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Corporate CDS spreads from the Eurozone crisis to COVID-19 pandemic: A Bayesian Markov switching model*

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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. It applies a large set of financial and economic variables and compares linear, two, three and four-regimes models in a sample post-subprime financial crisis up to the COVID-19 pandemic. Results indicate that more than two regimes are significant to model CDS spreads, and the four-regime model is the preferred one. The fourth regime activated during the COVID-19 pandemic and also in high volatility periods. The impact of the covariates changes across regimes.

JEL Code: C11, C24, G12.

Keywords: Corporate CDS index; Markov switching; Bayesian econometrics.

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1 Introduction

The credit default swap (CDS) is the most used derivative in credit risk hedging. According to Vogel et al. (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 these information are generated from banks' trading and hedging activity. Indeed, an increase in CDS spreads can be interpreted as an higher demand for credit protection, as financial institutions perceive a higher risk of these loans. Moreover, credit ratings, the natural instrument created to assign a credit rating, tend to be slow to change. Therefore, a deep understanding of the CDS spreads determinants is crucial for both policy makers interested in preserving the stability of the financial system and of financial insiders interested in managing credit and financial risks.

Multiple papers have studied the CDS market efficiency. The main findings are that several CDS markets are not efficient and statistically present significantly autocorrelated dynamics and time-varying efficiency. Byström et al. (2005) analyses 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 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 both 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. Sensoy et al. (2017) analyses 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 have also been studied. Blanco et al.

(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 U.S. (i.e. CTD option). Moreover, CDS spreads have become a powerful price discovery tool (Blanco et al., 2005; Schreiber et al., 2012; Lee et al., 2018). Their findings are united by the fact that CDS market leads stock and bond markets, and also equity market volatility.

There is a large literature on credit risk pricing, divided in 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 by means of 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, among others, by Collin-Dufresn et al. (2001). 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 of the variation is due to a common unknown systematic factor. Abid and Naifar (2006) estimate a multiple regression model finding that macroeconomic variables have a greater explanatory power than firm-specific ones. Similar results are achieved by Fu et al. (2020), Ericsson et al. (2009) and Blanco et al. (2005). In particular, the last one find that macroeconomic variables, such as interest rates, term structure, equity market returns and market volatility, have a larger and immediate impact on credit spreads, while CDS spreads are more sensitive to firm-specific variables. However, considering the long-run arbitrage-based equivalence, they are equally sensitive to both macro and firm-specific factors. In any case, theoretical determinants, which are used in structural models, must be considered in order to analyse credit risk.

Zhang et al. (2009) analyse changes in single-name CDS spreads considering both jump risk effects and firm-specific variables, explaining an additional 14% to 18% of spread variation.

Kajurová et al. (2014) analyses the CDS spreads determinants 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 finds that the explanatory variables' sign changes in relation with the economic conditions. The authors suggest that for efficient policy decisions, policy makers 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, see, for example, Ang and Bekaert (2002b,a), Alexander and Kaeck (2008) introduce a regime-dependent framework to analyse daily corporate CDS spread determinants of different CDS indexes. They apply a two-state Markov switching regression and find that the influence of theoretical determinants have a regime dependent behaviour and that the unknown systematic factor found in Collin-Dufresn et al. (2001) is due to the regime specific behaviour of CDS spreads.

Building on this, Riedel et al. (2013) apply a Markov switching model to estimate the credit cycle and study the spread determinants in emerging sovereign debt markets on a daily frequency 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 dynamics. Sabkha et al. (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 a better predictive power than non-linear models. Chan and Marsden (2014) study CDS spreads determinants in a Markov switching framework for both investment-grade and high-yield companies. They use a large set macroeconomic and firm-specific variables and find that the impact of monetary policy is significant in both tranquil and turbulent regimes. Guidolin et al. (2019) estimate a Markov switching vector error correction model and find evidence of non-linearities in the adjustment mechanism between corporate and CDS spreads.

This paper extends the literature on CDS spread determinants along three directions and provides new evidence on the functioning of CDS markets. First, we update the Alexander and Kaeck (2008) analysis in a new time range from the 2007-2009 crisis to the COVID-19 pandemic. Second, we extend the Collin-Dufresn et al. (2001) analysis by applying a Markov switching regression model in the evidence of a non-linear behaviour of CDS spreads. Third, we introduce a Bayesian Markov switching model which naturally account for parameter uncertainty and make more tractable the inference issues. We provide evidence of four volatility regimes in the CDS time series: low, normal, high and extremely volatility regimes. The extreme volatility regime is mainly, but not only, associated to the economic impact of COVID-19 pandemic, extending evidence among others in Gormsen and Koijen (2020) for European and US stock and bond market returns; and in Onali (2020) for VIX index. Baker et al. (2020) compare the COVID-19 period to past diseases (Spanish flu and Ebola), finding that COVID-19 pandemic has caused a stock market impact never seen before, with levels of volatility comparable to the ones of 2007-2009 crisis. Our analysis confirms it for CDS spreads and capture the COVID-19 dynamics with a separate regime. Finally, the impact of covariates differ significantly across regimes and a linear specification has a tendency to over-select variables, causing possible miss-interpretation of the relevance of macroeconomic variables.

The reminder of this work is organized as follows. Section 2 provides a description of the credit risk measures and of the CDS determinants used in the empirical analysis. Section 3 introduces the Markov switching regression framework for modelling credit risk. Section 4 reports the estimation results. Section 6 concludes.

