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How Does Climate Policy Affect Technical Change? An Analysis of the Direction and Pace of Technical Progress in a Climate-Economy Model

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Summary

This paper analyses whether and how a climate policy designed to stabilize greenhouse gases in the atmosphere is likely to change the direction and pace of technical progress. The analysis is performed using an upgraded version of WITCH, a dynamic integrated regional model of the world economy. In this version, a non-energy R&D Sector, which enhances the productivity of the capital-labor aggregate, has been added to the energy R&D sector included in the original WITCH model. We find that, as a consequence of climate policy, R&D is re-directed towards energy knowledge. Nonetheless, total R&D investments decrease, due to a more than proportional contraction of non-energy R&D. Indeed, when non-energy and energy inputs are weakly substitutable, the overall contraction of the economic activity associated with a climate policy induces a decline in total R&D investments. However, enhanced investments in energy R&D and in the energy sector are found not to “crowd-out” investments in non-energy R&D.

Keywords: Technical Change, Climate Policy, Stabilization Cost, R&D Investments

JEL Classification: C72, H23, Q25, Q28

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1. INTRODUCTION

It is now widely agreed that action is needed to control climate change. This calls for challenging cuts of global greenhouse gas (GHG) emissions throughout the whole century. The costs of the radical transformations needed to achieve a low-carbon economy are matter of vibrant discussions and are far from being completely understood. However, while some key issues have already been disentangled and are now broadly accepted, some others still need further investigation. For example, while the crucial role of technical progress in the context of climate change is well recognized, how would mitigation policies change its direction and pace?

Many other relevant questions remain unanswered. Will a low-carbon economy be more likely to have a higher or a lower rate of technological innovation? Will total R&D investments increase (e.g. to train new scientists and build new laboratories) or will research expenditure be cut to slow down economic growth? What would the likely impact of climate policy on the R&D sector be? Will enhanced investments in energy and climate-related R&D crowd out other forms of R&D investments? How will estimates of climate policy costs change in the presence of a detailed and articulated specification of endogenous technical change? (see Carraro, Grubb and Schellnhuber, 2006, for an introduction to this issue). The purpose of this paper is to address these questions in order to improve our understanding of the likely effects of a GHG stabilization policy on technical change and economic growth.

A first prerequisite for studying the dynamics of technical change is to model endogenous knowledge accumulation. We follow here the most commonly used approach by climate-economic modelers (Goulder and Schneider, 1999; Nordhaus, 2002; Buonanno, Carraro and Galeotti, 2003; Sue Wing, 2003; Popp, 2004; see also Löschel, 2002): technological advancements are assumed to originate from a knowledge stock accumulated through R&D investments.

A second necessary prerequisite is to model R&D investments in different sectors, or for different forms of R&D, in order to monitor how the increased R&D spending to reduce carbon emissions affects other R&D investments. In our analysis, we use two stocks of knowledge: one increases energy efficiency by augmenting the productivity of the energy input, while the other enhances the productivity of non-energy inputs. We thus follow Acemoglu (2002), who strongly argues that technical change is fundamentally *biased* and it is therefore important to disentangle those elements that affect the direction of technical change towards specific production factors. Such an approach allows us to monitor how the direction of innovation changes as relative prices vary, and how the overall economic structure changes as a consequence of a long-term GHG stabilization policy.

Is there any long-term bias of technical progress and is climate policy likely to reverse or exacerbate it? This is one of the questions addressed in this paper. In particular, by explicitly modeling endogenous and directed technical change, we can investigate the possibility that additional R&D investments for reducing carbon emissions come, at least in part, at the expense of other forms of R&D spending, thus partially offsetting the gains from the innovative effort induced by climate policy.

The idea that traditional R&D efforts are crowded out by climate-related R&D investments is often cited in the modeling literature and originates from the hypothesis that the supply of R&D inputs is inelastic: an increase in the demand of scientists (or laboratories) is assumed to increase the rental costs of these factors, while leaving the overall amount of research largely unaffected.

Unfortunately, the majority of models used for climate policy analysis has only one R&D stock and imposes ad hoc assumptions to take into account the alternative and competitive uses of R&D funds. For example, Nordhaus (2002) and Popp (2004) explicitly consider the opportunity cost of R&D when they measure the overall impact of modeling endogenous technical change on stabilization costs. However, R&D expenditure not directly related to de-carbonizing the economy is not explicitly modeled, but rather included in the economy-wide investment variable.

Even without modeling how non-climate-policy-induced R&D investments react to a GHG stabilization policy, Nordhaus believes that neglecting the competition between different forms of R&D would overestimate the benefit of endogenizing technical change and thus assumes an exogenous “crowding out” effect. In his view, the overall amount of R&D investment is fixed, both in the short and in the long run, and thus any increase of carbon-related R&D completely crowds out other forms of R&D. As pointed out by Gillingham, Newell and Pizer (2007), it is mainly because of this hypothesis that Nordhaus (2002) finds that knowledge accumulation has a limited effect on the optimal timing of mitigation efforts and on total mitigation costs.

Popp (2004) introduces ENTICE, a modified version of the DICE model, where energy efficiency increases when investing in R&D. Popp rejects the complete “crowding out” hypothesis of Nordhaus (2002), but not the idea that different forms of R&D necessarily compete against each other for the allocation of investment resources. Accordingly, in the base version of the ENTICE model, each dollar spent on energy R&D crowds out half as much investment in other forms of R&D. Since only energy R&D is explicitly modeled, Popp mimics the “crowding out” effect by subtracting the eroded

R&D resources from the amount of investments in the overall R&D stock.[1] With this assumption, Popp finds that when endogenous technical change is neglected there is a limited overestimation of stabilization costs of about 10 percent and that crowding out effects work against additional welfare gains.[2]

However, in the long-run time horizon usually assumed to study climate policy, the allocation of total R&D investments across different sectors should not be constrained, because a strong stabilization policy may induce higher expenditure in R&D to de-carbonize the economy, while maintaining the same level of investment in other forms of R&D. At the same time, it is not possible to rule out that forces other than the pure "crowding out" effects will turn a de-carbonized economy into a less technologically advanced economy. Goulder (2004) correctly points out that the increase of R&D in carbon-free energy and high efficiency equipment might be associated to lower investment in other sectors, with adverse effects on aggregate knowledge and productivity. For the fossil fuels extraction industry, it is reasonable to expect this contraction to be induced by both price and income effects, if stabilization costs reduce demand for goods in other knowledge- intensive industries. It is thus the "net" equilibrium R&D effect that determines the actual role of climate policy-induced technical change.

Goulder and Schneider (1999), Sue Wing (2003) and Gerlagh (2008) consider the effect of climate policy on total R&D investments rather than simply studying the re-allocation of R&D across sectors. They all find that induced technical change makes the economy more flexible to adjust to climate policy. Nevertheless, while Gerlagh (2008) finds that aggregate R&D investments increase substantially, Goulder and Schneider (1999) and Sue Wing (2003) find that they tend to decrease.

Goulder and Schneider (1999) first noted that climate policy affects the equilibrium amount of R&D and the rate of knowledge accumulation not only in the energy sector, but in all the other sectors where knowledge is used. With a dynamic general equilibrium model where knowledge is sector-specific and input- neutral – and where abatement policies affect the R&D investments of private firms and thus change the incentive to knowledge accumulation as well as input requirements across different sectors – they find that policy- induced technical change generally increases the equilibrium abatement effort. Nevertheless, gross abatement costs, in terms of GDP losses, increase with respect to a baseline in which induced technical change is not modeled. This result is explained by a positive and increasing opportunity cost of R&D: a carbon tax policy determines a re-allocation of R&D

[1] Popp (2004) also deals with market failures in the R&D sector, an issue that we do not discuss here.
[2] Imperfections in the market of knowledge may also reduce the potential gains of modeling induced technical change.

across sectors, and a fall in the aggregate level of R&D due to a slower growth of output, especially in the conventional energy fuel sector.

Building on the work of Goulder and Schneider (1999), Sue Wing (2003) develops a multi-sector general equilibrium model to study how knowledge is optimally reallocated in response to a carbon tax. However, choices are limited in his model because total R&D investment is assumed to be a fixed proportion of savings and the propensity to consume of the economy is given as in a Solow model. With this framework, Sue Wing finds that a carbon tax induces an inter-sectoral and intra-sectoral re-allocation of knowledge services and reduces the rate of knowledge accumulation, thus causing a decline of output.

Gerlagh (2008) develops an endogenous growth model where the level of output of the final good is a nested function of a generic intermediate good and of carbon-energy. The model allows for three different stocks of knowledge: one affecting the productivity of carbon-energy in the outer nest, one increasing the productivity of a capital-labor composite for the production of the intermediate good, and another increasing the productivity of a capital-labor composite for the production of carbon energy input. With this model structure, Gerlagh finds that induced technical change substantially increases the elasticity of emissions to a carbon tax and decreases the costs of emission reductions, especially when all knowledge stocks are free to respond to the policy stimulus. This result is explained by a reallocation of knowledge accumulation within the energy nest: energy- saving knowledge increases and energy- augmenting knowledge decreases.

This brief summary of the literature can help to understand the original features of our paper. We study the effects of climate policy on both the direction and the aggregate level of knowledge accumulation as in Goulder and Schneider (1999), Sue Wing (2003), and Gerlagh (2008), but we adopt a different set-up. First, we use WITCH, a Ramsey-type neoclassical optimal growth model in which investment decisions in a variety of energy and non-energy technologies are fully endogenous and 12 regions interact in a strategic setting (for a full description of the WITCH model see Bosetti, Carraro et al, 2006; Bosetti, Massetti and Tavoni, 2007). We introduce in WITCH a new module to endogenize directed technical change in order to highlight in a simple but coherent framework the dynamics of R&D investments induced by climate policy. R&D expenditures, and therefore knowledge accumulation, are factor- specific and can be directed towards increasing energy efficiency or towards rising productivity of non-energy inputs, namely capital and labor. By explicitly modeling two R&D capital stocks, we avoid exogenous assumptions on energy R&D crowding out, and we can then study how mitigation policies change the direction and the magnitude of technical change. Also, our detailed description of the energy sector allows us to study how the re-allocation of investments towards low-emitting, or carbon-free, electricity generation technologies might affect investments in other sectors.

Our findings are different from those in Goulder and Schneider (1999) and Sue Wing (2003). While these authors find that a carbon tax moves knowledge accumulation away from carbon- intensive sectors, and towards low-emitting sectors, we find that a mitigation policy not only re-allocates investments towards low-emitting or carbon-free technologies, but it also changes the direction of technical change. While under a Business as Usual (BaU) scenario technical change is directed towards capital and labor, the introduction of a climate policy readdresses technical change towards the energy sector. In addition, enhanced investments in energy R&D and in the energy sector are found not to “crowd-out” investments in non-energy R&D.

We also find that endogenizing technical change, no matter the sector in which it is introduced, has important consequences on GHG stabilization costs. We thus depart from Gerlagh (2008), in which endogenous technical change was found to affect the cost of climate policy only if modeled in the energy sector. More specifically, we find that omitting the effect of induced technical change in the non-energy sector underestimates the cost of the climate policy.

The rest of the paper is organized as follows: Section 2 describes the model and in particular how technical change has been endogenized. Section 3 explains the calibration procedure and, to this purpose, also reviews the main studies that estimate the elasticity of substitution between capital, labor and energy. Section 4 describes the basic features of our BaU scenario and introduces some historical evidence on R&D patterns. Section 5 introduces and discusses the stabilization policy scenario. Some sensitivity analysis has been carried out and is presented in Section 6. A concluding session summarizes our main findings.

