Markov switching regression model: 3-regimes						
1	**−0.073**	**0.224**	**0.359**	**−0.071**	1.868	−0.001	−0.004	**−0.003**	0.011	0.273	−2309.2	4651.6
2	−0.007	**0.162**	**0.567**	−0.082	1.793	**−0.101**	0.002	**−0.017**	0.043	1.502		
3	0.253	0.051	0.237	**−1.276**	0.094	−0.183	−0.127	**−0.044**	0.112	23.498		
						Panel D: Markov switching regression model: 4-regims						
1	**−0.071**	**0.215**	**0.345**	−0.057	1.637	0.002	−0.004	**−0.004**	0.006	0.246	−2271.6	4586.1
2	−0.039	**0.135**	**0.770**	**−0.150**	1.927	**−0.093**	−0.003	−0.003	**0.040**	0.965		
3	−0.145	**0.218**	0.066	**−0.564**	0.143	0.089	−0.020	**−0.062**	−0.025	1.466		
4	0.270	0.038	**0.461**	**−1.017**	0.067	**−0.354**	−0.062	−0.035	−0.006	25.380		
						iTraxx non financial seniors						
						Panel A: Linear regression model						
1	−0.023	**0.035**	**0.329**	**−1.018**	5.874	**−0.105**	0.004	**−0.008**	**0.047**	4.606	−3719.1	7458.7
						Panel B: Markov switching regression model: 2-Regimes						
1	**−0.087**	**0.191**	**0.414**	**−0.738**	**3.326**	0.002	0.002	−0.003	0.001	1.645	−3264.9	6550.6
2	0.416	**−0.099**	**0.281**	**−1.227**	−0.093	**−0.260**	−0.003	**−0.037**	0.172	20.825		
						Panel C: Markov switching regression model: 3-Regimes						
1	**−0.101**	**0.193**	**0.437**	**−0.686**	**3.431**	0.002	−0.002	−0.002	−0.004	1.461	−3237.7	6471.9
2	1.108	−0.161	**1.855**	−0.181	0.151	−0.998	0.988	−0.116	0.190	2.293		
3	0.371	0.007	0.154	**−1.264**	0.477	−0.096	0.005	**−0.044**	0.139	12.519		
						Panel D: Markov switching regression model: 4-Regimes						
1	−0.062	**0.318**	**0.290**	**−0.516**	2.451	0.020	−0.028	−0.002	0.011	0.604	−3154.9	6342.0
2	−0.091	**0.160**	**0.462**	**−0.831**	2.365	−0.007	0.020	−0.003	0.005	2.320		
3	1.817	−0.617	1.084	−0.170	−0.105	−0.821	2.090	−0.030	0.159	3.754		
4	0.371	−0.023	0.158	**−1.259**	0.366	−0.134	−0.167	**−0.068**	0.117	16.256		

Estimation results for the linear regression model ($s_t = 1$); the MS k-regimes ($s_t = k$ for the kth regime) applied iTraxx Non-Financials (top panel) and to the iTraxx Non-Financial Services (bottom panel). Bold numbers indicate zero is not included in the 95 % credible interval. The column ML reports the (log) marginal likelihood for the different specifications and the column DIC gives the Deviance information criterion.

6 Non-financials and Financial Seniors Indexes

In this section, we consider two sub-indices of the iTraxx: iTraxx Non-Financials and iTraxx Financial Seniors. The study of differences and similarities in the dynamics of the two indexes is relevant for achieving a better understanding of credit risk contagion among different sectors of the economy. This topic is highly relevant for investors interested in portfolio diversification and policymakers aiming at financial stability.

Table 6 reports a similar analysis to that of the iTraxx Main. In both cases, the 4-regimes model is preferred, following the marginal likelihood and the DIC. We discuss the detailed results for the two series separately. Several coefficients are significant when estimating the iTraxx Non-Financial: coefficients for volatility, stock market returns, the first and second factors, and lag of the index, and their signs are all economically plausible.