2 European CDS markets

2.1 Credit risk measures

A single-name credit default swap (CDS) is a contract in which two parties are involved. On one hand, the protection buyer, who pays periodic fixed payments to the counterparty until the CDS expires due to a credit event or maturity. On the other hand, the protection buyer, 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 basically 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 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, which is usually defined as either bankruptcy or restructuring of debt.

Its origin dates back to mid 90s. In 1994, JP Morgan created CDSs, in order to reduce credit risk exposure allowing to extend its loan capability. The CDS was written with the European Bank of Reconstruction and Development (EBRD) and the aim of the deal was to allow the bank to offer a line of credit of USD 5 billions to Exxon, maintaining balance sheet flexibility (Vogel et al., 2013). Over the years, CDSs have become more and more complex instruments, and saw a steady increase both in volumes and notional outstanding, reaching the peak of USD 60 trillions prior to the subprime crisis.

In 2008, the insurance giant AIG was one of the main CDSs seller. As stated by Dino Kos on Financial Times (ft.com), 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.

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 a standardization of the market, introducing central counterpartys (CCPs) in order to erase the counterparty risk (Aldasoro and Ehlers, 2018). These changes were introduced for European markets in 2009, with the small-bang protocol and two main features were introduced: the standardized coupon rates and the quoting conventions.

This paper focuses on the European iTraxx corporate index (labelled $\Delta iTraxx$ in Equations and Tables). 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. Their aim is to transfer risk in a more efficient way 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 by the 125 most liquid listed companies, with weight 0.8 for each constituent firm's CDS (icmagroup.org). Every 6 months[2] the index is updated, rolling out the firms that either defaulted/merged or do not respect the liquidity parameter, including new ones.

2.2 Explanatory variables

We review the explanatory variables to be used to predict the CDS spread. Several multi-factor analysis with both a firm-specific (microeconomic) and market-specific (macroeconomic) perspective have been examined as 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 in the

[1] Also known as "the Main".

[2] On 21th September and on 21th March of each year.

argument and the market-specific factors applied in them, skipping firm-specific variables.

In our analysis, the first three variables are derived from theory related to structural models (Merton, 1974) and are: firm's debt-to-equity ratio, firm's operation volatility and risk-free interest rate. The proxy for the equity component is represented by returns of 3 different equally-weighted portfolios composed by 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 time series are not available, in order to solve that problem we simply do not consider them, decreasing the number of stocks included in that portfolio ($\Delta StockMain, \Delta StockNon-financials, \Delta StockFinancialSeniors$). The firm's volatility is proxy by the VStoxx index, which is composed by implied volatility of options with Euro Stoxx 50 as underlying asset (ΔV). As risk-free rate we apply 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 et al. (2005); Byström (2006) and Avino and Nneji (2014), we also consider the lagged value of the iTraxx spreads. As suggested by Annaert et al. (2013) and Collin-Dufresn et al. (2001), we also include liquidity and macroeconomic indicators. As liquidity, we follow Collin-Dufresn et al. (2001) and apply the difference between the 10-year Euro swap rate and the 10-year Bund yield (Δliq). The first macroeconomic indicator is represented by Brent oil returns ($\Delta Brent$). Oil shocks are a common macroeconomic indicator used by analysts to assess the economy health. Sabkha et al. (2019) find that in high volatility regimes, sovereign credit volatility becomes high sensitive to these shocks. The second macroeconomic variable si the change in the Baltic Dry Index (ΔBDI) 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 of 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 and is seen by financial analysts as an efficient indicator

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

Paper	Model	Variables
Collin-Dufresne et al. (2001)	Linear	Interest rate level (10-y yield) and slope (10y-2y 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 principapal components of the term structure of yields
Avramov et al. (2007)	Linear	Equity return momentum, volatilitz index, price-to-book ratio, intersest level (5y yield) and slope (5y-3m yields), financial leverage, Fama and French factors: HML, SMB and MKT
Zhang et al. (2009)	Linear	Equity market returns, volatility index, interest rate level (3-m yield) and slope (10y-3m yields)
Ericsson et al. (2009)	Linear	Default swap spreads, volatility index, firm leverage, interest rate level (10y yield)
Sabhka et al. (2019)	FIAPARCH and SETAR	Equity market returns, voaltility index, government bond yields and debt, inflation, consumer confidence index, oil prices, oil volatility
Galil et al. (2013)	Linear	Interest rate level (5y yield) and slope (10y-2y 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)

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
Δ iTraxx Main	-0.015	2.505	0.801	21.81	-21.32	25.24
Δ iTraxx Non-financials	-0.011	2.103	2.676	46.89	-15.27	29.95
Δ iTraxx Financial Seniors	-0.024	3.137	0.776	23.50	-32.07	31.05
Δ Vstoxx	0.007	1.804	1.130	16.83	-11.90	17.76
Δ Stock Main (%)	0.021	1.161	-1.172	19.59	-13.19	9.020
Δ Stock Non-financials (%)	0.006	1.094	-1.604	22.93	-13.60	7.710
Δ Stock Financial Seniors (%)	0.010	1.592	-0.881	17.08	-15.65	12.52
Δ liq	0.000	0.016	-0.333	8.262	-0.100	0.090
Δ Brent (%)	-0.018	2.587	-0.298	18.07	-24.40	21.02
Δ BDI	-0.012	32.37	0.736	12.68	-194.0	281.0
Δ PC1	-0.070	0.164	0.430	5.664	-0.680	0.910
Δ PC2	0.000	0.030	0.531	9.862	-0.170	0.280

of economic activity. Lin et al. (2019) analyse the BDI spillover effects, finding that the BDI drives movements of equity, commodity and currency markets.

