

II. Economic impacts of climate change and mitigation

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For decades, economists have been studying the implications of climate change, in broad interdisciplinary cooperation with natural scientists. Despite significant advances, economic research continues to face formidable challenges. This section reviews what we know and examines the numerous and large uncertainties surrounding the economic impact of greenhouse gas emissions. Point estimates of GDP losses arising from limited climate change, as they are used in standard integrated assessment models, are typically not too large. However, they are based on partial representations of the impact channels. Moreover, the damage differs considerably across regions and income groups. Uncertainty and elements that are not covered, or only incompletely, in analyses of the cost of climate change suggest that the economic consequences of unabated greenhouse gas emissions could be dramatically worse than those point estimates. The section then goes on to provide an example of evidence-based design of climate mitigation policy. For this, it uses E-QUEST, a new version of the Commission's DSGE model QUEST, which has been developed to assess climate mitigation policies. The simulations show that pricing carbon might allow decarbonisation at little aggregate economic cost, depending on how the carbon tax revenues are used. These findings justify high ambition at all levels in operationalising climate mitigation targets such as the Paris Agreement's temperature goals and Europe's ambition to become climate-neutral by 2050. Climate change is a global challenge. Nonetheless, its impacts have specific euro-area dimensions, as they might e.g. affect economic convergence, prices or financial stability ⁽¹⁵³⁾.

II.1. Introduction

Climate change has been described as 'the ultimate challenge for economics' as significant gaps in our understanding and knowledge remain, despite an impressive number of articles and studies published over the past four decades ⁽¹⁵⁴⁾. Such gaps concern the analysis of the economic cost of greenhouse gas (GHG) emissions, the choice of effective mitigation tools, their timely implementation in view of damages that will occur with long lags as well as the coordination problem involved in tackling GHG externalities at a global level.

Any assessment of the economic impact of climate change involves both economic and bio-physical phenomena. Starting with the accumulation of GHG related to economic activity in the atmosphere, it involves understanding how the concentration of GHG in the atmosphere affects the climate ('climate sensitivity') and how atmospheric changes interact with other parts of

the Earth's systems. Only then can the impact of climate change on future economic activity ('damage') be estimated. This is the subject of the literature review in the first part of this section. While the channels through which warming affects the economy are global in nature, their impacts differ across regions. Within the euro area, such differentiated impacts ⁽¹⁵⁵⁾ could exacerbate economic divergence. Potential financial-stability impacts of climate change have also attracted heightened attention in the euro area ⁽¹⁵⁶⁾.

The second part of the section examines the economic impact of different policies to reduce the release of GHG into the atmosphere, using a new version of the Commission's QUEST model with a disaggregated energy sector. Mitigation policies are mostly designed to reduce the burning of fossil fuels ⁽¹⁵⁷⁾ and will affect output in economic sectors specialised in these activities. The aggregate economic impact of emissions reductions depends on the instruments used for mitigation and the structural adaptability of the economy. One question in this context is whether a 'double

⁽¹⁵³⁾ The authors wish to thank Frank Dentener, Quentin Dupriez, Sven Langedijk, Andrea Mairate, Arnaud Mercier, Yvon Slingenberg, Thomas Stoerk, Tom van Ierland and an anonymous reviewer for useful comments. This section represents the authors' views and not necessarily those of the European Commission.

⁽¹⁵⁴⁾ Nordhaus, W. (2019), 'Climate Change: The Ultimate Challenge for Economics', *American Economic Review* 109(6), 1991-2014; Burke, M. M. Craxton, C. Kolstad and C. Onda (2016), 'Some Research Challenges in the Economics of Climate Change', *Climate Change Economics* 7(2), 1650002.

⁽¹⁵⁵⁾ Szewczyk, W., L. Feyen, J.C. Ciscar, A. Matei, E. Mulholland and A. Soria (2020), 'Economic analysis of selected climate impacts: JRC PESETA IV project – Task 14', *JRC Technical Report*, Luxembourg.

⁽¹⁵⁶⁾ Giuzio, M., D. Krusec, A. Levels, A.S. Melo, K. Mikkonen and P. Radulova (2019), 'Climate change and financial stability' in: *ECB Financial Stability Review* May 2019.

⁽¹⁵⁷⁾ Greenhouse gases are also emitted in activities and processes that do not involve fossil fuels (e.g. methane from cattle farming and waste).

dividend' is possible, where mitigation not only limits the emission of GHG and the related rise in global temperatures but would also increase economic output and employment.

II.2. The economic impact of climate change

Standard integrated models of the climate and the economy use quantifications of the economic impact of climate change to assess the benefits of mitigation policy against a 'no-policy-change' baseline. However, our understanding of many relevant mechanisms determining the economic impact of climate change remains incomplete. It is also surrounded by large uncertainty that is known to be asymmetrical, and extremely negative events are likely (the probability distribution has a 'fat tail' on the downside). Our literature review looks at how economic impacts of climate change are estimated, covering existing modelling approaches and findings, and highlighting important missing elements and areas of dispute.

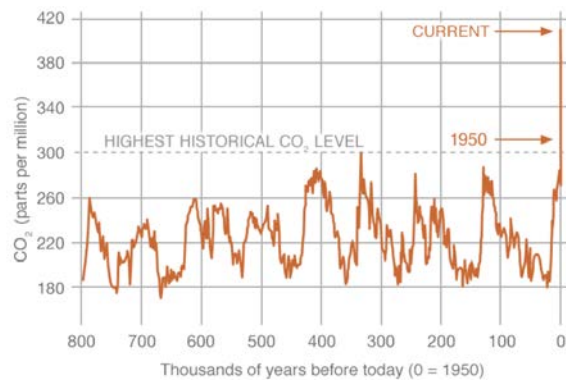
II.2.1. Climate dynamics

The emission of CO₂ due to economic activity has already increased its atmospheric concentration by around 50% compared to its previous peak going back hundreds of thousands of years (see graph II.1). Among other important gases, the concentration of CH₄ has well over doubled). Over the lifespan of the Earth, there has been even higher concentration, but corresponding to different geological periods and never a rate of rise as great as during the last century⁽¹⁵⁸⁾. Most of this change has taken place within a single human lifetime, and globally the trend is still accelerating. These are dizzyingly fast and large changes, and it is important to understand what they imply.

Graph II.1: **Atmospheric CO₂ concentration**

PROXY (INDIRECT) MEASUREMENTS

Data source: Reconstruction from ice cores.
Credit: NOAA



CO₂ reconstruction from air bubbles in ice cores; observational measurement in recent decades

Source: NASA and NOAA (2020).

To project the macroeconomic impact of climate change requires assumptions about the biophysical consequences of reaching a given level of GHG concentration. It is crucial to grasp the range of probable outcomes as point estimates may be a poor guide for economic policymakers.

Climate sensitivity. Our expectations of the amount of global heating that GHG concentrations will translate to in the future are defined through the concept of 'climate sensitivity'. This concept captures the estimated global average warming at the Earth's surface due to a doubling of atmospheric GHG from pre-industrial levels. The best guess estimate for climate sensitivity (CS) has been given as 3°C since a seminal report in 1979⁽¹⁵⁹⁾, although the Fifth IPCC Assessment Report (2014) demurred from providing such a best estimate (while keeping the same range as the Fourth IPCC Assessment Report).

⁽¹⁵⁸⁾ To illustrate, the CO₂ rate rise in the aftermath of the asteroid whose impact led to the extinction of dinosaurs was an order of magnitude lower than the current rate. See Wadhams, P (2016) *A Farewell to Ice*, Allen Lane

⁽¹⁵⁹⁾ Charney, J. et al (1979). *Carbon dioxide and climate: a scientific assessment*. Washington DC: National Academy of Sciences. See also IPCC (2007) *Fourth Assessment Report*

Graph II.2: Climate risks

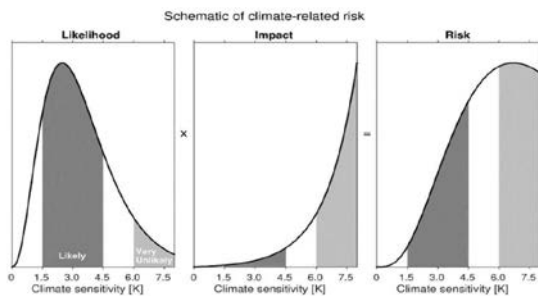


Figure 2. A schematic representation of how Likelihoods of a given outcome (e.g. of Climate sensitivity) combines with the impacts associated with each outcome to result in a risk to society (Sutton 2018).

Source: CRESCENDO (2020) 'Climate Sensitivity in CMIP6: some initial findings'.

What is often less understood is the degree of confidence and the probability distribution around CS estimates. As per the Intergovernmental Panel on Climate Change (IPCC), the likely range of climate sensitivity spans from 1.5°C to 4.5°C⁽¹⁶⁰⁾, where 'likely' corresponds to an agreed definition of above 66% probability⁽¹⁶¹⁾. Climate scientists tend to be able to robustly rule out the lower end of the likely CS distribution, but have had trouble bounding the upper end. A CS of 6°C or above is defined as 'very unlikely', corresponding to an up to 10% probability – yet the combination of a low probability with a large or even catastrophic outcome significantly affects the distribution of risks as illustrated⁽¹⁶²⁾ in Graph II.2⁽¹⁶³⁾.

Where the shape of the risk distribution differs significantly from that of the probability distribution, adequate policy-making requires addressing not only the question of “what is likely?”, but also “how bad could it be/what must we avoid?”⁽¹⁶⁴⁾ In other words, basing economic policy on the probability distribution rather than the risk distribution would be seriously misguided.

The IPCC, a UN umbrella body bringing together the global community of climate scientists whose flagship reports summarise the latest science and whose executive summaries for policy makers are approved by governments, assessed that a half a degree of difference in average global temperature change amounts to significant impact that rises in a non-linear fashion. Already between 1.5°C vs 2°C it projects a robust difference and significant impact in terms of water stress, food scarcity, heat-related deaths, forest fires, climate poverty, locked-in sea level rise and the loss of nature and ecosystem services on land and sea (see Graph II.3)⁽¹⁶⁵⁾. These impacts would also be likely to have knock-on implications such as increased migratory pressures.

⁽¹⁶⁰⁾ A recent and well-regarded paper, which feeds into the currently ongoing work on the IPCC's Sixth Assessment Report, narrows this range to 2.6°C-3.9°C. See Sherwood et al (2020) 'An Assessment of Earth's Climate Sensitivity Using Multiple Lines of Evidence', *Reviews of Geophysics*, 58:4

⁽¹⁶¹⁾ IPCC (2010) Guidance Note for Lead Authors

⁽¹⁶²⁾ Another illustration is that most people would not consider a probability of 'up to 10%' acceptable in the case of an airplane crashing or a bridge collapsing.

⁽¹⁶³⁾ We simulated different types of distribution in an attempt to reproduce figure 2 and were able to closely approximate with a Gamma distribution, with the impact following a function of fourth order.

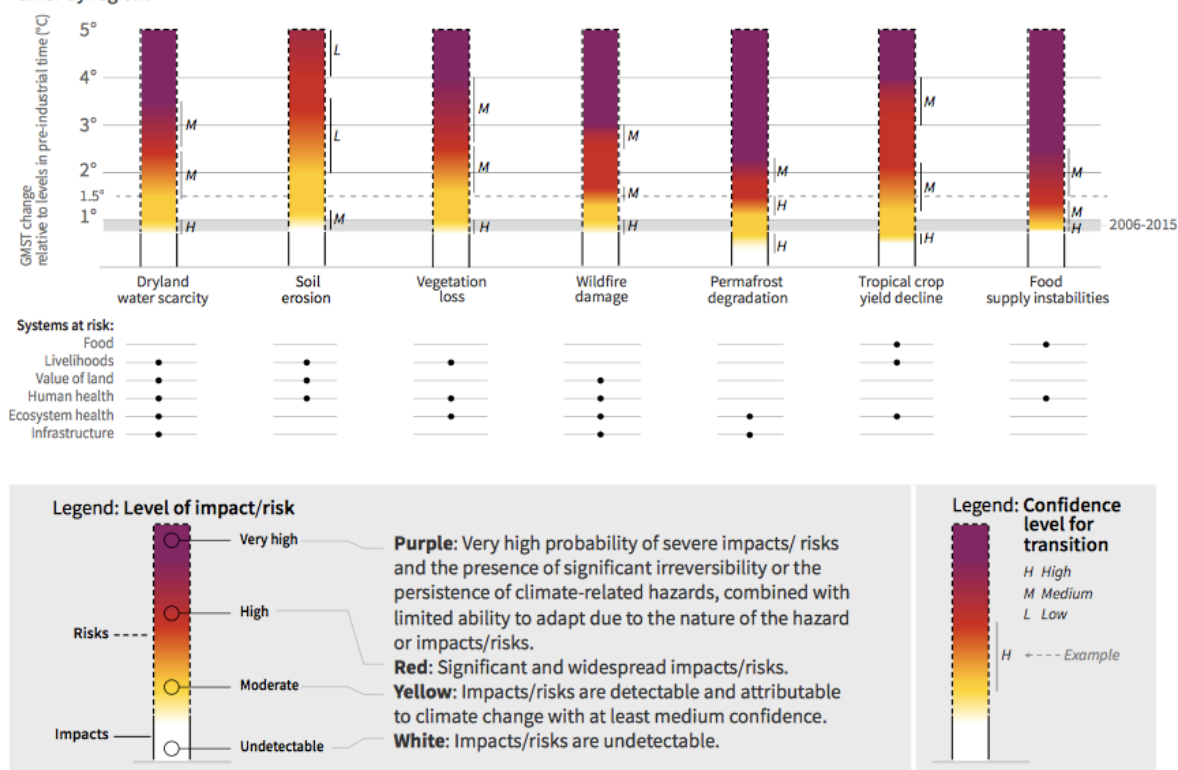
⁽¹⁶⁴⁾ See King, D. et al (2015) *Climate change: A risk assessment*. Cambridge University Centre for Science and Policy Rep.

