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THREE ESSAYS IN CLIMATE CHANGE ECONOMICS

David García León

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Dirigida por:

Gabriel Pérez-Quirós

A mi madre, mi padre y mis hermanos

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The decision of embarking on a PhD was no big deal at that moment. I was, to some extent, convinced about doing it and doing it good. By no means was I expecting the level of frustration, discouragement and distress that were waiting ahead. At the (very) end, though, everything is worth it. Life is a process and so is writing a thesis. A process of constantly learning, trapping, falling, falling, falling, rising and falling yet 100 times more... and rising. At the end of the day, you should follow your instinct and do not betray your ideas. Never regret not having done something you were certain you should have done. Enjoy the ride and the road.

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Contents

List of Tables

List of Figures

Resumen

La relación que une al ser humano con el medio ambiente ha sido, es y, posiblemente, será de carácter indisoluble. El hombre y el medio natural están interrelacionados y es ingenuo pensar que nuestras acciones no van a afectar en mayor o menor medida a nuestro entorno. Y viceversa. Es sensato, pues, pensar que los recientes cambios en los patrones climáticos en respuesta al continuo calentamiento global afectan a la manera en que nos comportamos, tomamos decisiones o producimos.

El análisis de esta relación, aunque siempre ha preocupado a la comunidad científica desde tiempos inmemoriales, ha permanecido en el letargo durante los últimos siglos, narcotizado por el efecto demoledor de la revolución industrial y el desarrollo del Estado del Bienestar. Tal ha sido este periodo de cadencia, que algunos autores han llegado a afirmar que el desarrollo económico en los tiempos modernos había dejado de depender del entorno, del cual se había llegado a disociar por completo mediante el uso de la tecnología y de las estructuras productivas avanzadas. Esta teoría es conocida en inglés con el término *economic decoupling*.

No ha sido hasta la última década que, al albur de la evidencia presentada por la comunidad científica, los investigadores y el público en general han sido conscientes de que la interrelación entre el ser humano y el medio ambiente no había cesado en ningún momento y que éste, a raíz de la emisión descontrolada de gases de efecto invernadero (GEI) estaba comprometiendo la estabilidad del sistema Tierra. El cambio climático antropogénico y las nefastas consecuencias proyectadas por su acción han supuesto un renacer de la preocupación por entender los mecanismos que rigen la relación entre el hombre y el medio y motivan originalmente el desarrollo de esta tesis.

Así, esta tesis estudia la relación economía-medio ambiente cuantitativamente en ambas direcciones. Por un lado, mide los efectos agregados en los sectores productivos de los recientes cambios en el comportamiento de las variables meteorológicas. Por otro lado, estudia las implicaciones económicas y medioambientales derivadas de adoptar distintas estrategias para combatir los daños producidos por el cambio climático.

Con un importante valor añadido. Además de facilitarnos estimaciones precisas de las implicaciones de la relación bidireccional ser humano-medio ambiente, esta tesis trata de arrojar luz sobre cómo esta relación se ha modificado con el tiempo: se ha mantenido estable, se ha intensificado o, por el contrario, es cada vez más débil. En términos científicos este aspecto se conoce como adaptación al cambio climático.

La adaptación al cambio climático es un concepto muy en boga que, todavía no ha sido explorado cuantitativamente con rigurosidad por la comunidad científica. El IPCC (*Intergovernmental Panel on Climate Change*), organismo internacional que evalúa los aspectos técnicos, tecnológicos y socio-económicos relativos al cambio climático, viene urgiendo en sus últimos Informes de Evaluación (*Assessment Reports*) a la comunidad científica de la importancia de estudiar con profundidad mediante ejercicios teóricos y empíricos el concepto de adaptación, pues éste supone uno de los pilares principales, junto con la mitigación, para luchar contra el cambio climático. Esta tesis recoge el guante del IPCC y trata de ahondar en el entendimiento de esta variable.

Esta tesis nace, en definitiva, con el objetivo de dar respuesta a dos preguntas sobre las que no existe todavía una respuesta categórica: "¿existe una relación entre renta agregada y clima?" y "¿cuál es la manera óptima de abordar la lucha contra el cambio climático en condiciones de incertidumbre?" La primera es una pregunta que corroe a los investigadores desde finales del s. XIX y que cobra especial relevancia en un contexto de constante incremento en las temperaturas. La segunda es consecuencia de un fenómeno que nos golpea incansable desde el siglo pasado y que supone un reto para la humanidad en los próximos años: el cambio climático.

Intentaremos responder a la primera pregunta sirviéndonos de un ejercicio empírico apoyado en técnicas econométricas y estadísticas, mientras que para la segunda desarrollaremos un modelo clima-economía adaptado para el análisis en entornos de incertidumbre, describiendo los resultados con formas de visualización novedosas.

Capítulo 1. Clima y renta: Lecciones de las principales regiones europeas

Se espera que el cambio climático antropogénico haga aumentar la temperatura media de la superficie terrestre inexorablemente en las próximas décadas. Según el IPCC, *"la temperatura media de la Tierra ascenderá durante el siglo XXI bajo todos los escenarios de emisiones de GEI analizados y este incremento se espera que se sitúe en el intervalo de 0.3ºC a 4.8ºC"*. A la luz de esta afirmación, se hace vital conocer el grado de exposición de las estructuras productivas a las variables medioambientales y cómo las primeras se ven afectadas por la naturaleza cambiante de las segundas. En particular, es urgente determinar si existe una relación entre los patrones meteorológicos y el producto interior bruto de las naciones, así como determinar el signo y la magnitud de esta relación. Es también crucial evaluar si los incrementos previstos en las temperaturas socavarán el potencial de crecimiento de estas naciones.

En el primer capítulo de esta tesis se explora la relación entre clima y actividad económica agregada sirviéndonos de una muestra con datos económicos y climáticos pertenecientes a las regiones de los principales países europeos. En particular, esta muestra abarcaría las regiones de los cinco mayores países europeos (Alemania, Reino Unido, Francia, Italia y España) para un periodo comprendido entre los años 1990 y 2012.

Tradicionalmente, la relación entre clima (temperatura, fundamentalmente) y actividad económica agregada se ha cuantificado a través de dos enfoques: el primero, apoyado en la literatura de la economía del desarrollo y crecimiento, examina la relación entre la temperatura media y el nivel de actividad agregado en una muestra de sección transversal de países. Este es el llamado método *hedónico* o *Ricardiano*, del cual fue pionero en este contexto Mendelsohn et al. (1994). Otros ejemplos de esta metodología aplicados a distintas áreas y sectores son los trabajos de Sachs y Wagner (1997); Gallup et al. (1998); Nordhaus (2006); Fisher et al. (2006) y, más recientemente, Tack et al. (2015). Utilizando datos contemporáneos a nivel municipal para 12 países de América. Dell et al. (2009) identifican una relación negativa entre renta y temperatura entre países e, incluso, entre regiones dentro de esos países. Estos autores sostienen que los países cálidos de su muestra tienden a ser más pobres, en una cuantía de 8.5% por cada 1°C adicional, lo que coincide cualitativamente con otros ejemplos de la literatura.

Otros autores, como Schelling (1992); Poterba (1993); Stern (2006); Nordhaus (2008); Tol (2009), apuntan en esa misma dirección. Adicionalmente, estudios como el llevado a cabo por Albuoy (2016) identifican una correlación negativa entre temperatura y productividad empresarial dentro de Estados Unidos. No obstante, existe otra corriente de autores que defienden que las correlaciones observadas en estos trabajos responden a una asociación espúrea entre temperatura y algunas características nacionales, tales como la calidad institucional. Entre esa corriente de pensamiento encontramos a Acemoglu et al. (2002), Easterly y Levine (2003), Rodrik et al. (2004). Su razonamiento descansa en el papel de las variables omitidas, mediante el cual la no inclusión en este tipo de regresiones de otras variables correlacionadas con la temperatura que explicarían también variaciones en la producción agregada en tiempos de prosperidad, sesgarían la importancia que se le da a las variables puramente geográficas en el enfoque *hedónico*. En este ejercicio, se trata de atenuar los efectos de la omisión de variables relevantes mediante la inclusión de un indicador sintético regional del nivel de reputación y calidad institucional a escala europea.

Existe una segunda y novedosa manera de enfocar este problema. Dell et al. (2012) examinan la relación histórica entre los cambios de temperatura y precipitaciones experimentados por un país y su economía utilizando como estrategia de identificación las variaciones exógenas anuales de las temperaturas y las precipitaciones. Dell et al.

(2012) encuentran un efecto negativo significativo entre el aumento de temperaturas y el crecimiento económico de los países estudiados, pero sólo para los países relativamente más pobres. En particular, sus estimaciones concluyen que un aumento de 1°C en la temperatura media de un determinado país reduciría la tasa de crecimiento del producto agregado *per cápita* de dicho país en alrededor de 1,3 puntos porcentuales. Para los países relativamente más ricos de su muestra, las variaciones en las temperaturas no tendrían un efecto discernible en el comportamiento de la renta agregada.

Las conclusiones de Dell et al. (2009) y Dell et al. (2012) son llamativas en cuanto que dejarían a la mayor parte del mundo desarrollado al margen de los efectos negativos del cambio climático. Efectos, por otra parte, descritos como universales y de carácter general para toda la Tierra por otras disciplinas científicas y enfatizados por los sucesivos informes del IPCC. Dada la relevancia de este asunto, aunque las afirmaciones de Melissa Dell y coautores fueran irrefutables, se hace necesario llevar a cabo ejercicios empíricos con diversas muestras que confirmen o desmientan estos mensajes. Determinar fielmente el grado de exposición de las economías desarrolladas al nivel de las temperaturas y a la variación de éste es crucial y es lo que nos ocupa en este ejercicio. A diferencia de los autores referidos, en este trabajo se tendrá en consideración la heterogeneidad en las características climáticas de cada país mediante el análisis regional de los mismos, paliando así, una posible fuente de falta de identificación presente al trabajar con datos agregados.

Existe, cada vez, una mayor evidencia que apunta a la existencia de vulnerabilidades de las economías más desarrolladas respecto a las condiciones medioambientales, implicando que la adaptación a las cambiantes condiciones climáticas en todos los márgenes es demasiado costosa. La mayoría de estos estudios se centran primordialmente en el análisis de la respuesta de los rendimientos agrícolas a eventos meteorológicos extremos (Roberts y Schlenker, 2011; Burke y Emerick, 2016). En contextos no agrícolas, Graff Zivin y Neidell (2014) documentan una respuesta negativa de la oferta laboral de individuos expuestos a entornos cálidos, mientras que Hsiang et al. (2013) argumentan que las altas temperaturas serían fuente de conflictos civiles, incluso en países ricos.

Más recientemente, Deryugina y Hsiang (2014) estudian la relación de las temperaturas medias diarias con la renta agregada anual de los condados de los Estados Unidos, encontrando un descenso medio de la productividad regional del 2% por cada 1°C adicional sobre 15°C. De manera similar, Colacito et al. (2014) documentan evidencia empírica en favor del efecto negativo de las temperaturas sobre el crecimiento económico en los Estados Unidos, especialmente en verano, usando datos procedentes de 135 estaciones meteorológicas.

En este capítulo se sigue el espíritu de los diversos trabajos de Melissa Dell y coautores con el fin de desarrollar en estudio de caso integral para Europa. Haciendo un barrido general al mapa europeo, tomando los países con mayor importancia en términos económicos (Alemania, Reino Unido, Francia Italia y España) y dada la dimensión geográfica de estos países, es posible encontrar un grado de heterogeneidad climática que nos faculta para explotar su relación con las variables macroeconómicas deseadas. Nos beneficiamos para este respecto de la distinción administrativa regional promovida por la Comisión Europea (NUTS), a través de la cual toda la UE es parcelada en distintos niveles de agregación. Este marco de actuación es el generalmente utilizado por los Estados Miembros para formular y aplicar las distintas políticas regionales, siendo así el marco apropiado para desarrollar nuestro estudio. En particular, las políticas medioambientales son diseñadas para el nivel NUTS 2 de agregación, que será el utilizado en este trabajo.

En la dimensión transversal de este estudio (enfoque *hedónico*), basándonos en la especificación econométrica de Dell et al. (2009), encontramos que 1°C adicional está asociado con un nivel medio de renta *per cápita* inferior en 1,6-2,2%. Esta relación negativa, en consonancia con lo descrito por Dell et al. (2012), se ve amplificada en las regiones relativamente más pobres. Complementamos este ejercicio analizando el impacto a corto plazo de las oscilaciones meteorológicas. Identificamos que una variación media de las temperaturas en 1°C en el año en curso penaliza el crecimiento potencial de las regiones europeas en una cuantía de 0,06 puntos porcentuales, lo que en términos acumulados representaría un efecto total en el largo plazo ligeramente superior a lo estimado en la primera fase de este estudio y que pone de manifiesto la posibilidad de adaptar a largo plazo los daños producidos por los cambios climáticos.

Capítulo 2. Un modelo recursivo con adaptación para la evaluación integral del cambio climático

Tal y como pone de manifiesto el IPCC en sus sucesivos Informes de Evaluación, la adaptación al cambio climático juega un papel crucial a la hora de gestionar adecuadamente los riesgos que este fenómeno plantea. Este argumento ha sido enfatizado en el recientemente difundido 5° Informe de Evaluación (AR5), donde se presta mucha atención a las fuerzas que impulsan los procesos de adaptación al cambio climático así como a los diversos efectos que estas fuerzas tienen. Ejemplos de adaptación son la construcción de diques, las transformaciones de los campos de cultivo o las vacunas. Los rendimientos de las inversiones en mitigación están restringidos por las grandes inercias climáticas y el lento funcionamiento del ciclo del carbón y de los GEI y sus frutos, por tanto, se dilatan bastante en el tiempo. Mientras, la potencialmente más cara inversión en adaptación, conlleva efectos palpables en el corto-medio plazo.

Está generalmente aceptado entre la comunidad científica que una estrategia satisfactoria para hacer frente al cambio climático debe contener cantidades positivas de mitigación y adaptación. No obstante, la combinación adecuada de estas magnitudes es todavía una cuestión no resuelta. Ambas opciones son necesarias porque sirven para reducir las vulnerabilidades al cambio climático a través de dos maneras complementarias pero distintas. Mediante la primera atacamos las causas mientras que la segunda aborda los efectos. Por tanto, parece natural incluir la inversión en adaptación en los Modelos Integrados de Evaluación (*Integrated Assessment Models* o IAM, en sus siglas en inglés), modelos muy usados para estudiar las implicaciones económicas de un sistema económico basado en las emisiones de GEI.

Un IAM para el cambio climático es un modelo multi-ecuación que relaciona la actividad económica agregada con un modelo simple de la dinámica climática y del ciclo del carbono para analizar los impactos económicos del calentamiento global. En otras palabras, es esencialmente un modelo dinámico de una economía con una externalidad endógena controlable mediante la emisión de GEI. Los modelos IAM han sido históricamente herramientas muy útiles para entender determinados aspectos de la economía del cambio climático—especialmente a la hora de describir los resultados fruto de complicadas interacciones entre grandes retardos y enormes inercias presentes en el ciclo de los GEI. Estos modelos han sido utilizados, por ejemplo, en el AR4 (Parry et al., 2007), AR5 (IPCC, 2013), el Informe Stern (Stern, 2006), y en el Interagency Working Group on Social Cost of Carbon (2010), desempeñando éste último un papel fundamental a la hora de diseñar la política federal de emisiones en los Estados Unidos. La metodología IAM fue iniciada con el desarrollo del modelo *Dynamic Integrated Climate Change*, más conocido como DICE (Nordhaus, 1991, 1993). Ejemplos actuales incluyen los modelos DICE o su versión regionalizada, RICE, (Nordhaus y Yang, 1996; Nordhaus y Boyer, 2000; Nordhaus, 2010; Nordhaus y Sztorc, 2013), el modelo PAGE (Hope et al., 1993; Hope, 2006), y el modelo FUND (Tol, 1999, 2013), entre otros.

En el segundo capítulo de esta tesis, se avanza en la modelización de la inversión en adaptación en el contexto de los IAMs. La integración de la adaptación en estos modelos está todavía en un estado primigenio. Sólo disponemos de unos pocos ejemplos en la literatura, en los cuales la inversión en adaptación se incluye de manera explícita. En este capítulo compararemos algunos de ellos enmarcados en el modelo DICE y estudiaremos como la proporción óptima entre mitigación y adaptación varía entre dichas especificaciones. Se mostrará como mitigación y adaptación se comportan como complementarios estratégicos, con cantidades siempre positivas de recursos asociadas a cada concepto a lo largo del tiempo.

El análisis integrado de la inversión en adaptación nos ayudará a sopesar los costes y beneficios así como los riesgos de estas políticas y debería proporcionar detalles relevantes para su desarrollo e implantación. En Patt et al. (2010), el lector puede sondear como los modelizadores han elegido describir la inversión en adaptación en el marco de los modelos de evaluación integrada. Recientemente, se han hecho esfuerzos para incluir adaptación explícitamente como una variable de control en los IAMs (de Bruin et al., 2009; Lecocq y Shalizi, 2007). Aún así, existe un amplio acuerdo a la hora de señalar que la adaptación debería estar mejor representada en estos modelos (Stern, 2006). En este capítulo, exploramos la designación óptima de adaptación bajo distintas especificaciones y estructuras de costes.

Para ello, utilizaremos el modelo DICE como nuestro modelo IAM de referencia. El modelo DICE estándar asume un único productor a nivel global, el cual debe elegir simultáneamente la cantidad óptima de tres tipos de variables: consumo actual, inversión en bienes de capital y grado de reducción de emisiones de GEI (mitigación). Este modelo se enriquece en este ejercicio para acompasar diferentes estrategias de adaptación y así analizar detenidamente cómo el *mix* óptimo de mitigación-adaptación se ve alterado de acuerdo a diferentes estrategias y costes. En primer lugar, introducimos el modelo AD-DICE basándonos en de Bruin et al. (2009), en el cual la adaptación proactiva se comporta como una variable de control que sólo tiene efecto en el periodo vigente, de tal manera que la adaptación de un periodo no afecta a los daños del periodo siguiente. Exploramos como el *mix* cambia en respuesta a distintas formas de la función de costes. Calibrando el modelo para imitar la senda óptima de mitigación del modelo DICE original, se demuestra cómo el *mix* óptimo se equilibra entre ambas variables, demostrando así la naturaleza complementaria de estos dos objetos. Es sólo después de alrededor de 100 años cuando la inversión en mitigación empieza a dominar claramente. Esto ocurre en respuesta a la reducción de costes de mitigación en los últimos años de la simulación. Se demuestra también que la composición del *mix* óptimo depende de manera crucial de la forma de la función de costes de protección.

Como algunos tipos de estrategias de adaptación tienen una naturaleza de *stock* en lugar de flujo, ya que sus efectos se disipan en el tiempo, en un segundo ejercicio exploramos la posibilidad de construir un *stock* de adaptación que afecte a nuestra economía persistentemente. Siguiendo a McCarl y Wang (2013), modificamos el modelo DICE original y observamos el comportamiento del *mix* óptimo en el tiempo bajo este nuevo comportamiento. Demostramos que la posibilidad de crear un stock de infraestructura adaptativa ayuda a combatir los efectos del cambio climático, creando incentivos para el planificador social para asignar una gran cantidad de recursos a la inversión en adaptación desde un principio, dilatando así una mitigación exhaustiva hasta que se hace urgente en el largo plazo cuando se alcanzan picos en las concentraciones atmosféricas de GEI.

Con el objetivo de preparar nuestro modelo para incorporar futuras modificaciones y con el ánimo de preparar el marco idóneo para realizar análisis en entornos de incertidumbre, en esta fase del proyecto formulamos el modelo DICE en modo recursivo. Para ello, seguimos la aproximación de Traeger (2014). Este autor ha presentado recientemente una versión de DICE con un número reducido de variables de estado, para ser resuelto con técnicas de programación dinámica. La reducción de variables de estado se consigue básicamente mediante una simplificación del ciclo del carbono y de las ecuaciones dinámicas que gobiernan las temperaturas. Esto nos deja un margen extra para poder incorporar nuevas características al modelo. Los beneficios de formular DICE en modo recursivo son, entre otros, que el modelo ahora no es sensible a ningún tipo de condición inicial/terminal, disponemos de las funciones de reacción del planificador social para realizar simulaciones alternativas y, sobre todo, crea el marco ideal para incluir distintos tipos de incertidumbre y/o añadir un comportamiento estocástico tanto a las variables como a los parámetros del modelo.

Capítulo 3. El equilibrio óptimo entre mitigación y adaptación al cambio climático: un análisis bajo incertidumbre

El cambio climático es un fenómeno golpeado por numerosas fuentes de incertidumbre, presentes tanto en los fenómenos climatológicos que lo gobiernan como en la modelización de las relaciones entre variables, y los investigadores deben esforzarse en incluir estas perturbaciones en sus modelos. Sin embargo, incluir dimensiones adicionales en los, ya de por sí, complejos modelos conlleva un coste no fácilmente asumible. Específicamente, hace que la mayoría de estos modelos sufran del mal de la dimensionalidad (*curse of dimensionality*). En el tercer capítulo de esta tesis, nos beneficiamos de la metodología propuesta por Traeger (2014), y adelantada en el capítulo anterior, para tratar de solventar estos problemas. Esta metodología descansa en una reducción de las variables de estado necesarias para describir fehacientemente la dinámica del ciclo del carbono.

En un intento de seguir avanzando en la modelización de la adaptación en el contexto de los modelos IAM, adaptamos en este capítulo esta nueva metodología con el fin de arrojar luz al problema de cómo se altera la composición del equilibrio entre mitigación y adaptación bajo distintos escenarios estocásticos.

El modelo DICE en modo recursivo trabaja explícitamente con agentes racionales operando en el tiempo en entornos potencialmente estocásticos. En este modelo, el planificador toma una secuencia de decisiones óptimas sujeto a diversas restricciones medioambientales. Si el entorno está sujeto a shocks exógenos, está claro que las decisiones óptimas futuras dependerán de la percepción del planificador de la magnitud de esos shocks. El modo de tomar decisiones en el presente en función de las condiciones actuales y las expectativas futuras reciben el nombre de formulación recursiva ya que explotan el hecho de que el problema de tomar la decisión mantiene la misma estructura con el tiempo, es decir, es recurrente. El uso de métodos recursivos hace posible tratar este rango de problemas dinámicos, ya sean determinísticos o estocásticos.

En el pasado, algunos autores han conseguido expresar el modelo DICE de manera recursiva. Por ejemplo, Kelly y Kolstad (1999, 2001) implementaron el modelo DICE-1994 como un modelo recursivo de programación dinámica y analizaron con detalle como el planificador aprende a tomar decisiones con el tiempo. Sin embargo, estos autores no consideran por separado el efecto de las contribuciones de la incertidumbre, el aprendizaje y la aleatoriedad en las políticas óptimas. Algunos años después, Leach (2007) utiliza la misma versión de DICE para demostrar como el aprendizaje se ralentiza cuando se añaden más fuentes de incertidumbre al modelo. Estas son, ambas, contribuciones seminales a la evaluación económica de la incertidumbre en el cambio climático. Una corriente distinta de la literatura introduce la incertidumbre en implementaciones no recursivas de IAMs. La más cercana a nuestra visión es la de Keller et al. (2004), los cuales estudian el aprendizaje en una versión anterior de DICE. No obstante, el hecho de trabajar con metodologías no recursivas sólo les faculta para estudiar un número reducido de escenarios. Son, estos, ejercicios que ofrecen pinceladas muy útiles de las respuestas de los agentes a la incertidumbre pero que, en ningún caso, pueden sustituir los análisis derivados de los métodos de programación dinámica estocástica. Finalmente, los métodos basados en análisis de Monte-Carlo son las aproximaciones más comunes al análisis de incertidumbre en la literatura de los IAM. Estos métodos, sin embargo, no modelizan la toma de decisiones bajo incertidumbre sino que presentan meros análisis de sensibilidad que trazan comportamientos medios en sucesivas simulaciones determinísticas.

Como se ha puesto de manifiesto en el capítulo anterior, adaptarse al cambio climático es clave para afrontar los efectos del calentamiento global y el IPCC ha hecho un llamamiento para que se avance en su comprensión y en su integración en los IAM. En el capítulo anterior se analizó cómo los diferentes esquemas de adaptación interfieren con la cantidad óptima asignada a mitigación en condiciones deterministas. Aquí, extendemos el análisis anterior para incluir distintas fuentes de incertidumbre que pueden alterar el comportamiento ideal del planificador. Incluir estas perturbaciones en el modelo podría distorsionar los resultados generales tal y como los conocemos hasta ahora. Por ejemplo, Lecocq y Shalizi (2010) encuentran en su modelo de equilibrio parcial que, cuando se habilita la incertidumbre, la mitigación se torna más eficiente en términos de costes que la adaptación.

En este capítulo se llevan a cabo una serie de experimentos que cubren un amplio menú de fuentes de incertidumbre que, potencialmente, pueden afectar a nuestro modelo. Dividimos estas incertidumbres en 4 grandes categorías y trabajamos con un ejemplo dentro de cada categoría. Primero, identificamos los comportamientos derivados del desconocimiento parcial de los valores de los parámetros del modelo (incertidumbre epistémica). En este campo, estudiaremos como trabajar con un valor desconocido de la sensibilidad climática afecta a las políticas óptimas y a las magnitudes básicas del modelo. Segundo, permitiremos la posibilidad de contar con procesos exógenos estocásticos gobernando la dinámica del modelo. Se presentará el estudio del crecimiento aleatorio de la tecnología de producción como ejemplo de esta categoría. A continuación, estudiaremos la incertidumbre asociada a la manera en que los individuos, ejemplificados en el planificador social, aprenden del pasado. En particular, equiparemos a nuestro modelo con la propiedad de aprendizaje Bayesiano, a través del cual, el agente tiene un determinado conocimiento *a priori* del valor de cierto parámetro que actualiza a medida que observa las variables realizadas cada periodo. Por último, estudiaremos el caso en que se permite la ocurrencia de catástrofes con cierta probabilidad. La manera de modelizar este escenario es facultar al modelo con la existencia de *puntos gatillo*, los cuales, una vez sobrepasados, alteran drásticamente la dinámica del modelo. Por supuesto, el valor de estos *puntos gatillo* es desconocido para el planificador social.

Con carácter general, identificamos que un crecimiento estocástico del nivel de tecnología apenas afecta a la composición de la cesta óptima de mitigación y adaptación mientras que la incertidumbre acerca del valor cierto de la sensibilidad climática y la posibilidad de que un *punto gatillo* golpee al sistema inclinan al planificador social a invertir relativamente más en mitigación. Se puede concluir que incluir incertidumbre en el modelo, cualquiera que esta sea, tiende a favorecer la duradera pero lenta en el tiempo inversión en mitigación frente a la instantánea pero efímera inversión en adaptación. Este estudio debería complementarse con una evaluación detallada de cómo se comportaría el modelo si se pudiera construir un stock de adaptación.

Conclusiones

Esta tesis estudia las implicaciones directas de la relación entre economía y medio ambiente, prestando atención a las relaciones causa-efecto en ambas direcciones. Por un lado, mide los efectos agregados en los sectores productivos de los cambios en los patrones climáticos que vienen ocurriendo en las últimas décadas. Por otro lado, evalúa cómo las diferentes estrategias a la hora de abordar los efectos del cambio climático afectan al medio ambiente. También estudia el proceso de adaptación al cambio climático y trata de medir su nivel de importancia para absorber los costes producidos por este fenómeno.

El primer capítulo, sirviéndose de una muestra de las regiones europeas más importantes, destapa nueva evidencia en favor de como las crecientes temperaturas repercuten negativamente tanto en el nivel agregado de actividad como en el potencial de crecimiento de los estados miembros. En consonancia con otros autores, también se muestra como este efecto se ve exacerbado en las regiones más desfavorecidas. A la luz de este hecho, los políticos y legisladores deberían tener en cuenta la heterogeneidad regional a la hora de formular las políticas medioambientales y de lucha contra el cambio climático. Esta heterogeneidad también debe tenerse en mente cuando se modelizan las interacciones entre clima y economía, por ejemplo, en los modelos IAM.

Dado que el cambio climático viene frecuentemente acompañado de la proliferación de eventos meteorológicos extremos, la existencia de efectos no lineales debería ser comprobada en futuros ejercicios. Al mismo tiempo, la evidencia microeconómica sugiere que las unidades fundamentales de producción, como el capital humano, podrían también exhibir comportamientos no lineales en respuesta a las temperaturas locales, tal y como ponen de manifiesto Graff Zivin y Neidell (2014). Esto abre una nueva brecha de investigación que será explorada en el futuro. En particular, utilizaremos para Europa técnicas recientemente propuestas por Burke et al. (2015) para una muestra de los Estados Unidos.

Al hilo del punto anterior, en un proyecto futuro, es mi objetivo estudiar las implicaciones en la economía real de otros fenómenos generalmente asociados al cambio climático, como por ejemplo, las sequías. Europa viene experimentando crecientes episodios de sequía en las últimas décadas. Estos eventos, cada vez más frecuentes, pueden poner en riesgo la sostenibilidad de la seguridad alimentaria del continente. Para evaluar este problema, tenemos que medir cuidadosamente el efecto neto de los recientes avances genéticos y agronómicos de las especies cultivadas y de los recientes cambios de las temperaturas en la sensibilidad a la sequía de los cultivos. A esta pregunta sólo se le puede dar respuesta empíricamente dado la cantidad de efectos de distinto signo y magnitud que confluyen. Históricamente, un obstáculo para medir la evolución de los cultivos ha sido la falta de datos precisos que cubrieran detalladamente todo el territorio. La proliferación de técnicas de muestreo modernos y el uso de satélites para medir parámetros de los cultivos puede ayudarnos a subsanar este problema.

Lobell et al. (2014) han desarrollado recientemente un estudio con estas características aplicado al cinturón del maíz del medio-oeste estadounidense. En este trabajo se identifica que, a pesar de que los rendimientos agrícolas han aumentado con carácter general durante el periodo estudiado gracias a los avances agronómicos centrados en aumentar la tolerancia de las semillas a la escasez de agua, la sensibilidad de algunos tipos de cultivos, como el maíz, es mayor ahora que al principio de la muestra. Un comportamiento similar podría ser esperado de los cultivos europeos pero ciertas divergencias respecto al caso americano pueden aparecer en respuesta a las distintas características geográficas y agronómicas y a las distintas decisiones de producción en Europa. Mi trabajo arrojaría luz a este crucial asunto que atañe al sector agrícola europeo.

