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Climate change implications for the catastrophe bonds market: An empirical analysis*

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Abstract

Since their introduction in the mid-1990s, the return per unit of risk or *multiple* on catastrophe (cat) bonds has steadily declined. This paper investigates whether this pattern is consistent with the historical evolution of natural disaster risk, using average multiple figures over the period 1997-2017. Assessing the accuracy of cat bond pricing is important, since about 50% of outstanding risk capital in the cat bonds market is currently exposed to Atlantic hurricanes -a risk that global warming, among other disruptions, is found to enhance- and pension and mutual funds in European and other OECD countries currently own about 30% of the market. In this respect, while our findings suggest that falling multiples are primarily related to the Fed's expansionary monetary stance and to portfolio shift effects, we do also find evidence of significant undervaluation of global warming risk in the cat bonds market. This finding, also in light of the unfailing appetite of institutional investors for such securities, casts doubts over the sanity of the market and over cat bonds as suitable investment products for risk averse investors. Sounder investment opportunities might be found in the green bonds market, which allows for the funding of immediate investment in climate change mitigation too.

Keywords: Catastrophe (cat) bonds and insurance-linked securities (ILS), mul- tiples, global warming, climate change, El Niño Southern Oscillation, Atlantic hurricanes, semiparametric dynamic conditional correlation model. *JEL classification*: G11, G23, C32

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1 Introduction

Catastrophe (cat) bonds are natural disaster risk-linked securities, whose purpose is to transfer natural disaster risk from an issuer/insurance company to bond market investors. When they purchase a cat bond, investors take on the risk of the occurrence of a specified natural disaster in return for payment. If the event occurs, investors will lose part or all of the capital invested, and the issuer will use that money to cover the damage. Cat bonds were created in the mid-1990s, after hurricane Andrew in 1992 sent 11 insurance companies into bankruptcy. Hurricane Andrew served as a wake-up call for the insurance industry, showing that the tail risk associated with natural disasters might be so severe that insurance companies themselves might not have enough reserves to cover it. Insur-ance securitization was then seen as an effective mechanism to spread natural disaster risk through nancial markets and investors.[1]

Since the inception of the catastrophe bond and insurance-linked securities (ILS) market, the volume of risk capital issued has grown rapidly, achieving a cumulative value of about US$ 105 billion by (August) 2018 (Figure 1; Plot 1). Current gures also point to an increase in the pace of expansion of the market in 2017 and 2018, i.e. +70% relative to the previous ve years, showing record high volumes of new issuances and outstanding capital of US$ 12 and 36 billion, respectively (Figure 1; Plot 2). Market depth and liquidity in the secondary market are also increasing, as revealed by active daily trading of cat securities (Artemis, 2017).

Despite these developments, the current volume of securitized capital (US$ 98 billion) is still less than 20% of global reinsurer capital (US$ 605 billion; Figure 1; Plot 3), pointing to substantial growth potential for the natural disaster-linked securities market. This potential is also suggested by the sizable participation of institutional investors in European and other OECD countries in the cat bonds market, who currently own about 30% of total assets (Figure 1; Plot 7).

These changes have been coupled with a steady decline in cat bond return per unit of risk or multiple, i.e. the coupon to expected loss ratio, which measures how many times expected loss investors receive in terms of coupon, yielding a measure of cat bonds riskiness (Figure 1; Plot 4). Cat bond multiples fell from a value of 8 in 2000 to about 4 in 2003. Since 2012 a new contraction in multiples has occurred, as they fell to a record low value of about 2 in 2017 and 2018 (see also Cummins, 2008).

Although the prolonged contraction in cat bond multiples is a phenomenon shared with more traditional asset classes, such as corporate bonds (Figure 1; Plot 6), and may be related to the response of monetary policy to recent nancial crises[2], it might also reflect a change in investors' perceptions of cat bonds, from " exotic" to standard diversi ~~cation instruments. In this resp~~ect, cat bonds and ILS returns are unrelated to macroeconomic factors, and therefore bring valuable diversi cation opportunities to portfolios comprising more traditional assets. The latter " zero-beta" property, coupled with sizable nominal returns -and possibly some underestimation of risk- might explain

[1]See Cummins (2008) for an introduction to cat bonds and an earlier assessment of the cat bonds market.

[2]For instance, since 2007 the Fed's balance sheet has risen by $3.5 trillion, from $0.9 trillion to $4.4 trillion. Engen et al. (2015) suggest that the effect of the entire Q.E. program was to reduce the 10-year term premium, and therefore the bond yield, by 120 basis points in 2013. Other central banks, such as the Bank of England, the Bank of Japan, and the European Central Bank have implemented similar policies. It is therefore likely that the globally expansionary monetary policy stance also determined a capital surplus in the reinsurance industry.

the unfailing appetite of mutual and pension funds for ILS securities, even despite the large losses accrued during 2017 (AON, 2018). However, concerns for the overall sanity of the market have also arisen.[3]

In the light of the above evidence and the increasing participation of low-risk profile investors, such as pension funds, in the cat bonds and ILS market, this paper deals with the important issue of whether cat bonds risk is currently perceived and priced correctly. In particular, we assess whether the falling trend in cat bonds multiples is consistent with the evolution of natural disaster risk, which is expected to increase due to climate change. In this respect, about 50% of outstanding risk capital in the cat bonds market is exposed to Atlantic hurricanes (Figure 1; Plot 5; Davies, 2017), whose intensity might increase with global warming, which also impacts natural oscillations, such as the El Niño Southern Oscillation (ENSO; IPCC, 2012; Cai et al., 2014; 2015).[4] The dynamics of the Loss/Risk ratio for Atlantic hurricanes are telling in this respect, showing an increasing level and volatility of inflicted damage per unit of cyclone intensity since the early 2000s, and a record high in 2017 (Figure 1; Plot 8).[5]

Despite this evidence, increased hurricane risk perception was documented after Katrina in August 2005, yet not after hurricane Ike in September 2008 or thereafter, suggesting that investors may have believed that the risk adjustment induced by Katrina was sufficient to account for future catastrophes (Guertler et al., 2016). Yet the substantial economic and human implications of recent events and the evolution of Atlantic hurricane risk due to climate change, cast serious doubts on this view. Hence, in addition to market-specific and financial factors, which have been the focus of the recent empirical literature (see for instance Braun 2011, 2016; Lane and Mahul, 2008; Guertler et al., 2016), cat bonds pricing appears to require investigation of the global warming phenomenon (GW) and of its implications for natural disaster risk. This provides the focus and original contribution of this paper to the emerging research area of Environmental Finance (Linnenluecke et al., 2016), especially in relation to the assessment of climate-related risks to the financial system and the required regulatory oversight.

To our knowledge, this is the first study to assess directly the implications of climate change on cat bonds multiple dynamics. More precisely, using the innovative framework of the semiparametric dynamic conditional correlation model (SP-DCC) by Morana (2015, 2019), we first assess the evidence for global warming in temperature anomalies, also in relation to greenhouse gas emissions. We then use the same framework to assess the effects of global warming on the environment, with particular reference to ENSO oscillation (El Niño/La Niña episodes) and Atlantic hurricane intensity. Finally, in the light of the global warming/climate change evidence, we use a predictive regression framework to investigate the long- and short-term drivers of cat bond multiples, accounting for monetary policy, financial and climatological factors. We are unaware of any previous study providing such an in-depth assessment of cat bonds risk in relation to climate change. Many central bank

[3] "Investors are already taking on a lot of risk for the returns they get; if a major loss just leads to a new rush of new cash into the market, questions about the sanity of the market are only going to get louder." (Davies, 2017).

[4] The intensity of 2017 Atlantic hurricane season appears to be related to ENSO anomalies. In fact, while an El Niño event was initially predicted for 2017, and expected to reduce Atlantic storm activity, cool-neutral conditions (La Niña) materialized instead, yielding the opposite effect.

[5] In 2017 there were 16 named storms; four of them reached hurricane intensity and six more were classified as major hurricanes; all of them occurred in a row, yielding the greatest number of consecutive hurricanes ever observed in the satellite era and the highest total accumulated cyclone energy (221 104kt2) since 2005. A total of over US$ 316.51 billion in damages were accrued and 464 fatalities occurred.

governors are now considering increasing regulatory oversight to address climate-related risks to financial stability, including carbon stress tests for banks and other relevant financial institutions, in order to assess the effects of an abrupt transition to a low-carbon economy in response to irreversible climatic catastrophes (Gros et al., 2016; Battiston et al., 2017). Hence, in this respect, our paper provides insights into some catastrophic risk origins, modelling and forecasting of their impact, originally contributing to the existing policy and scientific debate on the economic and financial implications of climate-change.

To summarize the main results of the study, we find evidence to support the global warming hypothesis, i.e. the direct connection of the warming trend in global temperatures to radiative forcing, also of anthropogenic origin (greenhouse gases emissions). Moreover, we provide clear evidence of important feedback effects of global warming for the natural environment, in terms of higher natural disaster risk and, therefore, higher cat bonds risk, at least with regard to the sizable portion of outstanding capital exposed to Atlantic hurricanes. In this respect, our results suggest that climate change risk might not yet have been properly incorporated in cat bond multiples. In fact, while falling cat bond multiples are primarily related to the Fed's expansionary monetary stance and to portfolio shift effects, we also find evidence of significant undervaluation of natural disaster risk.

One implication of this is that the overall sanity of the market and the suitability of cat bonds as diversification instruments for risk-averse investors, such as pension funds, appear to be important open issues, which call for further assessment and research. This is particularly true in light of the large growth potential of the cat bonds and ILS market and the unfailing appetite of institutional investors for such securities. We believe the sounder investment opportunities for institutional investors can be found in the green bonds market (Richardson and Reichelt, 2018), which allows for the funding of immediate investment in climate change mitigation, simultaneously providing a potential solution to the global savings-investment imbalance (Bagliano and Morana, 2017), in the case such investment policy was undertaken on a global scale too.