⁽¹⁶⁵⁾ IPCC (2018) *Special Report on Global Warming of 1.5°C*. For further context, the global mean cooling that produced the Last Glacial Maximum is estimated to have been around 6°C. Cf. Tierney et al (2020) 'Glacial cooling and climate sensitivity revisited', *Nature* 584, pp. 569–573

Graph II.3: Example of impacts: food supply risks and other instabilities.

A. Risks to humans and ecosystems from changes in land-based processes as a result of climate change

Increases in global mean surface temperature (GMST), relative to pre-industrial levels, affect processes involved in **desertification** (water scarcity), **land degradation** (soil erosion, vegetation loss, wildfire, permafrost thaw) and **food security** (crop yield and food supply instabilities). Changes in these processes drive risks to food systems, livelihoods, infrastructure, the value of land, and human and ecosystem health. Changes in one process (e.g. wildfire or water scarcity) may result in compound risks. Risks are location-specific and differ by region.



Source: IPCC Special Report on Climate Change and Land (2019).

Tipping points. The CS as such is not the only source of significant uncertainty surrounding climate change. Tipping points, i.e. ‘large-scale discontinuities’ in the climate system that are likely to be abrupt as well as irreversible on human timescales have been considered to be high (catastrophic) impact events but of low probability. While the scientific consensus on this point is not complete, leading scientists point to mounting evidence that (i) these events could be more likely than previously thought, (ii) some of these thresholds may already have been crossed, (iii) exceeding tipping points in one climate and ecological system can increase the risk of crossing them in others, and (iv) a global cascade, which would amount to ‘an existential threat to civilisation’, cannot be ruled out (166).

An example that appears perilously close to materialising is the loss of the remaining Arctic sea ice and its ability to reflect incoming solar energy back to space (albedo). A complete disappearance of Arctic sea ice during the sunlit part of the year may have a heating effect equivalent to one trillion tonnes of CO₂, as compared to the 2.4 trillion tonnes emitted since industrialisation (167). Another example is the release of carbon dioxide and methane from the melting Arctic permafrost and significant parts of the seabed whose estimated

(166) See Lenton et al (2019) ‘Climate tipping points — too risky to bet against’, *Nature* 575, 592-595. See also Rockström, J et al

(2009) ‘Planetary boundaries:exploring the safe operating space for humanity’, *Ecology and Society* 14(2): 32

(167) Some research is suggesting that recent trends could lead to an ice-free Arctic as early as the 2020s and others suggest 2030 or substantially later. Baseline calculations tend to assume that cloud cover would remain constant. In comparison, with a total loss of cloud cover, the total added warming could be three times greater. See Pistone, K., I. Eisenmann and V. Ramanathan (2019), ‘Radiative Heating of an Ice-Free Arctic Ocean’, *Geophysical Research Letters* 46(13), 7474-7480.

impact on the climate in this century varies, ⁽¹⁶⁸⁾ but where new processes are still being discovered, and where the latest observations and projections include severe changes occurring abruptly ⁽¹⁶⁹⁾.

A lesser known but no less important tail risk relates to the global rate of species extinction ⁽¹⁷⁰⁾, which is by now tens to hundreds of times higher than the average rate over the past 10 million years and is accelerating; ⁽¹⁷¹⁾ this in turn impacts the resilience of many remaining species. Most models only consider primary extinction ⁽¹⁷²⁾. For example, a scenario-based gridded global model for biodiversity ⁽¹⁷³⁾ suggests a 25-30% decline in plant biodiversity for 4 degrees warming and a 10-20% decline in vertebrate biodiversity, while noting that the exact relationships are uncertain. The rise in average temperature is, of course, not the sole or even the main factor in the current rate of biodiversity decline, which already far outstrips these figures ⁽¹⁷⁴⁾ (the most important factor overall appears to have been habitat destruction, although for some ecosystems such as coral reefs climate change is already the number one culprit).

Taking into account, in turn, co-extinction (the disappearance of consumers following the depletion of their resources) suggests that when critical environmental conditions are breached, even the most resilient organisms are susceptible to rapid extinction. A prominent model in this

regard ⁽¹⁷⁵⁾ found that even extremophile species went extinct close to global biodiversity collapse, which was identified around 5°C heating, and that the transition was abrupt.

Carbon drawdown. The planet would have already warmed far beyond the current 1.1°C if it had not been for oceans, plant mass and soil absorbing about half of the human-induced CO₂ emissions. Amplifying the rate and scale of drawing down excess carbon from the atmosphere is, however, not a get-out-of-jail card in case we fall short on policy to reduce emissions, but a necessary part of meeting the Paris targets even in the central scenario (i.e. not taking the fat tail risks from a higher CS or tipping points into account).

We do not currently have technology for cheap, large-scale non-biological carbon sequestration. What is more, our natural carbon sinks may also be increasingly compromised in this function due in large part to climate change itself. The global terrestrial carbon sink has been so far increasing, but tropical forests are now taking up a third less carbon than they did in the 1990s, owing to the impacts of rising temperatures, droughts and deforestation, among other things. The Amazon may turn into a net CO₂ emitter by the next decade ⁽¹⁷⁶⁾. As for the ocean sink, what appears to be clear is that its rate of CO₂ absorption varies significantly in ways that we are not currently able to predict ⁽¹⁷⁷⁾. While overall, Earth system models now suggest that terrestrial and ocean carbon sinks exhibit a *diminishing* marginal uptake of atmospheric CO₂ as a function of cumulative uptake and of temperature, many economic models investigated in a recent working paper fail to reflect the

⁽¹⁶⁸⁾ See Walter Anthony et al (2018) '21st-century modeled permafrost carbon emissions accelerated by abrupt thaw beneath lakes', *Nature Communications* 9(1); Yumashev et al (2019) 'Climate policy implications of nonlinear decline of Arctic land permafrost and other cryosphere elements', *Nature Communications* 10

⁽¹⁶⁹⁾ See e.g. Teufel, B and Sushama, L (2019) 'Abrupt changes across the Arctic permafrost region endanger northern development', *Nature Climate Change* 9

⁽¹⁷⁰⁾ The global scientific community as such has just taken the first steps to scope the interlinkages between biodiversity and climate change via an IPCC-IPBES co-sponsored workshop in December 2020, whose report will feed into the 2021 UN Conventions on climate change and on biodiversity.

⁽¹⁷¹⁾ IPBES (2019) *Summary for policymakers of the global assessment report on biodiversity and ecosystem services*. The driving factors range from habitat loss and industrial agricultural methods to climate change.

⁽¹⁷²⁾ I.e. they do not take into account the impact of species loss on the potential for other species to go secondarily extinct, due to co-extinctions of dependent species and extinctions that cascade through ecological communities.

⁽¹⁷³⁾ Watkiss, P., J. Troeltzsch, K. McGlade and M. Watkiss (eds). (2019). 'COACCH: The Economic Cost of Climate Change in Europe: Synthesis Report on Interim Results'. *Policy brief by the COACCH project*. The model calculates local terrestrial biodiversity intactness, and combines the resulting maps to obtain overall mean species abundance values.

⁽¹⁷⁴⁾ See IPBES (2019) op.cit; WWF (2020) *Living Planet Report 2020 - Bending the curve of biodiversity loss*. Almond, R.E.A., Grooten M. and Petersen, T. (Eds).

⁽¹⁷⁵⁾ Strona, G and Bradshaw, C (2018) 'Co-extinctions annihilate planetary life during extreme environmental change', *Scientific Reports* 8. The paper is so far uncontested in the literature.

⁽¹⁷⁶⁾ Hubau et al (2020) 'Asynchronous carbon sink saturation in African and Amazonian tropical forests', *Nature* 579. Forests in parts of Europe are also already severely compromised by drought, invasive insects and other climate change-driven phenomena, with e.g. 98% of trees in Frankfurter Stadtwald already sick or dead (https://www.fr.de/frankfurt/stadtwald-frankfurt-mehr-als-jeder-zehnte-baum-ist-tot-90113352.amp.html?fbclid=IwAR2zASmEoig86jFukWAHdNFC7ryuhgODzQOogIfj9rqKbwDdx6n_c05Tn_1). Cf. B. Schuldt et al. (2020) A first assessment of the impact of the extreme 2018 summer drought on Central European forests. *Basic and Applied Ecology*, vol. 45

⁽¹⁷⁷⁾ DeVries et al (2019) 'Decadal trends in the ocean carbon sink', *Proceedings of the National Academy of Sciences of the United States of America*

evolution of science in this regard and ⁽¹⁷⁸⁾ still assume *increasing* marginal uptake.

Structural parameter uncertainty. Uncertain structural parameters appear at several levels of the analysis of the economic impact of climate change (e.g. climate sensitivity and how this actually changes climate beyond temperature change (precipitation, long term weather patterns, etc.), feedback loops related to tipping points, damages related to large temperature changes discussed further below). Their interaction induces a critical ‘tail fattening’ of the (posterior-predictive) distributions of possible outcomes ⁽¹⁷⁹⁾. The relatively high probability of catastrophic outcomes compared to a normal distribution is thus a key feature of climate change.

II.2.2. Costs from rising temperatures

Just as the speed and scale of transmission from higher atmospheric concentrations of greenhouse gases to global surface temperatures is subject to fat-tailed uncertainty, there is also uncertainty about the economic damages higher temperatures will cause. Moreover, the degree to which damages occurring in the future should be discounted has been subject to fierce debate.

II. 2.2.a Damage functions

How will a higher global mean surface temperature affect economic outcomes? Damage functions in the literature are generally formulated in terms of share of GDP ⁽¹⁸⁰⁾ lost as a function of temperature change.

The direct economic impact of global warming is likely to depend on the sector of the economy (e.g. agriculture vs. manufacturing), the level of temperature change that has already occurred, the scope of damages taken into account as well as the initial climatic conditions in a particular geographic area. The damage functions typically used in the literature have been heavily criticised. Nonetheless, a discussion of the factors at play and the

uncertainties surrounding each of them appears necessary ⁽¹⁸¹⁾.

Not all damages that are plausible can be quantified or modelled, and models vary widely in the scope of damages they include, but always represent at best a partial representation of potential impact and related costs. The damages most commonly discussed in the literature are (the order does not reflect relative importance) ⁽¹⁸²⁾:

- *Agricultural output.* ⁽¹⁸³⁾ A higher atmospheric concentration of CO₂ boosts plant growth but affects food quality negatively. Agricultural output in cooler regions may benefit from moderate warming that prolongs the growing season, as long as this impact is not over-compensated by the impacts of increasing draught or other extreme weather events. By contrast, higher temperatures will affect agriculture negatively in areas already most vulnerable to draught and wildfires, in particular as they are likely to be accompanied by reduced rainfall in the same areas. On balance, the literature tends to suggest that a moderate increase of global temperatures leads to an increase of global agricultural output before the impact turns negative at higher temperatures. The strength of the carbon fertilisation effect is however disputed, and estimates of optimal growing temperature for different crops are surrounded by significant uncertainty. Additional uncertainties relate to the impact of increasing temperatures on weather variability

⁽¹⁷⁸⁾ Dietz et al (2020) ‘Are Economists Getting Climate Dynamics Right and Does It Matter?’, *CEISifo Working Paper* No. 8122

⁽¹⁷⁹⁾ Weitzman, M. (2011), ‘Fat-Tailed Uncertainty in the Economics of Catastrophic Climate Change’, *Review of Environmental Economics and Policy*, 5(2), 275–292.

⁽¹⁸⁰⁾ As often in economic models, GDP is used here as a shorthand for wellbeing. In our simulations, we will also use GDP and its main components, complemented with the employment impact of policy measures.

⁽¹⁸¹⁾ Farmer, J.D., C. Hepburn, P. Mealy and A. Teytelboym (2015), ‘A Third Wave in the Economics of Climate Change’, *Environmental and Resource Economics* 62, 329–357 point to lack of evidence about the underlying mechanisms, aggregation issues and a failure to take uncertainty explicitly into account. Pindyck (2013) ‘Climate Change Policy: What Do the Models Tell Us?’ *Journal of Economic Literature*, 51(3), 860–872.; describes the damage functions in standard IAMs as ‘completely ad hoc’. The literature on the economic impact of climate change is massive. For the sake of tractability, the discussion focusses on a selection of well-known IAMs, namely those used by the US Interagency Working Group (DICE, PAGE and FUND), the JRC’s Peseta IV model, the ENV-Linkages CGE model used by the OECD as well as the assessment under construction in the COACC project.

⁽¹⁸²⁾ The focus is here on physical phenomena affecting the economy. Indirect channels such as financial stability or inflation may play significant roles as well, see Giuzio et al (2019) op. cit., Andersson, M., C. Baccianti and J. Morgan (2020), ‘Climate change and the macro economy’, *ECB Occasional Paper* 243..

