CPB Memorandum

CPB Netherlands Bureau for Economic Policy Analysis

Sector(s)	:	International Economics
Unit(s)/Project	:	S6-133 Lissabon menselijk kapitaal (MODELS II)
Author(s)	:	Hugo Rojas-Romagosa
Number	:	244
Date	:	April 2010

Modelling Human Capital Formation in WorldScan[1]

We build new modelling capabilities in WorldScan –CPB's multicountry recursive dynamic CGE model– to address policy questions related to human capital and skill formation. To achieve this goal we revise and update the human capital satellite model by Jacobs (2005). In addition, new features are introduced into WorldScan to deal with human capital policies: i) a new production structure that incorporates capital-skill complementarity; ii) a constrained supply of high-skill workers in the R&D sector and; iii) more information is taken from the satellite model (i.e. skill-specific labour supply and efficiency changes, instead of only aggregated labour efficiency changes). Finally, this new version of WorldScan is used to evaluate current EU human capital policies. The new results have a similar dynamic pattern of macroeconomic pattern than previous WorldScan versions. However, now the Lisbon skill targets have a higher impact, while the R&D targets have lower effects due to the R&D workers constraints.

[1] This work has been financed under the specific targeted research project MODELS in Framework Program 6 of the European Union (see http://www.ecmodels.eu/). I want to thank Stefan Boeters, Nico van Leeuwen, Paul Veenendaal, Bas Straathof, Bas ter Weel and Frank van Erp for constructive discussions and help with this project.

Contents

1 Introduction

One of the pillars of the Lisbon strategy is to increase growth in the European Union and human capital formation has long been regarded as an important source of economic growth (Lucas, 1988; Barro and Sala-i-Martin, 1995). Consequently, to increase economic growth in the European Union, the Lisbon Agenda included several targets on education and training to be achieved by 2010. Using WorldScan –the CPB's multicountry recursive dynamic CGE model– Gelauff and Lejour (2006) presented a first assessment of the growth impact of these human capital policies. To estimate the labour productivity effect of the skill targets they used the human capital satellite model developed by Jacobs (2005). They found that reaching the five skill targets of the Lisbon process increased GDP in the EU by 0.5% in 2025 and by 1.7% in 2040. However, the satellite model contained many uncertain parameters and there are better alternative ways of linking both models.

The main goal of this study is to update and revise the satellite model by Jacobs (2005) and the way it is linked to the WorldScan model. The updating procedure included a literature review that checked for new empirical estimates of key parameters in the satellite model and new insights into economy-wide skill formation processes. Furthermore, we also updated some features of the WorldScan model itself. For instance, we change the production structure and we impose an empirically based constraint on the supply of high-skill workers in the R&D sector. These new features of WorldScan and the new human capital satellite model (NHK-SM) are used to address policy questions related to human capital and skill formation in the European Union.

The data and modelling updating process can be divided in several steps:

- In the first step, we build on the human capital satellite model developed by Jacobs (2005). This satellite model provides time-trend changes in labour efficiency associated with increases in different types of human capital levels. The model has a stylised cohort model that maps the target completion to changes in the skill structure of the labour force. To achieve higher skills, however, there are associated indirect schooling costs. In particular, workers must bear the opportunity cost of staying longer in school and devoting time to on-the-job training. This affects negatively the labour supply in the short run. The resulting new human capital satellite model (NHK-SM), however, has distinct features from the original satellite model. First, we use a different skill classification and we include three different skill types in WorldScan.[1] In particular, we follow the skill definitions from the QUEST III model of the European Commission (Roeger et al., 2008), where low-skill workers are those that did not completed

[1] We retain the low and high skill split from the GTAP database, but we incorporate high-skill workers that are specific to the R&D sector.

secondary education, medium-skill workers have a secondary education or higher, and high-skill workers have a tertiary degree in science or engineering or a second stage of tertiary education (PhD). We assume that these high-skill workers are perfect substitutes for medium-skill workers, but are a specific factor to the R&D sector. Secondly, we updated and revised some of the key exogenous parameters. This updating process has brought the NHK-SM in line with the recent literature. For instance, the elasticities of substitution between different skill groups have been changed based on recent econometric estimates and the new skill classification we use. One key change is the larger impact of cognitive skills –measured as standard deviations in test scores– on labour productivity. This particular update is based on the recent survey by Hanushek and Woessman (2008) who present micro and macro evidence of the link between cognitive skills and labour productivity.

- The second step consists in changing how the NHK-SM is linked to WorldScan. Instead of including only changes in aggregate labour efficiency, the new human capital version of WorldScan directly incorporates supply and efficiency changes for low and high-skill workers. In addition, we also use the share of R&D workers from the NHK-SM to obtain the values of R&D workers (R) used in WorldScan. In total, we have now five linkage variables from the NHK-SM into WorldScan.The human capital version also integrates the WorldScan version that includes an endogenous labour market and R&D activities. The labour market version of WS (Boeters and Van Leeuwen, 2010) includes endogenous labour supply at the extensive and intensive margin (i.e. participation and hours worked) and endogenous unemployment; while the R&D version of WS has a distinct R&D sector and R&D is a productive factor that also affects TFP growth.
- The third step is to update the core WorldScan model to allow for a productions structure where capital and high-skill labour are complements. In addition, following Goolsbee (1998) we add labour supply constraints to account for the empirical observation that the supply of specialized R&D workers is inelastic in the short run.
- Fourth, we estimate direct schooling costs. Even when the opportunity costs –already accounted for in the satellite model– are by far the most important costs, including direct costs improves the accuracy of the impact assessments. We use OECD data on expenditure by student and current enrolment rate from EuroStat to estimate the education expenditure as a percentage of GDP for our baseline case and when the Lisbon skill targets are implemented.
- The last step is to conduct sensitivity analysis on some of the key parameters of the NHK-SM.

Once the model has been setup, we analyse which country-specific policy instruments could be employed to quantitatively assess EU policies. There are many empirical studies that analyse the impact of educational policy on human capital formation and its relation with macroeconomic outcomes. However, the link between policy instruments and actual human capital outcomes is weak (cf. Webbink, 2005; Checchi, 2006). Thus, there are no robust and reliable empirical results that can be readily adapted to a CGE framework. With this limitation in mind, we use an approach based on what-if scenarios where the policy goals are reached with no clear distinction of the precise policy instruments (as in Gelauff and Lejour, 2006). Therefore, we analyse the macroeconomic impact of current EU human capital policies. In particular, we first analyse the general equilibrium effects of Lisbon Agenda human capital goals for each EU country.

Our results from the Lisbon Agenda evaluation using this new human capital version of WorldScan present the same pattern as previous studies (Gelauff and Lejour, 2006; Lejour and Rojas-Romagosa, 2008). Particularly, there is a significant positive impact on consumption and production, but this is only achieved after 2025, when the negative short-run effects (due to the initial indirect costs of a reduced labour supply) are absorbed and higher skill levels are finally attained. However, our results present higher positive impacts. This is due to the higher impact of cognitive skills, and the compounded effect of increased labour productivity on labour supply and employment through the endogenous labour market module. We also find that increases in the general level of cognitive skills by country have a significantly high positive impact on the macroeconomic aggregates.

Finally, the R&D workers supply constraint yields very different results from previous WorldScan estimations of the effects of R&D expansion policies.[2] When the expansion of the R&D sector is constrained by an inelastic supply of R&D workers, we still obtain an increase in the total expenditure in R&D, but this is reflected in higher wages for R&D workers at lower activity levels. This follows the findings of Goolsbee (1998) that R&D subsidies stimulate R&D wages but not necessarily activity levels. Therefore, this new version of WorldScan results in much smaller increases in R&D activity volumes –as a result of R&D subsidies– than in the previous WorldScan version.

[2] In Gelauff and Lejour (2006) WorldScan was employed to simulate the effects of reaching the 2.7% R&D expenditure target of the Lisbon Agenda.

2 New human capital satellite model (NHK-SM)

This section explains the main features of the NHK-SM. This version of the model retains the core structure of the model developed by Jacobs (2005). However, several fundamental changes were made from the original model. These new features alter the model in essential ways and some of the key parameters have been updated and revised. Therefore, this new version produces different results compared to the previous version.

In the rest of the section we describe the main characteristics of the satellite model and the revisions and changes that were made. For instance, the definition of skill groups was changed, some key parameter values where updated and for some parameters we conducted sensitivity analyses.

2.1 Defining skill groups

We define skill groups by school attainment following the International Standard Classification of Education from 1997 (ISCED-97). There are five skill groups in the satellite model, two low-skill and three high-skill groups. $L1$ corresponds to pre-primary and primary education (ISCED 0-1) and $L2$ is lower secondary education (ISCED 2). $M1$ includes upper secondary and post-secondary non-tertiary education (ISCED 3-4), $M2$ corresponds to workers with a first stage of tertiary studies (ISCED 5) excluding university students in mathematics, science and engineering (MSE) fields, which are included in the skill-type R , together with workers with a second stage of tertiary education (ISCED 6).Therefore, our R groups roughly corresponds to individuals with tertiary studies in mathematics, science and technology fields, plus individuals with a second tertiary degree (PhD) in all fields.

Although Jacobs (2005) used also five skill types, he classified $M1$ (our lowest high-skill group) as $L3$ (the highest low-skill group). However, we follow the standard convention of defining the ISCED 3-4 group as high-skill, i.e., high-school graduates are classified as high-skill workers. This creates a fundamental departure from the original satellite model. Moreover, it implies that one of the Lisbon Agenda targets –increasing the completion rates of secondary education– moves workers from the low-skill to high-skill classification, which has an impact on the proportion of low and high skilled workers in the labour force.

The initial number of workers in each skill group s is estimated using the schooling ranges described above. However, to estimate the number of years of schooling in the population and the number of extra years needed to move from one skill group to the other, we use a fixed number of schooling years per skill group. In particular, $L1$ corresponds to 6 years of schooling,

$L2$ with 9 years, $M1$ with 12 years, $M2$ with 16 years and R with 20 of schooling.[3] This means that S, the required number of years to move from one skill group to the other is given by: $S_{L1L2} = 3$, $S_{L2M1} = 3$, $S_{M1M2} = 4$, and $S_{MR} = 4$.[4] Using this educational-based classification, we obtain the number of workers N_{sry} by region r, skill s and year y.

In our simulations we work with the GTAP database,[5] using an aggregation with 23 regions and 9 sectors.[6] To be consistent with the regional classification, in the NHK-SM we work with the same classification but only for EU27 country members. Thus, the data for the 5-skill classification is taken from OECD (Education at a Glance) and from the LABOURSTA database from ILO for 2001.

2.2 Labour market dynamics

The first building block in the satellite model is the evolution of the stock of workers over time and how changes in formal schooling are fed into the model. The number of workers is not only aggregated over the skill-types defined above, but also over cohorts. In this sense, the NHK-SM can be regarded as a stylised cohort model. Current formal education policies only affect the flow of each new cohort entering the labour market, but not those already working –this can only be achieved by on-the-job training. This dynamic process is bound to limit the short term changes in the stock of human capital and the potential impact of education policies.

Defining $NT_{ry} = \sum_s N_{sry}$ as the total number of workers, we have that over time N evolves by:

$$NT_{ry+1} = NT_{ry} + i_{ry} - o_{ry} \tag{2.1}$$

where i_{ry} is the inflow of workers and o_{ry} is the outflow of workers. These variables, in turn, are determined by:

$$i_{ry} = \theta_r NT_{ry} \tag{2.2}$$

$$o_{ry} = \delta_r NT_{ry} \tag{2.3}$$

Labour force growth by region r is defined as $g_r = \theta_r - \delta_r$, where θ_r is the rate of inflow of new workers while δ_r is the rate of outflow of workers. The inflow (θ) and outflow (δ) rates are

[3] For all other fields, four extra years is a good approximation, but not for MSE workers. However, maybe the wage differential for MSE corresponds to earnings of 4-extra years for workers in other fields.

[4] These numbers approximately correspond with education systems in many countries. Country-specific differences however, are not expected to change the main results.

[5] The results in this paper used the GTAP version 6 database where the base year is 2001. However, the WorldScan model was recently updated to use the version 7 database with 2004 as its base year. The macroeconomic results are similar between both database versions.

[6] The detailed classification is given in Tables A.2 and A.1in the Appendix.

calibrated such that these match average population growth rates in each region over the period considered.[7] We assume that g_r is constant over time, since we do not associate changes in g_r with any of the human capital policies we are assessing. In particular, there are no changes for δ and θ associated with the implementation of the skill targets of the Lisbon Agenda. Thus, the effort to calibrate time and skill-specific cohort differences over a long period of time is not justified (in the estimation of the model we work with $y \in [0,40]$). There are other cohort differences that are not captured. For instance, training on the workplace and the quality of education is not defined by cohort, but in aggregate, as explained below.

2.3 Educational attainment

We proceed now to model the changes in formal education, which has two main components: the number of years of schooling (i.e. educational attainment) and the quality of schooling. We deal with the second part in the next section. Regarding educational attainment we begin by assuming that the current graduation rates are at their steady-state levels. This means that the composition of total investment between higher and lower education is constant. Since education curricula are being upgraded over time, one can think of these steady-state graduation rates as the share of relatively higher educated with respect to relatively lower educated workers, and not in absolute terms.[8]

If we define η_{sry} as the graduation rates for skill s, region r and year y, then we have that the total inflow of workers with skill s into the workforce is: $i_{sry} = \eta_{sry}\theta_r NT_{ry}$. We assume that the outflow rates for each skill category are the same as for the total work force, hence: $o_{sry} = \delta_r NT_{ry}$. Data on graduation rates is well documented and we use the data from the OECD's Education Database. With this information we have a baseline time path of the composition of skills and we can model changes in educational policies as changing the graduation rates η.

It is important to note that current graduation rates *do not* reflect the current share of low to high-skill workers. Current η values are higher for H than for L workers. Thus, these steady-state graduation rates are translated in our model into a slow adjustment process that upgrades the skill composition of the labour force over time. For example, in the current process of an ageing population in OECD countries, this may reflect older low-skill workers being replaced by younger high-skill workers.

[7] The data on population growth are provided by the United Nation's World Population Prospects (United Nations, 2003).

[8] Another alternative is to explicitly model the optimal decision of the households to invest in different human capital levels or skill-types. However, this will require a dynamic optimisation CGE framework and constructing such a model is beyond the scope of this study.

2.4 The importance of educational quality

Besides, educational attainment, human capital can also increase due to educational quality. In a recent paper, Hanushek and Woessman (2008) forcibly argue that cognitive skills play a key role in understanding the relation between education and economic outcomes. It is common practice to use school attainment as a measure of human capital. However, this variable only captures a part of human capital formation. This shortcoming is made clear by Hanushek and Woessman (2008) in the following equation:

$$H = \lambda F + \phi Q(S) + \delta A + \alpha X + v \tag{2.4}$$

where human capital H is determined by family inputs F, the quantity and quality of formal education $Q(S)$ (where S is school attainment), individual ability A, X which includes other relevant factors such as experience and health, and v that groups other non-observable factors.

