

Modelling Human Capital in WorldScan

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Abstract

We build new modelling capabilities in WorldScan –CPB’s 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) three skill groups, ii) a linkage between high-skill workers and R&D activities and ii) more information is taken from the satellite model. The new model is used to test current EU human capital policies. Our results have a similar pattern of macroeconomic outcomes, but with much larger effects than using previous WorldScan versions.

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1 Introduction

We include new modeling capabilities in WorldScan – the CPB in-house dynamic CGE model– to address policy questions related to human capital and skill formation. To achieve this goal we build on the human capital satellite model developed by Jacobs (2005). This satellite model provides time-trend changes in labor efficiency associated with increases in different types of human capital levels. To achieve higher skills, however, there are associated indirect costs. Workers must bear the opportunity cost of staying longer in school and devoting time to on-the-job training, and this affects negatively the labor supply in the short run.

The resulting human capital version of WorldScan, 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, instead of the commonly used low and high skill split. 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 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 this high-skill workers are perfect substitutes for medium-skill workers, but are a specific factor to the R&D sector.

Secondly, we update some of the key exogenous parameters. The elasticities of substitution between different skill groups has 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– in labour productivity. This particular update is based on the recent survey by Hanushek and Woessman (2008) where they present micro and macro evidence of the link between cognitive skills and labour productivity.

Third, we introduce 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 simulations. We use the OECD (2006) data on direct costs by pupil and by schooling level and we follow the strategy outlined in Lejour and Rojas-Romagosa (2008).

Finally, we also changed how the satellite model is linked to WorldScan. Instead of including only changes in labour efficiency, the new version of WorldScan directly incorporates a CES function of aggregate skills, where not only labour efficiency is changed, but also the levels of the three skill types and the general efficiency of these skills. This revised human capital version is then integrated into the WorldScan version that includes a new labour market module that features endogenous labour supply at the extensive and intensive margin (i.e. participation and hours worked) that includes an endogenous labor markets and a distinct R&D sector Boeters and van Leeuwen (2008).

Once the model has been set, we analyze which country-specific policy instruments can 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 analyze the macroeconomic impact of current EU human capital policies. In particular, we first analyze the general equilibrium effects of Lisbon Agenda human capital goals for each EU country. Later on, we estimate the impact of increasing the cognitive skill levels of the EU countries.

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 labor supply) are absorbed and higher skill levels are finally attained. However, our results present much higher positive impacts. This is due to the higher impact of cognitive skills, and 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.

2 Revision of the satellite model

We first present the main characteristics of the Satellite Model of Jacobs (2005) and explain the different revisions and updates that were done. Although the main features of the original satellite model remain, the new version of WorldScan produces different estimates based on new key parameters and a more intertwined linkage between the satellite model and the core WorldScan model.

2.1 Main features of the model

This section draws heavily from Jacobs (2005). We describe the main characteristics of the satellite model and the revisions and changes that were made.

2.1.1 Defining skill groups

We define skill groups by school attainment, i.e. 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. Thus, $L1$ corresponds to pre-primary and primary education (ISCED 0-1) and $L2$ is lower secondary education (ISCED 2). $H1$ includes upper secondary and post-secondary non-tertiary education (ISCED 3-4), $H2$ corresponds to workers with a first stage of tertiary studies (ISCED 5) excluding university students in mathematics, science and technology fields, which are included in $H3$, together with workers with a second stage of tertiary education (ISCED 6).¹ Therefore, our $H3$ groups roughly corresponds to individuals with tertiary studies in math, science and technology field, plus individuals with a second tertiary degree in all fields.

The initial number of workers in each skill group s is defined 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: $L1 = 6$, $L2 = 9$, $H1 = 12$, $H2 = 16$ and $H3 = 20$. This means that S , the required number of year to move from one skill group to the other is given by: $S_{L1L2} = 3$, $S_{L2L3} = 3$, $S_{LH} = 4$, and $S_{H1H2} = 4$.