2. DIRECTED TECHNICAL CHANGE IN THE WITCH MODEL

2.1. Short Model Description

WITCH - World Induced Technical Change Hybrid - is a regional integrated assessment model designed to provide information on the optimal responses of world economies to climate damages and related policy measures. WITCH is a hybrid model because it combines features of both top-down and bottom-up modeling: the top-down component consists of an inter-temporal optimal growth model in which the energy input of the aggregate production function has been expanded to yield a bottom-up like description of the energy sector. World countries are grouped in 12 regions whose strategic interactions are modeled using a game-theoretic approach. A climate module and a damage function provide the feedback on the economy of carbon dioxide emissions into the atmosphere.

WITCH's top-down framework guarantees a coherent, fully intertemporal allocation of investments that have an impact on the level of mitigation – R&D effort, investment in energy technologies, fossil fuel expenditures. The regional specification of the model and the presence of strategic interactions among regions – through GHG emissions, exhaustible natural resources, technological spillovers – allows us to account for the incentives to free-ride. Investment strategies are indeed determined by taking into account both economic and environmental externalities. In WITCH, the energy sector is described with a sufficient degree of detail and a reasonable characterization of future energy and technological scenarios. By endogenously modeling fuel (oil, coal, natural gas, uranium) prices, and the cost of storing the captured CO_2, the model can be used to evaluate the main impacts of mitigation policies on the energy system, in all its components. In the following section and in Appendix A, we selectively present some features and equations of the model that are functional to our analysis of technological change. For a thorough description of the model see Bosetti, Carraro et al. (2006) and for calibration details and a discussion of the baseline see Bosetti, Massetti and Tavoni (2007).

2.2. Directed Technical Change in the WITCH model

In previous versions of the WITCH model, only energy-related technological progress was endogenous. In this paper, we describe and use a more general version of the model in which two types of R&D – Non-Energy and Energy R&D – are introduced to study the direction of technical change and to better describe long-term productivity dynamics.

In the model, gross output, $GY(n,t)$, in country n at time t is produced by combining energy services, $ES(n,t)$, and capital-labor services $KLS(n,t)$ in a CES nest:[3]

$$GY(n,t) = TFP(n,t)\left[\alpha_Y(n)\cdot KLS^{\rho_Y} + (1-\alpha_Y(n))\cdot ES(n,t)^{\rho_Y}\right]^{1/\rho_Y} \qquad (1)$$

Net output, $Y(n,t)$, is obtained after accounting for the effects of climate change on production and for the expenditure for fuels and carbon capture and sequestration, as shown in detail in Appendix A. Energy services and capital-labor services are obtained by aggregating raw inputs to knowledge,

[3] Where $\rho = (\sigma - 1)/\sigma$ and σ is the elasticity of substitution.

which raises their productivity. We use, as a proxy of knowledge, the cumulated stocks of R&D in the Non-Energy and Energy sectors, $HKL\,(n,t)$ and $HE\,(n,t)$, respectively. As in Popp (2004), the aggregation between raw inputs and knowledge is assumed to follow a standard CES function:

$$ES(n,t)=\left[\alpha_{ES}(n)HE(n,t)^{\rho_{ES}}+(1-\alpha_{ES}(n))EN(n,t)^{\rho_{ES}}\right]^{1/\rho_{ES}} \qquad (2)$$

$$KLS(n,t)=\left[\alpha_{KLS}(n)HKL(n,t)^{\rho_{KLS}}+(1-\alpha_{KLS}(n))KL(n,t)^{\rho_{KLS}}\right]^{1/\rho_{KLS}} \qquad (3)$$

Calibration details are discussed in Section 3. The energy input $EN\,(n,t)$ is produced in the Energy sector of the economy and is described in detail in Bosetti, Massetti and Tavoni (2007). It basically consists of a series of nested CES functions that describe energy supply and demand at different levels of aggregation. Capital and labor are aggregated in a CES nest to produce the capital-labor raw input *KL* as follows:

$$KL(n,t)=\left[\alpha_{KL}(n)K_C(n,t)^{\rho_{KL}}+(1-\alpha_{KL}(n))L(n,t)^{\rho_{KL}}\right]^{1/\rho_{KL}} \qquad (4)$$

This is supported to some degree by the empirical literature that finds a higher elasticity of substitution between capital and labor than between any of the two inputs and energy (see van der Werf, 2007; Kemfert, 1998; Chang, 1994). As in previous versions of WITCH, the hybrid nature of the model allows us to portray endogenous technological change also from a bottom-up perspective, by letting Learning-by-Doing reduce the cost of power generation plants (see Appendix A for a more detailed presentation of the main equations of the WITCH model).

2.3. The R&D Sectors

Knowledge is produced standing on the shoulders of one nation's giants: investment in R&D is combined with the stock of ideas already discovered and produces new knowledge which will be the base for new discoveries in the following years. In the seminal paper by Romer (1990), the research sector productivity increases proportionally with the stock of knowledge cumulated in the past, giving rise to endogenous growth. Strong intertemporal spillovers for the economy as a whole are questioned by, among others, Jones (1995), and, in the specific narrower scope of our analysis, by Popp (2002), who finds that the energy R&D sector exhibits diminishing returns. Therefore, the production of new ideas, $Z\,(n,t)$, in the Energy and Non-Energy sectors is modeled as follows:

$$Z_{HE}(n,t) \;=\; a\, I_{HE}(n,t)^{b}\, HE(n,t)^{c}\,, \tag{6}$$

$$Z_{HKL}(n,t) \;=\; f\, I_{HKL}(n,t)^{g}\, HKL(n,t)^{h}\,. \tag{7}$$

where $b+c<1$ and $g+h<1$. We assume that obsolescence makes a fraction δ of past ideas not fruitful for the purpose of current innovation activity. As a consequence, the stocks of knowledge evolve according to the following law of motion:

$$HE(n,t+1) \;=\; HE(n,t)(1-\delta)+Z_{HE}(n,t) \tag{8}$$

$$HKL(n,t+1) \;=\; HKL(n,t)(1-\delta)+Z_{HKL}(n,t) \tag{9}$$

The decision variables of the model are investments in physical capital (for all different technologies in the energy sector and for the domestic capital stock), the two types of R&D investments and fuel expenditures for non-electric energy. As a consequence the decision to invest in Energy R&D and Non-Energy R&D, and therefore total R&D, is endogenous and determined in each country/region by solving a dynamic open-loop game. Therefore, crowding out effects are also endogenous. We will indeed be able to compute the reaction of both types of R&D investments to the introduction of climate policy and to compute the resulting crowding-out effect.

3. CALIBRATION

With respect to the standard version of the model, we use here an elasticity of substitution lower than unity for the final nest, in which *KLS* and *ES* are aggregated to produce final output. There is still substantial uncertainty on the best nesting structure and the most appropriate elasticity of substitution to describe the relationship between capital, labor and energy demand. However, there seems to be evidence in favor of a capital-labor nest that is subsequently aggregated to energy, with an elasticity of substitution lower than one. Let us provide an overview of the empirical evidence to shed some light on these issues.

As to the nesting structure, both van der Werf (2007) and Kemfert and Welsch (2000) estimate alternative nesting structure to select the most appropriate one. van der Werf (2007) estimates a two level CES production function for three combinations of capital (K), labor (L) and energy (E), for 12 OECD countries and 7 industries. He finds that the structure in which capital and labor are nested together and then combined to energy fits the data better than the nesting structure in which capital and energy are nested together and then combined to labor. Nevertheless, van der Werf (2007) finds that the null-hypothesis of a non-nested structure cannot be rejected. Kemfert and Welsch (2000) estimate a two-level CES function for Germany and get mixed results: at national level the KE-L structure fits data best, while at industry level and for 5 industries out of 7 the KL-E structure fits data best.

Several studies focus on the estimation of the elasticities of substitution between energy, capital and labor at industry level (Prywes, 1986; Manne and Richels, 1992; Chang, 1994; Kemfert, 1998; Kemfert and Welsch, 2000, Okagawa and Ban 2008), or both at national and industry level (van der Werf, 2007). These studies use the definition of "full elasticity" derived by Morishima, with the exception of Prywes (1986), Chang (1994) and van der Werf (2007) that estimate the Allen partial elasticities. The two measures differ and, as emphasized by Markandya and Pedroso-Galinato (2007), the former is generally lower than the latter. The different estimates are shown in Table 1.

Table 1. Elasticities of Substitution in the Empirical Literature (Adapted from Markandya and Pedroso Galinato, 2007)

K/L			L/E		
	0.88^{A}	Prywes (1986)		0.88^{A}	Prywes (1986)
	0.82^{M}	Kemfert (1998)		0.35^{A}	Chang (1994)
	0.793^{M}	Kemfert and Welsch (2000)		0.42^{M}	Kemfert (1998)
	0.224 to 0.616^{A}	van der Werf (2007)		0.167^{M}	Kemfert and Welsch (2000)
	0.07 to 0.33	Okagawa and Ban (2008)		0.517 to 0.863^{A}	van der Werf (2007)
K/E			KL/E		
	0.87^{M}	Chang (1994)		0.4	Manne and Richels (1992)
	0.65^{M}	Kemfert (1998)		0.42^{A}	Chang (1994)
	0.871^{M}	Kemfert and Welsch (2000)		0.5	Kemfert (1998)
	0.804 to 1.000^{A}	van der Werf (2007)		0.698	Kemfert and Welsch (2000)
	0.04 to 0.45	Okagawa and Ban (2008)		0.147 to 0.622^{A}	van der Werf (2007)
				0.00 to 0.64	Okagawa and Ban (2008)
KE/L					
	0.681 to 1.169^{A}	van der Werf (2007)			
	0.00 to 0.94	Okagawa and Ban (2008)			

A and M superscripts denote Allen and Morishima elasticities of substitutions, respectively.

As for technological change, van der Werf (2007) shows that the rates of factor-specific technological change differ significantly across factors, thus supporting our choice to introduce directed technical change in WITCH.

In the version of WITCH proposed in this paper, the elasticity between energy and capital-labor services, σ_Y, is set equal to 0.5. This choice is in line with models that aggregate capital, labor and energy analogously (see Table 1 and Manne et al., 1990; Whalley and Wigle, 1990). We adopt an elasticity of substitution between labor and capital, σ_{KL}, equal to 0.8 for all regions but China and South Asia, for which we allow for a greater elasticity of substitution (σ_{KL} equal to 0.85). In previous versions of the WITCH model, a unit elasticity had been assumed. The value chosen here fits better with the empirical estimates found in the literature (see Table 1).

We calibrate energy R&D as in Popp (2004). Parameters of the CES function between energy and knowledge and of the innovation possibility frontier are chosen to be consistent with historical levels, to reproduce the elasticity of Energy R&D to energy prices and to achieve a return four times the one of physical capital, thus taking into account the positive externality of knowledge creation. The elasticity of substitution between energy and energy knowledge, σ_{ES}, is accordingly set equal to 1.67 and the same is assumed for the elasticity between capital-labor and non-energy knowledge, σ_{KLS}. R&D investments in the non-energy sector are also assumed to yield a return four times higher than the interest rate. The initial stock of Non-Energy knowledge is calibrated to obtain R&D investments in the initial time period which are about 2% of GDP, a figure very close to the historical one (see Figure 1).