We use daily observations between the 22nd November 2013 and the 1st September 2020 for a total of 1704 observations.[3]

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

3 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 and Kaeck (2008) by adding more variables and assuming the relationship varies across regimes dynamically over

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

time.

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

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

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

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

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

Define $\mathbf{z}_t' = \boldsymbol{\xi}_t' \otimes (1, \mathbf{x}_t')$ with $\boldsymbol{\xi}_t = (\xi_{1t}, \ldots, \xi_{Kt})'$, $\mathbf{x}_t = (x_{1t}, \ldots, x_{nt})'$, and $\boldsymbol{\beta} = (\boldsymbol{\beta}_1', \ldots, \boldsymbol{\beta}_K')'$ with $\boldsymbol{\beta}_k = (\beta_{0k}, \beta_{1k}, \ldots, \beta_{nk})$. The allocation variables are used to write the random-coefficient regression model in equation (1) as a linear regression model

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

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

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 and Wong (1987)) and Monte Carlo simulation methods. Another advantage of the Bayesian approach is that it naturally accounts for parameter uncertainty in the analysis.

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

$$\begin{aligned}
\boldsymbol{\beta}_k &\overset{i.i.d.}{\sim} \mathcal{N}_{n+1}(\boldsymbol{\nu}_\beta, \Upsilon_\beta) \quad k = 1, \ldots, K \\
\sigma_k^2 &\sim \mathcal{IG}(a, b)\mathbb{I}_{\mathcal{A}}(\sigma_k^2), \quad k = 1, \ldots, K \\
\mathbf{p}_{k\cdot} &\overset{i.i.d.}{\sim} \mathcal{D}(\delta_1, \ldots, \delta_K), \quad k = 1, \ldots, K
\end{aligned}$$

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

In our data-augmentation framework the joint posterior distribution of parameters and latent variables given the observations is

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

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

The full conditional distribution of $\boldsymbol{\beta}$ is the following Gaussian distribution

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

where $\bar{\boldsymbol{\mu}}_\beta = \bar{\Upsilon}_\beta(\sum_{t=1}^{T} \mathbf{z}_t\gamma_t^{-1}y_t + \Upsilon_\beta^{-1}\boldsymbol{\nu}_\beta)$ and $\bar{\Upsilon}_\beta = \left(\sum_{t=1}^{T} \mathbf{z}_t\gamma_t^{-1}\mathbf{z}_t' + \Upsilon_\beta^{-1}\right)^{-1}$. The full conditional distribution of $\boldsymbol{\sigma}^2$ is a product of gamma distribution truncated on the set of identifying restrictions

$$f(\boldsymbol{\sigma}^2|\mathbf{y}_{1:T},\boldsymbol{\xi}_{1:T},\boldsymbol{\beta},\mathbf{p}) \propto \prod_{k=1}^{K} \mathcal{G}a(\bar{a}_k/2,\bar{b}_k/2)\mathbb{I}_{\mathcal{A}}(\boldsymbol{\sigma}^2) \tag{4}$$

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

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

where $\mathbf{p}_{-k} = (\mathbf{p}_{1\cdot},\ldots,\mathbf{p}_{k-1\cdot},\mathbf{p}_{k+1\cdot},\ldots,\mathbf{p}_{m\cdot})'$ 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 are obtained by iterating the prediction and updating steps for $t = 1,\ldots,T$,

$$\begin{aligned} p(\boldsymbol{\xi}_t = \boldsymbol{\iota}_j|\mathbf{y}_{1:t-1},\boldsymbol{\xi}_{1:t-1}) &= \sum_{i=1}^{m} p(\boldsymbol{\xi}_t = \boldsymbol{\iota}_j|\boldsymbol{\xi}_{t-1} = \boldsymbol{\iota}_i)p(\boldsymbol{\xi}_{t-1} = \boldsymbol{\iota}_i|\mathbf{y}_{1:t-1}) && (5)\\ p(\boldsymbol{\xi}_t|\mathbf{y}_{1:t},\boldsymbol{\xi}_{1:t}) &\propto p(\boldsymbol{\xi}_t|\mathbf{y}_{1:t-1})p(y_t|\mathbf{y}_{t-1-p:t-1},\boldsymbol{\xi}_t) && (6) \end{aligned}$$

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

$$p(\boldsymbol{\xi}_t = \boldsymbol{\iota}_j|\mathbf{y}_{1:T}) \propto \sum_{i=1}^{m} p(\boldsymbol{\xi}_t = \boldsymbol{\iota}_j|\boldsymbol{\xi}_{t+1} = \boldsymbol{\iota}_i,\mathbf{y}_{1:t})p(\boldsymbol{\xi}_{t+1} = \boldsymbol{\iota}_i|\mathbf{y}_{1:T}) \tag{7}$$

where $p(\boldsymbol{\xi}_t = \boldsymbol{\iota}_j|\boldsymbol{\xi}_{t-1} = \boldsymbol{\iota}_i) = p_{ij}$, with $\boldsymbol{\iota}_m$ the m-th column of the identity matrix and $p(y_t|\mathbf{x}_t,\boldsymbol{\xi}_t)$ is the density of y_t given $s_t = k$ that is the density $\mathcal{N}(\boldsymbol{\beta}_k'\mathbf{x}_t,\sigma_k^2)$ 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).