The rest of the paper is organized as follows. In Section 2 we introduce the data, while in Section 3 we review the literature on the econometric modelling of climate change and present our econometric model. Then, in Sections 4 and 5 we discuss the empirical results concerning global warming and risk pricing in the cat bonds market. Finally, Section 6 concludes. In the appendix, we report estimation details and Monte Carlo evidence for the SP-DCC estimator. Additional empirical results appear in the Online Appendix.

2 The data

Our climatological information set is monthly and spans the period 1978:12 through 2016:12, for a total of 457 observations. It consists of average land and ocean temperature anomalies for the entire globe (GL; 90S-90N) and seven zones, namely the Northern Hemisphere (NH; 0-90N), the Southern Hemisphere (SH; 90S-0), the Tropics (Trpcs; 20S-20N), the Northern Extratropic (NoExt; 20N-90N), the Southern Extratropic (SoExt; 90S-20S), the Northern Polar (NoPol; 60N-90N), the Southern Polar (SoPol; 90S-60S). Temperatures are measured in degrees Celsius.[6] We also include the Southern Oscillation Index (SOI) to track the temporal evolution of ENSO episodes. SOI measures the bi-

[6] The source is the NASA Goddard Institute for Space Studies. The data are available at http://www.nsstc.uah.edu/data/msu/v6.0/tlt/uahncdc_lt_6.0.txt.

modal variation in sea level barometric pressure between observation stations at Darwin (Australia) and Tahiti, and is expressed in standardized units.[7] Moreover, in order to measure Atlantic cyclones intensity, we consider the accumulated cyclone energy (ACE) index, which is available annually. The ACE index is calculated by squaring the maximum sustained surface wind in the system every six hours (knots) and summing it up for the season. It is expressed in 10^4kt2.[8]

According to the Intergovernmental Panel On Climate Change (IPCC) glossary, radiative forcing or climate forcing (RF) is the difference between insolation (sunlight) absorbed by the Earth and energy radiated back to space. Positive (negative) radiative forcing means Earth receives more (less) incoming energy from sunlight than it radiates to space. This net gain (loss) of energy will cause global warming (cooling). Causes of positive radiative forcing include changes in insolation and the concentrations of radiative active gases, commonly known as greenhouse gases, and aerosols, which, in large part, are the anthropogenic (human-made) contribution to global warming. Radiative forcing is measured in W/m2, as the sum of various components: Well-Mixed Greenhouse Gases (WMGG; carbon dioxide (CO_2), methane (NH4), nitrous oxide (N2O) and chlorofluorocarbons (CFCs)), Ozone (O3), Stratospheric Water Vapor (StrH2O), Reflective Tropospheric Aerosols (ReflAer), Tropospheric Aerosol Indirect Effects (AIE), Black Carbon Aerosols (BC), Snow Albedo (snowAlb), Stratospheric Aerosols (StrAer), Solar Irradiance (Solar), Land Use (including irrigation; LandUse).[9] As radiative forcing data are available at the annual frequency and up to 2011 only, the econometric analysis in Sections 4-5 uses forecasted radiative forcing data for the 2012-2016 period and monthly interpolation (Section 4 only). Details of the procedure implemented are provided in the Online Appendix (Table A1).

Concerning financial data, due to cat bond data sample limitations, we consider annual figures for the average multiple, i.e. the average coupon to expected loss ratio, for the period 1997 through 2017. The multiple measures how many times expected loss are investors receiving in terms of coupon, yielding therefore a measure of cat bonds riskiness. Figures for multiples refer to primary market issuances and are computed as straight average, not weighted by size of issue.[10] Moreover, we consider various interest rates, i.e. the effective federal funds rate, the BofA Merrill Lynch US corporate AA, BBB and BB option-adjusted spreads, US Treasury bills (3-month) and bonds (10-year) rates, and the Loss/Risk ratio for Atlantic hurricanes, which is computed as the ratio of total inflicted damages by Atlantic cyclones in 2017 US$ to their ACE index.[11] The Loss/Risk ratio then yields information on the evolving destructive power of Atlantic hurricanes, which should be priced by cat bonds exposed to such perils.

[7] SOI data are available at https://www.ncdc.noaa.gov/teleconnections/enso/indicators/soi/.

[8] ACE figures can be found at http://www.aoml.noaa.gov/hrd/tcfaq/E11.html.

[9] Radiative forcing data ara available at https://data.giss.nasa.gov/modelforce/Fe_H11_1880-2011.txt.

[10] Figures are available from Artemis at http://www.artemis.bm/deal_directory/cat_bonds_ils_average_multiple.htm

[11] Data for the federal funds rate, Treasury bills and bonds, and the AA, BBB, and BB corporate spreads are available from FRED, with acronyms FEDFUNDS, TB3MS, GS10, BAMLC0A2CAA, BAMLC0A4CBBB, and BAMLH0A1HYBB, respectively. Figures for total damages are available season by season on wikipedia; for instance, 2017 figures can be found at https://en.wikipedia.org/wiki/2017_Atlantic_hurricane_season.

3 Econometric modeling of temperature anomalies and global warming

The persistence properties of temperature anomalies have been subject to careful assessment in the climate econometrics literature. Two main competing views can be noticed, differing in terms of the statistical model employed to account for the warming trend detected in the data, rather than for its attribution to causing factors. In fact, while it is in general agreed that the warming trend is determined by radiative forcing, both of natural and anthropogenic origin, its stochastic or deterministic nature is contended.

On the one hand, Kaufmann et al. (2013) and Schmith et al. (2012) point to a stochastic trend in global and Northern (NH) and Southern (SH) hemisphere temperature anomalies, as generated by (and therefore cointegrating with) stochastic trends in radiative forcing components.[12] Feedback effects from temperature anomalies to radiative forcing have also been detected. For instance, Kaufmann et al. (2006) document a feedback loop in which temperature increases due to anthropogenic greenhouse gases change flow to and from the atmosphere in a way that the radiative forcing of greenhouse gases itself is increased, generating a further rise in temperature. Schmith et al. (2012) find that it is surface air temperature to adjust to the average temperature of the upper ocean, consistent with oceans' larger heating storage capacity than land.

On the other hand, Estrada and Perron (2017) point to a common nonlinear deterministic trend in total radiative forcing and temperature anomalies, with significant breaks in slope in the 1960s and 1990s, and stationary fluctuations about trend. More precisely, the first break is detected in 1962 (1968) and the second break in 1989 (1991) for NASA (HadCRUT4) data. This finding updates earlier evidence of trend stationarity and different timing in breaks for global and Northern/Southern hemisphere temperature anomalies, as reported by Gay et al. (2009) and Mills (2013)[13]. According to Estrada and Perron (2017), these breaks would have been determined by natural variability oscillations, such as the Atlantic Multidecadal Oscillation (AMO) for NH and the Antarctic Oscillation (AAO) for SH. On the other hand, the "hiatus", i.e. the 1998-2013 slowdown in the warming trend in global temperature, would have been caused by changes in radiative forcing, i.e. chlorofluorocarbons and methane reductions, rather than by natural variability factors, such as AMO or ENSO, or by lower solar activity (Kosaka and Xie, 2013).

Estrada and Perron (2017) also update earlier evidence concerning persistence properties of temperature fluctuations about deterministic trends, which would be best described by a weakly stationary process. This contrasts with previous evidence of Bloomfield (1992) and Baillie and Chung (2002), pointing to stationary long memory fluctuations in global, NH and SH temperature anomalies about a linear deterministic trend.

[12] Earlier evidence on integration and cointegration properties of temperature anomalies can be found in Stern and Kaufmann (2000), Kaufmann and Stern (2002), Kaufmann et al. (2006), Mills (2006). See also Chang et al. (2016) for recent evidence from nonstationarity analysis extended to the density function of temperature anomalies.

[13] See also Bloomfield (1992) for earlier evidence of determininistic trends in temperature anomalies. Moreover, see Mills (2006) for evidence of a more pronounced warming trend in NH temperatures since the 1970s, robust to stochastic or deterministic trend modeling.

3.1 The econometric model

The semiparametric dynamic conditional correlation model (SP-DCC; Morana, 2015, 2019) is defined by the following equations

$$\mathbf{y}_t = \boldsymbol{\mu}_t(\boldsymbol{\delta}) + \boldsymbol{\varepsilon}_t \tag{1}$$

$$\boldsymbol{\varepsilon}_t = \mathbf{H}_t^{1/2}(\boldsymbol{\delta})\mathbf{z}_t \tag{2}$$

where $\mathbf{y}_t$ is the $N \times 1$ column vector of the variables of interest; $\boldsymbol{\mu}_t(\boldsymbol{\delta})$ and $\mathbf{H}_t(\boldsymbol{\delta})$ are the $N \times 1$ conditional mean vector $E(\mathbf{y}_t|I_{t-1})$ and the $N \times N$ conditional variance-covariance matrix $Var(\mathbf{y}_t|I_{t-1})$, respectively; $\boldsymbol{\delta}$ is a vector of parameters and I_{t-1} is the sigma field. Finally, the random vector $\mathbf{z}_t$ is of dimension $N \times 1$ and assumed to be $i.i.d.N$ with first two moments $E(\mathbf{z}_t) = \mathbf{0}$ and $Var(\mathbf{z}_t) = \mathbf{I}_N$. In our application, $N = 9$ and $\mathbf{y}_t = \begin{bmatrix} GL & NH & SH & Trpcs & NoEext & SoExt & NoPol & SoPol & SOI \end{bmatrix}'$ is the 9×1 column vector containing data for temperature anomalies for the globe (GL) and various zones (NH, SH, $Trpcs$, $NoEext$, $SoExt$, $NoPol$, $SoPol$) and the Southern Oscillation Index (SOI).