Como se desprende del primer capítulo, una amplia desagregación espacial es clave en este tipo de estudios. Esto se manifiesta en que algunas áreas son más propensas, de acuerdo a su geografía y orografía, a sufrir episodios de sequía más intensos y prolongados. Al mismo tiempo, algunas variedades de cultivos son más eficientes a la hora de tolerar cambios abruptos en los patrones de temperatura y precipitación. Por tanto, desarrollar este trabajo con el máximo nivel de detalle geográfico es clave para obtener resultados significativos.

En el segundo y tercer capítulo, utilizando modelos IAM, se estudia la composición óptima de las estrategias para luchar contra el cambio climático. Se pone especial énfasis en cómo la existencia de incertidumbre puede alterar esa combinación óptima. La metodología empleada en estos capítulos presenta algunos beneficios o ventajas con respecto a la manera tradicional de formular y resolver los modelos IAM en la literatura. En particular, esta no es sensible a la especificación de distintas condiciones terminales del sistema y nos proporciona las funciones de reacción de los agentes, lo que es muy conveniente para simular escenarios alternativos. Además, crea el marco ideal para incluir características adicionales al modelo, como por ejemplo, la posibilidad de añadir incertidumbre o comportamientos estocásticos de las variables y parámetros que gobiernan el modelo.

Este análisis de incertidumbre es ejecutado en el capítulo 3 de la tesis, el cual representa una nueva aproximación al análisis dinámico de la adaptación al cambio climático mediante un modelo IAM recursivo. Muchas otras extensiones aparte de las llevadas a cabo pueden ser diseñadas y aplicadas dentro de este modelo: incertidumbre de los parámetros que rigen la función de daño, especificaciones alternativas de la función de daño, efectos persistentes de los shocks tecnológicos,... Adicionalmente, distintos tipos de adaptación podrían ser modelizados conjuntamente. Por ejemplo, Bosello et al. (2010) construyen un modelo más imbricado en el que se pueden encontrar distintos tipos de adaptación. En concreto, podemos distinguir entre adaptación anticipada (variable stock), adaptación reactiva (variable flujo) y acumulación de un stock conocimiento de adaptación reactiva. Estas extensiones de nuestro modelo se dejan para proyectos futuros.

En conjunto, esta tesis representa un compendio de evidencia y resultado teóricos que reflejan los efectos perniciosos del cambio climático en las economías desarrolladas, la limitada capacidad de estas economías para adaptarse a esos cambios y que muestra cómo la toma de decisiones bajo incertidumbre para luchar contra el cambio climático se inclina por atacar las causas más que los efectos de este proceso. Esta tesis manda también un mensaje a la comunidad científica y al público en general advirtiendo de la necesidad de abordar un recorte intensivo de las emisiones de GEI para evitar el agravamiento de estos efectos.

Esta tesis, además, supone el germen de una futura agenda de investigación basada en la cuantificación de los efectos en la economía real de los cambios medioambientales derivados del cambio climático y del análisis de las implicaciones que las decisiones humanas tienen en el medio ambiente. Espero poder hacerme cargo de esta agenda en el futuro inmediato.

Introduction

"People are part of the Earth system and they impact and are impacted by its materials and processes."

The relation between humans and the environment has been and will be indissoluble. We are interrelated and it is vague to think that our actions will not impact the functioning of our surrounding environment to a greater or lesser extent. And vice versa. It is reasonable to believe that recent changes in climatic patterns in response to ongoing global warming will affect the way we behave, the way we produce, or the way we take decisions.

This thesis studies the implications of the above relation in both directions. On the one side, it measures the effects in the productive sector of the recent changes in climatic patterns. On the other side, it assesses how different decisions about how to deal with climate damages affect the economy and the environment. With one important addition. Apart from measuring the implications in both directions, it is also in our interest to find out whether those effects are being intensified over time. To put it in another way, we want to know whether the human being is adapting to climate change and up to what extent this is happening.

Anthropogenically driven climate change is expected to increase average global temperatures inexorably in the upcoming decades. According to the *Intergovernmental Panel on Climate Change* (IPCC), *"Surface temperature is projected to rise over the 21st century under all assessed (emission) scenarios and that increase would range from* 0.3°C *to* 4.8°C *in response to different greenhouse gases emission pathways."* In light of this, it is essential to know up to which extent the economic system is exposed to environmental variables and how their changing nature affect economic performance. In particular, it is urgent to determine whether a relationship between weather and total income exists and quantify its sign and magnitude as well as assess whether projected increases in temperatures will undermine the ability of countries to grow.

In Chapter 1 we explore the relationship between weather and economic activity in assorted European regions. To do so, we construct a novel, regional dataset spanning from years 1990 to 2012 that covers the five largest countries in Europe and match it with aggregate income data. Looking at its cross-sectional dimension, we are able to identify the long-term (level) effect of weather on income. Moving then to its longitudinal dimension, we benefit from the exogenous year-to-year variations in weather to estimate the short-term impact (economic growth) of weather fluctuations. We find that one additional degree is associated with a decline in the level of *per capita* Gross Domestic Product (GDP) of 1.6% to 2.2%. In line with other authors, we find that this effect is exacerbated in poor regions. We also attenuate the omitted variable bias, very common in this approach, after controlling for regional institutional quality and reputation. By studying the short-term dynamics we demonstrate how global warming undermines the ability to grow of the latter. These results supply new evidence in favour of the negative effects of rising temperatures in certain areas of developed economies. In light of this, policy makers should account for regional heterogeneity when large-scale environmental policies are formulated. This heterogeneity should also be borne in mind when the interactions between climate and economy are modelled, for instance, in an Integrated Assessment Model (IAM).

As widely stated by the IPCC, adaptation plays a vital role as a way to manage the risks that climate change poses. This has been profoundly emphasized in the recently delivered 5^{th} Assessment Report (IPCC, 2013), where a great deal of attention is devoted to the forces driving adaptation to climate change as well as to the various impacts that adaptation may have. Examples of adaptation are the building of dykes, the changing of crop types, and vaccinations. The results of mitigation investment are constrained by climatic inertia and the slow workings of the carbon and other greenhouse gases cycles and hence take more time to be effective. While potentially more expensive, adaptation could have larger effects on impacts more quickly.

In Chapter 2 we advance in the modelling of adaptation within IAMs. Integrated Assessment Modelling of adaptation to climate change is still at its early stages. Only a few examples in which adaptation is explicitly included in IAMs can be found in the literature. In this chapter we compare some of them in the framework of the *Dynamic Integrated Climate Change*, aka DICE, model (Nordhaus, 2008), and study how the optimal balance between mitigation and adaptation varies across specifications. We show how adaptation and mitigation behave as strategic complementaries, with positive amount of resources allocated to each concept over time. However, the optimal adaptation-mitigation mix will depend critically on the nature of adaptation (flow *versus* stock) and the functions governing its behaviour, like the structure of protection costs. Moreover, we also cast the model in a recursive way, suitable for addressing analysis under uncertainty, including stochastic state variables or incorporating additional features, like Bayesian learning or the existence of tipping points.

Climate change is a phenomenon beset with major uncertainties and researchers should include them in IAMs. However, including further dimensions in IAMs comes at a cost. In particular, it makes most of these models suffer from the curse of dimensionality. In Chapter 3 we benefit from a state-reduced framework to overcome those problems. In an attempt to advance in the modelling of adaptation within IAMs, we apply this methodology to shed some light on how the optimal balance between mitigation and adaptation changes under different stochastic scenarios. We find that stochastic technology growth hardly affects the optimal bundle of mitigation and adaptation whereas uncertainty about the value of climate sensitivity and the possibility of tipping points hitting the system change substantially the composition of the optimal mix as both persuade the risk-averse social planner to invest more in mitigation. Overall, we identify that including uncertainty into the model tends to favour (long-lasting) mitigation with respect to (instantaneous) adaptation. Further research should address the properties of the optimal mix when a stock of adaptation can be built.

CHAPTER 1

Weather and Income: Lessons from the main European regions

1.1 Introduction

Climate change is expected to increase average global temperatures inexorably in the upcoming decades. In light of this, it is essential to know up to which extent the economic system is exposed to environmental variables and how their changing nature affect economic performance.[1] In particular, it is urgent to determine whether a relationship between weather and total income exists and quantify its sign and magnitude as well as to assess whether projected increases in temperatures will undermine the ability of economies to grow.

The relationship between temperature and aggregate economic activity has traditionally been quantified using two approaches. One approach, emphasised in the growth and development literature, has examined the relationship between average temperature and aggregate economic variables using cross-sections of countries. This is the so-called *hedonic* or *Ricardian* approach and was first applied to weather variables and economic outcomes by Mendelsohn et al. (1994). Further examples of this methodology applied to different sectors and regions are the case studies by Sachs and Warner (1997); Gallup et al. (1998); Nordhaus (2006); Fisher et al. (2006) and, more recently, Tack et al. (2015). Using contemporary sub-national data at the municipality level for 12 countries in the Americas, Dell et al. (2009) find that a negative relationship between income and temperature exists when looking within countries, and even looking within states within countries. The authors claim that hot countries tend to be poor, with national income falling 8.5% per degree Celsius in the countries' cross-section. The message in Dell et al. (2009) is seconded by several examples in the literature. For

[1]The 5$^{\text{th}}$ Assessment Report of the *Intergovernmental Panel on Climate Change* (IPCC, 2013) points out that "Surface temperature is projected to rise over the 21st century under all assessed (emission) scenarios". This increase in temperatures would range from from 0.3°C to 4.8°C according to different greenhouse gases emission pathways.

instance, Schelling (1992); Poterba (1993); Stern (2006); Nordhaus (2008); Tol (2009) also point in that direction using different approaches. Other studies, like Albuoy (2016), find a negative correlation between temperature and firm productivity within the United States.

However, some authors argue that the correlations spotted with the Ricardian approach are mainly driven by spurious associations of temperature with national characteristics such as institutional quality (e.g., Acemoglu et al., 2002; Easterly and Levine, 2003; Rodrik et al., 2004). Their reasoning hinges on the role of omitted variables, by which other correlated variables, such as a country's institutions or trade policy, drive prosperity in contemporary times, leaving no important role for geography. We will ignore this criticism during the first part of this study for the sake of comparison between our findings and those of Dell et al. but ultimately will address this issue by controlling for institutional quality and reputation using a multi-region government's quality index.

There exists a second and novel approach to weather and economic data. Dell et al. (2012) take an approximation to climate data different from cross-section data and micro evidence. They examine the historical relationship between changes in a country's temperature and precipitation and changes in its economic performance for a sample of 150 countries. Their main identification strategy rests on the exogenous year-to-year fluctuations in temperature and precipitation. They find a significant, large, negative effect of higher temperatures not only on the level of output but also on growth, but only in relatively poorer countries.[2] In particular their estimates identify that a 1°C rise in temperature in a given year would reduce economic growth by about 1.3 percentage points (pp), a quite substantial figure. According to these authors, changes in temperature would not have a robust, discernible effect on economic growth for rich countries.

The findings in Dell et al. (2009) and Dell et al. (2012), though remarkable, are subject to controversy, as most of the developed world would be left aside or hardly affected by the consequences following a continued increase in global temperatures. This scenario seems quite optimistic, especially after caring about the warning messages delivered by the IPCC in their successive series of reports. Even in the event that their conclusions were indisputable, the issue at hand has enough relevance to be worth a cross-check. Determining faithfully the exposure of well-developed economies to global warming is a major issue within the economics of climate change literature. Should wealthy economies be affected by temperature changes, then a much larger fraction

[2] The use of annual variation to estimate the impact of climate change was first proposed by Schlenker and Roberts (2009) and Deschênes and Greenstone (2007), who use annual county-level U.S. data to estimate the impact of weather on U.S. agricultural output.

of the global economy may be disturbed by climate change. Treating countries as a whole entity, without caring about the within-country weather heterogeneity may be a source of lack of identification that we will address in this exercise.

A continuously growing body of evidence suggests that even in well-developed countries some economic vulnerabilities could still remain, implying that adapting to all climatic conditions along all margins is too costly. Most studies are based primarily in the analysis of the response of agricultural yields to extreme weather events (Roberts and Schlenker, 2011; Burke and Emerick, 2016). In non-agricultural contexts, Graff Zivin and Neidell (2014) document a negative response of temperature-exposed labour supply and Hsiang et al. (2013) claim that high temperatures continue to elicit costly personal conflicts even in wealthy populations. More recently, Deryugina and Hsiang (2014) relate daily temperatures with annual income in the United States counties finding that this single environmental parameter still happens to play a significant role in the overall economic performance, with a decline in average productivity of roughly 2% per additional 1°C over 15°C. Similarly, Colacito et al. (2014) document empirical evidence on the negative effect of temperature in the economic growth of the United States, especially in summer. Again, they make use of nationally disaggregated weather and income data from 135 weather stations across the country. Even a negative relationship between rising temperatures and economic growth has been recently estimated by Bansal et al. (2015) using equity markets data.

We follow the spirit of Dell et al. (2009) and Dell et al. (2012) to develop an integral case study for Europe.[3] Having a quick glance at the European mainland map and looking at the larger countries in economic terms, that is, Germany, France, UK, Italy and Spain, and given the geographic dimensions of those countries, it is possible to find the heterogeneous (exogenous) variation in climate-related variables that enables us to exploit their relation with economic outcomes. We will benefit from the statistical classification enacted by the European Union (EU), the *Nomenclature of territorial units for statistics* (NUTS), through which the whole European map is parcelled into different levels and regions. This framework is generally used by Member States to apply their regional policies and is therefore the appropriate level for analysing regional/national problems. In particular, environmental policies within the EU are formulated in a regional (NUTS 2) level.[4]

[3]Contrary to the US case, there exists no centralised agency that gathers all the national weather records. Our main challenge amounts to gathering all the meteorological data and make it homogeneous for comparison.

[4]The regular report on the social, economic and territorial situation and development of the regions of the EU, which the Commission is required to produce every three years under Article 31 of Council Regulation (EC) No. 1083/2006 concerning the European Regional Development Fund, has so far been drafted mainly for the NUTS 2 level.

All in all, this paper sheds light into some insights of the climate-income relationship. First, we provide novel cross-sectional evidence using sub-national data for a set of well-developed countries. In particular, we find that an additional degree is attached to lower *per capita* income in an amount of 1.6-2.2%. This negative relationship is amplified for poor regions. At this point, we refute partially the findings in Dell et al. (2009). A direct implication of the above is that, if some regions are more prone to weather sensitivity, policy makers should develop regional-level policies that protect those regions to (possibly extreme) weather events. As a by-product of the previous point, when modelling the interplay between climate and the economy, researchers should take into account the possible regional heterogeneity and thus, propose models that incorporate this feature.[5] Second, we complement the previous approach with the short-term impact of weather fluctuations on economic performance and analyse how this and the previous magnitudes relate. We find that an increase of average temperatures of 1°C today hampers the growth potential of regions almost by 0.06 pp, a potentially large impact if the change in temperatures is permanent. As of poor regions, the net effect of a 1°C rise in temperature is to decrease growth rates by 0.084 pp, slightly larger than the full sample effect. This case study represents the first attempt to jointly document the short- and long-term relationship between weather variables and aggregate income for an homogeneous sample of European regions.

The remainder of this chapter is organised as follows. In Section 1.2, we describe all the data employed in this study and explain how it has been gathered. Section 1.3 explores the long-term relationship between weather and income by studying the cross-sectional dimension of our dataset and measures the omitted variable bias in our specification. Section 1.4 studies the short-term response of income to weather fluctuations. In Section 1.5, we try to reconcile the previous magnitudes by the use of a simple framework of convergence and adaptation. Finally, Section 1.6 concludes and suggests future avenues for research.

1.2 Data

As mentioned in the introduction, there exists no European-broad agency that assembles all the weather data required for this study. Besides that, the official European statistical agency, EUROSTAT, does not provide either a detailed breakdown of regional economic accounts prior to year 2000. Thus, the strategy in this paper has

[5]In this sense, Per Krusell and Anthony Smith in their yet unpublished manuscript "SimGlobe: A Global Economy-Climate Model with High Regional Resolution" are about to propose such a mechanism by adapting an heterogeneous agent dynamic macro model (the Aiyagari model) to an IAM context.

amounted to retrieve yearly data from national statistical offices and national climate agencies in order to construct a region-wide database as longitudinally largest as possible. The unit of reference we have opted for is the NUTS classification. The NUTS classification (*Nomenclature of territorial units for statistics*) is a hierarchical system for dividing up the economic territory of the EU for the purpose of the collection, development and harmonisation of EU regional statistics. We can identify several levels of NUTS: NUTS 0 correspond to counties; NUTS 1, to major socio-economic regions; NUTS 2, to basic regions for the application of regional policies; and NUTS 3, to small regions for specific diagnoses of EU regional policies.

The purpose of the creation of the NUTS classification is the socio-economic analyses of the European regions. While establishing a correlation between regions in terms of size, NUTS also provides several analytical levels. The 1961 Brussels Conference on Regional Economies, organised by the European Commission, found that NUTS 2 (basic regions) was the framework generally used by Member States to apply their regional policies and was therefore the appropriate level for analysing regional/national problems. For the purpose of appraising eligibility for aid from the Structural Funds, regions whose development is lagging behind (regions covered by the Convergence Objective) have been classified at the NUTS 2 level. The areas eligible under the other priority objectives have mainly been classified at the NUTS 3 level.

This study focuses on the five largest European countries for various reasons. Despite these countries belonging to a same geographic area and sharing institutional characteristics, they show enough variability both in terms of economic and weather patterns to make them suitable for a detailed econometric analysis. The heterogeneity in economic and weather variables can be easily spotted looking at the choropleth maps displayed in Figure 1.1, where *per capita* GDP and total sun hours are depicted for each region. A north-south polarisation is clearly observed, where northern regions tend to be richer and southern regions tend to be hotter. More specifically, looking at purely weather variables, we can note in Figure 1.2 that the south of Europe tends to be warmer and the north, wetter. But still, reasonable heterogeneity both between and within country can be observed.

Accordingly, we have decided to set the NUTS 2 level as the reference level for comparison except for Spain. Spain's NUTS 3 regions and NUTS 2 from the rest of countries in this sample overlap both in terms of average surface and population.[6] Moreover, this feature is also corroborated when we consider their weather pattern, which are again very heterogeneous, as it could be seen in Figure 1.2. Additionally, the relatively reduced number of Spanish NUTS 3 (51 regions) make them fairly manage-

[6]Please refer to Table 1.1 for further details.

able. It is worth mentioning that, for the case of France, we could have resorted also to the use of NUTS 3 data. Unfortunately, such detail in the breakdown of economic data is not provided by the French statistical office.

All regional economic figures have been collected from their respective national statistical offices. Their time span, fully described in Table 1.2, varies depending on the availability, ranging from an early start for the Spanish variables, dated back at 1980, to a more recent of the Italian, available from year 1995. Note also that British economic data come originally expressed in Sterling pounds. Hence, conversion to constant Euros using historical exchange rates has been necessary. As of weather variables, all of them have been provided also by the official weather organisms of each country (see more details at Table 1.2).

Our approach and that of Dell et al. (2009) differ substantially in terms of the data used. Firstly, they base their cross-section study on countries located on the western hemisphere whereas our sample is focused on the eastern hemisphere, which makes this one, as far as we know, the first attempt to developing a study relating weather and economic variables carried out for this area. Another relevant feature of our meteorological data is that all figures correspond to actual observed values collected directly from weather stations located within the NUTS of reference. In this respect, we have matched each NUTS with a weather station located in a geographic node close to the place where most of the economic activity is agglomerated.[7] Meanwhile, these authors make use of gridded weather data, which is the result of interpolating real weather data. In particular, they use the Matsuura and Willmott (2007) gridded dataset, which has a resolution of $1^{\circ} \times 1^{\circ}$.[8] The use of gridded data in weather analysis arise some potential pitfalls (see Aufhammer et al. (2013)), including the creation of a fictitious correlation between weather measures that could bias our conclusions. In our dataset, this issue is resolved by construction.

1.3 Cross-sectional evidence at the regional level

The theoretical background in which this section is embodied is the *Ricardian* (or hedonic) method applied to climatic variables that stems from the original work by Mendelsohn et al. (1994), which has been extensively used to measure the economic implications of climate change, especially in the agricultural sector. The idea behind this methodology is that climate shifts the production function for a determined economy. Producers in a certain area take climatic and geographic variables as given and

[7] Typically, this node corresponds to the capital or main city of the specific NUTS.
[8] $111km \times 111km$.

choose the optimal amount of output they want to produce and the corresponding optimal level of inputs required for that level of production, given perfect competition in both the input and output markets. With this reduced-form model, we estimate the relation between climate and value and other exogenous geographic variables.

Let us assume that the net present value of aggregate production in a determined region, V_i, is described by the following simplified equation

$$V_i = \int \left[\sum_j \sum_k P_j Q_{ij}(X_{ik}, Z_i) - \sum_k M_k X_{ik} \right] e^{-\varphi t} dt, \tag{1.1}$$

where P_j are the market prices of each output produced, Q_{ij} are the quantities of each output produced at each region i, X_{ik} is a vector of purchased inputs, M_k is a vector of input prices, Z_i is a vector of exogenous variables and φ is the *fixed* interest rate at which we discount future values. Producers within each region i choose the amount of outputs Q_{ij} and inputs required X_{ik} optimally, given prices. By solving (1.1) to maximise net revenues and by folding the vector of prices of outputs and inputs P_j, M_k into the vector of exogenous variables Z_i, V_i can be expressed as a function of only exogenous variables, $V_i = f(Z_i)$.

We base our estimations in the expression $V_i = f(Z_i)$ in order to examine the weather-income relationship in a multi-region level.[9] Resting on the Ricardian approach, the idea is to relate a dependent variable describing the value of all goods produced in a certain region with a set of geographic and weather (exogenous) variables to production, summarised in the vector Z_i. In a similar fashion to Dell et al. (2009), we estimate the cross-sectional relationship between climate variables—mean temperature and precipitation—, geographic variables and *per capita* income, with help of the following *Ricardian* regression[10]

$$\log(y_i) = \alpha_i + \beta_1 poor_i + \beta_2 temp_i + \beta_3 temp_i \times poor_i + \beta_4 precip_i + X_i^{'}\gamma + \epsilon_i, \tag{1.2}$$

where y_i represents *per capita* GDP in region i, $poor_i$ classifies regions as rich or poor in accordance to their level of *per capita* GDP being above or below the average sample

[9]It may well be the case that the reader could pose objections to the use of this methodology for a small subset of countries but as Bryan and Jenkins (2015) point out: "The only estimates that are unaffected by the small number of countries are the fixed parameters on individual-level predictors (the number of individuals per country is typically large): provided there is not also a random component attached to the slope, these parameters are estimated without bias and with the correct standard errors (and non-coverage rate)".

[10]By using variables in *per capita* terms, we avoid weighting observations by the economic size of each region.

analogue, $temp_i$ stands for annual average surface temperatures in region i, $precip_i$ denotes the total amount of rainfall collected in region i, and X_i represents a vector of region-specific geographic variables, such as elevation and distance to the sea. We estimate (1.2) for the whole sample of NUTS regions using Ordinary Least Squares. Standard errors are calculated clustering observations by NUTS 1 level.[11]

1.3.1 Basic results

The results from estimating (1.2) are presented in Table 1.3. As a benchmark, we begin in column (1) of Table 1.3 with a basic raw regression of *per capita* GDP on temperature for the whole sample of regions. In accordance with Dell et al. (2009), we identify a negative relation between economic activity and temperatures, but much more modest than what these authors find (8.5%). In particular, we observe a negative, significant relation between temperature and *per capita* GDP, by which an additional 1°C is associated on average with *per capita* GDP 2.2% smaller. This difference in magnitudes can be partly attributed to the fact that we are focusing on a sample of highly developed countries that could possibly accommodate changes in temperatures better than less developed countries. In fact, these figures are pretty much in accordance with those obtained by Deryugina and Hsiang (2014), who estimate a decline in productivity of 1.7% following an increase of 1°C for the United States. In column (2), we simply replicate the first regression but, this time, robust standard errors are enforced. To do so, we cluster observations using the immediate upper-level NUTS (NUTS 1 level, except for Spanish regions, in which NUTS 2 level applies). As it can be observed, standard errors increase slightly denoting a possible higher correlation within NUTS 1 regions. Robust standard errors will be calculated throughout the rest of specifications.

In column (3), we add some geographic variables to our specification as they are pretty correlated to weather characteristics. They are, namely, distance to the seaside and average altitude. The point estimate for the effect of temperature remains quite stable and features the same order of magnitude. In column (4), precipitations are incorporated into the regression. Its associated point estimate is slightly positive albeit not significant —pretty much in accordance with what other studies report— whereas the rest of estimates remain qualitatively the same. Columns (5) and (6) examine the relationship between weather conditions and income within countries. In column (5), we include country fixed effects (country FE) in an attempt to capture idiosyncratic features of each country. The point estimate of temperature preserves its sign and magnitude, that is, warmer 1°C temperatures are linked to a smaller *per capita* GDP

[11] NUTS 2 for Spain.

in an amount of around 3.1% of *per capita* GDP. These results confirm that the the sign of the cross-sectional relationship between temperature and income holds within countries, as well as across countries. The reader should note that these compact bunch of variables already explain a remarkable 60% of the variation of *per capita* GDP in the sample.

Relatively poorer regions are usually associated with lower income. We can find several examples in the literature illustrating this feature. For instance, in our seminal reference, Dell et al. (2009), this point is made explicit for the case of some American countries. The rationale behind is that those countries (regions) would have less resources to adapt to more hostile weather conditions and, hence, would be unable to decouple their economic activity from the environment. The question then will be whether this argument is also taking place in poorer regions within highly developed countries. The last column (6) represents an attempt to testing for the validity of this hypothesis. In our case, we find qualitatively similar results applied to our sample. In particular, we find that poor regions are relatively more affected by warmer temperatures in income terms.[12] Actually, the effect is highly significant, observing a relation of 3.8% lower *per capita* GDP associated with temperatures 1°C higher. The corresponding figure for rich regions remains significant, though, but halves with respect to the previous specification, indicating that poor regions are driving most of this effect. We interpret this as a structural weakness of poor regions to coping with higher temperatures. Interestingly, this feature in our sample takes place inside a group of "first world" countries.

At this point, some differences can be remarked in the take-away messages resulting from applying this approach at the country level and those stemming from an analysis in which the researcher studies regions as separate entities. Indeed, we find some regions that are more prone to be economically affected by rising temperatures although they actually belong to well established economies. Not only are poor countries the weakest link in the climate change process, but also poor regions within rich countries can suffer the consequences of global warming. As it can be inferred from these results, the effect of temperatures on poor regions is three times larger than that observed in relatively more developed regions. On a broader temporal perspective and considering the benchmark scenario projected by the IPCC envisaging an average increase in global temperatures of around 2°C for year 2100,[13] this would be associated in our simplified linear framework with regions being 6% poorer attributed to the sole effect of weather conditions.

[12] We define poor regions as the ones that are below the median *per capita* GDP of the whole sample

[13] Under the event of a total cut-off of greenhouse gases emissions today.

One of the most important question in social science concerns the causes of cross-country differences in economic development and economic growth. Why are some countries richer than others? Over the years many authors have attempted to respond to this question more or less successfully. A prominent list of economists spurred by a seminal article from Acemoglu et al. (2002) affirm that such differences would be mostly explained by diverse institutional development, leaving no role for geographic variables. In this specification we treat temperatures as a fixed variable for each region, which makes testing these alternative hypothesis challenging. But, since all regions within our sample belong to the European Union and the Euro area, it would be sensible to state that they share roughly the same institutional framework. Given that, we are still able to find differences across regions, which sets an argument in favour of the role of weather as a determinant of income divergence across places. In general, though, we can accept the role of the state as an umbrella that protects the productive infrastructure as all our temperature point estimates become more negative once we control for country-level fixed effects.[14]

1.3.2 Robustness and Channels

In an attempt to check for the validity of the results obtained in the previous paragraphs, some exercises have been designed and implemented. In particular, we have modified the reference year in a window of 5 years above and below the reference year (2000) and the same qualitative and quantitative results were obtained.[15] Another aspect that could be of interest is to gauge which branch of activity is most influenced by weather conditions and determine the sign of this relation. With the purpose of checking this statement, we proceed with the breakdown of *per capita* GDP in branches of activity, namely, agriculture, industry and services, and regress each of them on our control variables. The results are presented in Tables 1.4 through 1.6.

Surprisingly (or not) a positive and quite significant response to higher temperatures is observed when looking at agricultural output. In particular, an additional 1°C is attached to an average increase in agricultural activity ranging from 9% to 13% depending on the specification. Other authors find a similar result when analysing the response of agricultural output to a warmer environment. For instance, Deschênes and Greenstone (2007) find a positive response of warming to the productivity level of certain crops in the United Sates. Note that this effect is reasonably stable across regions, regardless their level of income. As one could easily expect, temperatures

[14]This conclusion will be challenged shortly, as we will measure the strength of the omitted variable bias in our specification in Section 1.3.3.

[15]These results can be obtained from the author upon request.

explain solely more than 8% of the variation of agricultural activity across regions. Again, the effect of precipitations is limited but eminently positive. The negative effects of temperature in activity accrued in *per capita* GDP are essentially due to industry and services according to our results. This can clearly be seen in Table 1.5 and Table 1.6. It can also be noted in both tables that this effect is exacerbated in poor regions, which is one of the main features obtained in our benchmark regression.

1.3.3 The role of omitted variables

The cross-section analysis of the relation between income and temperature typically features the classic omitted variable problem as described in Wooldridge (2002), which could result in potentially biased estimated coefficients resulting from the omission in our specification of explanatory variables that can be correlated with our regressors.

In particular, if we collect the set of included variables in our linear regression model under the vector X, with associated coefficient, β, and denote Z as the vector of omitted variables in our specification and δ its associated coefficient, our estimation of β conditional on our set of regressors,

$$E[\hat{\beta} \mid X] = \beta + (X'X)^{-1}X'Z\delta,$$

will be given by its actual value plus an estimation bias. This bias will depend on the magnitude and sign of both the correlation of X and Z and the point estimate of Z. Hsiang (2016) recommends that, since there does not exist any systematic method for determining whether any key variables are omitted from the estimated equation, the strategy to correct for this potential bias would amount to saturate the model with as many variables as possible. The omitted variable problem is manifested in this scenario through two different channels.