4 Empirical analysis

4.1 Preliminary analysis

As a initial step of our analysis, we update the linear regression model of Alexander and Kaeck (2008) with the enlarge 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 apply Bayesian inference to compute the marginal likelihood and compare it to the Markow swichting regressions. However, since we use weak diffuse priors, results are qualitative similar to OLS estimation.

The first row of the Table 3 reports the estimates of the linear regression. Seven over eight regressors are significantly different from zero and only the Baltic index is 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-Dufresn et al. (2001) and Alexander and Kaeck (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 et al., 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 range of 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 the investors' risk-aversion, re-allocating their investments toward stock markets.

The first principal components impacts, with the expected sign, significantly the corporate CDS spreads, meaning that upward shifts of the term structure imply a decrease in CDS spreads. The same result had been found both in Alexander and Kaeck (2008) and in their updated model. The second principal component is also significantly, differently from the original analysis of Alexander and Kaeck (2008). Therefore, changes in the yield curve's slope do affect positively CDS spreads. The

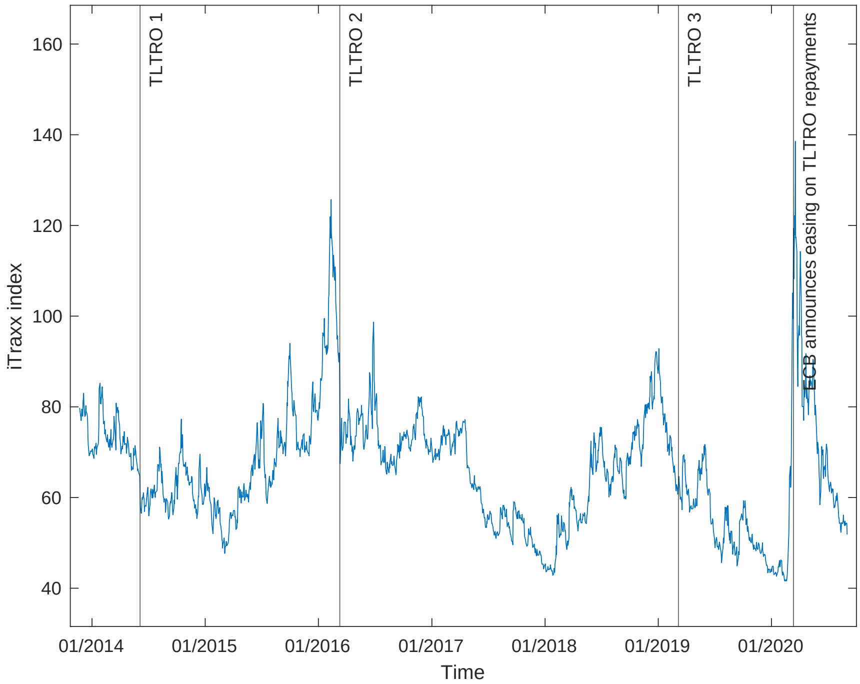

Figure 1: This figure represents the corporate iTraxx main index reaction to ECB announcements. In particular, from left to right, TLTRO 1, TLTRO 2, TLTRO 3 and the more recent announcement of policies to tackle the COVID-19 pandemic recession (ecb.europa.eu)

sensitivity of CDS spreads to changes in interest rates can also be seen empirically as in Figure 1. In fact, after the announcement of each TLTRO, policy action to invert the slope, it follows a decline in the iTraxx main index. Finally, the first lag has a negative impact on CDS.

To end this section, following Alexander and Kaeck (2008), we apply a rolling Chow test to check the parameters constancy and stability. Results indicate strong instability in the estimated parameters and we interpret this as an evidence of a non-linear relationship. Therefore, in the next section the regression model will be extended, considering an estimation method which accounts for non-linearity and regime dependent behaviour of CDS spreads.

4.2 Markov switching models

Table 3 reports the estimates of the Markov switching models with 2, 3 and 4-regimes. The significant difference with respect to the linear version is that zero is included in the 95% credible intervals in several parameter posteriors. In several cases, signs of the coefficients differ across regimes. VStoxx has a positive

Table 3: 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	ML	BIC
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	6519.3
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	-2663.7	5420.1
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	-2610.8	5360.6
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	-2539.3	5264.0
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	-2207.2	4460.7
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 k-th 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 BIC gives the Bayesian information criterion. The last Panel repeats the analysis stopping the sample in 2019.

sign in the first regime and a negative sign in the second regime in the model with 2 regimes or negative in the third regime in the 3-regime model and in the fourth regime in the 4-regime model. Similar sign changes can be observed for the Brent, BDI and the two PC variables. Furthermore, the liquidity is not significant in any regime in any model. 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 3 show that the 4-regimes specification has the highest (log) marginal likelihood value and the lowest Bayesian information criterion. Both statistics account for parameter size and penalize larger models. Despite this, our larger model is preferred. The difference is sizeable with the linear model, and the 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 in Appendix A.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 (mean posterior estimate of σ equals to 0.830 with respect to a value of 2.614 for the linear regression model). In the second regime, the one with moderate volatility (estimate equals of σ to 1.076), both implied volatility and the term structure slope are significant. Both posterior mean values are higher than in the linear regression model and in the other two regimes. In the third regime, the one with moderate-high volatility (estimate of σ equals 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.