⁽¹⁸³⁾ See Stern, N. (2007), *The Economics of Climate Change: The Stern Review*, Cambridge University Press; Ackermann, F. and C. Muniz (2012), ‘Climate damages in the FUND model: A disaggregated analysis’, *Ecological Economics* 77, 219–224. The range of climate impacts on plant growth has been narrowed down, see Toreti, A., D. Deryng, F.N. Tubiello et al. (2020), Narrowing uncertainties in the effects of elevated CO₂ on crops. *Nat Food* 1, 775–782;

and the incidence of pests and diseases that may put crop production at risk.

- *Fisheries*:⁽¹⁸⁴⁾ Changes to water temperature and salinity as well as the locations in which sea-ice can be found modify stratification and nutrient mixing in the oceans and are likely to lead to changes in species distribution and falling catch in some coastal regions. The impact on fisheries is expected to be most strongly negative in low latitudes, whereas it could be positive in northern Europe.
- *Tourism*:⁽¹⁸⁵⁾ Increasing global temperatures are expected to make some tourist regions less attractive (e.g. Alpine ski resorts) and exacerbate water scarcity in arid zones, while other tourist destinations might become more attractive. Impacts could therefore be negative or positive, depending on the region.
- *Economic disruption from storms and river floods*:⁽¹⁸⁶⁾ The occurrence of hurricanes directly depends on ocean surface temperature. Their average strength, though not necessarily their frequency is expected to increase with higher temperatures. As the water holding capacity of air increases with temperature (exponentially), the incidence of strong rainfall and flooding is expected to increase. Both mechanisms imply a convex relationship between temperature and storm and flood damage.
- *Damages from sea-level rise and coastal flooding*:⁽¹⁸⁷⁾ The cost related to even moderate warming-induced sea-level rises is substantial. The high concentration of economic activities in coastal and low-lying areas implies large damages or substantial costs for flood defences. People will

be displaced from unprotected or not sufficiently protected areas.

- *Energy production and use*:⁽¹⁸⁸⁾ Warmer average temperatures reduce the energy demand for heating and increase the energy demand for cooling. At the same time, different patterns of wind, cloud cover and precipitations could affect electricity production.
- *Ecosystem services*:⁽¹⁸⁹⁾ As explained above, the impact of rising temperatures on ecosystems is likely to be large. The resulting economic damage is complex and so far not well understood. Tol (2002) assumes it is a convex function of climate change.
- *Human health*:⁽¹⁹⁰⁾ This includes a variety of channels such as decreased mortality due to extreme cold and higher mortality due to heat waves, but also the spread of malnutrition, diarrhoea and vector-borne diseases, most prominently malaria. An additional channel, generally not covered in models relates to the health impact of interactions between climate-change and air pollution. The aggregate impact depends on whether the reduced mortality from cold waves outweighs the other channels. The transposition of human mortality into a metric of global welfare losses obviously requires assumptions about the economic value of human life that are fundamentally difficult.

⁽¹⁸⁴⁾ OECD (2015), *The Economic Consequences of Climate Change*, OECD publishing, Paris. and sources therein

⁽¹⁸⁵⁾ OECD (2015) op. cit.

⁽¹⁸⁶⁾ Knutson, T. et al. (2020), Tropical Cyclones and Climate Change Assessment: Part II: Projected Response to Anthropogenic Warming. *Bulletin of the American Meteorological Society* 101, E303–E322; Stern (2007), op.cit.

⁽¹⁸⁷⁾ Feyen L., J.C. Ciscar, S. Gosling, D. Ibarreta and A. Soria (editors) (2020), *Climate change impacts and adaptation in Europe: JRC PESETA IV final report*, Publications Office of the European Union, Luxembourg; Heslin, A., N. D. Deckard, R. Oakes and A. Montero-Colbert (2019), 'Displacement and Resettlement: Understanding the Role of Climate Change in Contemporary Migration', in: In: Mechler R., L. Bouwer, T. Schinko, S. Surminski and J. Linnerooth-Bayer (eds) *Loss and Damage from Climate Change. Climate Risk Management, Policy and Governance*, Springer, Cham.

⁽¹⁸⁸⁾ Després, J. and M. Adamovic (2020), 'Seasonal impacts of climate change on electricity production', *JRC Technical Report*, Luxembourg.

⁽¹⁸⁹⁾ IPCC (2014), *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Geneva; Van der Geest K. A. de Sherbinin, S. Kienberger, Z. Zommers, A. Sitati, E. Roberts and R. James (2019), *The Impacts of Climate Change on Ecosystem Services and Resulting Losses and Damages to People and Society*. In: Mechler R., Bouwer L., Schinko T., Surminski S., Linnerooth-Bayer J. (eds) *Loss and Damage from Climate Change. Climate Risk Management, Policy and Governance*. Springer, Cham. While the loss of biodiversity and climate change have common causes, and interact in various ways, biodiversity loss could have very negative consequences for humanity also in the absence of climate change. Tol, R. (2002), *Estimates of the Damage Costs of Climate Change: Part 1: Benchmark Estimates*, *Environmental and Resource Economics* 21, 47–73.

⁽¹⁹⁰⁾ Feyen et al (2020) op.cit., Ciscar, J.-C., J. Rising, R. E. Kopp and L. Feyen (2019), *Assessing future climate change impacts in the EU and the USA: insights and lessons from two continental-scale projects*, *Environmental Research Letters* 14, 084010; Carleton, T. and co-authors (2019), 'Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits', *NBER Working Paper* 27599. Burke, M. A. Driscoll, J. Xue S. Heft-Neal, J. Burney and M. Wara (2020), 'The Changing Risk and Burden of Wildfire in the US', *NBER Working Paper* 27423.

These assumptions matter as in some models the estimated impact of mortality has a large bearing on the estimated damages overall.

We next take a closer look at damage functions in a selection of well-known IAMs, models developed recently with a focus on the EU and articles that challenge the IAM benchmark. These models⁽¹⁹¹⁾ differ in the impact channels covered and the way in which they are modelled. For instance, the FUND 3.9 and PESETA IV integrated assessment models as well as the ENV-Linkages computable general equilibrium model and COACCH feature detailed accounts of (some of) the channels discussed above. The level of aggregation is higher in PAGE09, which features a ‘kinked’ damage function to reflect the possible triggering of a tipping point (e.g. an additional strong sea-level rise from the melting of the Greenland ice sheet). For the more recent versions of the DICE model, the disaggregated analysis of damages was abandoned in favour of an aggregate damage function. The latter is modelled so as to fit damage estimates in the literature, with a 25% additional damages added to correct for channels the literature does not account for.

The model-predicted economic impact of climate change crucially depends on the functional form of the damage function⁽¹⁹²⁾. As seen above, many impact channels suggest a convex relationship between rising temperatures and economic damages. However, in some areas, in particular agriculture, the impact of a small temperature increase above pre-industrial level may be globally positive. The aggregate damage function based on various estimates collected from the literature in Tol (2018)⁽¹⁹³⁾ can therefore be described as a piecewise linear function with a ‘kink’ at $dT=1^{\circ}$.

By contrast, Nordhaus and Moffat (2017)⁽¹⁹⁴⁾ conclude that the damage function providing the best fit with damages reported in the literature is quadratic. Also Howard and Sterner (2017)⁽¹⁹⁵⁾ conclude at a quadratic functional form. However, having extended the sample of surveyed damage estimates, corrected for duplication and omitted variables, they arrive at substantially higher damage estimates (see Table II.1).

A key output of the FUND, PAGE and DICE models is the estimated social cost of carbon, in other words the price of a ton of CO₂ that reflects the negative externalities of GHG emissions; Rose et al (2017)⁽¹⁹⁶⁾ examine the drivers of differences in the estimated social cost of carbon. Under standardised assumptions, the damage functions in DICE and PAGE are quite similar, for small temperature variations. Above 3°C, the discontinuity incorporated in the PAGE model leads to a faster increase of damages. Among the three, the FUND model stands out, mainly due to the feature that warming up to 5° is assumed to be beneficial to global agricultural output.

The impact estimates considered in these studies cluster around temperature changes of 2-4°C with few estimates for larger dT . As economic damage functions are calibrated with observations that relate to relatively small historical temperature changes and even weather variations,⁽¹⁹⁷⁾ it is natural that large uncertainty concerns any extrapolation to damages from stronger temperature variations. Lamperti et al (2018)⁽¹⁹⁸⁾ point to the possibility that interactions between heterogeneous agents may amplify the negative macroeconomic impacts of climate shocks substantially beyond what damage functions in

⁽¹⁹¹⁾ FUND 3.9 is described in Anthoff, D. and R. Tol (2014), *The Climate Framework for Uncertainty, Negotiation and Distribution (FUND). Technical Description, Version 3.9*. PAGE09 in Hope, C. (2011), ‘The PAGE09 Integrated Assessment Model: A Technical Description’, *Cambridge Judge Business School Working Paper 4/2011*, DICE 2016R in Nordhaus, W. (2017), ‘The social cost of carbon: Updated estimates.’ *Proceedings of the U. S. National Academy of Sciences*. The description of PESETA IV is in Feyen et al. (2020) op. cit. Finally, ENV-Linkages is described in OECD (2015) op. cit. and COACCH in Watkiss et al (2019) op. cit.

⁽¹⁹²⁾ Bretschger, L. and A. Pattarki (2019), ‘As Bad as it Gets: How Climate Damage Functions Affect Growth and the Social Cost of Carbon’, *Environmental and Resource Economics* 72, 5–26.

⁽¹⁹³⁾ Tol, R. (2018), The Economic Impacts of Climate Change, *Review of Environmental Economics and Policy* 12 (1), 4–25

⁽¹⁹⁴⁾ Nordhaus, W., and A. Moffat (2017), ‘A Survey of Global Impacts of Climate Change: Replication, Survey Methods, and a Statistical Analysis’, *NBER Working Paper* No. 23646.

⁽¹⁹⁵⁾ Howard, P. and T. Sterner (2017), ‘Few and Not So Far Between: A Meta-analysis of Climate Damage Estimates’, *Environmental and Resource Economics* 68, 197–225.

⁽¹⁹⁶⁾ Rose, S., D. Diaz and G. Blanford (2017), ‘Understanding the Social Cost of Carbon A Model Diagnostic and Inter-Comparison Study’, *Climate Change Economics* 8(2), 1750009.

⁽¹⁹⁷⁾ IMF (2020), in World Economic Outlook, Washington; Howard and Sterner (2017) op. cit. A survey of different empirical approaches is in Auffhammer, M. (2018), ‘Quantifying Economic Damages from Climate Change’, *Journal of Economic Perspectives* 32(4), 33–52.

⁽¹⁹⁸⁾ Lamperti, F., G. Dosi, M. Napoletano, A. Roventini and A. Sapio (2018), ‘Faraway, So Close: Coupled Climate and Economic Dynamics in an Agent-based Integrated Assessment Model’, *Ecological Economics* 150, 315–339.

Table II.1: Examples of damage functions

| model (author) | dT (°C)(a) | damage (% of GDP) (b) | functional form | method | remarks |
|-------------------------------|------------|-----------------------|---------------------------|---|---|
| Tol (2018) | 1 | -0,7 | piecewise linear | estimated on the basis of point estimates from a literature survey | |
| | 2 | 0,6 | | | |
| | 6 | 6,3 | | | |
| PESETA IV (Feyen et al, 2020) | 1,5 | 0,3 | quadratic | several impact channels modelled | estimate for the EU |
| | 3 | 1,4 | | | |
| | 4 | 1,9 | | | |
| PAGE 09 (Hope, 2011a) | 3 | just under 2% | complex | several impact channels modelled | estimate for the EU |
| DICE 2016R (Nordhaus, 2016) | 3 | 2,0 | quadratic | estimated on the basis of point estimates from a literature survey | |
| | 6 | 8,2 | | | |
| ENV-Linkages (OECD, 2015) | 1,5 | 1,0 | complex | Examination of different sectoral impacts | Damages by 2060 |
| | 4,5 | 3,3 | | | |
| COACCH (Watkiss et al, 2019) | 2,4 | 3 | complex | Multi-model examination of so far 3 sectors: coastal floods, river floods, transport infrastructure | estimates for EU. RCP 4.5 (0.7 trn EUR pa) and RCP 8.5 (2.6 trn EUR p.a). %age for 2085 based on 1.5% GDP growth. |
| | 4,3 | 10 | | | |
| Howard and Sterner (2017) | 3 | 7-8 | quadratic | Literature survey, adjusting for duplication and omitted variable bias | global. Excluding catastrophic damages as above, but including catastrophic damages |
| | 3 | 9-10 | | | |
| Burke et al (2017) | 2 | 18 | close to linear / concave | Impact of observed temperature variations on labour and agriculture | global. Long-run, differentiated response scenario as reported (ED fig 6). |
| | 4 | 43 | | | |
| Weitzman (2012) | 6 | 50 | exponential | by assumption | global |
| | 12 | 99 | | | |

(a) global mean surface temperature change compared to pre-industrial level; (b) loss of GDP compared to no-climate-change baseline by 2100 (unless otherwise stated)

Source: European Commission compilation from the quoted articles.

standard IAMs suggest. Weitzman (2012)⁽¹⁹⁹⁾ argues that from the viewpoint of insuring against the possibility of catastrophic outcomes, it would be preferable to consider an exponential damage function. Starting from the impact of annual temperature variations on output in a large sample of countries, Burke et al (2015)⁽²⁰⁰⁾ conclude that the global damage function is close to linear, but much steeper than those used in most IAMs.