The first channel plays a part when climate change impacts are estimated focusing on one exogenous weather variable in isolation, say, temperature. Point estimates could present a bias as long as other weather variables correlated with temperature (precipitations, for example) are not explicitly included in our specification. As pointed out in Aufhammer et al. (2013), the sign of the omitted variable bias will depend on the location under study, with hot areas generally showing negative correlation whereas positive correlation can be found in more temperate areas. Even areas of positive and negative correlation can coexist in the case where relatively large countries are analysed, which is our case. We solve this problem by including both temperatures and precipitations in our exercise, accompanied by other exogenous geographic variables, like elevation or distance to the seaside.

The second source of omitted variable bias is related to the criticism by some authors, like Acemoglu et al. (2002), Easterly and Levine (2003) or Rodrik et al. (2004), who claim that cross-country (cross-region) differences in income in modern times are basically explained by differences in institutional factors inherent to each area, like institutional quality and governance or the degree of corruption, leaving no role for geographic or weather variables. This should not concern us if weather variables are understood as purely exogenous variables, as the omission of these variables would not distort our estimates. However, if we consider that climate can be correlated with those factors, we must necessarily control for them.

This poses a problem to our exercise, as a massive number of characteristics describing institutional development are susceptible to be incorporated in our regression. A shortcut to including hundreds of variables is finding a synthetic measure of institutional quality that loyally summarises different regional institutional developments.

The *European Quality of Government Index* (EQI) is the result of novel survey data on corruption and governance at the regional level within the EU and the first source of data to date that allows researchers to compare the quality of governments within and across countries in a multi-country, multi-region context. Surveys are based on a series of questions trying to cover three different pillars: quality, impartiality and corruption. The sub-national regions are at the NUTS 1 or NUTS 2 level, depending on the country. The data is standardized with a mean of zero, and higher scores imply higher quality of institutions and governance. Two releases of the EQI are available, as the survey was conducted in first in 2010 and then again in 2013. For 2013, the EQI13 (Charron et al., 2015) contains 206 regions based on a survey that was answered by 85.000 citizen respondents. Basic results of the EQI and its quality pillar are described in Figure 1.3.

The EQI's spatial resolution is slightly different from that adopted in our study. In order to match both, we have used EQI's NUTS2 data for Spain, Italy and France and EQI's NUTS1 data for Germany and UK. Then, we estimate the following equation

$$\log(y_i) = \alpha_i + \beta_1 poor_i + \beta_2 temp_i + \beta_3 temp_i \times poor_i + \beta_4 precip_i + \beta_5 EQI_i + X_i^{'}\gamma + \epsilon_i, \quad (1.3)$$

adopting the EQI13 index as our benchmark measure of regional institutional quality. Since the correlation of temperatures and the EQI is negative (around -0.6) and the effect of institutional reputation on aggregate income is allegedly positive, *ex ante* our original point estimates of temperatures obtained by estimating equation (1.2) are expected to be downward biased.

The EQI we use is constructed and released in 2013. Meanwhile, the year of reference for all our estimations has been year 2000 throughout the paper. It seems reasonable to think that this index describes the contemporaneous quality of institutions, not that of year 2000. Accordingly, we update our year of reference to 2011 (the last year a balanced data set is available) to accommodate the previous fact.[16]

Estimated coefficients and their standard errors can be found in Table 1.7. In column (1), a raw regression of income on temperatures and precipitations that replicates for year 2011 the regressions featured in Table 1.3 can be observed. This estimation yields already familiar results of around 3% less *per capita* GDP per additional degree in poor regions. In column (2) we try to attenuate the possible omitted variable bias resulting from not controlling for institutional environment by including the regional EQI13 index. As it can be observed, the overall negative effect of temperatures on income decreases moderately and becomes both negligible and non-significant. The expected downward bias of our original temperature point estimates is confirmed at this stage and hence the overestimation of the raw effect of temperatures on aggregate *per capita* GDP. The coefficient associated with the EQI index is positive and significant but relatively small. However, we find that the additional effect for poorer regions remains significant and quantitatively very similar to that of the previous specification, demonstrating its independent nature and confirming our main result in previous regressions. Though, as a consequence of the general effect of temperature on income decreasing its magnitude, the overall temperature effect in relatively poorer regions diminishes if compared with column (1), with an additional degree being associated with a level of *per capita* GDP 1.2% lower in those regions, even when the institutional role is accounted for.

Then, column (3) represents a robustness exercise to confirm the findings in the previous column. In this specification, the EQI13 index, that overall encompasses three pillars (quality of institutions, impartiality and corruption) is replaced by an indicator addressing only institutional quality issues (we call it EQI13q) in an attempt to isolate the degree of institutional development as a explanatory factor of aggregate income. The message behind our new specification is qualitatively equivalent to that delivered when we use the standard EQI13 index. Finally, column (4) reproduces the previous regression taking year 2012 as the reference year. Even though some regions are not available this year, the additional effect for poor regions remain stable at around 1.5% less *per capita* GDP per additional degree but the overall effect for these regions becomes not discernible from zero. The effect in rich regions is now positive but not significant.

[16]The reader may now observe that point estimates can differ slightly from those presented in previous sections.

1.4 The effects of weather fluctuations in aggregate income

In this section, we are going to make use of the longitudinal dimension of our dataset in order to comprehend the dynamic effects of weather variation in economic activity. Our main identification strategy uses year-to-year fluctuations in temperature and precipitation to identify changes in economic performance. We can then use panel data econometric techniques to inform whether temperature impacts regional growth rates or simply the level of income.

Although our time span is not as large as the one used by Dell et al. (2012), we still fulfil a minimum requirement of having at least $T \geq 20$ for all the 169 regions observed, which is a pre-requisite to accept the validity of these results. Looking at Table 1.8, we can document the extent of temperature and precipitation fluctuations in our sample. It can be easily seen that precipitations are quite more volatile (almost double) than temperatures and that, along our sample, it can hardly be seen a deviation of more than 1°C of average values once we control for year or regional effects. Also, the variability observed in average temperatures is substantial as evidenced by looking at the decadal variation in average temperatures shown in Figure 1.4, where a discernible increase in temperatures is observed in almost all regions for the period studied.

The suggested empirical framework for this section follows the derivation in Bond et al. (2010). Let us consider the simple economy[17]

$$Y_{it} = e^{\beta T_{it}} A_{it} L_{it}, \tag{1.4}$$

where total output in region i at time t is determined by the total amount of population L in that region, whose productivity is affected by the general level of technology A and the effect of an exogenous weather variable, denoted by T. Let us assume also that technology grows each period at a constant region-specific rate, g, but is also affected by the environment, i.e.

$$\frac{\Delta A_{it}}{A_{it}} = g_i + \gamma T_{it}. \tag{1.5}$$

Taking logs in (1.4) and differencing with respect to time, we have

[17] This reasoning can be extended to more general dynamic panel models that incorporate richer lag structures and lagged dependent variables.

$$\frac{d}{dt}log(Y_{it}) = \frac{d}{dt}\beta T_{it} + \frac{d}{dt}log(A_{it}) + \frac{d}{dt}log(L_{it})$$
$$g_{it} = \beta(T_{it} - T_{it-1}) + g_i + \gamma T_{it}.$$

Hence,

$$g_{it} = g_i + (\beta + \gamma)T_{it} - \beta T_{it-1}. \tag{1.6}$$

This is our dynamic growth equation, where g_{it} is the growth rate of output.[18] The level effects of weather shocks on output, which come from equation (1.4), appear through β. The growth effects of weather shocks, which come from (1.5), appear through γ.

The growth equation (1.6) allows separate identification of level effects and growth effects through the examination of transitory weather shocks. In particular, both effects influence the growth rate in the initial period of the shock. The difference is that the level effect eventually reverses itself as the weather returns to its prior state. By contrast, the growth effect appears during the weather shock and is not reversed. The growth effect is identified in (1.6) as the summation of the temperature effects over time. This reasoning will extend to scenarios where temperature effects play out more slowly. Accordingly, in order to capture the whole dynamic effect of temperatures on income we will estimate panel regressions of the form

$$g_{it} = \theta_i + \theta_{Ct} + \sum_{j=0}^{J} \rho_j T_{it-j} + \varepsilon_{it}, \tag{1.7}$$

where θ_i are region fixed effects, θ_{Ct} are country-time fixed effects, ε_{it} is an error term clustered simultaneously by region and region-year (following the two-way clustering of Cameron et al., 2011), and T_{it} is a vector of annual average temperature with up to J lags included.

1.4.1 Main Results

In the previous section we have identified that hotter regions in Europe are also the poorer, with a subtle but significant relationship of around 3% less output per additional degree. We have also documented that the channels through which this pernicious effects are manifested are the industrial and services branches, not the agricul-

[18] Similarly to Section 1.3, we will work with variables in *per capita* terms to avoid weighting observations by the economic size of each region.

tural, which benefits from warmer conditions. Once said that, it seems reasonable to measure the extent to which European regions are susceptible from suffering the consequences of increasingly warmer temperatures in response to climate change. To do so, we will look at the potential of short-term weather variation to alter the year-to-year economic performance of regions, that is, their immediate ability to grow.

As mentioned, we will identify the short-term impact of weather variation by estimating equation (1.7) applied to our sample.[19] In a first exercise we focus on the contemporaneous effect of weather on economic growth by switching off the lag structure of temperatures ($J = 0$). Column (1) of Table 1.9 shows a positive and statistically significant relationship between temperature fluctuations and growth on average across all regions. Note, though, that this is a very simplistic regression in which we relate growth solely with current temperatures. In column (2), once when we account for country fixed effects, the estimate attached to temperatures changes its sign denoting a negative impact of warming conditions on growth. In particular, an increase of average temperatures of 1°C today hampers the growth potential of regions almost by 0.065 pp, which turns out to be of a modest nature but, if that effect results to be permanent, once accumulated, yields not negligible figures.[20] In a world with no adaptation, and assuming all countries being equal and growing at a stable constant rate (+2%), our panel estimates imply that a 1°C permanent shock in a certain country would solely explain the cross-sectional correlation between temperature and per capita income after 25 years. In practice, however, adaptation to climate change may mitigate these effects substantially.

In their paper on the relation between economic growth and weather conditions, Dell et al. (2012) claim that poor countries are more prone to suffering the consequences of an increase of temperatures. We are keen on testing their results in our sample by looking at sample of developed economies. Hence, in column (3), we interact temperature with a dummy for a country being "poor", defined as having below-median *per capita* GDP in a year of reference.[21] The coefficient on the interaction between the "poor" dummy and temperature is negative and statistically significant, indicating substantial heterogeneity between poor and rich regions. As shown in the last row of the table (which reports the sum of the main effect of temperature and its interaction

[19] Growth rates of *per capita* GDP are proxied via logarithmic differences as follows: $g_{it} = 100 * [\log(pcGDP_{it}) - \log(pcGDP_{it-1})]$

[20] For instance, the level effect of this result is of almost 2% in 25 years time, nearly 4% in 50 years time and of 7.5% in 100 years. Under the IPCC's scenario of an average increase of temperatures of 2°C, that would cost to European regions two-digit figures (more than 11% assuming a further increase in temperatures in 50 years) in terms of *per capita* income.

[21] Our year of reference will be 1995. Similar results are obtained when this year of reference is modified.

with the poor dummy), the net effect of a 1°C rise in temperature is to decrease growth rates in poor regions by 0.086 pp. Put another way, since the standard deviation of annual temperature once country fixed effects, region x year, and poor country x year fixed effects are removed is 0.20 degrees (see Table 1.8 for more details), the estimates in Table 1.9 imply that a one standard deviation increase in annual temperature is associated with a reduction in growth of about 0.017 pp. A two-standard deviation yearly increase in temperatures (0.4°C) would imply lower economic growth in an amount of 0.04 pp. Ours and the results from Colacito et al. (2014) are the first to document a negative and statistically significant relationship between rising temperatures and economic growth in a developed economy.

Lastly, in column (4), we incorporate precipitations to our empirical model. We decide to include it only in the last specification as this variable proved to have an ambiguous effect in the previous section. No matter what, it is always advisable to control for rainfall effects in order to cross-check the results obtained in the previous column. As it can be observed, the point estimates remain very stable, both qualitatively and quantitatively. We have to remark now that the point estimate of temperatures for rich regions is now not statistically significant. In other words, we cannot reject the null hypothesis of this value being equal to zero, which confirms the findings obtained in the cross-section dimension (see Table 1.3), and those of Dell et al. (2012), that is, in rich regions (countries) typically a positive but rarely statistically significant temperature relation is found.

In order to disentangle the channels through which the negative short-term effect of weather fluctuations in the economy spreads, we repeat the above exercise substituting the dependent variable by its branches' equivalent, namely, agriculture, industry and services. Those results are presented in Tables 1.10 through 1.12. We identify a very negative, sound impact of increasing temperature in agricultural aggregated output of almost 0.23 pp less growth per additional degree in poor regions. Again, the effect is exacerbated in poor regions as opposed to rich regions, in which the decay in growth represents an equivalent of nearly 0.14 pp. Moving to the industrial aggregate income, we cannot identify any discernible effect of weather variables in activity. Up to some extent, this sector represents *ex ante* a branch traditionally regarded to be less affected by environmental conditions. On the other hand, we find a positive significant impact of temperature on services only in poor regions. This result could be attached to the plausible beneficial effects of warming to the tourism sector. In any respect, our conclusions do not differ much from that obtained by Dell et al. (2012), highlighting common places between European countries and the rest of the world. Note also that these exercises are reduced-form, and therefore do not identify the possibly complex structural relationships between temperature, growth, and other outcomes.

A set of robustness exercises have been carried out in order to test for the validity of our results. First, since income data from Italian regions is only available from year 1995, including Italy in the overall exercise comes at the cost of reducing substantially the panel dimension so as to have a balanced panel of data. This is why we have repeated the analysis removing Italian regions. Without this country we can enlarge our temporal dimension back to 1991. However, quantitative and qualitative results are obtained when running regressions similar to those described by equation (1.7).

We also check the robustness of the results by including lags of the regressors into the benchmark specification. Accordingly, we consider more flexible models with up to 5 lags of temperature and precipitations. Table 1.13 presents the results from estimating (1.7) with no lags, 1 lag, 3 lags and 5 lags. All temperature and precipitations are interacted with poor region dummies. We also report the cumulative effect of temperature for poor regions. As it can be observed in the last row of Table 1.13, the effect remains stable and statistically significant across specifications at around -0.07 to -0.09 pp. However, from 3 lags onwards the cumulative effect dilutes, which can be plausibly attributed to the still scarce longitudinal dimension of our dataset. Surely, a cross-check of this exercise should be attempted once we are in possession of a more prolonged dataset. By comparing columns (1-4) to (5-8), we confirm that the effect of precipitations is again very subtle as the point estimates of temperatures in poor regions remain similar regardless we control or not for precipitations.

1.5 Bridging short- and long-term results: Adaptation and convergence

In possession of the previous results (long- and short-term relationship), we will try to fill the gap between the two magnitudes by making use of a simple framework derived in Dell et al. (2009) by which, we will attempt to disentangle these differences as the response to the action of two specific mechanisms, namely, convergence and adaptation. First, convergence forces may pull lagging regions and make them catch up with their neighbours by offsetting temperature effects, so that it limits the cross-sectional income differences that can be sustained. Second, over longer periods, regions may adapt to their changing climate. The panel growth estimates reflect responses to climate shocks. To the extent that individuals adjust their behaviour to permanent temperature changes, e.g., by switching to more resilient crops, industries, and technologies. Adaptation is a concept particularly relevant in the climate change literature and is one of the main focus of the IPCC in terms of alleviating the pernicious effects of climate change. This simple exercise will give us a flavour of the importance of the adapting behaviour of individuals to cope with climate change.

All in all, we have found a permanent relationship between temperatures and the level of GDP of about 3% in poor regions whereas the short-term effect of temperatures on growth represent a decline of 0.086 pp. To reconcile the long-run cross-sectional relationships documented in Section 1.3 with the short-run growth effects of temperature estimated in Section 1.4, we consider the above mentioned mechanisms: convergence and adaptation. With help of a very naive but illustrative exercise, we will bring forward these two important economic and climatic concepts, about which few empirical estimates are available.

Following the derivations in Appendix 1.B, we have that in the very long-run, the cross-sectional relation between income and temperature is described by the following inequality

$$\frac{dE[logy_i]}{d\bar{T}_i} = \frac{\gamma + \rho}{\varphi}, \tag{1.8}$$

where γ captures the short-run effect of temperature shocks on growth, as identified in (1.7). The parameter ρ captures the degree of adaptation over the long-run to average temperature levels, potentially offsetting the short-run temperature effects. Meanwhile, the parameter $\varphi \in (0, 1)$ captures the rate of convergence. Equation (1.8) is an inequality with four unknowns, three of which we have estimates for whereas the fourth will be imported from estimates in the literature. The left-hand side of (1.8) is the cross-sectional regression parameter in the regression of income on temperature, i.e., $\beta = -0.022$ (see Table 1.3). As noted in Section 1.4, the short-run growth coefficient is approximately $\gamma = -0.0058$.

By means of setting $\rho = 0$ in (1.8), we are able to turn off the adaptation channel in order to isolate the effect of convergence and analyse its implications. In this scenario, reconciling the short-run and long-run temperature effects is achieved when $\varphi = \frac{\gamma}{\beta}$. To do so, we require $\varphi = \frac{-0.0058}{-0.022} = 0.2636$, which is relatively too high if compared with other values of convergence offered in the literature. For example, in developed countries within-country convergence coefficients estimates range approximately between 0.02 and 0.03. These results point in the direction of adaptation as the key factor to bridge long-term and short-term results. Over the long run, areas may adapt to difficult geographic conditions. Adaptation in this context would range from the modification of the nature of the inputs used to produce to technological changes or changes in the intensity in which production factors are used.

In a second exercise, we let adaptation forces play. Accordingly, we estimate the value of ρ using our findings for β and γ and imposing a specific convergence rate, φ. If we rearrange equation (1.8), we have that $\rho = \beta\varphi - \gamma$. If we let the upper-bound cross-country convergence estimate $\varphi = 0.05$, we obtain $\rho = 0.0047$ so that 81% of the short-run growth effect is offset in the long-run, so that the long-run growth rate effect of being 1°C warmer is -0.0011, i.e., 0.1 pp per year. Note, however, that this value depends critically on the convergence rate that we are imposing. Thus, we have to adopt these values with caution.

1.6 Conclusion

Climate change is expected to increase average global temperatures inexorably in the upcoming decades, which urges the need for reliable measures of how our economies are exposed to environmental variables and how their changing nature affect economic performance. In a first exercise, Dell et al. (2009) successfully documented a negative relation between temperatures and income for poor countries working with a cross-country sample of sub-national data of 12 countries in the Americas in which less developed countries were relatively oversampled. In particular they found national income falling 8.5% per degree Celsius. On a separate study, the same authors studied a panel formed by more than 150 countries around the world by looking at the dynamics of the relation of temperatures and income along the period 1950-2003 finding a negative, significant effect of temperatures in economic growth only for poor countries of around -1.1 pp per additional degree. Two straight forward messages derive from those results: first, the increase in temperatures that we are witnessing due to global warming will be benevolent or, at least, will not imply harmful consequences for rich countries/regions. Second, for the sake of comparison and completion, it would be worth reproducing both exercises for a same set of countries (or regions). This study addresses both arguments.

To do so, we have constructed a dataset covering income and meteorological variables at the NUTS level for the five largest European countries. This dataset show some features that make it unique and are worth mentioning: first, all weather data correspond to actual observed weather stations matched with the NUTS unit of reference. In this way, we avoid the use of gridded weather data, which could result in biased interpretation of the results. Second, and equally important, the fact of resorting to the NUTS level present further advantages, as it enables us to account for the weather heterogeneity within country. Also, it is the level at which regional policies, like environmental, are formulated. Hence, our findings could help to formulate more efficient environmental policies.

In the cross-section (long run) analysis, we find qualitatively similar results to Dell et al. (2009). Specifically, we distinguish a negative, significant, tempered relation between temperatures and aggregate income in our sample. More precisely, an additional degree is attached to lower personal income in 1.6-2.2%. This negative relationship is amplified for poor regions. Other authors, like Deryugina and Hsiang (2014) find similar results for the United States. In general, and in accordance with Dell et al. (2009), the effect of precipitations is diffuse but eminently positive, although not significant. Other geographic variables, such as elevation and distance to the sea show residual importance. The role of the state as a protective umbrella is made explicit as all our temperature point estimates become more negative once we control for country-level fixed effects. We can derive from these results that, unlike Dell et al. (2009) claim, well-developed economies are not fully decoupled from environmental conditions and would probably be harmed if temperatures are to increase unless some adaptation process takes place. We also try to attenuate the omitted variable bias, very common in this approach. Our results remain fairly stable for poor regions after controlling for regional institutional quality and reputation through the EQI index.

By exploiting the longitudinal dimension of our dataset, we now have the chance to benefit from the stochastic variation in weather variables and try to estimate their effect on the short-term dynamics of income. This is covered in Section 1.4. Overall, we find that an increase of average temperatures of 1 degree today hampers the growth potential of regions almost by 0.065 pp, which in accumulated terms represents an overall effect in the long-run slightly larger than the one estimated in the previous section. As of poor regions, the net effect of a 1°C rise in temperature is to decrease growth rates in poor regions by 0.084 pp, where again poor regions are a bit more penalised than rich regions. Our results, together with those of Colacito et al. (2014) are the first to document a negative, significant relationship between rising temperatures and economic growth in the context of developed economies. Once again, we find no relevant statistical evidence about the effect of precipitations in the short-term economic performance of regions. These findings go in parallel with those of other authors in the literature. Surprisingly, and opposed to the previous section, we find a robust, negative effect of temperatures and precipitations in the agricultural output, as a measure of the adverse effects of sudden and abrupt deviations of average weather values, namely, floods, droughts or frost damages, on the performance of crops.

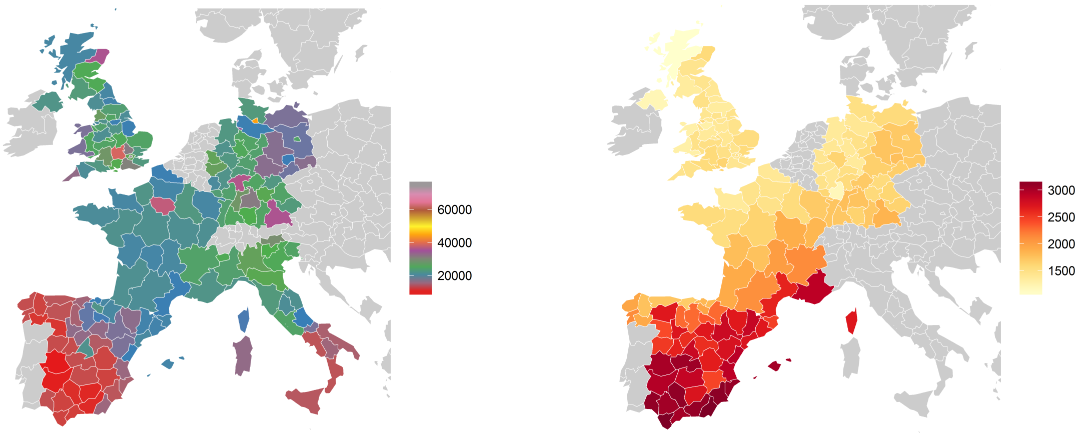
Using a sample of European regions, the results in this paper unveil new evidence in favour of how ongoing rising temperatures harm both the level and the ability to grow of developed economies. In accordance with other authors, we also show how this negative effect is exacerbated in relatively poorer regions. In light of this, policy makers should account for regional heterogeneity when environmental policies are formulated at a large scale. This heterogeneity should also be borne in mind when the interactions between climate and economies are modelled (for instance, in Integrated Assessment Models of climate change). Since climate change is usually accompanied by extreme weather events, the existence of weather non-linear effects in our economies should be tested. At the same time, micro evidence suggest that fundamental productive units exhibit highly non-linear responses to local temperatures, as suggested in Graff Zivin and Neidell (2014). This suggests a new avenue of research that will be covered in future projects.

1.A Tables and Figures

Table 1.1: Descriptive statistics of NUTS regions

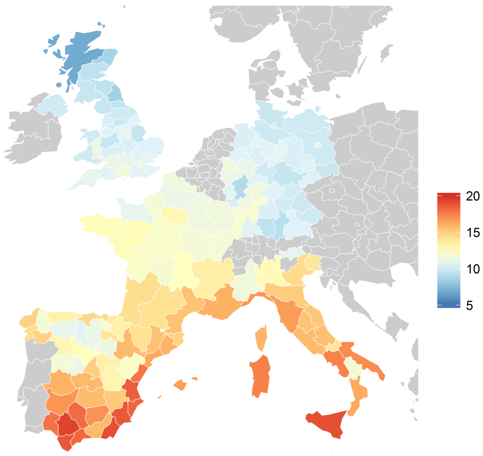
country	NUTS 2			NUTS 3		
	area	population	regions	area	population	regions
France	24340	2455	22	6328	638	100
Germany	9398	2165	39	867	200	412
Italy	14352	2829	22	2740	541	110
Spain	26631	2362	18	8576	761	51
United Kingdom	6574	1648	37	1750	438	139

Notes: Average surface is expressed in km^2. Population is measured in thousands. Surface and population figures stem from year 2007. Source: Eurostat.

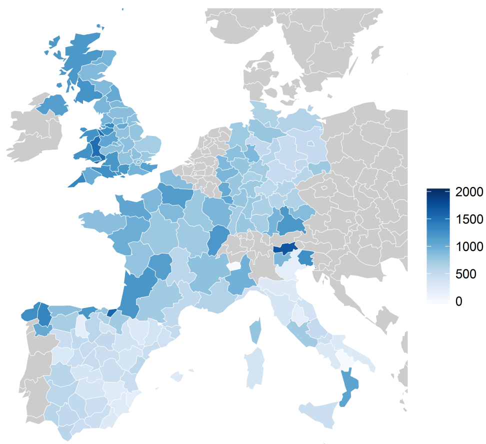


(a) *per capita* GDP (€) (b) Total sun hours (Not available for Italy)

Figure 1.1: Accounting for regional heterogeneity in Europe. Year 2000



(a) Temperatures (°C)



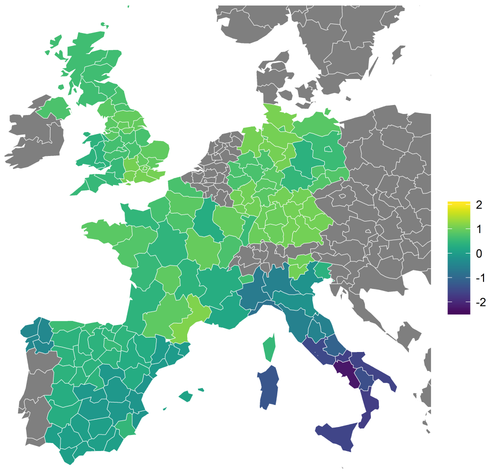
(b) Precipitations (mm/year)

Figure 1.2: Weather patterns in some regions of Europe. Year 2000

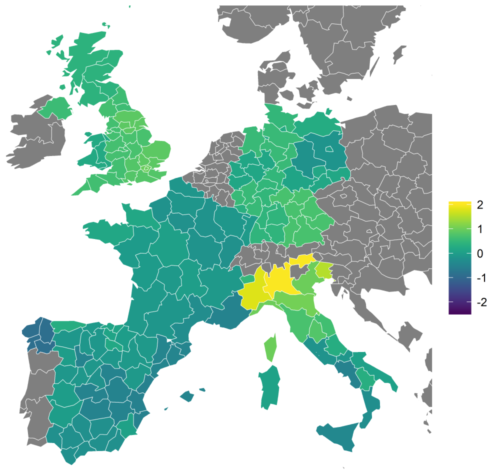
Table 1.2: Data sources

country	economic	period	weather	period
France	INSEE	1990-2012	Meteo France	1949-2013
Germany	DESTATIS	1992-2013	DWD	1900-2014
Italy	ISTAT	1995-2012	METEOAM	1995-2013
Spain	INE	1980-2013	AEMET	1948-2014
United Kingdom	ONS	1995-2012	Met Office (UKCP09)	1981-2012

Notes: This table reflects the total availability of data. Note that not all data, especially the meteorological, intervene in this study. Sources: INSEE, *Institut national de la statistique et des études économiques*; DESTATIS, *Statistiches Bundesamt*; ISTAT, *Instituto Nazionale di Statistica*; INE, *Instituo Nacional de Estadística*; ONS, *Office for National Statistics*; *Meteo France*; DWD, *Deutscher Wetterdienst*; METEOAM, *Servizio Meteorologico dell'Aeronautica Militare Italiana*; AEMET, *Agencia Española de Meteorología*; UKCP09, *UK Met Office Climate Projections*.



(a) The *EQI* index. Year 2013.



(b) The *EQI* index. Quality pillar. Year 2013.

Figure 1.3: The *EQI* index. Accounting for institutional reputation across European regions.

