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D4.3.2 – Policy briefs on climate-related uncertainty measures and policy implications

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Local Physical Climate Uncertainty

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Executive Summary

Climate change increases physical climate uncertainty—the challenge of characterizing variations in Earth's climate system. This uncertainty has significant economic and policy implications, particularly at the local level. Granular measures are essential for two reasons: (1) they improve estimates of uncertainty's economic impact, aiding resource allocation for climate mitigation, and (2) they identify localized risks, guiding adaptation efforts where needed most.

This policy brief presents "Local Physical Climate Uncertainty" (Cavaliere, et al., 2025), which constructs local uncertainty indexes using temperature data from 44 grid points across Italy. While focused on monthly temperature fluctuations, the methodology can be extended to other climate variables, such as rainfall, and applied at finer spatial resolutions (e.g., individual weather stations).

Findings show a marked increase in temperature uncertainty since the 1980s, particularly in coastal regions. A key application of these measures is estimating uncertainty's effect on regional GDPs, highlighting its role in economic decision-making and climate adaptation policies.

Physical Climate Uncertainty

Uncertainty refers to the dispersion of a random quantity that is being predicted. In everyday life, it can severely affect the ability to plan and the psychological well-being. Rising climate uncertainty affects the ability to manage weather fluctuations, respond to extreme events, as well as plan and implement necessary policies, with broad social implications. Being a key determinant of economic choices and collective welfare, uncertainty in climate plays a central role in public debates. Therefore, measuring it is essential to study its dynamics and to assess its effects. Uncertainty can arise from different sources (Cai, 2021): this paper focuses on modelling and measuring the uncertainty stemming from temperatures dynamics. Building on the influential work of (Jurado, et al., 2015), uncertainty measurement involves making dynamic forecasts of the variable(s) of interest and then predicting the dispersion of values from those forecasts—known as 'conditional volatility'.
Following the influential work of, measuring uncertainty essentially consists of forming dynamic forecasts of the variable(s) of interest and then form dynamic predictions of values' dispersion from such forecasts, the so-called "conditional volatility". This work studies temperatures, which, as all variables of the climate system, is distributed differently across different locations. Building a set of disaggregated measures of climate, instead of building a synthetic index, is crucial in providing more accurate estimates of climate change impact on the economic system (Bilal & Känzig, 2024) and, obviously, more precise indications to citizens and policymakers about what is going to happen.

Step one: forming temperatures' forecasts

The first challenge is the large number of time series to forecast – 44 observational units. Indeed, a standard Vector Auto-Regressive (VAR) model would imply the estimation of a great number of parameters compared to the number of observations, leading to noisy estimates. A solution to this is represented by the Dynamic Factor Models (DFMs), where the auto-regressive structure is estimated on a reduced number of factors that well summarize the original data only. Notice that DFMs conceptually imply 2 steps in the estimation: the formation of the factors and the estimation of the autoregressive parameters. Since joint estimation methods exist, they will be used here. The results in terms of forecasting power are indeed different, with the 2-step procedure producing R^2 of the individual series always above 0.9, while the 1-step procedure go as low as 0.55. Nonetheless, the uncertainty measurements will not be affected by this, as shown later.