The calibration of the Non-Energy R&D innovation possibility frontier and the elasticity of substitution between the Non-Energy knowledge stock and the capital-labor aggregate is based on the model performance in terms of output elasticity to R&D investments (as detailed in Table 2), for which a sufficient empirical evidence is available.

Table 2. Elasticity of Output with respect to Non-Energy R&D

	2002	2022	2042	2062	2082	2102
USA	0.09	0.09	0.09	0.10	0.10	0.10
OLDEURO	0.07	0.07	0.07	0.07	0.07	0.08
NEWEURO	0.03	0.03	0.04	0.04	0.05	0.05
KOSAU	0.07	0.07	0.07	0.08	0.08	0.09
CAJAZ	0.09	0.09	0.09	0.10	0.10	0.10
TE	0.04	0.04	0.05	0.05	0.06	0.06
MENA	0.03	0.03	0.03	0.04	0.04	0.04
SSA	0.00	0.00	0.00	0.00	0.00	0.00
SASIA	0.03	0.03	0.04	0.04	0.04	0.05
CHINA	0.04	0.04	0.05	0.05	0.06	0.06
EASIA	0.02	0.02	0.02	0.02	0.03	0.03
LACA	0.02	0.03	0.03	0.03	0.03	0.03

Cross-section econometric studies that use firm- or industry- level data to estimate the elasticity of specific industries' output with respect to private R&D, find a range of values between 0.05 and 0.60, with a central tendency around 0.10 and 0.20. Estimates from studies that use economy-wide data to measure GDP elasticity with respect to private R&D are not many and find elasticities from 0 to 0.60, with a central tendency around 0.10. Coe and Helpman (1995) find a value of 0.23 for G7 countries and a value of 0.08 for non-G7 OECD countries. Lichtenberg (1992) finds the elasticity to be equal to 0.07 when poorer economies are included in the sample. Table 2 displays the elasticity of gross output with respect to R&D in the Non-Energy sector for all WITCH countries/regions, at different time intervals. Base-year values are generally consistent with the central tendencies of the empirical literature briefly summarized above.[4] Most interestingly, we are able to replicate the difference of elasticities between high- and low- income countries/regions and the model endogenously displays a (mild) degree of convergence of elasticities across time, in line with output per capita convergence rates.

4. BASELINE SCENARIO

From the baseline scenario – which corresponds to the non-cooperative Nash equilibrium of the WITCH model under the assumption of no mitigation policy – we obtain the equilibrium investment trajectories, together with the equilibrium R&D investments, GWP and consumption path. Table 3 summarizes baseline trends of major variables and indicators of interest. GWP increases over the whole century, starting from 34 trillions in 2002 to 246 trillions in 2102. Population grows at a declining rate and eventually stabilizes at about 9.5 billions at the end of the century. Income per capita expands five-fold. Interestingly, while the energy intensity of the world economy decreases, coherently with historical observations, the carbon intensity of energy slightly increases, showing a preference for cheap coal based electricity generation in the BaU. The gains in energy efficiency explain the reduction of emissions per unit of output, which is another desirable property of our BaU; however, the strong expansion of output offsets all efficiency gains and overall carbon emissions increase throughout the century, leading to a doubling of CO_2 concentrations in the atmosphere.

While investments in final good capital and in the energy sector decline as a share of GWP, the model yields a rather constant path of R&D expenditure as share of GWP. As a result, the fraction of investment devoted to knowledge creation is increasing. The model yields a slightly declining path of

[4] See the review in Congressional Budget Office (2005).

Energy R&D as share of GWP, a first increasing and then declining path of Non-Energy R&D as share of GWP, and a declining rate of Energy to Non-Energy R&D investments.

Table 3. Baseline Trend of Major Variables

	2002	2022	2042	2062	2082	2102
GWP (Trillions, 1995 USD)	34	64	106	153	200	246
World Population (billions)	6.2	7.6	8.5	9.0	9.3	9.5
GWP Growth Rate (20 years average)	3.2%	2.5%	1.8%	1.4%	1.1%	--
Population Growth Rate (20 years average)	1.0%	0.6%	0.3%	0.2%	0.1%	--
Carbon Intensity of Energy (Ton C / Toe)	0.691	0.710	0.728	0.737	0.733	0.716
Energy Intensity (Toe / USD)	0.287	0.239	0.198	0.164	0.139	0.121
Carbon Intensity of Output (Ton C / USD)	0.198	0.170	0.144	0.121	0.102	0.087
CO_2 concentrations in the atmosphere (ppm)	369	421	511	593	673	749
Investment in final good capital (Trillions, 1995 USD)	7.6	13.0	19.6	26.5	33.3	39.9
Investment in R&D (Trillions, 1995 USD)	0.84	1.70	2.89	4.26	5.51	6.14
Investment in Energy Sector (Trillions, 1995 USD)	0.36	0.59	0.78	0.95	1.11	1.27
Investment in Final Good Capital (% GWP)	22.29%	20.25%	18.50%	17.36%	16.68%	16.19%
Investment in Energy Sector (% GWP)	1.07%	0.91%	0.74%	0.62%	0.55%	0.52%
R&D expenditure (% GWP)	2.476%	2.656%	2.730%	2.790%	2.761%	2.492%
Non-Energy R&D (% GWP)	2.454%	2.636%	2.711%	2.772%	2.742%	2.475%
Energy R&D (% GWP)	0.022%	0.019%	0.019%	0.019%	0.019%	0.017%
Energy R&D (% Total investment in R&D)	0.884%	0.734%	0.684%	0.671%	0.670%	0.679%
Non-Energy R&D knowledge stock per worker (index)	1.00	0.89	1.03	1.37	1.83	2.35
Energy R&D knowledge stock per worker (index)	1.00	1.00	1.16	1.41	1.70	1.97

Table 4 and 5 show output-growth accounting for three representative countries/regions: the high income USA, the fast growing CHINA and the least advanced Sub-Saharan Africa (SSA). Table 4 shows how raw inputs, labor, capital and Non-Energy R&D contribute to the growth rate of the "capital-labor services" aggregate (KLS). Table 5 displays the same exercise for the aggregate "energy services" (ES). In italics, for each country/region, we report the growth rate of KLS and EN; immediately below the average yearly contribution of each input to the growth rate of the sectoral output is computed. Averages are calculated over twenty-year time periods.

Table 4. Contribution of Raw Inputs to the Growth Rate of Capital-Labor Services (Average Annual Growth Rates)

	2002-2021	2022-2041	2042-2061	2062-2081	2082-2102
USA					
capital-labor services	*1.14%*	*0.68%*	*0.42%*	*0.29%*	*0.22%*
labor	0.39%	0.20%	0.06%	0.01%	0.00%
capital for final good production	0.73%	0.39%	0.26%	0.18%	0.13%
non-energy R&D knowledge stock	0.02%	0.09%	0.11%	0.11%	0.08%
CHINA					
capital-labor services	*2.20%*	*1.47%*	*0.73%*	*0.43%*	*0.29%*
labor	0.40%	0.08%	-0.08%	-0.09%	-0.04%
capital for final good production	1.68%	1.18%	0.60%	0.34%	0.21%
non-energy R&D knowledge stock	0.12%	0.21%	0.21%	0.17%	0.13%
Sub Saharan Africa (SSA)					
capital-labor services	*3.51%*	*2.47%*	*1.67%*	*1.17%*	*0.90%*
labor	1.42%	1.01%	0.64%	0.40%	0.28%
capital for final good production	2.07%	1.44%	1.01%	0.76%	0.60%
non-energy R&D knowledge stock	0.02%	0.02%	0.01%	0.01%	0.01%

Table 5. Contribution of Raw Inputs to the Growth Rate of Energy Services (Average Annual Growth Rates)

	2002-2021	2022-2041	2042-2061	2062-2081	2082-2102
USA					
energy services	*1.50%*	*0.63%*	*0.22%*	*0.10%*	*0.06%*
energy	1.51%	0.62%	0.21%	0.08%	0.04%
energy R&D knowledge stock	0.00%	0.01%	0.01%	0.01%	0.01%
CHINA					
energy services	*3.88%*	*2.30%*	*1.00%*	*0.47%*	*0.24%*
energy	3.83%	2.27%	0.98%	0.45%	0.22%
energy R&D knowledge stock	0.05%	0.03%	0.02%	0.02%	0.01%
Sub Saharan Africa (SSA)					
energy services	*4.10%*	*2.62%*	*1.81%*	*1.45%*	*1.29%*
energy	4.07%	2.60%	1.80%	1.44%	1.29%
energy R&D knowledge stock	0.04%	0.02%	0.01%	0.01%	0.01%

As displayed in the table, in both USA and CHINA growth becomes more and more (Non-Energy) R&D driven.[5] Population growth and capital investments remain instead a major source of growth of the capital-labor services aggregate in Sub-Saharan Africa, while R&D plays only a minor role in

[5] A negative value, in this and in the following analogous tables, means that the input has a decreasing time-trend. In table 4.2, the population of China is assumed to stabilize at about mid-century and then to slightly decline.

explaining growth throughout the century in this less advanced economy. Table 5 shows that, in the BaU, Energy R&D knowledge plays only a minor role in explaining growth of energy services in all three countries/regions. Increasing energy-demand is mainly satisfied by increases in the energy input.

WITCH's equilibrium R&D investment trajectories are in line with historical trends of both aggregate R&D and Energy R&D expenditures, as shown in Figure 1 and Figure 2. Figure 1 shows both the historical levels of total R&D over GDP for the OECD countries and the equilibrium values of the same ratio as determined in the baseline scenario. Historical data show a slightly increasing trend over the past 25 years, starting from 1.9% in 1981 and reaching 2.25% in 2005. The same trend is predicted in the baseline scenario, with total R&D over GDP increasing from 2.55% in 2007 to almost 2.8% after 70 years, and then decreasing to 2.5% at the end of the century.

Figure 1. R&D as Percentage of GDP

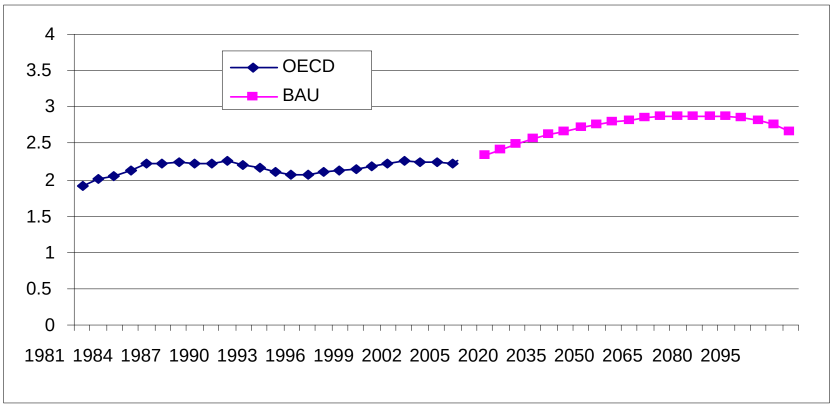
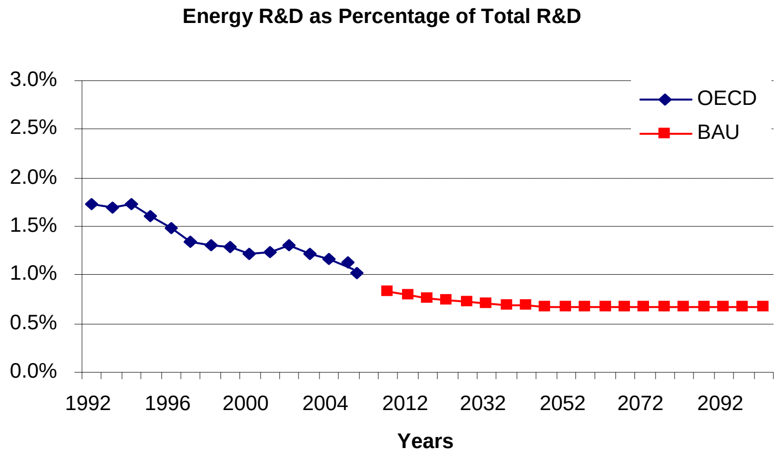


Figure 2 shows the historical values of energy R&D over total R&D for OECD countries. The trend is decreasing, starting from 1.7% in 1992 and dropping to 1.1% in 2005. A decreasing trend is also derived under our baseline scenario as shown in the same figure 2. Energy R&D as percentage of total R&D slowly decreases across the century from about 0.9% to 0.7% in 2102. Technical change is therefore mainly capital-labor augmenting and this trend is even reinforced across the century because wages, endogenously determined, increase faster than equilibrium fuel prices.