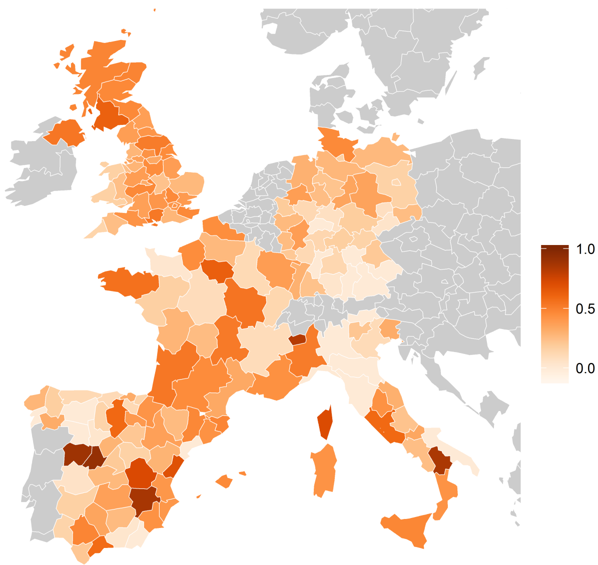


Figure 1.4: Average temperature variation. Decade 2000 against decade 1990 (°C)

Table 1.3: Long-term relationship. All Regions

	(1)	(2)	(3)	(4)	(5)	(6)
temperature	-0.022***	-0.022***	-0.023***	-0.021**	-0.031***	-0.016*
	(0.006)	(0.007)	(0.008)	(0.010)	(0.009)	(0.009)
temperature × poor region						-0.022***
						(0.004)
precipitation				0.002	0.005	0.000
				(0.007)	(0.005)	(0.003)
geographic variables	No	No	Yes	Yes	Yes	Yes
country FE	No	No	No	No	Yes	Yes
N	168	168	168	168	168	168
R^2	0.085	0.085	0.196	0.197	0.599	0.712
temp. effect on poor regions						-0.038***
						(0.010)

Notes: In all the regressions, the dependent variable is the logarithm of the regional *per capita* GDP. Under *Geographic variables* we find elevation and distance to coast. The reference year is 2000. Column (1) depicts a simple OLS regression of the dependent variable on temperature. Column (2) replicates column (1) but calculates robust standard errors by NUTS 1 level (NUTS 2 for the case of Spain). Column (3) adds a set of geographic variables as controls. Column (4) incorporates precipitations. Columns (5) and (6) include country fixed effects. Column (6) incorporates the interaction effect of temperature in poor regions. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 1.4: Agriculture. Long-term relationship. All Regions

	(1)	(2)	(3)	(4)	(5)	(6)
temperature	0.099***	0.099***	0.114***	0.126***	0.099	0.087
	(0.026)	(0.033)	(0.035)	(0.038)	(0.073)	(0.076)
temperature × poor region						0.017*
						(0.020)
precipitation				0.017	0.031	0.035
				(0.032)	(0.054)	(0.056)
geographic variables	No	No	Yes	Yes	Yes	Yes
country FE	No	No	No	No	Yes	Yes
N	168	168	168	168	168	168
R^2	0.079	0.079	0.096	0.099	0.435	0.438
temp. effect on poor regions						0.075
						(0.168)

Notes: In all the regressions, the dependent variable is the logarithm of the regional *agricultural* per capita *GDP*. Under *Geographic variables* we find elevation and distance to coast. The reference year is 2000. Column (1) depicts a simple OLS regression of the dependent variable on temperature. Column (2) replicates column (1) but calculates robust standard errors by NUTS 1 level (NUTS 2 for the case of Spain). Column (3) adds a set of geographic variables as controls. Column (4) incorporates precipitations. Columns (5) and (6) include country fixed effects. Column (6) incorporates the interaction effect of temperature in poor regions. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 1.5: Industry. Long-term relationship. All Regions

	(1)	(2)	(3)	(4)	(5)	(6)
temperature	-0.127***	-0.127***	-0.124***	-0.111***	-0.127*	-0.106
	(0.033)	(0.048)	(0.045)	(0.055)	(0.074)	(0.074)
temperature $\times$ *poor region*						-0.031*
						(0.017)
precipitation				0.020	0.025	0.018
				(0.046)	(0.080)	(0.081)
geographic variables	No	No	Yes	Yes	Yes	Yes
country FE	No	No	No	No	Yes	Yes
N	168	168	168	168	168	168
R^2	0.082	0.082	0.345	0.347	0.632	0.638
temp. effect on poor regions						-0.137**
						(0.076)

Notes: In all the regressions, the dependent variable is the logarithm of the regional *industrial* per capita *GDP*. Under *Geographic variables* we find elevation and distance to coast. The reference year is 2000. Column (1) depicts a simple OLS regression of the dependent variable on temperature. Column (2) replicates column (1) but calculates robust standard errors by NUTS 1 level (NUTS 2 for the case of Spain). Column (3) adds a set of geographic variables as controls. Column (4) incorporates precipitations. Columns (5) and (6) include country fixed effects. Column (6) incorporates the interaction effect of temperature in poor regions. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 1.6: Services. Long-term relationship. All Regions

	(1)	(2)	(3)	(4)	(5)	(6)
temperature	-0.052*	-0.052*	-0.066*	-0.056	-0.007	0.016
	(0.029)	(0.034)	(0.036)	(0.047)	(0.069)	(0.065)
temperature × poor region						-0.033*
						(0.019)
precipitation				0.015	0.044	0.037
				(0.040)	(0.062)	(0.062)
geographic variables	No	No	Yes	Yes	Yes	Yes
country FE	No	No	No	No	Yes	Yes
N	168	168	168	168	168	168
R^2	0.018	0.018	0.312	0.314	0.617	0.627
temp. effect on poor regions						-0.018
						(0.071)

Notes: In all the regressions, the dependent variable is the logarithm of the regional *services* per capita *GDP*. Under *Geographic variables* we find elevation and distance to coast. The reference year is 2000. Column (1) depicts a simple OLS regression of the dependent variable on temperature. Column (2) replicates column (1) but calculates robust standard errors by NUTS 1 level (NUTS 2 for the case of Spain). Column (3) adds a set of geographic variables as controls. Column (4) incorporates precipitations. Columns (5) and (6) include country fixed effects. Column (6) incorporates the interaction effect of temperature in poor regions. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 1.7: Long-term relationship. The role of omitted variables.

	(1)	(2)	(3)	(4)
temperature	-0.014*	0.002	-0.002	0.019
	(0.007)	(0.010)	(0.010)	(0.020)
temperature × poor region	-0.015***	-0.014***	-0.015***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.003)
precipitation	-0.012**	-0.006	-0.008*	0.001
	(0.005)	(0.005)	(0.004)	(0.006)
EQI		0.003**	0.050	0.060
		(0.001)	(0.032)	(0.036)
geographic variables	Yes	Yes	Yes	Yes
country FE	Yes	Yes	Yes	Yes
N	144	144	144	57
R^2	0.446	0.453	0.451	0.664
temp. effect on poor regions	-0.029***	-0.012*	-0.016*	0.006
	(0.007)	(0.006)	(0.011)	(0.020)

Notes: In all the regressions, the dependent variable is the logarithm of the regional *per capita* GDP. Under *Geographic variables* we find elevation and distance to coast. The reference year is 2011 in all the columns, except the last one (2012). Column (1) depicts an OLS regression of the dependent variable on temperature and precipitations. Column (2) incorporates EQI13 index as a control variable. Column (3) is identical to (2), but uses EQI13q, the quality pillar component of EQI13. Column (4) reproduces column (3) taking year 2012 as reference. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 1.8: Observed temperature and precipitation variation (1990-2012)

Proportion of Nuts-years with temperature (...)°C above/below total mean temperature						
	0.2	0.4	0.6	0.8	1	1.2
Raw data	0.721	0.463	0.293	0.176	0.104	0.055
After removing Nuts-year fixed effects	0.366	0.122	0.048	0.022	0.012	0.007
Proportion of Nuts-years with precipitations (...)$*100mm$ above/below total mean precipitations						
	0.5	1	1.5	2	2.5	3
Raw data	0.705	0.445	0.256	0.145	0.078	0.049
After removing Nuts-year fixed effects	0.666	0.392	0.215	0.113	0.067	0.043

Notes: NUTS fixed effects are obtained at the NUTS 1 level in regions from Germany, United Kingdom, France and Italy and at the NUTS 2 level in Spanish regions.

Table 1.9: Short-term relationship. All Regions

	(1)	(2)	(3)	(4)
temperature	0.178**	-0.064***	-0.034*	-0.022
	(0.038)	(0.023)	(0.019)	(0.017)
temperature × poor region			-0.052**	-0.058**
			(0.026)	(0.026)
precipitation				0.036
				(0.028)
country FE	No	Yes	Yes	Yes
N	3246	3246	3246	3241
R^2	0.029	0.469	0.469	0.470
temp. effect on poor regions			-0.086***	-0.080***
			(0.029)	(0.029)

Notes: In all the regressions, the dependent variable is the year on year growth rate the regional *per capita* GDP. Column (1) describes a simple OLS regression of the dependent variable on temperature. Column (2) replicates column (1) but includes country FE. Column (3) incorporates the interaction effect of temperature in poor regions. Column (4) incorporates precipitations. * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 1.10: Agriculture. Short-term relationship. All Regions

	(1)	(2)	(3)	(4)
temperature	0.202**	-0.152**	-0.093	-0.135**
	(0.078)	(0.060)	(0.070)	(0.067)
temperature × poor region			-0.104	-0.095
			(0.105)	(0.102)
precipitation				-0.158**
				(0.062)
country FE	No	Yes	Yes	Yes
N	3282	3282	3282	3277
R^2	0.001	0.400	0.400	0.401
temp. effect on poor regions			-0.196***	-0.229***
			(0.084)	(0.084)

Notes: * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 1.11: Industry. Short-term relationship. All Regions

	(1)	(2)	(3)	(4)
temperature	0.275***	-0.065	-0.056	-0.055
	(0.055)	(0.043)	(0.050)	(0.049)
temperature × poor region			-0.015	-0.020
			(0.069)	(0.069)
precipitation				-0.010
				(0.033)
country FE	No	Yes	Yes	Yes
N	3282	3282	3282	3277
R^2	0.017	0.338	0.338	0.337
temp. effect on poor regions			-0.071	-0.075
			(0.057)	(0.060)

Notes: * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 1.12: Services. Short-term relationship. All Regions

	(1)	(2)	(3)	(4)
temperature	0.438***	0.066**	0.025	0.024
	(0.062)	(0.028)	(0.026)	(0.028)
temperature × poor region			0.072**	-0.074**
			(0.030)	(0.030)
precipitation				0.002
				(0.016)
country FE	No	Yes	Yes	Yes
N	3282	3282	3282	3277
R^2	0.065	0.765	0.765	0.765
temp. effect on poor regions			0.097***	0.098***
			(0.026)	(0.027)

Notes: * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

Table 1.13: Short-term relationship under various lag structures. All Regions

	(1) No lags	(2) 1 lag	(3) 3 lags	(4) 5 lags	(5) No lags	(6) 1 lag	(7) 3 lags	(8) 5 lags
temperature	-0.034*	-0.034*	-0.027	-0.033	-0.028	-0.030	-0.028	-0.016
	(0.019)	(0.019)	(0.020)	(0.023)	(0.019)	(0.020)	(0.020)	(0.023)
temperature × poor regions	-0.052*	-0.133	-0.062	0.169	-0.051*	-0.126	-0.065	0.157
	(0.026)	(0.206)	(0.275)	(0.299)	(0.026)	(0.216)	(0.262)	(0.307)
L1: temperature × poor regions		0.081	0.036	-0.158		0.077	0.048	-0.146
		(0.211)	(0.403)	(0.382)		(0.217)	(0.412)	(0.396)
L2: temperature × poor regions			0.134	0.234			0.199	0.339
			(0.558)	(0.568)			(0.579)	(0.595)
L3: temperature × poor regions			-0.168	-0.292			-0.237	-0.327
			(0.503)	(0.549)			(0.525)	(0.558)
precipitations	No	No	No	No	Yes	Yes	Yes	Yes
N	3246	3237	3055	2794	3241	3230	3043	2779
R^2	0.014	0.469	0.475	0.482	0.470	0.470	0.478	0.486
temp. effect on poor regions	-0.086***	-0.087***	-0.053	-0.022	-0.079***	-0.079***	-0.035	-0.014
	(0.029)	(0.030)	(0.437)	(0.410)	(0.025)	(0.025)	(0.432)	(0.440)

Notes: * denotes significance at 10 pct., ** at 5 pct., and *** at 1 pct. level.

1.B Analytics of Adaptation and Convergence

For the sake of clarity, we reproduce here the derivations of Dell et al. (2009) aimed at bridging the results from the long- and short-term approaches to studying the relation between weather and aggregate income. Consider the growth specification

$$\frac{d \log y_i(t)}{dt} = g + \rho \bar{T}_i + \gamma T_i(t) + \varphi(\log y_*(t) - \log y_i(t)) \; for \, t \geq 0, \tag{1.9}$$

where $\log y_i(t)$ is the log *per capita* income in region i at time t, $T_i(t)$ is the temperature in that area, $\bar{T}_i$ is the (long-term) average temperature level in region i, and $\log y_t(t)$ is the relevant frontier level of income to which the region converges. The parameter γ captures the short-run effect of temperature shocks on growth, as would be identified in a panel specification, as the one described in equation (1.7). The parameter ρ captures the degree of adaptation over the long-run to average temperature levels, potentially offsetting the short-run temperature effects. Meanwhile, the parameter $\varphi \in (0, 1)$ captures the rate of convergence. We further assume that all regions start, at time zero, with the same level of *per capita* income, $\log y_{i0} = c$ for all i. Note that since (1.9) applies to all regions, including region *, then

$$E[\log y_{*t}] = c + (g + (\gamma + \rho)\bar{T}_*)t.$$

Here we provide a formal derivation of equation (1.8), which is the integrated form of (1.9). First, we observe from (1.9) that

$$\frac{d \log y_*(t)}{dt} = g + \rho \bar{T}_* + \gamma T_*(t).$$

Next, define a variable $\hat{y}(t) = \log y_i(t) - \log y_*(t)$, and rewrite (1.9) as

$$\frac{d\hat{y}(t)}{dt} = \frac{d(\log y_i(t) - \log y_*(t))}{dt} = \rho(\bar{T}_i - \bar{T}_*) + \gamma(T_i(\tau) - T_*(\tau)) + \varphi \hat{y}(t).$$

If we integrate the above expression once, we find

$$\hat{y}(t) = bt + \gamma \int_0^t h(\tau) \, \mathrm{d}\tau - \varphi \int_0^t \hat{y}(\tau) \, \mathrm{d}\tau,$$

where $b = \rho(\bar{T}_i - \bar{T}_*)$ and $h(\tau) = T_i(\tau) - T_*(\tau)$ (which is stochastic). Since this is linear we can take expectations and change the order of integration, producing

$$E[\hat{y}(t)] = bt + \gamma \int_0^t E[h(\tau)]\,\mathrm{d}\tau - \varphi \int_0^t E[\hat{y}(\tau)]\,\mathrm{d}\tau.$$

Noting that $E[h(\tau)] = \bar{T}_i - \bar{T}_*$, this integrated differential equation can be written as

$$E[\hat{y}(t)] = mt - \varphi \int_0^t E[\hat{y}(\tau)]\,\mathrm{d}\tau, \tag{1.10}$$

where $m = (\gamma + \rho)(\bar{T}_i - \bar{T}_*)$. Equation (1.10) can be solved by repeated substitution of $E[\hat{y}(t)]$. In particular, substituting once provides

$$E[\hat{y}(t)] = mt - \varphi \int_0^t (m\tau - \varphi \int_0^\tau E[y(\tau')]\,\mathrm{d}\tau')\,\mathrm{d}\tau \quad = mt - \varphi m\frac{t^2}{2} - \varphi^2 \int_0^t \int_0^\tau E[y(\tau')]\,\mathrm{d}\tau'\,\mathrm{d}\tau.$$

With an infinite set of substitutions and integrating all terms in m we have

$$E[\hat{y}(t)] = m\sum_{j=0}^{\infty}(-1)^j\varphi^j\frac{t^{j+1}}{(j+1)!} + \lim_{n\to\infty}\varphi^n \int_0^t \int_0^\tau \int_0^{\tau'} \cdots \int_0^{\tau'\{n\}} E[\hat{y}(\tau'^{\{n\}})]\,\mathrm{d}\tau'^{\{n\}} \ldots \mathrm{d}\tau'\,\mathrm{d}\tau.$$

The second term on the right hand side limits to zero. This follows because (i) $\varphi < 1$, and (ii) $E[\hat{y}(\tau'^{\{n\}})] < c$ where c is a positive definite constant. The limit is thus less than $\lim_{n\to\infty}\varphi^n\frac{c^n}{n!} = 0$.

The integrated form can therefore be written

$$E[\hat{y}(t)] = \frac{m}{\varphi}\sum_{j=1}^{\infty}(-1)^{j+1}\varphi^j\frac{t^j}{j!},$$

which is equivalently recognised as

$$E[\hat{y}(t)] = \frac{m}{\varphi}(1 - e^{-\varphi t}).$$

Recalling the definitions of $\hat{y}(t)$ and m, we have

$$E[\log y_i(t) - \log y_*(t)] = \frac{\gamma + \rho}{\varphi}(\bar{T}_i - \bar{T}_*)(1 - e^{-\varphi t}), \tag{1.11}$$

which is equation (1.8) in the text once we set $t \to \infty$ (long-run).

CHAPTER 2

A dynamic programming Integrated Assessment Model of Climate Change with adaptation

2.1 Introduction

As widely stated by the *Intergovernmental Panel on Climate Change* (IPCC), adaptation plays a vital role as a means of dealing with the risks that climate change poses. Adaptation to climate change is a broad concept that can be understood as the adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates the damages or exploit beneficial opportunities. Adaptation measures to combat climate change entail both benefits and costs. The overall impact of an adaptation measure comes from deducting costs of planning, preparing for, facilitating, and implementing that measure from the avoided damage costs or the accrued benefits following its adoption and implementation. Examples of adaptation are the building of dykes, the changing of crop types, and vaccinations.[1]

The necessity of increasing adaptation-based strategies as complements of mitigation measures (reduction of CO_2 emissions) has been profoundly emphasized in the recently delivered IPCC's 5$^{\text{th}}$ Assessment Report (AR) (IPCC, 2013), where a great deal of attention has been devoted to the forces driving adaptation to climate change as much as to the various impacts that adaptation to climate change may have (IPCC, 2014a,b). The results of mitigation investment are constrained by climatic inertia and the slow workings of the carbon/greenhouse gases (GHG) cycle and hence take more time to be effective. While potentially more expensive, adaptation could have larger effects on impacts more quickly. As a result of that, it has become commonly accepted that a successful climate strategy should compound mitigation and adaptation. The accurate combination between adaptation and mitigation that can best address climate change is still an open question. Both options are needed because they can reduce cli-

[1] See Fankhauser and Soare (2013) for a comprehensive guide of adaptation strategies and different measures of adaptation to combat climate change.

mate change vulnerability through two different, but complementary manners. The first channel decreases its causes while the second addresses its effects. Therefore, it seems natural to include adaptation within an Integrated Assessment Model (hereafter, IAM).

A so-called IAM for climate change is a multiequation computerised model linking aggregate economic growth with simple climate dynamics to analyse the economic impacts of global warming. In other words, it is essentially a dynamic model of an economy with a controllable GHG-driven externality of endogenous greenhouse warming. IAMs have proven themselves useful for understanding some aspects of the economics of climate change—especially in describing outcomes from a complicated interplay of the very long lags and huge inertias involved. They have been used, for example, by the AR4 (Parry et al., 2007), AR5 (IPCC, 2013), the Stern Report (Stern, 2006), and the Interagency Working Group on Social Cost of Carbon (2010), which plays a central role in defining current U.S. government policies around carbon emissions. The IAM approach was pioneered with the development of the DICE model (Nordhaus, 1991, 1993). Current examples include the DICE/RICE models (Nordhaus and Yang, 1996; Nordhaus and Boyer, 2000; Nordhaus, 2010; Nordhaus and Sztorc, 2013), the PAGE model (Hope et al., 1993; Hope, 2006), the FUND model (Tol, 1999, 2013), and the WITCH model Bosetti et al. (2006), among others.

Integrated analysis of adaptation can assess the costs, benefits, and uncertainties of these policies, and ought to be able to provide important insights for their development and implementation. In Patt et al. (2010), the reader can survey how modellers have chosen to describe adaptation within an Integrated Assessment framework. Recent efforts have gone further towards making adaptation explicit by including adaptation as a specific control variable within IAMs (de Bruin et al., 2009; Lecocq and Shalizi, 2007). Still, there is broad agreement that more needs to be done to get adaptation better represented within those models (Stern, 2006). In this chapter, we help to understand how adaptation forces work by exploring the optimal intertemporal balance between mitigation and adaptation under various adaptation settings.

We will use the Dynamic Integrated Climate Change (DICE) model as our reference IAM. The standard DICE model assumes that a single world producer must choose levels for three simultaneously determined variables: current consumption, investment, and greenhouse gases reduction. We will enrich the DICE model so as to encompass different adaptation strategies and then analyse carefully how the optimal mix of mitigation and adaptation changes under different adaptive strategies and cost settings. First, we will introduce the AD-DICE model based on de Bruin et al. (2009), in which proactive adaptation is a control variable that only has an effect in the current period so that one period's adaptation does not affect damages in the next period. We will explore how the mix varies in response to different cost structures. Calibrating the model so as to mimic the optimal mitigation policy of the original DICE model, we show how the optimal mix between mitigation and adaptation is balanced in both variables, demonstrating the strategic complementarities between mitigation and adaptation. It is only after a hundred years that mitigation forces start to dominate. This occurs in response to a falling abatement cost structure in the last years of the simulation. We also show that the composition of this mix depends crucially on the shape of the protection cost curve.

Since some types of adaptive strategies have a stock nature that can have long lived effects, we allow in a second exercise the possibility of building a stock of adaptation that impacts the economy with some lag. Following McCarl and Wang (2013), we will modify the standard formulation of DICE and study how the optimal balance of mitigation-adaptation encompasses the new adapting behaviour. We show that the possibility of building a stock of adaptation that helps to combat climate change effects, creates incentives to allocate a relatively greater amount of resources to adaptation from the beginning and deter strong mitigation until it is extremely urgent at the expense of having a very large peak of carbon stock in the atmosphere.

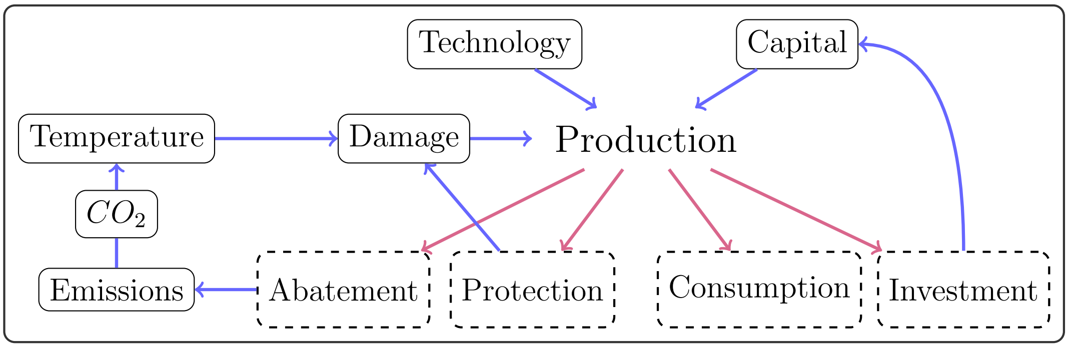
With the objective of preparing our framework model to further enhancements and uncertainty analysis, we cast the DICE in a recursive way. To do so, we follow the work by Traeger (2014). This author has recently promoted a state-reduced, recursive dynamic programming implementation of the DICE model which, in its basic specification, has only 4 state variables. Basically, the reduction is achieved by simplifying the carbon cycle and the temperature delay equations. This leaves us with some margin to enrich the model with new features or uncertain components. We provide some benefits of casting the model in a recursive way. In particular, the recursive AD-DICE is not sensitive to the specification of the terminal conditions and provides us with the policy functions to run alternative simulations. Also, it sets the perfect environment to include further dimensions in our model. In particular, it enables us to properly include different types of uncertainties and/or stochastic behaviour of certain variables and parameters.

The remainder of this chapter is organised as follows. In Section 2.2, we present the benchmark DICE model and introduce the recursive AD-DICE. In Section 2.3 some benefits of the recursive formulation are presented. Section 2.4 performs a preliminary analysis of the mitigation-adaptation optimal mix under deterministic conditions and different adaptation costs and strategies. Section 2.5 will provide some concluding remarks.

2.2 The model

In this section we present the main ingredients of the version of the DICE model that we will use in this study. We will describe its general functioning and all the equations involved.[2] In particular we will distinguish between those processes relative to the economic aspects of the model from those stemming from the climatic relationships. We will show how these two sectors interrelate through the damage function. Next, following de Bruin et al. (2009), we will incorporate adaptation to our model and formulate the whole system in a recursive way, obtaining as a by-product the Bellman equation that describes its dynamics. We will also provide a computationally convenient way of representing the model, that is, the normalised Bellman equation.

Figure 2.1: AD-DICE model workflow



2.2.1 The recursive DICE model

The DICE model is a simple climate-economy model that, with a small bunch of equation and variables, loyally depicts the carbon cycle and optimally allocates investment and mitigation decisions.[3] Inspired by the Ramsey model (embodied in the neoclassical growth theory), DICE is a tractable intertemporal optimisation model of economic growth and climate impacts. The DICE model is a global model that aggregates different (homogeneous) countries into a single level of output, capital stock, technology and emissions. In this model the world is assumed to have a well-defined set of preferences, represented by a social welfare function, which ranks different paths of consumption. The social planner chooses the optimal path of consumption (trading off carbon mitigation and capital investment) that maximises the social welfare objective function.

[2]Further details and derivations can be found in Traeger (2014).
[3]The motivation and processes governing this model are fully described in Nordhaus (2008).

Welfare is the discounted sum of utility over time, where the constant relative risk aversion utility function expresses preferences over per capita consumption

$$W = \sum_{t \in T} \frac{1}{(1+\delta_u)^t} \left[L_t \frac{\left(\frac{C_t}{L_t}\right)^{1-\eta}}{1-\eta} \right], \quad T = \{0, 1, \ldots, \infty\}, \tag{2.1}$$

where W is total social welfare, C_t is the level of this generation's consumption, L_t denotes total population at time t, δ_u is the rate of social time preferences at which future utility streams are discounted. Hence, it is used to compare utility across different generations. The parameter η captures the aversion of the social planner to having unequal consumption per capita across generations, that is, it measures the degree of risk aversion to consumption inequality. Also, since we are working with a constant relative risk aversion (CRRA) utility function, its inverse $(1/\eta)$ denotes the intertemporal elasticity of substitution in consumption. In DICE utility increases in population and per capita consumption, with diminishing marginal utility from the latter.

Economic sectors in the DICE model

In DICE, our simplified economy makes investments in capital, thereby abstaining from consumption today in order to increase consumption in the future. The DICE model extends this approach by including the "natural capital". In other words, we can see concentrations of GHG as negative natural capital and emissions reductions as investments that raise the quantity of natural capital. By devoting output to emissions reductions, economies reduce consumption today vet prevent economically harmful climate damage and thereby increase consumption possibilities in the future.

The production equation of our simplified economy is a standard Cobb-Douglas production function, which uses as inputs endogenous capital K_t, exogenous labour L_t, and exogenous labour augmenting technology A_t. This output, if unmitigated, has associated carbon intensity, resulting in greenhouse gas emissions that warm the atmosphere. Hence, the gross (potential) output at time t would amount to

$$Y_t^{gross} = (A_t L_t)^{1-\kappa} K_t^{\kappa}, \tag{2.2}$$

where κ represents the share of capital in production.

Population, L_t, which simultaneously represents labour, and technology, A_t, will grow at an annual growth rate of $g_{L,t}$ and $g_{A,t}$, respectively. Population at time t is given by the following equation

$$L_t = L_0 + (L_\infty - L_0)(1 - \exp(-g_L^* t)), \tag{2.3}$$

where L_0 denotes the initial global population and L_∞ the value to which this variable steadily converges, or asymptotic population. The parameter g_L^* characterises the speed of convergence from initial to the asymptotic population value. By solving this difference equation we have that the equation defining annual population growth in DICE has the continuous time approximation

$$g_{L,t} = \frac{g_L^*}{\frac{L_\infty}{L_\infty - L_0}\exp(g_L^* t) - 1}. \tag{2.4}$$

The outstanding technology level in the economy, A_t, grows at an exponentially declining rate

$$g_{A,t} = g_{A,0}\exp(-\delta_A t), \tag{2.5}$$

leading to the analytic continuous time solution

$$A_t = A_0 \left(\exp g_{A,0} \frac{1 - \exp(-\delta_A t)}{\delta_A} \right). \tag{2.6}$$

Production in the DICE model requires a determined proportion of carbon, carbon intensity, which is emitted into the atmosphere. We assume an exogenous decrease of the carbon intensity of production, indicating a progressive decarbonisation of the economy. This propensity to emit carbon grows at the (decreasing) rate $g_{\sigma,t} = g_{\sigma,0}\exp($-$\delta_\sigma t)$, leading to the continuous time representation

$$\sigma_t = \sigma_0 \left(\exp g_{\sigma.0} \frac{1 - \exp(-\delta_\sigma t)}{\delta_\sigma} \right). \tag{2.7}$$

We can partially lessen the amount of emitted carbon by paying for abating emissions. The abatement cost coefficient Ψ_t falls exogenously over time and is given by

$$\Psi_t = \frac{\sigma_t}{a_2} a_0 \left(1 - \frac{1 - \exp(g_\Psi^* t)}{a_1} \right). \tag{2.8}$$

The parameter a_0 denotes the initial cost of the backstop (in 2005), a_1 denotes the ratio of initial over final backstop, and a_2 denotes the cost exponent. The rate g_Ψ^* captures the speed of convergence from the initial to the final cost of the backstop.

The cost of mitigation (as a proportion of output) is given by a convex power function of the decision variable for carbon mitigation, μ, in which the marginal cost of mitigation increases more than linearly with μ

$$\Lambda(\mu_t) = \Psi_t \mu_t^{a_2}. \tag{2.9}$$

One of the most studied components in the literature of climate change and one of its foundational parts of the economic model of IAMs is the climate "damage function", which specifies how temperatures or other aspects of climate ultimately affect economic activity. In the DICE model, the damage function takes the form

$$D(T_t) = \frac{1}{1 + b_1 T_t^{b_2}}. \tag{2.10}$$

Climate damages act as a claim on output, reducing the amount that can be spent on either welfare-improving consumption today or investment in the future capital stock. DICE uses an aggregate damage function that gives the fraction of economic output lost to temperature during time period t, formulated as a quadratic function of T_t, the equilibrium change in global mean surface temperature above the pre-industrial level. At the optimum, the social planner sets the level of greenhouse gas such that the marginal cost of mitigation is equal to the marginal benefit of avoided climate impacts over the model time path.

DICE calibrates the b parameters to match cross-sectional estimates of climate damages reviewed in Tol (1999) and then adjusts damages up by 25% to incorporate other non-monetised damages, such as impacts on bio-diversity, and to account for potentially catastrophic scenarios, such as sea level rise, changes in ocean circulation, and accelerated climate change.[4] The DICE model uses this common proportional damage function for the entire world.