It is also important to note that "climate" refers to a distribution of variables. This means that "climate change" implies some form of non-stationarity in the variables describing it. This poses a second challenge to traditional statistical methods to use for the first step forecasts, which usually rely on the assumption of stationarity. More specifically, evidence of global warming points towards, at least, a shift in the central tendency of temperatures' distribution. For this reason, in this work, temperatures time series are decomposed into a "trend" component and a "cycle" component. In this way, the cyclic component is mean-stationary by construction and the trend component mirrors the non-stationary part more clearly, improving the efficacy of more sophisticated techniques that can be applied to non-stationary variables. Moreover, the system autoregressive behaviour might be different at different time scales, so performing separated estimations has the potential to provide more accurate predictions. Whether global warming should be represented by a deterministic or stochastic trend has been the subject of debate, with more recent evidence pointing towards a better fit of the stochastic one (Chang, et al., 2020). For completeness, this work considers both deterministic trends and stochastic ones, represented as 12-year moving averages. The deterministic trend is modelled as a contiguous segment, a linear trend shifting to an exponential, with break date and functional form chosen optimally with standard criteria. The moving average length is chosen considering that climatic cycles with periods higher or lower than 12 years form two well separated clusters. High-frequency fluctuations include the seasonal cycle, which is exactly one year long, the "El Niño-Southern Oscillation," which lasts between 2 and 7 years, and solar cycles, which range from 10 to 12 years, while those with a lower frequency all span more than two decades (such as the "Pacific Decadal Oscillation", between 20 and 30 years, and the "Atlantic Multidecadal Oscillation", longer than 60 years). This is also in line with the fact that the trend component is called to capture potential unit roots, which in a 140 year long sample are difficult to distinguish from a stationary process with a cycle longer than 12 years anyway.

In the end, all the cyclical components prove to be stationary by standard tests, and all stochastic trends show unit-root-like behavior. The number of factors can be chosen by several optimality rules. In this work it is followed (Alessi, et al., 2010), which suggests the use of 4 factors for both the set of cycle series and the stochastic-trend ones. For the stochastic-trend series, a I(1) Vector Error Correction Model

(VECM) in the style of (Barigozzi, et al., 2021) is estimated, relying on a sole cointegration relationship.

Step two: forming conditional expectations of forecasting errors volatility

Once predictions are formed, the aim of the second step is producing predictions of the forecasting errors volatility. As common in the literature, to enforce the non-negativity requirement of volatility in the prediction model, it is the natural logarithm of the squared forecasting errors to be fitted. These series qualitatively present more regular dynamic behaviors and are associated to a greater probability of being generated by a normal distribution, which helps in the following estimations.
First, we examine the stationarity of these series. For cycle-series, evidence suggests no unit roots but indicates structural breaks, possibly involving mean shifts and trend changes. Standard information criterion are not decisive in choosing a uniform modelling strategy. A uniform modelling assuming a break in the constant only is preferred after a visual inspection of the average value of volatility across locations, in Figure 1. This echoes the observation of homogenous