The assumed ease and degree of adaptation to climate change has an important bearing on overall estimated damages and is one driver behind differences across damage functions in different models.⁽²⁰¹⁾ In general, over short periods, path dependency and sunk costs related to capital or skills that are becoming obsolete are likely to hinder adaptation, but substitution becomes easier over longer periods as new capital and skills are accumulated. Behavioural change by individuals

could facilitate both adaptation and mitigation⁽²⁰²⁾. Smooth adaptation may however be more complicated if the direct damage from climate change varies widely across regions and sectors.

The economic impact of climate change may be felt more strongly by poorer households than richer ones⁽²⁰³⁾. It is also is not evenly distributed across space. The largest impact of rising temperatures on economic output are projected for tropical and subtropical regions. This affects the comparability of the estimated damages reported in Table II.1, as damages in the EU (given for PESETA, PAGE and COACCH) would tend to be smaller in relation to GDP than global ones. Also within the EU, negative impacts, in particular from droughts, are expected to be more pronounced in the Mediterranean and Atlantic region than in central and northern Europe⁽²⁰⁴⁾. Globally, the geographical areas where the negative physical impacts are likely to be highest comprise many low- to middle-income countries. There is however

⁽¹⁹⁹⁾ Weitzman, M. (2012), 'GHG Targets as Insurance Against Catastrophic Climate Damages', *Journal of Public Economic Theory*, 14 (2), 221–244.

⁽²⁰⁰⁾ Burke, M., S. M. Hsiang and E. Miguel (2015), 'Global non-linear effect of temperature on economic production', *Nature* 527, 235–239.

⁽²⁰¹⁾ Ackermann, F. and C. Munitz (2016), 'A critique of climate damage modeling: Carbon fertilization, adaptation, and the limits of FUND', *Energy Research & Social Science* 12, 62–67; Rose et al (2017) op. cit.; Ciscar et al, (2019) op. cit., OECD, 2015, op.cit.

⁽²⁰²⁾ Terzi, A. (2020), 'Crafting an effective narrative on the green transition', *Energy Policy* 147, 111883.

⁽²⁰³⁾ Islam, S.N. and J. Winkel (2017), 'Climate Change and Social Inequality', *UN DESA Working Paper* 152.

⁽²⁰⁴⁾ Szewczyk, et al (2020) op. cit. The recent draughts in central and northern Europe underline that temporary deviations from such general trends are well possible, see also Toreti et al. (2019), The Exceptional 2018 European Water Scesaw Calls for Action on Adaptation, *Earths Future* 7(6), 652-663.

disagreement in the literature as to whether a higher level of GDP per capita per se makes countries less vulnerable to the effects of climate-change⁽²⁰⁵⁾.

The relation between temperature increases and economic damage is subject to large uncertainties, possibly even more so than the geophysical factors driving climate sensitivity. This relates both to the degree of knowledge about the factors identified above, omitted economic sectors (e.g. construction and transport) and other omitted factors such as migration, conflict, or disruptions of international trade⁽²⁰⁶⁾.

An important generally omitted factor is ecosystem services. Among the models surveyed here, only the FUND model directly accounts for ecosystem services, but remains limited to the ‘warm-glow’ effect, i.e. people’s hypothetical willingness to pay for the conservation of biodiversity, landscapes etc. A more complete picture requires a firmer understanding of the vulnerability of complex ecosystems in their interaction with human activity and wellbeing beyond their recreational function to include provisioning and regulating functions such as pollination, soil conservation, flood control, water and air purification. Ecosystems accounting is aimed at filling this gap, but is not yet sufficiently developed to provide a quantification of the different impact channels involved⁽²⁰⁷⁾.

More generally, the formulation of damage functions in the models surveyed here may not represent the latest knowledge about climate impacts⁽²⁰⁸⁾. Uncertainty related to threshold effects and nonlinearities in climate sensitivity also affects the estimated damage functions.

II 2.2 b Discounting future damages

The damages from climate change are set to occur over a time horizon stretching far into the future. Relatively modest differences in the way future damages are discounted can therefore have a large impact on their calculated net present value. Following the publication of the Stern Report in 2007, the discounting of climate damages and the weighting of future generations’ welfare compared to the present generation’s have become the subject of fierce debate. This ‘Stern-Nordhaus controversy’ focussed on differences in the social cost of carbon estimated by the Stern Report, which used the PAGE model, and by Nordhaus (2008), which used the DICE model, and on the sensitivity of policy recommendations to the discount rate used⁽²⁰⁹⁾.

Following the notation in Espagne et al (2016), the parameters that enter the discounting of future outcomes are the pure social rate of time preference (ρ), the expected long-term growth rate of per capita output (or consumption) (g) and the elasticity of the marginal utility of consumption (α) such that the discount rate (r) is defined as $r = \rho + \alpha g$.

The assumed long-term growth rate of the world economy (see Table II.2) does not play a major role in the ‘controversy’. Conceptually, there is broad agreement that there should be discounting for the expected increase in future generations’ consumption possibilities. This may however be more complex if the uncertainty surrounding growth is taken into account⁽²¹⁰⁾.

The consumption elasticity α is set at 1 in the Stern Report and at 2 in Nordhaus’ DICE model. It has been noted that the high aversion of inequality across generations incorporated in the Stern Review’s low ρ may sit at odds with a rather low preference for equality of consumption within a

⁽²⁰⁵⁾ Tol (2018) argues that this is the case, whereas Burke et al (2015) find no evidence that advanced economies faced decreasing damages from temperature variations as they became wealthier.

⁽²⁰⁶⁾ Tol, (2002) op. cit., Burke et al, (2015 op. cit.), Pindyck, (2013) op. cit.

⁽²⁰⁷⁾ On the assessment of ecosystem services see OECD, 2015, Anthoff and Tol, 2013; Tol, 2002; IPCC, 2014. On ecosystem accounting see Constanzu et al (2014); La Notte, A., S. Vallecillo, C. Polce, G. Zulian and J. Maes (2017), ‘Implementing an EU system of accounting for ecosystems and their services: Initial proposals for the implementation of ecosystem services accounts’, *JRC Technical Report*, Luxembourg. However, our knowledge of biodiversity and ecosystems remains very limited as pointed out by Mora, C., D. Tittensor, S. Adl, A. Simpson and B. Worm (2011): ‘How Many Species Are There on Earth and in the Ocean?’, *PLoS Biol* 9(8): e1001127.

⁽²⁰⁸⁾ Rose et al (2017) op. cit; Dietz et al (2020) op. cit.

⁽²⁰⁹⁾ Nordhaus, W. (2008), ‘A question of balance : weighing the options on global warming policies’, New Haven, Yale University Press. Espagne, E., F. Nadaud, B. Perissin and A. Pottier (2012), ‘Disentangling the Stern/Nordhaus Controversy: Beyond the Discounting Clash’, *FEEEM Working Paper* No. 61.2012.

⁽²¹⁰⁾ National Academies of Sciences, Engineering, and Medicine (2017), ‘*Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide*’, Washington DC: The National Academies Press.

given generation incorporated in the consumption elasticity α ⁽²¹¹⁾.

The controversy mostly crystallised on the assumed social time preference rate. Nordhaus argues that it should be chosen in such a way that r equals an observable (market) real return on investment, on the grounds that this is the rate against which economic actors will also evaluate abatement investments. By contrast, Stern argues that, on ethical grounds present and future generations should be treated equally. Pure time discounting should only reflect the risk of the extinction of humankind, (i.e. that future generations may not exist). He therefore sets $\rho=0.1\%$. The resulting discount rate is $r=1.4\%$. Other authors have suggested that ρ could be interpreted as a policy variable, indicating the degree to which policy makers prefer the wellbeing of their voters over that of future generations. A more recent survey suggests that ‘around 2%’ is a discount value that received a lot of support among experts ⁽²¹²⁾.

Table II.2: Examples of discounting parameters in the IAM literature

| | $r=\rho+ag$ | r | ρ | α | g |
|------------------------|-------------|---------|--------|----------|---------|
| Stern (2007) | | 1,4 | 0,1 | 1 | 1,3 |
| Dasgupta (2007) | | | 0,1 | 2-4 | |
| Weitzman (2007) | 6 | | 2 | 2 | 2 |
| Nordhaus (2008) | 5,5 | | 1,5 | 2 | 2 |
| Hope (2011) | 3-3.2 | | 1,0 | 1,2 | 1.7-1.9 |
| Anthoff and Tol (2014) | | | 1,0 | (1) | |
| Drupp et al (2018) | | 'ca. 2' | | | |

Source: European Commission compilation from the cited articles.

This literature review highlights the asymmetric risks around existing quantifications. Omitted channels / variables, the incomplete coverage of non-linearities and recent insights from climate science suggest that the actual damages from global warming will be larger than most point estimates in the literature, probably by a substantial margin. The

business-as-usual baseline to which mitigation policy should be compared is unlikely to be a sustainable one, and could well turn out to be unaffordable.

We refrain from formulating our own quantification of damages for the assessment of the European Union’s mitigation policy below. First, the literature review suggests that one should consider ranges of possible outcomes rather than point estimates. Second, damages follow the emission of GHG with long lags. Damages that are generally assessed at the horizon of 2100 may not be easy to integrate into our model assessment that focuses on the coming 30 years. Third, we restrict our analysis of mitigation policy to the EU, which accounts for only about 8% of global GHG emissions. Such unilateral climate action policies would have very limited effect on global temperature rise and the corresponding economic damages over our simulation horizon.

II.3. The economic impact of mitigation policies

The analysis in this section focuses on the design of climate mitigation policies. The objective of climate mitigation policy is to limit the increase of global mean temperatures to a level deemed sufficiently safe. To implement the Paris Agreement, the Commission has proposed aiming at zero net GHG emissions by 2050 ⁽²¹³⁾.

Our quantitative assessment of climate mitigation policies makes use of selected simulation results from the E-QUEST model. E-QUEST is an extension of the European Commission’s standard QUEST model with energy and sectoral disaggregation ⁽²¹⁴⁾. The E-QUEST model used for the assessment is set up for two regions, the European Union (EU) and the rest of the world (R). In each region, the economy consists of

⁽²¹¹⁾ Dasgupta, P. (2007), ‘Commentary: The Stern Review’s Economics of Climate Change’, National Institute Economic Review 199, 4-7. See also Weitzman, M. (2007), ‘A Review of The Stern Review on the Economics of Climate Change’, *Journal of Economic Literature*, XLV (September), 703–724.

⁽²¹²⁾ A more detailed discussion on the ethical underpinnings of discounting climate damages and the consequences of applying alternative concepts of intergenerational justice in climate models can be found e.g. in the articles by Davidson as well as Caney in Walsh, A., S. Hormio and D. Purves (eds.) (2017), ‘*The Ethical Underpinnings of Climate Economics*’, Routledge. See also Pindyck (2013) op; cit.; Drupp, M., M. Freeman, B. Groom, and F. Nesje (2018), ‘Discounting Disentangled’, *American Economic Journal: Economic Policy*, 10(4): 109–134.

⁽²¹³⁾ European Climate law proposal to achieve EU climate neutrality: <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020PC0080&from=E.N.>

⁽²¹⁴⁾ This section largely builds on the detailed E-QUEST model description and its application to analyse the impact of reaching the EU climate targets: Varga, J., Röger, W. and J. in 't Veld (forthcoming) E-QUEST - A multi-region sectoral dynamic general equilibrium model with energy. Directorate General Economic and Financial Affairs, European Commission. Discussion Papers. For the standard QUEST model, see Burgert, M., Roeger, W., Varga, J., in 't Veld, J. and Vogel, L. (2020). A Global Economy Version of QUEST. Simulation properties. European Economy Discussion Papers 126. Directorate General Economic and Financial Affairs, European Commission.

households, firms, a monetary and a fiscal authority. The model distinguishes two types of households, liquidity or not liquidity constrained ones, depending on their access to financial markets. Both household types offer differentiated labour services to firms in three skill levels: low, medium and high-skilled. In each region, firms produce differentiated goods and services for domestic and foreign markets. Production requires labour, general (non-energy) capital, a composite of intermediate goods and a composite of fossil fuel-intensive, ‘dirty’ and electricity-intensive, ‘clean’ capital-energy bundle ⁽²¹⁵⁾.

The main innovation of E-QUEST compared to the standard QUEST model is the modelling of substitution possibilities between the fossil fuel and electricity-intensive capital technologies. The model incorporates two of the most often used channels in energy and climate policy models to capture clean technological progress: i) efficiency improvements in using clean capital and ii) productivity improvements in producing clean capital. The first type of technological progress is modelled through autonomous energy efficiency improvement (AEEI), which implies that the clean energy use (i.e. electricity) per unit of output declines over time. AEEI is a frequently used approximation of energy-saving technological change in computable general equilibrium (CGE) models ⁽²¹⁶⁾. The second type of technological progress is modelled through learning-by-doing in our model. Learning-by-doing has been employed in the literature of energy and climate policy models to account for the simple observation that production performance either in the form of productivity or cost reductions tends to improve with the accumulation of experience. Technology ‘learning rates’ are now widely employed by researchers and policy analysts to project future trends in the energy and environmental domains ⁽²¹⁷⁾.