In order to ease the numerical approximation of the problem, for a given number of basis in the capital dimension, we normalise capital and consumption in effective labour units. In this way, we can reduce the node density required to achieve a given precision in the approximation. Hence, we define

$$k_t = \frac{K_t}{A_t L_t} \quad \text{and} \quad c_t = \frac{C_t}{A_t L_t},$$

yielding the (labour effective) gross production $y_t^{gross} = k_t^{\kappa}$. Accordingly, net production is derived by subtracting abatement expenditure and climate damages to gross production

$$y_t = \frac{1 - \Lambda(\mu_t)}{1 + D(T_t)} k_t^{\kappa} = \frac{1 - \Psi_t \mu_t^{a_2}}{1 + D(T_t)} k_t^{\kappa}. \tag{2.11}$$

[4]See Nordhaus and Sztorc (2013) for further details

Investment in capital goods (law of motion of capital) is residually determined by subtracting the non-consumed part from net production

$$k_{t+\Delta t} = [(1-\delta_k)^{\Delta t} k_t + y_t \Delta t - c_t \Delta t] \exp[-(g_{A,t} + g_{L,t})\Delta t], \tag{2.12}$$

where δ_k is the annual rate of capital depreciation.

Climatic (geophysical) sectors in the DICE model

The distinctive feature of this model is the inclusion of several geophysical relationships that link the economy with the different factors affecting climate change. These relationships include the carbon cycle, radiative forcing equations and climate change equations, most of them being borrowed from the specialised literature. In the DICE model the only GHG that is subject to emissions control is industrial CO_2, which is, the major contributor to global warming.

Non-industrial CO_2 emissions and radiative forcing from non-CO_2 greenhouse gases are governed by the following equations. Emissions of CO_2 from land use change an forestry (LUCF) are assumed to decline exponentially following

$$B_t = B_0 \exp(-\delta_B t). \tag{2.13}$$

Non-CO_2 greenhouse gases are assumed exogenous to the model and cause the following (external) radiative forcing[5]

$$EF_t = EF_0 + 0.01(EF_{100} - EF_0) \times \min\{t, 100\}. \tag{2.14}$$

To model the relation between air in the atmosphere and the oceans, an exogenous estimate of the atmosphere-ocean temperature differential, which regulates cooling of the atmosphere caused by the oceans' heat capacity

$$\Delta T_t = \max\left\{0.7 + 0.02t - 0.00007t^2, 0\right\}. \tag{2.15}$$

Total GHG (anthropogenic) emissions are the sum of industrial emissions and emissions from land use change and forestry B_t.

$$E_t = (1-\mu_t)\sigma_t A_t L_t k_t^{\kappa} + B_t, \tag{2.16}$$

where the first (industrial) are proportional to gross production $A_t L_t k_t^{\kappa}$, and the emis-

[5] Radiative forcing is a measure for the change in the atmospheric energy balance. The reader may think of it as the flame that greenhouse gases turn on to slowly warm the planet over time.

sion intensity of production σ_t, and they are reduced by the emission control rate μ_t. The flow of CO_2 emissions accumulates in the atmosphere. Atmospheric carbon in the next period is the sum of pre-industrial carbon M_{pre}, current excess carbon in the atmosphere $M_t - M_{pre}$ net of its (natural) removal, and anthropogenic CO_2 emissions

$$M_{t+\Delta t} = M_{pre} + (M_t - M_{pre})(1 - \delta_{M,t})^{\Delta t} + E_t \Delta t. \tag{2.17}$$

The pre-industrial emission stock M_{pre} is the steady state level in the absence of anthropogenic emissions. Equation (2.17) is our approximation to the carbon cycle.

In order to get an overall reduced number of state variables in our formulation of the recursive problem, the carbon cycle is approximated in a very stylised way, using an exogenous removal rate of atmospheric CO_2, $\delta_{M,t}$, that assumes a declining rate of abating emissions from pre-industrial levels

$$\delta_{M,t} = \delta_{M,\infty} + (\delta_{M,0} - \delta_{M,\infty}) \exp\left[-\delta_M^* t\right]. \tag{2.18}$$

The overall atmospheric temperature change is a delayed response to radiative forcing

$$F_{t+\Delta t} = \eta_{forc} \frac{\ln \frac{M_{t+\Delta t}}{M_{pre\ ind}}}{\ln 2} + EF_t, \tag{2.19}$$

which is the result of the forcing caused by atmospheric CO_2 and the non-CO_2 forcing that follows the exogenous process EF_t. Note that the forcing parameter η_{forc} contains the climate sensitivity parameter, which characterises the equilibrium warming response to a doubling of pre-industrial CO_2 concentrations. The temperature state's equation of motion is

$$T_{t+\Delta t} = (1 - \sigma_{forc}) T_t + \sigma_{forc} \frac{F_{t+\Delta t}}{\lambda} - \sigma_{ocean} \Delta T_t. \tag{2.20}$$

The parameter σ_{forc} captures the warming delay and σ_{ocean} quantifies the ocean cooling in a given time step that derives from the atmospheric ocean temperature difference ΔT_t. The parameter λ denotes the ratio of forcing to temperature increase under a doubling of CO_2 concentration. The last term in the equation replaces the oceanic temperature state in DICE.

2.2.2 The recursive AD-DICE model

Next, we feed the original DICE model with extra features. In particular, we include adaptation as a separate choice variable. Now, adaptation and mitigation investments will compete and available resources to combat climate change will be allocated efficiently between those two variables. We will write the Bellman equation associated to this new specification.

Instantaneous adaptation *à la de Bruin*

Adaptation directly decreases the total damages of climate change. But adaptation choices are potentially quite different to mitigation decisions and differ in cost. These costs are referred to as protection costs. While the original DICE model assumes that adaptation is included in the damage function and is implicitly assumed to be optimal, we rather include adaptation explicitly in the model. Following de Bruin et al. (2009), we model adaptation as a decision variable chosen by the planner that has some benefits and costs. Accordingly, total damages of climate change are split into the sum of residual damages and protection costs

$$D_t = RD_t(GD_t, p_t) + PC_t(p_t), \tag{2.21}$$

where residual damages RD_t are the "unprotected" part of total damages[6]

$$RD_t = GD_t(1 - p_t),$$

whereas gross damages amount to

$$GD_t = 1 + b_1 T_t^{b_2},$$

and protection costs take the form

$$PC_t = \gamma_1 p_t^{\gamma_2},$$

with p_t representing the optimal level of protection chosen each period. In this setup, optimal mitigation and adaptation are jointly modelled and both decisions are separable. In this setup, adaptation and mitigation will behave as economic substitutes. In the original DICE model, mitigation is set by the marginal damage cost. In this framework, the adaptation level is chosen so as to minimise net damages plus adaptation costs, while the mitigation level is chosen to minimise the aggregate of net damages and adaptation costs plus mitigation costs.

[6]We could play along with another alternative specifications of the damage function. For example, $RD_t = \frac{GD_t}{p_t}$.

The Bellman equation

An optimal decision has to be made at each period in which we solve the model. The Bellman equation reduces the complexity of the decision tree by breaking it up into a trade-off between current consumption utility and future welfare, where future welfare is a function of the climatic and economic states in the next period. The best possible total value of present and future welfare is the so-called value function $V(K_t, M_t, T_t, t)$.[7]

$$V(K_t, M_t, T_t, t) = \max_{C_t, \mu_t, p_t} L_t \frac{\left(\frac{C_t}{L_t}\right)^{1-\eta}}{1-\eta} \Delta t + \exp\left(-\delta_u \Delta t\right) V(K_{t+\Delta t}, M_{t+\Delta t}, T_{t+\Delta t}, t + \Delta t). \tag{2.22}$$

This maximisation problem is subject to the equations of motion of capital (2.12), carbon (2.17), and temperature (2.20), and the following constraints

$$0 \leq C_t \leq Y_t, \quad 0 \leq \mu_t \leq 1 \quad \text{and} \quad 0 \leq p_t \leq 0.8, \tag{2.23}$$

where we have imposed that not more than 80% of unmitigated damages can be adapted. This is adapted from de Bruin et al. (2009), who base their assumptions on a deep review of the adaptation literature. The decision variable for carbon mitigation, μ, equals the fraction of emissions from the business-as-usual emissions projections that are avoided through decarbonisation.

As we have noted from the beginning, one of the main features of our approach is that we can faithfully describe the mechanics of the original DICE model using only four state variables. These variables are produced capital K_t, the stock of atmospheric carbon M_t, atmospheric temperature T_t, and time t. It is convenient to our approach to include time as a state variable for a number of reasons: it makes it possible to contract the Bellman equation to an arbitrary precision and enables us to solve the model for an infinite time horizon with an arbitrary time step.[8]

Given the value function, we can analyse the control rules and simulate different representations of the optimal policy over time. For the simulation, we either fit a continuous control rule, or we forward-solve the Bellman equation, knowing the value function, starting from the initial state.

[7] For numerical considerations, we will work with the normalised version of this Bellman equation.

[8] Bear in mind that Nordhaus' DICE model is solved within a 10-year time step. However, given our time flexibility, we will calibrate and solve the model in a more illustrative 1-year time step.

The normalised Bellman equation

The original Bellman equation formulation (2.22) presents some drawbacks. In particular, since capital will eventually take very large numerical values, our numerical optimiser will struggle to find the optima along that grid if we choose a small number of nodes. However, if we proceed as many economic models, by normalising by effective labour units we can gain accuracy very cheaply by shrinking the set where capital stock belongs. Thus, we restate the key variables in effective labour units, that is, $c_t = \frac{C_t}{A_t L_t}$ and $k_t = \frac{K_t}{A_t L_t}$, we can express the general Bellman equation (2.22) as follows:[9]

$$V^*(k_t, M_t, T_t, t) = \max_{c_t, \mu_t, p_t} \frac{c_t^{1-\eta}}{1-\eta}\Delta t + \beta_{t,\Delta t} V^*(k_{t+\Delta t}, M_{t+\Delta t}, T_{t+\Delta t}, t+\Delta t), \tag{2.24}$$

where

$$\beta_{t,\Delta t} = \exp\left(\left(-\delta_u + g_{A,t}\left(1-\eta\right) + g_{L,t}\right)\Delta t\right) \tag{2.25}$$

represents a growth-adjusted discount factor. It depends on time because of the non-constant growth rates in DICE's exogenous processes. Without normalising capital to effective labour units we would need a much larger state space for capital to cover at least a reasonably long time horizon.

2.2.3 Solving the model

We solve the normalised Bellman equation (2.24) by help of the function iteration algorithm described in Appendix 2.B. We approximate the value function V^* by using a set of Chebychev polynomials basis and updating coefficients by collocation at the Chebychev nodes.

A convenient strategy for the numerical implementation of the model is to maximise over the abatement cost rather than over the abatement rate μ_t as the algorithm behaves more efficiently by searching on this magnitude. Analogously, we maximise over PC_t rather than p_t. The two are strictly monotonic transformations of each other so that the nature of the problem remains unchanged. The optimal choices in the problem must satisfy the following system of inequalities

[9] Further details on this derivation can be found in Traeger (2014)

$$\begin{pmatrix} 1 & \frac{k_t^{\kappa}}{1+b_1 T_t^{b_2}} & \frac{k_t^{\kappa}}{1+b_1 T_t^{b_2}} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} c_t \\ \Lambda_t \\ PC_t \end{pmatrix} \leq \begin{pmatrix} y_t \\ \Psi_t \\ PC_{max} \end{pmatrix} \qquad \text{with} \quad c_t, \Lambda_t, PC_t \geq 0,$$

which derive straight from (2.23). The first row is simply telling us that quantities devoted to consumption, mitigation and adaptation must not exceed total production in a given year. The second row states that, on the event of full mitigation ($\mu_t = 1$), mitigation costs cannot be larger than Ψ_t ($\Lambda(1) = \Psi_t \cdot 1^{a_2} = \Psi_t$). Analogously, there exists a ceiling, PC_{max}, for adaptation costs at $PC_{max} = \gamma_1 \cdot 0.8^{\gamma_2}$.

Since we also have to approximate the value function over the state variable t on the interval $[0, \infty)$, we have to restrict its natural unboundedness, as this poses a clear inconvenient when generating the approximation grid.[10] Hence, we perform a strictly monotonic transformation that maps $t \in [0, \infty)$ to

$$\tau = 1 - \exp(-\zeta t) \in [0, 1).$$

We set $\zeta = 0.02$ and refer to τ as artificial time. Hence, we generate the grid on the time axis using Chebychev nodes on the interval $[0, 1)$.

We run the resulting code in Matlab using the *compecon* optimiser as presented in Miranda and Fackler (2002). Since each of the optimisation at the different Chebychev nodes is independent conditional on the time step, we can compute each of them independently. Hence, we make use of the Parallel Programming Toolbox in Matlab to parallelise that process so that the whole process speeds up nearly 4 times.[11]

2.3 Some benefits of the recursive formulation

Almost all IAMs, including DICE, are solved using a simple solution technique: the model is truncated to a finite horizon so that standard non-linear programming methods may be applied with standard software packages. We denote this technique the finite horizon method. This method, though convenient has some limitations: First, it does not work well on stochastic models for which certainty equivalence does not hold. The finite horizon method is not recursive and thus requires specification of all possible

[10] Alternatively, we could reduce the state space to only 3 dimensions, if we are willing to step back discretely in time from a finite planning horizon. The solution algorithm is similar to the one described above. However, it becomes more important to start with a good initial guess. See Cai et al. (2015) for an example of solving the DICE model over a finite time horizon.

[11] In Windows 10, Intel i7-2600 @3.40GHz PC. Matlab R2011a.

realizations of the random variables over time. Hence for a stochastic problem spanning hundreds of years such as climate change, only the simplest possible random variables are possible. This advantage of our approach will made explicit in the next chapter. Second, inference is difficult because the solution produces only an optimal solution path, and says nothing about the relationship between the solution and the state variables and parameters. Third, it does not compute the policy function, then the model cannot be simulated for alternative starting conditions or realizations of the random variables without resolving the entire model. Finally, the solution method can be sensitive to the specification of the terminal conditions, which makes sensitivity analysis difficult.

The recursive formulation will be useful, not only to solve and compare different specifications of the model under deterministic conditions but will also prepare the necessary framework to include different uncertain and/or stochastic scenarios (This will be done in the next chapter). In particular, our accompanying applications have the necessary precision to analyse the differences that future stochasticity, or the anticipation of learning, have on today's optimal policy. The non-recursive methodology would only allow for a few discrete uncertain events, or exogenous learning over three discrete state of the world realisations at one given time. Alternatively to recursive methods, Monte-Carlo analysis of the non-linear programming solution to the model are the most common approach to addressing uncertainty in the integrated assessment literature. However, Monte-Carlo methods, as traditionally implemented in this niche of the literature, do not model decision making under uncertainty. They present a sensitivity analysis that averages over deterministic simulations.

Another two additional features of our solution technique are the following: First, we have managed to cast and solve the model in an annual basis, which enables us with some additional degrees of freedom for including more timely additional characteristics or constraints to our model. Second, we take benefit of the independent nature of the resolution of the Bellman equation at different grid points to implement the code in a parallel way. This implies faster total solution time and eases the curse of dimensionality that these types of models typically suffer.

2.4 Basic magnitudes and time paths

In this subsection we present the main magnitudes, as obtained from a basic calibration of our model. When calibrating the model our main purpose was to match the optimal mitigation policy derived from the original DICE model. Thus, we adopt most of the values proposed by Nordhaus (2008) with the exception that, now, we run the model in an annual step rather than decadal. Hence, some parameters affecting the dynamics of natural processes are modified accordingly. Both climatic and economic parameters are described in Table 2.1 and Table 2.2, respectively.

In this setup, adaptation and mitigation decisions are separable and both are modelled as economic substitutes, that is, more mitigation (adaptation) reduces the need for adaptation (mitigation). In the optimal policy solution we will find bundles with both adaptation and mitigation because mitigation cannot avoid all climate change and adaptation cannot avoid all impacts. Because of the slow working of the carbon cycle, few of the benefits of abating emissions will be felt in the short-run. That is why it is necessary to both adapt and mitigate immediately.

We run the model in an annual step ($\Delta t = 1$) starting at year 2010. Basic results are depicted in Figure 2.2. As it can be observed in Figure 2.2a, emissions will not cease to grow in the coming years resulting in an increasing atmospheric CO_2 concentration, describing a hump-shaped time path that will peak in a two centuries‘ time horizon. Accordingly, because of the direct relation between damages and carbon concentration, damages of climate change follow a similar shape, as depicted in Figure 2.2c. Abated emissions increase steadily over the period until full abatement is reached. Despite mitigation efforts, CO_2 concentrations do not stop growing in the early years due to the extremely high inertias featured in the (simplified) carbon cycle. In Figure 2.2b we can observe that, given the cost structure of abatement, we reach a point in time (around year 2175) when full abatement of emissions is optimal. This behaviour is maintained beyond this point.

As for the optimal mitigation-adaptation mix (Figure 2.3), it shows positive and almost balanced amount of resources allocated to each category, demonstrating the strategic complementarities between mitigation and adaptation. It is only after a hundred years that mitigation forces start to dominate. This occurs in response to a falling abatement cost structure in the last years of the simulation. Thus, according to our model, in order to combat climate change in the efficient way, the short-term optimal policy would consist of a mixture of adaptation measures and investments in mitigation, even though the latter will only decrease damages in later periods. The first channel decreases its effects while the second addresses its causes.

Our attempt is the first to analyse the optimal composition and time path of the mitigation-adaptation mix by implementing the AD-DICE model in a recursive way. This poses some barriers to compare our results to other findings in the literature. Additionally, specific figures will depend crucially on the employed framework, the adaptation modelling's strategy and the basic calibration of the main parameters in the model. However, some general messages can be extracted. Similarly to us, Bosello et al. (2010) — building on the WITCH model (Bosetti et al., 2006)–, find that the two climate strategies behave as complements and they both need to be part of an optimal strategy to fight climate change, although both strategies compete about scarce resources. They also show that, in a world without catastrophic events, adaptation is unambiguously the preferred option by a factor of 3. Meanwhile, we advocate for a balanced composition of the two strategies in the early years. However, to obtain their results they need to resort to extremely low temporal discount factors. Meanwhile, their benchmark time composition of the mix is quite similar to ours: mitigation has to be anticipated because environmental and technological inertia delays its benefits in the far future.

2.4.1 Alternative protection costs

Immediately after our first assessment of the magnitude and timing of adaptation and mitigation, we evaluate how adaptation decisions respond to different protection costs. Specifically, we propose a notably different protection cost function with a different shape. The new function implies higher protection costs for low levels of adaptation, that is, it assumes a decreasing marginal cost of protection, possibly reflecting the accumulation of know-how when investing in adapting goods/knowledge. The new protection cost function takes the form

$$PC_t^* = \gamma_1 \left(\frac{1}{1 - p_t} \right)^{\gamma_2} . \tag{2.26}$$

Protection costs are given as a function of the level of protection. In this exercise, we assume that this function is decreasing with the level of protection, meaning that it is cheaper to protect us against the adverse effects of climate change when the desired level of protection is high. Implicit in this assumption is the fact that, building new infrastructures headed to protect is equivalent to a high level of protection.

We can look at the behaviour of the basic variables of the model in Figure 2.4. Similarly to our benchmark case, the CO_2 concentration path follows a hump-shaped trajectory over our simulation period. In this case, though, we reach a maximum level of CO_2 stock in the atmosphere earlier in time. This comes as a result of mitigation becoming relatively cheaper very rapidly. Since it is optimal to start to strongly mitigate after a few decades, the maximum level of carbon concentration at its highest moment decreases considerably, compared to the benchmark scenario. The rest of variables follow a similar pattern to the original formulation.

Adaptation and mitigation are still affected by each other in the same way as in the original protection cost specification. Adaptation increases the benefits of mitigation in earlier periods and decreases them in later periods. Since it is still optimal to invest in adaptation and it is cheaper as we increase the desired level, the new optimal mix (Figure 2.5) describes how more ($> 50\%$) resources are now allocated to adaptation at the beginning of time. Given that adaptation is relatively cheaper when the level of adaptation is low, it is optimal to favour adaptation in earlier periods. However, since the cost structure of adaptation penalises high levels of resources allocated to adaptation (we should understand this as the maintenance cost of adaptation measures and adaptation infrastructures), now it becomes optimal to strongly shift our optimal bundle to more mitigation. Consequently, full abatement of emission is reached earlier in time, compared to the basic calibration scenario.

2.4.2 Cumulative adaptation: The ADS-DICE model

The way in which adaptation is modelled in de Bruin et al. (2009) results in adaptation having effect only in the current period so that one period's adaptation does not affect damages in the next period, therefore ignoring the sometimes considerable time-lags between the costs and benefits of adaptation measures. This assumption seems quite restrictive, especially if we are working in a yearly time step. Besides that, the intrinsic nature of some types of adaptation investments, like the construction of dykes, has a long lasted impact that would be worth modelling.

One can rather think of adaptation as an investment that accumulates an stock of knowledge, infrastructure, and etcetera, that yields profits with some lags of time. In that spirit, we follow the approach by McCarl and Wang (2013) by allowing the creation of a stock of adaptation as if the 'adaptation capital' accumulates over the years. Therefore, the resulting optimal adaptation decisions adjust to current and future climate change damages rather than those in a single year. The incorporation of a stock of adaptation boils down to including a new state variable that we will denote Sp_t which evolves according to

$$Sp_{t+\Delta t} = (1-\beta_p)^{\Delta t} Sp_t + Ip_t, \tag{2.27}$$

where Ip_t is equal to the total investment in protection. The residual damage function would amount to

$$RD_t = GD_t(1-p_t),$$

with

$$1 - p_t = \alpha + (1-\alpha)e^{-rSp_t},$$

where α represents a percentage of unavoidable damage. As in the previous approach, decisions on the level of adaptation and mitigation are separable but compete for investment funds.

The (normalised) Bellman equation will feature and additional state variable Sp_t denoting the accumulated adaptation stock

$$V^*(k_t, M_t, T_t, Sp_t, t) = \max_{c_t, \mu_t, p_t} \frac{c_t^{1-\eta}}{1-\eta}\Delta t + \beta_{t,\Delta t} V^*(k_{t+\Delta t}, M_{t+\Delta t}, T_{t+\Delta t}, Sp_{t+\Delta t}, t+\Delta t),$$

with its respective transition equation

$$Sp_{t+\Delta t} = (1-\beta_p)^{\Delta t} Sp_t + Ip_t.$$

The rest of restrictions in (2.22) also hold.

As a result of weak mitigation in earlier periods, the total stock of carbon in the atmosphere (Figure 2.6a) reaches a much higher level than what is achieved in the benchmark CO_2 setting. Abatement of emissions remains low overall during the next to centuries until the point where strong mitigation is the only option to combat the extraordinary amount of CO_2 levels, as seen in Figure 2.6b. At this point the total amount of damages created in the economy are too high, of an order of magnitude 4 times greater than in the benchmark model (Figure 2.6c).

The fact that we can build a stock of adaptation that helps to combat climate change effects, creates incentives to allocate a relatively greater amount of resources to adaptation from the beginning and deter strong mitigation until it is extremely urgent. This behaviour can be easily seen in Figure 2.7. More than half of the investment resources are systematically deviated to build adaptation infrastructures up to the point where strong mitigation efforts are needed to absorb climate change consequences.

In this scenario we have persistent adaptation plus unadaptable damages and investment competition. Looking at Figure 2.7, our temporal investment allocation results show that both adaptation and mitigation are simultaneously employed as strategic complements much as found in the benchmark specification. We do show in our results a great immediate role for adaptation with a longer run transition to mitigation as the damages from GHG concentrations increase.

2.5 Conclusion

Integrated assessment modelling of adaptation to climate change is still at its early stages. The AD-DICE model by de Bruin et al. (2009) is one of the few examples in which adaptation is explicitly included in an IAM as a separable choice variable. Incorporating new features into IAMs is highly desirable but comes at a cost. In particular, it makes most of these models suffer from the curse of dimensionality.

To overcome this problem, we adapt a recent methodology proposed by Traeger (2014) which casts the well established Nordhaus' DICE model in a recursive way, making it particularly suitable for incorporating additional characteristics to the model. At the same time, it reduces the state space to only four state variables, thus, making the model accessible to be solved in a regular computer. With this methodology in mind, we extend the original DICE model and incorporate adaptation à la de Bruin thus specifying adaptation as a separate decision variable and perform a thorough analysis of different types of adaptation strategies under various scenarios.

In a preliminary exercise we calibrate and solve the model in its deterministic setup and analyse its basic properties. Overall, our model reproduces quite faithfully the major features of the original DICE model. In particular, it predicts a hump-shaped time path for atmospheric CO_2 concentrations with a peak in a two centuries' time horizon. Accordingly, damages of climate change follow a similar shape. Abated emissions increase steadily over the period until full abatement is reached. Despite mitigation efforts, CO_2 concentrations don't stop growing in the early years due to the extremely high inertias featured in the (simplified) carbon cycle. As for the optimal mitigation-adaptation mix, it shows positive and almost balanced resources allocated to both variables, demonstrating the strategic complementarities between mitigation and adaptation. It is only after a hundred years that mitigation forces start to dominate. This occurs in response to a falling abatement cost structure in the last years of the simulation. Thus, according to our model, in order to combat climate change in the efficient way, the short-term optimal policy would consist of a mixture of adaptation measures and investments in mitigation, even though the latter will only decrease damages in later periods. The first channel decreases its effects while the second addresses its causes. Our results qualitatively resemble those of Bosello et al. (2010), applied to the WITCH model. In particular, we both find that mitigation and adaptation behave as strategic complements but compete for scarce resources in the short-term.

In subsequent exercises, we show that the final composition and timing of the adaptation-mitigation mix depends crucially on both the assumed shape of the protection cost function and the accumulative nature of the adaptation stock. We exemplify the first situation by choosing an alternative protection cost function that, in contrast with the original formulation, penalises low levels of protection. As a result, the total amount invested in protection is greater than in the benchmark case but, it decreases very rapidly since more resources are deviated to mitigate. In the second case (ADS-DICE model), the fact that adaptation investments have a delayed and persistent effect in the economy makes that the resources needed to maintain an optimal level of protection are fewer than in the benchmark scenario. Again, in the distant future, mitigation becomes more attractive due to shrinking operative costs and, as a result, the mitigation share increases.

The methodology employed in this chapter show some potential benefits and advantages with respect to the traditional way of casting and solving the DICE model, namely, it is not sensitive to the specification of the terminal conditions and provides us with the policy functions to run alternative simulations. Also, it sets the perfect environment to include further dimensions in our model. In particular, it enables us to properly include different types of uncertainties and/or stochastic behaviour of certain variables and parameters. This will be addressed in the next chapter.