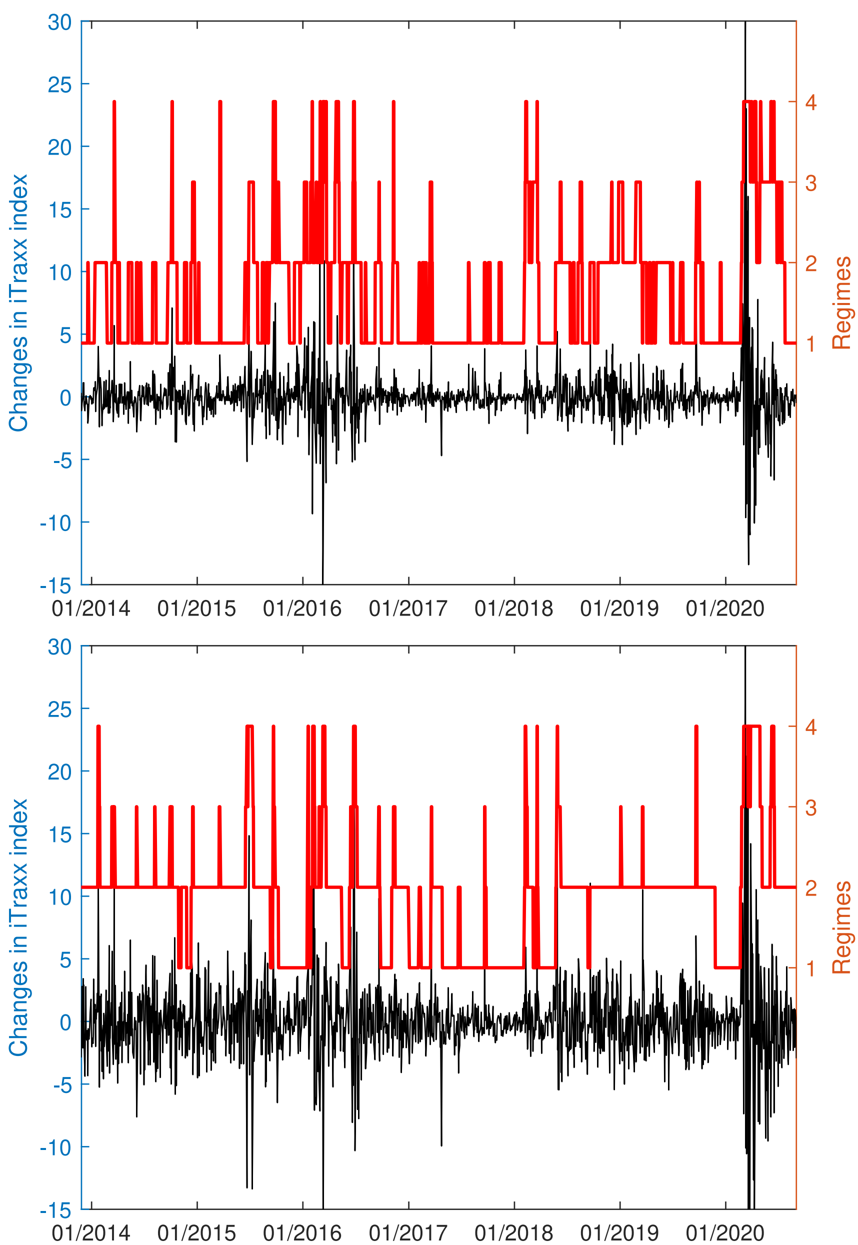

Figure 4: Time series of the Δ*iTraxxNon-Financial* (top, black solid) and Δ*iTraxxFinancialSeniors* (bottom, black solid) and the estimated hidden regimes for the 4-regime model (red stepwise).

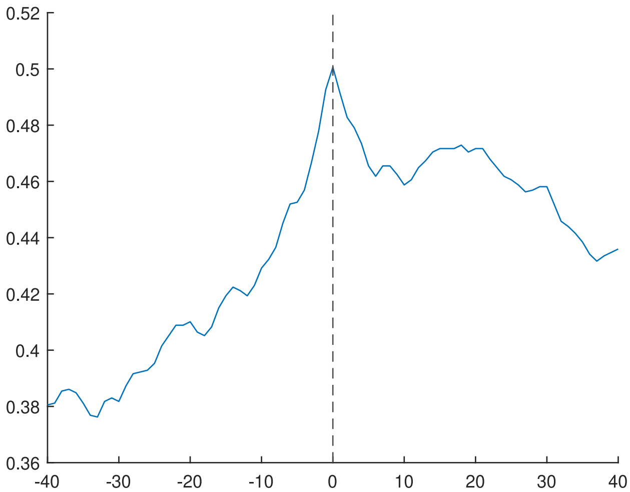

Figure 5: Concordance statistic (vertical axis) at various lags given by the value k in (6) (horizontal axis) between Δ*iTraxxNon-Financial* and Δ*iTraxxFinancialSeniors* estimated regimes.