We explore six scenarios to study the economic effect of reaching the 2050 climate neutrality target set by the European Union. Taking the most frequently used policy scenarios in the environmental economics literature, we test for the possibility of double dividends, i.e. positive environmental and economic effects from climate mitigation policies through environmental taxes and their recycling.

The first reference case implements regulations, i.e. the government imposes restrictions on the economy-wide use of fossil fuels without any additional carbon taxes ⁽²¹⁸⁾. In the subsequent five scenarios, the government levies carbon taxes on all final and intermediate consumption of fossil fuel in the EU ⁽²¹⁹⁾. We ensure the comparability of the scenarios by imposing the same emission trajectories for each sector in every scenario while reaching an overall 93% cut in emissions by 2050 ⁽²²⁰⁾. We compare the economic effects of five main recycling options under the carbon taxation case:

- reduction in lump-sum taxes,
- personal income tax (PIT) cuts for low-skilled households only,
- consumption tax cuts,
- reduction in capital taxes (excluding dirty capital) and
- recycling via ‘clean’ subsidies to support the purchase of clean capital goods.

The scenarios set a logistic emission reduction path and let the model find the solution for the required carbon tax (or the shadow price of carbon in the regulation scenario). The simulated emission path reaches the 2030 targeted reductions of 55% and then reduces emissions further by 93% in 2050

⁽²¹⁵⁾ There are seven aggregated sectors in the model: a fossil fuel and a fuel-intensive capital producing sector, an electricity and an electricity-intensive capital producing sector, a sector manufacturing non-energy related capital goods, an emission-intensive sector and an aggregate of the remaining economic sectors.

⁽²¹⁶⁾ Webster, M., Paltsev, S., and Reilly, J. 2008. Autonomous efficiency improvement or income elasticity of energy demand: Does it matter? *Energy Economics*, 30(6):2785–2798.

⁽²¹⁷⁾ Rubin, E. S., Azevedo, I.M.L., Jaramillo, P. and Yeh, S. (2015). A review of learning rates for electricity supply technologies, *Energy Policy* 86(C): 198-218.

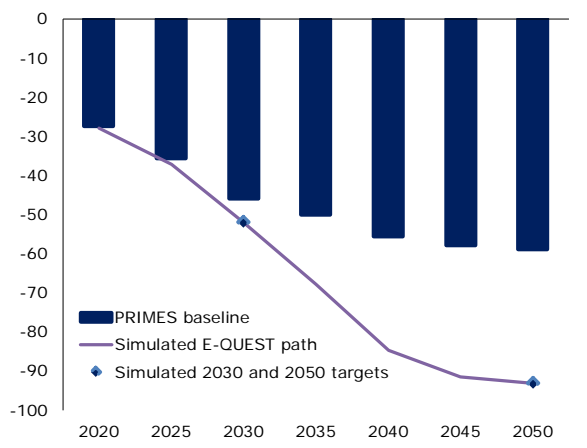
⁽²¹⁸⁾ Technically, we impose a shadow price on emissions without any direct fiscal revenue.

⁽²¹⁹⁾ A cap-and-trade system of controlling greenhouse gas emissions (such as the EU’s emissions trading system) works in the same way as carbon taxes in the model. We assume that the government sets the carbon tax as the price of emission allowance to control the level of annual emissions in the domestic economy. The modelling does not represent GHG removals required to achieve overall net zero greenhouse gas emissions.

⁽²²⁰⁾ Note that the scenarios are equivalent in terms of delivering the same annual emission reductions while using different policy instruments.

relative to its 1990 level. The model takes into account the effect of already existing climate mitigation measures to limit GHG emissions based on the PRIMES energy model simulations ⁽²²¹⁾. These underlying PRIMES model simulations form a baseline that already assumes a reduction of about 45% and 58% of EU GHG emissions relative to the 1990 level by 2030 and 2050 respectively (see Graph II.4) ⁽²²²⁾.

Graph II.4: Emission reductions and targets



(1) % of 1990 level

Source: PRIMES and E-QUEST simulations.

Graph II.5 shows the macroeconomic effects of the different policies that aim for the EU goal of net zero emissions in 30 years (by 2050). Note that we focus on the direct economic effects of these policies, and we do not model the environmental feedback effects in these simulations. The GDP results confirm that imposing carbon taxes on the use of fossil fuel and using the revenue to reduce the burden of taxation elsewhere is economically more beneficial compared to regulatory measures which do not yield additional tax revenues. Under regulation, GDP losses can reach 2% in the long run by 2050, while losses are typically lower under carbon taxation, with the lowest losses when revenue is used to reduce capital taxes and

subsidise clean capital purchases (around -0.6%). Except for our regulation scenario, recyclable tax revenues are gradually increasing up to a peak and diminishing afterwards following a Laffer-curve shape as the more stringent emission reduction requirements command increasing carbon prices. Note that while economists tend to favour environmental taxes over non-market regulatory instruments, such as technology standards or bans on polluting goods, environmental regulations are widely used for their potential benefits, which cannot be captured in standard macroeconomic models ⁽²²³⁾.

The ranking of GDP results by recycling instruments also reflects the ranking of taxes by their distortive effects in the economy. Reducing lump-sum taxes, which are the least distortive, has the least dampening effect on the cost of climate policy. This is followed by consumption taxes (VAT). Labour tax reductions targeted at lower income groups with a higher marginal propensity to consume reduce output losses stemming from carbon taxes further. Taxes on capital are most distortive, and recycling carbon tax revenue to reduce these has larger impact. The most beneficial scenario in terms of GDP effects is the recycling of carbon revenues into subsidies on the purchase of clean capital and capital tax reduction.

Graph II.5 also helps us to understand what drives the difference between the recycling options by decomposing the GDP effects from the expenditures side.

In terms of consumption losses, we can see that subsidies given to households to help them to purchase clean capital provides the biggest cushion against the increasing burden of taxing fuel, which makes the use of dirty energy gradually more costly.

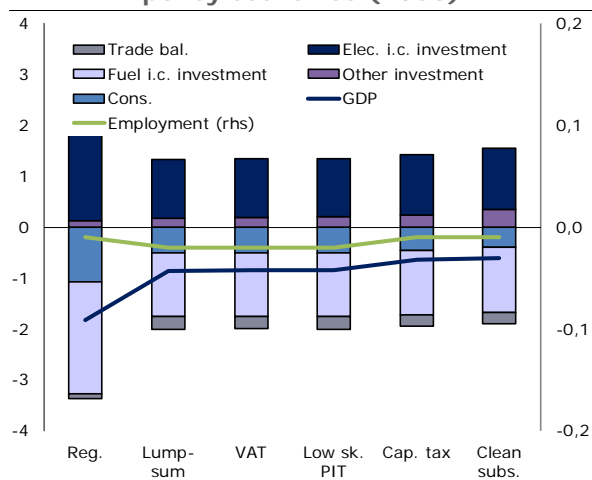
We can see that the capital tax reduction and clean subsidy scenarios, which are the most beneficial from an economic point of view, also lead to higher investment in general capital and clean capital compared to other recycling options.

⁽²²¹⁾ E3MLab/ICCS. (2014). PRIMES model. National Technical University of Athens. https://ec.europa.eu/clima/sites/clima/files/strategies/analysis/models/docs/primes_model_2013-2014_en.pdf

⁽²²²⁾ In technical terms, we exogenise the emission path according to the PRIMES model simulation results. The PRIMES baseline accounts for the current policy measures and technology trends. In order to have a policy neutral baseline with the least distortion in the structure of relative prices and taxes, which could influence the economic efficiency of the subsequent scenarios, we use carbon taxes that induce the necessary relative prices for reaching the target and lump-sum tax recycling that mitigates the effect of changing the tax-structure.

⁽²²³⁾ This can be partly due to the easier legislative procedure or public acceptance of non-market instruments over taxes. See Bovenberg, A., L., and Goulder, H., L. (2002) Environmental Taxation and Regulation. In Handbook of Public Economics, Elsevier, Volume 3, 2002, pp. 1471-1545. Editor(s): Alan J. Auerbach, Martin Feldstein

Graph II.5: Macroeconomic effect of climate policy scenarios (2050)



GDP and employment (rhs): % deviation from baseline. Consumption, fuel-intensive investment, electricity-intensive investment, other investment, trade balance: deviation in % of baseline GDP.

Source: E-QUEST simulations.

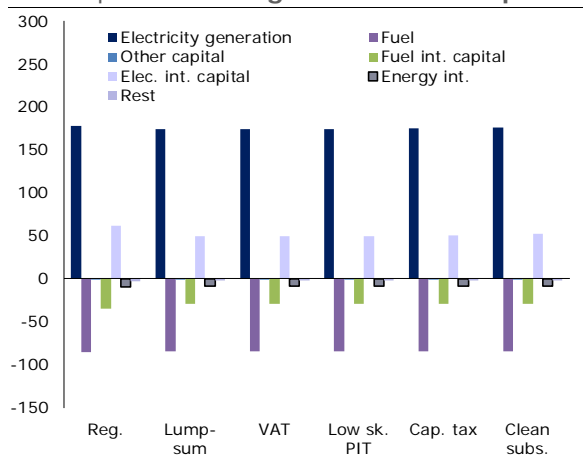
The employment effects are only slightly negative in the long run, because the sectoral shift to electricity-intensive industries can largely compensate for the shrinking labour demand in the fossil fuel-intensive industries.

Graph II.6 shows the required contribution of sectoral output adjustment to the transition towards a carbon neutral economy. While electricity generation more than doubles, fossil fuel supply diminishes by more than 80% relative to the baseline. The shift in energy sources towards electricity mirrors a similar transformation in the capital production sectors from fossil fuel intensive capital to electricity-intensive capital.

At this point, it is worth taking a snapshot of our climate policy measures in the long run by looking at how they perform along the lines of the two possible dividends: their environmental and welfare effects. Goulder (1995) ⁽²²⁴⁾ surveyed the theoretical and empirical evidence on the double dividend hypothesis and distinguished between the strong and the weak form of the double dividend.

⁽²²⁴⁾ Goulder, L. H. (1995). Environmental Taxation and the 'Double Dividend': A Reader's Guide. *International Tax and Public Finance* 2(2): 157–183.

Graph II.6: Change in sectoral output



% deviation from baseline, by 2050.

Source: E-QUEST simulations.

The weak form of the double dividend hypothesis requires that the efficiency costs of a revenue-neutral environmental tax reform are lower if the additional revenues from the environmental taxes are used to cut distortionary taxes compared to the case where these revenues are recycled in a lump-sum fashion. The strong form of the double dividend hypothesis requires that an environmental tax reform improves not only environmental quality but also non-environmental welfare.

We can focus on the GDP, consumption and employment effects of the five main carbon revenue-recycling scenarios, reducing lump-sum taxes, low-skilled labour taxes, capital taxes, VAT, or providing green (clean) subsidies. Note that by the construction of our scenarios, each of these policies yields the same environmental effects, as we impose the same emission reduction path for easier comparison. However, our policies perform differently in terms of economic benefits and welfare. Our first observation is that the weak form of double dividend as defined by Goulder (1995) is easily satisfied. Recycling the revenues by reducing any of the distortionary taxes can improve the GDP, consumption or employment effect relative to our lump-sum scenario. In line with the meta-analysis of Freire-González (2017) ⁽²²⁵⁾, the strong form of double dividend is much harder to achieve. In terms of GDP or consumption, our policies cannot reach positive effects. In terms of employment, the policies perform somewhat

⁽²²⁵⁾ Freire-González, J. (2017) Environmental taxation and the double dividend hypothesis in CGE modelling literature: A critical review. *Journal of Policy Modeling* 40: 194–223.

better, but still slightly negative employment effects arise.

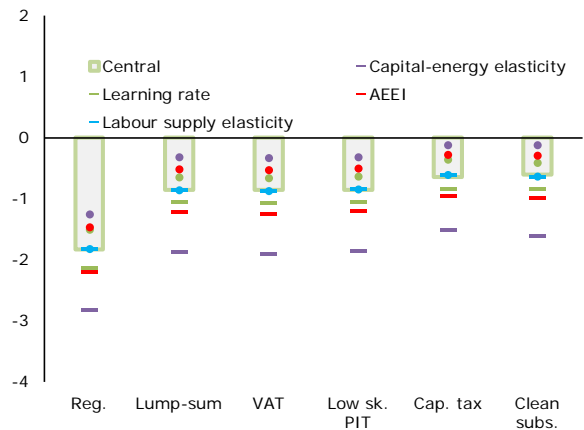
We conclude our analysis by performing a sensitivity analysis with respect to some of the most critical parameters of the model. We take an interval of +/-25% of the original calibrated values for the corresponding parameters shown below, approaching the lower and upper end of the estimates in the relevant literature:

- elasticity of substitution between the clean and dirty capital-energy bundle (6)
- learning-by-doing rate (10%)
- autonomous energy efficiency improvement rate (1% p.a.)
- labour supply (Frisch) elasticity (0.25).

Focusing on the GDP by 2050, Graph II.7 shows the sensitivity of the results using column bars for the central scenarios discussed in the previous sections and coloured markers for the lower and upper bounds for the corresponding parameters. Note that in each case, the larger (smaller) is the parameter value, the more optimistic (pessimistic) is our calibration scenario in terms of the main macroeconomic variables. The graph below offers a number of interesting insights into the sensitivity of our results and also points to the need of future research on the most important parameters determining the policy outcomes.