2.A Tables and Figures

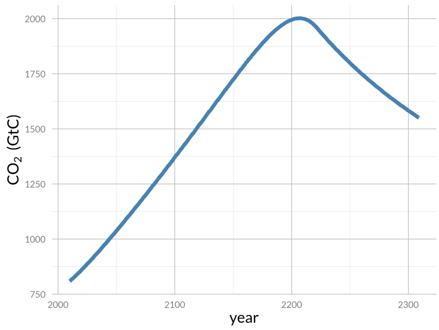
Table 2.1: Parameters of the model (Climatic)

Climatic parameters		
T_0	0.76	In °C, temperature increase of pre-industrial in 2005
M_{pre}	596	In GtC, pre-industrial stock of CO_2 in the atmosphere
M_0	808.9	In GtC, stock of atmospheric CO_2 in 2005
$\delta_{M,0}$	1.4%	initial rate of CO_2 removal from the atmosphere per year
$\delta_{M,\infty}$	0.4%	Asymptotic rate of CO_2 removal from the atmosphere per year
δ_M^*	1%	Rate of convergence to asymptotic rate of atmospheric CO_2 removal
B_0	1.1	In GtC, initial CO_2 emissions from LUCF
δ_B	1.05%	Growth rate of CO_2 emission from LUCF per year
s	3.08	Climate sensitivity (equilibrium temperature response to doubling of atmospheric CO_2 concentration w.r.t. pre-industrial)
η_{forc}	3.8	Forcing of CO_2-doubling
λ	1.23	Ratio of forcing to temperature increase under CO_2-doubling
EF_0	-0.06	External forcing in year 2000
EF_{100}	0.3	External forcing in year 2100 and beyond
σ_{forc}	3.2%	Warming delay, heat capacity atmosphere, annual
σ_{ocean}	0.7%	Parameter governing oceanic temperature feedback, annual

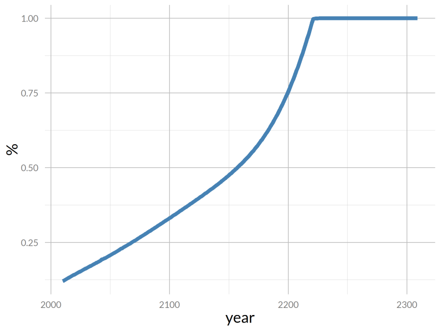
Table 2.2: Parameters of the model (Economic)

Economic parameters

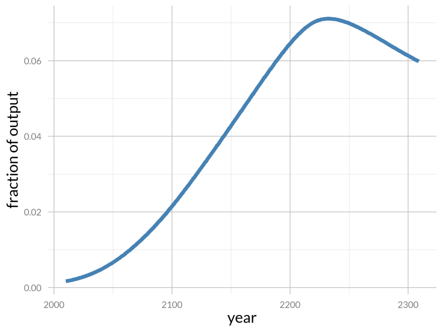
η	-2	Intertemporal consumption smoothing preference
b_1	0.284%	Damage coefficient
b_2	2	Damage exponent
γ_1	0.115	Protection coefficient
γ_2	3.6	Protection exponent
β_p	10%	depreciation of Stock of Adaptation
α	20%	percentage of unavoidable damage
r	1.43	Stock of Adaptation's discount factor
δ_u	1.5%	Pure rate of time preference per year
L_0	6514	In millions, population in 2005
L_∞	8600	In millions, asymptotic population
g_L^*	3.5%	Rate of convergence to asymptotic population
K_0	137	In trillion 2005-USD, initial global capital stock
δ_K	10%	Depreciation rate of capital per year
κ	0.3	Capital elasticity in production
A_0	0.0058	Initial labour productivity; corresponds to total factor productivity of 0.02722 used in DICE
$g_{A,0}$	1.31%	Initial growth rate of labour productivity corresponds to total factor productivity of 0.9% used in DICE, per year
δ_A	0.1%	Rate of decline of productivity growth rate per year
σ_0	0.1342	CO_2 emissions per unit of output in 2005
$g_{\sigma,0}$	-0.73%	Initial rate of decarbonisation per year
δ_σ	0.3%	Rate of decline of the rate of decarbonisation per year
a_0	1.17	Cost of backstop in 2005
a_1	2	Ratio of initial over final backstop cost
a_2	2.8	Cost exponent
g_Ψ^*	-0.5%	Rate of convergence from initial to final backstop cost



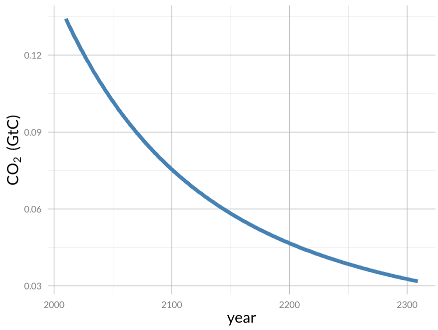
(a) CO_2 level



(b) Abatement rate)



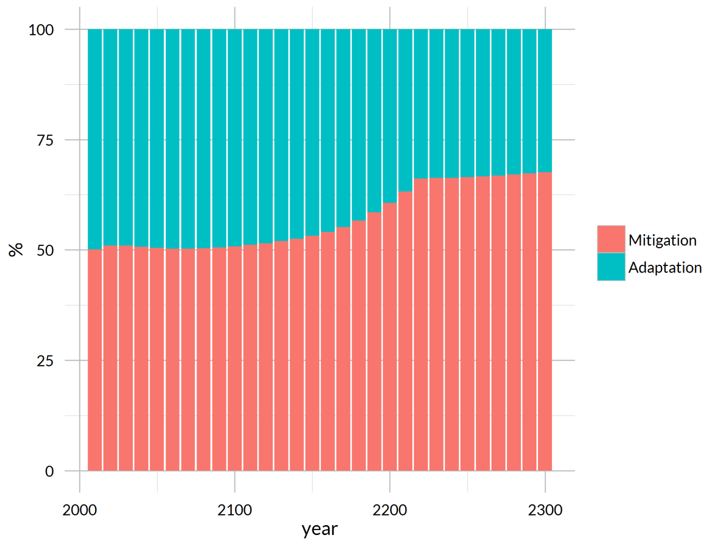
(c) Investment rate

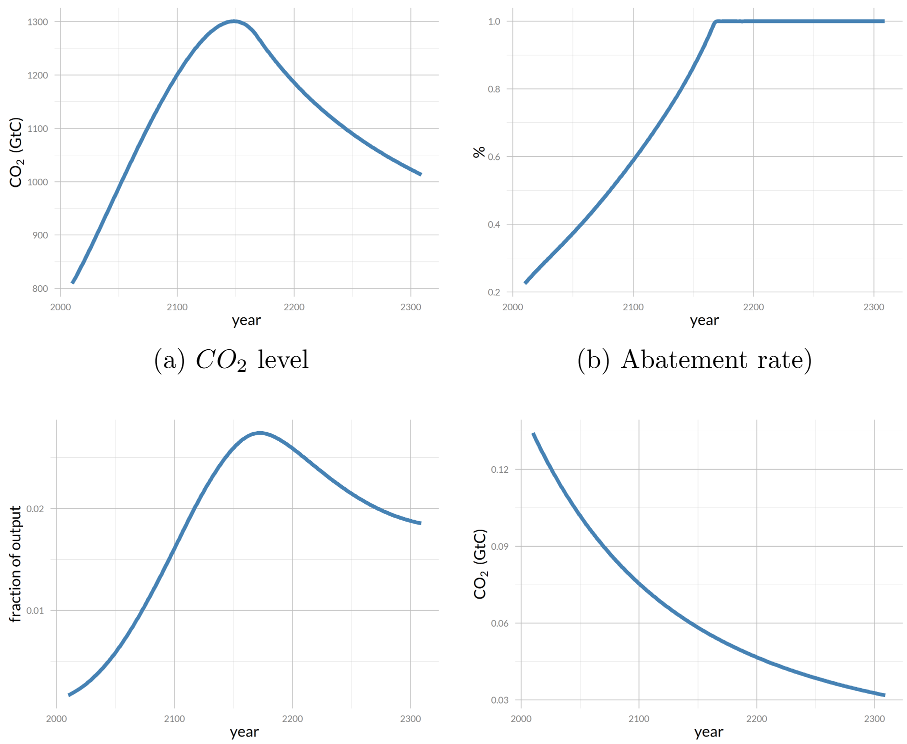


(d) CO_2 emissions)

Figure 2.2: Benchmark AD-DICE

Figure 2.3: Adaptation-Mitigation mix (benchmark AD-DICE)



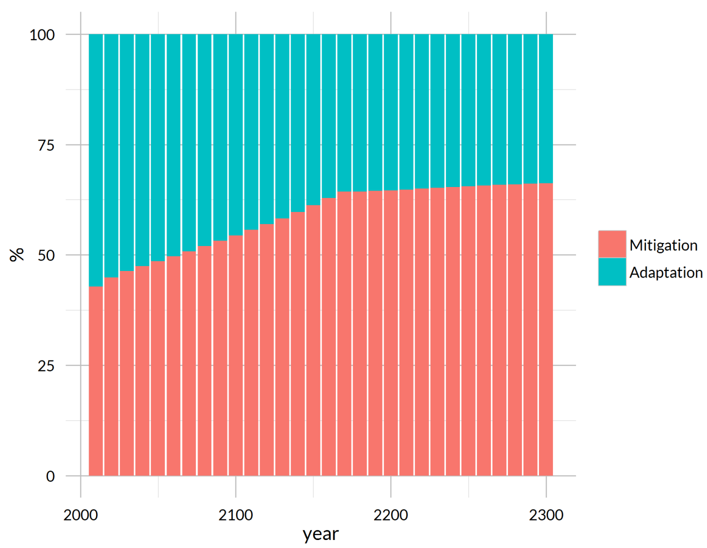


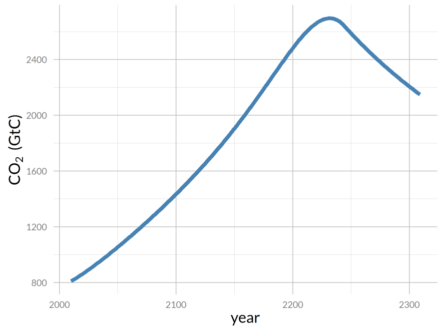
(a) CO_2 level (b) Abatement rate)

(c) Investment rate (d) CO_2 emissions)

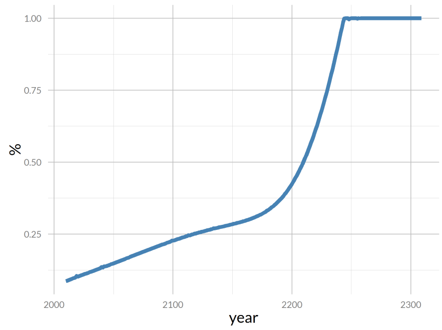
Figure 2.4: AD-DICE (alternative protection costs)

Figure 2.5: Adaptation-Mitigation mix (alternative protection costs)

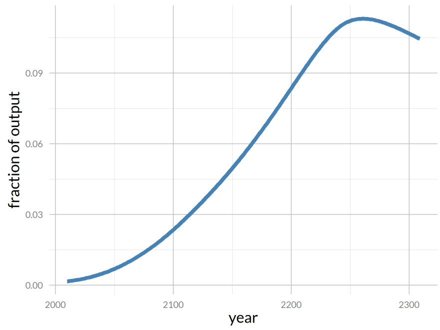




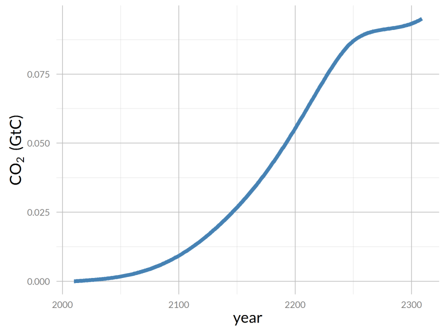
(a) CO_2 level



(b) Abatement rate)



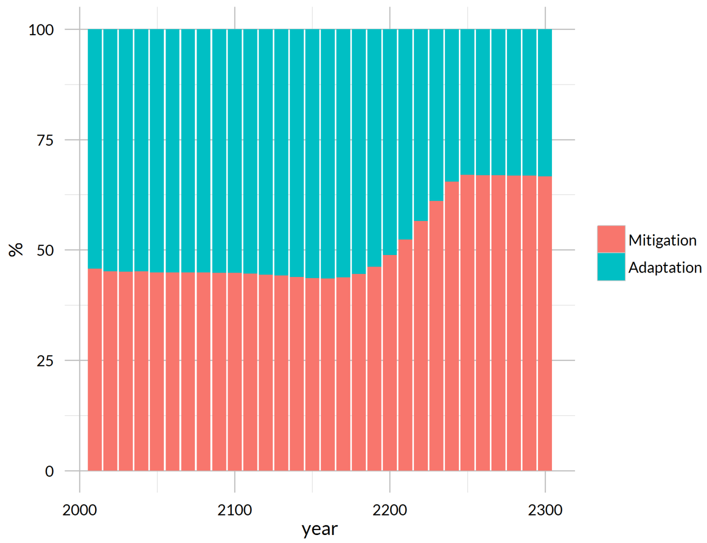
(c) Total Damages



(d) Stock of Adaptation)

Figure 2.6: ADS-DICE

Figure 2.7: Adaptation-Mitigation mix (ADS-DICE)



2.B Solution of the model

There are different approaches to studying dynamic problems. In our case, since it is infeasible to find a closed form solution we have to resort to numerical methods to find a solution to the dynamic problem. Within numerical methods we find again a variety of ways to approximate a solution, among which, we choose value function iteration. This type of solution to the model basically amounts to finding a *fixed point* in our Bellman equation. Next we describe the basics of our algorithm.

2.B.1 The Value Function Iteration algorithm

Denote by a our vector of control variables and assume that we summarise all our state variables into the vector x subject to the equation of motion

$$x_{t+1} = g(a_t, x_t).$$

With t denoting calendar time, and defining s as time-to-go before the end of the problem, $s = T - t$, we write the value function as $V^s(x) = V^*(x,t)$. The dynamic programming equation for $s \geq 1$ is

$$V^s(x) = \max \left\{ U(a,x) + \beta V^{s-1}(g(a,x)) \right\}, \tag{2.28}$$

with the boundary condition

$$V^0(x) = \max_a U(a,x), \tag{2.29}$$

where the superscript denotes the number of decisions remaining after the current decision.

The algorithm begin by finding the solution to the problem on the right side of equation (2.29) to obtain the function $V^0(x)$. Substituting that function into equation (2.28) for $s = 1$, we then solve the resulting problem to obtain $V^1(x)$. Proceeding iteratively, we solve the T one-stage problems. At each stage, s, we obtain two functions: the decision rule, denoted as $a^s(x) = \arg\max U(a,x)$, and the value function $V^s(x)$. We use the value function for the "backward sweep", increasing s, approaching the initial time period. We may use either the decision rule or the stored value functions for the "forward sweep". Given the initial condition, the value of $x_t = \bar{x}$, we can find the trajectory of the optimally controlled state variables. In general, we can neither calculate nor store exact solutions for the value function or the control rule. We therefore approximate the value function in each step. Given the value function, we obtain the control rule from a quasi-static optimization problem. Hence, we will only approximate and store the value function, and not the control rule. In order to approximate the value function we will have to decide on the intervals over which we approximate the function and the approximation method.

A summary of the value function iteration algorithm would read

1. Initialisation

   (a) Choose how to approximate the value function. Usually this step involves the choice of:

      i. basis functions to approximate the value function,

      ii. interval of the state space on which to approximate the value function,

      iii. interpolation nodes at which you evaluate the optimization problem.

   (b) For $s = 0$ ($T = \infty$), pick an initial guess for the approximate value function V^0. Set $s = 1$ and proceed to step (c).

2. Iteration

   (c) Maximise the right hand side of the Bellman equation (2.28) for s.

   (d) Approximate the solution of the maximization step. Usually this step involves solving for the coefficients of the basis vectors. You obtain the value function V^s.

   (e) Increment time to go s by 1 and repeat steps (c) and (d) until a break criterion is satisfied up to a given tolerance, usually related to the change of the value function or the basis coefficients from one iteration to the next.

3. Simulation

   (f) Simulate the system dynamics by solving the Bellman equation (2.28) iteratively forward in time. Starting with the initial condition $x_t = \bar{x}$, the simulation solves a sequence of quasi-static optimization problems, given the (approximate) value functions at every point in time. If we fitted the policy functions in the earlier steps, we can use these directly to simulate the system dynamics. In the stochastic case, we can simulate using expected draws as a proxy, and then also simulate large sets of truly random paths and determine distributional properties.

In the case where $T = \infty$, we have an autonomous problem and we usually store only the current and the previous value function. We keep track of the last iteration's value function so that the break criterion can evaluate changes from one iteration to the next. In the case of an infinite time horizon, s is not the time to go, but simply counts the iterations starting from our initial guess.

2.B.2 (Value) Function approximation

Even if we knew the function V^{s-1}, it would rarely be the case that we could find a closed from solution for function V^s. Assume we cannot find a closed form solution but want to solve the problem exactly (up to numerical precision). Then, we would have to solve the maximization problem for every $x \in X$ and store the optimisation result, i.e. the value of the function V^s, for every point. Given $X \subset \mathbb{R}$ is uncountable, this procedure is infeasible. But we can approximate continuous functions on a compact support $X \subset \mathbb{R}$ arbitrarily closely by a (countable) sequence of polynomials. In general, there are different countable basis of function spaces. Let us denote a sequence of orthonormal basis functions by $\phi_0, \phi_1, \phi_2, \ldots$. Then, every function f in the corresponding space can be written as

$$f = \sum_{i=0}^{\infty} c_i^* \phi_i,$$

with coefficients in $\mathbb{R}$

$$c_i^* = \int_X \phi_i(x) f(x) dx. \tag{2.30}$$

A countable infinite series is still too much to keep track of. We therefore resort to a finite subset of the basis. In addition, we have to find an efficient way of dealing with the integration in equation (2.30). A simple but effective approach replaces the integral by a sum, evaluating both functions only at a finite set of points, the so-called interpolation nodes $x_1, \ldots, x_J$. Then, we obtain the approximate formula

$$f \approx \sum_{i=0}^{N} c_i \phi_i \quad \text{with} \quad c_i = \sum_{j=1}^{J} \phi_i(x_j) f(x_j) = \Phi_i' \mathbf{f}. \tag{2.31}$$

In the value function approximation, we fit the value function V^s to the solution of the maximisation problem on the right hand side of the Bellman equation (2.24). Here, the vector $\mathbf{f}$ corresponds to the solution of the Bellman equation at the interpolation nodes. We use the vectors $\mathbf{\Phi_i}$ to find the coefficients of the basis functions ϕ_i, given only the finite vector of values at the interpolation nodes (of $\mathbf{f}$ or the maximisation problem). We use the functions ϕ_i whenever we need to evaluate the approximated function between different interpolation nodes.

The strategy consists of choosing a sequence of J points, our interpolation nodes, $x_0, x_1, \ldots, x_{J-1}$ on an interval $[a, b]$; $x_0 = a$ and $x_{J-1} = b$. We generate the value of the function that we seek to approximate at each of these nodes. We also choose N basis functions $\phi_i(x)$, $i = 0, 1, \ldots, N-1$. We approximate the function of interest as a linear combination of these basis functions evaluated at the nodes.

Given the values of $f(x_j)$ and the basis functions $\phi_i(x)$, the curve-fitting problem is to minimize the distance between the estimated values, $\hat{f}(x_j)$, and the observed values, $f(x_j)$. Define

$$\begin{pmatrix} \hat{f}(x_0), \\ \hat{f}(x_1), \\ \vdots \\ \hat{f}(x_{J-2}), \\ \hat{f}(x_{J-1}), \end{pmatrix} = \begin{pmatrix} \phi_0(x_0) & \phi_0(x_0) & \cdots & \phi_0(x_0) & \phi_0(x_0) \\ \phi_0(x_0) & \phi_0(x_0) & \cdots & \phi_0(x_0) & \phi_0(x_0) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \phi_0(x_0) & \phi_0(x_0) & \cdots & \phi_0(x_0) & \phi_0(x_0) \\ \phi_0(x_0) & \phi_0(x_0) & \cdots & \phi_0(x_0) & \phi_0(x_0) \end{pmatrix} \begin{pmatrix} c_0 \\ c_1 \\ \vdots \\ c_{N-2} \\ c_{N-1} \end{pmatrix}$$

or using matrix notation

$$\hat{\mathbf{f}} = \mathbf{\Phi} \mathbf{f},$$

where $\hat{\mathbf{f}}$ is a $J \times 1$ vector of estimated values of f, evaluated at the J nodes; $\mathbf{\Phi}$ is an $J \times N$ "interpolation matrix"; and $\mathbf{c}$ is the $N \times 1$ vector of "basis coefficients". Define $\mathbf{f}$ as the $J \times 1$ vector with j'th element the known value $f(x_j)$. For $J \geq N$, the vector $\mathbf{c}$ that minimises the Euclidean distance between $\hat{\mathbf{f}}$ and $\mathbf{f}$ is the familiar Ordinary Least Squares estimator

$$\mathbf{c} = \left(\mathbf{\Phi}'\mathbf{\Phi}\right)^{\mathbf{-1}} \mathbf{\Phi}'\mathbf{f}. \tag{2.32}$$

The inverse exists because of the assumption that the basis functions ϕ_i are linearly independent, and $J \geq N$. The approximation of the function $f(x)$ is $\hat{f}(x) = \phi(x)\mathbf{c}$.

For the application at hand, consider the problem once the nodes and the basis functions have been chosen. Here V^s, rather than f, is the function that we want to approximate. At $s = 0$ we solve the problem on the right side of equation (2.29) for each of the nodes, resulting in the J values (not functions) $V^0(x_i)$, $i = 0, 1, \ldots, J-1$, which we denote in vector form as $\mathbf{V^0}$. We obtain the basis coefficients as above, yielding $\mathbf{c^0} = \left(\mathbf{\Phi}'\mathbf{\Phi}\right)^{\mathbf{-1}} \mathbf{\Phi}'\mathbf{V^0}$. The superscript 0 identifies these as the basis coefficient at the 0 iteration, i.e. at the final stage of the problem. Our estimate of the function $V^0(x)$ is $\hat{V}^0(x) = \phi(x)\mathbf{c^0}$. We now proceed iteratively, at each stage replacing the true but unknown function V^{s-1} with its approximation $\hat{V}^{s-1}(x) = \phi(x)\mathbf{c^{s-1}}$. For example, at stage s, given $\mathbf{c^{s-1}}$, we solve

$$\mathbf{V}_j^s \equiv \max_a \left\{U(a, x_j) + \beta\phi(g(a, x_j))\mathbf{c^{s-1}}\right\}$$

for each each of the J nodes x_j, $j = 0, 1, \ldots, J-1$. At stage $s = 0$ we can claim that we know the values of $V^0(x_j)$, subject to the limits of numerical accuracy. At stages $s > 0$, matters are slightly different. The state $s > 0$ problem is conditioned on the estimate, rather than the true value, of the $s-1$ value function. Therefore, we have only estimates $V^s(x_j)$, not the actual value $V^s(x_j)$. We write this estimate for the values at the nodes as the vector $\mathbf{V^s}$. The stage s basis coefficients are $\mathbf{c^s} = (\mathbf{\Phi'\Phi})^{-1}\,\mathbf{\Phi'V^s}$. Our approximation of the value function at stage s is $\hat{V}^s(x) = \phi(x)\mathbf{c^s}$.

By using approximations, we replace the difficult problem of finding a function at each stage, with the considerably simpler problem of finding a vector of coefficients. Rather than having to store functions in memory, we only have to store vectors of coefficients. Note also that interpolation matrix, $\mathbf{\Phi}$, does not vary over stages. That matrix depends only on our choice of basis functions and of nodes, so we need to compute the matrix $(\Phi'\Phi)^{-1}\,\Phi'$ only once. Moreover, in the case where the basis vectors $\mathbf{\Phi_i}$ are orthogonal, the matrix $\mathbf{\Phi'\Phi}$ is a diagonal matrix and we can do without matrix inversion.

At each stage we obtain the J values

$$a_j^s \equiv \arg\max \left\{U(a, x_j) + \beta\phi(g(a, x_j))\mathbf{c^{s-1}}\right\}. \tag{2.33}$$

It is important to note that, even if the initial condition for x equals a node, optimal behaviour likely causes the next-period state variable to lie between nodes. Therefore, we need the function approximation $\hat{V}^s(x) = \phi(x)\mathbf{c^s}$ rather than just the vector $\mathbf{V_j^s}$.

CHAPTER 3

The optimal balance between Mitigation and Adaptation to Climate Change: An analysis under uncertainty

3.1 Introduction

Climate change is all about uncertainty: uncertainty governing the natural processes involved, uncertainty derived from its long-term scope and uncertainty on how agents endogenise and react to those phenomena. Most IAMs (including DICE) are deterministic and way too complex to enable a proper incorporation of uncertainty. Monte-Carlo methods are the most common approach to addressing uncertainty in the Integrated Assessment literature. However, Monte-Carlo methods, as implemented in this strand of literature, do not model decision making under uncertainty. They present a sensitivity analysis that averages over deterministic simulations.

In the past some authors have managed to address uncertainty in the framework of the DICE model. For instance, Kelly and Kolstad (1999, 2001) build a careful, recursive implementation of the DICE-1994 model to analyse learning time in detail, but they do not consider the separate contributions of uncertainty, learning and stochasticity on near term optimal policies. Leach (2007) adopts a similar methodology to show that learning about the carbon cycle slows down as additional uncertainty enters the model. All these works represent pioneering contributions to the analysis of uncertainty in the literature of climate change. A different set of papers introduce uncertainty into non-recursive implementations of Integrated Assessment Models. In this spirit, we find that Keller et al. (2004) introduce uncertainty and learning into an earlier version of DICE. However, as noted in the earlier chapter, working with non-recursive methods only allows us to deal with a finite (reasonably small) set of uncertain events. For many applications, such as individual uncertain events, they deliver interesting insights. However, these studies cannot replace comprehensive uncertainty evaluations using state of the art stochastic dynamic programming methods.

The quantitative analysis of optimal climatic policies under uncertainty requires a recursive dynamic programming implementation of IAMs. Such implementations are subject to the curse of dimensionality. Every increase in the dimension of the state space is paid for by a combination of (exponentially) increasing processor time, lower quality of the value or policy function approximations, and reductions in the uncertainty domain. However, Traeger (2014) has recently delivered a state-reduced, recursive dynamic programming implementation of the DICE model which, in its basic specification, has only four state variables.[1] This leaves us with some extra margin to enrich the model with new features. Traeger's methodology incorporates uncertainty in every period and the decision maker solves for the optimal policy by reacting to the anticipated future resolution of uncertain future shocks.

As emphasised in the earlier chapter, adaptation to climate change is key to confront climate change impacts and the IPCC has made a plea for advancing in its comprehension and its integration within IAMs. In particular, adaptation would drive resources away from mitigation, as it directly decreases the total damages of climate change. Still, both strategies will remain complementaries because if the social planner does not mitigate (curb) carbon emissions, the stock of carbon in the atmosphere could become unmanageable and, as a consequence, so would global temperature.

Since both mitigation and adaptation must cohabit to fight climate change, a relevant question would be whether or not investment in adaptation would buy time for mitigating. In other words, we would like to know the optimal combination of mitigation and adaptation and determine its path. This combination is known in the literature as the "optimal mix" and the IPCC has successively emphasised in their AR4 (Klein et al., 2007) and AR5 (Mimura et al., 2014) the need for advancing in its study. Using different frameworks, some authors, such as Tol (2005); Tulkens and van Steenberghe (2009); Bosello et al. (2010); Auerswald et al. (2011); Antweiler (2011); Ebert and Welsch (2012); Bréchet et al. (2013) or Markandya et al. (2014) have tried to address the optimal combination of these two magnitudes reporting opposite views: some find that adaptation may appear preferable, especially in developing countries whereas the need for urgent mitigation has also been argued. The inherent message is that their conclusions rest heavily on the assumptions behind their models and, thus, seems difficult to give a clear answer to this question.

The objective of this chapter is, given an optimal composition of the mitigation-adaptation strategies stemming from the deterministic results obtained in Chapter 2,

[1]Basically, this reduction is achieved by simplifying the carbon cycle and the temperature delay equations.

analyse how its optimal dynamics varies when uncertainty is allowed into our model. To do so, we will introduce adaptation *à la de Bruin* in our model and allow for different sources of uncertainty. Including uncertainty into the model may potentially distort results as we already know them. For instance, Lecocq and Shalizi (2010) find on their partial equilibrium model that the cost effectiveness of mitigation is found to increase with regard to adaptation when uncertainty is introduced into their model.

Uncertainties hitting the model can be divided into four broad categories and an example of each group is provided in this study. First, we identify uncertainties about the value of the parameters of the model (epistemic). We will study how an unknown value of climate sensitivity would affect optimal policies and other basic magnitudes. Second, we allow the exogenous processes that govern the dynamics of the model to behave stochastically. We will present stochastic labour-augmenting technology growth as an example. Third, we will include uncertainties in the way individuals (social planner) learn from the past. In particular we will equip our model with Bayesian learning, thanks to which policymakers have a certain prior about the value of certain parameters of the model and update their beliefs in response to the observation of realised variables. Fourth, we will study the possibility of the occurrence of catastrophes, allowing for the existence of tipping points in an undetermined point in time.

The results from allowing for uncertainty in our framework are most of them qualitatively similar across experiments and aim at favouring mitigation with respect to adaptation as a method of insurance against potentially future adverse scenarios. The reason underlying this result is that the social planner fears the pernicious consequences derived from an uncontrolled level of carbon in the atmosphere obtained as a result of very adverse future scenarios. In future exercises, it would be reasonable to extend this result to different adaptation mechanisms, like the one proposed by Bosello et al. (2010), where anticipatory adaptation (modelled as a stock variable), reactive adaptation (modelled as a flow variable) and accumulation of reactive adaptation knowledge can be distinguished.

The remainder of the chapter is organised as follows. In Section 3.2 we will include uncertainty generically into the AD-DICE model and state the Bellman equation. Section 3.3 will draw some messages about the optimal mitigation-adaptation decision if we are myopic about the value of climate sensitivity. In Section 3.4 we will study how a stochastic technology growth affects our model. Section 3.5 will address how the optimal mix varies if individuals learn over the years about the uncertain parameters governing the model. Section 3.6 explores the possibility of having irreversible tipping points that compromise the stability of the system. Finally, Section 3.7 concludes.

3.2 The AD-DICE model under uncertainty

DICE deals explicitly with rational economic agents operating through time in stochastic environments. In this setup, a decision maker must choose a sequence of actions through time subject to some environmental restrictions. If the environment is subject to unpredictable outside shocks, it is clear that the best future actions depend on the magnitude of these shocks. The way of deciding on the immediate action to take as a function of the current situation is called a recursive formulation because it exploits the observation that a decision problem of the same general structure recurs each period.[2] The use of recursive methods makes it possible to treat a wide variety of dynamic economic problems, both deterministic and stochastic. The power of dynamic programming, relative to an alternative such as nonlinear programming, is most evident with stochastic problems.

Our version of DICE resembles closely the stochastic dynamic programming implementation of DICE by Kelly and Kolstad (1999) and its posterior adaptation by Traeger (2014). The main contribution of the latter is to reduce the number of states needed to represent the climate side of the model without sacrificing its benchmark performance in capturing the interaction between emissions and the increase in temperature. Such reduction of the state space is crucial to allow for additional state variables needed to capture uncertainty and avoid the curse of dimensionality.[3] To model the adaptation behaviour, we rely on the work by de Bruin et al. (2009), which allows us to separately choose between mitigation and adaptation at every optimisation stage. The reader should refer to Figure 2.1 of Chapter 2 to have a glimpse of the detailed workflow of the model. The equations and processes governing the model are fully described in Section 2.2.

Under uncertainty, the social planner optimal sequence of decisions has to take into account not only the current realisation of the uncertain variables, but also the expected future values of those random variables. This is represented in our value function by including additional states summarised in the vector Φ_t. We then would write the value function as $V(k_t, M_t, T_t, \Phi_t, t)$,

$$V(k_t, M_t, T_t, \Phi_t, t) = \max_{c_t,\mu_t,p_t} L_t \frac{c_t^{1-\eta}}{1-\eta}\Delta t + \beta_{t,\Delta t} E\left[V(k_{t+\Delta t}, M_{t+\Delta t}, T_{t+\Delta t}, \Phi_{t+\Delta t}, t+\Delta t)\right], \tag{3.1}$$

which is an augmented version (for uncertainty) of equation (2.24).[4]

[2] Recursive methods in economics were extensively introduced by Stokey et al. (1989).

[3] We cut the number of state variables almost to half with respect to the original DICE formulation.

[4] Again, bear in mind that this expression is the normalised version of the Bellman equation, in

We solve the model using the algorithm presented in Appendix 2.B. Expectations are approximated numerically using the procedure described in Appendix 3.B. We run the resulting code in Matlab using the *compecon* optimiser as described in Miranda and Fackler (2002). Since each of the optimisation at the different Chebychev nodes is independent conditional on the time step, we can compute each of them independently. Hence, we make use of the *Parallel Programming Toolbox* in *Matlab* to parallelise that process so that the whole process speeds up nearly 4 times.[5] Once solved, we can quickly simulate a large set of runs and depict statistical properties.

3.3 Uncertainty about climate sensitivity

A paradigmatic source of uncertainty is that arisen due to imperfect knowledge of the parameters governing the dynamics of the model. We call it parametric (or epistemic) uncertainty. The present system is represented by a very large set of parameters. One of those whose calibration arises more controversy is climate sensitivity. The reader should recall that climate sensitivity is the equilibrium temperature response to doubling of atmospheric CO_2 concentration with respect to pre-industrial levels and is represented by s in our model. Despite significant advances in climate science, the "likely" range has been 1.5°C to 4.5°C for over three decades, with a "most likely" value of 3°C. In 2007, the IPCC narrowed the likely range to 2-4.5°C. It reversed its decision in 2013, reinstating the old range. The AR5 also removed the 3°C "most likely" value.