Their significance varies substantially across regimes, and no variable is significant in all four regimes. Other variables keep the same level of significance.

Standard deviations vary across regimes, with the one in the fourth regime very large. The top panel of Figure 4 shows the second regime is more often selected for the iTraxx Non-Financial than the main index. This is associated with a lower frequency of the first regime. The fourth regime is again associated with the COVID-19 crisis and other high-volatility periods.

The results are qualitatively similar for iTraxx Financial Seniors: only implied volatility, stock market returns, and the term structure level have a significant impact. For the third regime, no covariate has a significant contribution, whereas, in the fourth regime, stock returns and the first factor are significant, with evidence similar to the main iTraxx index. Residual volatility estimates are more significant for the second and third regimes than those for the main iTraxx index, but not for the first one. Moreover, the value in the fourth regime is smaller than that for the iTraxx Non-Financial. The bottom panel of Figure 4 shows a different regime pattern for the iTraxx Financial Seniors than the other two indices: the second regime is more often selected; the fourth regime is important in the COVID-19 crisis but also in 2016. The third regime is the one less often selected. The dynamic of the Financial Seniors index is similar to the main index, since 60 % of the sample period they are in the same regime. In contrast, the Non-Financial and Financial Seniors are in the same regime 43 % of the time. The concordance statistics at lag k between the prevalent regime of the Financial and Non-Financial indexes is defined as follows.

$$C_k = \frac{1}{T-2\tau}\sum_{t=\tau+1}^{T-\tau} \mathbb{I}\left(s_{t-k}^{FIN} - s_t^{NON-FIN}\right) \tag{9}$$

with $k = -\tau, -\tau + 1, \ldots, 0, \ldots, \tau - 1, \tau$. The statistic is presented in Figure 5 and its asymmetry suggests a leading-lagging relationship between the two sectors. Precisely, the Financial Seniors index seems to lead the Non-Financial index considering the higher value of the concordance statistics for positive values of k (Financial Seniors index leading) than for negative values of k (Financial Seniors index lagging). The higher value is when the statistic is computed contemporaneously ($k = 0$).

7 Conclusions

This paper extends the line of research about the European corporate iTraxx spreads determinants. It extends the macroeconomic variables previously applied to the literature on CDS spread determinants, and it works with a four-state Markov switching framework, where the third and fourth regimes are novel in literature to take into account the extreme levels of volatility.

The analysis supports the application of a four-regime specification with low volatility, normal volatility, high volatility, and extreme volatility periods linked to economic and financial distress. The extreme volatility regime is mainly associated with the economic impact of the COVID-19 pandemic but also with some higher volatility periods, confirming the high uncertainty of CDS spreads. The impact of covariates differs significantly across regimes, and a linear specification tends to over-select variables, causing possible misinterpretation of the relevance of macroeconomic variables. Brent and term structure factors become relevant for explaining CDS dynamics after the outbreak of the COVID-19 pandemic. Alternative shrinkage priors suggest that the main covariates are VStoxx index and equity index. At the same time, the heterogeneity between regimes is mainly observed in the effect of liquidity and equity – apart from the differences in variance. Given the relationship between risk aversion and CDS spread, time-varying transition probabilities driven by uncertainty measures can be considered for future research following Kauf and mann (2015). Similarly, a comparison of the different alternatives for measuring the term structure of the interest rate, such as the Nelson–Siegel framework or latent factor models, can be considered to study the robustness of the results.

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Appendix A: Full Conditional Posteriors for Alternative Priors

Apart from the main full conditional posteriors presented in Section 4.3, the alternative priors involve extra update steps. In the case of Laplace prior with 1-level, the full conditional distributions of these steps are:
- $1/\omega_{pk}|\mathbf{y}_{1:T},\ldots \sim \mathcal{IGA}(\overline{c}_{pk},\overline{d})$, where $\mathcal{IGA}$ refers to the inverse Gaussian distribution with parameters $\overline{c}_{pk}=\sqrt{\lambda^2/\beta_{pk}^2}$ and $\overline{d}=\lambda^2$;
- $\lambda^2|\mathbf{y}_{1:T},\ldots \sim \mathcal{G}(\overline{r},\overline{\delta})$, where $\overline{r}=K(n+1)+r$ and $\overline{\delta}=1/(\sum_p\sum_k\omega_{pk}/2+1/\delta)$.