First, the results show that the elasticity of substitution between clean and dirty technologies plays a crucial role in the magnitude of the GDP results. For each scenario, increasing (decreasing) the substitution possibilities between clean and dirty capacities significantly improves (worsens) the long-run GDP effects. Under the high elasticity case, the clean subsidy and the capital tax recycling scenarios can result in negligible, only slightly negative GDP effects. On the other hand, the output effects can go down to -3% under the low substitution elasticity case with solely regulation-based climate policy. Similarly, we can also see that both the learning-by-doing rates and the AEEI rates have a significant effect on the GDP results. This shows that the uncertainty surrounding these factors can play an important role. However, our GDP results are robust for the Frisch labour supply elasticity.

Graph II.7: Sensitivity analysis



% deviation of GDP from baseline, by 2050.

Source: E-QUEST simulations. The round markers correspond to the upper limit and the horizontal bars mark the lower bound of the respective parameter.

To put these results into perspective, most of the estimated effects of ambitious climate change policies reported in Stern (2007) cluster between -5% to +2% of national and world output by 2050. In most cases, the estimates are small, around 1% or less relative to baseline output⁽²²⁶⁾. Our results are also in the range of previous impact assessments analysing the long-term EU climate strategy with estimated effects between -1.3% to +2.2% of EU GDP by 2050⁽²²⁷⁾.

II.4. Conclusion

No region of the world is immune to the negative economic impacts arising from global warming. In the euro area, specific challenges could arise from a differentiated impact, for example between coastal and continental or southern vs northern regions, which could exacerbate economic divergence, as well as posing threats to price stability and financial stability.

⁽²²⁶⁾ The full range of estimates spans between -15% to +4% of output. This variation in the estimates is driven by the characteristics of the individual models. Models that can rely only on energy conservation tend to show substantial costs because this mitigation option becomes quickly exhausted over time. On the other hand, general equilibrium models with richer mitigation options, revenue recycling possibilities and technological learning point to less negative effects. The E-QUEST model also belongs to this class of general equilibrium models.

⁽²²⁷⁾ These effects are also reported relative to the baseline without an explicit damage function.

https://ec.europa.eu/clima/sites/clima/files/docs/pages/com_2018_733_analysis_in_support_en_0.pdf.

The most recent 2030 Climate Target Plan was restricted to the 2020-2030 horizon.

The literature on the economic impact of climate change is vast. The overview in this section has looked at the impact of GHG concentrations on global temperatures and the impact of climate change on economic output. Standard IAMs incorporate economic damages caused by GHG emissions that, over the time horizon 2020 to 2100 look limited when compared to global GDP growth over the past decades. The representation of damages in these models is however incomplete. A common theme in the literature is the nature of the limitations of our knowledge about factors that mean that damages could be severely worse than anticipated. Such uncertainty relates for example to the non-linear economic consequences of rising temperatures, and the timing of tipping points beyond which climate change and ecosystem damage become irreversible. Other important mechanisms are left out for lack of knowledge of how to quantify them. It therefore appears crucial to highlight the large downside risks. When communicating on model results, the focus should be more on the range of plausible scenarios rather than on point estimates.

Mitigation policy itself does not necessarily come with large costs for the economy as a whole. The model simulations presented here show that mitigation policy under certain conditions affects aggregate economic output and employment only little at the same time as it brings net GHG emissions close to zero by 2050. Obviously, decarbonisation requires massive structural change, represented in the simulations by the phasing out of almost all fossil fuel extraction and the substitution towards renewable energy in the production process. The simulations suggest that this is compatible with a limited impact on aggregate output. The sensitivity analysis highlights that the degree of substitutability of energy sources as well as continued efficiency gains in renewables are important drivers of these outcomes. However, even under more pessimistic assumptions, the cost of mitigation remains manageable.

As we have not integrated a damage function in the simulations, our simulation results do not include the harm avoided thanks to climate mitigation policy. Nonetheless, our findings provide guidance for the implementation of the European Green Deal.

The negative impacts of climate change are non-linear in increasing global temperatures. This in itself justifies ambitious mitigation targets such as the Paris Agreement's temperature goals and Europe's ambition to become climate-neutral by 2050 and the proposal to tighten the intermediate targets for 2030. As omitted mechanisms and incomplete knowledge imply large risks of significantly bigger damages at any level of temperature increase, climate policy needs to also serve a risk management function in parallel with adaptation to climate change impacts that are inevitable even in the best-case scenario.

The green transition will trigger large sectoral shifts in economic activity, with a need for accompanying social and regional policy. In the euro area, the ECB is also pondering adaptations to its monetary strategy in response to the impact of climate change. Policies that help further technical progress in the renewables sector will also ease the transition. The scope and complexity of this endeavour calls for a systemic approach as reflected in the 'green oath' whereby all policy areas are held to do no harm ⁽²²⁸⁾.

At the same time, the numerous unknowns and risk factors related to the assessment of the economic impact of GHG emissions call for further development of analytical tools (e.g. refinement of 'damage functions') and conceptual frameworks (e.g. understanding the role of services provided by threatened ecosystems in generating material wellbeing).

⁽²²⁸⁾ Commission Communication 'The European Green Deal', COM(2019)640final.

III. Fiscal policy implications of uncertain fiscal outcomes

By Philipp Mohl and Gilles Mourre

This section analyses the impact of the uncertainty that fiscal outcomes can have on expected fiscal efforts. The findings highlight that discretionary fiscal adjustments are subject to large uncertainty, as measured ex post by the forecast errors in EU countries from 2000, even if the forecasts used are unbiased. Results from panel regressions reveal that Member States frequently do not adjust their expected fiscal effort to uncertain fiscal outcomes in the form of forecast errors. We find that Member States react only late and asymmetrically to forecast errors, relaxing the fiscal effort in case of positive surprises and leaving it unchanged in case of negative ones.

III.1. Introduction

Uncertainty is inherent to economic developments. The Great Recession in 2008/2009 illustrates the effect of unforeseen events on the economy. The risk of contagion effects called into question the very viability of the euro-area project⁽²²⁹⁾. However, it does not take a very deep crisis to see that uncertainty is an unavoidable feature of the economy.

Uncertainty also affects fiscal policy. In the short and medium term, much of the uncertainty about fiscal policy comes from shocks to the macroeconomic environment and the impact of these shocks on fiscal variables.⁽²³⁰⁾ In the longer term, the main sources of fiscal uncertainty stem from potential growth, implicit interest rates on public debt, health-care or ageing expenditure and contingent liabilities⁽²³¹⁾.

The COVID-19 pandemic clearly highlights the implications of uncertainty for fiscal policy. According to the Commission 2020 autumn forecast, fiscal deficit and public debt are projected to increase considerably in 2020 and 2021. The outlook covers large differences across Member

States and is surrounded by a high degree of uncertainty.

Against this background, this section analyses the impact of uncertainty of fiscal outcomes on the expected fiscal efforts. The main objective is to analyse whether and under which conditions Member States react to uncertainty by adjusting their expected fiscal effort. While the analysis is backward looking, its implications are also relevant for the recovery from the COVID-19 crisis.

It is structured as follows. Sub-section 2 gives an overview of the main types of uncertainty indicators, which take different perspectives. Sub-section 3 presents stylised facts of the uncertainty measure used for the analysis, namely the forecast error of the fiscal effort. Sub-section 4 describes the empirical strategy, before sub-section 5 presents the main findings. Finally, Sub-section 6 concludes.

III.2. Uncertainty: different measures and perspectives

While uncertainty is inherently unobserved, four types of indicators have been used to measure it⁽²³²⁾.

First, dispersion indicators. They mostly focus on the divergence of opinions of forecasters or

⁽²²⁹⁾ Buti, M. and P. Padoan, (2013), 'How to make Europe's incipient recovery durable: End policy uncertainty', *VOX*, 12 September.

⁽²³⁰⁾ Beling, V., Benedek, M., de Mooij, R. and M. Norregaard (2014), 'Tax buoyancy in OECD countries', *IMF Working Paper* No. 14/110, Mourre, G. and S. Princen (2015), 'Tax revenue elasticities corrected for policy changes in the EU', *European Economy. Economic Papers* 18; Mourre, G., Astarita, C. and A. Maftai (2016), 'Measuring the uncertainty in predicting public revenue', *European Economy, Economic Papers* 39; Fioramanti, M., Gonzalez Cabanillas, L., Roelstraete, B. and S. Ferrandis Valterra (2016), 'European Commission's forecasts accuracy revisited: Statistical properties and possible causes of forecast errors', *ECFIN Discussion Paper* 27; Koester, G. and C. Priesmeier (2017), 'Revenue elasticities in euro area countries', *ECB Working Paper* 1989.

⁽²³¹⁾ Auerbach, A. (2014), 'Fiscal uncertainty and how to deal with it', Hutchings Center on Fiscal and Monetary Policy at *Brookings Working Paper* 6, 15 December.

⁽²³²⁾ For descriptions of uncertainty indicators see also Vašíček, B. (2018), 'Impact of uncertainty shocks in the euro area', European Commission (2018), *Quarterly Report on the Euro Area*, Vol. 16, No.3, pp. 25-40; Meinen, P. and O. Roehle (2017), 'On measuring uncertainty and its impact on investment: cross-country evidence from the euro area', *European Economic Review*, Vol. 92, pp. 161-179 or Jurado, K., Ludvigson, S. and S. Ng (2015), 'Measuring uncertainty', *American Economic Review*, Vol.105, No. 3, pp. 1177-1216. To encompass all dimensions, some authors build synthetic indicators combining different measures (European Central Bank (2016), 'The impact of uncertainty on activity in the euro area', *ECB Economic Bulletin* 8.

survey respondents, but also on the divergence of firm-growth rates within industries. Such indicators assume that a high (low) dispersion indicates a high (low) level of uncertainty⁽²³³⁾. A positive feature of dispersion indicators is that they are typically based on a large number of observations. Nevertheless, some caveats exist. First, agents' opinions may display systematic biases due to financial incentives⁽²³⁴⁾. Second, dispersions across respondents may be explained by differences in available information or in their implications⁽²³⁵⁾. Third, dispersion may be caused by time lags in the release of surveys, since forecasters rarely make predictions at the same point in time.

Second, stock market volatility indicators. The volatility of stock market data has been frequently used as a proxy for uncertainty. Financial-market data are available at high frequency, which allows measuring their volatility at different periods. Nevertheless, it cannot be ruled out that these indicators change for reasons other than uncertainty, for instance because of changes in risk aversion or economic confidence⁽²³⁶⁾. In addition, stock market data can be less relevant in smaller countries.

Third, forecast errors measures. These are based on the difference between forecast and outturn data. They assume that a low (high) deviation between forecast and outturn data of macroeconomic⁽²³⁷⁾ or financial markets data⁽²³⁸⁾

is a sign of a low (high) level of uncertainty. While it is possible to calculate forecast errors for many variables⁽²³⁹⁾, they are typically not available at high-frequency level. Furthermore, it cannot be ruled out that these indicators change for reasons other than uncertainty.

Fourth, news-based indicators. These are indicators that count words related to uncertainty in media sources. The more often these words occur, the higher the degree of uncertainty⁽²⁴⁰⁾. The main caveats with news-based measures are potential biases due to the subjectivity this entails (e.g. availability of media sources, choice of newspapers, search words). Furthermore, there are limitations to data availability, especially for smaller countries.

In the following, we show how uncertainty has evolved in the EU using the types of uncertainty measures presented above (Graph III.1 1). We consider the dispersion of forecasters' opinion (ECB SPF), volatility on the financial market (VSTOXX) and economic policy uncertainty (EPU).

Uncertainty indicators show marked differences, depending on their perspective: economic, financial or political uncertainty⁽²⁴¹⁾. Such uncertainty measures spike at different points in time and exhibit low correlations. The correlation is even negative between the EPU and the dispersion of macroeconomic forecasts (-0.08), and it only reaches a level of close to 0.3 between the ECB SPF and the VSTOXX.

⁽²³³⁾ Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I. and S. Terry (2018), 'Really uncertain business cycles', *Econometrica*, Vol. 86, No. 3, pp. 1031-1065; Bachmann, R., Elstner, S., E. Sims (2013), 'Uncertainty and economic activity: Evidence from business survey data', *American Economic Journal: Macroeconomics*, Vol. 5, No. 2, pp. 217-49; Abel, J., Rich, R., Song, J., J. Tracy (2016), 'The measurement and behavior of uncertainty: Evidence from the ECB survey of professional forecasters', *Journal of Applied Econometrics*, Vol. 31, No. 3, pp. 533-550.

⁽²³⁴⁾ Jurado et al. (2015), *op.cit.*

⁽²³⁵⁾ Diether, K., Malloy, C. and A. Scherbina (2002), 'Differences of opinion and the cross section of stock returns', *The Journal of Finance*, Vol. 57, No. 5, pp. 2113-2141; Mankiw, N., Reis, R. and J. Wolfers (2003), 'Disagreement about inflation expectations', *NBER Macroeconomics Annual* 18, pp. 209-248; Vašíček (2018), *op. cit.*

⁽²³⁶⁾ Bekaert, G., Hoerova, M. and M. Duca (2013), 'Risk, uncertainty and monetary policy', *Journal of Monetary Economics*, Vol. 60, No. 7, pp. 771-788.