We start with a simple but powerful exercise. The social planner ignores the actual value of climate sensitivity but has a guess of it. She solves the problem as if this guess was the actual value of s. In particular, she assumes that climate sensitivity takes a deterministic value of 3.08 (borrowed from the deterministic scenario).[6] Then, we present a sensitivity analysis of our results by assuming that the actual climate sensitivity values stem from the realisation of the following random variable

$$\tilde{s} \sim N(\mu_s, \sigma_s^2)$$

centred at $\mu_z = 3.08$ and standard deviation $\sigma_z = 2.7\%$. Typically, this parameterisation will yield values belonging to the interval (1.5,4.5), which are claimed by the IPCC

which capital is expressed in effective labour units. Without normalising capital, we would need a much larger state space for capital to cover at least a reasonably long time horizon.

[5] In a Windows 10, Intel i7-2600 @3.40GHz PC. Matlab R2011a.

[6] The rest of parameters take the same values as in the benchmark specification. Please refer to Tables 2.1 and 2.2 in Chapter 2 for further details.

as “likely” values of this parameter. After solving the problem, we run a set of $N = 100$ simulations projecting the model forward for each of the respective realised values of climate sensitivity, taking optimal rules as fixed. This exercise tries to illustrate how outcomes behave over time if the social planner has a guess about the value of climate sensitivity and this guess does not get modified over time. In other words, the social planner is *myopic* about the true value of s.

A description of some of the basic results can be found in Figure 3.1. The model features essentially the basic properties of the standard AD-DICE model but now the degree of variability of the basic magnitudes increase in response to climate sensitivity miscalculations. As depicted in the various panels of Figure 3.1 the main variables of the model behave similarly to the benchmark specification and most of them fluctuate symmetrically around the median values.

Lower (higher) climate sensitivity will decrease (increase) mitigation relative to adaptation. The rationale behind is that if emissions cause less climate change, there will be lower damages. This will lead to lower levels of mitigation and adaptation. These latter results are gently summarised in Figure 3.2. Specifically, a slow climatic response diverts resources to instantly adapt to climate change in the short-run (more than half of the resources are devoted to adaptation) although the long-term optimal behaviour still yields a stable equilibrium of the mix (60% mitigation - 40% adaptation). Conversely, if high climate sensitivity applies, mitigation is relatively more beneficial to combat climate change. As a result, a ratio of 75%-25% quickly becomes optimal. In this case, we can find optimal full abatement of emissions in the very long run.

3.4 Stochastic technology growth

Now we present an analysis of the optimal mix between mitigation and adaptation when fundamental processes governing the dynamics of the model are stochastic. Among these sources of uncertainty, we can find randomness in shocks affecting the growth of technology, the accumulation of carbon, the evolution of temperatures, and so forth.

One of the processes traditionally considered to be crucial for climatic outcomes is by far the growth in total factor productivity (TFP). The reason is that TFP is the main driver of economic growth in the long run, and output tends to dominate emissions trends and therefore climate change. In this experiment, we will assume that the rate of technological progress is uncertain. The technology level enters the Cobb–Douglas production function and determines the overall productivity of the economy. A shock in the growth rate permanently affects the technology level in the economy. The technology level in the economy, A_t, follows the equation of motion

$$\tilde{A}_{t+1} = A_t \exp[\tilde{g}_{A,t}] \qquad \text{with} \quad \tilde{g}_{A,t} = g_{A,0} \exp[\delta_A t] + \tilde{z}_t. \tag{3.2}$$

3.4.1 Normalised Bellman equation under stochastic technology growth

As in the benchmark formulation, it is convenient to use the normalised Bellman equation (3.1) to ease the numerical calculations. In this respect, we follow closely Jensen and Traeger (2014). To express variables in effective labour units, we normalise by the deterministic technology level, A^{det}.[7] Its dynamic behaviour responds to the following equation

$$A_{t+1} = A_t^{det} \exp[\bar{g}_{A,t}] \qquad \text{with} \quad \bar{g}_{A,t} = g_{A,0} \exp[\delta_A t].$$

If we define $a_t = \frac{A_t}{A_t^{det}}$ as the deviation of the current technology level away from its respective deterministic value, then the technology deviation at $t+1$

$$\tilde{a}_{t+1} = \frac{\tilde{A}_{t+1}}{A_{t+1}^{det}} = \frac{\exp\left(\tilde{g}_{A,t}\right) A_t}{\exp\left(g_{A,t}\right) A_t^{det}} = \exp\left(\tilde{z}_t\right) a_t$$

will be a random variable that will lead us to a new normalised Bellman equation

$$V^*(k_t, M_t, T_t, a_t, t) = \max_{c_t, \mu_t, p_t} \frac{c_t^{1-\eta}}{1-\eta} \Delta t + \beta_{t,\Delta t} E\left[V^*(k_{t+\Delta t}, M_{t+\Delta t}, T_{t+\Delta t}, \tilde{a}_{t+\Delta t}, t+\Delta t)\right].$$

After this renormalisation some equations will differ slightly from those presented in the benchmark formulation of the model. In particular, the gross product per effective unit of labour (previously, $y_t^{gross} = k_t^{\kappa}$) now reads

$$y_t^{gross} = a_t^{1-\kappa} k_t^{\kappa},$$

where it now incorporates the stochastic deviations of technology away from its deterministic level. Accordingly, yearly CO_2 emissions derived from industrial emission will change so that total CO_2 emissions now follow

$$E_t = (1-\mu_t)\sigma_t A_t^{det} a_t^{(1-\kappa)} L_t k_t^{\kappa} + B_t,$$

where B_t represents total emissions from land use change. The rest of equations hold as presented in Section 2.2.

[7] $A^{det} \equiv$ level of technology in the certainty scenario ($z_t = 0$, $\forall t$)

Calibration of the *iid* technology growth shock

Our set of simulations analyse the consequences of an *iid* shock

$$\tilde{z}_t \sim N(\mu_z, \sigma_z^2).$$

Following Jensen and Traeger (2014), we set the standard deviation to $\sigma_z = 2.6\%$, a somewhat conservative value if compared with the usual calibration of *iid* technology growth shocks in the empirical macro literature, which corresponds to twice the initial technology growth rate in the deterministic scenario.

For the sake of comparison between specifications, the mean of the technology shock, μ_z, is calibrated so as to have on average a similar technology path as in the deterministic scenario. Still, this calibration displays enough variability once different technology paths are simulated.

$$\begin{aligned}
\tilde{A}_{t+j} &= \tilde{a}_{t+j} A_{t+j}^{det} = \exp\left(\tilde{z}_{t+j-1}\right) \tilde{a}_{t+j-1} A_{t+j}^{det} \\
&= \exp\left(\tilde{z}_{t+j-1} + \tilde{z}_{t+j-2}\right) \tilde{a}_{t+j-2} A_{t+j}^{det} \\
&= \exp\left(\sum_{j'=0}^{j-1} \tilde{z}_{t+j'}\right) a_t A_{t+j}^{det}.
\end{aligned}$$

Then

$$\begin{aligned}
E\left[\tilde{A}_{t+j}\right] &= E\left[\exp\left(\sum_{j'=0}^{j-1} \tilde{z}_{t+j'}\right) a_t A_{t+j}^{det}\right] \\
&= \exp\left(\sum_{j'=0}^{j-1} \left(\mu_z + \frac{\sigma_z^2}{2}\right)\right) a_t A_{t+j}^{det} \\
&= \exp\left(j\left(\mu_z + \frac{\sigma_z^2}{2}\right)\right) a_t A_{t+j}^{det}.
\end{aligned}$$

Hence, if we set $\mu_z = -\frac{\sigma_z^2}{2}$, we have that

$$E\left[\tilde{A}_{t+j}\right] = a_t A_{t+j}^{det},$$

which is not more than the deterministic value of technology at time $t + j$.

3.4.2 Main results

In Figure 3.3 we observe the overall results after running 100 simulations with $\sigma_z = 2.6\%$ and $\mu_z = 3.38 \cdot 10^{-4}$. As it emerges from the upper left panel of Figure 3.3, technology deviations do not represent a major force to deviate from the optimal mix under a potential deterministic scenario.[8] Only subtle changes in response to transitory deviations are observed in the optimal allocation between mitigation and adaptation. As a consequence, the observed atmospheric CO_2 stock gravitates also around the deterministic values, as noted in Figure 3.3b. The bottom panels of Figure 3.3 depict the evolution of the stock of capital in our simulated states of the world, which respond directly to the uncertain path of technology.

Meanwhile, Figure 3.4 compares the deterministic optimal path of the mix with the median values resulting from our simulated series. In general, we may state that including uncertainty in the technology level favours adaptation as it stems from the parallel shift of the mix downwards. Specific levels of the mix will depend on the magnitude of the shocks.

The total amount of resources allocated to mitigation are described in Figure 3.5a. Abatement expenditure is measured as a fraction of gross output. This variable is a function of the emission control rate (abatement rate). This abatement rate characterises the percentage of emissions avoided under a climate policy, as compared to a laissez-faire world. As observed, total mitigation decreases relative to total output because positive technology shocks incline the social planner to produce more and thus, release more CO_2 in good years. Accordingly, the median level of CO_2 in the atmosphere is slightly larger along time, as it can be seen in Figure 3.5b, with CO_2 peaking at a higher level, later than in the deterministic case.

3.5 Learning about uncertain climate sensitivity

In this section we will address how optimal decisions vary if individuals learn over the years about the uncertain parameters governing the model. Similarly to Section 3.3 we will assume that climate sensitivity is not known but in this case we will have a guess of its value.[9] This guess will be updated at each iteration through Bayesian learning once the stock of carbon and temperature are observed. In particular we will assume

[8] Each point in these pictures is visually weighted according its probability density, that is, darkest shaded areas represent locations most probably visited whereas lighter areas denote less likely outcomes.

[9] Recall that climate sensitivity captures the equilibrium warming from doubling the CO_2 concentration with respect to pre-industrial levels.

that the social planner is unsure about the true value of climate sensitivity, s, but holds the following prior

$$\tilde{s}_0 \sim \Pi(s) = \mathcal{N}(\mu_{s,0}, \sigma^2_{s,0}).$$

In addition to its uncertain nature due to unknown climate sensitivity, atmospheric temperature is also stochastic, insofar as it responds to random weather fluctuations. These weather fluctuations are normally distributed with mean zero. Thus, for a given value of climate sensitivity, s, temperature behaves according to the following law of motion

$$\tilde{T}_{t+1} = (1 - \sigma_{forc})T_t + \sigma_{forc} s \left[\frac{\ln \frac{M_t}{M_{pre}}}{\ln 2} + \frac{EF_t}{\eta_{forc}} \right] - \sigma_{ocean} \triangle T_t + \tilde{\epsilon}_t. \tag{3.3}$$

For a given value of s, since ϵ follows a normal distribution, so will do temperature

$$\tilde{T}_{t+1} \sim \mathcal{N}(\mu_{T,t+1}(s), \sigma^2_T),$$

with variance σ^2_T, known and exogenous.[10]

The temperature mean is obtained from taking expectations in equation (3.3) is

$$\mu_{T,t+1} = s\chi_t(M_t, t) + \xi_t(T_t, t),$$

where

$$\chi_t(M_t, t) = \sigma_{forc} \left(\frac{\ln \frac{M_t}{M_{pre}}}{\ln 2} + \frac{EF_t}{\eta_{forc}} \right),$$
$$\xi_t(T_t, t) = (1 - \sigma_{forc})T_t - \sigma_{ocean} \triangle T_t.$$

Assuming the above prior and its respective updating rule, a predictive rule for temperatures can be obtained.[11] In particular, the mean of the prior at time $t+1$ is

$$\mu_{s,t+1} = \frac{\chi^2_t \sigma^2_{s,t} \frac{\hat{T}_{t+1} - \xi_t}{\chi_t} + \sigma^2_T \mu_{s,t}}{\chi^2_t \sigma^2_{s,t} + \sigma^2_T},$$

whereas the variance is updated through

[10] Empirical estimates suggest annual volatility in global mean temperature in $\sigma^2_T = 0.042$.
[11] See Jensen and Traeger (2013) to check the full derivation of these results.

$$\sigma_{s,t+1}^2 = \frac{\sigma_T^2 \sigma_{s,t}^2}{\chi_t^2 \sigma_{s,t}^2 + \sigma_T^2}. \tag{3.4}$$

As a result, the decision maker learns faster the lower the temperature stochasticity and the larger the carbon stock. We must add to the state variables governing the model (k, M, T and t) those responsible for updating the climate sensitivity prior $\Pi(s)$, namely, $\mu_{s,t}$ and $\sigma_{s,t}^2$. Meanwhile, the predictive equation of temperature governs the realisation of temperature in $t+1$ accounting for stochasticity and climate sensitivity uncertainty. More precisely, $\hat{T}_{t+1} \sim \mathcal{N}(\chi_t \mu_{s,t}, \chi_t^2 \sigma_{s,t}^2 + \sigma_T^2)$.

The Bellman equation reads now as follows

$$\begin{aligned} V^*(k_t, M_t, T_t, t, \mu_{s,t}, \sigma_{s,t}^2) = &\max_{c_t, \mu_t, p_t} \frac{c_t^{1-\eta}}{1-\eta} \Delta t \\ &+ \beta_{t,\Delta t} E \left[V^*(k_{t+\Delta t}, M_{t+\Delta t}, \tilde{T}_{t+\Delta t}, t+\Delta t, \tilde{\mu}_{s,t+\Delta t}, \tilde{\sigma}_{s,t+\Delta t}^2) \right]. \end{aligned} \tag{3.5}$$

The new Bellman equation has six state variables: three physical state variables (k, M, T) and three informational variables $(t, \mu_{s,t}, \sigma_{s,t}^2)$ that characterise the state of the system.

As in the previous section, we simulate the system forward 300 steps using the optimal control obtained in the estimation phase. In this exercise, we assume that the social planner holds an accurate prior about the mean of climate sensitivity equal to its actual value ($\mu_{s,0} = 3$) but she is slightly unsure about her belief ($\sigma_{s,0}^2 = 3$). These beliefs are updated each period so that the social planner gradually learns about how correct are her beliefs through the observation of realised variables. Additionally, each year an exogenous, additive shock $\epsilon_t \sim \mathcal{N}(0, \sigma_T^2)$ affects global temperature, with $\sigma_T^2 = 0.042$. Random fluctuations of temperature will add an extra degree of complexity to how the planner disentangles the actual value of climate sensitivity.

The compendium of simulated optimal mix strategies are depicted in Figure 3.6. The risk-averse social planner now decides to mitigate relatively more as she is uncertain about whether the desired mitigation level will be able to cope with the expected increase in temperatures. As the prior becomes more certain (decrease in the prior variance shown in Figure 3.7) the optimal mix returns to more balanced values. However, it does not recover the values shown in the deterministic case. The median behaviour of the optimal mix is shown in Figure 3.8, where a notable shift in the relative importance of mitigation is observed. Having more accurate guesses of actual climate sensitivity let the social planner calculate more precisely real damages, which entitles her to fighting more efficiently against them. A direct implication of the above is that total mitigation increase rapidly during the first years after 2010 (see Figure 3.9a). The planner assigns a greater amount of resources to control emissions, as compared to the deterministic case. This desire for early strong mitigation has a direct impact on CO_2 concentrations, as drawn in Figure 3.9b, where a maximum is observed around year 2150 at a level of approximately 1.400 gigatonnes of carbon. After that point, CO_2 concentration start gradually to decrease.

3.6 Tipping points

The evolution of climate variables entails different sources of uncertainty inherent to the climate system. Despite most climate change models predict an overall robust increase in global temperatures at the end of the present century, it is not excluded that the occurrence of certain climatic phenomena could provoke a series of abrupt, sudden changes in the system that may end being non-reversible. Tipping points are understood as irreversible shifts in system dynamics that occur upon crossing a threshold in the state space. In a climate change context, tipping points have been modelled differently by several authors. Some examples are the work by Cai et al. (2015) and Diaz (2015). We will follow the approach by Lemoine and Traeger (2014), in which the social planner does not know the exact location of this threshold. The probability of a tipping point occurring, known as the hazard rate, is endogenous and depends on the evolution of the state variables, which in turn depends on policy choices as well as on the stochastics governing the system. The social planner learns that regions that she has already visited are free of tipping points. Crossing the threshold shifts the world from the pre-threshold regime to a post-threshold regime with permanently altered system dynamics. Optimal pre- and post-threshold policies together determine the welfare loss triggered by the tipping point.

We evaluate a tipping point of prominent concern in the climate change literature: this tipping point increases the climate feedbacks that amplify global warming, that is, it increases the effect of emissions on temperature. In particular climate sensitivity will shift from 3°C after doubling CO_2 concentrations in the pre-threshold regime to 4°C in the post-threshold regime. The new dynamics can include melted ice sheets, large methane releases, or disruptive forest ecosystems; lowering temperature would not undo any of these changes. Optimal policy in the pre-threshold regime must consider its effect on both the pre- and post-threshold value functions, but once the state variables cross the threshold, optimal policy depends only on post-threshold dynamics. Therefore, we solve the model recursively, starting with the post-threshold problem and then substituting the solution into the pre-threshold problem.

The system passes from the pre-threshold level ($\psi_t = 0$) into the post-threshold regime ($\psi_{t+1} = 1$) when cumulative temperature change T_{t+1} crosses an unknown threshold, $\hat{T}$. We assume an uniform prior distribution for thresholds. This distribution recognises that more warming entails more threshold risk. The uniform distribution for T means that every temperature between the maximum temperature previously reached and an upper bound $\bar{T}$ has an equal chance of being the threshold. The probability of crossing the threshold between periods t and $t+1$ conditional on not having crossed the threshold by time t is

$$h(T_t, T_{t+1}) = \max\left\{0, \frac{\min\left\{T_{t+1}, \bar{T}\right\} - T_t}{\bar{T} - T_t}\right\}. \tag{3.6}$$

This expression is the hazard of crossing the tipping point. As the world reaches higher temperatures without reaching a threshold, the social planner learns that the threshold is above the current temperature and updates his beliefs by moving probability density from the newly safe region to the remaining unexplored temperatures.

For the sake of clarity in the exposition, let summarise our set of state variables in the vector S whereas our control variables will be denoted by x. In the post-threshold world the Bellman equation would read

$$V_1^*(S_t) = \max_{x_t} u(x_t, S_t) + \beta_t \int V_1^*(S_{t+1}) dP, \tag{3.7}$$

whereas the pre-threshold Bellman equation reads as follows

$$V_0^*(S_t) = \max_{x_t} u(x_t, S_t) + \beta_t \int \left[(1 - h(T_t, T_{t+1}))\, V_0^*(S_{t+1}) + h(T_t, T_{t+1}) V_1^*(S_{t+1})\right] dP. \tag{3.8}$$

This maximisation problem will be subject to the usual restrictions, now described by their compact notation

$$S_{t+1} = g_1(x_t, \epsilon_t, S_t) \quad \text{and} \quad x_t \in \Gamma(S_t),$$

where the first equation describes the law of motion of the state variables and the second term assures that our control variables will belong to a feasible set.[12] The novel aspect here is that the law of motion of the model's state variables now depends on the vector ϵ_t of *iid* shocks, whose distribution is characterized by the probability measure P.

Because of the stochasticity in the equations of motion, we take expectations over

[12] These restrictions are described with detail in chapter 2.

the next period's value functions and over the hazard rate (via the integral). We approximate expectations using a Gauss-Legendre quadrature rule with 8 nodes. Once we have solved for V_1 in (3.7), we find V_0 as the fixed point in (3.8).

3.6.1 Main results

The first step of this exercise involves the resolution of the Bellman equation under the possibility of crossing a tipping point that triggers worse environmental conditions (we would pass from $s = 3$ in the pre-threshold world to $s = 4$ after the tipping point is hit). With this experiment we try to estimate the effect that the sole inclusion of this undetermined trigger point may have in the inferred optimal policies, paying special attention to the composition of the optimal mix. We will check whether the social planner insures herself against this potential danger. Accordingly, the Bellman equation that the planner faces takes the form

$$V_0^*(S_t) = \max_{x_t} u(x_t, S_t) + \beta_t \left[(1 - h(T_t, T_{t+1}))\, V_0^*(S_{t+1}) + h(T_t, T_{t+1}) V_1^*(S_{t+1}) \right], \quad (3.9)$$

where V_1^* represents the optimal response in the post-threshold scenario and V_0^* corresponds to the optimal pre-threshold response if we take into account the possibility of an undetermined tipping point in time.[13] We approximate both value functions, feeding the values of V_1^* into the resolution of V_0^* and then simulate the system as if the tipping point never occurs. We also assume expected draws of the weather shock. The mere inclusion of the possibility of tipping points in the model result in an increase of the mitigation motive as shown in Figure 3.10. In this way, the social planner prevents the occurrence of the tipping point by mitigating relatively more as compared to the benchmark scenario. Total mitigation increases with respect to the deterministic scenario as a result of facing every period the possibility of the system collapsing. This behaviour can be observed in Figure 3.11, where total expenditure in abating emissions relative to output is permanently higher than in the deterministic case.

3.6.2 Stochastic temperature

In the next experiment, we include a new source of uncertainty represented by an exogenous random additive shock which impacts global temperatures each period. This shock will be distributed as $\tilde{\epsilon}_{Tt} \sim \mathcal{N}(0, \sigma^2_{T\epsilon})$, with $\sigma^2_{T\epsilon} = 0.042$.[14] Each period, exoge-

[13] The post-threshold scenario involves an increase of climate sensitivity from 3 to 4.

[14] Further details in Lemoine and Traeger (2014).

nous weather fluctuations affect global atmospheric temperatures and thus, the law of motion of temperatures behaves analogously to (3.3). The general Bellman equation described in (3.8) applies and temperature is now stochastic.

In general, and qualitatively close to the results presented in Section 3.5, the social planner decides to react to the uncertainty created by both tipping points and stochastic temperatures by favouring emissions abatement with respect to adaptation to climate change impacts. This behaviour is clearly visible in Figure 3.12, where an upward parallel shift of the optimal mix curve is observed. Optimal mitigation grows steadily relative to adaptation over the first years until it stabilises in later years around a range of 75% of climate investments.

3.6.3 Stochastic damage

Lastly, we explore the possibility of facing an uncertain damage function. This would be the equivalent of having an imperfect estimate of the functional form of the damage function. In this sense, we enable some deviations in its realisation each period. With this experiment, we try to measure the degree of sensitivity of the social planner against uncertainties in the effect on output of temperature changes. Conceptually, this is very similar to the case where we are unsure about the true value of climate sensitivity but this time the effect is manifested through the damage function. Hence, we modify the shape of the climate damage function and let a multiplicative random shock in temperature intervene each period. The new gross damage function reads

$$GD_t = 1 + b_1(\tilde{\epsilon}_{Dt} T_t)^{b_2},$$

where the independent, normally distributed multiplicative shock $\tilde{\epsilon}_{Dt} \sim \mathcal{N}(1, \sigma^2_{D\epsilon})$ with $\sigma^2_{D\epsilon} = 0.0068$.[15]

The results are qualitatively analogous to those derived with stochastic temperatures as it can be observed in Figure 3.13. In this case, though, given the calibration of the damage shock, the planner can accommodate easily the variations in the damage function so that results are numerically close to those presented in the deterministic case. But the results of this exercise share most of the common features of the previous simulations, namely, in the presence of uncertainty in the processes governing the dynamics of the model, the social planner prefers to deviate more resources to long-lasting mitigation with respect to more instantaneous but short-lived adaptation. The risk-averse nature of the social planner acts in favour of less volatile future consumption scenarios. Familiarly to other scenarios where the planner is inclined to intensively

[15] See Lemoine and Traeger (2014) for further details on the calibration of this parameter.

mitigate, the resulting concentration of CO_2 in the atmosphere peaks earlier and at a lower level, compared to our deterministic benchmark scenario. This can be seen in Figure 3.14.

3.7 Conclusion

Incorporating new features into IAMs is highly desirable but comes at a cost. In particular, it makes most of these models suffer from the curse of dimensionality. To overcome this problem we adapt a recent methodology proposed by Traeger (2014) which casts the well established Nordhaus' DICE model in a recursive way, making it particularly suitable for uncertainty analysis. At the same time, it reduces the state space to only four state variables, thus, making the model accessible to be solved in a regular computer. By adopting this methodology, we echo the IPCC's call for greater integration of adaptation within Integrated Assessment modelling and extend the original DICE model by incorporating adaptation à la de Bruin, that is, specifying adaptation as a separate decision variable. Then, we perform a thorough analysis of the optimal balance between mitigation and adaptation under various stochastic scenarios.

In a first exercise, we solve the model for an assorted amount of different climate sensitivities. Recall that climate sensitivity is the reaction of the system, in terms of mean air temperature, to a doubling of the CO_2 concentration. Climate sensitivity is an unknown parameter, reportedly said to show a positive value around 3. We confirm that climate sensitivity is crucial in determining how the system behaves. Very high values cannot be easily accommodated by efficiently mitigating nor adapting damages. On a second exercise, we assume a random path for technology. Technology enters directly into the production function and is reported to be the major source of distortion in the basic properties of the DICE model. Our results suggest that, indeed, technology growth amounts to be a great source of distortion. If we look at the mitigation-adaptation mix, we can infer that adaptation is more efficient in coping with an uncertain technology scenario.

Next, we include the possibility of dealing with an unknown climate sensitivity. The planner, though, holds a prior of its value and learns gradually about its certain value through time thanks to the observation of realised climatic variables. Hence, we equip our model with Bayesian learning about climate sensitivity. Consequently, the observation of realised temperature will be itself imperfect and so will be the updates of our priors. The results show that, the higher the degree of ignorance of the social planner about the true value of climate sensitivity (higher variance), the more she will try to protect herself with the help of more mitigation relative to adaptation.

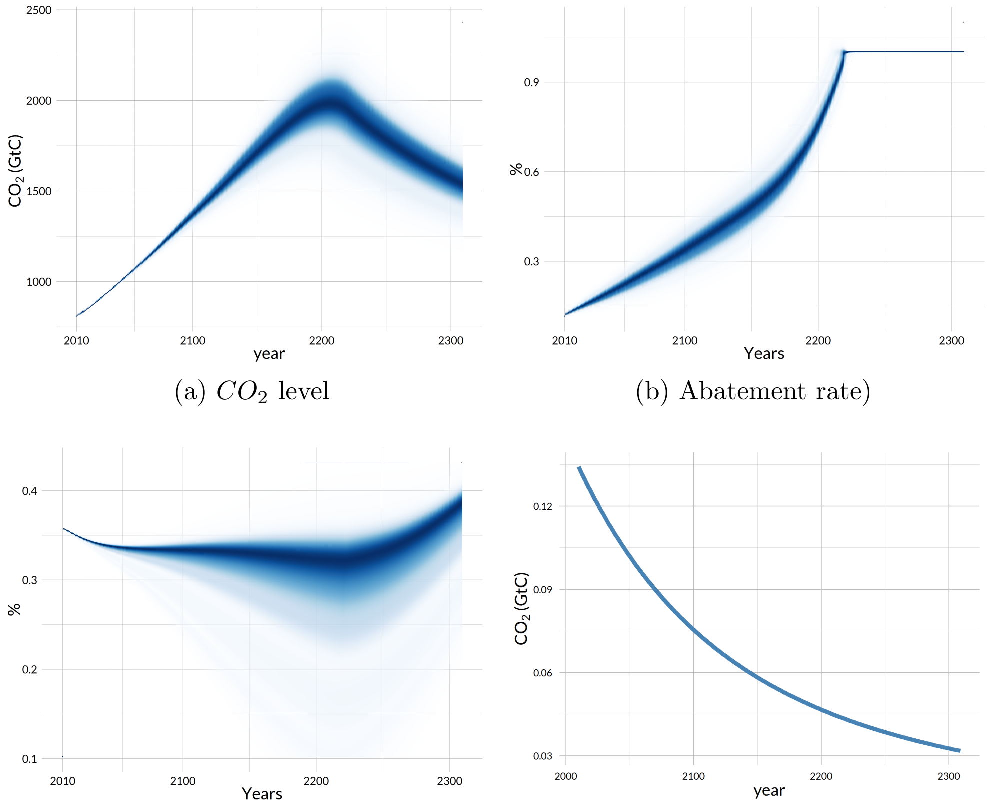
Lastly, we feed our model with a very interesting feature in the context of climate change: the possibility of crossing a determined (unknown) temperature threshold or tipping point after which the dynamics of the system behaves notably different. In our example, this change in the dynamics is manifested by an increase in climate sensitivity from 3 to 4. We analyse the effect in the optimal mix under three different scenarios: deterministic, stochastic temperatures and stochastic damages. The results are all qualitatively similar and all aim at favouring mitigation with respect to adaptation as a method of insurance against potentially future adverse scenarios.

Only a few examples about the dynamically optimal strategy to fight climate change under uncertainty can be found in the literature and their results are qualitatively very similar to ours. Antweiler (2011) finds that the optimal mix would depend crucially on the cost of adaptation relative to mitigation (as we found in Chapter 2) and on the sensitivity of climate change and existence of tipping points. Similarly to us, this author also finds that uncertainty about the values of the latter would bias the policy choice. In particular, an expected slow-speed, slow-risk climate change would deviate resources from mitigation to adaptation and high risk scenarios would tilt out strategy from adaptation to mitigation. Auerswald et al. (2011), on the other hand, do not analyse the temporal dimension of the problem but, in accordance to our findings, they find that uncertainty about the future damages from climate change forces countries to invest in adaptation and mitigation measures as two alternative forms of self-insurance complements.

There exists great debate on the grounds for prioritising efforts on mitigation relative to adaptation. According to our results, a risk-aware (risk-averse) global policymaker should allocate more resources, but not only, to mitigation efforts to fight climate change. This result comes from the interplay of the huge inertias and delays involved in the Earth system and the risk associated to uncertain, catastrophic events in the distant future. It is true, however, that the marginal impact of adaptation investment may differ across countries (regions). Typically, lower developed countries would benefit greatly from climate change adaptation measures and this would affect total climate damages. We would need to model different sensitivities to adaptation investments to embed this feature in our model. An adaptation of our methodology applied to the regional RICE model (Nordhaus and Yang, 1996) would be useful for this purpose.

This study represents a new approach to the dynamic analysis of adaptation to climate change within a simplified recursive IAM fed with various potential sources of uncertainty. Many other additional features can be further incorporated into this model: uncertainty in the parameters governing the damage function, alternative damage function specifications, persistent effects of technology shocks, and so forth. Additionally, different types of adaptation could be jointly modelled. For example, Bosello et al. (2010) construct a more involved framework in which they distinguish between anticipatory adaptation (modelled as a stock variable), reactive adaptation (modelled as a flow variable) and accumulation of reactive adaptation knowledge. A sensitivity analysis of these results in response to different attitudes of the social planner towards risk could also be worthwhile. These extensions are left for future research papers.