3.1.1 The specification of the conditional mean function

We employ an univariate Adaptive-X-AR(m) model for each of the N elements in the mean vector $\boldsymbol{\mu}_t(\boldsymbol{\delta})$, i.e.

$$\phi_i(L)\, y_{i,t} = c_{i,t} + \varepsilon_{i,t} \qquad i = 1, ..., N \tag{3}$$

where $\phi_i(L) = 1 + \phi_{i,1}L + ... + \phi_{i,m}L^m$ is a polynomial in the lag operator with all the roots outside the unit circle; $c_{i,t}$ is a level component specified according to the general p-order Fourier function in radiative forcing (RF)

$$c_t = c_0 + \sum\nolimits_{j=1}^{s} c_j I_{j,t} + c_2 RF_t + \sum\nolimits_{j=1}^{p} \gamma_j \sin(2\pi j RF_t^*) + \sum\nolimits_{j=1}^{p} \delta_j \cos(2\pi j RF_t^*) \qquad \mathbf{MX} \tag{4}$$

where $RF_t^* = \frac{RF_t - \min RF_t}{\max RF_t - \min RF_t}$ is RF_t scaled to range between 0 and 1, and $I_{j,t}$ is a generic step dummy variable with unitary values set according to the Bai-Perron structural break tests.

We also use the nested specification

$$c_t = c_0 + c_2 RF_t + \sum\nolimits_{j=1}^{p} \gamma_j \sin(2\pi j RF_t^*) + \sum\nolimits_{j=1}^{p} \delta_j \cos(2\pi j RF_t^*) \qquad c_2 = 0 \qquad \mathbf{MXR}$$

which omits the dummy break variable, and therefore relates the underlying evolution in the series to RF only, as foreseen in the original Gallant flexible functional form.

3.1.2 The specification of the conditional variance function

Concerning the conditional variance-covariance matrix $\mathbf{H}_t(\boldsymbol{\delta})$, we assume that the elements along its main diagonal, i.e. the conditional variances $Var(y_{i,t}|I_{t-1}) \equiv h_{i,t}$, follow a GARCH(1,1) process

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \qquad i = 1, ..., N \tag{5}$$

subject to the usual restrictions to ensure that the conditional variances are positive almost surely at any point in time.

Moreover, we define the off-diagonal elements of $\mathbf{H}_t(\boldsymbol{\delta})$, i.e. the conditional covariances $Cov(y_{i,t}, y_{j,t}|I_{t-1}) \equiv h_{ij,t}$, according to the *polarization* identity of the covariance operator

$$h_{ij,t} = \frac{1}{4}\left[Var_{t-1}(y_{i,t} + y_{j,t}) - Var_{t-1}(y_{i,t} - y_{j,t})\right] \qquad i, j = 1, ..., N \qquad i \neq j. \tag{6}$$

By defining the aggregate variables $y^{+}_{ij,t} \equiv y_{i,t} + y_{j,t}$ and $y^{-}_{ij,t} \equiv y_{i,t} - y_{j,t}$, and assuming a GARCH(1,1) process for their conditional variances $Var_{t-1}(y^{+}_{ij,t}|I_{t-1}) \equiv h^{+}_{ij,t}$ and $Var_{t-1}(y^{-}_{ij,t}|I_{t-1}) \equiv h^{-}_{ij,t}$, one then has

$$h_{ij,t} = \frac{1}{4}\left[h^{+}_{ij,t} - h^{-}_{ij,t}\right] \qquad i, j = 1, ..., N \qquad i \neq j \tag{7}$$

where

$$h^{+}_{ij,t} = \omega^{+}_{ij} + \alpha^{+}_{ij}\varepsilon^{+2}_{ij,t-1} + \beta^{+}_{ij}h^{+}_{ij,t-1} \qquad i, j = 1, ..., N \qquad i \neq j \tag{8}$$

$$h^{-}_{ij,t} = \omega^{-}_{ij} + \alpha^{-}_{ij}\varepsilon^{-2}_{ij,t-1} + \beta^{-}_{ij}h^{-}_{ij,t-1} \qquad i, j = 1, ..., N \qquad i \neq j \tag{9}$$

with $\varepsilon^{+}_{ij,t} = \varepsilon_{i,t} + \varepsilon_{j,t}$ and $\varepsilon^{-}_{ij,t} = \varepsilon_{i,t} - \varepsilon_{j,t}$.

See the Appendix for details on QML estimation of the model and Monte Carlo results.

3.1.3 Connections with available modelling strategies

In terms of properties, the proposed SP-DCC model - with Adaptive-X-AR specification for the conditional mean - is fully consistent with the climate econometrics literature, pointing to a common driver in trend temperature anomalies and radiative forcing (Kaufmann et al., 2013; Schmith et al., 2012; Estrada and Perron, 2017), as well as to structural breaks in temperature anomalies, caused by natural oscillations (Gay et al., 2009; Mills, 2013, Estrada and Perron, 2017; McKitrick and Vogelsang, 2014). Moreover, the dynamic conditional covariance matrix specification allows for the detection of time-varying conditional variances and correlations, so far unnoticed in the literature. In this respect, the proposed SP-DCC model might then yield further information on the global warming/climate change phenomenon, in terms of evolving comovement of temperature anomalies, transmission of heat shocks across non overlapping geographical zones and feedback effects on natural phenomena, such as, for instance, the ENSO cycle and Atlantic hurricanes.

4 Empirical results

QML estimates of the models are reported in Table 1, Panel A (MX) and Panel B (MXR). As shown by the diagnostics reported in Table 1, all models are well specified and show a similar coefficient of determination, highest for GL, NH and SH (0.70-0.80), intermediate for NoExt, SoExt and SOI (0.40-0.60), lowest for NoPol and SoPol (0.10-0.30). Concerning the specification of the break dummies for the MX model, as shown in the Online Appendix (Table A2), the $UD{-}max$ test points to a single break point, located about the mid-/end 1990s (1995 through 1998) and therefore concurrent with some El Niño episodes of interest (weak: 1995-1996; very strong: 1997-1998) and the fading away of the cooling effect of the vulcanian eruption in the Philippines (Mt. Pinatubo in 1991). See McKitrick and Vogelsang (2014) for similar findings.

As pointed out by Cai et al. (2014, 2015), when assessing the warming trend in temperature anomalies, extreme ENSO events should be properly accounted for, as they might exercise longer lasting and more sizable effects on average temperatures than normal events, especially at the tropics. This might explain some peculiar results for Trpcs, i.e. the weaker connection of its trend component with radiative forcing and its different autoregressive structure, relative to other anomalies.[14]

In the light of the above findings, we have then selected MXR as best model. As shown in Table 1 (Panels A, B), the estimated impact of radiative forcing on temperature anomalies is always nonlinear and direct, since some of the trigonometric transforms of RF are significant for all the temperature series and enter the regression function with positive parameters (see γ_3, γ_4, γ_5, δ_3 and δ_5). Moreover, when significant, also the estimated parameter for RF itself is positive (c_2). As shown in Figure 2, the overall radiative forcing component in temperature anomalies yields a fairly smooth trend, accounting not only for their recent rise and mid-end 1990s level switch, but also for the 1998-2013 warming hiatus. This is consistent with Estrada and Perron (2017), who also relate the hiatus to radiative forcing (CFC and methane reductions), rather than to natural phenomena such as ENSO or lower solar activity. See also Kosaka and Xie (2013) on this issue. Hence, our results yield support to the "global warming (GW) hypothesis", as an increase in radiative forcing, also of anthropogenic origin (i.e. greenhouse gas emissions), would lead to an increase in trend temperature anomalies.

Our results also have implications for the recent debate on the feedback effects of GW for the natural environment, showing, for instance, that GW might destabilize natural oscillations, such as ENSO, by increasing their amplitude/frequency and by shifting their teleconnection (Cai et al., 2014; 2015). Our findings are supportive of this view, since, given the definition of the SOI index, the negative estimated coefficient for RF (γ_4) implies that global warming (cooling) enhances the amplitude of El Niño (La Niña) events. Interestingly, the linkage between RF and ENSO is highly nonlinear and similar to what detected for Trpcs, the geographical zone which is most closely and directly affected by ENSO.

4.1 Robustness check

In order to check the robustness of our conclusions to data extension and interpolation, models MX and MXR were also estimated omitting the forecasted RF data and using the raw step function data, rather than their smoothed values. The results are reported in Tables A4 and A5 in the Online Appendix, respectively. By comparing figures reported in Tables 1 and A4, it can then be concluded that the results are strongly robust to sample updating, as omitting the last five years of forecasted data leaves even point estimates virtually unchanged. Moreover, comparing estimates reported in Tables 1 and A5 shows that the contribution of RF to the determination of temperature anomalies is also very robust to smoothing, in terms of both sign and magnitude of the estimated coefficients, albeit some differences in the selected type or order of the trigonometric components can be noted in few cases. However, according to information criteria, models using smoothed

[14] The consensus view is that ENSO accounts for 10%-30% of the inter seasonal and longer-term change in average temperatures, but only little of the global mean warming trend, which is driven by radiative forcing (Kaufmann et al., 2013; Schmith et al., 2012; Estrada and Perron, 2016).

RF data are always preferred to models using step function RF data, apart from three out of eighteen cases (GL and NoExt for MX; Trpcs for MXR). Finally, also robust is the evidence in support of the "global warming" hypothesis, as model selection shows that MX and MXR models are superior to a comprehensive set of competing specifications omitting the RF series (see Table A3).

4.2 The conditional variance of anomalies

The estimated conditional standard deviations for temperature anomalies and SOI are plotted in Figure 3. As shown in the plots and Table 1, all temperature series show the GARCH property, i.e. clusters of very sizable changes (of both signs) alternating with clusters of less sizable changes (of both signs). Moreover, the overall GL volatility level has been rising since the late 1980s, stabilizing at a higher value until the hiatus set it in the late 1990s. A lower level for GL volatility has then persisted thereafter, until a new volatility rise started about 2010, concurrent with the steepening in the GL trend. Hence, temperature level and volatility seem to be directly related: as a consequence, GW might also destabilize temperatures.