Hanushek and Kimko (2000) already emphasized that pure quantity measures of education are a very crude measure of skill. However, Hanushek and Woessman (2008) show that incorporating cognitive skills (based on test scores) in combination with traditional quantitative measures (i.e. using $Q(S)$ instead of only S) greatly increases the explanatory power of human capital with respect to economic growth, income distribution and wage determination. Moreover, the information contained in test scores indirectly includes the family inputs, individual abilities and other factors, all of which are not easily measured. Finally, there is significant country variation in these quality measures that can be used to assess changes in country-specific policies.

It is difficult to track the earnings effects of increased cognitive skills. This requires information on the test scores at the time of schooling, and later on data on labour earnings. However, US longitudinal data is available that can make this estimations possible. Reviewing these studies, Hanushek and Woessman (2008) find that a standard deviation in test scores increases future earnings by 12%. Moreover, they offer several reasons why this estimate can be considered as a lower bound. For instance, the skill-premium has increased over time and this is not captured by the time of the available longitudinal data. This value of 12% represents a significant increase from the previous value used in Jacobs (2005), which was based on a 8% value based on the survey by Krueger (2003). Thus, we can expect a much higher macroeconomic impact of changes in the quality of education and/or test scores. Using these insights we use the test score data from the OECD Programme for International Student Assessment (PISA) to measure cognitive skills.[9] On the other hand, the causal relation between

[9] The International Adult Literacy Study (IALS) and the Trends in International Mathematics and Science Study (TIMSS) are other possible indicators of cognitive skills' variations in time and by region.

test scores and productivity has not been thoroughly proven. Thus, these estimations can suffer from endogeneity bias. In Section 6 we conduct sensitivity analysis with different values for the effect of test scores on productivity. We find that this is a key parameter in the model.

2.5 Learning-by-doing

Workers can acquire human capital through schooling, but also by learning-by-doing at the workplace. This implies both formal (on-the-job training) and informal learning effects.[10] This is modelled in Jacobs (2005) by simplifying the human capital production function used by Heckman et al. (1998):

$$H_{sabt+1} = H_{sabt} + \widetilde{A}_{sa} \left(I_{sa}\right)^{\alpha_s} \left(H_{sabt}\right)^{\beta_s} \tag{2.5}$$

where human capital H is indexed over skill type s, ability a, age b and time t. The time devoted to learning-by-doing (LbD) is defined by I and $\widetilde{A}$ is a productivity parameter related to the ability to learn. Implicitly, this function is assuming that human capital does not depreciate. This assumption is supported by the empirical observation that wages do not generally decrease nor is there substantial *LbD* at the end of working careers.

To aggregate between cohorts and skill groups Jacobs (2005) assumes that $\alpha_s = \beta_s = 1$ for all s. This implies that returns to learning-by-doing I_{sa} do not diminish with the human capital level. This allows to aggregate individuals (with different ability and ages) into:

$$H_{st+1} = H_{st}(1 + \widetilde{A}_s \chi_{st}) \tag{2.6}$$

where χ is the weighted average fraction of time invested in *LbD*, such that:

$$\chi_{st} = \frac{\sum_{sa} I_{sa} H_{sabt}}{\sum_{sa} I_{sa}} \tag{2.7}$$

Using 2.6 we obtain the growth rates of *LbD* (γ):

$$\gamma_s = \frac{H_{st+1} - H_{st}}{H_{st}} = \widetilde{A}_s \chi_{st} \tag{2.8}$$

Furthermore, it is assumed that the ability to generate human capital through *LbD* ($\widetilde{A}_s$) is equal for all skills s and that the time devoted to *LbD* (χ_{st}) is independent of s and constant over time.[11] This allows us to have a constant *LbD* growth rate γ for all skill types. However, we do

[10] On the satellite model by Jacobs (2005) the whole effect was referred to as on-the-job training (OJT). However, the human capital accumulation process that is being modelled is broader than just including formal on-the-job training activities and includes also informal training in the job effects. Therefore, the concept of learning-by-doing (LbD) captures much better the essence of this human capital accumulation process, since OJT is only one particular way in which workers are upgrading their skills.

[11] There is little empirical evidence about the values of these parameters for different skill categories. Thus, for simplicity they are assumed to be the same.

allow γ to vary across regions. Therefore, γ_r is the key parameter in the model that summarizes the effects of *LbD* on human capital accumulation.

2.6 Efficiency units of labour

To calibrate the value of γ we use the work by Mincer (1962) and Heckman et al. (1998). They estimate that the fraction of life-time human capital gathered through *LbD* (ω) is 50% and 23% respectively. Assuming that total working years is in average $T = 40$ we obtain that the number of efficiency units of labour NE_{rsT} for region r, skill s at year T is given by:

$$NE_{rsT} = (1+\gamma)^T NE_{rs0} \tag{2.9}$$

Taking NE_{rs0} to be the human capital gathered through schooling before any work experience at $y = 0$, then we have:

$$NE_{rsT} = \omega NE_{rsT} + NE_{rs0} \tag{2.10}$$

Combining 2.9 and 2.10 we can calibrate γ as:

$$\gamma = \left(\frac{1}{1-\omega}\right)^{1/T} - 1 \tag{2.11}$$

Using the estimates of Heckman et al. (1998) that $\omega = 0.23$ we get that $\gamma = 0.0066$. If we use $\omega = 0.5$ from Mincer (1962), then $\gamma = 0.0175$. Jacobs (2005) decided to use $\gamma = 0.01$, which implies that $\omega = 0.33$, i.e., *LbD* generates one third of life-time human capital.[12]

Since on-the-job training (*LbD*) is a continuous process, the *initial* stock of human capital (expressed in terms of number of workers by school attainment) has to be updated to include the skills already obtained by the workers through past *LbD*.

Taking N_{rs0} as the number of workers at $y = 0$, we adjust this value to efficiency units of labour (NE) using the following equation:

$$NE_{rs0} = (1+\gamma)^{\overline{T}} N_{rs0} \tag{2.12}$$

where $\overline{T} = 20$ is the average working experience of the population and γ_{r0} is the initial value of gamma.

2.7 Dynamic evolution of human capital stocks

To obtain an overall function of human capital accumulation, we combine the dynamic evolution of the labour market together with the human capital acquired through formal schooling and

[12] In our sensitivity analysis we assess how the results change when we use the values of $\gamma = 0.0066$ and $\gamma = 0.0175$.

LbD. The following dynamic function determines how human capital stocks (defined as efficiency units of labour) evolve over time:

$$NE_{sry} = (1+\gamma-\delta_r)NE_{sry-1} + NET_{ry-1}\theta_r\eta_{sry}Q_{ry} \tag{2.13}$$

$$NET_{ry} = \sum_s NE_{sry} \tag{2.14}$$

where NET_{ry} is the total labour supply in region r in year y, and NE_{sry} is the number of efficiency units of labour indexed by the five different skill levels s. Equation 2.13 is the key equation of the NHK-SM and determines the evolution of human capital stocks over time. Equation 2.13 consists of four main components:

- First, it represents the dynamic evolution of the working force population as defined in section 2.2. Note that we are implicitly assuming that each cohort has the same LbD accumulation parameter γ and that differences in the quality of education (given by Q_{ry}) are also independent of cohort size.[13]
- Formal educational attainment is determined by the graduation rates parameter η_{sry}. The second term in equation 2.13 defines the new inflow of human capital by skill. First, $\theta_r NT_{ry-1}$ indicates the total number of new workers in year y, while η_{sry} indicates the fraction of that particular cohort that graduates in each skill-level. We have that $\sum_s \eta_s = 1$ when the composition of the labour force is not changing between skills, but $\sum\limits_s \eta_s < 1$ when we have policy shocks that result in some students staying longer in school to increase the cohort's schooling attainment.
- Q_{ry} is a quality indicator of the new inflow of workers by region and year. We start with $Q = 1$ and indicate increases in the quality of education through $Q > 1$, which only affects the newly graduated workers and not the overall working force. Note that there is no need to have $Q(r)$ differences between countries at the initial year, since any quality differences between countries is implicit in the baseline wage differentials between countries.
- Finally, learning-by-doing is determined in the first term of equation 2.13. The human capital stock of the former year is updated to include the growth rates γ of aggregate human capital due to LbD.

It is important to note that the accumulation process builds upon the acquired human capital of all the population. The efficiency units of newly graduated students are a fraction of the accumulated efficiency units of labour of previous years NET_{ry-1}, and not a fraction of the total raw number of workers in the that previous year: $\widetilde{NT}_{ry} = \sum_s \widetilde{N}_{sry}$, where

[13] In principle, there is not enough data to obtain time-specific past observations of quality (Q) and γ parameters that can be calibrated to obtain a present value of efficiency units of labour over different cohorts. However, assuming the educational quality has been increasing over time, then the presence of fatter cohorts with more work experience and LbD can be compensated with thinner cohorts with less LbD but higher Q.

$\widetilde{N}_{sry} = (1-\delta)\widetilde{N}_{sry-1} + \widetilde{NT}_{ry-1}\eta_{sry}$. In this sense, we can think of the human accumulation process embedded in equation 2.13 as general knowledge that is transmitted over time from older to younger cohorts, instead of job-specific knowledge that is not directly transferable to younger cohorts. This assumption is crucial to the results of the NHK-SM. When we used an accumulation process that does not accumulate over efficiency units, but over $\widetilde{NT}_{ry}$ (number of workers), the overall impact of our counterfactual simulations is greatly reduced. This is a direct consequence of the initial stock of human capital by new cohorts being sizable smaller and thus, the growth of human capital is much slower. Any policy changes that affect new cohorts (affecting for instance η and Q) take much longer to have an impact on the overall stock of human capital. Moreover, even changes in the *LbD* parameter γ are also less influential since they are not transmitted to the human capital stock of new cohorts.

2.8 Disaggregated human capital production function

Through the parameters in equation 2.13, namely: γ , η and Q, we can estimate how human capital policies affect the human capital accumulation process by each skill-type. To use these inputs into the core WorldScan model, however, we first need to aggregate the five skill types we have: $L1$, $L2$, $M1$, $M2$ and R, into the low-skill (L) and high-skill (H) This is the classification for which we have data in the core WorldScan model.[14]

Using the time path of the different skill types in efficiency units NET_{ry} from equation 2.13, we aggregate the five groups using a nested CES function, which is commonly used in CGE models. Then we have:

$$L_{ry} = A_{ry}\left[\alpha_{L1ry}\left(N_{L1ry}\right)^{\rho_L} + \alpha_{L2ry}\left(N_{L2ry}\right)^{\rho_L}\right]^{\frac{1}{\rho_L}} \tag{2.15}$$

$$H_{ry} = B_y A_{ry}\left[\alpha_{M1ry}\left(N_{M1ry}\right)^{\rho_H} + \alpha_{M2ry}\left(N_{M2ry}\right)^{\rho_H} + \alpha_{Rry}\left(N_{Rry}\right)^{\rho_H}\right]^{\frac{1}{\rho_H}} \tag{2.16}$$

where L_{ry} is aggregated low skill and H_{ry} is aggregated high skill; α_{sry} are the share parameters of each skill level $s = L1, L2, M1, M2, R$, with $\alpha_{L1ry} + \alpha_{L2ry} = 1$,and $\alpha_{M1ry} + \alpha_{M2ry} + \alpha_{Rry} = 1$. The elasticity of substitution between the two different low-skilled workers is σ_L, with $\rho_L = 1 - \frac{1}{\sigma_L}$. In the same fashion, σ_H is the elasticity of substitution between the high skill groups: $M1$, $M2$ and R. Following Card (2009) and the papers cited there, we assume that $L1$ and $L2$ are perfect substitutes, such that $\frac{1}{\sigma_L} = 0$. This means that, at least in OECD countries, workers that do not finish high-school are perfect substitutes and do thus, can perform the same

[14] An original objective of this study was to collect and calibrate data to explicitly use three skill levels in WorldScan. However, this task proved too ambitious, since it required a huge database work to collect and calibrate the data for most regions of the GTAP database. Currently, the USITC is working on splitting the current two skills into five skills using occupational-based data (Weingarden and Tsigas, 2009). We do, however, use the number of R&D workers (R) as an input from the NHK_SM into WorldScan.

set of tasks. Furthermore, we assume that $\sigma_H = 1.44$, which is the estimated elasticity of substitution between high-school and college graduates in the United States (Katz and Murphy, 1992; Heckman et al., 1998).[15,16] Since the skill classification is different, the use of different elasticities is another departure of the NHK-SM from the satellite model by Jacobs (2005).[17]

In addition, we introduce skill-biased technological change (SBTC) in the model through the parameter B_y in equation 2.16. We assume that B is growing at a constant rate of τ:

$$B_{y+1} = (1+\tau)B_y \tag{2.17}$$

$$B_0 \equiv 1 \tag{2.18}$$

The SBTC growth parameter τ is calibrated to reflect the growing wage differential (Δ) between high-skill (H) and low-skill (L) workers, where $\Delta = \frac{dw_H}{w_H} - \frac{dw_L}{w_L}$. Jacobs (2004) summarises empirical estimates for skill-biased technological change in the US, which generate a wage differential increase of approximately 3% per year. However, for European countries this number is substantially lower and in Jacobs (2005) he uses $\Delta = 1.5\%$. Log-linearising the aggregate marginal rate of transformation between H and L, at constant relative supplies, we get:

$$\tau \equiv \frac{dB}{B} = \frac{\Delta}{1 - 1/\sigma} \tag{2.19}$$

Using an elasticity of substitution between L and H of $\sigma = 2$, then we get the calibrated value $\tau = 0.03$.[18] Finally, we need to obtain the values for the share parameters (α_{sry}) from the disaggregated functions. However, these share are generally unknown. As explained in Jacobs (2005), these shares are estimated using Mincer rates of return (β) and the number of years required to move from one skill-level to the other (S). The resulting calibration equations are:

$$\alpha_{L1ry} = \frac{1}{1 + \exp \mu L_{ry}} \tag{2.20}$$

$$\alpha_{L2ry} = \frac{\exp \mu L_{ry}}{1 + \exp \mu L_{ry}} \tag{2.21}$$

$$\mu L_{ry} = \beta_{Lr} S_{L1L2} + (1-\rho_L) \ln \left(\frac{N_{L2ry}}{N_{L1ry}} \right) \tag{2.22}$$

[15] This value for the elasticity of substitution has been recently validated by the work of Caselli and Coleman (2006).

[16] Taking the skill classification strictly, this elasticity value informs about the substitution between $M1$ (high-school graduates) and the aggregate of $(M2+R)$, which are college graduates or higher. With information about elasticity of substitution between $M2$ and R, we can nest a sub-aggregate with both skill types. However, we did not find empirical observations for this particular elasticity and thus, we use σ^H for all three high-skill categories.

[17] He used $\sigma_L = 3$ (where he defines $L = L1 + L2 + M1$) and $\sigma_H = 1.2$ (for $H = M2 + R$). While the elasticity of substitution between these definitions of L and H is $\sigma = 1.5$.