Any variable is significant in all four regimes, and only implied volatility is significant in the first and second regime, in both cases with a positive coefficient; stock prices are significant in the first and last regime with a negative coefficient; the slope of the term structure is significant in the second and third regime but with different signs. Hence, macroeconomic variables added to explain CDS spreads, as

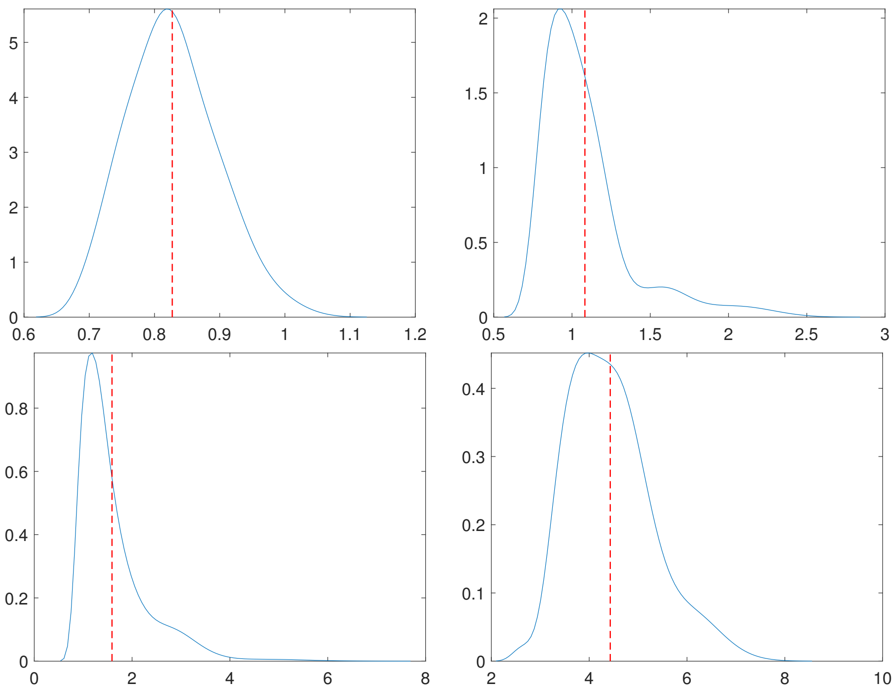

Figure 2: Estimates of the regime-specific variance σ_k^2 (dashed lines) and their posterior distributions (solid lines) in the 4-regimes model fitted to $\Delta iTraxx$. From top-left to bottom-right the posterior distribution in regimes from 1 to 4.

suggested by Collin-Dufresn et al. (2001) and Annaert et al. (2013), are of benefit in the linear regression, allowing to increase the explained variations, but less in the Markov switching framework.

Volatility estimates in regime 1, 2 and 3 are lower than the one for the linear regression model whereas the estimate in the fourth regime is almost twice larger, see also Figure 2 for the full posterior distribution.

Figure 3 shows the estimated hidden states (top), the log-volatility process (bottom). The first regime with lower volatility is the most probable over time, in particular in the years 2017-2018. There is more heterogeneity with the other three regimes. In some cases the second regime anticipates or follows the third regime, but other times there is not a connection among them. The COVID-19 pandemic is mainly associated to the fourth regime, and also other periods, such as the beginning of 2016, distinguished by high volatility in the series are estimated