Interesting patterns can be detected for the other zones too. For instance, temperature volatility appears to be on a upward trend for NH and NoExt and on a downward trend for SH and SoExt. Also noteworthy is the volatility spike in Trpcs, concurrent with the extreme 1997-1998 El Niño event. Overall, these findings have important implications for both temperature forecasting and the pricing of financial instruments traded to hedge against temperature risk.

The GARCH property is detected also for the SOI index. Moreover, as shown in Figure 3, a sizable increase in SOI overall volatility can be noted since the mid-2000s, pointing to more "unstable ENSO" over time. This finding is interesting and surely deserves further assessment, particularly in connection with the concurrent steepening in the temperature trend induced by radiative forcing (see Figure 2), and, therefore, with additional potential feedback effects of GW on the ENSO cycle. We are unaware of previous contributions to the literature pointing to GARCH properties of temperature anomalies and SOI. In this respect, the integrated variance (IGARCH) property is consistent with the recurrent changes in the overall volatility level also noticed, yet not explicitly modelled.

4.3 Conditional correlations and global warming

Conditional covariances and correlations are estimated by means of the polarization identity in (7), which requires the estimation of the conditional variance for the aggregated anomaly and SOI series $y^+_{ij,t}$ and $y^-_{ij,t}$, i.e. $\hat{h}^+_{ij,t}$ and $\hat{h}^-_{ij,t}$, using the corresponding aggregated residuals $\hat{\varepsilon}^+_{ij,t}$ and $\hat{\varepsilon}^-_{ij,t}$.

As for the 9 original series, an IGARCH(1,1) specification is selected also for any of the 72 aggregates. A summary of the results is provided in Figure 4, where boxplots for the p-value of the Box-Ljung tests for serial correlation and conditional heteroskedasticity are plotted for the 81 standardized residual series. As shown in the plots, all models are well specified, showing white noise standardized residuals. Given the selected single decay factor IGARCH (1,1) specification (0.99; not reported), positive definiteness at each point in time of the conditional variance-covariance and correlation matrices is granted.

Comparison with the Constant Conditional Correlation model (CCC) yields strong support for the modeling of time-varying conditional correlations across temperature series and SOI. In fact, SP-DCC is preferred to CCC, yielding a lower BIC information criterion, i.e. -9.5651 versus -9.2682 (not reported). SP-DCC is also preferred to Engle (2002) DCC (BIC = -9.3973; not reported).[15] This finding is fully consistent with the results of the Monte Carlo analysis reported in the Appendix, showing that SP-DCC outperforms Engle (2002) DCC in the IGARCH(1,1) framework.

In Figure 5 we plot the conditional correlations for non overlapping zones in the Northern and Southern hemispheres, i.e. NH/SH, NoExt/SoExt, NoPol/SoPol. An upward sloping trend can be detected in all cases, revealing increasing comovement of temperature anomalies over time. We interpret this finding as further evidence in support of the "global warming hypothesis", in terms of a common trend-driver across temperature anomalies, i.e., RF.

In Figure 6 we plot the conditional correlations of the SOI index versus various temperature anomalies. In the plots, we also include the Oceanic Niño Index (ONI), which is the standard indicator used to identify El Niño (warm) and La Niña (cool) events in the tropical Pacific.[16] As shown in the Figure, the conditional correlation of SOI versus the anomaly for the tropics (Trpcs/SOI) is mostly negative in sign, consistent with the effects of El Niño (La Niña) events. In fact, a *contraction* (increase) in SOI, i.e. an El Niño (La Niña) event, is associated with an *increase* (reduction) in temperature at the tropics above (below) normal levels. Moreover, the very strong El Niño events of 1982, 1997-1998 and 2016 make the conditional correlation more negative (up to -0.2), i.e. they enhance the heat transfer. This is consistent with the general recognition that ENSO is an asymmetric phenomenon and that extreme ENSO events are different from moderate events (Cai et al., 2014 and 2015). The asymmetric feature of ENSO is visible at the global level and at the poles too, since also the conditional correlations of SOI versus the global (GL/SOI), Northern polar (NoPol/SOI) and Southern polar (SoPol/SOI) temperature anomalies become negative, or more negative, during the strongest El Niño episodes in the sample.

Moreover, while the ENSO cycle might contribute to explain persistent changes in global temperature, it appears to be unable to account for the global warming evidence, i.e. for the warming trend in global temperature. In this respect, GL/SOI is, in fact, weakly positive on average, rather than negative. On the other hand, the downward trend in the negative Trpcs/SOI and NoPol/SOI correlations, and the persistently negative SoPol/SOI correlation since 2010, are indicative that the ENSO heat transfer has increased on average over time, consistent with the feedback effects of global warming on the ENSO cycle detected at the trend level.

Additional results, concerning the ENSO teleconnection and its evolving properties, are reported in the Online Appendix.

4.4 Further implications of global warming for natural disaster risk

In the light of the above results, given current greenhouse gases emission dynamics, an increase in trend global temperature and more intense - and possibly unstable - ENSO oscillation and associated disruptive phenomena, i.e. cyclones, floods and droughts, should

[15] Details are available upon request from the authors.

[16] The ONI is computed as the running 3-month mean SST anomaly for the Niño 3.4 region (i.e., 5°N-5°S, 120°-170°W). Data are available at http://www.cpc.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml.

also be expected. The deep economic and human implications of the 2014-2016 El Niño event, as well as of the hyperactive 2017 Atlantic hurricane season, are the most recent evidence consistent with this view.[17]

In this Section we then further assess the predictability of climate-change related disasters. In particular, since about half of current outstanding risk capital in the cat bonds market is exposed to Atlantic hurricane risk (Figure 1; Plot 5; Davies, 2017), we investigate the linkage between radiative forcing, i.e. the GW driver, and Atlantic hurricanes intensity, as measured by their accumulated cyclones energy (ACE). As shown in Figure 7, since the mid-1990s Atlantic storms intensity has peaked during five episodes, i.e. 1995, 1998-1999, 2003-2005, 2010 and 2016-2017 (top plot, shaded areas); simple eyeball inspection reveals that RF well tracks ACE trend developments, and, therefore, might be a useful conditioning variable in an econometric model for hurricanes risk.

4.4.1 An econometric model of hurricanes risk

Our econometric analysis of hurricanes risk is based on the following parsimonious reduced form Adaptive-X-AR model

$$\begin{aligned} \phi(L)ACE_t &= \gamma(L)RF_t + \sum\nolimits_{i=1}^{p} \theta(L)\sin(2\pi i RF_t^*) + \delta(L)h_{GL,t}^{1/2} + \varepsilon_t \\ \varepsilon_t &\sim i.i.d.N(0,\sigma^2) \end{aligned} \quad (10)$$

where $\phi(L) = 1 + \phi_1 L + ... + \phi_m L^m$, $\theta(L) = \theta_1 L + ... + \theta_n L^n$, $\gamma(L) = \gamma_1 L + ... + \gamma_o L^o$, and $\delta(L) = \delta_1 L + ... + \delta_q L^q$ are polynomials in the lag operator with all the roots outside the unit circle, RF (RF^*) is radiative forcing (normalized to range in the $[0,1]$ interval), $h_{GL}^{1/2}$ is the annualized volatility of the global temperature anomaly yield by the monthly econometric model[18]. For numerical convenience all the variables are reported in standardized units.

Model selection has been implemented following a general to specific reduction approach, allowing for up to five lags of each variables.[19] The selected econometric model is reported in Table 2, Panel A. In addition to the Adaptive-X-AR model, we also report two nested specifications, i.e. the AR model, which neglects past climatological information ($\gamma(L) = \theta(L) = \delta(L) = 0$), and the Adaptive-X model, which neglects past ACE information ($\phi(L) = 1$). According to residual diagnostics, all the models are well specified. However, the adaptive models perform better than the AR model in terms of fit and information criteria: the coefficient of determination is 0.71 for the Adaptive-X-AR model and 0.59 for the Adaptive-X model; only 0.07 for the AR model. See also Figure 7 (high-center plot).

[17] The 2014-2016 El Niño event contributed to the most (least) active tropical cyclone season on record for the Central Pacific basin (Australian region) and to the formation of some systems outside of the season boundaries within the North Atlantic, Eastern and Southern Pacific basins. Various countries around the world, including Africa, Central America, South-East Asia and Pacific Islands, were affected by below or above-average rainfall and flooding, increased food scarcity, susceptibility to illnesses and forced displacement (UNOCHA, 2016). Moreover, the severity of 2017 Atlantic hurricanes season has also been related to ENSO anomalies, i.e. to the occurence of cool-neutral (La Niña) rather than warm (El Niño) conditions.

[18] It is computed as $\left(\sum\nolimits_{i=1}^{12} h_{GLi,t}\right)^{1/2}$ $t = 1979, ...2016$.

[19] We also considered other potential conditioning variables, as for instance SOI level and volatility. However, the preferred econometric model did not include the latter variables.

From the solved long-run equation (Table 2, Panel A), it can be noticed that an increase in either radiative forcing or temperature volatility leads to a long-term increase in ACE, and therefore in Atlantic hurricane risk. Hence, Atlantic hurricanes intensity/risk would be enhanced by global warming, also consistent with the feedback effects of GW on ENSO. As found for temperature anomalies and ENSO, given the significance of the trigonometric term, also the linkage between RF on ACE is highly nonlinear.

As shown in Table 2, Panel B, the remarkable in sample performance of the Adaptive-X-AR and Adaptive-X models is not due to overfitting. In fact, both models largely dominate the AR model also in terms of out of sample forecasting accuracy. In this respect, we perform two forecasting exercises, using 2/3 of the sample for estimation (1984-2006) and 1/3 for forecasting (2007-2017); in the first exercise parameters are estimated over the period 1984-2006 and then kept constant; in the second exercise, rolling one-step ahead forecasts are generated, updating parameter estimates at each step; for both cases, we also report results when the last observation in the sample (year 2017) is omitted from the forecasting horizon, due to its outlying value. As shown in the Table, a 40%-50% $RMSFE$ reduction is yield by the adaptive models relative to the AR and naive forecasting models, independently of the forecasting horizon. The performance of the adaptive models is similar, with the Adaptive-X-AR model slightly outperforming the Adaptive-X model when forecasts are generated recursively.