Regarding the Horseshoe prior, the extra steps are:
- $\tau_{pk}|\mathbf{y}_{1:T},\ldots \sim \mathcal{IG}(1,1/\eta_{pk}+\beta_{pk}^2/(2\lambda^2))$;
- $\lambda^2|\mathbf{y}_{1:T},\ldots \sim \mathcal{IG}((K(n+1)+1)/2,1/\xi+1/2\sum_p\sum_k\beta_{pk}^2/\tau_{pk})$;
- $\eta_{pk}|\mathbf{y}_{1:T},\ldots \sim \mathcal{IG}(1,1+1/\tau_{pk})$;
- $\xi|\mathbf{y}_{1:T},\ldots \sim \mathcal{IG}(1,1+1/\lambda^2)$.

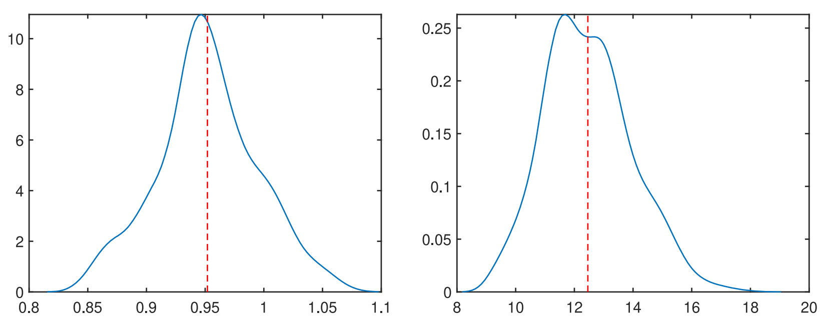
The 2-level priors have similar steps, but the shrinkage is applied to each covariate-effect towards the mean-effect across states. In the Laplace prior case, the following full conditional distributions are used:
- $1/\omega_{pk}|\mathbf{y}_{1:T},\ldots \sim \mathcal{IGA}(\overline{c}_{pk},\overline{d}_p)$, where $\mathcal{IGA}$ refers to the inverse Gaussian distribution with parameters $\overline{c}_{pk}=\sqrt{\lambda^2/(\beta_{pk}-\alpha_p)^2}$ and $\overline{d}_p=\lambda_p^2$;
- $\lambda_p^2|\mathbf{y}_{1:T},\ldots \sim \mathcal{G}(\overline{r},\overline{\delta}_p)$, where $\overline{r}=K+r$ and $\overline{\delta}=1/(\sum_k\omega_{pk}/2+1/\delta)$.
- $\boldsymbol{\alpha}|\mathbf{y}_{1:T},\ldots \mathcal{N}_{n+1}(\overline{g},\overline{H})$, where $\overline{g}=\overline{H}\left(X_\beta'\Upsilon_\beta^{-1}\beta\right)$, $\overline{H}=\left(X_\beta'\Upsilon_\beta^{-1}X_\beta+R^{-1}\right)^{-1}$, $X_\beta=(\widetilde{\boldsymbol{\xi}}_{01},\ldots,\widetilde{\boldsymbol{\xi}}_{n1},\widetilde{\boldsymbol{\xi}}_{02},\ldots,\widetilde{\boldsymbol{\xi}}_{n2},\ldots,\boldsymbol{\xi}_{0M},\ldots,\widetilde{\boldsymbol{\xi}}_{nM})'$, $\widetilde{\boldsymbol{\xi}}_{sk}=(\widetilde{\xi}_{0,sk},\widetilde{\xi}_{1,sk},\ldots,\widetilde{\xi}_{n,pk})'$ and $\widetilde{\xi}_{p,sk}=\mathbb{I}(s=p)$.