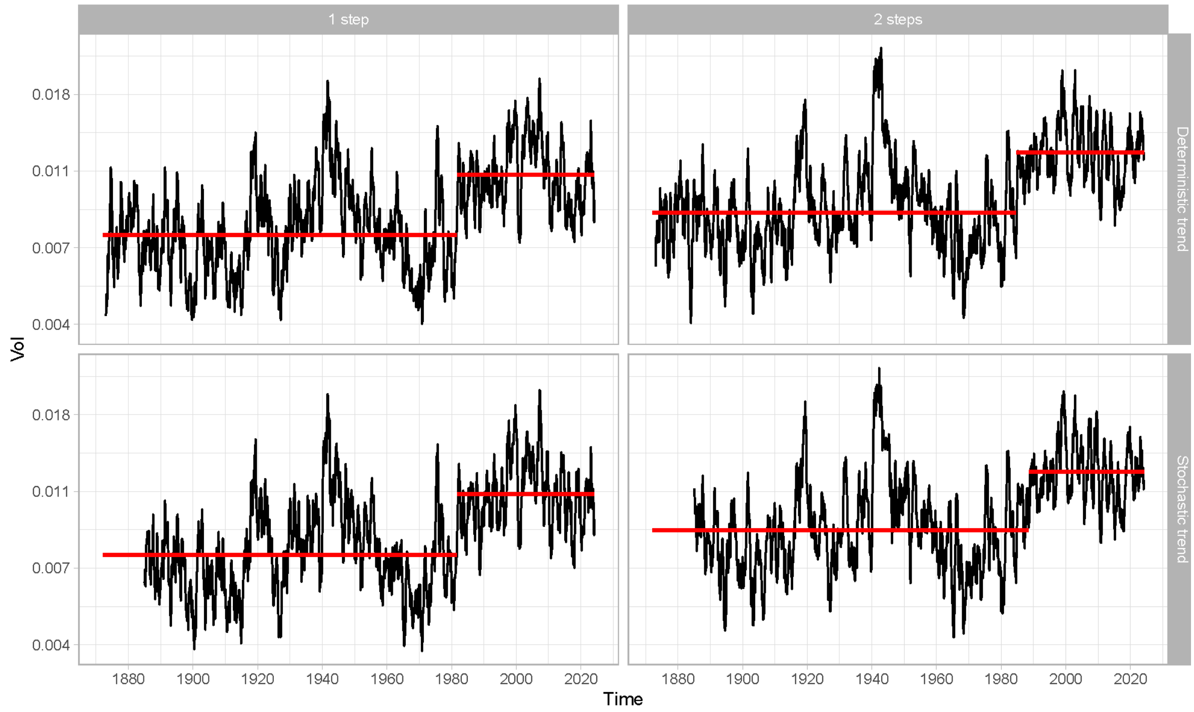

Figure 1. Cross-sectional average of cycle-temperature volatility. Upper charts refer to forecasting errors of series de-trended deterministically, lower ones stochastically. Charts on the left refer to forecasting errors obtained using a 1-step methodology, while on the right are from the use of a 2-step method.

signs in the constant shifts, as opposed to heterogenous signs in the time trend slope changes, which would suggest an usual non-monotonous relation between climate change and temperatures uncertainty. For the stochastic-trend series volatility, models with changes in the time trend dominate those with a break in the constant only, so the former are employed. It should be noted that these structural break directly speak to the conditional expectations of the series' volatility, so they constitute a first element of the uncertainty measures.

The second element is the part of volatility that can be forecasted with time series methods. These can be applied on the de-meaned and de-trended volatilities, as they are now stationary. For the cyclical series and the stochastic-trends the optimal number of factors would be one, with only 15% of total variance explained. Therefore, a univariate approach is followed, by fitting S-ARMA models, chosen relying on the Akaike Information Criterion, for each of the individual volatility series. Combining volatility expectations from deterministic and autoregressive models, uncertainty series for all geographical units can be obtained.