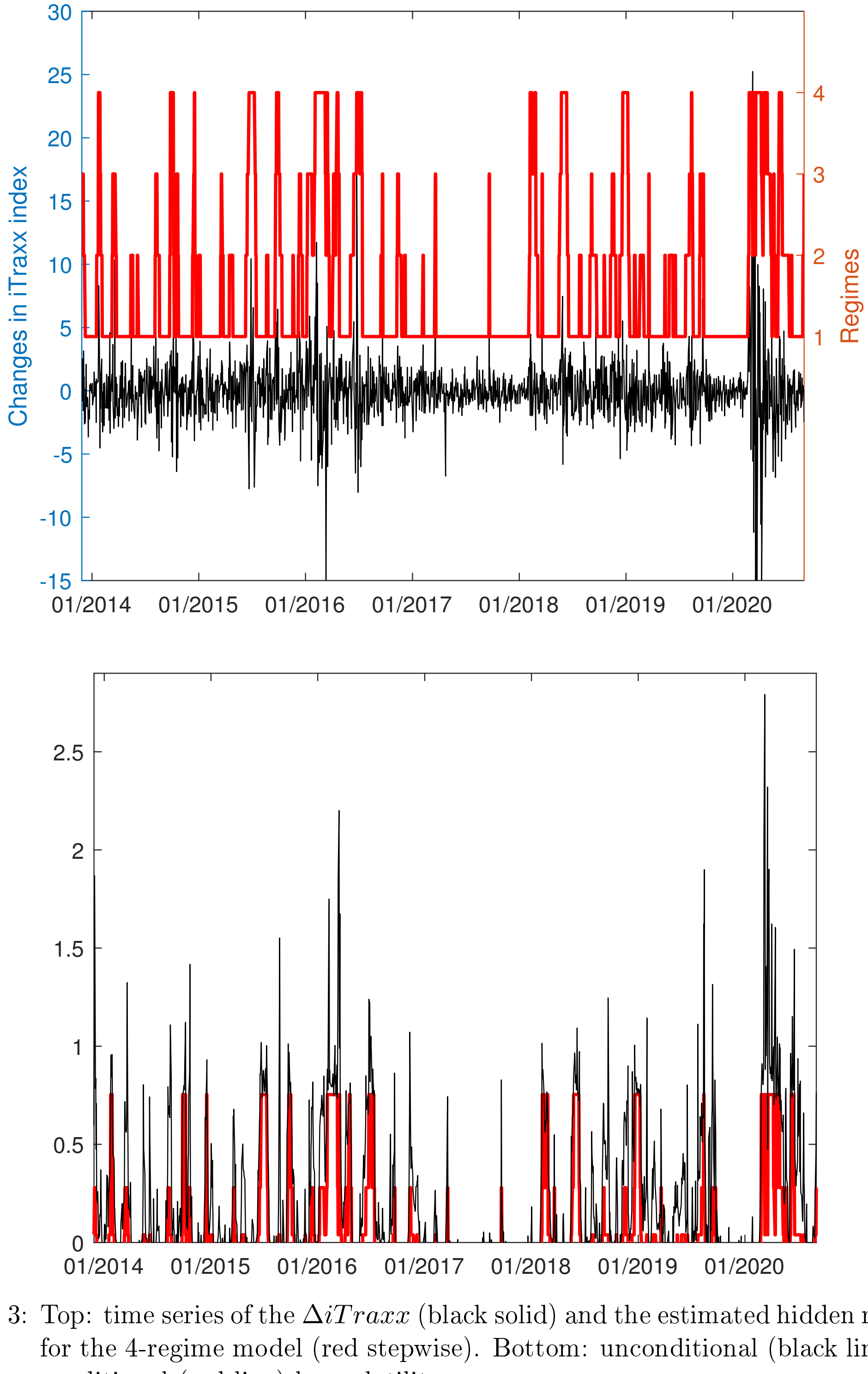

Figure 3: Top: time series of the $\Delta iTraxx$ (black solid) and the estimated hidden regimes for the 4-regime model (red stepwise). Bottom: unconditional (black line) and conditional (red line) log-volatility process.

by the fourth regime. 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 $\widehat{V(y_t|s_t)}, \boldsymbol{\theta}$, 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 regimes.

Finally, we investigate the impact of the COVID-19 pandemic by ending the data in December 2019 and dropping from the sample the pandemic period. Our results confirm that the best model is the 4-regime Markov switching regression (see Panel E of Table 3). 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 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 4 reports a similar analysis to that of the iTraxx Main. In both cases, the 4-regimes model is preferred in terms of marginal likelihood and BIC. 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 have zero not included in the credible interval and their signs are all economically plausible. Their significance varies substantially across regimes and no variable is significant in all four regimes. Other variables keep the same level of significance.

Table 4: 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	ML	BIC
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	6516.7
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	-2216.9	4526.5
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	-2056.9	4252.8
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-regimes												
1	**-0.071**	**0.215**	**0.345**	-0.057	1.637	0.002	-0.004	**-0.004**	0.006	0.246	-1942.1	4069.6
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	7484.5
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	-3111.4	6315.5
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	-3037.1	6213.2
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	-2939.5	6064.4
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 k-th 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 BIC gives the Bayesian information criterion.