2.1.2 Disaggregated human capital production function

In a first stage, firms decide upon the optimal quantities of each of the five sub-levels of human capital, which are disaggregated in the satellite model.

$$L_{ry} = A_{Lry} [\alpha_{L1,ry} (N_{ryL1})^{\rho_L} + \alpha_{L2,ry} (N_{ryL2})^{\rho_L}]^{\frac{1}{\rho_L}} \quad (1)$$

$$H_{ry} = A_{Hry} [\alpha_{H1,ry} (N_{ryH1})^{\rho_H} + \alpha_{H2,ry} (N_{ryH2})^{\rho_H} + \alpha_{H3,ry} (N_{ryH3})^{\rho_H}]^{\frac{1}{\rho_H}} \quad (2)$$

where r indexes regions and y corresponds to years; α_s are the share parameters of each skill level $s = L1, L2, H1, H2, H3$; σ_L is the elasticity of substitution between the two different low-skilled workers and $\rho_L = 1 - \frac{1}{\sigma_L}$. In the same fashion, σ_H is the elasticity of substitution between the three groups of high-skilled workers. Following Card (2009) and the papers cited there, we assume that $L1$ and $L2$ are perfect substitutes, such that $\frac{1}{\sigma_L} = 0$ and we assume that $\sigma_H = 2$. Finally, A_{Lyr} and A_{Hyr} are general efficiency parameters that value the different productivities (or wage differentials) between the different skill levels by year and region. Defining the Mincer rates of

¹Jacobs (2005) classified $H1$ as $L3$. However, we follow the standard convention of defining the ISCED 3-4 group as high-skill.

return as $\beta_L = \frac{\ln w_{L2} - \ln w_{L1}}{S_{L1L2}}$, then the additional productivity level expected from a higher share of $L2$ in aggregated L is:

$$A_{Ly+1,r} = (1 + \beta_{Lr} S_{L1L2} L2_{yr}) \quad (3)$$

In a similar way, we define:

$$A_{Hy+1,r} = (1 + \beta_{Hr} S_{H1H2} H2_{yr} + \beta_{Hr} S_{H1H3} H3_{yr}) \quad (4)$$

The correct share parameters α_H and α_L are generally unknown. Thus, we estimate the share parameters using the Mincer rates of return (β) and the number of years required to move from one skill-level to the other (S).

$$\alpha_{L1,ry} = \frac{1}{1 + \exp \mu L_{ry}} \quad (5)$$

$$\alpha_{L2,ry} = \frac{\exp \mu L_{ry}}{1 + \exp \mu L_{ry}} \quad (6)$$

$$\mu L_{ry} = \beta_{L1L2r} S_{L1L2} + (1 - \rho_L) \ln \left(\frac{N_{ryL2}}{N_{ryL1}} \right) \quad (7)$$

$$\alpha_{H1,ry} = \frac{1}{1 + \exp \mu H1_{ry} + \exp \mu H1_{ry} \exp \mu H2_{ry}} \quad (8)$$

$$\alpha_{H2,ry} = \frac{\exp \mu H1_{ry}}{1 + \exp \mu H1_{ry} + \exp \mu H1_{ry} \exp \mu H2_{ry}} \quad (9)$$

$$\alpha_{H3,ry} = \frac{\exp \mu H1_{ry} \exp \mu H2_{ry}}{1 + \exp \mu H1_{ry} + \exp \mu H1_{ry} \exp \mu H2_{ry}} \quad (10)$$

$$\mu H1_{ry} = \beta_{H1H2,r} S_{H1H2} + (1 - \rho_H) \ln \left(\frac{N_{ryH2}}{N_{ryH1}} \right) \quad (11)$$

$$\mu H2_{ry} = \beta_{H2H3,r} S_{H2H3} + (1 - \rho_H) \ln \left(\frac{N_{ryH3}}{N_{ryH2}} \right) \quad (12)$$

2.1.3 Country-specific Mincer returns

First, we assume that the average Mincer rate of return, β , in the EU27 is 8% per year. This follows the empirical findings surveyed by Card (1994), Ashenfelter *et al.* (1999) and 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:

$$\beta_r = 0.08 - \pi (e_r - e_{EU}) \quad (13)$$

$$\beta_{L,r} = 0.08 - \pi (e_{L,r} - e_{L,EU}) \quad (14)$$

$$\beta_{H,r} = 0.08 - \pi (e_{H,r} - e_{H,EU}) \quad (15)$$

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 low and high skills, respectively. There are three Mincer rates β to be estimated by country. β_r is the returns between higher and lower skills, $\beta_{L,r}$ are the return rates between the three low-skill groups and $\beta_{H,r}$ between the two 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. Such that:

$$e_r = \frac{L1_r * 6 + L2_r * 9 + H1_r * 12 + H2_r * 16 + H3_r * 20}{N} \quad (16)$$

$$e_{L,r} = \frac{L1_r * 6 + L2_r * 9}{N_{L,r}} \quad (17)$$

$$e_{H,r} = \frac{H1_r * 12 + H2_r * 16 + H3_r * 20}{N_{H,r}} \quad (18)$$

where N is the total number of workers and N_L the low skill workers and N_H the high skill ones. All variables are taken from the initial baseline year 2001.