[18] In the NHK_SM, σ does not play an important role since the aggregation between our low and high skill categories is only done for descriptive reasons, but it is not used to create the linkage variables that are fed to the core WorldScan model. Moreover, τ is not changing between our baseline and policy counterfactual, so its value does not change our results.

$$\alpha_{M1ry} = \frac{1}{(1+\exp\mu M_{ry})+(\exp\mu M_{ry}\exp\mu H_{ry})} \tag{2.23}$$

$$\alpha_{M2ry} = \frac{\exp\mu M_{ry}}{(1+\exp\mu M_{ry})+(\exp\mu M_{ry}\exp\mu H_{ry})} \tag{2.24}$$

$$\alpha_{Rry} = \frac{(\exp\mu M_{ry}\exp\mu H_{ry})}{(1+\exp\mu M_{ry})+(\exp\mu M_{ry}\exp\mu H_{ry})} \tag{2.25}$$

$$\mu M_{ry} = \beta_{Hr} S_{M1M2} + (1-\rho_H)\ln\left(\frac{N_{M2ry}}{N_{M1ry}}\right) \tag{2.26}$$

$$\mu H_{ry} = \beta_{Hr} S_{MR} + (1-\rho_H)\ln\left(\frac{N_{Rry}}{N_{M2ry}}\right) \tag{2.27}$$

To obtain the country-specific Mincer rates of return (β), we assume that the average β in the EU27 is 8% per year. This follows the empirical findings surveyed by Card (1994); Ashenfelter et al. (1999); Harmon et al. (2003). However, each country has specific Mincer returns, which also vary between skill groups. This will capture heterogeneity between countries and education levels. The estimated Mincer rates are given by the following equations:

$$\beta_r = 0.08 - \pi\,(e_r - e_{EU}) \tag{2.28}$$

$$\beta_{Lr} = 0.08 - \pi\,(e_{Lr} - e_{L,EU}) \tag{2.29}$$

$$\beta_{Hr} = 0.08 - \pi\,(e_{Hr} - e_{H,EU}) \tag{2.30}$$

where e is the average number of years of education in region r (or the EU) and e_L and e_H denote the average number of years for each skill group. There are three Mincer rates β to be estimated by country. β_r denotes the returns between higher and lower skills, $\beta_{L,r}$ are the return rates between the two low-skill groups and $\beta_{H,r}$ between the three high-skill groups. In this specification, we use the EU27 as the definition of EU.

Harmon et al. (2003) find that each additional year of education on average approximately lowers the Mincer rate of return with 1%, hence we set $\pi = 0.01$. This specification allows for higher returns to education for countries with lower average levels of education like Spain and Portugal. Returns to education are accordingly smaller for highly educated countries like the Scandinavian countries. We approximate the average levels of education in each country using data on the education composition of the workforce and making an assumption on the number of years of schooling it takes to complete each level of education. All variables are taken from the initial baseline year 2001 (i.e. $y = 0$), such that:

$$e_r = \frac{N_{L1r0}*6+N_{L2r0}*9+N_{M1r0}*12+N_{M2r0}*16+N_{Rr0}*20}{NT_{r0}} \tag{2.31}$$

$$e_{L,r} = \frac{N_{L1r0}*6+N_{L2r0}*9}{N_{L1r0}+N_{L2r0}} \tag{2.32}$$

$$e_{H,r} = \frac{N_{M1r0}*12+N_{M2r0}*16+N_{Rr0}*20}{N_{M1r0}+N_{M2r0}+N_{Rr0}} \tag{2.33}$$

3 New linkage between NHK-SM and WorldScan

In this section we describe how the satellite model by Jacobs (2005) was linked to WorldScan. We then proceed to explain the new linkage variables between the NHK-SM and WorldScan.

3.1 Previous linkage

In the previous satellite model, all labour was aggregated into a single labour variable using a CES function:

$$G_{ry} = A_{ry}\left[\alpha_{L,ry}\left(L_{ry}\right)^{\rho} + \alpha_{H,ry}\left(H_{ry}\right)^{\rho}\right]^{\frac{1}{\rho}} \tag{3.1}$$

where L_{ry} and H_{ry} are the stocks of labour from equations 2.15 and 2.16, with shares given by $\alpha_{L,ry} + \alpha_{H,ry} = 1$. A_{ry} is a general efficiency parameter and $\rho = 1 - \frac{1}{\sigma}$, where $\sigma = 2$ is the elasticity of substitution between both aggregated skill levels. As done before, the share parameters α are calibrated using Mincer rates of return (β) between low and high skill education and the number of schooling year that takes to move from low to the high skill category is $S_{LH} = 3$. Then the estimation of the share parameters is done using these equations:

$$\alpha_{Lry} = \frac{1}{1+\exp\mu} \tag{3.2}$$

$$\alpha_{Hry} = \frac{\exp\mu_{ry}}{1+\exp\mu} \tag{3.3}$$

$$\mu_{ry} = \beta_r S_{LH} + (1-\rho)\ln\left(\frac{H_{ry}}{L_{ry}}\right) - \rho\ln B_y \tag{3.4}$$

Using equation 3.1 the linkage with the core WorldScan model was done using a single variable: the labour efficiency parameter ε. This labour efficiency parameter was defined as:

$$\varepsilon_{ry} = \frac{G^S_{ry} - G^B_{ry}}{G^B_{ry}} \tag{3.5}$$

where G^S_{ry} is the aggregated labour for region r in year y for the counterfactual simulation S, while G^B_{ry} is the value of G in the baseline B. Changes in ε_{ry} were directly fed into WorldScan as an exogenous increase in the labour efficiency parameter (CLP_QN).

To a large extent, using this summary variable was feasible in the previous satellite model because of the skill classification that was used. As explained below, one of the skill targets of the Lisbon Agenda is to increase the number of secondary graduates, which is translated as a decrease in $L2$ and a increase in $M1$. Since both skill categories where aggregated under low-skill L in Jacobs (2005), applying the Lisbon Agenda targets did not change the relative supply of L and H. However, in our skill classification of the NHK-SM, $M1$ is part of the high-skill H aggregate and the target to reduce $L2$ and increase the number of secondary graduates $M1$ directly affects the relative supply of L and H. As mentioned above, we follow the standard convention of defining $M1$ as high-skill labour and thus, implementing the Lisbon targets does change the stock of both skill types L and H.

3.2 New linkage variables

In the new human capital version of WorldScan we incorporate information using the disaggregated labour values L and H, instead of using the aggregated value G. These values are taken from equations 2.15 and 2.16. Moreover we divide the L and H changes into a volume parameter ($LSUPMN\_SK$) and a labour efficiency parameter ($CLP\_QN\_$). This division allows us to track changes in the relative supply of L and H and changes in the efficiency units of labour for each skill aggregation L and H. Finally, we also use the share of R&D workers from the NHK-SM to obtain the values of R&D workers (R) used in WorldScan. In total, we have now five linkage variables from the NHK-SM into WorldScan. In this new formulation, moreover, it is not necessary to aggregate both labour types in a G_{ry} function as done previously. Hence, the values of σ and the share parameters α_{Lry} and α_{Hry} are not relevant for our results.

The procedure to separate the human capital labour supply (volume) changes from the labour efficiency changes is the following. First, we use the number of workers as defined in $\widetilde{N}_{sry}$, which includes only the terms in equation 2.13 that are associated with volume changes, such that:

$$\widetilde{N}_{sry} = N^B_{sry-1}(1-\delta_r) + NT^B_{ry-1}\theta_r\eta_{sry} \tag{3.6}$$

$$\widetilde{NT}_{ry} = \sum_s \widetilde{N}_{sry} \tag{3.7}$$

$$\widetilde{N}_{Lry} = \widetilde{N}_{L1ry} + \widetilde{N}_{L2ry} \tag{3.8}$$

$$\widetilde{N}_{Hry} = \widetilde{N}_{M1ry} + \widetilde{N}_{M2ry} + \widetilde{N}_{Rry} \tag{3.9}$$

where N^B_{sry} is the value of N in the baseline. We use N^B instead of $\widetilde{N}$ in equation 3.6 because we want to see changes in the composition of the workforce with respect to the baseline. On the other hand, using $\widetilde{N}$ creates a dynamic process where the changes in η's are accumulated over time and instead of seeing shifts between skill groups, we have overall changes in the number of workers with respect to the baseline.

We then estimate the volume change parameter $LSUPMN\_SK_{vfry}$, where v indexes the counterfactual version and $f = L, H$. The volume changes are given by the following equations, where $\widetilde{N}^B_{sry}$ is the value of $\widetilde{N}_{sry}$ in the baseline:

$$LSUPMN\_SK_{vfry} = \frac{\widetilde{N}^v_{fry}}{\widetilde{N}^B_{fry}} \tag{3.10}$$

Secondly, we derive the labour efficiency change, which is given by the change in L_{ry} and H_{ry} when the volume change is not present. This pure efficiency-units value does not include the volume changes is defined as N^e_{sry}:

$$N^e_{sry} = NE^B_{sry-1}(\gamma^i_{ry} - \delta_r) + NET^B_{ry-1}\theta_r \eta^B_{sry} Q^i_{ry} \tag{3.11}$$

$$L^e_{ry} = A_{ry}\left[\alpha_{L1ry}\left(N^e_{L1ry}\right)^{\rho_L} + \alpha_{L2ry}\left(N^e_{L2ry}\right)^{\rho_L}\right]^{\frac{1}{\rho_L}} \tag{3.12}$$

$$H^e_{ry} = B_y A_{ry}\left[\alpha_{M1ry}\left(N^e_{M1ry}\right)^{\rho_H} + \alpha_{M2ry}\left(N^e_{M2ry}\right)^{\rho_H} + \alpha_{Rry}\left(N^e_{Rry}\right)^{\rho_H}\right]^{\frac{1}{\rho_H}} \tag{3.13}$$

where the new variables γ^i_{ry} and Q^i_{yr} are index values of γ and Q that are accumulated over years: $\gamma^i_{ry} = (1+\gamma_r)^y$ and $Q^i_{ry} = (Q_r)^y$. The use of these indexes –instead of their time unvarying values– is required to adjustment the values of NE^B_{sry} that do not include the counterfactual higher values for γ_r and Q_r. Therefore, the values for N^e_{sry} are including the effects of efficiency changes in γ_r and Q_r into the baseline values of NE_{sry}, but do not include the volume changes associated with the parameters δ_r, θ_r and η_{sry}. Finally, the labour efficiency parameter CLP_QN_{vfry} is defined as changes in the L^e_{ry} and H^e_{ry} from each counterfactual simulation v with respect to the baseline values:

$$CLP\_QN_{vLry} = \frac{L^{ev}_{ry}}{L^B_{ry}}$$

$$CLP\_QN_{vHry} = \frac{H^{ev}_{ry}}{H^B_{ry}}$$

4 Human capital version of WorldScan

Besides the way in which the NHK-SM is linked to the core WorldScan (WS) model, we also change the lower nests of the production structure and we impose two constrains related to the supply of R&D workers in the R&D sector. These changes are significant departures from the previous version of WS. Thus, we rename this version as the human capital version of WS. This version has been integrated with the R&D version and the endogenous labour market versions (Boeters and Van Leeuwen, 2010).

4.1 New production structure

We also change the production structure in WorldScan. The previous version of WorldScan assumed that high and low-skilled labour were aggregated through a Cobb-Douglas function. However, Krusell et al. (2000) find that a significant part of the skill premia can be explained by the use of a neoclassical production functions with capital-skill complementary. They argue that the elasticity of substitution between capital and low-skill labour is higher than between capital and high-skill labour. Thus, they build a production structure where high skilled labour and capital equipment are first aggregated using a CES function with elasticity σ_{HK} and this composite is then nested together with low skilled labour in a CES function with elasticity σ_{HL}. They then empirically estimate both these elasticities with US data and find that $\sigma_{HL} = 1.67 > \sigma_{HK} = 0.67$, which confirms their theoretical model of capital-skill complementarity.

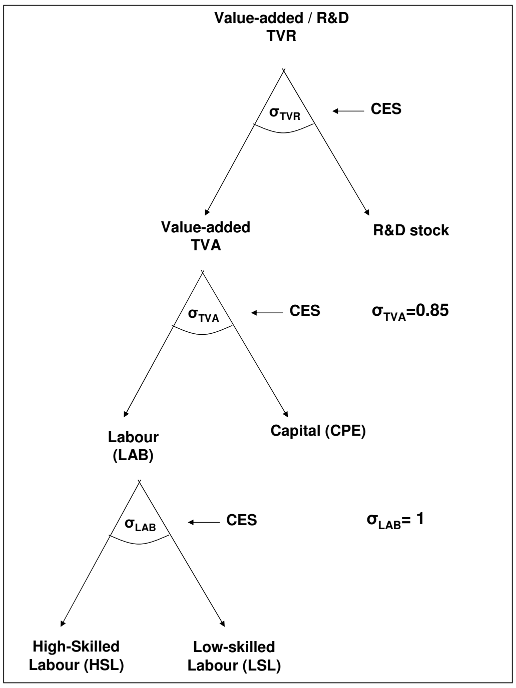
In the previous version of WorldScan both labour types are first aggregated in a Cobb-Douglas function and then aggregated with capital. The stock of R&D then enters in the same nest as the value added composite of capital and labour (see Figure 4.1). In the previous linkage used by Jacobs (2005) the labour efficiency parameter ε_{ry} was implemented as a shock to the labour aggregate (LAB) and it was assumed that the stock of low-skill LSL and high-skill workers HSL was constant.[19]

To bring WorldScan up to date with the recent literature, we use the insights of Krusell et al. (2000). Therefore, we change the lower value-added nest of the production structure in WorldScan and we also use their estimated elasticities of substitution (σ_{HL}, σ_{HK}). See Figure 4.2.

There are two main differences between WS and Krusell et al. (2000). First, they divided

[19] This was made possible in Jacobs (2005) by defining $L3$ as workers with completed secondary education, a definition that is otherwise used as high-skill in most of the literature. Thus, the achievement of Target 3 of the Lisbon Agenda –an increase in the completion rates of secondary education– could be reached without changes in the stocks of L and H. However, we follow the standard convention and thus, will have changes in the stock of both skill types.

Figure 4.1 Previous production structure in WorldScan

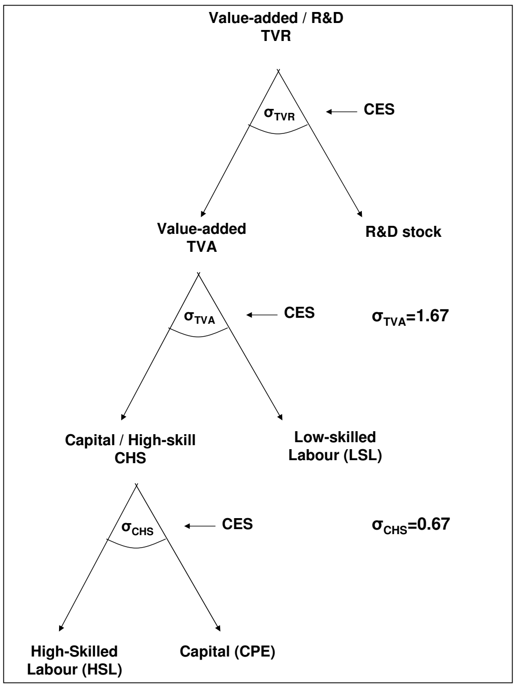


capital between structures and equipment, and argued that it was capital equipment which is complementary to skilled labour, while capital structures where included in an upper nest in the production structure. However, in the GTAP database there is only an aggregated value of capital and it is not possible to disaggregate both capital definitions in WorldScan. Secondly, Krusell et al. (2000) define skilled workers as $M2+R$, while our high skill definition also includes $M1$. Hence, we can not strictly follow the structure used by Krusell et al. (2000), but this is a better approach than just assuming the previous production structure, which does not have any empirical backup.