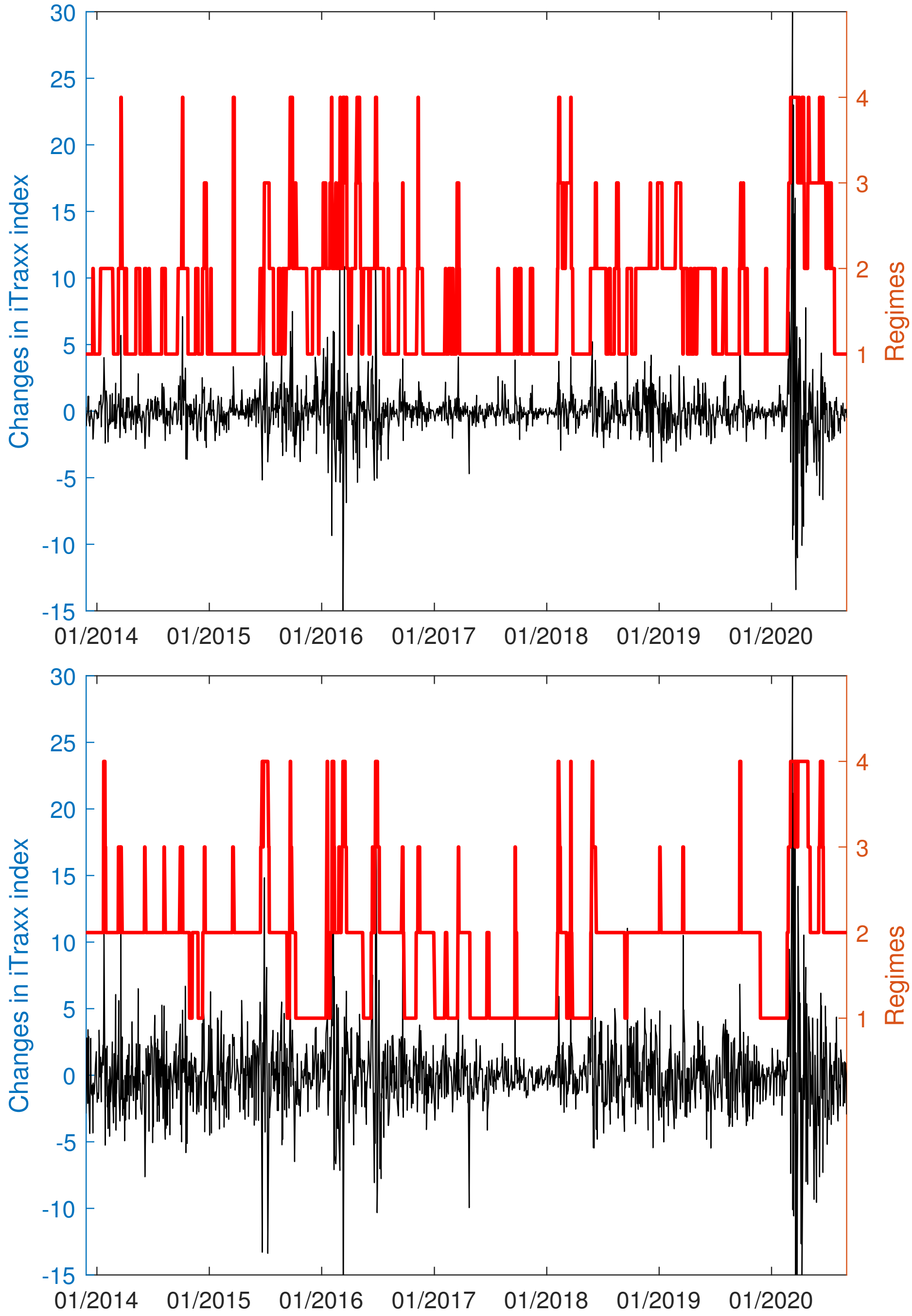

Figure 4: Time series of the $\Delta iTraxxNon-Financial$ (top, black solid) and $\Delta iTraxxFinancialSeniors$ (bottom, black solid) and the estimated hidden regimes for the 4-regime model (red stepwise).

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 but also previous periods of high volatility.

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, evidence similar to the main iTraxx index. Residual volatility estimates are more significant for the second, 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 dynamics of the Financial Seniors index is more similar to the main index since 60% of the sample period they are in the same regimes, whereas the Non-Financial and Financial Seniors are in the same regimes 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

$$C_k = \frac{1}{T-2\tau} \sum_{t=\tau+1}^{T-\tau} \mathbb{I}(s_{t-k}^{FIN} - s_t^{NON-FIN}) \tag{8}$$

with $k = -\tau, -\tau+1, \ldots, 0, \ldots, \tau-1, \tau$. The statistics 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 being the concordance statistics higher 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 statistics is computed contemporaneously ($k = 0$).

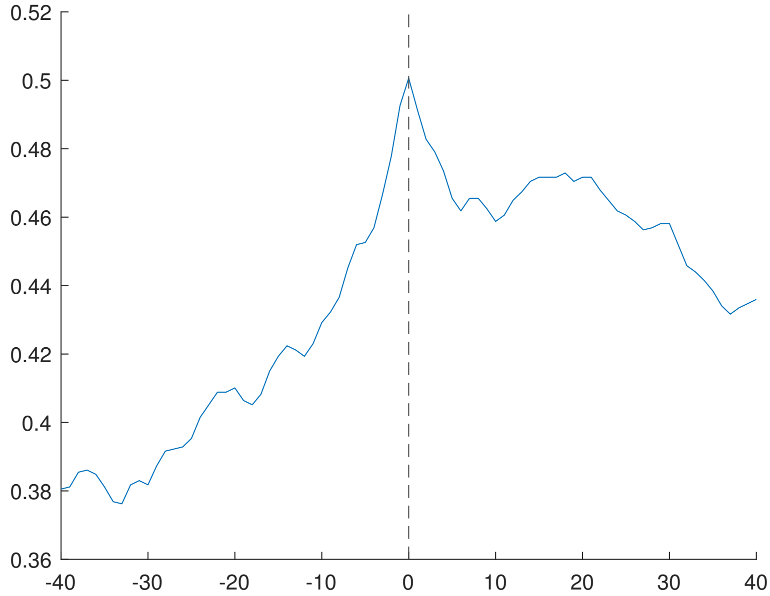

Figure 5: Concordance statistic (vertical axis) at various lags given by the value k in (5) (horizontal axis) between $\Delta iTraxxNon-Financial$ and $\Delta iTraxxFinancialSeniors$ estimated regimes.

6 Conclusions

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

The analysis supports the application of a four-regimes 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 to the economic impact of COVID-19 pandemic, but also to some higher volatility periods, confirming the high uncertainty of CDS spreads. The impact of covariates differ significantly across regimes and a linear specification has a tendency to over-select variables, causing possible miss-interpretation 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.