In the case of Horseshoe prior:
- $\tau_{pk}|\mathbf{y}_{1:T},\ldots \sim \mathcal{IG}(1,1/\eta_{pk}+(\beta_{pk}-\alpha_p)^2/\left(2\lambda_p^2\right))$;

- $\lambda_p^2|y_{1:T},\ldots \sim \mathcal{IG}((K+1)/2, 1/\xi_p + 1/2\sum_k(\beta_{pk}-\alpha_p)^2/\tau_{pk})$;
- $\eta_{pk}|y_{1:T},\ldots \sim \mathcal{IG}(1, 1+1/\tau_{pk})$;
- $\xi_p|y_{1:T},\ldots \sim \mathcal{IG}\left(1, 1+1/\lambda_p^2\right)$.
- $\boldsymbol{\alpha}|y_{1:T},\ldots \mathcal{N}_{n+1}(\overline{g},\overline{H})$, where $\overline{g}=\overline{H}\left(X_\beta'\Upsilon_\beta^{-1}\beta\right)$, $\overline{H}=\left(X_\beta'\Upsilon_\beta^{-1}X_\beta+R^{-1}\right)^{-1}$, $X_\beta = (\widetilde{\xi}_{01},\ldots,\widetilde{\xi}_{n1},\widetilde{\xi}_{02},\ldots,\widetilde{\xi}_{n2},\ldots,\xi_{0M},\ldots,\widetilde{\xi}_{nM})'$, $\widetilde{\xi}_{sk}=(\widetilde{\xi}_{0,sk},\widetilde{\xi}_{1,sk},\ldots,\widetilde{\xi}_{n,pk})'$ and $\widetilde{\xi}_{p,sk}=\mathbb{I}(s=p)$.

B Additional Results

B.1 2-Regimes Markov-Switching Model



cc

Figure 6: Posterior distributions (solid lines) and estimate (dashed lines) of the regime-specific variance σ_k^2 in the 2-regimes model fitted to Δ*iTraxx*. The posterior distribution in regimes 1 and 2 in the columns from left to right.

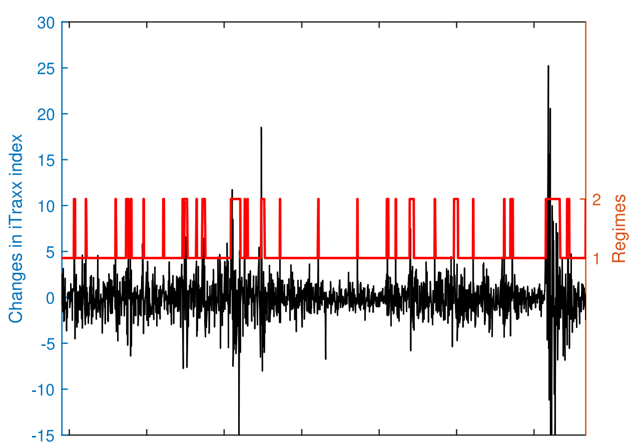


Figure 7: Time series of the ΔiTraxx (black solid) and the estimated hidden regimes for the 2-regime model (red stepwise).

B.2 3-Regimes Markov-Switching Model

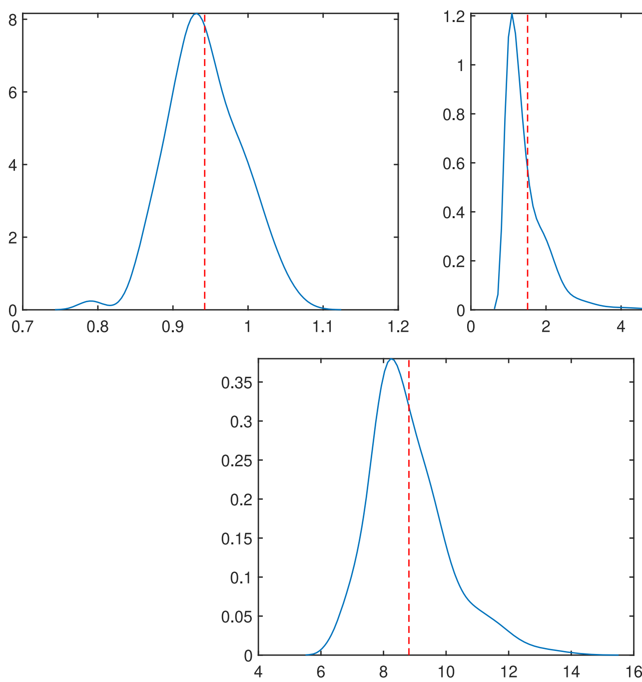


Figure 8: Posterior distributions (solid lines) and estimate (dashed lines) of the regime-specific variance σ_k^2 in the 3-regimes model fitted to Δ*iTraxx*. The posterior distribution in regime 1, 2, and three in the columns from left to right.