4.2 New constraints on the supply of R&D workers

The second main innovation in the new human capital version of WS is that we explicitly use the information of R&D workers (R). This is the fifth linkage variable between the NHK-SM and WorldScan. In addition, we also use the insights of Goolsbee (1998) about the inelastic supply of R&D workers in the short run. With both ideas, we constrain the supply of R workers in WS as explained below.

Figure 4.2 Production structure for human capital version of WorldScan



4.2.1 Current R&D modelling in WorldScan

This subsection is taken from chapter 3 in Lejour et al. (2006). R&D stocks in sector s and year y (RS_{sy}) are treated as capital stocks. Sectoral R&D expenditure (investment) is given by:

$$IR_{sy} = [RS_{sy} - (1-\delta_{RD})RS_{sy-1}]\,p_R \tag{4.1}$$

where δ_{RD} is the depreciation rate of the R&D stock, and p_R is the user cost of R&D. The investment price of R&D (p_{RD}) is defined as:

$$p_{RD} = pp_{RD}\,(1+t_{RD}) \tag{4.2}$$

where pp_{RD} is the producer price of R&D and t_{RD} is the tax rate on R&D investment. In Gelauff and Lejour (2006) the R&D targets of the Lisbon Agenda are reached by substantial increases in the R&D subsidies, which was modelled as changes in t_{RD}, with $t_{RD} < 0$ to denote subsidies instead of taxes.

The optimal R&D stock by sector is derived from cost minimization, which implies that the marginal product of the sectoral R&D stock equals the user costs of R&D. User costs (p_R) equal the investment price for R&D (p_{RD}) times the sum of the risk-free return on R&D (which we assume to be equal to the real interest rate, r), a risk premium (O_{RD}) and the depreciation rate

(δ_{RD}). Thus:

$$p_R = p_{RD}\left(r + O_{RD} + \delta_{RD}\right) \tag{4.3}$$

Following Carson et al. (1994) the depreciation value is set at: $\delta_{RD} = 0.11$ .Finally, the value of the R&D stocks enters the production structure as the cost share of R&D α_{r_d}:

$$\alpha_{r\_d} = p_R RS_{sy} \tag{4.4}$$

It is assumed that R&D stocks enter in the value-added nest of the production structure together with the CES nesting of capital and labour (see Figure 4.1) with an elasticity of substitution $\sigma_{VA} = 0.9$. This implies that R&D is not a very good substitute for physical and human capital.[20]

R&D is produced by the R&D sector. This is a separate production sector in WorldScan. Its production structure is based on the input structure of the R&D sector in the US. This is one of the few countries that explicitly distinguishes a R&D sector in its national accounts. The R&D sector only produces for domestic firms and there is no international trade of R&D.

4.2.2 R&D potential and employed workers

An important fact is that the main input of the R&D sector is high-skilled labour, which accounts for around 60% of the value added of the R&D sector. If we assume that R&D high-skill tasks can only be performed by R (our definition of R&D workers) then we can impose the constraint that the current number of employed high-skill workers in the R&D sector (R^c) cannot exceed the number of potential R&D workers (R^p). From the NHK-SM we obtain the share of R workers (R^s) as a fraction of the total number of H workers. These are workers that have enough skills to become R&D workers, but do not necessarily have to be employed by the R&D sector. Thus, potential R&D workers (R^P) are defined in WS as:

$$R^p = R^s * LSUPMN\_(HSL, TOT, WLD, r) \tag{4.5}$$

where $LSUPMN\_(HSL, TOT, WLD, r)$ is the number of HSL workers in region r. The current number of employed R&D workers (R^c) is taken from WS using the following equation:

$$R^c = \frac{CST\_WN\_(HSL, R\_D, WLD, r)}{LEMFPN\_(HSL, TOT, WLD, r)} \tag{4.6}$$

where $CST\_WN\_(HSL, R\_D, WLD, r)$ is the value-added (in billion US$) of high-skill labour in the R&D sector and $LEMFPN\_(HSL, TOT, WLD, r)$ is the gross wage of HSL. This first

[20] There are not many applied models which have incorporated the R&D stock, nor are there good estimates of the substitution between R&D and other inputs.

constraint is given by the complementarity equation:

$$w_R \geq w_H \qquad \perp \qquad R^p \geq R^c \tag{4.7}$$

The wage of R workers w_R is equal to w_H the wage for the high-skill aggregate H if potential R&D workers are larger than the currently number of employed R&D workers. On the other hand, if the current number of R&D workers exceeds R^p then the wages of the R&D workers increases above w_H and in equilibrium we have: $R^p = R^c$.

In practice, equation 4.7 is almost never binding, since the potential number of R&D workers is much larger than the current demand of R&D workers for most countries.

4.2.3 Inelastic supply of R&D workers

Another critical change to WorldScan is that now we model R workers as quasi-specific to the R&D sector. In other words, R workers can work in any sector of the economy, but the R&D sector must use R workers. As mentioned above, we assume that all the H workers employed in the R&D sector are R workers. Thus, the R&D sector is intensive in the use of R workers. Moreover, following the analysis from Goolsbee (1998) the supply of R&D workers is assumed to be relatively inelastic in the short-run. Therefore, we create an additional constraint in the R&D sector, where the number of new R workers can only increase by a specific proportion every year. This mechanism creates additional pressures to the wage of R&D workers (w_R) when the demand of R&D services increases. In particular, if there is a substantial R&D subsidy –as in the R&D simulations of the Lisbon Agenda– then the sector can not fully adjust by increasing the quantity of services provided, and some of the extra expenditure goes into increasing w_R: the payment to R&D workers which become relative scarcer.

Goolsbee (1998) estimates the elasticity of R workers entering the R&D sector (ϕ) to be very low: $\phi = 0.2$. This determines that potential R&D workers that are employed in other sectors, only enter into the R&D sector gradually in response to higher wages. This insight is translated into the following constraint:

$$R^s_y = R^s_{y-1}\left(1 + \phi \frac{w_{Ry} - w_{Ry-1}}{w_{Ry-1}}\right) \tag{4.8}$$

$$w_R \geq w_H \qquad \perp \qquad R^s \geq R^c \tag{4.9}$$

where R^s_y is the supply of R&D workers in year y.[21] When the supply of R&D workers is lower than the demand for R workers (R^c) then w_R increases to attract new R workers in the following period.[22] However, the adjustment process is gradual under this new constraint, while previously

[21] The term R^s_{y-1} is actually defined as the maximum value between R^s_{y-1} in the baseline and R^s_{y-1} in the counterfactual.

[22] Note that the constraint in equation 4.8 is only binding in the counterfactual simulations, when R&D subsidies are imposed and the demand for R workers is strongly increased. The constraint is not binding in the baseline scenarios.

in WS the number of R&D workers where greatly increased after a policy shock. Under the previous assumptions a rise in R&D expenditures was translated in an increase of R&D output, while costs (w_R) were assumed to remain close to the baseline levels. On the other hand, with our new setting, an explosive increase in R&D expenditures is met with an increase in both w_R and the activity volumes of R&D output. This complies with the insights of Goolsbee (1998) that big increases in R&D expenditures do not assure an increase in R&D real output, but can be translated into higher wages for R&D workers.

5 Human capital policies

5.1 Instrumenting policies

Even though there is a vast literature analysing the effect of particular policy instruments on human capital outcomes, there is little empirical evidence that can be directly incorporated into a CGE model. For instance, there are no broad empirical estimates that can be used to assess the effect of public expenditure on the quality of education. Hanushek (2003) reports that expenditure-based policies (e.g. teacher's salary, class size, early schooling) are found to have yielded little improvements, while incentive-based policies are recommended (i.e. competition between schools, performance pay). However, recent surveys by Webbink (2005) and Checchi (2006) mention that the previous literature was mostly invalidated by the presence of endogeneity issues and they survey recent papers that do find a positive effect of expenditure, when endogeneity is taken care of.

However, there are studies that link macroeconomic outcomes to changes in human capital levels. These studies can be used to assess the impacts of human capital changes in a what-if approach, where we assume that the goals of the policies are achieved and we analyse only their macroeconomic impact. For example, a large literature analyses the links between human capital with growth. Sianesi and Van Reenen (2003) review this literature and find a robust relation between school enrolment rates and per capita GDP growth. However, there it is still controversial if these effects are static or dynamic. Moreover, this relation seems to be related to other factors, such as the country's development level, the efficiency of education expenditure, and the quality of the work force, among others. As part of this literature, a recent paper by Canton (2007) finds that a one year increase in the average education level of workers increases labour productivity by 7-10% in the short run and by 11 to 15% in the long run. Recent papers point out that the investment efficiency in different skill levels is related to the distance from the technological frontier. In particular, countries close to the frontier should invest more in tertiary education (see for example Vandenbussche et al., 2006). In what follows, we describe the human capital policies that are directly simulated in the new version of WorldScan.

5.2 Lisbon Agenda and cognitive skills

Using the NHK-SM and the new human capital version of WS we can estimate the macroeconomic effects of implementing the five Lisbon objectives on education and training. We compare these results with Gelauff and Lejour (2006) in the following section. The Lisbon Agenda mentions the following five goals should be attained by 2010:

1. An EU average rate of no more than 10% early school leavers should be achieved.
2. At least 85% of 22 year olds in the European Union should have completed upper secondary education.
3. The percentage of low-achieving 15 year olds in reading literacy in the European Union should have decreased by at least 20% compared to the year 2000.
4. The European Union average level of participation in Lifelong Learning should be at least 12.5% of the adult working age population (25-64 age group).
5. The total number of graduates in mathematics, science and technology in the European Union should increase by at least 15% by 2010 while at the same time the level of gender imbalance should decrease.

For the assessment of cognitive skills, we use the PISA test scores and estimate the macroeconomic impact of increases in these test scores, which can be related to increases in the cognitive skills of the new cohorts. This exercise is similar to the implementation of Target 3 of the Lisbon Agenda.

5.3 Policy simulations

In this section we describe how the different human capital policies are modelled into the NHK-SM. Then we present the simulation results when the NHK-SM output is linked to the new human capital version of WorldScan

5.3.1 Assessing the Lisbon Agenda

Here we present how the five different policies of the Lisbon Agenda related to skills and education are implemented in the NHK-SM. In the last subsection we present the full macroeconomic impact when the inputs from the satellite model are fed into WorldScan. This section is based on the methodology developed in Jacobs (2005) and implemented in Gelauff and Lejour (2006).

Targets 1 and 2: Early school leavers and secondary school completion

Target 1 implies a shift of graduates from skill categories $L1$ to $L2$, while Target 2 needs a shift from $L2$ to group $M1$. Both targets can be modelled by changes in the graduation rates η_{sry}. For Target 1 we reduce the graduation rates of $L1$ (η_{L1ry}) and increase η_{L2ry} (i.e. there are less early school leavers and thus, more students graduating as $L2$ and less as $L1$). Target 2 implies a decrease in η_{rL2} and increase in secondary graduates $M2$, i.e., η_{M1ry} rises.

These changes in the graduation rates have to be done in such a way that we maintain the constraint: $\sum_s \eta_{rs} = 1$. The graduation rates are defined using a EU-wide increase that is calibrated to achieve both targets. However, this does not imply that all member countries have to make the same adjustments, and we then translate the EU-wide changes into country-specific changes. These changes are based on a proportionality principle where countries closer to the target have to do less than countries further away from the targets.

On the other hand, the opportunity costs of increased number of schooling years is modelled as a transition path where η_{rM1} and η_{rL2} reach their new values only after a three year adjustment period. This reflects the fact that students that were going to graduate as $L1$ have to spend three more years in school to graduate as $L2$, and those students that where going to graduate as $L2$ also have to study three more years to graduate as $M1$. Therefore, in this transition period $\sum_s \eta_{rs} < 1$, implying that less people graduates and joins the work force –compared to the baseline case– and this creates a temporary reduction in labour supply and total output.

Figure 5.1 reports the percentage change in aggregate labour efficiency (ε_{ry}) that results from achieving skill targets 1 and 2 of the Lisbon Agenda.[23] This percentage changes correspond to the former linkage variable ε_{ry}. Although we have now five linkage variables, instead of one, in the following graphs we use ε_{ry} as a summary variable that indicates how the policy changes are affecting the aggregate labour supply. In addition, we show the simulation effects starting in 2001 in the following figures, but when we link the NHK-SM variables with WS we use a 10-year delay such that the implementation of the Lisbon Agenda is assumed to have economic effects until 2011.

As expected, there is a short-term decrease in the labour efficiency units due to opportunity costs of longer years in school. This initial decrease is compensated with higher efficiency units in the long-run.

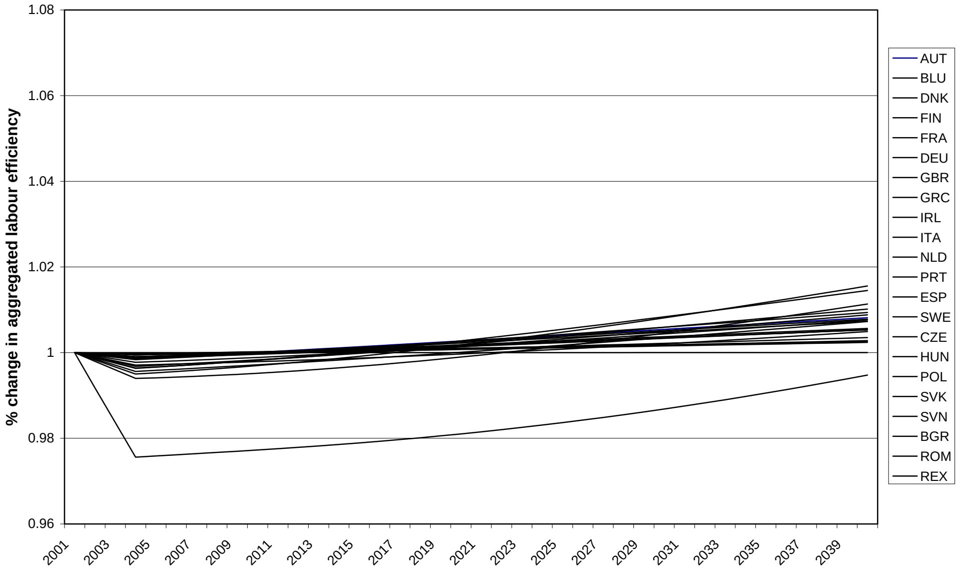
Target 3: Achievement in literacy

The EU bases this target on the PISA test scores. The PISA scores on literacy follow –by construction– a standard normal distribution with mean $\mu = 500$ and standard deviation $\sigma = 100$. Low achieving 15 year old's are individuals with a PISA score less than about 407. Currently, about 17.2% of the EU population has a low achievement in literacy. To model the increase in literacy with rise the mean score (μ^*). The other option, to reduction the standard deviation of scores (σ^*) has the limitation that it implies a reduction for the high-performance students.

It is important to remark that since we are modelling this target as an overall increase in the test scores –and not particularly for low-achieving students– the implementation of this target is in fact assessing the impact of an overall increase in the cognitive skills of all students.