Figure 2. Energy R&D as Percentage of Total R&D



Most interestingly, capital-labor augmenting technical change is energy-biased in our model. This means that R&D investments are mainly directed towards the capital-labor aggregate, but they increase the productivity of the energy input relative to the productivity of the capital-labor aggregate. This emerges clearly from the analysis of equation (10), in which we derive the ratio of the marginal products of energy (EN) and capital-labor (KL):

$$\frac{MP_{EN}}{MP_{KL}} = \frac{(1-\alpha_Y(n))(1-\alpha_{ES}(n))\left[\alpha_{ES}(n)HE(n,t)^{\rho_{ES}} + (1-\alpha_{ES}(n))EN(n,t)^{\rho_{ES}}\right]^{\frac{\rho_Y}{\rho_{ES}}-1} EN(n,t)^{\rho_{ES}-1}}{\alpha_Y(n)(1-\alpha_{KLS}(n))\left[\alpha_{KLS}(n)HKL(n,t)^{\rho_{KLS}} + (1-\alpha_{KLS}(n))KL(n,t)^{\rho_{KLS}}\right]^{\frac{\rho_Y}{\rho_{KLS}}-1} KL(n,t)^{\rho_{KLS}-1}} \qquad (10)$$

As discussed above, the elasticity of substitution between *KLS* and *ES* is lower than the elasticity of substitution between KL and HKL in the model, i.e. $\rho_Y < \rho_{KLS}$. For this reason capital-labor augmenting technical change increases the relative marginal product of *EN*. Thus, *KL*-augmenting technical change is *energy*-biased. In other words, *KL*-augmenting technical change is *pollution*-biased and knowledge advancements *per se* are not necessarily good for the environment. This result derives from the assumption of complementarity between the *KLS* nest and *ES* intermediate inputs in the final output nest and the high elasticity of the Non-energy knowledge stock with respect to capital-labor input: any increase in the productivity of *KL* increases the demand of *EN* more than the demand for *KL*.

5. STABILIZATION POLICY

5.1 Gross World Product, Consumption and Total Investments.

We use the WITCH model to study how an ambitious climate policy might affect the direction and pace of technical change. Let us assume that world countries agree to stabilize CO_2 concentrations at 450 ppm.[6] Let us also assume that they agree to introduce a global cap and trade scheme as main climate policy tool. Initial allocations are grandfathered according to an equal per capital allocation rule. This is a simplified policy scheme, but useful to analyze the optimal reactions in terms of R&D investments and thus the direction and pace of technical change.

For an easy comparison between the stabilization and baseline scenarios, Tables 6, 7 and 8 display the same variables and indicators already portrayed in Tables 3, 4 and 5. According to WITCH, the CO_2 stabilization policy just briefly described reduces Gross World Product (GWP) over the whole optimization interval 2002-2102. Discounted costs, measured as reductions of net GDPs and aggregated over regions, are 3.9% of baseline discounted GWP. Investments in capital, with respect to the baseline scenario, decline in absolute terms and as share of GWP; investments in the energy sector absorb instead a higher share of GWP.

Table 6. Stabilization Trends of Major Variables

	2002	2022	2042	2062	2082	2102
GWP (Trillions, 1995 USD)	34	63	103	143	183	225
World Population (billions)	6.2	7.6	8.5	9.0	9.3	9.5
GWP Growth Rate (20 years average)	3.2%	2.5%	1.7%	1.2%	1.0%	--
Population Growth Rate (20 years average)	1.0%	0.6%	0.3%	0.2%	0.1%	--
Carbon Intensity of Energy (Ton C / Toe)	0.690	0.550	0.419	0.306	0.246	0.173
Energy Intensity (Toe / USD)	0.286	0.178	0.118	0.085	0.073	0.082
Carbon Intensity of Output (Ton C / USD)	0.197	0.098	0.049	0.026	0.018	0.014
CO_2 concentrations in the atmosphere (ppm)	369	408	431	441	444	447
Investment in final good capital (Trillions, 1995 USD)	7.5	12.5	18.2	23.1	28.3	34.2
Investment in R&D (Trillions, 1995 USD)	0.84	1.65	2.68	3.69	4.58	5.07
Investment in Energy Sector (Trillions, 1995 USD)	0.32	0.59	0.82	1.10	1.45	1.85
Investment in Final Good Capital (% GWP)	22.18%	19.78%	17.67%	16.16%	15.46%	15.21%
Investment in Energy Sector (% GWP)	0.94%	0.93%	0.79%	0.77%	0.79%	0.83%
R&D expenditure (% GWP)	2.47%	2.60%	2.60%	2.58%	2.50%	2.26%
Non-Energy R&D (% GWP)	2.43%	2.55%	2.53%	2.49%	2.41%	2.18%
Energy R&D (% GWP)	0.04%	0.05%	0.07%	0.09%	0.09%	0.08%
Energy R&D (% Total investment in R&D)	1.43%	1.85%	2.66%	3.46%	3.77%	3.64%
Non-Energy R&D knowledge stock per worker (index)	1.0	0.9	1.0	1.3	1.6	2.0
Energy R&D knowledge stock per worker (index)	100.00%	111.38%	148.34%	206.27%	272.33%	332.02%

[6] This target is approximately equivalent to stabilize all GHG concentrations at 550 ppm.

Table 7. Contribution of Raw Inputs to the Growth Rate of Capital-Labor Services (Average Annual Growth Rates)

	2002-2021	2022-2041	2042-2061	2062-2081	2082-2102
USA					
capital-labor services	*1.12%*	*0.64%*	*0.34%*	*0.19%*	*0.15%*
labor	0.39%	0.20%	0.06%	0.01%	0.00%
capital for final good production	0.71%	0.36%	0.19%	0.11%	0.10%
non-energy R&D knowledge stock	0.02%	0.08%	0.09%	0.08%	0.06%
CHINA					
capital-labor services	*2.11%*	*1.43%*	*0.66%*	*0.35%*	*0.25%*
labor	0.40%	0.08%	-0.08%	-0.09%	-0.04%
capital for final good production	1.59%	1.14%	0.54%	0.28%	0.18%
non-energy R&D knowledge stock	0.11%	0.20%	0.19%	0.15%	0.11%
Sub Saharan Africa (SSA)					
capital-labor services	*3.18%*	*2.48%*	*1.65%*	*1.26%*	*1.00%*
labor	1.41%	1.00%	0.63%	0.40%	0.28%
capital for final good production	1.76%	1.46%	1.01%	0.85%	0.71%
non-energy R&D knowledge stock	0.01%	0.01%	0.01%	0.01%	0.01%

Table 8. Contribution of Raw Inputs to the Growth Rate of Energy Services (Average Annual Growth Rates)

	2002-2021	2022-2041	2042-2061	2062-2081	2082-2102
USA					
energy services	*0.40%*	*-0.79%*	*-1.65%*	*-0.84%*	*-0.23%*
energy	0.38%	-0.82%	-1.70%	-0.89%	-0.27%
energy R&D knowledge stock	0.02%	0.03%	0.05%	0.05%	0.04%
CHINA					
energy services	*2.18%*	*0.87%*	*-0.83%*	*-0.42%*	*-0.02%*
energy	2.13%	0.82%	-0.88%	-0.46%	-0.05%
energy R&D knowledge stock	0.06%	0.05%	0.05%	0.04%	0.03%
Sub Saharan Africa (SSA)					
energy services	*2.23%*	*0.97%*	*-0.16%*	*0.75%*	*1.27%*
energy	2.18%	0.94%	-0.18%	0.73%	1.25%
energy R&D knowledge stock	0.04%	0.03%	0.03%	0.02%	0.02%

Energy R&D investments increase substantially to improve energy efficiency. However, equilibrium Non-Energy R&D investments are found to be lower than in the baseline scenario. The contraction of knowledge generation in the Non-Energy sector offsets increased knowledge creation in the Energy sector. As a total R&D investments are lower and the pace of knowledge accumulation is slowed down as displayed in Table 6. This determines a lower contribution of R&D investments to capital-labor services growth with respect to the baseline scenario, as Table 7 clearly shows. The contribution of the Energy knowledge stock to Energy services growth increases instead, as shown in Table 8.

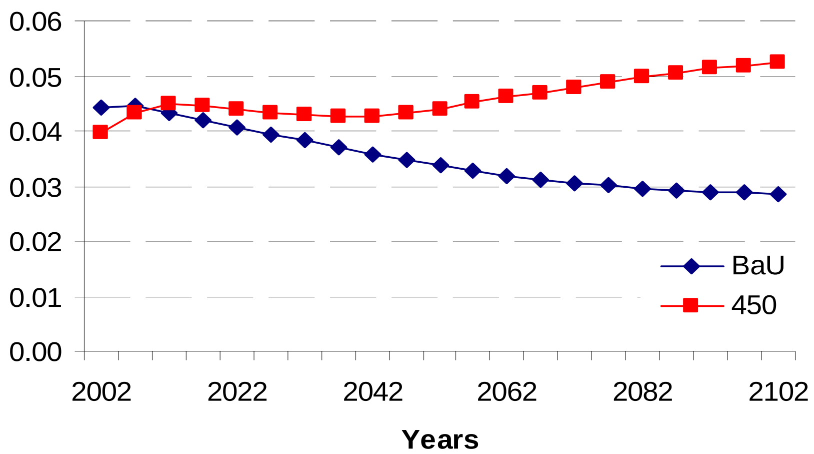
Let us now examine the R&D equilibrium paths in both the baseline and stabilization scenarios in greater detail.

5.2 Energy and Non-Energy Investments

As specified above (Equation 1), gross output is obtained from a combination of energy services produced by the Energy Sector and capital-labor services produced in the Non-Energy sector. Investments in the Energy Sector include all investments in electricity generation technologies, operation and maintenance expenditures for power plants (as well as nuclear waste management and transportation costs for captured carbon emissions), and investments in Energy R&D. Investments in the Non-Energy sector are allocated between Non-Energy R&D and the overall economy capital stock, which is combined with labor.