In Figure 7 (low-center and bottom plots) we compare actual ACE values with the forecasts yield by the Adaptive-X-AR model, for the case of recursive estimation. In the comparison we also consider (spline) smoothed ACE figures in order to highlight the ability of the Adaptive-X-AR model to track trend developments in ACE, consistent with the view that RF/GW might affect the long-term behavior of natural phenomena too. Visual inspection provides clear-cut confirmation of predictability for *trend* Atlantic hurricanes intensity (and disruptions), based on climatological information.

Hence, in the light of current radiative forcing and climate change developments, the risk of more intense Atlantic hurricanes appears to be on a rising trend, also consistent with recent evidence on their Loss/Risk ratio level and volatility (Figure 1; Plot 8).

Then, on a rising trend would also be cat bonds risk, at least for that sizable portion of outstanding capital exposed to Atlantic hurricanes. Whether the falling trend in the average cat bonds multiple, and its record low value scored in 2017 and 2018, is consistent with accurate pricing of the embedded natural disaster risk is the open issue that we address in the following Section.

5 Assessing risk dynamics in the catastrophe bonds market

To date, most of the contributed work on cat bonds pricing has been concerned with contingent claims or equilibrium models, while econometric models have been used only in a minority of studies.[20] In this respect, the most comprehensive econometric analyses available are the panel data studies of Guertler et al. (2016) and Braun (2016), which investigate 387 secondary market transactions and 437 primary market tranches, respectively, over the period June 1997 through December 2012. In addition to the expected loss, which accounts for the bulk of cross-sectional risk premia variability (about 80%),

[20] See Braun (2011) for a detailed account of the literature.

various market specific and financial factors have been assessed.[21] For instance, Braun (2016) points to the rate-on-line index, the BB corporate bond spread, geographical location and type of sponsor as additional pricing factors in the primary market; Guertler et al. (2016), in addition to the BB spread, also find that deal complexity, rating and the phase of the reinsurance cycle are significant conditioning variables for the secondary market.[22]

Recent evidence also points to some sensitivity of cat bonds pricing to evolving Atlantic hurricanes risk. In this respect, Guertler et al. (2016) have shown that the premium rose for cat bonds with hurricane perils after Katrina in August 2005, yet not thereafter (for instance, after Ike in September 2008), suggesting that investors might have believed that the risk adjustment induced by Katrina was sufficient to account for future catastrophes. Yet the deep economic and human implications of recent events and the evolving properties of Atlantic hurricanes risk, in relation to climate change, cast serious doubts over this view.

5.1 An econometric analysis of cat bonds pricing

The predictive regression framework employed in this study is best suited not only to assess the impact of changing investors' perceptions about evolving climate change-related risk, but also to assess the role of monetary policy and shifting portfolio composition in accounting for shrinking risk premia over time. Predictability of risk premia in this context is fully consistent with "market rationality", as it is the result of variation in risk or willingness to bear risk, rather than of irrational swings of prices away from fundamental values (Fama and French, 1989).

Specifically, our analysis is focused on the determinants of the average cat bonds multiple in the primary market ($MULT$). Hence, tranche-specific factors are not considered and we only focus on financial markets variables, i.e., interest rates, and climate-change related variables.

As shown in Figure 1 (Plot 6), the falling trend in the average multiple is a feature shared also with corporate bonds. In the literature, this pattern is often associated with the expansionary monetary policy stance pursued by the Fed to counteract the deflationary effects of the dot-com and subprime financial crises, and therefore to the falling trend in the federal funds rate (FFR) and the implementation of the $Q.E.$ policy (Eigen et al., 2015).

However, coherent with the different risk exposure, trend dynamics in the average cat bond multiple and corporate rate spreads also show some differences. For instance, $MULT$ has been much less affected by the subprime financial crisis than corporate bonds. Indeed, the comovement between AA and BBB corporate bond spreads is much stronger than between AA or BBB spreads and $MULT$. This is fully consistent with the different type of risk exposure of cat bonds in relation to corporate bonds, i.e. natural disaster rather than business cycle conditions. This "zero-beta" property of cat bonds and the change in institutional investors' perception about the characteristics of these assets, from exotic to standard diversification instruments, might be at the origin of their extensive

[21] See also Lane and Mahul (2008).

[22] Interestingly, the positive linkage between cat bond premia and BB corporate spreads appears to have strengthened with the occurrence of the subprime financial crisis, particularly after the bankruptcy of Lehman Brothers (Guertler et al., 2016). Moreover, this linkage also appears to get stronger in periods of financial distress (Cumming and Weiss, 2009; Carayannopoulos and Perez, 2015).

participation in the market.

5.1.1 Integration and cointegration properties

In the light of the stochastic nonstationarity of the average multiple and corporate spreads (Table 3, Panel A), we have then assessed their cointegration and error correction properties. As shown in Table 3 (Panel A), concerning the specification of the unrestricted reduced form model, a parsimonious first order VAR model yields residuals consistent with a white noise process (not reported).[23] Within this framework, we have then tested for cointegration using the Johansen Trace test. According to the Trace statistics there is evidence of two cointegrating relationships (10% significance level) and therefore of two common trends accounting for the long-term evolution of risk premia and the federal funds rate. The identification of the cointegrating vectors yields two irreducible homogenous cointegration relationships: the former relates $MULT$ to FFR; the latter relates the AA and BBB spreads.[24]

Also consistent and clear-cut are the error correction properties of the average multiple and the corporate spreads. In fact, according to the estimated loadings, $MULT$ corrects its disequilibrium with FFR, which, on the other hand, is weakly exogenous. Moreover, also corporate spreads correct relative to the $MULT/FFR$ disequilibrium. Hence, following a contraction in FFR, and therefore a widening in the $MULT/FFR$ disequilibrium ceteris paribus, $MULT$, AA and BBB would tend to decrease, consistent with the view that associates the declining trend in bond spreads to the expansionary monetary policy stance.

Moreover, AA corrects also relative to its disequilibrium with BBB, pointing to some contagion in the corporate bonds market. In particular, following an increase the default risk for BBB bonds, the default risk for AA bonds would also raise. On the other hand, no response to the BBB/AA disequilibrium can be noted for cat bonds, consistent with the fact that cat bonds are not sensitive to business cycle risk.

5.1.2 Error correction modelling of cat bond multiples

Given the aim of this study, error correction modeling concerns $MULT$ only. In addition to lagged values (in changes) for $MULT$, FFR, AA and BBB, we consider lagged changes for the 10-year US Treasury bond rate ($TB10Y$), the 3-month US Treasury Bills rate ($TB3M$) and the BB spread (BB), in order to investigate portfolio diversification effects related to changes in investors' preferences. Moreover, in order to assess investors' perception of evolving climate change risk, we have also considered past values for temperature volatility (h_{GL}) and past changes in radiative forcing (RF), accumulated cyclones energy (ACE) and the Atlantic hurricanes Loss/Risk ratio (damages in 2017 US$ to ACE ratio; LR).[25] In the light of the results of this study, pointing to significant feedback effects of global warming (radiative forcing) on the intensity of the ENSO cycle

[23] The p-values of the vector AR 1-2, Heteroskedasticity and Normality tests are 0.084, 0.200 and 0.107, respectively.

[24] The analysis was repeated including also the BB spread and the US Treasury bill (TB3M) and bond (TB10Y) rates. The empirical results confirm the separation of the cointegration space into three homogenous bivariate relationships involving FFR, TB10Y, TB3M and MULT, and into two bivariate relationships involving AA, BBB and BB. Details are available upon request from the authors.

[25] Additional ADF test results are available upon request from the authors.

and Atlantic hurricanes, these variables might be expected to convey information on cat bonds riskiness, at least concerning those instruments exposed to Atlantic hurricanes.

In Table 3, Panel B, we report some alternative specifications for the error correction model, allowing to evaluate the incremental explanatory power of conditioning information, relative to the inclusion of the error correction term alone. Hence, our econometric analysis of the average cat bonds multiple is based on the reduced form error correction model

$$\phi(L)\Delta MULT_t = c + \theta_0\left[MULT_{t-1} - FFR_{t-1}\right] + \theta(L)\Delta z_t + \varepsilon_t \tag{11}$$

where $\varepsilon_t \sim i.i.d.N(0,\sigma^2)$, $\phi(L) = 1+\phi_1 L+...+\phi_m L^m$ and $\theta(L) = \theta_1 L+...+\theta_n L^n$ are polynomials in the lag operator with all the roots outside the unit circle, $[MULT_{t-1} - FFR_{t-1}]$ is the error correction term, and $\Delta z_t = \Delta AA_t$, ΔBB_t, ΔBBB_t, ΔFFR_t, $\Delta TB3M_t$, $\Delta TB10Y_t$, ΔLR_t, ΔRF_t, ΔACE_t, $h_{GL,t}$.

Given the small sample available, we consider up to five lags for each of the conditioning variables z_t at the time and implement a general to specific procedure for model reduction. As shown in Table 3, Panel B, all the models are well specified according to standard misspecification tests, but only the inclusion of financial information, particularly lagged BBB and BB spreads, yields a sizable increment in explanatory power relative to the benchmark model. In this respect, $MULT$ reacts to its disequilibrium with FFR in the very short-term (within 1 year), then to corporate bond spreads at the 2/3-year horizon, and then to Treasury bill and bond rates at longer horizons (5-year). The above pattern is then consistent with the view that sees falling multiples as the consequence of the expansionary monetary policy stance pursued by the Fed and of changes in the investors' preferences/portfolio shifts.