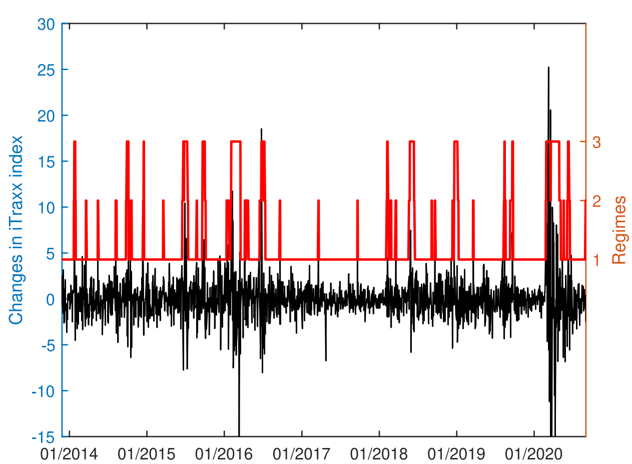


Figure 9: Time series of the Δ*iTraxx* (black solid) and the estimated hidden regimes for the 3-regime model (red stepwise).

B.3 Special Cases of the MSR and Sensitivity to Alternative Priors

See Tables 7, 8 and 9.

Table 7: Estimation results for iTraxx Main under different priors and levels

S_t	β_0	$\Delta iTraxx_{t-1}$	ΔV_t	$\Delta Stock_t$	Δliq_t	$\Delta Brent_t$	ΔBDI_t	$PC1_t$	$PC2_t$	σ^2	ML	DIC
Panel A: Markov switching regression model (2 levels normal prior)												
1	**−0.1112**	−0.0194	**0.2158**	**−0.6392**	2.2459	0.0023	−0.0228	−0.005	0.0054	0.4369	−2711.3	5449.2
2	−0.0527	−0.0094	**0.4346**	**−1.0301**	3.0125	−0.035	0.0058	-5e-04	0.0137	1.0543		
3	0.2578	0.0606	−0.0637	**−1.7143**	2.3716	−0.0359	0.0208	**−0.0369**	−0.0336	2.4517		
4	0.3666	**−0.2985**	0.4185	**−1.4906**	2.0061	−0.0537	0.0732	0.0127	0.1496	21.1184		
Ave.	0.0719	−0.0482	0.2027	−0.9624	1.934	−0.0139	0.0201	7e-04	0.0264			
Panel B: Markov switching regression model (1 level LASSO prior)												
1	**−0.111**	−0.0253	**0.2077**	**−0.6498**	0.2112	0.0021	−0.0227	−0.0053	0.005	0.43	−2712.8	5459.8
2	−0.0539	−0.0147	**0.4638**	**−1.0363**	0.4198	−0.0353	8e-04	8e-04	0.0188	0.9957		
3	0.1211	0.0903	−0.0149	**−1.5374**	0.1477	0.0019	0.0244	**−0.0359**	−0.0636	2.2445		
4	0.1856	**−0.2173**	0.2697	**−1.3725**	0.0264	−0.1921	0.0495	−0.0041	0.1583	20.2295		
Panel C: Markov switching regression model (2 levels LASSO prior)												
1	**−0.1121**	−0.0239	**0.2055**	**−0.6512**	2.2202	0.0021	−0.023	−0.0051	0.005	0.4308	−2709.7	5451.8
2	−0.055	−0.0122	**0.4454**	**−1.0453**	3.5468	−0.0359	0.0047	5e-04	0.0192	1.0132		
3	0.157	0.0793	−0.0256	**−1.5348**	5.7352	−0.0173	0.0239	**−0.0375**	−0.0701	2.1844		
4	0.2829	**−0.2457**	0.2719	**−1.5603**	1.5823	−0.1342	0.0624	0.0014	0.1658	20.0481		
Ave.	0.0463	−0.0363	0.2029	**−1.0633**	1.5234	−0.0403	0.0248	0.0095	0.0326			
Panel D: Markov switching regression model (1 level Horseshoe prior)												
1	**−0.0887**	−0.0121	**0.2218**	**−0.6371**	0.0793	-6e-04	−0.015	−0.0045	0.0014	0.4277	−2711.2	5448.6
2	−0.0262	−0.0023	**0.4616**	**−1.0741**	0.3737	−0.0182	6e-04	-2e-04	0.0135	0.9709		
3	0.0651	0.04	0.0089	**−1.3846**	5.7974	−0.0286	0.0135	**−0.03**	−0.036	2.2403		
4	0.0431	−0.1563	0.0687	**−2.0082**	−0.0067	−0.0738	0.0184	3e-04	0.0497	19.5401		
Panel E: Markov switching regression model (2 levels Horseshoe prior)												
1	**−0.0651**	0.0055	**0.3035**	**−0.8183**	2.3411	−0.0098	−0.0044	−0.0015	0.0124	0.7072	−2758.8	5551.0
2	**7.3228**	0.053	−0.0779	**−1.6513**	−8.6916	−0.0667	0.1156	0.045	0.0763	1.1788		
3	**−7.6057**	0.0505	**0.911**	**−1.9504**	−13.9093	−0.0275	−0.7921	−0.0524	0.0426	1.6703		
4	0.0145	0.0098	−0.0089	**−1.6736**	8.9173	−0.0108	0.0175	**−0.0198**	−0.0025	3.0694		
Ave.	−0.019	0.0247	0.1487	**−1.5773**	1.0802	−0.0185	0.0142	−0.0098	0.0206			