3.A Tables and Figures



(a) CO_2 level

(b) Abatement rate)

(c) Investment rate

(d) CO_2 emissions)

Figure 3.1: AD-DICE (uncertain climate sensitivity)

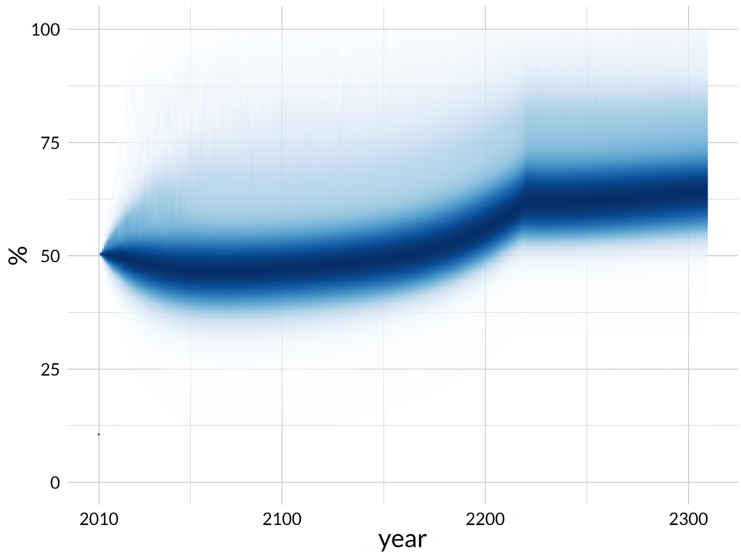
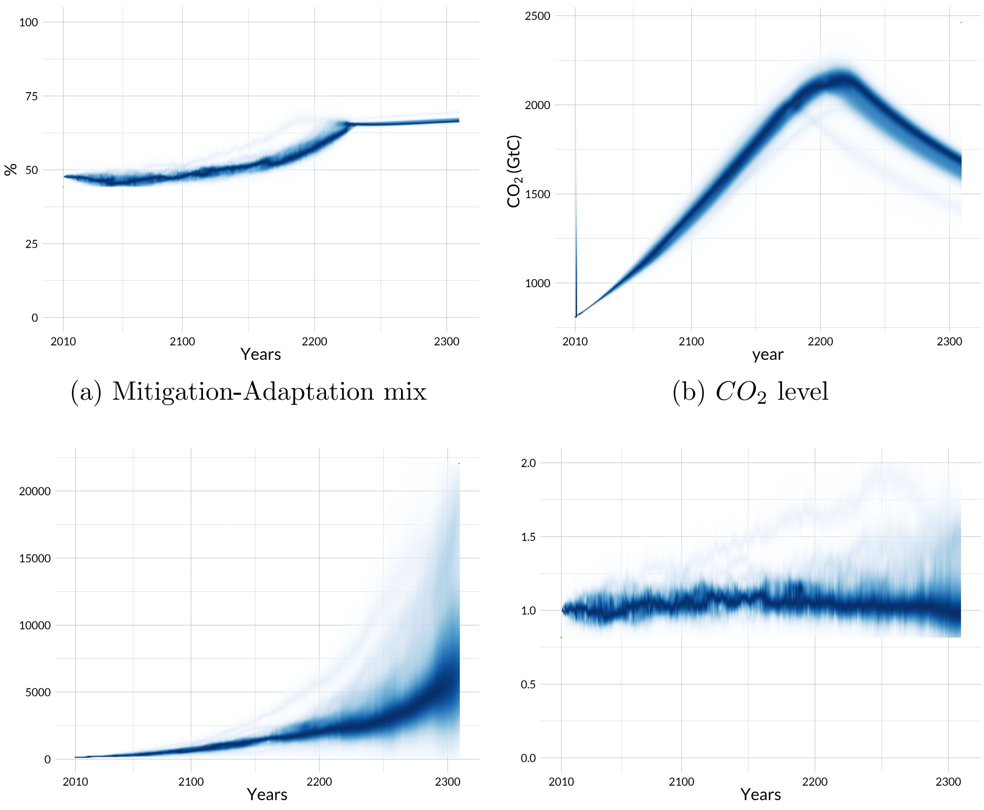


Figure 3.2: Mitigation-Adaptation mix (uncertain climate sensitivity)

*This figure depicts the median ($N = 100$) optimal response of the social planner. The mix is defined as [mitigation/(mitigation+adaptation)]*100.*



(a) Mitigation-Adaptation mix

(b) CO_2 level

(c) Capital

(d) technology deviation)

Figure 3.3: AD-DICE (uncertain technology)

*All pictures feature shaded areas according to probability density. The mix is defined as [mitigation/(mitigation+adaptation)]*100.*

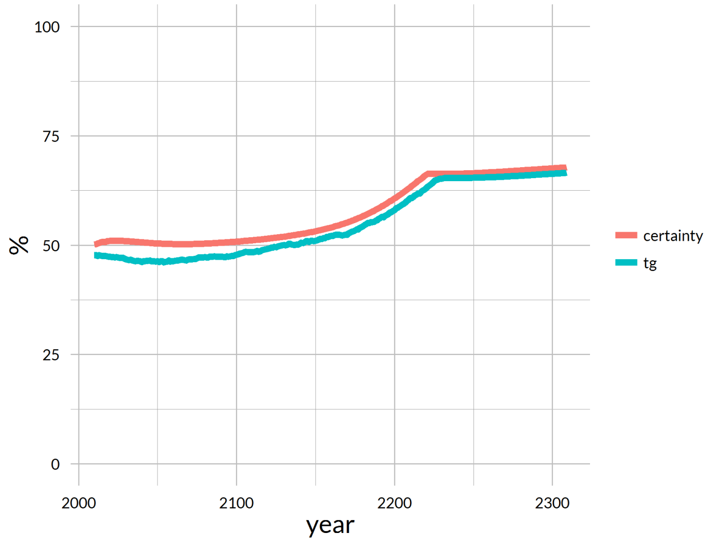
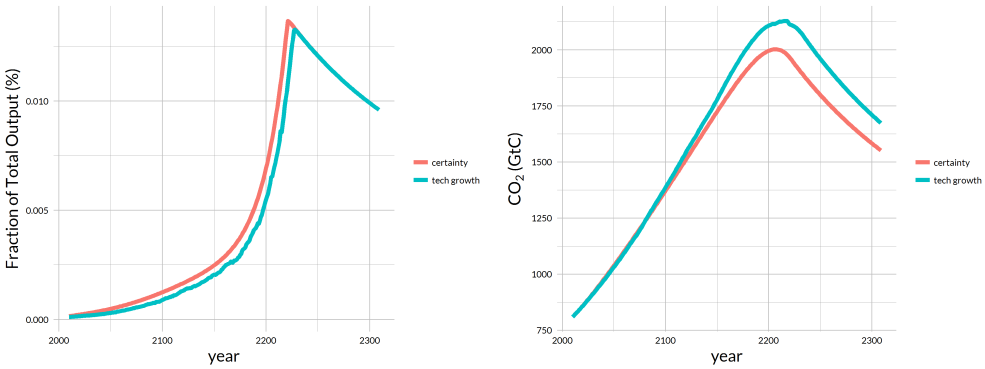


Figure 3.4: Mitigation-Adaptation mix (deterministic versus stochastic technology growth)

This figure depicts the median ($N = 100$) response of the social planner against the optimal response under the benchmark model. Each period technology deviates from its deterministic path according to an additive shock of standard deviation $\sigma_z = 2.6\%$ and mean $\mu_z = 3.38 \cdot 10^{-4}$.



(a) Abatement expenditure

(b) CO_2 level

Figure 3.5: Total mitigation and CO_2 concentration (deterministic versus stochastic technology growth)

This figure describes the median ($N = 100$) time path of total abatement expenditure (left) and CO_2 concentration in the atmosphere (right) against their optimal path under the benchmark (deterministic) model. Each period technology deviates from its deterministic path according to an additive shock of standard deviation $\sigma_z = 2.6\%$ and mean $\mu_z = 3.38 \cdot 10^{-4}$.

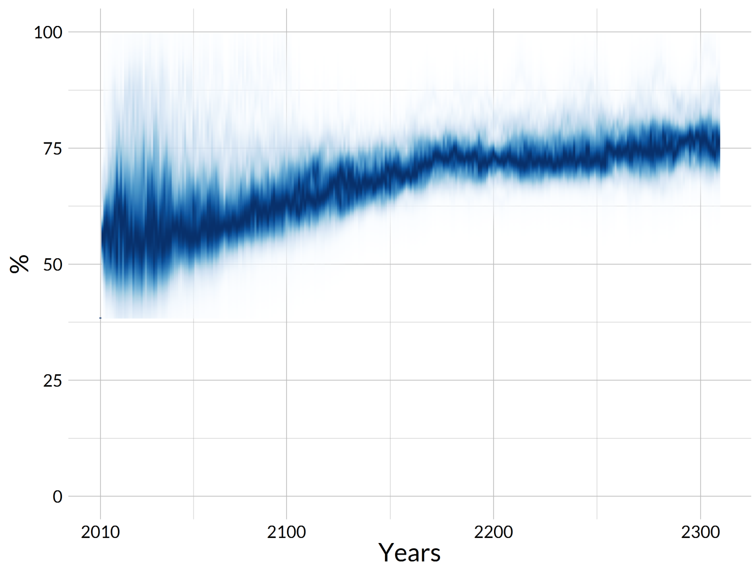
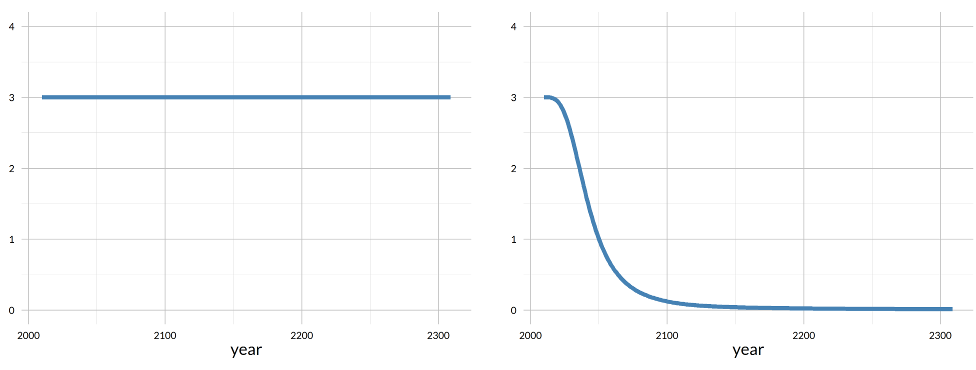


Figure 3.6: Mitigation-Adaptation mix (Bayesian learning about climate sensitivity)

*This figure depicts the optimal paths of the mitigation-adaptation mix after running $N = 100$ simulations. Lines are shaded according to its probability density. The mix is defined as [mitigation/(mitigation+adaptation)]*100.*



(a) Prior mean (b) Prior variance

Figure 3.7: Bayesian learning. Evolution of priors

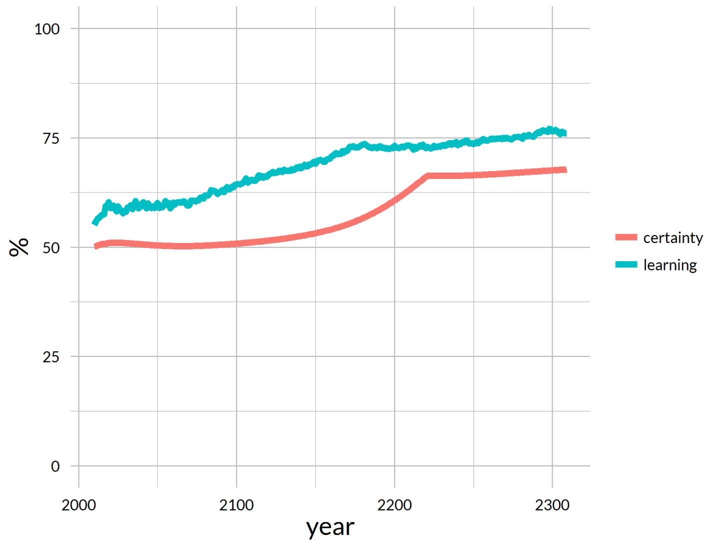
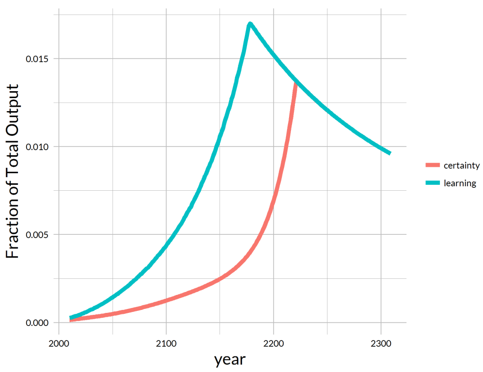
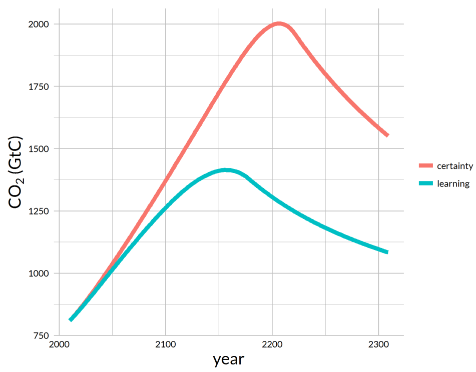


Figure 3.8: Mitigation-Adaptation mix (deterministic versus Bayesian learning)

This figure depicts the median ($N = 100$) response of the social planner against the optimal response under the benchmark model. The planner holds an initial prior centred at the true value $\mu_{s,0} = 3$ and variance $\sigma^2_{s,0} = 3$. In addition temperatures oscillates each period in response to a shock of mean 0 and variance $\sigma^2_T = 0.42$.



(a) Abatement expenditure



(b) CO_2 level

Figure 3.9: Total mitigation and CO_2 concentration (deterministic versus stochastic Bayesian learning)

This figure describes the median ($N = 100$) time path of total abatement expenditure (left) and CO_2 concentration in the atmosphere (right) against their optimal path under the benchmark (deterministic) model. The planner holds an initial prior centred at the true value $\mu_{s,0} = 3$ and variance $\sigma^2_{s,0} = 3$. In addition temperatures oscillates each period in response to a shock of mean 0 and variance $\sigma^2_T = 0.42$.

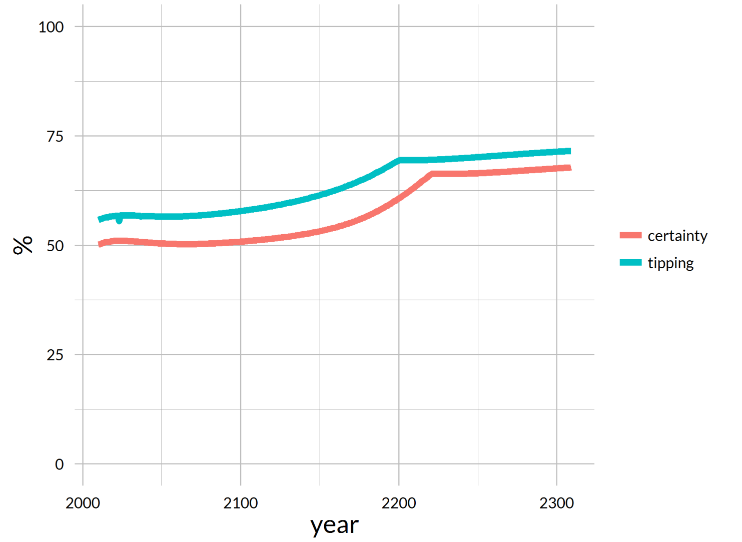


Figure 3.10: Mitigation-Adaptation mix (deterministic versus tipping points)

We simulate a path that happens to never cross a threshold in order to see how the social planner adjusts to the possibility over time. Results are for $\overline{T} = 3°\mathrm{C}$.

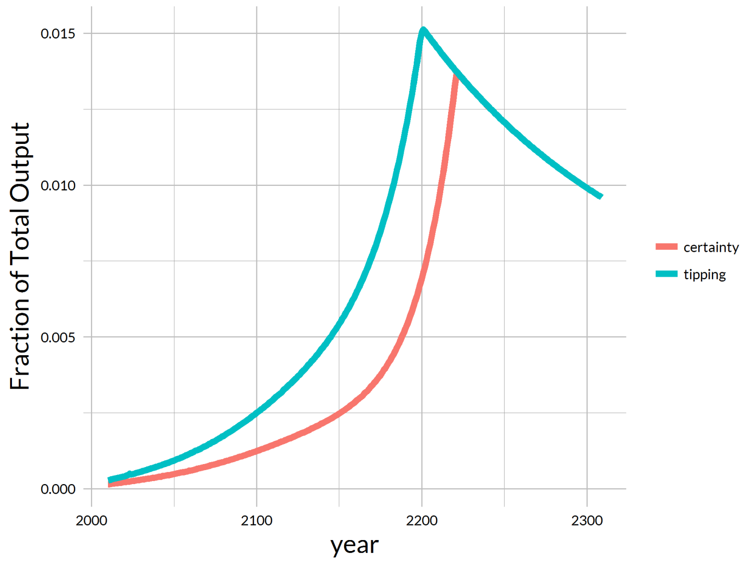


Figure 3.11: Optimal abatement expenditure (deterministic versus tipping points)

This figure describes the median ($N = 100$) *time path of total abatement expenditure against their optimal path under the benchmark (deterministic) model. We simulate a path that happens to never cross a threshold in order to see how the social planner adjusts to the possibility over time. Results are for* $\overline{T} = 3°\mathrm{C}$.

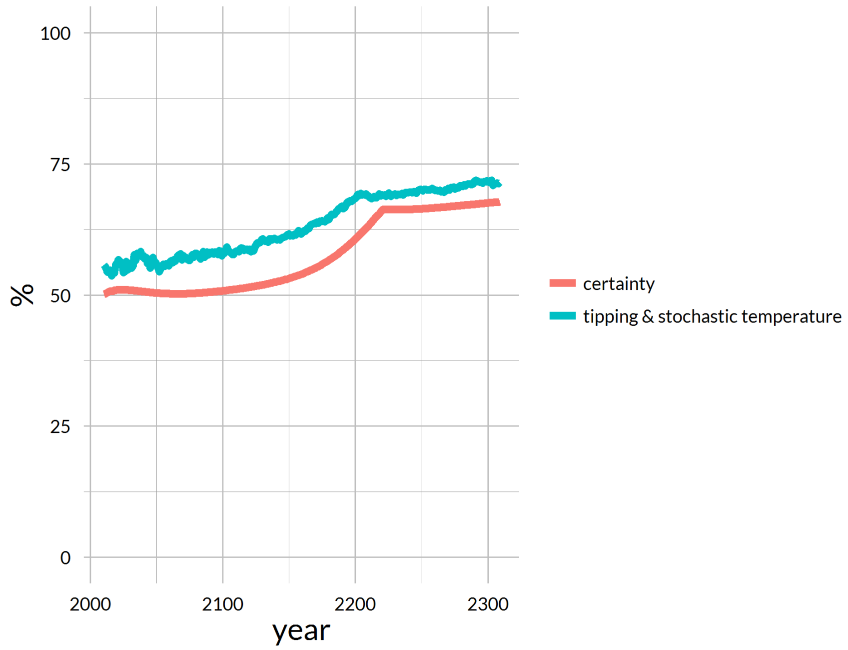


Figure 3.12: Mitigation-Adaptation mix (deterministic versus tipping & stochastic temperature)

This figure depicts the median ($N = 100$) response of the social planner against the optimal response under the benchmark model. We simulate a path that happens to never cross a threshold in order to see how the social planner adjusts to the possibility over time. Results are for $\overline{T} = 3°\mathrm{C}$.

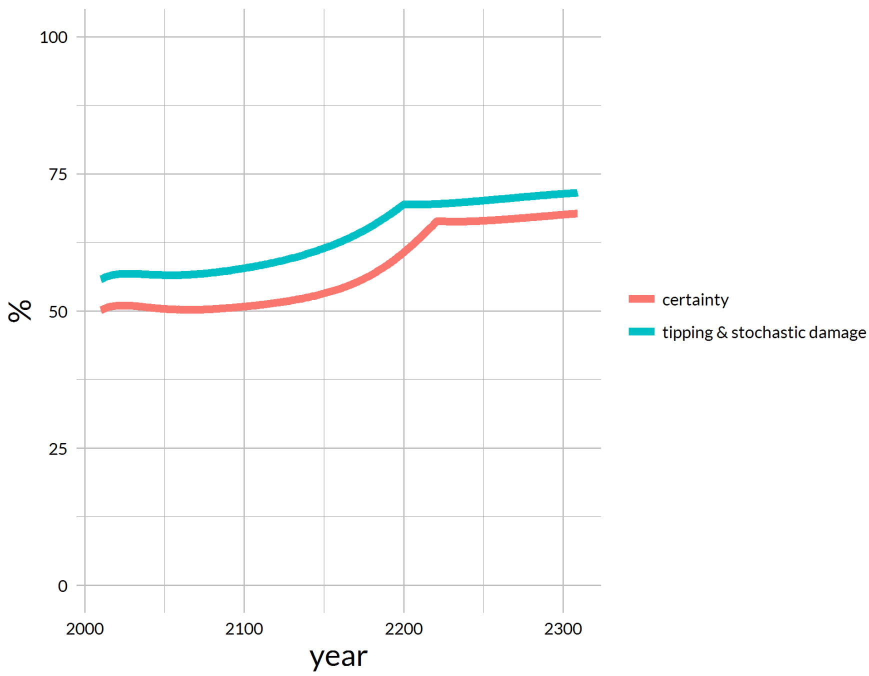


Figure 3.13: Mitigation-Adaptation mix (deterministic versus tipping point & stochastic damage)

This figure depicts the median ($N = 100$) response of the social planner against the optimal response under the benchmark model. We simulate a path that happens to never cross a threshold in order to see how the social planner adjusts to the possibility over time. Results are for $\overline{T} = 3°\text{C}$.

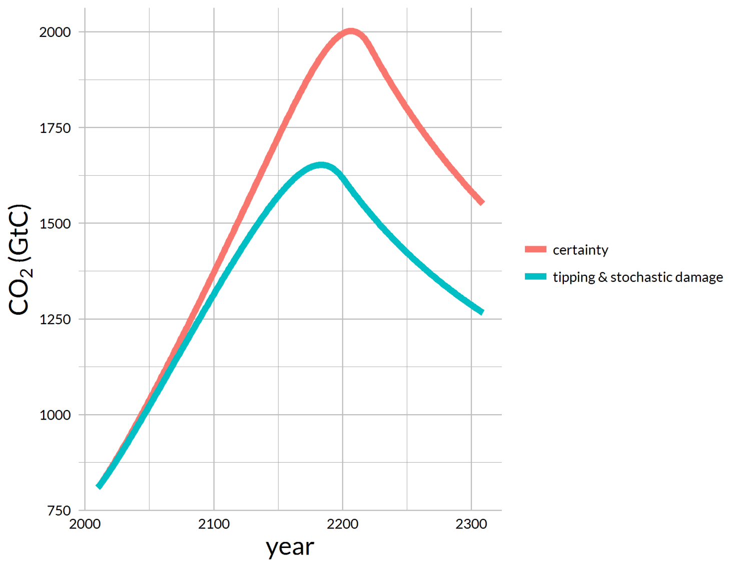


Figure 3.14: CO_2 concentration (deterministic versus tipping point & stochastic damage)

This figure describes the median ($N = 100$) time path of CO_2 concentration in the atmosphere against the optimal path of CO_2 under the benchmark (deterministic) model. We simulate a path that happens to never cross a threshold in order to see how the social planner adjusts to the possibility over time. Results are for $\overline{T} = 3°$C.

3.B Approximating expectations in the AD-DICE model

In a generic way, the introduction of uncertainty in our model boils down to adopting a stochastic equation of motion for our state variables, x, such that, at time τ, their law of motion is given by

$$x_{\tau+1} = g(a_\tau, x_\tau, \varepsilon_\tau),$$

which replaces the deterministic equation of motion $x_\tau = g(a_\tau, x_\tau)$, as presented in Appendix 2.B. Here, ε_τ is the time τ realisation of an *iid* random variable with known distribution. The dynamic programming equation reads now as

$$V^s(x) = \max_a E_\varepsilon \left\{ U(a, x) + \beta V^{s-1}(g(a, x, \varepsilon)) \right\}.$$

The solution to this functional equation proceeds as in the deterministic case, except that now we have to take expectations at every stage. If ε is distributed continuously, Gaussian quadrature presents an efficient approximation to the expectation integral. The L quadrature nodes and the L weights in the sum are selected to match the first $2L$ moments of the distribution

$$\int_Z z^k p(z) dz = \sum_{l=1}^{L} \omega_l x_l^k \quad \text{for } k = 0, \ldots, 2L-1.$$

Hence we approximate the expectation

$$E_\varepsilon \left\{ U(a, x) + \beta V^{s-1}(g(a, x, \varepsilon)) \right\} \approx U(a, x) + \beta \sum_{l=1}^{L} \omega_l V^{s-1}(g(a, x, \varepsilon_l)).$$

Given an estimate of the value function at stage $s-1$, $\hat{V}^{s-1}(x) = \phi(x)c^{s-1}$, at stage s we obtain

$$V_j^s = \max_a U(a, x) + \beta \sum_{l=1}^{L} \omega_l \phi(g(a, x_j, \varepsilon_l))c^{s-1}.$$

We calculate the stage s basis coefficients c^s as described in the (Value) Function approximation method shown in Appendix 2.B to obtain an estimate of the stage s value function, $\hat{V}^s(x) = \phi(x)c^s$, and proceed to stage $s+1$. This strategy goes on recursively up to a desired break criterion for the vector of coefficients, c.[16]

[16] We set this break criterion at 10^{-4}.

Concluding Remarks

This thesis studies the implications of the relation between economies and the environment paying attention to the effects in both directions. On the one side, it measures the effects in the productive sector of the change in weather variables that is taking place in recent years. On the other side, it assesses how different decisions about how to deal with climate damages impacts the environment. It also studies the process of adaptation of climate damages by human decisions and tries to measure its degree of importance in absorbing climate change damages.

The first chapter, using a sample of European regions, unveils new evidence in favour of how ongoing rising temperatures harm both the level and the ability to grow of developed economies. In accordance with other authors, it also shows how this negative effect is exacerbated in relatively poor regions. In light of this, policy makers should account for regional heterogeneity when environmental policies are formulated at a large scale. This heterogeneity should also be borne in mind when the interactions between climate and the economy are modelled, for instance, in IAMs. Since climate change is usually accompanied by extreme weather events, the existence of weather non-linear effects in productive economies should be tested. At the same time, micro evidence suggest that fundamental productive units exhibit highly non-linear responses to local temperatures, as suggested in Graff Zivin and Neidell (2014). This suggests a new avenue of research that will be covered in future projects. In particular, we will follow the techniques employed in Burke et al. (2015) for the U.S. to our sample of European regions.

Closely related to the previous topic, in a future project, it is my aim to study the implications in real economies of other phenomena usually associated to climate change, like droughts. Europe has experienced drought episodes increasingly over the past decades. These ever more frequent events could pose threats to Europe's food security and to the stability of the domestic agri-food market. To assess this statement we first have to carefully measure the net effect of recent genetic, agronomic and environmental changes on drought sensitivity of crops. This remains an open empirical question (some positive and some negative effects). An obstacle to measuring progress in farmers' fields has been lack of accurate field-level data on both environmental conditions and yield performance that span a range of drought conditions and time.

Lobell et al. (2014) have recently developed a similar study applied to the corn belt in the U.S. Midwest. They identify that, despite crop yields have generally increased over the studied period thanks to agronomic changes in plants' drought tolerance, the sensitivity to droughts of some crop varieties, like maize, is greater now than it was at the beginning of the sample. A similar response of European crops could be expected but many heterogeneities could arise due to different geographic, agronomic, or productive motives. My study will shed light onto the reactivity of European-based fields to drought events. I will also estimate the private adaptation potential of crop fields to droughts by interpreting the difference between the impacts of climate change projected using the short-run (limited adaptation) and long-run (substantial adaptation) response curves, as presented in Lobell and Moore (2014, 2015).

As learnt from the first chapter, great spatial disaggregation is key because some areas are more prone to suffering from drought events due to geographic and orographic characteristics. At the same time, some crop varieties will bear more efficiently with abrupt changes in average climate patterns. Hence, deploying my study at the finest disaggregation level available is crucial to obtain meaningful results.

As of the next two chapters, I study different decision bundles about how to deal with climate change impacts using an IAM. I put special emphasis on how allowing for uncertainty may alter those decisions. The methodology employed in these chapters show some potential benefits and advantages with respect to the traditional way of casting and solving the DICE model, namely, it is not sensitive to the specification of the terminal conditions and provides us with the policy functions to run alternative simulations. Also, it sets the perfect environment to include further dimensions in the model. In particular, it enables us to properly include different types of uncertainties and/or stochastic behaviour of certain variables and parameters.

This is done in Chapter 3, which represents a new approach to the dynamic analysis of adaptation to climate change within a simplified recursive IAM fed with various potential sources of uncertainty. Many other additional features can be further incorporated into this model: uncertainty in the parameters governing the damage function, alternative damage function specifications, persistent effects of technology shocks,... Additionally, different types of adaptation could be jointly modelled. For example, Bosello et al. (2010) construct a more involved framework in which different types of adaptation can be found. In particular, they distinguish between anticipatory adaptation (modelled as a stock variable), reactive adaptation (modelled as a flow variable) and accumulation of reactive adaptation knowledge. These extensions are left for future research papers.

Overall, this thesis represents a compendium of evidence reflecting the adverse effects of climate change in modern economies, the limited capacity of humans to adapt to those effects and shows how uncertainties present in the decision-making procedures favour tackling climate damages by directly addressing the causes rather than fighting against its effects. This thesis also sends a message to the scientific community and to the general public about the need to persuade in a prompt and intensive abatement of greenhouse gas emissions to avoid the aggravation of adverse climate change effects.

Finally, this thesis set the seeds of a future research agenda based on the quantification of the economic and social implications resulting from environmental changes and the analysis and measurement of the effects that human-made decisions have in the environment. I look forward to undertaking this agenda in the immediate future.

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