[23] The outlier in the figure is Portugal, which had very low secondary graduation rates in 2001.

Figure 5.1 EU27, Labour efficiency gains for Targets 1 and 2

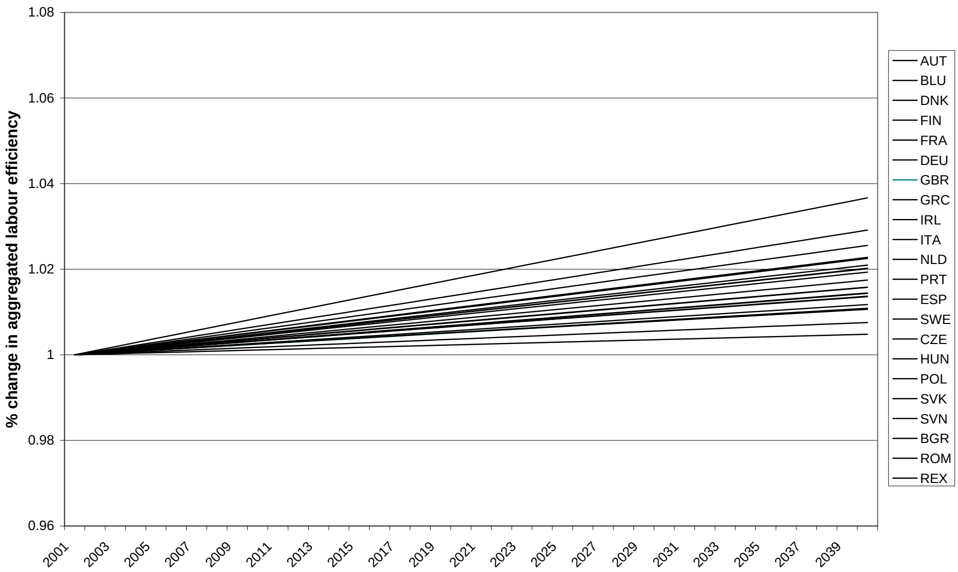


Let $\phi(p,\mu,\sigma)$ denote the cumulative normal distribution up to p with mean μ and standard deviation σ. p is the percentile below which students are low achieving. The fraction of low achieving students decreases from $p = 0.172$ to $p^* = 0.137$. Consequently, reaching the Lisbon targets follows from solving $\phi(p^*,\mu^*,\sigma^*) = 0.137$. If the mean is increased and the standard deviation is held at old levels ($\sigma^* = \sigma$), then with $\sigma = 100$ and $p^* = 0.137$ we find that $\mu^* = 516$. Therefore, average test scores μ need to increase with 3% over the whole student body to generate this reduction in low achievement in literacy. An increase of 3% on the average of the test scores equals 16% of one standard deviation ($\Delta\mu = 0.16\sigma$). From the empirical estimates reviewed in Hanushek and Woessman (2008) we use the value of a 12 percent increase in earning per standard deviation increase. With a return of 12% per standard deviation in test scores, a 0.16σ increase in the average scores on literacy implies a monetary return of 1.9% in wages. We therefore increase the average quality of human capital of all school-leavers with 1.9% across all schooling types hence Q will rise from $Q_{EU} = 1$ to $Q^*_{EU} = 1.019$. Therefore, nothing happens with the skill composition of the work force as a result of an equal increase in the level of human capital over all workers. Thus, the target is reached by using the same procedure of before. From the EU target of $Q^*_{EU} = 1.019$, country-specific target are estimated considering how far they are from the target.[24]

We show the changes in labour efficiency in Figure 5.2 Here there is a substantial increase in

[24] In our sensitivity tests we change the values of the wage return per standard deviation in the test scores. This turns out to be a key parameter in the model.

Figure 5.2 EU27, Labour efficiency gains for Target 3



labour efficiency for all countries, this also reflects the increased effect of cognitive skills on overall human capital levels.

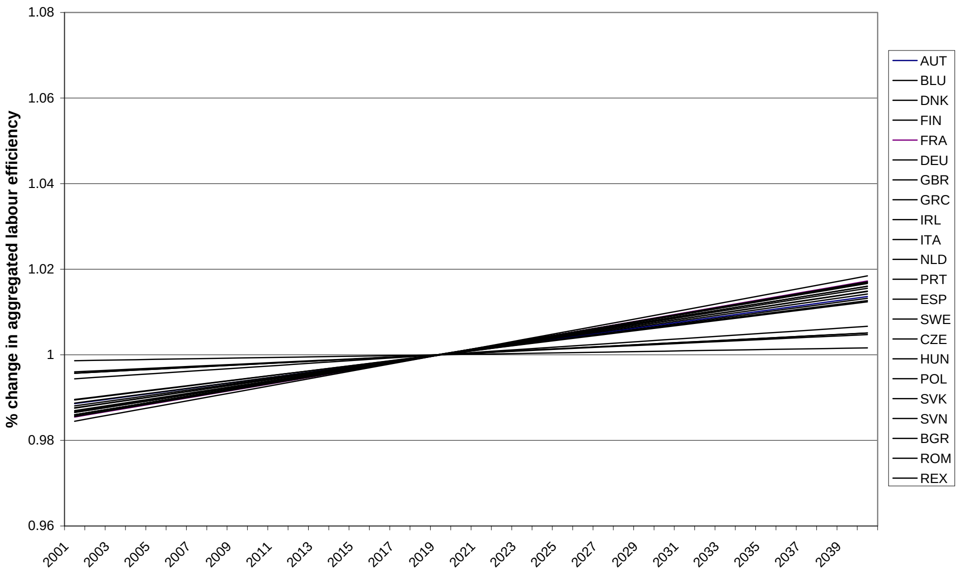
Target 4: Lifelong learning

Currently, the EU average of workers that participated in formal on-the-job (OJT) training programs in the last month is 8,5% of the work force. If we assume that each training program costs one working day per week, then the current fraction of labour time devoted to training activities equals $4/20 * 8.5\% = 1.7\%$ of total labour time, based on 20 working days per month. This is equivalent to 1.7% of total working time per year. The target implies that the fraction of the workforce participating in training during the last month increases to 12.5% of the work-force. Hence total labour time devoted to training activities has to increase to 2,5% because $4/20 * 12.5 = 2.5\%$. Consequently, total labour time devoted to formal training activities increases from 1.7% to 2.5%, which results in the new fraction of training time $\chi^* = 0.158$[25] Therefore, the EU new average growth rate of OJT becomes: $\gamma^{EU*} = 0.067 * 0.158 = 1.06\%$ per year. Furthermore, aggregate labour input in the Lisbon scenario decreases from $A = 1$ to $A^{EU} = \frac{1-\chi^{EU*}}{1-\chi^{EU}} = \frac{1-0.158}{1-0.15} = 0.99$.

We allow for a country specific implementation of the Lisbon target, following the same procedure as in previous targets. Note that most of the LbD is done without formal training

[25] It is assumed in the baseline that $\chi = 0.15$ or that 15% of workers time is devoted to OJT. To arrive at $\chi^* = 0.158$, we add the increase in OJT time estimated from ε, where $\varepsilon = 2.5\% - 1.7\% = 0.8\%$

Figure 5.3 EU27, Labour efficiency gains for Target 4



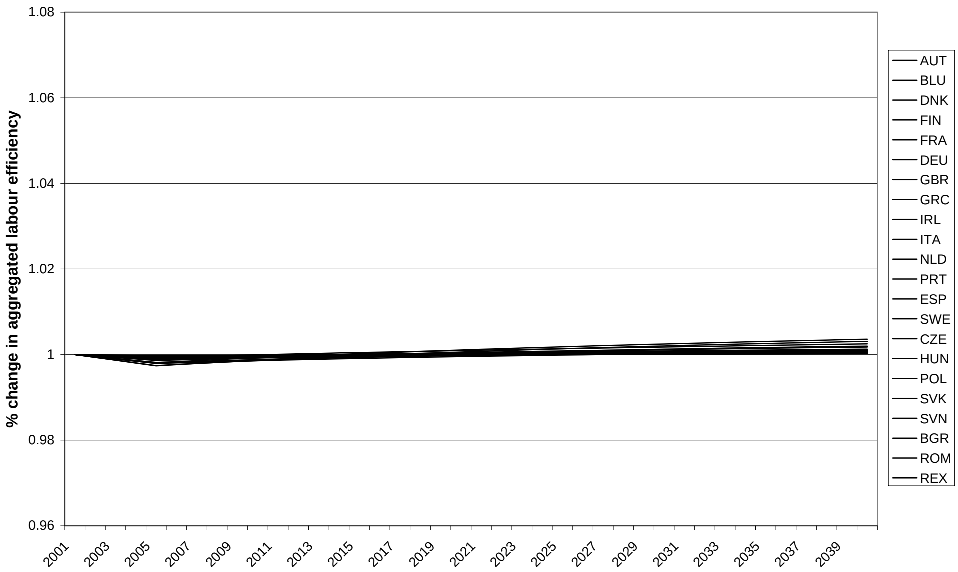
programs. This follows from the assumption that most *LbD* skills are obtained as "skill-begets-skill" effects of human capital gathered on the job (Heckman, 2000).

To estimate γ^* first it has to be assumed that there is a baseline productivity of training $\widetilde{A} = \frac{\gamma}{\chi} = \frac{0.01}{0.15} = 0.067$. Then, to estimate the gains in γ of increased time in OJT, we use: $\gamma^* = \widetilde{A}\chi^* = 0.067 * 0.158 = 1.06\%$. This target implies two changes. First, an increase of $\gamma = 0.01$ to $\gamma^*_{EU} = 0.0106$. Second, the aggregate labour input A decreases, given that workers spend more time learning, from $A_{EU} = 1$ to $A^*_{EU} = 0.99$. Again, there is a country-specific target adjustment based on the relative distance to the EU targets. Figure 5.3 shows the implications of OJT increases. The impact of this target is also substantial, with a short-term decrease due to the opportunity costs of formal training programs.

Target 5: Mathematics, science and technology students

This target is achieved assuming that all countries increase by 15% there number of R workers and decrease $M2$ in the same amount. This is done by changing the graduation rates for η_{rM2} and η_{rR} correspondingly. As in Targets 1 and 2, we estimate the opportunity costs by having a transition period where $\sum_s \eta_{rs} < 1$. The changes in labour efficiency for this target are depicted in Figure 5.4. Again we see the pattern of initial decreases with a long-term increase in labour efficiency. However, for this target the positive effects are very small. In the core version of WorldScan we link the stock of R workers to the output of the R&D sector. Thus, this target may have a more significant impact when we run the CGE model. An increase in the potential

Figure 5.4 EU27, Labour efficiency gains for Target 5



number of R workers facilitates the expansion of the R&D sector, which in turns has positive spillovers to productivity changes.

Lisbon All: combining the five targets

The last simulation is a combination of all the four previous policy shocks. This provides the compounded effect of the skill policies in the Lisbon Agenda. Figure 5.5 shows the results.

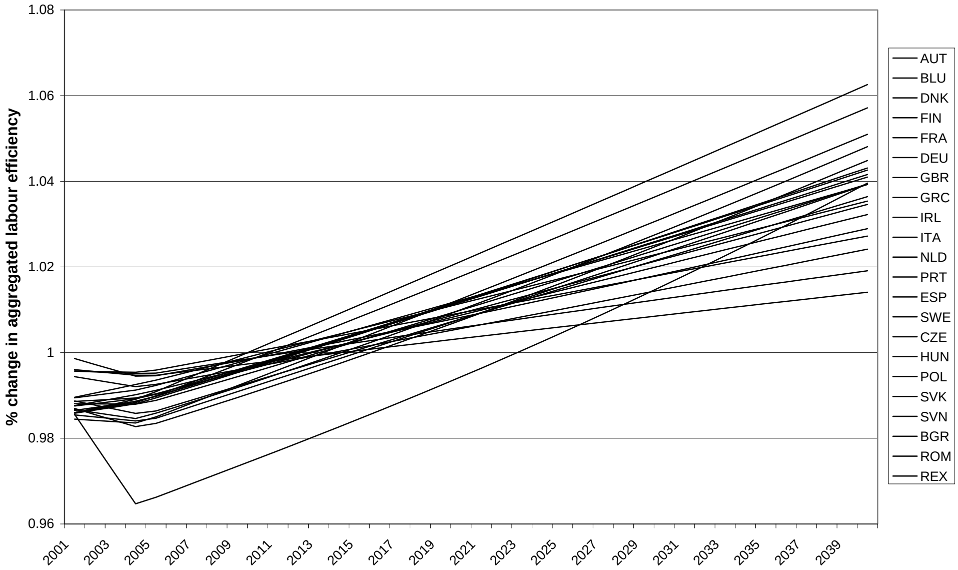
In this accumulated simulation the opportunity costs are clearly visible at the beginning of the period, while most EU countries begin to experience positive labour efficiency changes around 2015. The outlier in this series is Portugal, which starts with high levels of $L1$ and has a more dramatic adjustment path to comply with the skill targets.

However, These effects are including the supply and the efficiency changes associated with the Lisbon Agenda. When we use our five linkage variables, we can observe the distinct effects that are later used in the human capital version of WorldScan. First we present the efficiency shocks for high-skill labour (HSL) are shown in Figure 5.6.

The evolution of this variable presents again the same evolution as ε_{ry} with an initial decrease –reflecting the opportunity costs of formal education and OJT– followed by an exponential increase that reflects higher formal skill levels, OJT and quality of education. For low-skill labour (LSL) we have similar results, which are shown in Figure 5.7.

Although the dynamic pattern is the same as for high-skill, the magnitude is smaller for low-skill. On the other hand, the supply effects do not follow this pattern of initial decrease and

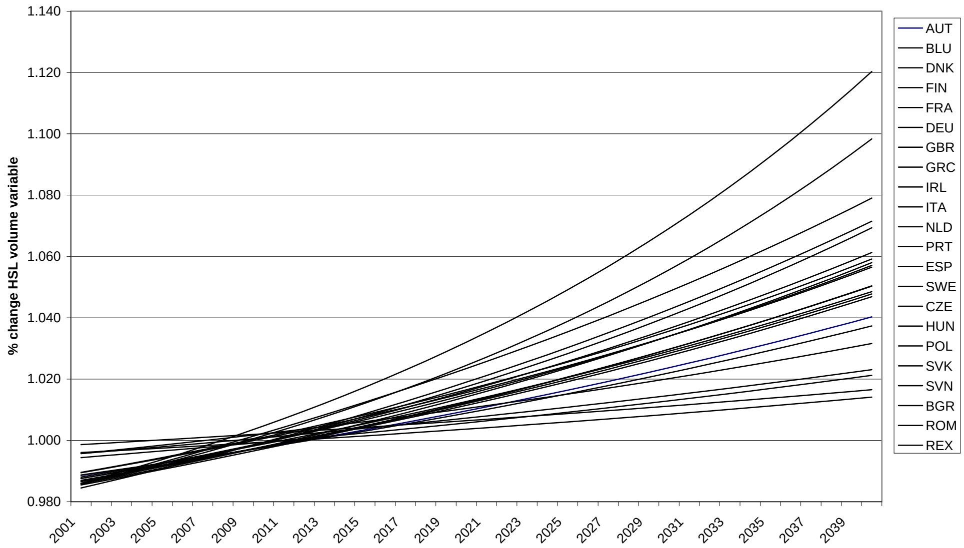
Figure 5.5 EU27, Labour efficiency gains for all Lisbon targets



future increase, but have instead an initial shock that create a persistent change over time. In the case of *HSL* the initial shock is positive (see Figure 5.8), but negative for *LSL* (see Figure 5.9).[26]

The positive *HSL* shock does not compensate exactly with the negative *LSL* shock, since

Figure 5.6 EU27, Labour efficiency changes for high-skill labour for all Lisbon Targets



[26] Again, the outlier in both graphs is Portugal, which had very low initial secondary graduation rates.