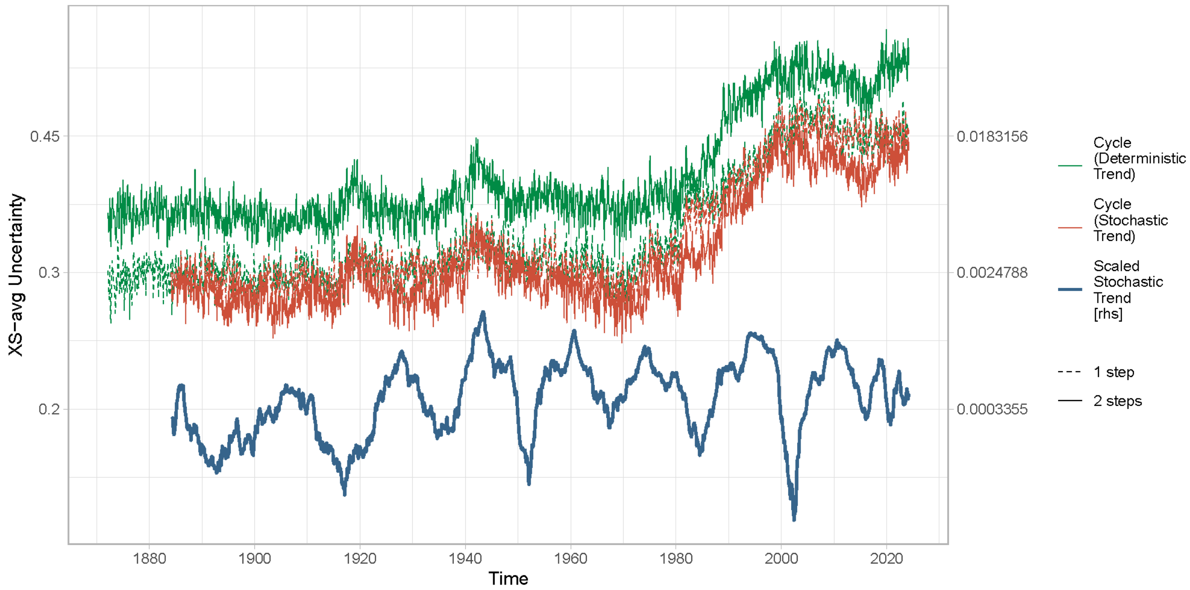

Figure 2. Cross-sectional average of temperature uncertainty. Green and red lines refer to the "cyclical" components of temperatures and take the values reported on the left-hand-side y-axis. The blue line refers to the "trend" component (the stochastic only) and takes the values reported on the right-hand-side y-axis.

The average of these is plotted in *Figure 2*. It can be observed a huge increase in the uncertainty of cyclical fluctuations of temperatures after the 1980s, which is around the same time as the average temperature started raising exponentially. Less stark results are visible from the stochastic-trends uncertainty average series, although the dynamic post-1980 also looks significantly different from that of previous decades. While in the averages of cycle uncertainty there is only one structural break in the mean around the 1980s being statistically significant, while in the stochastic-trend one there are two: at the beginning of the XX century and at the end of it. The bulk of uncertainty dynamics, anyway, comes from the cyclical part.

The main focus of this work, however, is the *local* estimates. As cyclical uncertainty is more relevant by orders of magnitude, those are also the series discussed here. Figure 3 shows the increase in the uncertainty in the different locations used for this analysis. It can be observed that the Adriatic coastal regions, together with Aosta