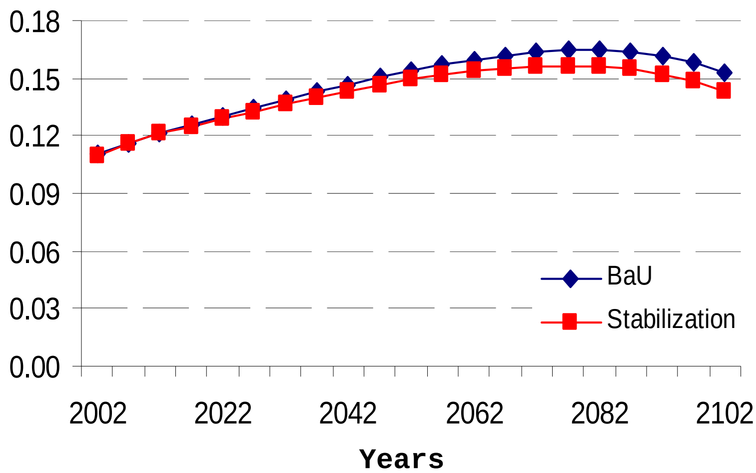
The ratio of Energy to Non-Energy investments declines in the Baseline scenario, while it increases when a stabilization policy is implemented (see Figure 3). The reason is that resources devoted to investment are diverted towards the energy sector to build capital-intensive and O&M demanding carbon-free electricity generation capacity, and to increase energy efficiency by augmenting the energy R&D capital stock.

Figure 3. Energy to Non-Energy Investment Ratio



In the Non-Energy Sector, we can distinguish between investments to increase the stock of Non-Energy R&D and general capital investments. In the BaU scenario, the ratio between the two increases substantially and the economy becomes more and more knowledge- intensive. Under a stringent stabilization policy, we find that the equilibrium ratio between Non-Energy R&D investments and general investments in the capital stock is increasing as well, but the time path is lower with respect to an economy without a carbon constraint (see Figure 4.). This result is explained by the exogenous population dynamics, which keep labor force unchanged under the stabilization scenario, and a weak substitutability between capital and labor.[7] Climate policy induces a contraction of economic activity and exerts a pressure to reduce investments in the Non-Energy sector. However, labor force cannot adjust and cannot be easily substituted by capital. As a result the downward pressure in the Non-Energy sector is accommodated by a proportionally greater reduction of Non-Energy knowledge, and thus by a contraction of Non-Energy R&D investments.

Figure 4. Ratio between Non-Energy R&D Investment and Capital Investments



5.3 Energy R&D and Non-Energy R&D Investments.

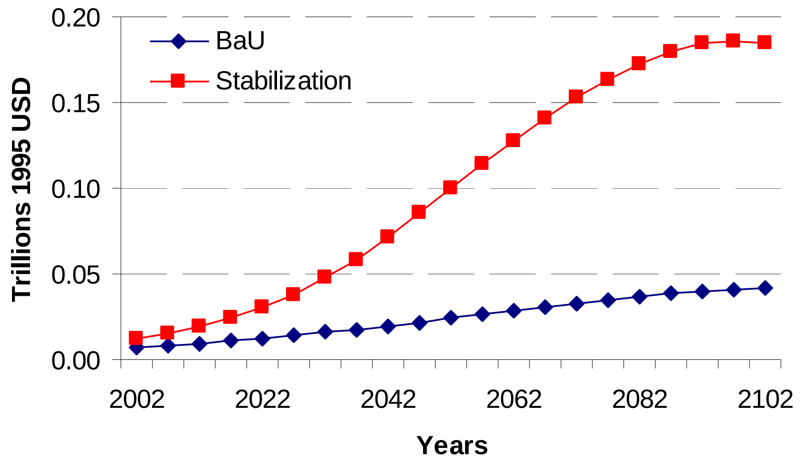
Energy R&D investments increase substantially under the CO_2 stabilization policy, as shown in Figure 5. The need to increase energy efficiency modifies the equilibrium ratio of Energy R&D to Non-Energy R&D investments from a declining path, over the century, to a rising one. Contrary to what found by Goulder and Schneider (1999) and Sue Wing (2003), we find that climate policy strongly re-directs investments to Energy R&D and to the energy sector in general. Therefore, in an

[7] For a full description of population dynamics see Bosetti, Massetti and Tavoni (2007).

unconstrained economy (without a stabilization target and the related climate policy), R&D is directed to augment the productivity of the capital-labor aggregate, which becomes relatively scarcer with respect to energy, as population growth slows down worldwide. In a carbon constrained economy, instead, the price of the energy input grows faster than the price of the Non-Energy input, and thus R&D resources are directed to increase energy efficiency.

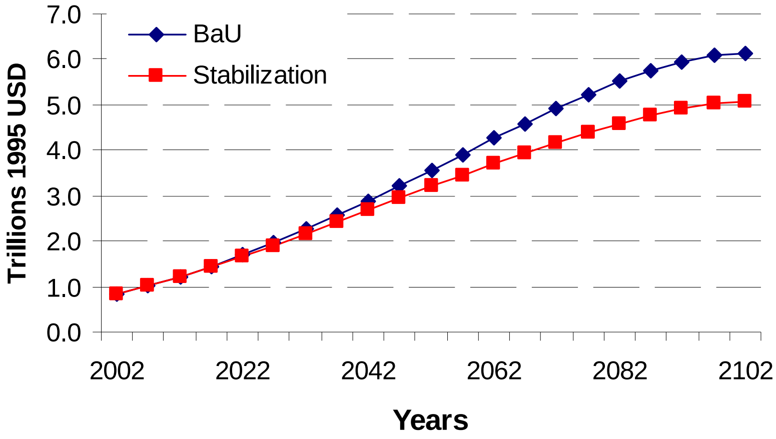
Nonetheless, the drop in Non-Energy R&D is larger than the sharp increase in Energy R&D. As a consequence, at the equilibrium, overall expenditure in R&D decreases, as illustrated in Figure 6. This result confirms what found by Goulder and Schneider (1999) and Sue Wing (2003).

Figure 5. Energy R&D Investments



There are two driving forces behind this result. First, as emphasized above, the level of economic activity is lower when a carbon constraint is introduced and Non-Energy R&D is therefore accordingly reduced. Second, as shown in Figure 4, the equilibrium ratio of Non-Energy R&D investments to capital investments is lower in the presence of a stabilization target than without climate policy.

Figure 6. Total Investments in R&D



A wide concern has been expressed in the literature that the increase in Energy R&D induced by climate policy might come at the expenses – i.e. "crowd out" – of other types of knowledge investments (Nordhaus, 2002; Popp, 2004). As a consequence, the benefits of induced technical change should be evaluated net of the costs arising from a lower knowledge accumulation in other sectors of the economy. By modeling two R&D sectors we are now in a good stance to explore this issue with greater transparency than in previous analyses.

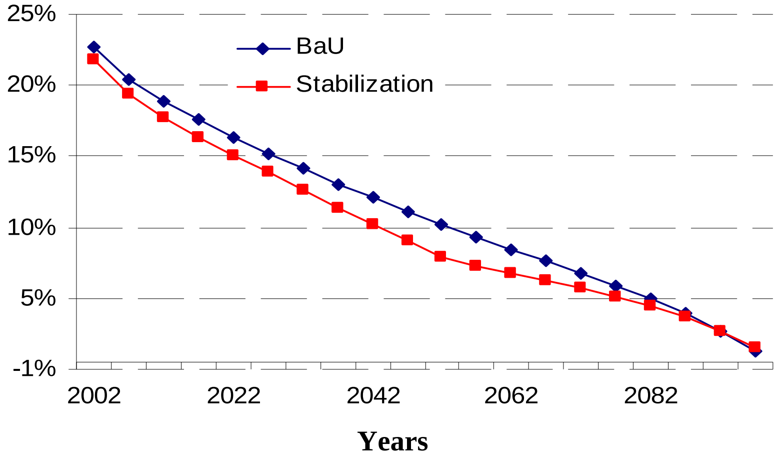
We define the Energy R&D crowding-out effect on Non-Energy R&D as the reduction in investments in the latter, directly or indirectly caused by an increase of investments in the former. Our definition is straightforwardly borrowed from macroeconomic theory, where the crowding out effect of government expenditure on private investments is a well-established result (see, for example, Mankiw 2003). Following closely the macroeconomic approach to the crowding out issue, we say that Energy R&D crowds-out Non-Energy R&D if the higher expenditure for increasing energy efficiency, *ceteris paribus*, has the effect to increase the opportunity cost of capital and thus to reduce investments in Non-energy R&D (as well as all other types of investment).[8]

[8] A narrower approach is sometimes employed to discuss crowding out effects in the climate change literature. According to this view, the amount of resources available to invest for the development of new technologies is in large part fixed and the expansion of some activities must necessarily come, at least for a significant fraction, at the expense of some others. This is indeed a non negligible issue in the short- and medium-term, as emphasized by Goolsbee (1998). However, when looking at the long-term, as in all climate policy analyses, it is unclear why economies should not be able to meet an increase in the demand of R&D investments. There might be a conflict between R&D resources and other types of investments, but hardly a close competition between different forms of R&D themselves. In our analysis, we determine equilibrium R&D investments when

In our set-up, we investigate R&D investments assuming that economies are free to optimally allocate resources among sectors. Sector-specific knowledge stocks are not interchangeable, but R&D investments are. It is thus possible, in principle, to expand Energy R&D investments without reducing Non Energy R&D expenditures, until the long term equilibrium ratio between the two knowledge stocks is reached.

However, we find that mitigation policy reduces the growth rate of Non-Energy R&D investments, as pictured in Figure 7. What are the economic forces behind this result? Does this contraction result from a crowding out effect of increased investment in Energy R&D?

Figure 7. Growth Rate of Investments in Non-Energy R&D



Let us start exploring this issue from a theoretical perspective. To this purpose, we built a simplified version of the model (described in Appendix B in detail), from which we can derive the following Proposition 1:

Proposition 1 *At each time t, the conditions characterizing the equilibrium trade-off between knowledge accumulation in the energy sector and consumption, and knowledge accumulation in the capital-labor sector and consumption are:*

$$\frac{\partial Y(t)}{\partial HE(t)}\frac{\partial HE(t)}{\partial I_{HE}(t-1)}+\frac{I_{HE}(t)}{I_{HE}(t-1)}=\beta\frac{c(t)}{c(t-1)}$$

---

economies are free to optimally allocate investments under a climate policy. We thus rule out the Goolsbee type crowding out effect.

$$\frac{\partial Y(t)}{\partial HKL(t)}\frac{\partial HKL(t)}{\partial I_{HKL}(t-1)}+\frac{I_{HKL}(t)}{I_{HKL}(t-1)}=\beta\frac{c(t)}{c(t-1)}$$

Proof : See Appendix B.

From the two conditions above we can easily derive:

$$\frac{I_{HKL}(t)}{I_{HKL}(t-1)}=\underbrace{\frac{I_{HE}(t)}{I_{HE}(t-1)}}_{A}+\underbrace{\frac{\partial Y(t)}{\partial HE(t)}\frac{\partial HE(t)}{\partial I_{HE}(t-1)}}_{B}-\underbrace{\frac{\partial Y(t)}{\partial HKL(t)}\frac{\partial HKL(t)}{\partial I_{HKL}(t-1)}}_{C} \quad (12)$$

Equation (12) allows us to identify the different channels through which mitigation policy affects the rate of growth of investments in Non-Energy R&D. First, from equation (12) we can rule out any "*direct*" crowding out effect by Energy R&D. The positive sign of the first term on the RHS (A) shows instead that an increase in Energy R&D investments has a direct positive effect on the growth rate of investments in Non-Energy R&D. However, the effect of an increase in Energy R&D investments also depends on the magnitude of the change of the marginal product of Energy R&D investments and of the marginal product of Non-Energy R&D investments, the second (*B*) and the third (*C*) term on the RHS of equation (12), respectively.