2.1.4 Aggregated human capital production function

In the satellite model, all labor is aggregated into a CES production function:

$$G_{ry} = A_{ry} [\alpha_{L,ry} (L_{ry})^\rho + \alpha_{H,ry} (B_y H_{ry})^\rho]^\frac{1}{\rho} \quad (19)$$

where L_{ry} and H_{ry} are the stocks of low and high-skilled labour in region r in year y , with shares given by $\alpha_{L,ry} + \alpha_{H,ry} = 1$. A_{ry} is a general efficiency parameter and B_y is a parameter denoting skill-biased technological change (SBTC). If σ is the elasticity of substitution between both skill levels, then: $\rho = 1 - \frac{1}{\sigma}$.

Thus, we apply the Mincer rates of return (β) to various types of education levels to identify the share parameters in general equilibrium up to the elasticity of substitution (σ). We then fix the elasticity of substitution at some reasonable value ($\sigma = 1.5$) to fully specify the aggregate sub-production function.

The estimation of the share parameters is done using these equations:

$$\alpha_{L,ry} = \frac{1}{1 + \exp \mu_{ry}} \quad (20)$$

$$\alpha_{H,ry} = \frac{\exp \mu_{ry}}{1 + \exp \mu_{ry}} \quad (21)$$

$$\mu_{ry} = \beta_r S_{LH} + (1 - \rho) \ln \left(\frac{H_{ry}}{L_{ry}} \right) - \rho \ln B_y \quad (22)$$

where β_r is the country-specific Mincer rates of returns for the extra years of schooling from low to high-skills. It is assumed that to move from low to high-skills you need three extra years of schooling, i.e. $S_{LH} = 3$.

The SBTC parameter B is assumed to grow by 1.5% each year, so we set $\tau = 0.045$ in the following equation:

$$B_{y+1} = (1 + \tau) B_y \quad (23)$$

$$B_0 \equiv 1 \quad (24)$$

2.1.5 Efficiency units of labour

Given ongoing on-the-job training (OJT) process, the *initial* stock of human capital (expressed in terms of school attainment) has to be updated to include the skills already obtained by the workers through past OJT. Taken N_{rs0} as the number of workers in region r , skill group s at $y = 0$, we adjust this value to efficiency units by the following equation:

$$N_{rs1} = (1 + \gamma_0)^T N_{rs0} \quad (25)$$

where $T = 20$ is the average working experience of the population and γ_0 is the initial value of gamma.

2.1.6 Dynamic evolution of human capital stocks

Human capital stocks evolve over time following a stylized cohort model represented by the following equations:

$$N_{rs,y+1} = (1 + \gamma) N_{rsy} + \eta_{rs} Q_{rsy} \theta_r NT_{ry} - \delta_r N_{rsy} \quad (26)$$

$$NT_{ry} = \sum_s N_{rsy} \quad (27)$$

where NT is the total labour supply and N_s indexes the five different skill levels: two for low-skilled workers ($L1, L2$) and three for high-skilled workers ($H1, H2, H3$). N_{ry} is thus the human capital stock in region r in year y .

The growth rates of aggregate human capital due to on the job training (OJT) are given by γ . Following Jacobs (2005) not much is known about γ , so he assumes that γ is equal for all skill types and set $\gamma = 0.01$, which corresponds to life-time human capital generated by OJT of 33%.²

The η 's indicate the fraction of each cohort that graduates in each skill-level. Therefore, we must have that: $\sum_s \eta_s = 1$. Q_{rsy} is a quality indicator of the new inflow of workers by skill class, region and year.

The labour force growth is regulated by g_r : the general population growth rate, θ_r is the inflow of new workers while δ_r is the outflow of workers, then $g_r = \theta_r - \delta_r$. The inflow (θ) and outflow (δ) rates are calibrated such that these match average population growth rates in various countries over the period considered. The data on population growth are provided by the UN's World Population Prospects.

To sum up, the baseline parameters without a country/year dimension are:

$$\begin{aligned} \sigma &= 1.5 & S_{L1L2} &= 3 & \gamma &= 0.01 \\ \sigma_H &= 2 & S_{LH} &= 3 & T &= 20 \\ \sigma_L &= \infty & S_{H1H2} &= 4 & \tau &= 0.045 \\ A &= 1 & S_{H2H3} &= 4 & Q_{y=0} &= 1 \end{aligned}$$

Country-specific variables $\eta_{rs}, \theta_r, \delta_r, N_{rs,0}$ are taken from different sources, as explained in the appendix.