⁽²³⁷⁾ Klomp, J. and J. de Haan (2009), 'Political institutions and economic volatility', *European Journal of Political Economy*, Vol. 25, No. 3, pp. 311-326; Mohl, P. and D. Sondermann (2013), 'Has political communication during the crisis impacted sovereign bond spreads in the euro area?', *Applied Economics Letters*, Vol. 20, No. 1, pp. 48-61; Auerbach (2014), *op. cit.*; Abel, J., Rich, R., Song, J. and J. Tracy (2016), 'The measurement and behavior of uncertainty: Evidence from the ECB survey of professional forecasters', *Journal of Applied Econometrics*, Vol. 31, No. 3, pp. 533-

550; Rossi, B., Sekhposyany, T. and M. Souprez, (2017), 'Understanding the sources of macroeconomic uncertainty', *Barcelona Graduate School of Economics Working Papers* 920.

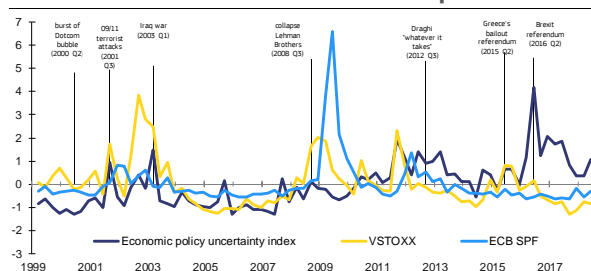
⁽²³⁸⁾ Brown, K., Harlow, W. and S. Tinic (1988), 'Risk aversion, uncertain information, and market efficiency', *Journal of Financial Economics*, Vol. 22, No. 2, pp. 355-385.

⁽²³⁹⁾ Jurado et al. (2015), *op. cit.*

⁽²⁴⁰⁾ Baker, S., Bloom, N. and S. Davis (2016), 'Measuring economic policy uncertainty', *The Quarterly Journal of Economics*, Vol. 131, No. 4, pp.1593-1636.

⁽²⁴¹⁾ For the dispersion of indicators we take data from the ECB's Survey of Professional Forecasters (SPF) and estimate the cross-sectional variance of 1-year rolling forward forecast point predictions of Eurozone GDP growth (Abel et al. (2016), *op. cit.*). In terms of financial-markets measures we use the VSTOXX, which measures the volatility of the EURO STOXX 50, as well as the bond spread between the German and Greek 10-year government bonds. Finally, the news-based measure is shown by the Economic Policy Uncertainty index, which is applied to Europe (Baker et al. (2016), *op. cit.*).

Graph III.1: Evolution of uncertainty indicators for the EU in comparison



Source: ECB, European Commission, Baker, Bloom and Davis, Bloomberg.

The VSTOXX and the bond spreads measure specifically the uncertainty of financial markets. The VSTOXX increased significantly in reaction to the 9/11 terror attacks, the 2003 Iraq war and the collapse of Lehman Brothers. It decreased progressively after ECB President Mario Draghi's 'Whatever it takes' speech in July 2012 and increased again in 2015 in the context of Greece's bailout referendum.

The economic policy uncertainty (EPU) index focuses on political events. The EPU index showed significant increases in reaction to the 9/11 terror attacks or the Iraq war; two events which also triggered reaction in the financial uncertainty indicators. By contrast, the EPU index did not spike following the fall of Lehman Brothers but it increased following the Brexit referendum, while the measures of financial market and macroeconomic uncertainty (e.g. dispersion of indicators) remained at low levels.

Dispersion in the ECB Survey of Professional Forecasts (SPF) primarily measures macroeconomic uncertainty. This indicator shows a spike of uncertainty right after the collapse of Lehman Brothers. The delay compared to the financial indicators around 2009 and 2012 reflects a difference in their nature: the measure of macroeconomic uncertainty peaked after that of financial uncertainty because risks were first observed on the financial market and their materialisation fuelled the risk of contagion to the real economy. The recent referendums on the UK's membership of the EU and Greece's financial assistance programme were accompanied by increases in measures of political risk but did not trigger sizeable reactions in measures of macroeconomic uncertainty.

III.3. Stylised facts using our uncertainty measure: forecast errors of the fiscal effort

Our key measure for uncertain fiscal outcomes is the forecast error of the fiscal effort. Our analysis focuses on the fiscal effort, as measured by the change in the structural balance, since it is a key indicator of the Stability and Growth Pact (SGP) ⁽²⁴²⁾. We assess the uncertainty of the fiscal effort with the third type of uncertainty indicator presented above, namely the forecast error (Sub-section 2). Our uncertainty indicator corresponds to the 18-month-ahead forecast error for year t and is defined as the difference between the forecast for t made in autumn of $t-1$ and the actual (outturn) value for t as observed in spring of $t+1$. The use of the autumn forecast allows us to take into account Member States' draft budgetary plans. As a result, a positive (negative) forecast error means that the fiscal effort turned out to be smaller (higher) than expected, implying a negative (positive) surprise.

The forecast error is based on Commission forecast reports. We compute the forecast errors for Member States using real-time data from Commission forecast vintages between autumn 2000 and spring 2018. Our analysis shows that Commission forecasts represent an unbiased forecast with satisfactory forecasting properties ⁽²⁴³⁾. By contrast, forecasts produced by domestic authorities may be overly optimistic in order to avoid potential procedural consequences in case of non-compliance with the targets ⁽²⁴⁴⁾. For this reason, we argue that our forecast error indicator represents an *ex post* measure of uncertainty for Member States.

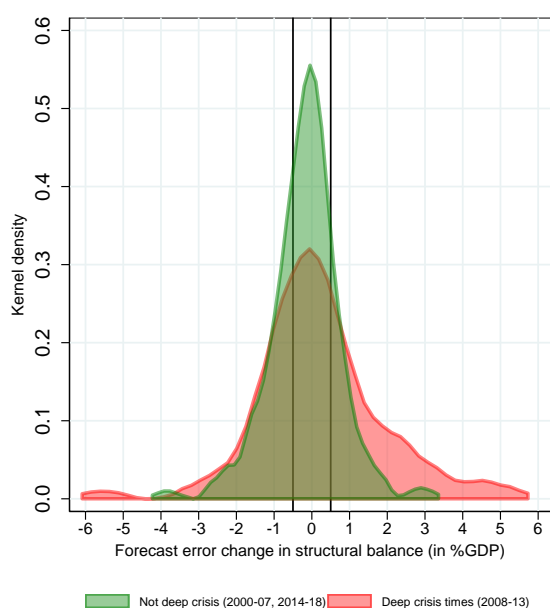
⁽²⁴²⁾ The structural balance adjusts the overall government balance for the impact of the economic cycle as well as for certain one-off revenues (e.g. sales of telecommunication licences) and one-off capital transfers (e.g. financial assistance to the banking sector). In the preventive arm of the SGP, the required fiscal adjustment is also measured by the expenditure benchmark.

⁽²⁴³⁾ We ran tests for bias in the Commission's projections, by simply regressing the forecast error on a constant and testing if this constant is statistically different from zero. Our findings show that the forecast of the fiscal effort does not show a bias for country aggregates (EU, euro area, CEEC) and for all 28 Member States apart from Croatia. For Croatia, the number of observations is limited, since it only joined the EU in 2013. The results broadly confirm similar tests (González Cabanillas, L. and A. Terzi (2012), 'The accuracy of the European Commission's forecasts re-examined', *European Economy. Economic Papers* 476, European Commission (2020), 'Performance of spending rules at EU and national level – a quantitative assessment, Report on public finances in EMU', *European Economy, Institutional Paper*, 24 July 2020.

⁽²⁴⁴⁾ Frankel, J. and J. Schreger (2013), 'Over-optimistic official forecasts and fiscal rules in the eurozone', *Review of World Economics*, Vol. 149, No. 2, pp. 247-272.

Our results show that the forecast errors of the fiscal effort can be sizeable, not only in times of deep crisis (Graph III.2). It is true that the forecast errors were particularly large during the 2008/2009 Great Recession. During this period, more than 70% of the forecast errors exceeded 0.5 pp. of GDP (see white Kernel in Graph III.2). In addition, the forecast errors were mostly positive, explaining the right-skewed distribution. However, also outside times of deep crisis, sizeable forecast errors exceeding 0.5 pp. occurred in around 50% of cases (see green Kernel in Graph III.2).

Graph III.2: Distribution of forecast errors of the fiscal effort (EU-28 Member States)



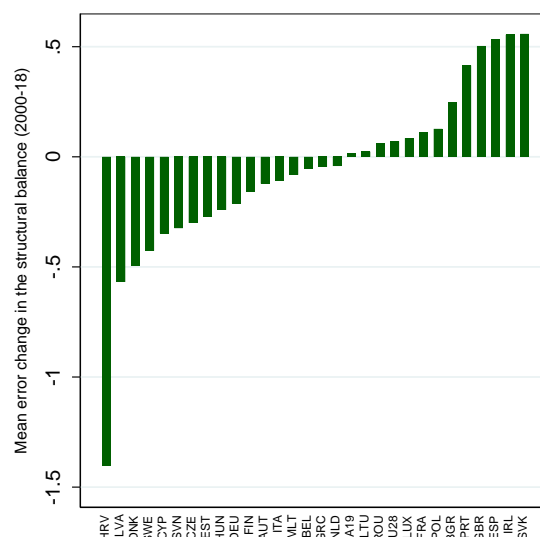
(1) Note: Our uncertainty indicator corresponds to the 18-month-ahead forecast error for year t and is defined as the difference between the forecast for t made in autumn of $t-1$ and the actual (outturn) value for t observed in spring of $t+1$. A positive (negative) forecast error corresponds to a negative (positive) surprise. The calculations are based on real-time data from Commission forecast vintages from 2000-2019. For data availability reasons, the cyclically-adjusted balance is used before 2006 instead of the structural balance.

Source: Commission forecast from different vintages.

The forecast error of the fiscal effort was non-negligible for many Member States. For the EU as a whole, positive and negative 18-month-ahead forecast errors offset each other over the period 2000 to 2018, resulting in a mean error close to zero. However, at country level, the forecast error seems to be more persistent. Over the entire period, on average around 20 (15) percent of the Member States overestimated the fiscal effort by on average 0.25 (0.5) pp. (Graph III.3). The mean error represents only a rough indicator of the

forecast quality, since positive and negative errors can offset each other, thus limiting the size of the error.

Graph III.3: Mean error of fiscal effort by country



(1) Note: See footnote of Graph III.2 for more information.

Source: Commission forecast from different vintages.

III.4. Empirical strategy

Using a panel data approach, we analyse Member States' reaction to uncertainty based on an augmented fiscal reaction function. The analysis concentrates on all Member States using real-time data from Commission forecast reports between autumn 2000 and spring 2019.

The analysis is conducted in two steps. As a first step, the key drivers of the expected fiscal effort are determined using a classical fiscal reaction function, which is augmented with the forecast error of the fiscal effort. This allows us to get a first rough idea of whether Member States learn from past uncertainty (i.e. a 'learning effect'). The specification looks as follows:

$$\Delta sb_{i,t+1}^{AF,t} = \beta_1 cycle_{i,t+1}^{AF,t} + \beta_2 debt_{i,t-1}^{AF,t} + \beta_3 FE(\Delta sb_{i,t-1}) + \beta_4 X_{i,t}^t + \vartheta_t + \theta_i + \varepsilon_{i,t} \quad (1)$$

where the superscript t refers to the time of the publication of the Commission forecast report, while subscript t refers to the year to which the figure applies and i stands for the Member State.

For instance, the dependent variable $\Delta sb_{i,t+1}^{AF,t}$ is the expected fiscal effort for year $t+1$ as projected in the Commission autumn forecast report of year t .

The independent variables are selected in line with the literature ⁽²⁴⁵⁾. We control for two key variables used in the fiscal reaction function literature, namely the economic cycle ('cycle' in equation 2), as measured by the change in the output gap, and the government's budget constraint in the form of the debt-to-GDP ratio ('debt'). The setup reflects the rationale of the EU fiscal governance framework, which requires a larger fiscal effort in good economic times and/or in the presence of high public debt for Member States that still need to reach a sound fiscal position (their MTO) ⁽²⁴⁶⁾. A key variable of interest is the forecast error of the fiscal effort. Our uncertainty indicator corresponds to the 18-month-ahead forecast error for year t and is defined as the difference between the forecast for t made in autumn of $t-1$ and the actual (outturn) value for t as observed in spring of $t+1$. The forecast error of the fiscal effort is denominated in equation 2 as $FE(\Delta sb_{i,t-1})$. The remaining independent variables are summarised in vector X . They include the forecast error of the output gap, key indicators for EU fiscal rules (dummy variables for Member States who are in EDP and/or have achieved their MTO) and the election year (the percentage share of months of a given year before an election) ⁽²⁴⁷⁾. Furthermore, the specification includes year- (ϑ) and country-fixed effects (θ_i), while $\varepsilon_{i,t}$ represents an error term.