To isolate the total effect of an increase in Energy R&D, we have performed an exercise in which, in the BaU scenario, we impose an Energy R&D expenditure path equal to the equilibrium path in the stabilization scenario. This exercise is designed to identify the amount of non-energy R&D that would be displaced by an exogenous increase in energy R&D, with virtually no price effect. We must emphasize that, in running our test, we do not make any additional restriction to the other choice variables in the model whose equilibrium path is thus adjusted to the new assumptions in the R&D sector. Simulation results show that Non-Energy R&D investments respond positively to an increase in Energy R&D, revealing a (mild) degree of complementarity between the two knowledge stocks.

In addition, using equation (12) and numerical results from simulations in the stabilization scenario, we can provide an explanation for the reduction of the rate of investments in Energy R&D that depends on the structure of the economy, as portrayed in the model, and not on the "crowding out" hypothesis usually proposed in the literature. The decrease in the rate of investments in Non-Energy R&D can indeed be explained by the effect of mitigation policy on the marginal product of Energy

R&D investments and on the marginal product of Non-Energy R&D investments, the second (*B*) and the third term (*C*) on the RHS of equation (12), respectively.

As to the marginal product of investments in Energy R&D, since the mitigation policy increases investments to achieve higher energy efficiency and induces a substitution from Energy Services (ES) to Capital-Labor services (KLS), the equilibrium path determined in the stabilization scenario shows that $\partial HE/\partial I_{HE}$ is always lower than in the BaU scenario and $\partial Y/\partial HE$ is instead always higher because of a higher KLS/ES ratio. The combination of the two effects results in a contraction of *B* in the first 60 years (due to the strong effort in Energy R&D investments) and in an expansion in the last 40 years of the century (due to a marked shift away from energy in the outer nest), with respect to the BaU scenario.

As to the marginal product of investment in Non-Energy R&D, *C* on the RHS, its absolute value is always higher than in the BaU scenario because both $\partial HKL/\partial I_{HKL}$ and $\partial Y/\partial HKL$ increase. The first term increases because of the reduction of Non-Energy R&D investments, the latter increases because, as discussed in Section 4, our model features energy-biased technical change – i.e. higher investments in Non-Energy R&D trigger higher demand of energy services (ES). Therefore, when an ambitious climate policy is implemented, energy demand can be reduced by slowing down the pace of accumulation of the pollution augmenting Non-Energy knowledge stock, thus increasing its marginal product.

5.4 Induced Technical Change and the Cost of Climate Policy.

In this section we compare the cost of the stabilization policy under alternative assumptions about induced technical change (ITC). We consider four alternative scenarios.

In the first one, we assume that it is not possible to change the Non-Energy knowledge stock and we exogenously set it equal to its equilibrium BaU level. In the second scenario, we maintain the assumption that Non-Energy knowledge stock is exogenously set at its BaU level, and we make the additional assumption that investments in Energy R&D partly crowd out Non-energy R&D (we assume a 50% crowding out as in Popp, 2004). In the third scenario, we assume that it is not possible to adjust the Energy knowledge stock, which is exogenously set equal to its BaU level. In the fourth scenario, we assume that both knowledge stocks are exogenously set at their BaU level.

For each scenario, we compare the effect of the stabilization policy on the price of carbon permits and on discounted climate policy costs, measured as the ratio between net discounted GWP losses and the net discounted GWP in the BaU scenario. Both indicators are widely used to assess the implications of alternative scenarios of ITC on climate policy costs.

Table 9. Percentage change of permit prices under alternative scenarios

	2002	2022	2042	2062	2082	2102
No ITC_HKL	0.31%	0.36%	0.63%	1.14%	1.50%	0.12%
Crowding-out	-0.31%	0.28%	0.52%	0.90%	1.26%	0.11%
No ITC_He	0.62%	0.69%	0.99%	1.49%	1.84%	0.15%
No ITC	0.00%	1.09%	1.61%	2.49%	3.34%	0.24%

As to the price of emission permits, we find that ITC always lowers the equilibrium profile of carbon prices, as shown in Table 9. It is interesting to notice that omitting ITC in the Energy Sector leads to a higher overestimate of carbon prices than in the scenario where Non-Energy ITC is excluded.

Finally, let us focus on global GWP losses. The most interesting conclusion is as follows. If pollution-augmenting technical change is omitted, the cost of stabilizing CO_2 concentrations decreases. Therefore, by focusing only on energy R&D, the cost of climate policy is *underestimated* (from 3.9% to 3.6% of global GWP in our model).

Therefore, neglecting ITC tends to overestimate the total cost of climate policy. However, if only Energy R&D is endogenized and can be induced by climate policy, the total cost is underestimated.

A sensitivity analysis of the main results reported in this section is contained in Appendix C. Our sensitivity analysis, performed with respect to the values of the main elasticities of substitution assumed in this paper, confirms our results.

6. CONCLUSIONS

To improve our understanding of the effects of climate policy on technological change, we have introduced directed technical change in WITCH. In this new version of the model, R&D expenditures, and therefore knowledge accumulation, are factor- specific and can be directed either towards increasing energy-efficiency or towards increasing the productivity of Non-Energy inputs, namely capital and labor.

By explicitly modeling the equilibrium dynamics of two R&D capital stocks, we avoid making implicit assumptions on energy R&D crowding-out, and we can study how mitigation policies change the direction and the magnitude of technical change.

Then, we analyzed the implications of a climate policy whose target is to stabilize CO_2 concentrations in the atmosphere at 450ppmv at the end of the century. Simulation results show that this policy induces an increase of Energy R&D investments, as expected. More specifically, the stabilization target requires enhanced energy efficiency and thus switches the ratio of Energy R&D to Non-Energy R&D investments from a declining path to a rising one.

Therefore, contrary to findings in Goulder and Schneider (1999) and Sue Wing (2003), we obtain that climate policy strongly re-directs investments to Energy R&D, and to the energy sector in general. However, the contraction in Non-Energy R&D is greater than the substantial increase in Energy R&D. Therefore, the equilibrium total R&D expenditure is smaller in the stabilization scenario than in the BaU scenario. This latter result was also in Goulder and Schneider (1999) and Sue Wing (2003).

We also find that there is no direct competition between the Energy and Non-Energy R&D (no crowding out), despite the contraction of Non-Energy R&D investments. The decline of this latter variable can be explained as follows. First, a major cause of the Non-Energy R&D investments reduction is output contraction induced by the stabilization policy, which in turn induces a lower demand of capital-labor services and a lower investment in Non-Energy R&D. Second, technical change is mainly capital-labor augmenting and energy-biased in our baseline. This implies that Non-Energy R&D investments are *pollution*-biased and are therefore strongly discouraged under climate policy.

Therefore, our results suggest that a greater expenditure on energy R&D under a stabilization policy might not lead to a lesser effort on other types of R&D, and thus to negative macroeconomic consequences. Output contraction is the reason of lower total R&D investments, and not vice-versa.

Finally, sensitivity analysis on key elasticities of substitution has shown that our results are robust to a wide range of key elasticities' values.

Our results challenge the widespread intuition that a low-carbon world would be a world with a higher rate of technological innovation. By using the WITCH model, we have shown that R&D efforts to increase energy efficiency and to de-carbonize the energy sector will increase enormously if a stringent climate policy is implemented. However, since they represent a small fraction of overall R&D expenditure, this expansion of knowledge creation in the energy sector might be not sufficient to compensate for the contraction of R&D expenditure in other sectors, induced by a lower level of economic activity.

Finally, it is clear that when energy and other inputs are complements – as suggested by many empirical studies – any capital-labor augmenting technical change is fundamentally a *pollution*-biased technical change and is thus discouraged by price signals induced by climate policy.

The consequence for studies that aim at assessing the economic cost of climate policy is as follows. The role of technical change to achieve GHG concentration stabilization targets is crucial. If a study neglects the impact of climate stabilization on technical change, it will overestimate the cost of climate policy, as clearly shown in Edenhofer (2006). However, if a study considers the impact of climate policy only on energy-related and carbon-free technical change, the cost of climate policy will be underestimated. A proper assessment of the cost of climate policy must take into account the contrasting effects induced on both Energy and Non Energy R&D and related consequences.[9]

[9] A proper assessment of the cost of climate policy should also take into account several other factors, ranging from technological availability to delayed participation of developing countries. Some preliminary results are in Bosetti, Carraro and Tavoni, 2008.

Appendix A: Model Equations and List of Variables

In this Appendix, we reproduce the main equations of the WITCH model. For a full description of the model please refer to Bosetti, Massetti and Tavoni (2007). The list of variables is reported at the end of this Appendix.

In each region, indexed by *n*, a social planner maximises the following utility function:

$$W(n) = \sum_t U\left[C(n,t), L(n,t)\right] R(t) = \sum_t L(n,t)\left\{\log\left[c(n,t)\right]\right\} R(t)\,, \tag{A1}$$

where *t* represents 5-year time spans and the pure time preference discount factor is given by:

$$R(t) = \prod_{v=0}^{t}\left[1+\rho(v)\right]^{-5}\,, \tag{A2}$$

where the pure rate of time preference $\rho(v)$ is assumed to decline over time. Moreover, $c(n,t) = \frac{C(n,t)}{L(n,t)}$ is per capita consumption.

Economic module

The budget constraint defines consumption as net output less investments:

$$\begin{aligned} C(n,t) = {} & Y(n,t) - I_C(n,t) - I_{R\&D,EN}(n,t) - I_{R\&D,KL}(n,t) \\ & - \sum_j I_{R\&D,j}(n,t) - \sum_j I_j(n,t) - \sum_j O\&M_j(n,t) \end{aligned} \tag{A3}$$

Where *j* is an index identifying different energy technologies. Output is produced via a nested CES function that combines a capital-labor aggregate and energy; capital and labor are obtained from a CES function. The climate damage Ω reduces gross output. To obtain net output we also subtract the fuel costs *f* and the costs of CCS:

$$\begin{aligned} Y(n,t) = {} & \frac{TFP(n,t)\left[\alpha_Y(n)\cdot KLS^{\rho_Y} + (1-\alpha_Y(n))\cdot ES(n,t)^{\rho_Y}\right]^{1/\rho_Y}}{\Omega(n,t)} \\ & - \sum_f \left(P_f(n,t) X_{f,extr}(n,t) + P_f^{\text{int}}(t) X_{f,netimp}(n,t)\right) \\ & - P_{CCS}(n,t) CCS(n,t) \end{aligned}\,. \tag{A4}$$

Total factor productivity $TFP(n,t)$ evolves exogenously with time. Energy services are an aggregate of energy and a stock of knowledge combined with a CES function:

$$ES(n,t) = \left[\alpha_{HE}(n) HE(n,t)^{\rho_{ES}} + \alpha_{EN}(n) EN(n,t)^{\rho_{ES}}\right]^{1/\rho_{ES}}\,. \tag{A5}$$

Energy is a combination of electric and non-electric energy:

$$EN(n,t) = \left[\alpha_{EL} EL(n,t)^{\rho_{EN}} + \alpha_{NEL} NEL(n,t)^{\rho_{EN}}\right]^{1/\rho_{EN}}\,. \tag{A6}$$

Each factor is further decomposed into several sub-components. Factors are aggregated using CES, linear and Leontief production functions. Capital-labor services are obtained aggregating a capital-labor input and a knowledge stock with a CES function:

$$KLS(n,t) = \left[\alpha_{HKL}(n) HKL(n,t)^{\rho_{KLS}} + \alpha_{KL}(n) KL(n,t)^{\rho_{KLS}}\right]^{1/\rho_{KL}} \tag{A7}$$