Figure 5.7 EU27, labour efficiency changes for low-skill labour for all Lisbon targets

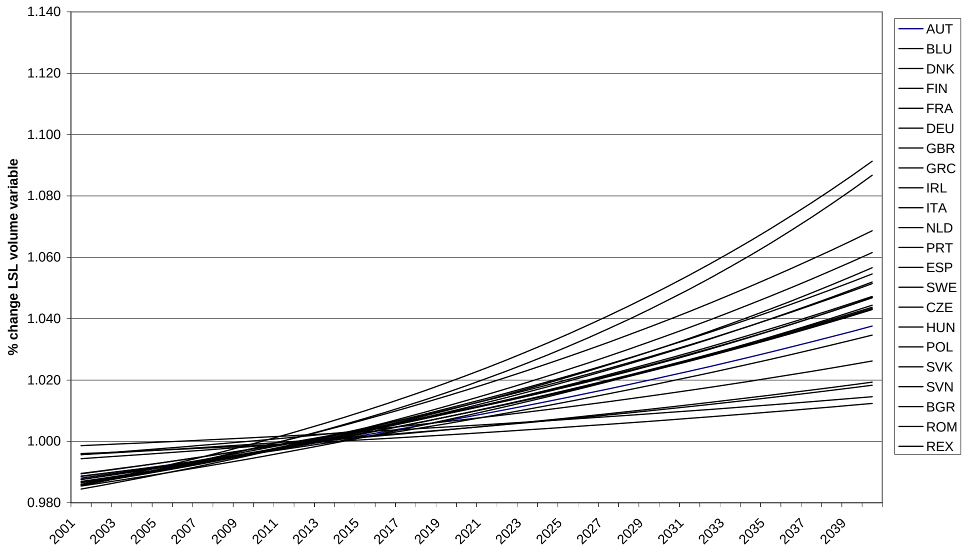


Figure 5.8 EU27, labour supply changes for high-skill labour for all Lisbon targets

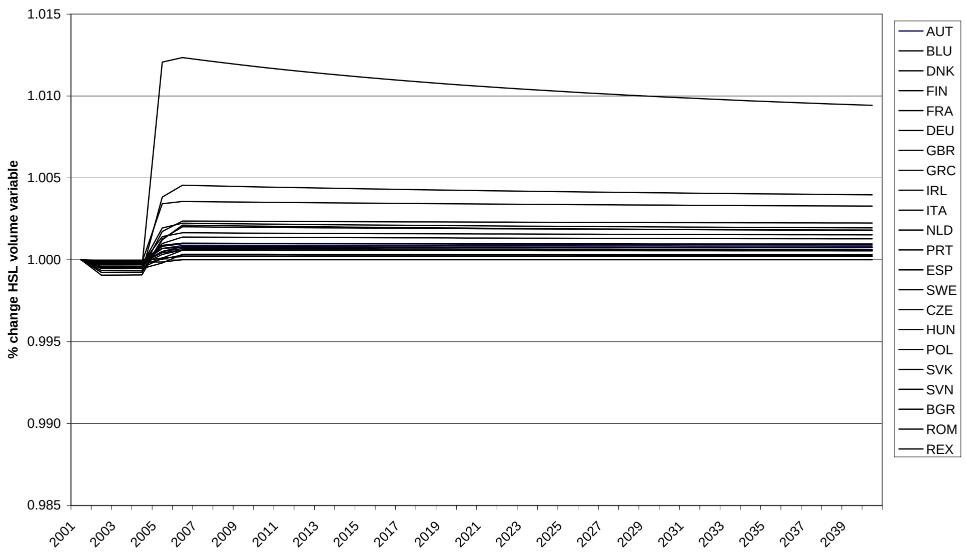
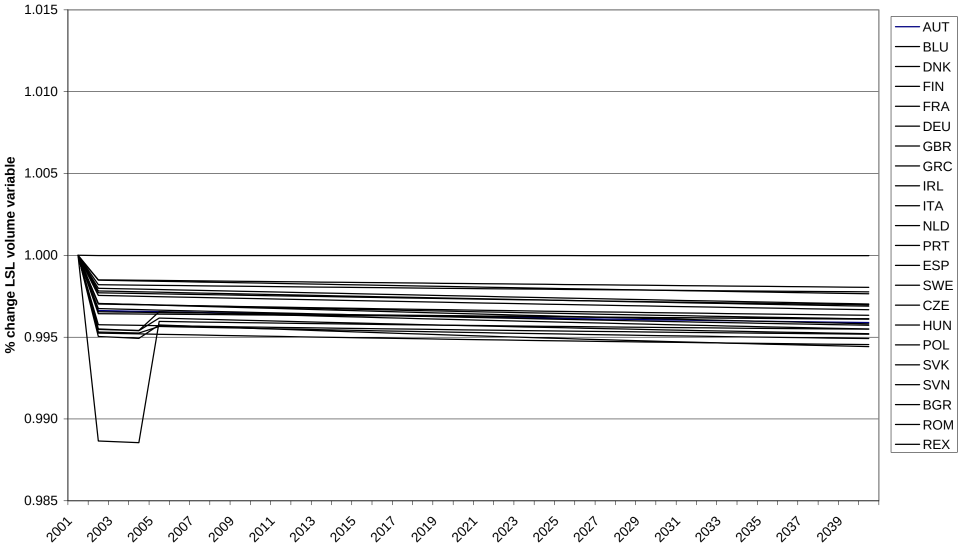


Figure 5.9 EU27, labour supply changes for low-skill labour for all Lisbon targets



there are differences in the amount of both types of labour by region. However, the labour supply shock is constructed such that total number of workers in the last year are equal in the baseline and in the policy counterfactual. What changes is the composition of skills: A higher relative supply of high skill and lower relative supply of low-skill workers.

5.3.2 Macroeconomic effects of the skill targets of the Lisbon Agenda

Integrating the satellite model changes into the new human capital version of WorldScan produces the macroeconomic outcomes in Table 5.1. We observe very small or negative changes until 2020, but then the long-run impacts are significant. GDP increases by 2.1% with respect to the baseline case and consumption by 1.9%. These changes are higher (GDP is 0.4% higher) than the previous evaluations from the Lisbon Agenda using the former version of the satellite model and WorldScan (Gelauff and Lejour, 2006). This result is due to a higher impact of cognitive skills on labour productivity, as well as to the secondary effects that higher labour productivity has on the labour market. This is shown by an increase in labour supply and a decrease in unemployment that raises total employment by 0.5%.

Thus, the new version of WorldScan produces a similar pattern of macroeconomic changes. In particular, there is a short term reduction in consumption followed by an increase in the long term. However, the new version produces larger effects due to the revisions made to the NHK-SM, which has a better accounting of the impact of increased human capital and skill formation on labour productivity.

Table 5.1 EU27, Macroeconomic results for all Lisbon targets, % changes from baseline

	2020	2030	2040
GDP	− 0.2	0.9	2.1
Consumption	− 0.2	0.7	1.9
Labour supply total	− 0.1	0.1	0.3
LSL	− 0.2	0.0	0.2
HSL	0.2	0.3	0.4
Employment total	− 0.1	0.2	0.5
Unemployment total	0.0	0.0	− 0.1
Real average wage	− 0.1	0.5	1.3
Wage LSL as % of wage HSL	0.2	0.4	0.5
Labour productivity	0.0	0.6	1.4

Source: Own estimations using WordScan human capital version.

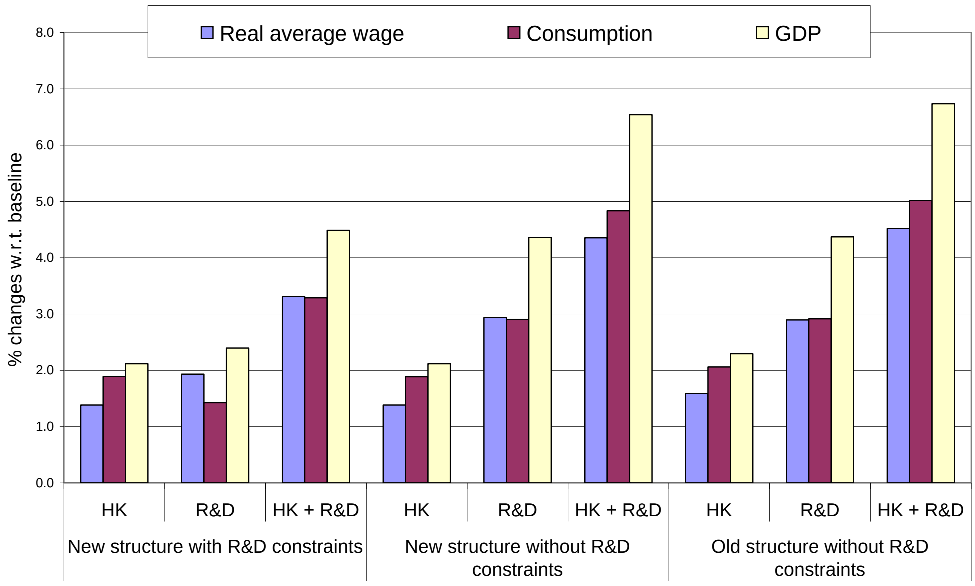
The NHK-SM shocks yield an increase on labour productivity, as well as in the initial reduction of the supply of low-skill labour (LSL) and the increase in HSL supply. An important element is that total labour supply in the CGE model is increasing as a consequence of the endogenous labour mechanisms in the model. The labour productivity increase is rising wages, which in turn increases the endogenous supply of labour. Thus, even though the initial movements in the labour supply for both skill types are consistent with the NHK-SM shocks until 2020, later on the labour supply for both skill types is expanding.

We now compare the macroeconomic results using the new human capital version of WorldScan with results from other model specifications. For instance, we examine how the introduction of the R&D workers constraints affects the macroeconomic results. Figure 5.10 shows the changes in real average wage, consumption and GDP with respect to baseline values when using different WorldScan versions. The first column (HK) shows the results for the human capital policies of the Lisbon Agenda. This corresponds to the Lisbon All scenario where we apply jointly the five skill targets of the Lisbon Agenda. The second column (R&D) refers to the implementation of the R&D expenditures target of the Lisbon Agenda (i.e. increase R&D expenditure to 2.7% of GDP). Finally, the third column combines both human capital and R&D targets of the Lisbon Agenda.

The first three sets of columns refer to the new version of the model, which has a new production structure and incorporates the R&D constraints (inelastic supply of R&D workers). The second set uses the new production structure but does not include the R&D constraints; while the last set of columns refers to the previous version of WorldScan. All the results refer to 2040, when the full effects of both policies are reached.

Analysing the new version (new structure with R&D constraints) we observe that the human capital and R&D policies have similar results with GDP increasing around 2%, while

Figure 5.10 EU27, main macroeconomic changes using different WorldScan model specifications, % changes w.r.t. baseline in 2040

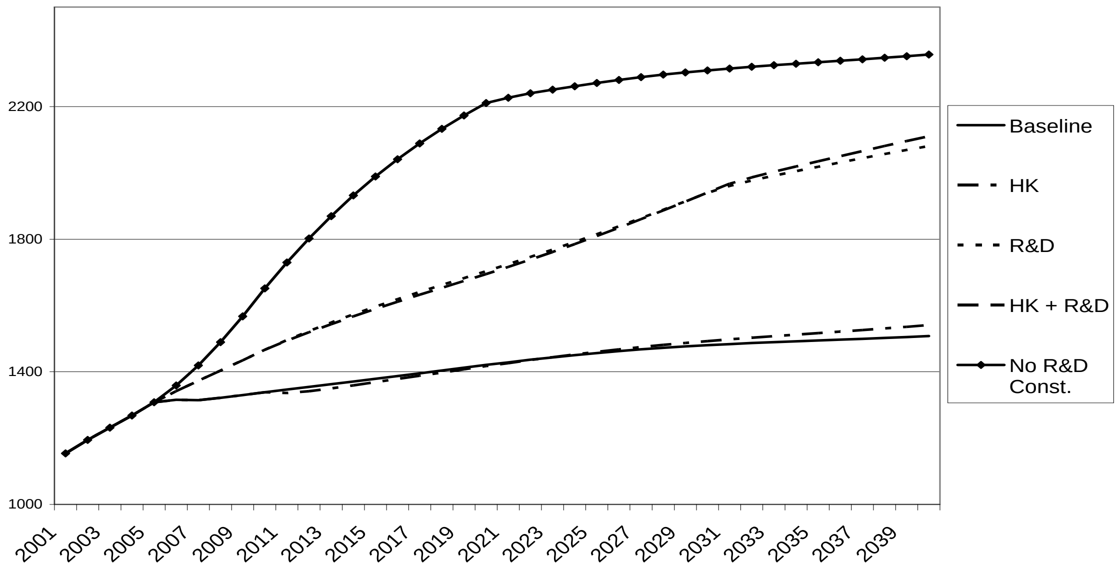


consumption is 0.5% higher and wages are 0.5% lower with the HK policies. In addition, the combination of both policies (HK + R&D) yields roughly the sum of the effects of both policies. In other words, there are no strong complementarity effects of applying both policies simultaneously.