In a second step, we refine our specification to find out if the sign, size and/or persistency of the forecast error matters for the reaction of

Member States. Since forecast errors are an unavoidable part of fiscal projections, we do not expect Member States to react to all kinds of uncertainty. However, a myopic disregard of repeated errors or large-scale uncertainty can do serious damage to a Member State's public finances. Therefore, we use the following panel interaction model to find the conditions under which the forecast error becomes significant:

$$\Delta sb_{i,t+1}^{AF,t} = \beta_1 cycle_{i,t+1}^{AF,t} + \beta_2 debt_{i,t-1}^{AF,t} + \beta_3 FE(\Delta sb_{i,t-1}) + \beta_4 X_{i,t}^t + \beta_5 FE(\Delta sb_{i,t-1}) \cdot D_{i,t}^{AF,t} + \beta_6 D_{i,t}^{AF,t} + \vartheta_t + \theta_i + \varepsilon_{i,t} \quad (2)$$

where D represents a dummy variable that is equal to 1 if the forecast error is positive (i.e. representing a negative surprise) and/or large (exceeding 0.25 or 0.5 pp. of GDP) and/or persistent (i.e. repeated forecast errors of up to 3 years). To find out if these elements have an impact on the expected fiscal effort, the dummy variable is interacted with the forecast error. We can then derive the marginal effect, which measures how a marginal change of the forecast error affects the fiscal effort as follows:

$$\frac{\partial \Delta sb}{\partial FE(\Delta sb)} = \beta_3 + \beta_5 D_{i,t} \quad (3)$$

The equation shows that the marginal effect depends on the value of the dummy variable D . The marginal effect is defined as $\beta_3 + \beta_5$ if the dummy variable is equal to 1 (e.g. forecast error shows a negative surprise), whereas it simplifies to β_3 if the dummy variable is 0 (e.g. forecast error shows a positive surprise) ⁽²⁴⁸⁾. In addition, the standard errors for both events can be calculated based on the variance-covariance matrix.

We apply different estimation techniques. In terms of the estimation approach, we apply three different techniques. We first estimate the model with simple LSDV estimations using White heteroscedasticity robust standard errors ⁽²⁴⁹⁾. In

⁽²⁴⁵⁾ See for instance, Bohn, H. (1998), 'The behaviour of U.S. public debt and deficits', *The Quarterly Journal of Economics*, Vol. 113(August), pp. 949-963, Checherita-Westphal, C. and V. Žďárek(2017), 'Fiscal reaction function and fiscal fatigue: Evidence for the euro area', *ECB Working Paper* 2036, Combes, J., Minea, A. and M. Sow (2017), 'Is fiscal policy always counter-(pro-) cyclical? The role of public debt and fiscal rules', *Economic Modelling*, Vol. 65, pp. 138-146, European Commission (2011), 'Public Finances in EMU', *European Economy* 3, September.

⁽²⁴⁶⁾ European Commission (2019), 'Vade Mecum on the Stability and Growth Pact – 2019 edition', *Institutional Paper* 101, 2 April.

⁽²⁴⁷⁾ Election year is defined as the share of month in a given year before the election (e.g. if the election takes place in October 2019, the value of the variable is 10/12 in 2018 and 5/6 in 2019 and 1/6 in 2018. Please note that we tested a range of alternative control variables e.g. the partisanship (left vs. right). We also tested for the sensitivity of the economic cycle by using the level of the output gap and the real GDP growth rate. However, the results do not change.

⁽²⁴⁸⁾ For the specification and interpretation of interaction terms see Brambor, T., Clark, W. and M. Golder (2006), 'Understanding interaction models: Improving empirical analyses', *Political Analysis*, Vol. 14, No. 1, pp. 63-82, Braumoeller, B. (2004), 'Hypothesis testing and multiplicative interaction terms', *International Organization*, Vol. 58, No. 4, pp. 807-820.

⁽²⁴⁹⁾ White, H. (1980), 'A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity', *Econometrica*, Vol. 48, No. 4, pp. 817-838.

addition, we provide further evidence by running first-difference and system-GMM regressions in order to control for endogeneity⁽²⁵⁰⁾. We consider the forecast error and the output gap to be endogenous. Due to the small sample size, the set of internal instrumental variables is restricted to up to 2 lags and the matrix of instruments is then ‘collapsed’⁽²⁵¹⁾. We test the validity of the GMM specification with AR(1,2) and Hansen tests.

III.5. Main findings

Our baseline model largely confirms the findings of the fiscal reaction function literature (Table 1). We find strong evidence of pro-cyclical fiscal policy, as shown by the negative and significant coefficient of the change in the output gap. In addition, an increase of the debt-to-GDP ratio tends to lead to a fiscal tightening. Moreover, election years appear to be significantly linked to a loosening of the fiscal effort. The initial years of the Great Recession (2008-09) seem to have resulted in a significant loosening of the fiscal adjustment. Finally, Member States that have achieved their MTOs seem to set looser fiscal adjustment plans, while there is no evidence that an EDP affects the expected fiscal effort. The findings are robust to the estimators used (columns 1-5)⁽²⁵²⁾.

A rough first assessment indicates no significant learning effect (Table 1). To get a rough first idea whether Member States learn from past episodes of uncertainty, we augment the model with the forecast error of the fiscal effort. Since the consequences of increased uncertainty may only kick in after repeated forecast errors have occurred, we assess the impact of time lags in greater detail. We run our empirical analyses by adding the lagged forecast error in a stepwise fashion, beginning with a lag of 1 year (column 3) and ending up with specifications comprising the forecast error with a lag of up to 2 (column 4) and 3 years (column 5). The results indicate that an increase (decrease) in the forecast error does not

have a statistically significant impact. The findings of the other independent variables remain broadly unchanged.

Table III.1: **Regression results: augmented baseline model**

| | LSDV | | SYSGMM | | |
|--------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Δ OG (t+1) | -0.324*** (-4.962) | -0.460*** (-3.145) | -0.345*** (-3.325) | -0.330*** (-3.136) | -0.393*** (-3.598) |
| Public debt (t) | 0.009*** (2.732) | 0.006*** (3.652) | 0.006*** (2.878) | 0.003 (1.149) | 0.006*** (4.506) |
| Crisis dummy (2008-09) | -0.778*** (-3.528) | -0.763** (-2.432) | -3.060*** (-4.743) | -2.256*** (-4.940) | -1.955*** (-6.338) |
| Election year (t+1) | -0.000 (-1.549) | -0.001*** (-2.622) | -0.002*** (-3.770) | -0.001** (-2.358) | -0.001*** (-3.648) |
| MTO achievement (t) | -0.279*** (-3.140) | -0.179** (-2.333) | -0.166 (-1.628) | -0.251*** (-2.704) | -0.106 (-1.364) |
| EDP (t) | 0.098 (1.325) | 0.136 (1.631) | 0.006 (1.061) | 0.168 (1.366) | 0.068 (0.817) |
| Forecast error OG (t-1) | -0.048 (-1.250) | -0.005 (-0.083) | -0.170** (-2.174) | -0.075 (-1.207) | -0.025 (-1.030) |
| Forecast error Δ SB (t-1) | | | -0.003 (-0.060) | 0.012 (0.179) | 0.068 (1.491) |
| Forecast error Δ SB (t-2) | | | | 0.066 (1.384) | 0.031 (0.720) |
| Forecast error Δ SB (t-3) | | | | | 0.030 (0.910) |
| # countries | 28 | 28 | 28 | 28 | 28 |
| # observations | 410 | 410 | 399 | 371 | 343 |
| Wald time dummies | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Forecast error Δ SB (size) | | | -0.003 | 0.078 | 0.129 |
| Forecast error Δ SB (p-value) | | | 0.952 | 0.858 | 0.136 |
| AR(1) (p-value) | | 0.004 | 0.005 | 0.007 | 0.023 |
| AR(2) (p-value) | | 0.455 | 0.363 | 0.58 | 0.788 |
| Hansen (p-value) | | 0.520 | 0.476 | 0.274 | 0.245 |
| # instruments | | 24 | 30 | 31 | 32 |

(1) Estimations are based on the least square dummy variable estimator using heteroskedasticity-robust standard errors (LSDV). In addition, the use of system-GMM (SYSGMM) estimators follows Blundell and Bond (1998), where we consider the output gap and the forecast error variables to be endogenous. Due to the small sample size, the set of internal instrumental variables is restricted to up to 2 lags and the matrix of instruments is then ‘collapsed’. The standard errors are corrected following Windmeijer (2005). AR(1,2) and Hansen tests confirm the validity of the GMM specifications (Roodman, 2009a, b). Note that the coefficients and standard errors of the forecast error cannot be interpreted if the variable is included in the regression with several lags (columns 3-5). As a consequence, we report the size of forecast errors coefficients (row ‘forecast error Δ SB (size);’) We then use a simple Wald test to check whether this short-term elasticity is statistically different from zero (‘forecast error Δ SB (p-value)’). ***, ** and * denote statistical significance at 1, 5 and 10% respectively.

Source: European Commission.

Robustness tests broadly confirm the main findings. First, we shorten the sample to re-run the regressions for the period since 2005. The reason for this is that the structural balance has been used in fiscal surveillance only since 2005, while the cyclically-adjusted balance was used earlier than that⁽²⁵³⁾. Second, we assess the sensitivity of our findings by using different estimation techniques as described above. Overall, our key findings do not change much in both cases.

⁽²⁵⁰⁾ Blundell, R. and S. Bond (1998), ‘Initial conditions and moment restrictions in dynamic panel data models’, *Journal of Econometrics*, Vol. 87, No. 1, pp. 115-143.

⁽²⁵¹⁾ The standard errors are corrected following Windmeijer, F. (2005), ‘A finite sample correction for the variance of linear efficient two-step GMM estimators’, *Journal of Econometrics*, Vol. 126, No. 1, pp. 25-51.

⁽²⁵²⁾ We also tested for a broad range of additional independent variables (such as the current account balance, openness, ageing), which, however, turned out to be not statistically significant.

⁽²⁵³⁾ The structural balance corresponds to the cyclically-adjusted balance excluding one-offs and certain temporary measures.

We then revise our empirical strategy to find out if Member States learn from past episodes of uncertainty. A myopic disregard of repeated or large-scale uncertainty can do serious damage to the public finances. In order to take this factor into account, we assess the sign, size and persistence of the forecast error in greater detail. We distinguish between negative surprises (i.e. positive forecast errors) and positive ones (i.e. negative forecast errors). We also test if large or very large negative or positive surprises (0.25 pp. or 0.5 pp. of GDP) had an impact. Finally, we test if repeated (large) negative or positive surprises had an impact on Member States' expected fiscal effort.

Our findings of the refined test of the learning effect can be summarised as follows (Table 2):

- **Sign of the forecast error.** Our results show that neither negative surprises (i.e. a *positive* forecast error) nor positive surprises of the fiscal forecast (i.e. a *negative* forecast error) have a statistically significant impact on the expected fiscal effort.
- **Size of the forecast error.** Similarly, *large* or *very large* negative surprises do not cause a significant effect on the expected fiscal effort if they occur only once. This finding holds, irrespective of the sign (positive or negative) and the size (0.25 pp. or 0.5 pp. of GDP) of the forecast error. Similarly, the occurrence of one (very) large forecast error in the past (up to three years) has no statistically significant impact on the expected fiscal effort.
- **Persistence of forecast errors.** We assess up to three lags to assess the impact of persistent forecast errors. We find evidence that persistent forecast errors have an impact on the expected fiscal effort. The strength of the impact depends, however, on the size of the forecast error: Overall, we find only a weak impact in case of negative surprises, but a strong one for positive ones. To be more precise, in case of negative surprises, only a *repeated and very large negative* surprise (i.e. exceeding 0.5 pp. of GDP) leads to a statistically significant impact in the form of a fiscal tightening. It is important to note, however, that this is a rather rare event that only occurs in around 3% of all observations since 2000 (13 out of 399). The main result is only valid in case of three very large negative surprises that are repeated in a

row. By contrast, we cannot find significant results if the very large negative surprise occurred only 2 years in a row or in 2 out of 3 years. At the same time, repeated positive surprises have a rather strong impact, resulting in a fiscal loosening.

III.6. Conclusions

This section finds that Member States tend to react only very late and asymmetrically to the uncertainty surrounding the fiscal effort. We show that uncertain economic outcomes in the form of the forecast error of the fiscal effort have been an integral part of fiscal projections in the EU since 2000. Nevertheless, the results from panel regressions reveal that Member States frequently do not adjust their expected fiscal effort to economic shocks. We find that Member States only late and asymmetrically react to forecast errors, relaxing the fiscal effort in case of positive surprises and leaving it unchanged in case of negative ones.

Table III.2: Regression results conditional on forecast characteristics

| | | Type of surprise | |
|--------------------------|-------------------------|------------------|----------|
| | | Negative | Positive |
| Sign | | 0,08 | 0,01 |
| Size | Large | 0,05 | -0,02 |
| | Very large | 0,01 | -0,03 |
| Per- sistence | Repeated | | |
| | • 2 years in a row | -0,02 | -0.16* |
| | • 3 years in a row | 0,02 | -0.20** |
| | Repeated and large | | |
| | • 2 years in a row | -0,11 | -0.02** |
| | • 3 years in a row | -0,07 | -0.49** |
| | Repeated and very large | | |
| | • 2 years in a row | 0,15 | -0.27** |
| | • 3 years in a row | 0,19* | -0,30 |

(1) Forecast errors of the fiscal effort (i.e. the change in the structural balance) are considered to be large (very large) if they exceed 0.25(0.5) pp. The table shows the size and significance level of the marginal effect, which measures the impact of a marginal increase of the forecast error if the forecast characteristic (sign, size, persistence) is fulfilled (see equation (3)). The findings are based on the same sample and estimation techniques as described above. A reading example of the quantitative assessment: a negative surprise tends to have a small positive impact on the expected fiscal adjustment (the size of the coefficient is 0.08), which is, however, not statistically significant at the 10% level. ***, ** and * denote statistical significance at 1, 5 and 10% respectively.

Source: European Commission.