The capital-labor input is a CES combination of capital and labor. Labor is assumed to be equal to population and evolves exogenously.

$$KL(n,t)=\left[\alpha_K(n)K_C(n,t)^{\rho_{KL}}+\alpha_L(n)L(n,t)^{\rho_{KL}}\right]^{1/\rho_{KL}} \tag{A8}$$

Final good capital accumulates following the standard perpetual rule:

$$K_C(n,t+1) = K_C(n,t)(1-\delta_C)+I_C(n,t). \tag{A9}$$

New ideas which contribute to the stock of energy knowledge, $Z_{HE}(n,t)$, are produced using R&D investments, $I_{R\&D,EN}(n,t)$, together with the previously cumulated knowledge stock $HE(n,t)$:

$$Z_{HE}(n,t) = a\, I_{HE}(n,t)^b\, HE(n,t)^c \cdot \tag{A10}$$

Similarly, new ideas in the non-energy sector are generated as follows:

$$Z_{HKL}(n,t) = f\, I_{HKL}(n,t)^g\, HKL(n,t)^h \tag{A11}$$

The two knowledge stocks evolve as follows:

$$HE(n,t+1) = HE(n,t)(1-\delta)+Z_{HE}(n,t) \tag{A12}$$
$$HKL(n,t+1) = HKL(n,t)(1-\delta)+Z_{HKL}(n,t) \tag{A13}$$

For illustrative purposes, we show how electricity is produced via capital, operation and maintenance and resource use through a zero-elasticity Leontief aggregate:

$$EL_j(n,t)=\min\left\{\mu_{n,j}K_j(n,t);\tau_{n,j}O\&M_j(n,t);\varsigma_j X_{j,EL}(n,t)\right\}. \tag{A14}$$

Capital for electricity generation technologies accumulates as follows:

$$K_j(n,t+1)=K_j(n,t)\left(1-\delta_j\right)+\frac{I_j(n,t)}{SC_j(n,t)}, \tag{A15}$$

where, for selected technologies, the new capital investment cost *SC(n,t)* decreases with the world cumulated installed capacity by means of Learning-by-Doing:

$$SC_j(n,t)=B_j(n)\sum_t\sum_n K_j(n,t)^{-\log_2 PR_j}. \tag{A16}$$

Operation and maintenance is treated as an investment that fully depreciates every year. The resources employed in electricity production are subtracted from output in equation A3 and A4. Their prices are calculated endogenously using a reduced-form cost function that allows for non-linearity in both the depletion effect and in the rate of extraction:

$$P_f(n,t)=\chi_f(n)+\pi_f(n)\left[Q_f(n,t-1)/\overline{Q}_f(n,t)\right]^{\psi_f(n)} \tag{A17}$$

where Q_f is cumulative extraction of fuel f:

$$Q_f(n,t-1)=Q_f(n,0)+\sum_{s=0}^{t-1}X_{f,extr}(n,s). \tag{A18}$$

Each country covers consumption of fuel f, $X_f(n,t)$, by either domestic extraction or imports, $X_{f,netimp}(n,t)$, or by a combination of both. If the country is a net exporter, $X_{f,netimp}(n,t)$ is negative.

$$X_f(n,t) = X_{f,extr}(n,t) + X_{f,netimp}(n,t) \tag{A19}$$

Climate Module

GHGs emissions from combustion of fossil fuels are derived by applying stoichiometric coefficients to the total amount of fossil fuels minus the amount of CO_2 sequestered:

$$CO_2(n,t) = \sum_f \omega_{f,CO_2} X_f(n,t) - CCS(n,t). \tag{A20}$$

When a cap on emission (CAP) is included we have an additional equation, constraining emissions, given the possibility to sell and buy permits:

$$CO_2(n,t) = CAP(n,t) + NIP(n,t) \tag{A21}$$

In addition, carbon permits revenues/expenses enter the budget constraint:

$$\begin{aligned} C(n,t) = {} & Y(n,t) - I_C(n,t) - I_{R\&D,EN}(n,t) - I_{R\&D,KL}(n,t) \\ & - \sum_j I_{R\&D,j}(n,t) - \sum_j I_j(n,t) - \sum_j O\&M_j(n,t) - p(t)NIP(n,t) \end{aligned} \tag{A3'}$$

The damage function impacting output varies with global temperature:

$$\Omega(n,t) = \frac{1}{1 + \left(\theta_{1,n} T(t) + \theta_{2,n} T(t)^2\right)}. \tag{A22}$$

Temperature increases through augmented radiating forcing *F(t)*:

$$T(t+1) = T(t) + \sigma_1 \{F(t+1) - \lambda T(t) - \sigma_2 [T(t) - T_{LO}(t)]\} \tag{A23}$$

which in turn depends on CO_2 concentrations:

$$F(t) = \eta \left\{ \log\left[M_{AT}(t) / M_{AT}^{PI}\right] - \log(2) \right\} + O(t), \tag{A24}$$

caused by emissions from fuel combustion and land use change:

$$M_{AT}(t+1) = \sum_n \left[CO_2(n,t) + LU_j(t)\right] + \phi_{11} M_{AT}(t) + \phi_{21} M_{UP}(t), \tag{A25}$$

$$M_{UP}(t+1) = \phi_{22} M_{UP}(t) + \phi_{12} M_{AT}(t) + \phi_{32} M_{LO}(t), \tag{A26}$$

$$M_{LO}(t+1) = \phi_{33} M_{LO}(t) + \phi_{23} M_{UP}(t). \tag{A27}$$

Model variables are denoted with the following symbols:

W = welfare
U = instantaneous utility
C = consumption
c = per-capita consumption
L = population
R = discount factor

Y = production
I_c=investment in final good
$I_{R\&D, EN}$=investment in energy R&D
$I_{R\&D,KL}$=investment in non-energy R&D
I_j=investment in technology j
$O\&M$=investment in operation and maintenance
TFP=total factor productivity
K_c=final good stock of capital
ES=energy services
KLS=capital-labor services
KL=capital-labor aggregate
Z_{HE}=flow of new energy knowledge
Z_{HKL}=flow of new non-energy knowledge
Ω= damage
P_j= fossil fuel prices
X_j= fuel resources
P_{CCS}= price of CCS
CCS=CO_2 sequestered
HE=energy knowledge
EN=energy
EL=electric energy
NEL=non-electric energy
K_j= stock of capital of technology j
SC_j=investment cost
CO_2= emissions from combustion of fossil fuels
NIP = Net import of carbon permits
p = Price of carbon permits
M_{AT} = atmospheric CO_2 concentrations
LU = land-use carbon emissions
M_{UP} = upper oceans/biosphere CO_2 concentrations
M_{LO} = lower oceans CO_2 concentrations
F = radiative forcing
T= temperature level

Appendix B: Simplified WITCH model and Proof of Proposition 1

In this Appendix, we use a simplified version of the WITCH model, in which we omit some features such as labor inputs, operation and maintenance costs and the damage cost of climate change, to prove Proposition 1. We focus our analysis on the outer nest of the model, thus also omitting the detailed description of the energy sector. For clarity's sake, let us skip the regional index. The list of variables is reported in the previous page. In the simplified WITCH model, a social planner maximizes the following utility function:

$$W = \sum_t \left\{ \log[c(t)] \right\} \beta^t$$

subject to:

$$c(t) = Y(t) + I_C(t) + I_E(t) + I_{HE}(t) + I_{HKL}(t) + p_f X_f(t)$$
$$K_C(t+1) = (1-\delta_C)K_C(t) + I_C(t)$$
$$EN(t+1) = E\left(I_{EN}(t), X_f(t)\right)$$
$$HE(t+1) = HE(t) + I_{HE}(t)^b HE(t)^c$$
$$HKL(t+1) = HKL(t) + I_{HKL}(t)^g HKL(t)^h$$
$$Y(t) = TFP(t)\left[KLS(t)^{\rho_Y} + ES(t)^{\rho_Y}\right]^{1/\rho_Y}$$
$$ES(t) = \left[HE(t)^{\rho_{ES}} + EN(t)^{\rho_{ES}}\right]^{1/\rho_{ES}}$$
$$KLS(t) = \left[HKL(t)^{\rho_{KLS}} + KL(t)^{\rho_{KLS}}\right]^{1/\rho_{KLS}}$$

Let L be the Lagrangian :

$$L = \sum_{t=0}^{T} \frac{u(c_t)}{(1+\rho)^t} + \sum_{t=0}^{T} \phi_t^1 \left(Y(t) - c(t) - I_E(t) - I_{HE}(t) - I_{HKL}(t) - p_f X_f(t) + (1-\delta)K_c(t) - K_c(t+1)\right)$$
$$+ \sum_{t=0}^{T} \phi_t^2 \left(E\left(I_{EN}(t), X_f(t)\right) - EN(t+1)\right) + \sum_{t=0}^{T} \phi_t^3 \left(HE(t) + I_{HE}(t)^b HE(t)^c - HE(t+1)\right)$$
$$+ \sum_{t=0}^{T} \phi_t^4 \left(HKL(t) + I_{HKL}(t)^g HKL(t)^h - HKL(t+1)\right)$$

The associated first order conditions are:

$$\frac{\partial L}{\partial c(t)} = \frac{\beta^t}{c(t)} - \phi_t^1 = 0 \tag{B1}$$

$$\frac{\partial L}{\partial I_E(t)} = \phi_t^2 \frac{\partial(E(t))}{\partial I_E(t)} - \phi_t^1 = 0 \tag{B2}$$

$$\frac{\partial L}{\partial I_{HE}(t)} = \phi_t^3 b I_{HE}(t)^{b-1} HE^c(t) - \phi_t^1 = 0 \tag{B3}$$

$$\frac{\partial L}{\partial I_{HKL}(t)} = \phi_t^4 g I_{HKL}(t)^{g-1} HE^h(t) - \phi_t^1 = 0 \tag{B4}$$

$$\frac{\partial L}{\partial X_f(t)} = \phi_t^2 \frac{\partial(E(t))}{\partial X_f(t)} - \phi_t^1 p_f = 0 \tag{B5}$$

$$\frac{\partial L}{\partial K_C(t)} = \phi_t^1 \frac{\partial Y(t)}{\partial K_C(t)} + (1-\delta)\phi_t^1 - \phi_{t-1}^1 = 0 \tag{B6}$$

$$\frac{\partial L}{\partial EN(t)} = \phi_t^1 \frac{\partial Y(t)}{\partial EN(t)} - \phi_{t-1}^2 = 0 \tag{B7}$$

$$\frac{\partial L}{\partial HE(t)} = \phi_t^1 \frac{\partial Y(t)}{\partial HE(t)} - \phi_{t-1}^3 + \phi_t^3 + \phi_t^3 c I_{HE}(t)^b HE^{c-1}(t) = 0 \tag{B8}$$

$$\frac{\partial L}{\partial HKL(t)} = \phi_t^1 \frac{\partial Y(t)}{\partial HKL(t)} - \phi_{t-1}^4 + \phi_t^4 + \phi_t^4 h I_{HKL}(t)^g HE^{h-1}(t) = 0 \tag{B9}$$

We can now prove Proposition 1. By replacing (B3) into (B8), we obtain:

$$bI_{HE}(t)^{b-1}HE^{c}(t)\frac{\partial Y(t)}{\partial HE(t)}+1+cI_{HE}^{b}(t)HE^{c-1}(t)=\frac{\phi_{t-1}^{3}}{\phi_{t}^{3}} \qquad \text{(B10)}$$