We find significant differences when we compare the results using the new WorldScan version and the version without R&D constraints. The HK policy results are very similar, but as expected the R&D results are considerably higher when there are no constraints in the supply of R&D workers. The increases in GDP and consumption are reduced by around 50% by the R&D constraints. Finally, we find small differences when we compare the versions with the new and old production structure (both without R&D constraints). The only sizable effect is that the HK results are higher with the old production structure. Therefore, the most significant difference, in terms of macroeconomic results, is the introduction of the R&D constraints. To analyse in detail how the R&D constraints are working we plot the R&D activity levels in Figure 5.11

We observe how the effects of the R&D subsidies affect the R&D activity levels when the labour supply of R&D workers is constrained to increase. Note that for all the R&D scenarios the target of 2.7% of R&D expenditure with respect to GDP is reached. However, for the R&D simulations and the combined R&D and human capital policies, the R&D activity levels are well below the values for the unconstrained simulations. This implies that the increase in the R&D expenditure is reflected in a very sizeable increase in the wages for the *R* workers. This is shown

Figure 5.11 EU27, R&D activity levels for different scenarios



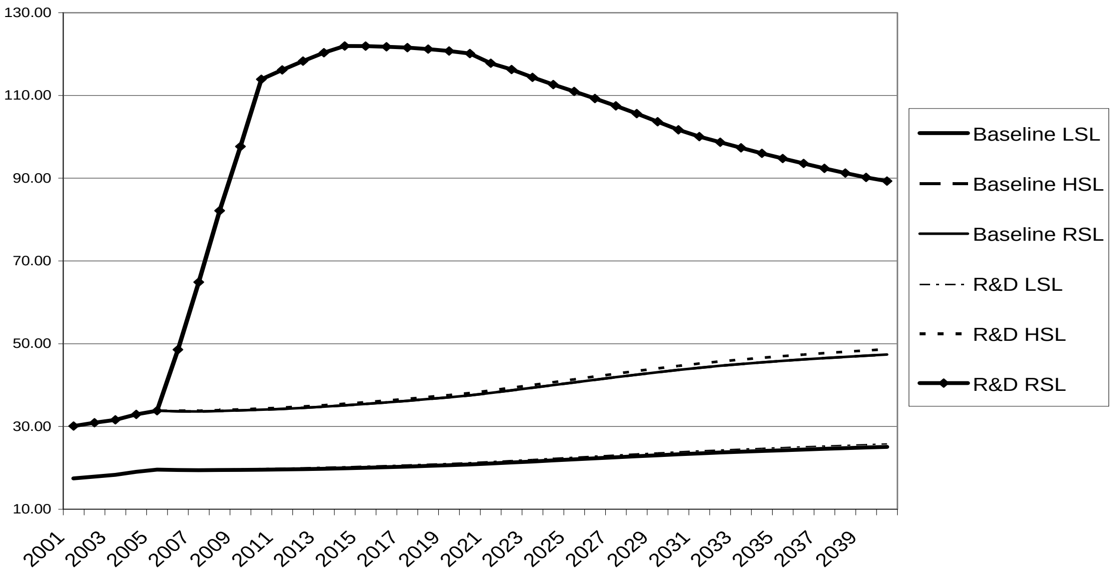
in Figure 5.12, where we observe three distinct wage groups. The lowest wages correspond to low-skill labour (LSL), the middle wages to high-skill labour and *R* workers (RSL) in the baseline (when their wages equal HSL wages) and the highest wages correspond to the RSL workers in the R&D policy simulations.

As expected the huge R&D labour demand expansion of the R&D subsidies is reflected in an explosive increase of RSL wages. By 2020 these wages are more than 3 times higher than the HSL wages. This is an unrealistic result that reflects the huge increase in R&D expenditures targeted by the Lisbon Agenda. However, we have also designed a mechanism in the new human capital version of WorldScan where we limit the RSL wage increase with a corresponding lower R&D subsidy. This provides a more realistic adjustment path of R&D workers wages and can eventually (with a low enough restriction on the wage increase) limit the R&D expenditure increase.

5.4 Estimation of direct schooling costs

Total schooling costs can be divided between direct costs (i.e. actual expenditures in teachers wages, school buildings, etc.) and indirect costs (the opportunity cost for students attending school and thus, not earning a wage). Indirect costs are the most significant schooling costs. However, direct schooling costs are also significant. While we have estimated the indirect costs of schooling in the NHK-SM, in this section we estimate the direct costs.

Figure 5.12 EU27, wages for each skill-type by scenario



The estimation of direct schooling costs requires a separate accounting of the possible costs for the government that are associated with the Lisbon skill targets. In particular, for targets 1, 2 and 5 extra time for schooling is needed. The decrease in school dropouts and the increase in the completion rates of upper secondary education needs extra schooling years. The same holds for the increase in the number of graduates from mathematics, sciences and engineering. For target 4 of lifelong-learning, we assume this is mainly learning obtained in the job and financed by firms. For target 3 for decreasing illiteracy we assume that no extra education costs are required because pupils do not stay for a longer time period at school. Of course it could require extra costs due to specialized teaching or other extra educational activities. However, recall that from the literature overview we did before, it was hard to establish strong links between policies and cognitive skill improvements. Thus, it is also difficult to estimate the direct costs associated with the implementation of target 3 and we do not take them into account.

To estimate the costs associated with extra schooling, we use data from OECD (2008) on annual expenditures per student for all services by educational level. We aggregate the data into our five skill categories (see Table 5.2).

We then use data from EuroStat on the number of students enrolled by educational level in 2005 and multiply it by expenditure per student. This gives us the total expenditure on education by country in 2005. Using GDP data from OECD (also PPP converted USD) we obtain the expenditure on education as a percentage of GDP. Our estimates are comparable to the data from EuroStata, where the expenditure on education in the EU27 is 5.1% of GDP.

Table 5.2 Annual expenditure per student by skill level, PPP converted USD, 2005

	L1	L2	M1	M2	R
AUT	8,259	9,505	10,028	11,394	15,028
BGR	3,910	4,538	4,695	5,130	7,059
BLU	6,648	7,731	7,731	8,046	11,960
CZE	2,812	4,864	4,830	3,105	7,019
DEU	5,014	6,200	10,282	6,938	13,351
DNK	8,513	8,606	10,197	14,959	14,959
ESP	5,502	7,211	7,211	9,059	10,301
FIN	5,557	8,875	6,441	7,582	12,285
FRA	5,365	7,881	10,311	9,483	11,486
GBR	6,361	7,167	7,167	8,842	13,506
GRC	5,146	8,423	8,423	3,417	7,661
HUN	4,780	5,165	7,586	7,740	11,002
IRL	5,732	7,352	7,680	7,386	10,468
ITA	6,835	7,599	7,682	7,420	8,032
NLD	6,266	8,166	7,225	8,719	13,883
POL	3,312	2,971	3,131	4,883	5,593
PRT	4,871	6,555	6,381	6,785	8,787
REX	3,384	3,802	4,033	2,883	4,386
ROM	3,910	4,538	4,695	5,130	7,059
SVK	2,806	2,430	3,026	5,131	5,783
SVN	6,364	7,994	5,565	7,037	8,573
SWE	7,532	8,091	8,292	8,281	15,946

Source: OECD (2008).

The following step is to estimate how the total number of graduated students changes with the application of the Lisbon targets. First, we use data on number of current graduated students (G_{sr}) from the OECD.stat online database. We then use the changes in the graduation rates from the baseline (η^B_{sry}) and the graduation rates from the scenario where all the Lisbon skill targets are implemented (η^L_{sry}). Given targets 1 and 2, we have an increase in graduates from upper secondary ($M2$), while target 5 implies an increase in R graduates. Then $\widetilde{g}_{sr} = \frac{G_{sr} * \eta^L_{sry}}{\eta^B_{sry}}$ is the increase in the number of graduates from both targets. If we define X as the expenditure per student, then the direct schooling costs (DSC^L) of the Lisbon Agenda are given by:

$$DSC^L_{sr} = DSC^B_{sr} + \widetilde{g}_{sr} X_{sr} Y_s \tag{5.1}$$

where $\widetilde{g}_{sr} = 0$ if $s = L1, L2, M2$ and $\widetilde{g}_{sr} > 0$ if $s = M1, R$. Finally Y_s is the number of extra schooling years that takes to fulfil the new graduation targets by skill type. Recall that $S_{L2M1} = 3$ (it takes 3 years to move from $L2$ to $M1$) and $S_{M2R} = 4$, which are the relevant values for the implementation of the Lisbon targets 1, 2 and 5. We assume that to achieve the new graduation rates, part of the new students that are graduating where already studying at the same educational level (i.e. previous dropout students that were not graduating) and the other part are new students that take the full S years to graduate. Thus, we use $Y_{M2} = 1.5$ and $Y_R = 2$.

With this information we obtain the education expenditure as percentage of GDP once the skill targets are implemented. These results are presented in Table 5.3. As expected, the increase in direct costs of schooling are relatively small. It represents 0.15% of GDP for a weighted EU average. Since GDP is estimated to increase by around 2% using our WS simulations, then this increase does not significantly affect the macroeconomic results. It is important to note, however, that these are crude estimates of the potential increase in direct schooling costs. We had to use average expenditure per student (since we do not have data on marginal costs), we are not certain of how many more schooling years (Y) in average it takes to achieve the new graduation rates and we are not dealing with demographic changes that can affect the number of enrolled students and the corresponding marginal schooling costs.

Table 5.3 Education expenditure as percentage of GDP

	Baseline	Lisbon	difference
AUT	5.61%	5.67%	0.07%
BLU	6.34%	6.45%	0.11%
CZE	4.13%	4.20%	0.07%
DEU	4.08%	4.15%	0.08%
DNK	7.27%	7.40%	0.13%
ESP	5.17%	5.39%	0.22%
FIN	6.26%	6.38%	0.12%
FRA	5.58%	5.80%	0.22%
GBR	6.52%	6.71%	0.20%
GRC	4.18%	4.25%	0.08%
HUN	7.37%	7.52%	0.15%
IRL	4.42%	4.56%	0.14%
ITA	4.89%	5.02%	0.13%
NLD	4.71%	4.84%	0.12%
POL	6.45%	6.64%	0.19%
PRT	6.02%	6.33%	0.31%
SVK	4.29%	4.39%	0.09%
SWE	6.76%	6.86%	0.10%
EU average	5.33%	5.48%	0.15%

Notes: The EU average is weighted by total enrolment. No data on number of graduates for BGR, ROM ,SVN and REX.
Source: Own estimations based on OECD (2008) and OECD.stat database.

6 Sensitivity analysis

In this section we conduct sensitivity analysis with respect to some of the key parameters of the new model. First, we summarize the main baseline parameters without a country/year dimension:

$\sigma_H = 1.44$	$S_{L1L2} = 3$	$\gamma = 0.01$	$\Delta = 0.015$
$\sigma_L = \infty$	$S_{LH} = 3$	$\omega = 0.33$	$\tau = 0.03$
$\sigma = 2$	$S_{M1M2} = 4$	$T = 40$	$\phi = 0.2$
$\beta_{EU} = 0.08$	$S_{M2R} = 4$	$\overline{T} = 20$	

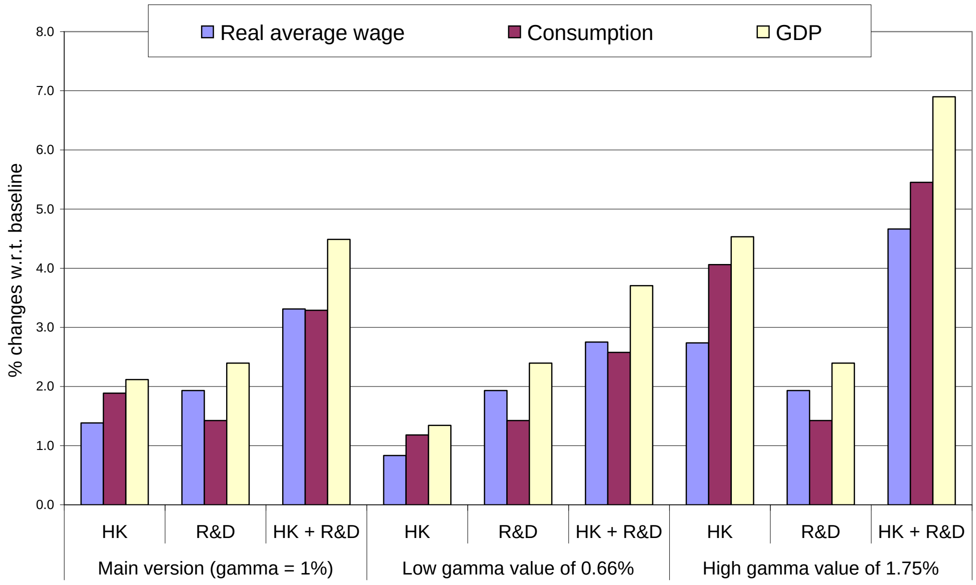
The rest of the baseline parameters are country-specific: η_{rs}, θ_r, δ_r, N_{sr0}. These parameters are taken from different sources, as explained above. Of these country-specific parameters we only change η as part of our counterfactual simulations. The other country-specific parameters, as well as Δ, τ, T and $\overline{T}$, are not changing between our baseline scenario and our policy counterfactual scenarios. Thus, changing their values does not affect the macroeconomic results of the counterfactuals.

The parameters that are left can be classified in two groups. The first group consists of the parameters used to calibrate the share values (α 's): β and the S values. We do not expect these parameters to produce significant changes in our results, since they only affect indirectly the values of L and H through the α values. The second groups consists of the learning-by-doing parameter γ, the R&D workers supply elasticity ϕ, and the substitution elasticities σ, σ_H and σ_L. We expect that changing the values of the parameters in this second group can have a significant impact on our overall results.

First, we conducted sensitivity analysis to the elasticity of substitution parameters. However, the scope to change these values is limited since both σ_L and σ_H are supported extensively in the literature. Thus, the only change we made was using $\sigma_H = 1.5$ and we did not find significant changes in our main macroeconomic results. On the other hand, recall that $\sigma = 2$ is the elasticity of substitution between the L and H labour aggregates. The corresponding aggregated labour value (G) was employed in the old satellite model, but we do not use G anymore. Thus, changes in σ do not affect our results.

The second parameter we analysed was γ, the variable that corresponds to *LbD* and the amount of general knowledge that is transmitted to the new cohorts entering the workforce. This last effect is directly derived from equation 2.13. We took $\gamma = 0.01$ from Jacobs (2005), which corresponds to $\omega = 0.33$, i.e., *LbD* generates one third of life-time human capital. On the other hand, Heckman et al. (1998) estimated that $\omega = 0.23$ and thus, $\gamma = 0.0066$. Finally, from Mincer (1962) we have that $\omega = 0.5$ and then $\gamma = 0.0175$. In Figure 6.1 we present the macroeconomic

Figure 6.1 EU27, main macroeconomic changes using different γ values, % changes w.r.t. baseline in 2040

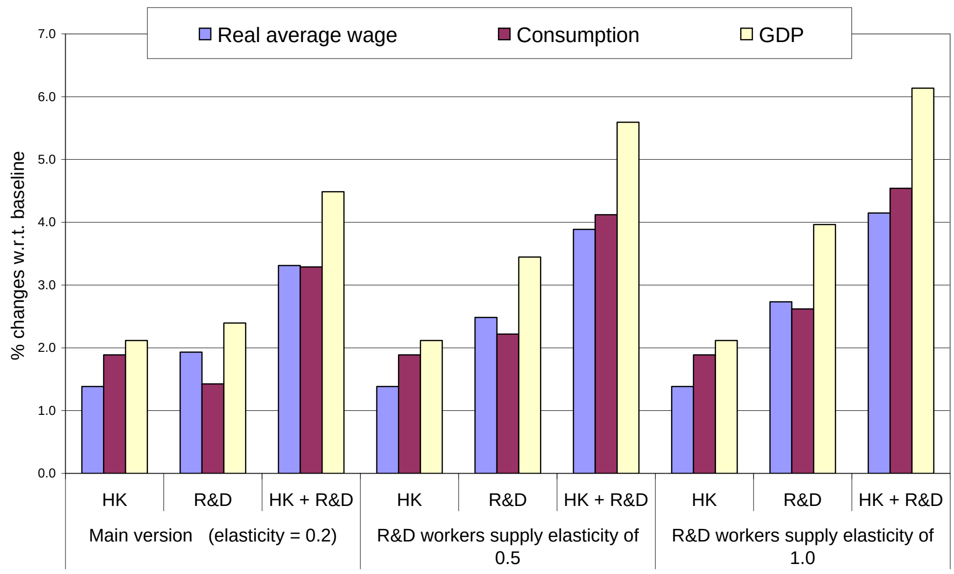


results using these three values of γ. Comparing the values for the human capital (HK) counterfactuals, we find that our results are very sensitive to different γ values. For instance, with $\gamma = 0.66\%$ the increases of GDP and consumption are almost half of those using $\gamma = 1\%$. Conversely, with a high γ value of 1.75%, GDP and consumption have an increase of more than double of that with $\gamma = 1\%$. Thus, we can conclude that the value of the γ parameter is crucial to assess the impact of human capital policies. However, it does not affect much the effects of R&D policies.