Moreover, the estimated impact of climate change variables on $MULT$ is either not statistically significant, as for RF, or significantly negative, as for ACE, h_{GL} and LR. Hence, $MULT$ is not significantly related to changes in radiative forcing, and an increase in temperature volatility, Atlantic hurricanes intensity or in the Loss/Risk ratio for Atlantic hurricanes would be even followed by a decrease in $MULT$ in the medium-term. Overall, these findings appear to be inconsistent with cat bonds accurately pricing the evolving climate change risk.

In order to consider the contribution of the various conditioning variables jointly, a final error correction model has been specified by including all the lagged variables which were found significant in the partial error correction analyses above, i.e.

$$\Delta MULT_t = c + \theta_0\left[MULT_{t-1} - FFR_{t-1}\right] + \boldsymbol{\theta}'\Delta\mathbf{g}_t + \varepsilon_t \tag{12}$$

where $\Delta\mathbf{g}_t = [\ \Delta AA_{t-2}\quad \Delta BB_{t-3}\quad \Delta BBB_{t-3}\quad \Delta TB3M_{t-5}$
$\Delta TB10Y_{t-5}\quad \Delta FFR_{t-5}\quad h_{GLt-2},\ \Delta LR_{t-5},\ \Delta ACE_{t-5}]'$ and $\boldsymbol{\theta}$ is the corresponding vector of parameters, i.e. $\boldsymbol{\theta} = [\ \theta_{2,AA}\quad \theta_{3,BB}\quad \theta_{3,BBB}\quad \theta_{5,TB3M}\quad \theta_{5,TB10Y}\quad \theta_{5,FFR}\quad \theta_{2,h_{GL}}\quad \theta_{5,LR}\ \theta_{5,ACE}]'$.

Its final specification, obtained through a general to specific reduction strategy, is reported in Table 3, Panel C. As shown in the Table, the final econometric model is very parsimonious, well specified and accounts for about 65% of $MULT$ variability.

In order to asses whether this finding might be due to overfitting, the model is also estimated omitting the last five observations (2013-2017); one-step ahead out of sample forecasts are then generated, without updating parameter estimates; as shown by the RMSFE reported in the Table, the final econometric model shows much higher forecasting accuracy than the model including the error correction term only; it also performs better than many of the other candidate partial specifications. We regard these results as evidence of stability and reliability of the estimated dynamic relationship.

In terms of determinants of $MULT$ short-run dynamics, the implications of the joint error correction analysis are consistent with the results of the partial one. In fact, a contraction in FFR would lead to a contraction in $MULT$ due to disequilibrium correction (monetary policy stance effect); moreover, an increase in the $TB3M - FFR$ spread is associated with a contraction in $MULT$ within five years. This result is somewhat reminiscent of the linkage between bond returns and the term spread (Fama and French, 1989). However, due to the type of risk exposure, it possibly points to portfolio shift effects, more than to sensitivity of cat bonds to short-term business cycle fluctuations. Finally, the negative linkage between $MULT$ and LR is also confirmed, casting doubts over accurate pricing of the evolving climate change risk in the cat bonds market.[26]

6 Conclusions

Since their introduction in the mid-1990s, the market for catastrophe bonds and insurance linked securities (ILS) has developed rapidly, achieving over US$ 30 billion of outstanding capital in 2018. Owner composition of cat bonds has also been changing over time. While in the early 2000s cat bonds were largely owned by hedge funds and reinsurance companies, currently institutional investors, including pension and mutual funds, own about 30% of the assets. These changes have been coupled by a steady decline in the return per unity of risk or *multiple*, from a value of 8 in the early 2000s to a record low value of 2 in 2017 and 2018. Whether this pattern in cat bond risk premia is consistent with the historical evolution of natural disaster risk is an open issue, particularly in the light of the large share of outstanding capital exposed to Atlantic hurricanes, a risk that climate change - among other disruptions - is expected to enhance.

Given the above evidence, the extensive participation of low-risk profile investors, such as pension funds, and the large growth potential of the cat bonds and ILS market, this paper then deals with the important open issue of whether cat bonds risk is currently correctly perceived and priced. To our knowledge, this is the first study in the literature assessing whether the falling trend in multiples is consistent with the evolution of natural disaster risk and the implications of climate change for the cat bonds and ILS market.

To summarize the main results of the study, we find evidence to support the global warming hypothesis, i.e. the direct connection of the warming trend in global temperatures to radiative forcing, also of anthropogenic origin (greenhouse gases emissions). Moreover, we provide clear evidence of important feedback effects of global warming for the natural environment, in terms of higher natural disaster risk, associated with more intense ENSO cycle and Atlantic hurricanes activity, and, therefore, higher cat bonds risk, at least with regard to the sizable portion of outstanding capital exposed to Atlantic hurricanes. In this respect, our results suggest that climate change risk might not yet have been properly incorporated in cat bond multiples. In fact, while falling cat bond multiples are primarily related to the Fed's expansionary monetary stance and to portfolio shift effects, we also find evidence of significant undervaluation of natural disaster risk. This is not somewhat surprising, in light of the inconclusive available empirical evi-

[26] A similar finding holds also when the LR (L/ACE) ratio is scaled by world GDP $((L/GDP)/ACE)$ or when the weather-insured damages to world GDP ratio is employed in the regression, as an alternative to LR. These results are available upon request to the authors.

dence on the pricing of climatic change in financial markets (Monasterolo and De Angelis, 2018).

Many central bank governors have recently started considering increasing regulatory supervision to address climate-related risks to financial stability. Such measures include carbon stress tests for banks and other financial institutions to assess the effects of an abrupt transition to a low carbon economy in response to irreversible climate catastrophes (Gros et al., 2016; Battiston et al., 2017). Our paper contributes to the policy and scientific debate over the economic and financial implications of climate change by providing insights into the origins of some catastrophic risks, and by modelling and forecasting their impact. On the one hand, insurance and reinsurance companies need to be more aware of certain properties of Atlantic hurricanes. In this respect, our findings have implications for the modelling of these natural phenomena, whose intensity, and therefore destructive power, appears to be predictable. On the other hand, the results of our study raise questions over the sanity of the cat bonds market and the suitability of cat bonds as diversification instruments for risk-averse investors, such as pension funds. This is particularly true in light of the large growth potential of the cat bonds and ILS market and the unfailing appetite of institutional investors for such securities, despite the significant losses incurred, especially in 2017. We believe that sounder opportunities for institutional investors can be found in the *green bonds* market, which allows for the funding of immediate investment in climate change mitigation (Richardson and Reichelt, 2018), by shifting its ultimate costs to future generations, i.e. those who are likely to benefit the most from environmental preservation (Sachs, 2014; Flaherty et al., 2017). Morover, on a global scale, investment in the green bonds market might contribute to financial stability, by reducing the savings–investment imbalance, often seen at the origin of the recent episodes of financial turmoil (Bagliano and Morana, 2017).

Finally, our results also have important implications for central bank regulatory supervision. While such supervision is timely and needs intensification, it should consider an additional layer of risk, related to the implications of the irreversible consequences of climatic change. For example, a dramatic reduction of greenhouse gas emissions, that is, an abrupt transition to a low carbon economy, might not reverse in any way the consequences of climate change, within any meaningful human time span. This is because of the permanent effect of temperature increases beyond 2° Celsius with respect to pre-industrial levels, i.e. the shutdown of the large ocean circulation systems, sea level rise and the large-scale melting of permafrost (IPCC, 2018). Policymakers, as well as laymen and financial agents, do not yet fully understand the economic, financial, and human implications of this additional layer of risk. Our study also highlights the importance of additional awareness in this respect.

7 Appendix A1. Estimation of the SP-DCC model

Consistent and asymptotically Normal estimation of the SP-DCC model (Morana, 2015, 2019) is obtained by QML, following a multi-step procedure similar to Engle (2002). Hence, consider the Gaussian joint log-likelihood for the model in (1)-(2)

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(N\log(2\pi) + \log|\mathbf{H}_t| + \boldsymbol{\varepsilon}_t'\mathbf{H}_t^{-1}\boldsymbol{\varepsilon}_t\right), \tag{13}$$

which, following Engle (2002), is written as

$$
\begin{aligned}
L &= -\frac{1}{2}\sum_{t=1}^{T} N\log(2\pi) + 2\log|\mathbf{D}_t| + \boldsymbol{\varepsilon}_t'\mathbf{D}_t^{-1}\mathbf{D}_t^{-1}\boldsymbol{\varepsilon}_t) \\
&\quad -\frac{1}{2}\sum_{t=1}^{T}(-\mathbf{z}_t'\mathbf{z}_t + \log|\mathbf{R}_t| + \mathbf{z}_t'\mathbf{R}_t^{-1}\mathbf{z}_t)
\end{aligned} \tag{14}
$$

where $\mathbf{D}_t = diag\left(h_{1,t}^{1/2}, ..., h_{N,t}^{1/2}\right)$ and the conditional correlation matrix $\mathbf{R}_t$ is defined as $\mathbf{R}_t = \mathbf{D}_t^{-1}\mathbf{H}_t\mathbf{D}_t^{-1}$.

The log-likelihood function in (14) can then be decomposed into the sum of a *volatility part*

$$
L_v(\boldsymbol{\theta}) = -\frac{1}{2}\sum_{t=1}^{T}\left(N\log(2\pi) + 2\log|\mathbf{D}_t| + \boldsymbol{\varepsilon}_t'\mathbf{D}_t^{-1}\mathbf{D}_t^{-1}\boldsymbol{\varepsilon}_t\right) \tag{15}
$$

and a *correlation part*

$$
L_C(\boldsymbol{\theta}, \boldsymbol{\phi}) = -\frac{1}{2}\sum_{t=1}^{T}\left(-\mathbf{z}_t'\mathbf{z}_t + \log|\mathbf{R}_t| + \mathbf{z}_t'\mathbf{R}_t^{-1}\mathbf{z}_t\right), \tag{16}
$$

and estimation is performed in the following steps. Firstly, the mean equation model in (1) is estimated equation by equation by QML, i.e. the misspecified likelihood

$$
L_m(\boldsymbol{\vartheta}) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\log(2\pi) + \log\sigma_i^2 + \frac{\varepsilon_{i,t}^2}{\sigma_i^2} \tag{17}
$$

is maximized by separately maximizing each term.