2.2 Integration into WorldScan

The former version of WorldScan assumed that high and low-skilled labour were nested through a Cobb-Douglas utility function and the linkage with the Satellite Model was achieved by increasing a

²With workers employed by $Y = 40$ years, and where ω is the percentage of life-long human capital generated by OJT, then:

$$\gamma = \exp\left(\frac{-\ln(1-\omega)}{Y}\right) - 1$$

The value of $\gamma = 0.01$ corresponds to a rough average of ? who estimate that $\omega = 0.23$ and Mincer (1962) with $\gamma = 0.5$

labour efficiency parameter ε , that exogenously increased the amount of labour in the value-added nest of the factor demand function. Where the labour efficiency parameter was defined as:

$$\varepsilon_{ry} = \frac{G_{ry}^{Scex} - G_{ry}^{Base}}{G_{ry}^{Base}} \quad (28)$$

where G_{ry}^{Scex} is the aggregated CES function of low and high skill workers for region r in year y for the scenario (counterfactual) X; while G_{ry}^{Base} is the value of G in the baseline.

The new version of WorldScan with human capital incorporates directly the changes in L and H into the core model, such that we have now a CES function:

$$G_{ry} = A_{ry} [\alpha_{L,ry} (L_{ry})^\rho + \alpha_{H,ry} (B_y H_{ry})^\rho]^\frac{1}{\rho} \quad (29)$$

Moreover, the $H3$ factor is crucial to the R&D sector, in a way that it is quasi-specific to this sector.

3 Human capital policies

Even though there is a vast literature analyzing 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, the effect of public expenditure in education. Hanushek (2003) finds 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 analyze only their macroeconomic impact.

For example, a large literature analyzes the links between human capital with growth. Sianesi and van Reenen (2003) review this literature and find a robust relation school enrolment rates and per capita GDP growth. However, there is still controversy as 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 labor productivity by 7-10% in the short run and by 11 to 15% in the long run. Recent papers point 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.

3.1 Lisbon Agenda

Using the improvements on data and modelling, we can test again for the implications 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.

3.2 The importance of cognitive skills

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:

$$H = \lambda F + \phi Q(S) + \delta A + \alpha X + \nu \quad (30)$$

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 , and X which includes other relevant factors such as experience and health.

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 explain why this estimate can be considered as a lower bound, e.g. because 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) and the International Adult Literacy Study (IALS), to measure cognitive skills.

3.3 Incorporating direct schooling costs

The estimation of direct costs was initially explored in Lejour and Rojas-Romagosa (2008). This includes a separate accounting of possible direct costs of schooling for the government. In particular, for the Lisbon target's 2 and 5 extra time for schooling is needed. The completion of upper secondary education needs extra schooling years and the same holds for the increase for students in math and sciences, because in general these studies require an extra year of schooling compared to studies in arts. For target 4 of lifelong-learning, we assume this is mainly on the job learning so no extra costs for teaching are required. Also 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, but we do not take this into account. Data are hard to

come by to estimate these extra costs and we guess that we overestimate the costs for the two other targets, 2 and 5.

We first take the relative increase in schooling years in 2010 needed to fulfil the Lisbon skills targets. Ignoring fixed costs in schooling it is possible to estimate the extra government costs for teaching and school buildings by relating the average increase in schooling years to the average costs in schooling. Because we do not have recent and accurate data on costs per student, our rough estimate is based on total government expenditures on schooling as a share of GDP. On average, schooling increases from 12.3 to 12.5 years in Europe, which is about a 3% rise. Since government expenditure on schooling is 5.2% of GDP on average, then government costs increase by 0.16% of GDP if the target is reached in 2010. In time, it is expected that expenditure on schooling will decrease because the number of pupils and students will drop due to ageing. Based on the demographic patterns, we reduced the share of government spending on education in GDP. This last pattern, in turn, reduces the increase in costs associated with achieving the skills targets. Ideally we should use marginal costs on education instead of average costs. Given the existence of fixed costs in education, our estimations are probably an upper bound.

4 Policy simulations

In this section we describe how the different human capital policies are modeled into WorldScan and we present the new simulation results.