The next parameter we evaluate is the supply elasticity of R&D workers (ϕ). In Figure 6.2 we show the macroeconomic results for three values of ϕ. The value in the main version of $\phi = 0.2$ is taken from Goolsbee (1998), which gives an unelastic response in supply. When we evaluate the implications of higher elasticity values of $\phi = 0.5$ and $\phi = 1$, we find that the impact of the R&D policy simulations is increasing. When comparing these results with those in Figure 5.10, we find that a supply elasticity of one provides very similar results to when we do not include the R&D constraints in the model. In other words, increasing ϕ to 1 is almost equivalent to eliminating the R&D constraints in our human capital version of WorldScan.

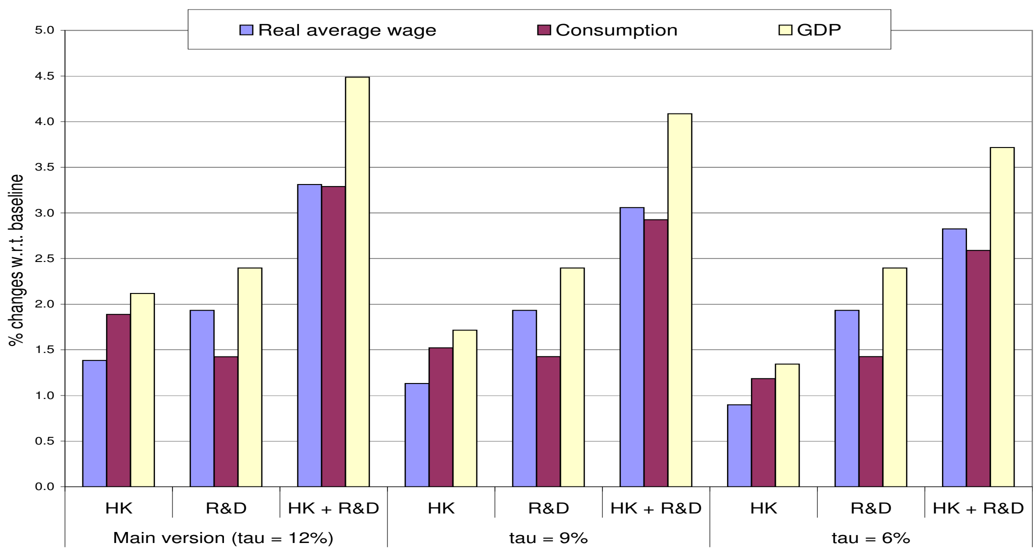
Finally, we conduct sensitivity analysis on the effects of test scores on labour productivity. Recall from Section 2.4 that we took the value cited by Hanushek and Woessman (2008) that one standard deviation in test scores is associated with a 12% increase in wages. We define this parameter as τ and try different counterfactual simulations for values of 9% and 6%. The dynamic pattern of an initial decrease in GDP and consumption together with a subsequent

Figure 6.2 EU27, main macroeconomic changes using different R&D workers supply elasticities, % changes w.r.t. baseline in 2040



increase after 2020 is maintained. However, the impact of the skill targets are significantly reduced when we use lower values of τ. The results are shown in Figure 6.3. Therefore, τ is a key parameter in the new human capital version of WorldScan.

Figure 6.3 EU27, main macroeconomic changes using different test-scores/productivity relations, % changes w.r.t. baseline in 2040



7 Summary

We have described the revisions and updates performed on the satellite model of Jacobs (2005). The revised satellite model (NHK-SM), in conjunction with the new features of the WorldScan version with human capital, provide a richer analytical tool to evaluate the macroeconomic impact of human capital policies. Although we cannot model the link between policy instruments and human capital outcomes, this new human capital version of WorldScan provides relevant information concerning the relative impact of different human capital policies and the trade-off between short-term opportunity costs and long-term benefits from increased levels of skills within the workforce.

In addition, we incorporate the results of the most recent and relevant economic literature. For instance, using Hanushek and Woessman (2008) we adjust the effect of cognitive skills on human capital stocks; Krusell et al. (2000) provides the basis for changing the production structure of WorldScan to account for the complementarity of capital and high-skill labour; while the insights of Goolsbee (1998) provides us with a more realistic impact of R&D subsidies on R&D activities.

Appendix A Sectoral and regional aggregations in WorldScan

Table A.1 WorldScan regional aggregation

	Region code	Region definition
1	AUT	Austria
2	BLU	Belgium & Luxembourg
3	DNK	Denmark
4	FIN	Finland
5	FRA	France
6	DEU	Germany
7	GBR	United Kingdom
8	GRC	Greece
9	IRL	Ireland
10	ITA	Italy
11	NLD	Netherlands
12	PRT	Portugal
13	ESP	Spain
14	SWE	Sweden
15	CZE	Czech Republic
16	HUN	Hungary
17	POL	Poland
18	SVK	Slovakia
19	SVN	Slovenia
20	REX	Rest EU27 (Cyprus, Malta, Latvia, Estonia, Lithuania)
21	ROE	Rest OECD (Japan, Australia, Canada, New Zealand, Switzerland, Mexico, Korea & Turkey)
22	USA	United States
23	AAT	Rest of the World

Table A.2 GTAP sectors and WorldScan sectoral aggregation

	GTAP Code	GTAP Description	WorldScan Codes and aggregation	
1	**PDR**	Paddy rice	**AGO**	Agriculture, oil & mining
2	**WHT**	Wheat	**AGO**	Agriculture, oil & mining
3	**GRO**	Cereal grains nec	**AGO**	Agriculture, oil & mining
4	**V_F**	Vegetables, fruit, nuts	**AGO**	Agriculture, oil & mining
5	**OSD**	Oil seeds	**AGO**	Agriculture, oil & mining
6	**C_B**	Sugar cane, sugar beet	**AGO**	Agriculture, oil & mining
7	**PFB**	Plant-based fibers	**AGO**	Agriculture, oil & mining
8	**OCR**	Crops nec	**AGO**	Agriculture, oil & mining
9	**CTL**	Bovine cattle, sheep and goats, horses	**AGO**	Agriculture, oil & mining
10	**OAP**	Animal products nec	**AGO**	Agriculture, oil & mining
11	**RMK**	Raw milk	**AGO**	Agriculture, oil & mining
12	**WOL**	Wool, silk-worm cocoons	**AGO**	Agriculture, oil & mining
13	**FRS**	Forestry	**AGO**	Agriculture, oil & mining
14	**FSH**	Fishing	**AGO**	Agriculture, oil & mining
15	**COA**	Coal	**ENG**	Energy
16	**OIL**	Oil	**AGO**	Agriculture, oil & mining
17	**GAS**	Gas	**ENG**	Energy
18	**OMN**	Minerals nec	**LTM**	Low tech. manufacture
19	**CMT**	Bovine meat products	**LTM**	Low tech. manufacture
20	**OMT**	Meat products nec	**LTM**	Low tech. manufacture
21	**VOL**	Vegetable oils and fats	**LTM**	Low tech. manufacture
22	**MIL**	Dairy products	**LTM**	Low tech. manufacture
23	**PCR**	Processed rice	**LTM**	Low tech. manufacture
24	**SGR**	Sugar	**LTM**	Low tech. manufacture
25	**OFD**	Food products nec	**LTM**	Low tech. manufacture
26	**B_T**	Beverages and tobacco products	**LTM**	Low tech. manufacture
27	**TEX**	Textiles	**LTM**	Low tech. manufacture
28	**WAP**	Wearing apparel	**LTM**	Low tech. manufacture
29	**LEA**	Leather products	**LTM**	Low tech. manufacture
30	**LUM**	Wood products	**LTM**	Low tech. manufacture
31	**PPP**	Paper products, publishing	**LTM**	Low tech. manufacture
32	**P_C**	Petroleum, coal products	**ENG**	Energy
33	**CRP**	Chemical, rubber, plastic products	**MHM**	Medium-high tech. manuf.
34	**NMM**	Mineral products nec	**MLM**	Medium-high tech. manuf.
35	**I_S**	Ferrous metals	**MLM**	Medium-high tech. manuf.
36	**NFM**	Metals nec	**MLM**	Medium-high tech. manuf.
37	**FMP**	Metal products	**MLM**	Medium-high tech. manuf.
38	**MVH**	Motor vehicles and parts	**MHM**	Medium-high tech. manuf.
39	**OTN**	Transport equipment nec	**MHM**	Medium-high tech. manuf.
40	**ELE**	Electronic equipment	**HTM**	High tech. manufacture
41	**OME**	Machinery and equipment nec	**MHM**	Medium-high tech. manuf.
42	**OMF**	Manufactures nec	**LTM**	Low tech. manufacture
43	**ELY**	Electricity	**ENG**	Energy
44	**GDT**	Gas manufacture, distribution	**ENG**	Energy
45	**WTR**	Water	**OSR**	Other services
46	**CNS**	Construction	**OCS**	Other commercial serv.
47	**TRD**	Trade	**OCS**	Other commercial serv.
48	**OTP**	Transport nec	**TRA**	Transport
49	**WTP**	Water transport	**TRA**	Transport
50	**ATP**	Air transport	**TRA**	Transport
51	**CMN**	Communication	**OCS**	Other commercial serv.
52	**OFI**	Financial services nec	**OCS**	Other commercial serv.
53	**ISR**	Insurance	**OCS**	Other commercial serv.
54	**OBS**	Business services nec	**OCS**	Other commercial serv.
55	**ROS**	Recreational and other services	**OSR**	Other services
56	**OSG**	Public Administration, Defense, Education, He	**OSR**	Other services
57	**DWE**	Dwellings	**OSR**	Other services

References

Ashenfelter, O., C. Harmon and H. Oosterbeek, 1999, A review of estimates of the schooling/earnings relationship, with tests for publication bias, *Labour Economics*, vol. 6, no. 4, pp. 453–470.

Barro, R. and X. Sala-i-Martin, 1995, *Economic Growth*, McGraw-Hill, New York.

Boeters, S. and N. van Leeuwen, 2010, A labour market extension for WorldScan: Modelling labour supply, wage bargaining and unemployment in a CGE framework, CPB Document 201, CPB Netherlands Bureau for Economic Policy Analysis.

Canton, E., 2007, Social returns to education: Macro-evidence, *De Economist*, vol. 155, no. 4, pp. 449–468.

Card, D., 2009, Immigration and inequality, NBER Working Paper 14683.

Card, D.E., 1994, Earnings, schooling, and ability revisited, NBER Working Paper 4832.

Carson, C., B. Grimm and C. Moylan, 1994, A satellite account for research and development, *Survey of Current Business*, vol. 74, no. 11, pp. 37–71.

Caselli, F. and W.J. Coleman, 2006, The world technology frontier, *American Economic Review*, vol. 96, no. 3, pp. 499–521.

Checchi, D., 2006, *The Economics of Education: Human Capital, Family Background and Inequality*, Cambridge University Press.

Gelauff, G. and A. Lejour, 2006, Five Lisbon highlights: The economic impact of reaching these targets, CPB Document 104.

Goolsbee, A., 1998, Does government R&D policy mainly benefit scientists and engineers?, *American Economic Review*, vol. 88, no. 2, pp. 298–302.

Hanushek, E.A., 2003, The failure of input-based schooling policies, *Economic Journal*, vol. 113, pp. F64–F98.

Hanushek, E.A. and D.D. Kimko, 2000, Schooling, labor-force quality, and the growth of nations, *The American Economic Review*, vol. 90, no. 5, pp. 1184–1208.

Hanushek, E.A. and L. Woessman, 2008, The role of cognitive skills in economic development, *Journal of Economic Literature*, vol. 46, no. 3, pp. 607–668.

Harmon, C.P., H. Oosterbeek and I. Walker, 2003, The returns to education: Microeconomics, *Journal of Economic Surveys*, vol. 17, no. 2, pp. 115–155.

Heckman, J.J., 2000, Policies to foster human capital, *Research in Economics*, vol. 54, no. 1, pp. 3–56.

Heckman, J.J., L. Lochner and C. Taber, 1998, Explaining rising wage inequality: Explanations with a dynamic general equilibrium model of labor earnings with heterogeneous agents, *Review of Economic Dynamics*, vol. 1, no. 1, pp. 1–58.

Jacobs, B., 2004, The lost race between schooling and technology, *De Economist*, vol. 152, no. 1, pp. 47–78.

Jacobs, B., 2005, Simulating the Lisbon skills targets in WorldScan, CPB Memorandum 135.

Katz, L.F. and K.M. Murphy, 1992, Changes in relative wages, 1963-1987: Supply and demand factors, *Quarterly Journal of Economics*, vol. 107, no. 1, pp. 35–78.

Krueger, A.B., 2003, Economic considerations and class size, *Economic Journal*, vol. 113, no. 485, pp. F34–F63.

Krusell, P., L.E. Ohanian, J.V. Ríos-Rull and G.L. Violante, 2000, Capital-skill complementarity and inequality: A macroeconomic analysis, *Econometrica*, vol. 68, no. 5, pp. 1029–1053.

Lejour, A.M. and H. Rojas-Romagosa, 2008, International spillovers of domestic reforms: The joint application of the Lisbon Strategy in the EU, CPB Discussion Paper 105.

Lejour, A.M., P. Veenendaal, G. Verweij and N.I. van Leeuwen, 2006, Worldscan: A model for international economic policy analysis, CPB Document 111.

Lucas, R.E., 1988, On the mechanics of economic development, *Journal of Monetary Economics*, vol. 22, no. 1, pp. 3–42.

Mincer, J., 1962, On the job training: Costs, returns and some implications, *Journal of Political Economy*, vol. 70, no. 5, pp. 50–79.

OECD, 2008, *Education at a Glance 2008*, OECD, Paris.

Roeger, W., J. Varga and J. in ’t Veld, 2008, Structural reforms in the EU: A simulation-based analysis using the QUEST model with endogenous growth, Mimeo, European Commission, DG ECFIN.

Sianesi, B. and J. van Reenen, 2003, The returns to education: Macroeconomics, *Journal of Economic Surveys*, vol. 17, no. 2, pp. 157–200.

United Nations, 2003, World population prospects: The 2002 revision, Pop/db/wpp/rev.2002/4/f1, United Nations Population Division.

Vandenbussche, J., P. Aghion and C. Meghir, 2006, Growth, distance to frontier and composition of human capital, *Journal of Economic Growth*, vol. 11, no. 2, pp. 97–127.

Webbink, D., 2005, Causal effects in education, *Journal of Economic Surveys*, vol. 19, no. 4, pp. 535–560.

Weingarden, A. and M. Tsigas, 2009, Labor statistics for the GTAP database, Mimeo, U.S. International Trade Commision, Research Division, Office of Economics, Washington DC.