Then, using the estimated conditional mean residuals $\hat{\boldsymbol{\varepsilon}}_t$, the volatility part of the likelihood (15) is maximized with respect to the conditional variance parameters; since (15), given (5), is the sum of individual GARCH likelihoods, i.e.

$$
L_v(\boldsymbol{\theta}) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\log(2\pi) + \log h_{i,t} + \frac{\hat{\varepsilon}_{i,t}^2}{h_{i,t}}, \tag{18}
$$

the volatility part is maximized by separately maximizing each term.

Finally, rather than maximizing the correlation part in (16), conditional to the estimated mean residuals and conditional variances delivered by the former two steps, SP-DCC maximizes the sum of individual GARCH likelihoods for the aggregates $y_{ij,t}^{+}$ and $y_{ij,t}^{-}$, i.e.

$$
\begin{aligned}
L_{SP}(\boldsymbol{\phi}) &= -\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j>i}^{N}\left(\log(2\pi) + \log h_{ij,t}^{+} + \frac{\hat{\varepsilon}_{ij,t}^{+2}}{h_{ij,t}^{+}}\right) \\
&\quad -\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j>i}^{N}\left(\log(2\pi) + \log h_{ij,t}^{-} + \frac{\hat{\varepsilon}_{ij,t}^{-2}}{h_{ij,t}^{-}}\right)
\end{aligned} \tag{19}
$$

which is jointly maximized by separately maximizing each term. Hence, the conditional variances for the aggregates $h_{ij,t}^{+}$, $h_{ij,t}^{-}$, $i, j = 1, ..., N$, $i \neq j$, are estimated equation by equation by means of QML, using the aggregates of the conditional mean residuals $\hat{\varepsilon}_{ij,t}^{+} = \hat{\varepsilon}_{i,t} + \hat{\varepsilon}_{j,t}$ and $\hat{\varepsilon}_{ij,t}^{-} = \hat{\varepsilon}_{i,t} - \hat{\varepsilon}_{j,t}$. The conditional covariances are then estimated by means of the polarization identity, i.e. the off-diagonal elements of $\mathbf{H}_t$, $h_{ij,t}$, $i, j = 1, ..., N$, $i \neq j$, are computed as

$$
\hat{h}_{ij,t} = \frac{1}{4}\left[\hat{h}_{ij,t}^{+} - \hat{h}_{ij,t}^{-}\right] \qquad i, j = 1, ..., N \qquad i \neq j. \tag{20}
$$

The conditional correlation matrix $\mathbf{R}_t$ is finally estimated as $\hat{\mathbf{R}}_t = \hat{\mathbf{D}}_t^{-1}\hat{\mathbf{H}}_t\hat{\mathbf{D}}_t^{-1}$, where $\hat{\mathbf{D}}_t = diag\left(\hat{h}_{1,t}^{1/2}, ..., \hat{h}_{N,t}^{1/2}\right)$ and the correlation part in (16) can be evaluated provided $\hat{\mathbf{R}}_t$ is positive definite at each point in time. See Morana (2015, 2019) for ex-post corrections that can be implemented in the case of a non positive definite correlation matrix.

Hence, the proposed approach to maximize the log-likelihood function is to find

$$\hat{\boldsymbol{\vartheta}} = \arg\max \left\{ L_m\left(\boldsymbol{\vartheta}\right) \right\} \tag{21}$$

$$\hat{\boldsymbol{\theta}} = \arg\max \left\{ L_v\left(\boldsymbol{\theta}\right) \right\} \tag{22}$$

$$\hat{\boldsymbol{\phi}} = \arg\max \left\{ L_{SP}\left(\boldsymbol{\phi}\right) \right\} \tag{23}$$

and then use these values to evaluate $L_C(\boldsymbol{\theta}, \boldsymbol{\phi})$.

Despite the above procedure does not ensure the maximization of the joint log-likelihood in (14), consistent and asymptotically Normal QML estimation can be conjectured, under the usual standard assumptions, and grounded on the consistency and asymptotic Normality of QML univariate estimation of the GARCH(1,1) conditional variance model for the individual and aggregated series. For the latter model the optimal QML properties have been shown to hold not only for the stationary case, but also for the integrated and the (mildly) explosive ones, also when the devolatilized innovation is non Gaussian and non i.i.d., provided its fourth moment is bounded. We point to Morana (2019) for details and to the Section below for supporting Monte Carlo results.

8 Appendix A2: Small sample performance of SP-DCC

This section explores the small sample performance of SP-DCC (Morana, 2015, 2019), together with other standard estimation methods. Hence, consider the following bivariate GARCH(1,1) model

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = H_t^{\frac{1}{2}} \begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} \qquad \begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix} \sim i.i.dN(0, I_2) \tag{24}$$

where

$$H_t = \begin{bmatrix} h_{1t} & h_{12t} \\ h_{12t} & h_{2t} \end{bmatrix}. \tag{25}$$

The conditional covariance matrix follows the bivariate process

$$\begin{aligned} \begin{bmatrix} h_{1t} & h_{12t} \\ h_{12t} & h_{2t} \end{bmatrix} &= \begin{bmatrix} \omega_1 & \omega_2 \\ \omega_2 & \omega_3 \end{bmatrix} + \begin{bmatrix} \beta_1 & \beta_2 \\ \beta_2 & \beta_3 \end{bmatrix} \begin{bmatrix} h_{1t-1} & h_{12t-1} \\ h_{12t-1} & h_{2t-1} \end{bmatrix} \\ &+ \begin{bmatrix} \alpha_1 & \alpha_2 \\ \alpha_2 & \alpha_3 \end{bmatrix} \begin{bmatrix} y_{1t-1}^2 & y_{1t-1}y_{2t-1} \\ y_{1t-1}y_{2t-1} & y_{2t-1}^2 \end{bmatrix}, \end{aligned} \tag{26}$$

or, in its VECH form,

$$\begin{bmatrix} h_{1t} \\ h_{12t} \\ h_{2t} \end{bmatrix} = \begin{bmatrix} \psi_1 \\ \psi_2 \\ \psi_3 \end{bmatrix} + \begin{bmatrix} \beta_1 & 0 & 0 \\ 0 & \beta_2 & 0 \\ 0 & 0 & \beta_3 \end{bmatrix} \begin{bmatrix} h_{1t-1} \\ h_{12t-1} \\ h_{2t-1} \end{bmatrix} + \begin{bmatrix} \alpha_1 & 0 & 0 \\ 0 & \alpha_2 & 0 \\ 0 & 0 & \alpha_3 \end{bmatrix} \begin{bmatrix} y_{1t}^2 \\ y_{1t}y_{2t} \\ y_{2t}^2 \end{bmatrix}. \tag{27}$$

It is possible to substitute $h_{it} = y_{it}^2 - \eta_{it}$ into (25), in order to obtain the VARMA representation for the squared processes

$$\begin{aligned} &\begin{bmatrix} (1-(\alpha_1+\beta_1)L) & 0 & 0 \\ 0 & (1-(\alpha_2+\beta_2)L) & 0 \\ 0 & 0 & (1-(\alpha_3+\beta_3)L) \end{bmatrix} \begin{bmatrix} y_{1t}^2 \\ y_{1t}y_{2t} \\ y_{2t}^2 \end{bmatrix} = \\ &= \begin{bmatrix} \psi_1 \\ \psi_2 \\ \psi_3 \end{bmatrix} + \begin{bmatrix} (1-\beta_1 L) & 0 & 0 \\ 0 & (1-\beta_2 L) & 0 \\ 0 & 0 & (1-\beta_3 L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \\ \eta_{3t} \end{bmatrix} \end{aligned} \tag{28}$$

where

$$E\eta_{it}^2 = E(z_{it}^2-1)^2 Eh_{it}^2 = \frac{(\kappa_i - 1)h_i^2\left\{1-(\beta_i+\alpha_i)^2\right\}}{(1-\beta_i^2-2\alpha_i\beta_i-\alpha_i^2\kappa_i)}$$

and $\kappa_i = E\left(z_{i,t}^4\right)$.

The contemporaneous aggregation of model (28) leads to an ARMA(3,3) unless, for some i and j, $(\alpha_i+\beta_i) = (\alpha_j+\beta_j)$, i.e. unless the case of root cancellation holds. For example, consider the process $(y_{1t}+y_{2t})$ and assume $(\alpha_1+\beta_1) = (\alpha_2+\beta_2)$; then the contemporaneous aggregation of model (28) leads to an ARMA(2,2) for the squared aggregate $(y_{1t}+y_{2t})^2$, that is

$$\begin{aligned}
& \left[1-\left((\alpha_3+\beta_3)+(\alpha_1+\beta_1)\right)L+\left((\alpha_3+\beta_3)(\alpha_1+\beta_1)\right)L^2\right]\left(y_{1t}^2+2y_{1t}y_{2t}+y_{2t}^2\right) \\
= \;& \psi+\left[(1-(\alpha_3+\beta_3)L)(1-\beta_1L)\eta_{1,t}\right]+\left[(1-(\alpha_3+\beta_3)L)(1-\beta_2L)2\eta_{2,t}\right] \\
& +\left[(1-(\alpha_1+\beta_1)L)(1-\beta_3L)\eta_{3,t}\right],
\end{aligned}$$

where $\psi = (1-(\alpha_3+\beta_3))(\omega_1+2\omega_2)+(1-(\alpha_1+\beta_1))\omega_3$.