Which re-arranged yields

$$bI_{HE}(t)^{b-1}HE^{c}(t)\frac{\partial Y(t)}{\partial HE(t)}+\frac{\Delta HE(t+1)}{\Delta HE(t)}=\frac{\phi_{t-1}^{3}}{\phi_{t}^{3}} \qquad \text{(B11)}$$

Since:

$$\frac{\partial L}{\partial I_{HE}(t-1)}=\phi_{t-1}^{3}bI_{HE}(t-1)^{b-1}HE^{c}(t-1)-\phi_{t-1}^{1}=0 \qquad \text{(B12)}$$

From (B3) and (B12), we have:

$$\frac{\phi_{t-1}^{3}}{\phi_{t}^{3}}=\frac{\phi_{t-1}^{1}}{\phi_{t}^{1}}\frac{bI_{HE}(t)^{b-1}HE^{c}(t)}{bI_{HE}(t-1)^{b-1}HE^{c}(t-1)} \qquad \text{(B13)}$$

Replacing (B13) into (B11) yields:

$$\frac{bI_{HE}(t-1)^{b-1}HE^{c}(t-1)}{bI_{HE}(t)^{b-1}HE^{c}(t)}bI_{HE}(t)^{b-1}HE^{c}(t)\frac{\partial Y(t)}{\partial HE(t)}+\frac{bI_{HE}(t-1)^{b-1}HE^{c}(t-1)}{bI_{HE}(t)^{b-1}HE^{c}(t)}\frac{\Delta HE(t+1)}{\Delta HE(t)}=\frac{\phi_{t-1}^{1}}{\phi_{t}^{1}}$$ which can be re-arranged as:

$$\frac{\partial Y(t)}{\partial HE(t)}\frac{\partial HE(t)}{\partial I_{HE}(t-1)}+\frac{I_{HE}(t)}{I_{HE}(t-1)}=\frac{\phi_{t-1}^{1}}{\phi_{t}^{1}} \qquad \text{(B14)}$$

Finally, from (B1) and (B14), we have:

$$\frac{\partial Y(t)}{\partial HE(t)}\frac{\partial HE(t)}{\partial I_{HE}(t-1)}+\frac{I_{HE}(t)}{I_{HE}(t-1)}=\beta\frac{c(t)}{c(t-1)}$$

And, similarly, from (B1), (B4) and (B9), we obtain:

$$\frac{\partial Y(t)}{\partial HKL(t)}\frac{\partial HKL(t)}{\partial I_{HKL}(t-1)}+\frac{I_{HKL}(t)}{I_{HKL}(t-1)}=\beta\frac{c(t)}{c(t-1)} \qquad \text{(B15)}$$

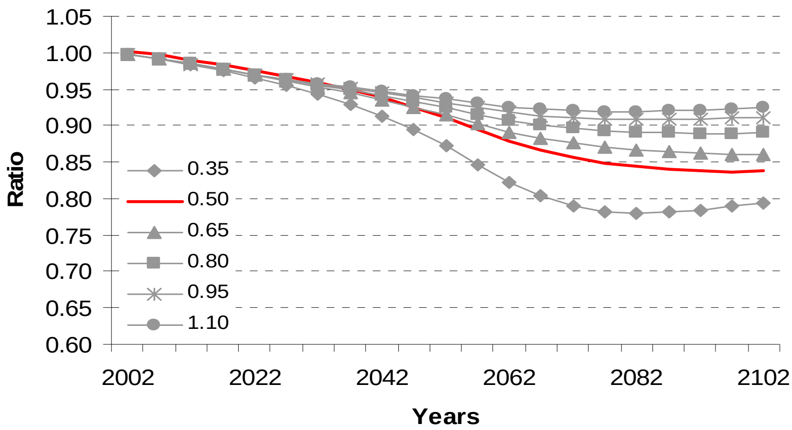
Which proves Proposition 1.

Appendix C: Sensitivity Analysis

In this Appendix, let us present the results of the sensitivity analysis on key elasticities of substitution designed to check the robustness of the findings discussed in the previous section. Specifically, we concentrate the analysis on the effects of assuming different values for the elasticity of substitution between capital-labor services (KLS) and energy services (ES), between the capital-labor aggregate (KL) and the capital-labor R&D knowledge stock (HKL) and between capital (K) and labor (L). For each elasticity of substitution, keeping the others unchanged, we have selected values in a reasonable range around the value previously assigned. The model has been re-calibrated each time to reproduce the base year.[10] BaU and stabilization policy runs have been performed for each set of parameters and then compared pair-wise.

We first consider the elasticity of substitution in the top Y nest (see equation 1), which associates KLS to ES with elasticity of substitution equal to 0.5. The limited substitutability between energy and capital-labor services induces a weak substitution effect when climate policy makes energy relatively more expensive than capital-labor services. Since production decreases in the stabilization scenario, the demand of capital-labor services shrinks. This induces a reduction of R&D directed to increase the productivity of the capital-labor aggregate. The contraction is such to offset the increase in R&D directed to the energy sector for any of the elasticity values tested, as shown in Figure 8. To a greater (lower) value of the elasticity of substitution corresponds a lower (greater) reduction of R&D investments.

Figure 8. Sensitivity Analysis: Elasticity of Substitution, Y. Ratio of R&D Investments under Stabilization to R&D Investments in Baseline

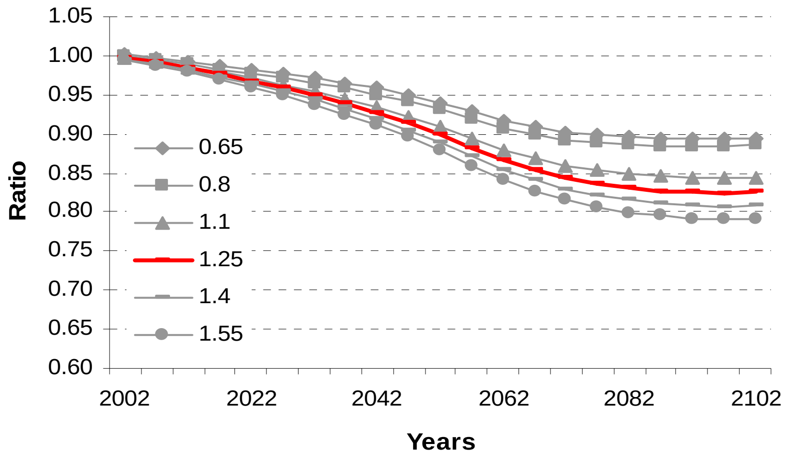


We then reset the elasticity of substitution in the outer nest Y to 0.5 and we test different values for the elasticity of substitution between KL and HKL, in the KLS nest (see equation 3). Figure 9 shows that the effect of increasing (decreasing) the substitutability between inputs is reversed with respect to the outer nest Y. To a greater (lower) elasticity of substitution between KL and HKL corresponds a greater (lower) reduction of R&D investments.

The downward shift of capital-labor services induced by climate policy (quite strong with a low elasticity of substitution in the outer nest Y), is entirely absorbed by the inputs K and HKL alone, since labor demand is, at the equilibrium, equal to population, which is fixed. Accordingly, with a given elasticity of substitution between capital and labor, the greater (lower) the substitutability between knowledge and the capital-labor aggregate, the greater (lower) the opportunity to convey the reduction of KLS towards Non-Energy Knowledge, and thus the lower (greater) the investment in Non-Energy R&D.

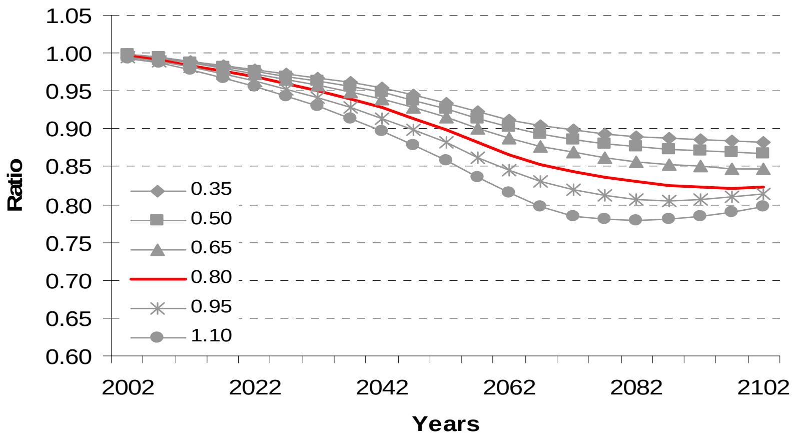
Figure 9. Sensitivity Analysis: Elasticity of Substitution, KLS. Ratio of R&D Investments under Stabilization to R&D Investments in Baseline

[10] Dynamic calibration, however, has not been performed. Accordingly, baselines may differ among themselves. The objective c sensitivity analysis is not to check the effect of a new modelling feature on optimal investments, but rather to verify how aggregate changes when a stabilization policy is implemented, under different values of key elasticities of substitution.



Similar results are obtained when performing the sensitivity analysis on the KL nest, which aggregates capital (K) and labor (L). Figure 10 shows that the lower (greater) the substitutability between K and L, the lower (greater) the contraction of Non-Energy R&D when a climate policy is enforced.

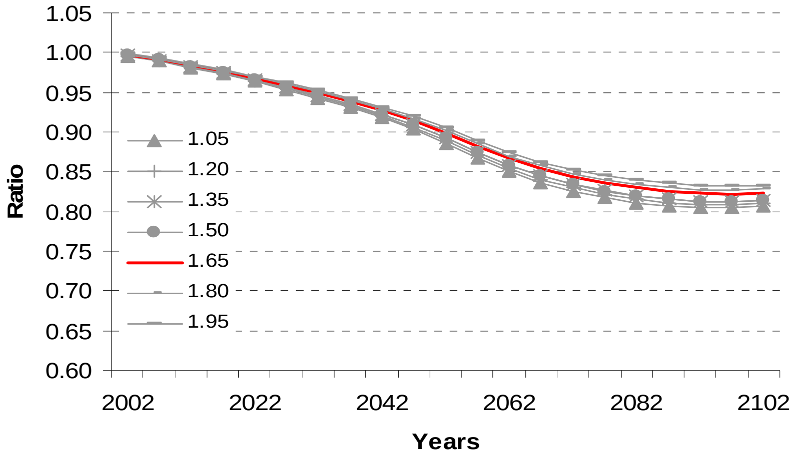
Figure 10. Sensitivity Analysis: Elasticity of Substitution, KL. Ratio of R&D Investments under Stabilization to R&D Investments in Baseline



As discussed above, this result is explained by the fixed supply of labor which reduces the possibilities to contract output from the KL nest. The lower (greater) the possibility to substitute capital to labor, the lower (greater) the possibility to convey the contraction of KLS towards the capital stock (K), for a given elasticity of substitution in the KLS nest. As a result, the greater (smaller) the elasticity between capital and labor, the smaller (greater) the contraction of Non-Energy R&D investments.

Figure 11 shows sensitivity results for the ES nest, in which Energy is combined with Energy knowledge (see equation 2). As expected, the lower (greater) the substitutability between the two inputs, the greater (lower) the contraction of R&D investments in a stabilization scenario.

Figure 11. Sensitivity Analysis: Elasticity of Substitution, ES. Ratio of R&D Investments under Stabilization to R&D Investments in Baseline



To conclude, the sensitivity analysis presented in this Appendix confirms the main conclusions reached in Section 5.

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