The MS k-regimes ($s_t = k$ for the kth regime) applied to the iTraxx main. Bold numbers indicate zero is not included in the 95 % credible interval. The column ML reports the (log) marginal likelihood for the different specifications and the column DIC gives the Deviance information criterion.

Table 8: Coefficients comparison between LRM and MSR (only variance).

β_0	$\Delta \mathrm{iTraxx}_{t-1}$	ΔV_t	$\Delta \mathrm{Stock}_t$	$\Delta \mathrm{liq}_t$	$\Delta \mathrm{Brent}_t$	$\Delta \mathrm{BDI}_t$	$PC1_t$	$PC2_t$
Panel A:Linear regression model								
0.007	**−0.066**	**0.120**	**−1.393**	**6.379**	**−0.055**	0.007	**−0.006**	**0.031**
Panel B:Markov switching regression model: 4-regimes								
−0.0609	**0.0025**	**0.2709**	**−0.9807**	**2.2316**	**−0.0164**	**-3e-04**	**−0.0045**	**0.0112**

Estimation results for the iTraxx main. The MSR assumes 4-regimes. The column ML reports the (log) marginal likelihood for the different specifications and the column DIC gives the Deviance information criterion.

Table 9: Prior variance by coefficients (Υ_β) under different priors and levels.

β_0	$\Delta iTraxx_{t-1}$	ΔV_t	$\Delta Stock_t$	Δliq_t	$\Delta Brent_t$	ΔBDI_t	$PC1_t$	$PC2_t$
Panel A: Markov switching regression model (1 level LASSO prior)								
0.28	0.22	0.30	0.52	0.45	0.23	0.23	0.22	0.23
0.26	0.23	0.46	0.70	0.54	0.24	0.23	0.23	0.22
0.30	0.28	0.27	0.95	0.47	0.25	0.24	0.25	0.28
0.38	0.32	0.38	0.86	0.45	0.33	0.30	0.23	0.30
Panel B: Markov switching regression model (2 levels LASSO prior)								
1.60	1.50	1.60	2.04	18.41	1.44	1.40	1.52	1.66
1.52	1.49	1.74	1.98	18.18	1.46	1.53	1.53	1.68
1.73	1.46	1.65	2.18	35.40	1.43	1.49	1.41	1.56
1.79	1.63	1.75	2.20	19.98	1.47	1.42	1.44	1.72
Panel C: Markov switching regression model (1 level Horseshoe prior)								
0.06	0.01	0.16	2.84	0.77	0.01	0.05	0.01	0.02
0.02	0.04	1.13	11.82	4.37	0.02	0.03	0.00	0.01
0.19	0.02	0.03	7.58	434.05	0.06	0.02	0.03	0.04
0.07	0.24	0.14	31.16	4.61	0.08	0.16	0.01	0.05
Panel D: Markov switching regression model (2 levels Horseshoe prior)								
0.36	0.21	0.73	12.34	268.70	0.03	0.05	0.01	0.06
2.69	0.11	2.89	2.93	83.02	0.11	0.02	0.00	0.06
0.51	0.11	2.00	8.80	2647.47	0.07	0.10	0.01	0.12
0.43	0.30	0.69	7.61	635.04	1.09	0.09	0.01	0.45

Estimation results for the iTraxx main. The MSR assumes 4-regimes. The column ML reports the (log) marginal likelihood for the different specifications and the column DIC gives the Deviance information criterion.

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