In addition, when $(\alpha_1+\beta_1) = (\alpha_2+\beta_2) = (\alpha_3+\beta_3) = \gamma$, the aggregate process for the squared aggregate $(y_{1t}+y_{2t})^2$ is an ARMA(1,1)

$$\begin{aligned}
& [1-\gamma L]\left(y_{1t}^2+2y_{1t}y_{2t}+y_{2t}^2\right) \\
= \;& \phi+[1-\beta_1L]\eta_{1,t}+[1-\beta_2L]2\eta_{2,t}+[1-\beta_3L]\eta_{3,t},
\end{aligned}$$

where $\phi = \omega_1+2\omega_2+\omega_3$.

Similar findings hold for other combinations of (28), such as the squared difference process as considered by SP-DCC. Therefore, although the SP-DCC model represents an approximation for this framework (DVECH-GARCH(1,1)), when the case of root cancellation arises this approximation gets more accurate. This seems to be the message from the following Monte Carlo simulation.

8.1 Monte Carlo results

We generate model (24)-(25) using a sample size of 1000 observations, 2500 replications and the following three parameter structures:

$$\begin{aligned}
& MODEL(i)\ for\ i=1,2,3 \\
& \boldsymbol{\omega}_i = \begin{bmatrix}\omega_1 & \omega_2\\ \omega_2 & \omega_3\end{bmatrix} = \begin{bmatrix}.01 & 0\\ 0 & .01\end{bmatrix} \\
& \boldsymbol{\alpha}_i = \begin{bmatrix}\alpha_1 & \alpha_2\\ \alpha_2 & \alpha_3\end{bmatrix} = \begin{bmatrix}.1 & .1\\ .1 & .1\end{bmatrix} + \begin{bmatrix}U(0-x_i) & U(0-x_i)\\ U(0-x_i) & U(0-x_i)\end{bmatrix} \\
& \boldsymbol{\beta}_i = \begin{bmatrix}\beta_1 & \beta_2\\ \beta_2 & \beta_3\end{bmatrix} = \begin{bmatrix}.9 & .9\\ .9 & .9\end{bmatrix} - \boldsymbol{\alpha} + \begin{bmatrix}U(0-x_i) & U(0-x_i)\\ U(0-x_i) & U(0-x_i)\end{bmatrix} \\
& with\ x_1 = 0.01\ \ x_2 = 0.03\ \ x_3 = 0.06
\end{aligned}$$

At each replication, the matrices $\boldsymbol{\alpha}_i$ and $\boldsymbol{\beta}_i$ are randomly generated by summing up a constant matrix and a random matrix, whose elements have a random uniform distribution ranging from 0 through 0.01, 0.03 and 0.06 for MODEL 1, MODEL 2 and MODEL 3, respectively. This is to measure the impact of the departure from the possible root cancellation case on the small sample properties of SP-DCC. Moreover, when generating $\boldsymbol{\alpha}_i$ and $\boldsymbol{\beta}_i$, we allow for positive definite matrices only, since this condition guarantees that H_t is positive definite. In the simulation we compare three alternative estimators: the multivariate (i.e. bivariate) GARCH ML estimator (ML), the ML-DCC (Engle, 2002; DCC) estimator and SP-DCC. In the Monte Carlo exercise we assess the ability of the various models to estimate the conditional correlation process $\rho_{12t} = h_{12t}/h_{1t}^{1/2}h_{2t}^{1/2}$, $t = 1,...,1000$.

Results for the $RMSE$ of the conditional correlation, i.e. $RMSE = \left(\frac{1}{T}\sum_{t=1}^{1000}\left(\hat{\rho}_{12t}-\rho_{12t}\right)^2\right)^{1/2}$, are reported in the box-plots in Figure A1. Not surprisingly, ML has the best performance. DCC shows also a very good performance, comparable with ML; the performance of SP-DCC is also comparable with the other methods, depending on the parameterization choice. This is notwithstanding SP-DCC is an approximation for this specific framework. It is interesting to observe the change of performance across the different models. In particular, SP-DCC tends to suffer when the gap between the $\alpha_i + \beta_i$ gets wider as in MODEL 3. On the other hand, for MODEL 1 the performance of SP-DCC and DCC are very close, for MODEL 2 are similar, while some deterioration of SP-DCC performance can be noted for MODEL 3. As the case of root cancellation is rather frequent in empirical applications, we expect MODEL 1 and MODEL 2 being indicative of the empirical performance of SP-DCC with real data, where the sums $\alpha_i + \beta_i$ might even tend to approach one.

8.1.1 The IGARCH case

The Integrated GARCH (IGARCH) process arises when $(\alpha_i+\beta_i) = 1$. For this case, the SP-DCC model is no more an approximation. Indeed, for this case, any combination of model (28) preserve the ARMA(1,1) parametrization and therefore any combination of y_{1t} and y_{2t} also preserve the IGARCH(1,1) structure. As a consequence SP-DCC uses the correct specification to estimate the conditional correlations. These considerations have been tested through some Monte Carlo simulations.

We generate model (24)-(25) assuming that the conditional covariance matrix follows an IGARCH(1,1) process. We consider a single decay factor driving the dynamics of the conditional covariance such that the following three parameter structures are considered:

$$
\begin{aligned}
&MODEL(j)\ for\ j = 4, 5, 6 \\
&\boldsymbol{\omega}_j = 0.0001 * \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} + \begin{bmatrix} U(0 - x_j) & 0 \\ 0 & U(0 - x_j) \end{bmatrix} \\
&\boldsymbol{\alpha}_j = \begin{bmatrix} 0.05 & 0.05 \\ 0.05 & 0.05 \end{bmatrix} + \begin{bmatrix} U(0 - x_j) & U(0 - x_j) \\ U(0 - x_j) & U(0 - x_j) \end{bmatrix},\ \boldsymbol{\beta}_j = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} - \boldsymbol{\alpha}_j \\
&with\ x_4 = 0.01\ \ x_5 = 0.03\ \ x_6 = 0.06
\end{aligned}
$$

The exercise compares the performance of four different competitors: 1) the pseudo-ML estimator as discussed in Zaffaroni (2008) that estimates a single decay factor (MLC), 2) the ML estimator that does not impose a single decay factor (ML), 3) SP-DCC and 4) DCC. The reason for the inclusion of ML is that both SP-DCC and DCC do not impose the single decay factor; we can then compare the performance of three estimators that do not know the data generation process. The empirical results are also reported in Figure A1 (MODELS 4 and 5). Since the performance of the models is unaffected by the selected parameterization, for reason of space we omit to report the results for the intermediate case (0.03). Beside MLC showing the best results, SP-DCC always performs better than DCC and even ML. This confirms that when the IGARCH(1,1) framework arises, SP-DCC represents a fully valid candidate in estimating the conditional correlations.

8.1.2 The UVECH case

Now consider model (24)-(25) with the following unrestricted VECH representation:

$$
\begin{bmatrix} h_{1t} \\ h_{12t} \\ h_{2t} \end{bmatrix} = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix} + \begin{bmatrix} \beta_1 & \beta_2 & \beta_3 \\ \beta_4 & \beta_5 & \beta_6 \\ \beta_7 & \beta_8 & \beta_9 \end{bmatrix} \begin{bmatrix} h_{1t-1} \\ h_{12t-1} \\ h_{2t-1} \end{bmatrix} + \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_3 \\ \alpha_4 & \alpha_5 & \alpha_6 \\ \alpha_7 & \alpha_8 & \alpha_9 \end{bmatrix} \begin{bmatrix} y_{1t}^2 \\ y_{1t}y_{2t} \\ y_{2t}^2 \end{bmatrix} \tag{29}
$$

In this case neither the marginal processes y_{1t}^2, y_{2t}^2, $y_{1t}y_{2t}$, nor a combinations of them follows an ARMA(1,1) process. In addition, also the GARCH specifications of y_{1t} and y_{2t} do not follow a GARCH(1,1) model. For comparison purposes we generate the bivariate process as shown in Hafner (2008; p.476). Results comparing the $RMSE$ of the conditional correlations are shown in Figure A1 (MODEL 6). Note that the model in (29) has 21 parameters and this represents a challenge for ML estimation. Indeed, given the problem of convergence faced by the numerical optimization, due to the high number of parameters, we employ the true values of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ as initial values for the likelihood. This explains why the boxplot for MLC is far below the others. Also in this exercise ML is the bivariate maximum likelihood estimator of a Diagonal VECH (as used before). In this framework ML is then an approximate ML or a QML estimator, as it estimates only the diagonal elements of model (29). As shown in the Figure, in this most unrestricted case SP-DCC slightly outperforms both ML and DCC. This is consistent with findings in Morana (2019), showing that the implied conditional covariance parameterization of SP-DCC is more general than the one assumed under the usual DVECH-GARCH(1,1) model, accounting for some spillover effects in conditional covariance. In particular, Morana

(2019) shows that SP-DCC for the generic i, j processes can be seen as a halfway model between the bivariate VECH-GARCH(1,1) and DVECH-GARCH(1,1) models. Similar to the DVECH-GARCH(1,1), it assumes a univariate GARCH(1,1) structure for the conditional variance of the individual series; similar to the non-diagonal VECH-GARCH(1,1) model, it allows for some spillovers effects of past conditional variances and innovations on the conditional covariance for the involved individual series. Conditional to the validity of the GARCH(1,1) specification for the individual and aggregated series (which can be assessed empirically), SP-DCC should then grant more flexible and accurate modelling of second conditional moments than competing DCC approaches, which, by assuming a diagonal VECH structure, neglect spillover effects without any testing. This is exactly what the simulation exercise seems to point out.

Overall, the Monte Carlo results are very promising: SP-DCC model represents a simple and valid candidate regardless of the fact that it might be an approximate model in general. Moreover, relative to competing DCC approaches, it allows for more flexible modelling, accounting for some spillover effects, and easy handling of large sample sizes, in both the temporal and longitudinal dimensions.

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