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A Additional results

A.1 2-regimes Markov-switching model

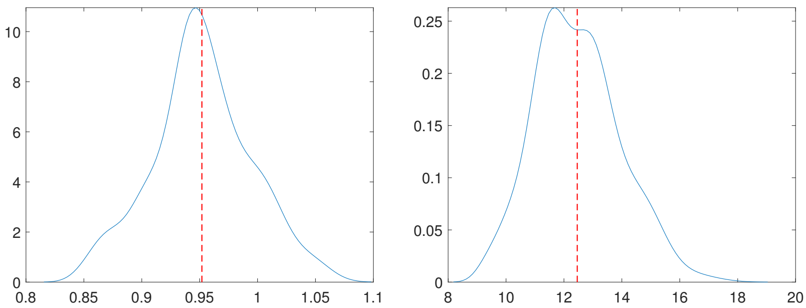

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Figure 6: Posterior distributions (solid lines) and estimate (dashed lines) of the regime-specific variance σ_k^2 in the 2-regimes model fitted to $\Delta iTraxx$. The posterior distribution in regime 1 and 2 in the columns from left to right.

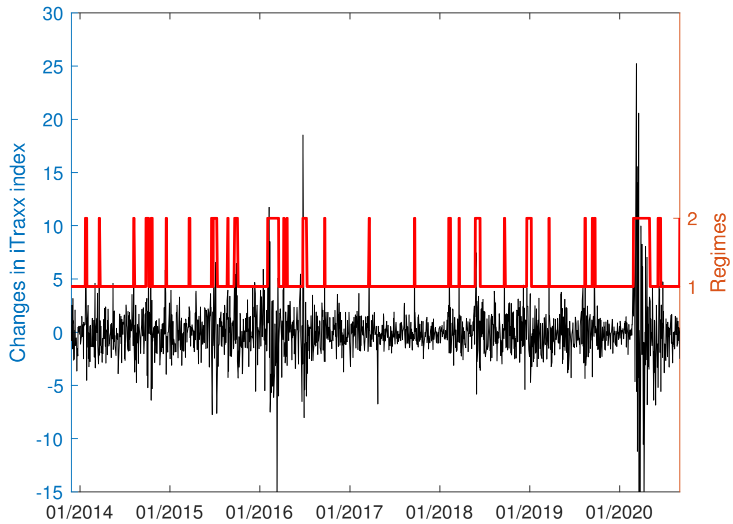

Figure 7: Time series of the $\Delta iTraxx$ (black solid) and the estimated hidden regimes for the 2-regime model (red stepwise).

A.2 3-regimes Markov-switching Model

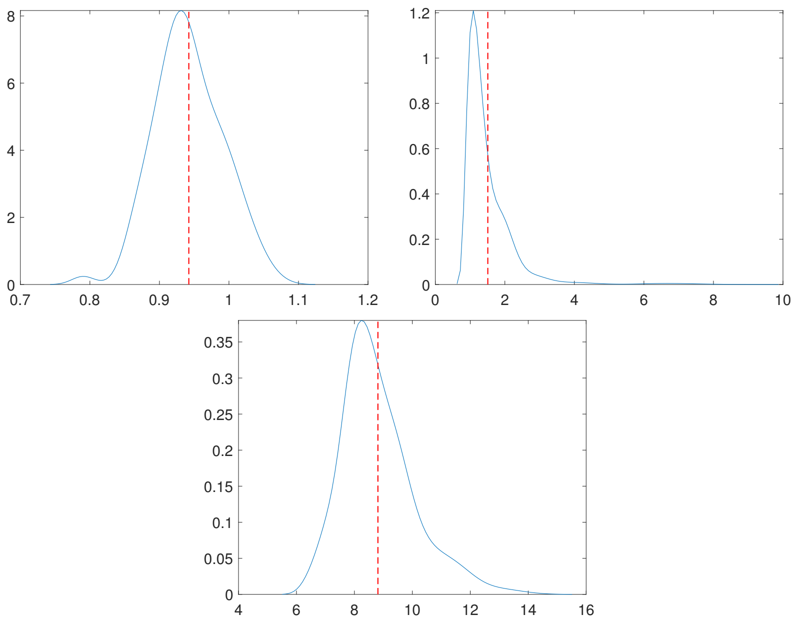

Figure 8: Posterior distributions (solid lines) and estimate (dashed lines) of the regime-specific variance σ_k^2 in the 3-regimes model fitted to $\Delta iTraxx$. The posterior distribution in regime 1, 2 and 3 in the columns from left to right.

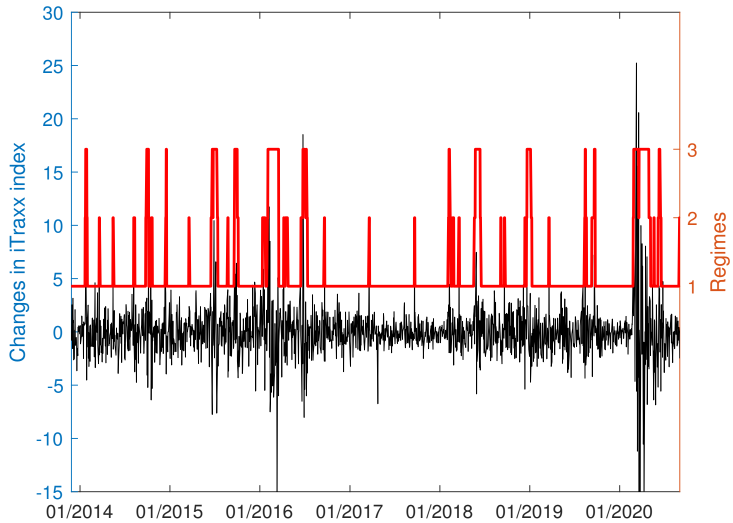

Figure 9: Time series of the $\Delta iTraxx$ (black solid) and the estimated hidden regimes for the 3-regime model (red stepwise).