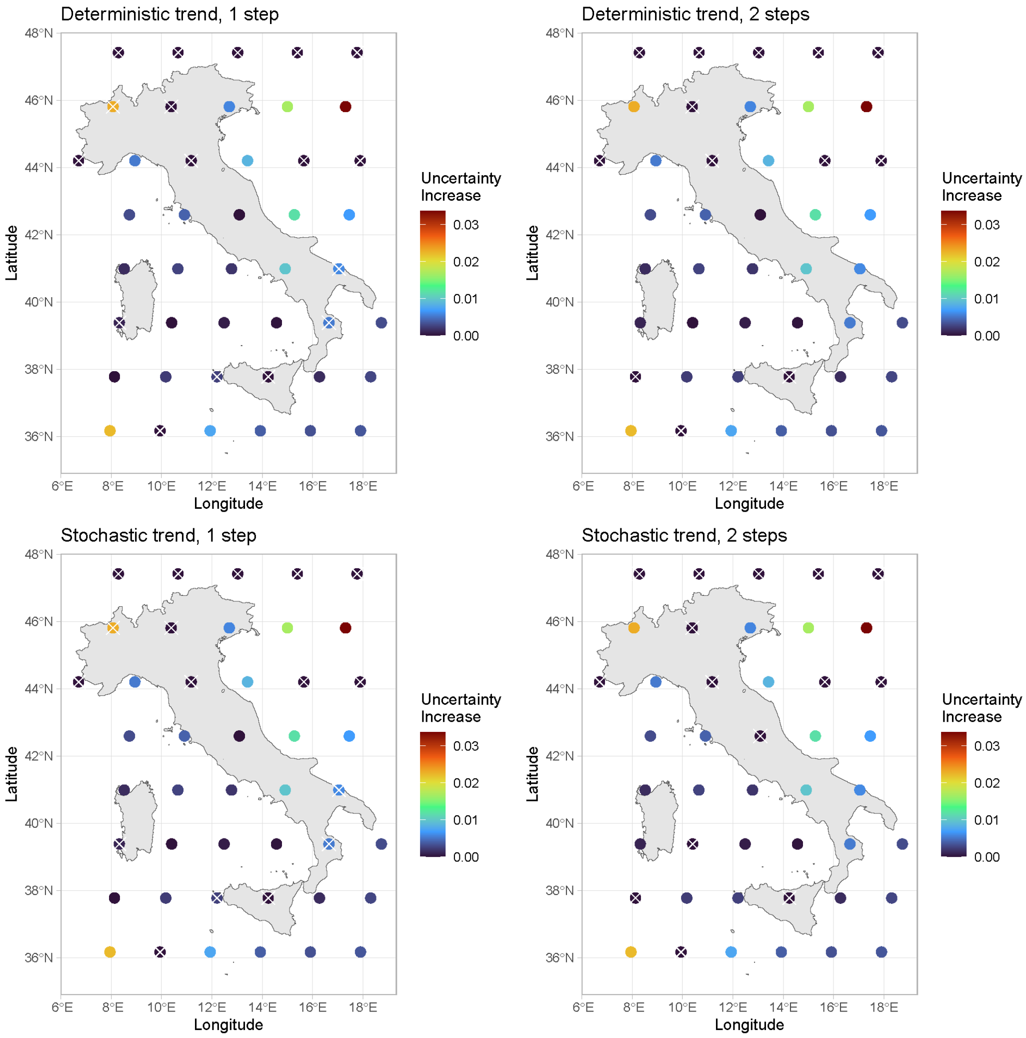

Figure 3. Increases in the conditional means of local volatilities – "cycle" components only. Dots crossed by a white 'X' are not statistically different from zero at the 5% confidence level.

Valley and Friuli-Venezia Giulia are the areas most impacted.

Policy Options and Analysis

Option 1: Push for climate mitigation

- Analysis: The overall climate uncertainty in Italy has increased.
- Policy Implications: Making plans will be more and more difficult, possibly hindering investments, which can be especially harming for a transition to a green economy.

Option 2: local climate adaptation

- Analysis: Some Italian regions are more exposed to increases in uncertainty than others.
- Policy Implications: there are non-trivial choices to make in terms of allocation of resources employed for local climate adaptation.

Recommendations

1. **Do not focus on expected changes only:**
    - Predicting climatic conditions is becoming more difficult. Raising awareness of the need to change the decision-making paradigm could be a cost-effective measure.
    - When estimates of costs associated to climate are considered, place special care into whether uncertainty costs are considered.

2. **Allocate resources to directly address the issue:**
    - The overall extent of increase in climate uncertainty in Italy is dependent on the magnitude of global climate change. Therefore, the first course of action possible is to devote resources to limit it.
    - Climate adaptation measures are mostly local. Resource allocation decisions should begin as soon as possible. Whether more resources should be devoted to regions with higher uncertainty or more rapidly increasing uncertainty is a highly political choice, but it should rely on further analysis exploiting similar local indexes of uncertainty to assess its economic impact.

Implementation Considerations

I. **Extension potential:**
   - The statistical methodology is relatively simple and can be applied to much different geographical and temporal scales, as well as to different climatic variable.
   - The application of these indexes in a study of the economic impact is straightforward.

II. **Limited methodology sophistication:**
   - The simplicity of the statistical model applied has clear advantages, but more sophisticated methods to form expectations of temperatures could be employed.

Conclusion

This policy brief underscores the growing challenge of local physical climate uncertainty in Italy. More specifically, our findings highlight significant regional disparities in temperature uncertainty increases, with more notable increases in coastal areas. By leveraging granular uncertainty measures, policymakers can better assess the economic impact of climate variability and allocate resources for targeted adaptation strategies.

To enhance resilience against rising climate uncertainty, Italy should integrate uncertainty considerations into climate policy, refine local adaptation plans, and invest in predictive models. Regular policy evaluations and a proactive approach to uncertainty mitigation will ensure adaptive capacity in the face of ongoing climate change.

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