4.1 Assessing the Lisbon Agenda

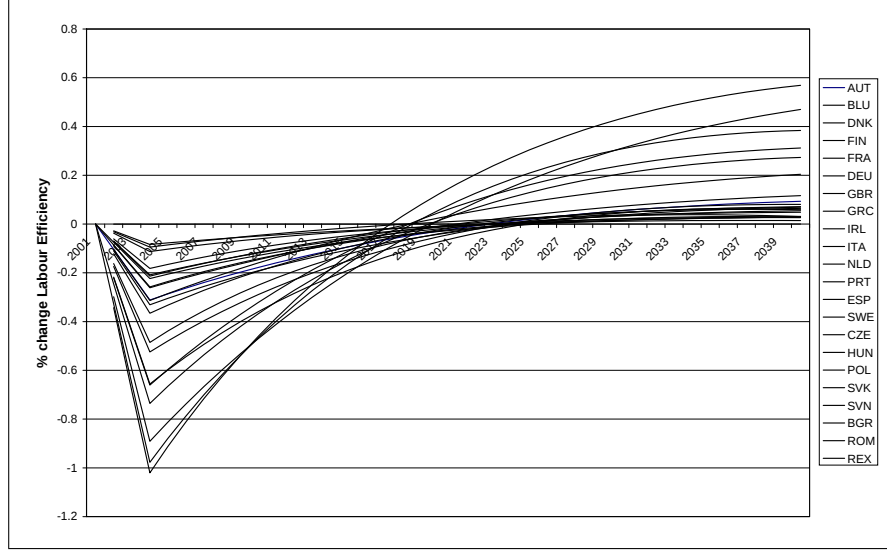
Here we present how the five different policies of the Lisbon Agenda related to skill and education are implemented in the satellite model. In the last subsection we present the full macroeconomic impact when the inputs from the satellite model are fed into the new version of WorldScan.

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

Both targets imply a reduction of the number of workers in skill groups $L1$ and $L2$ with a compensating increase for group $H1$. Thus, both targets imply changes in the graduation rates η_{rs} . In principle, the target should affect only η_{rL2} , but for some countries, also $\eta_{r,L1}$ is changed, reflecting that an effort on primary education must also be done to achieve the target. To compensate for the reduction in $L1$ and $L2$, η_{rH1} has to increase to maintain the identity: $\sum_s \eta_{rs} = 1$. The graduation rates are defined using a EU-wide increase, that is later translated 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.

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



On the other hand, the opportunity costs of increased number of schooling years is modeled as a transition path where η_{rH1} 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 were going to graduate as $L2$ also have to study three more years to graduate as $H1$. 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 reduction in total output.

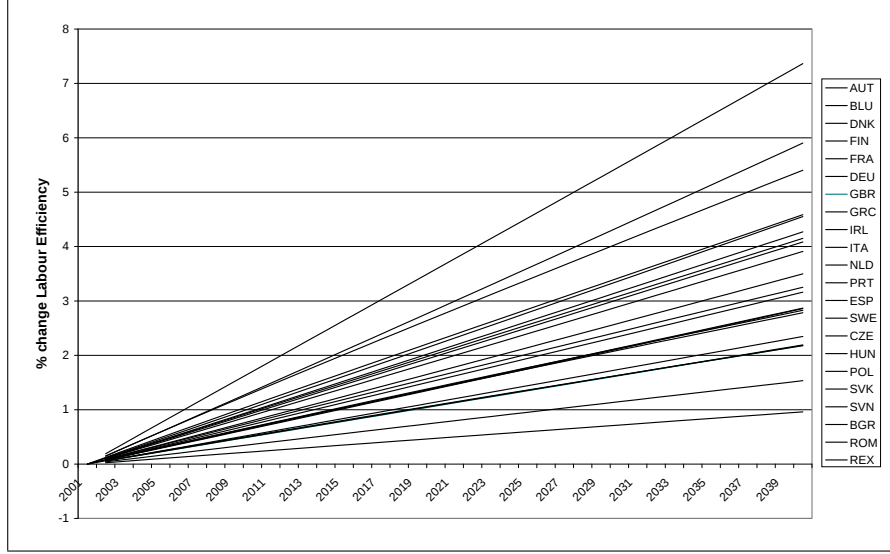
Figure 1 reports the percentage change in labour efficiency that results from achieving skill targets 1 and 2 of the Lisbon Agenda. As expected, there is a short-term decrease in the labour efficiency unit due to opportunity costs of longer years in school. This initial decrease is compensated with higher efficiency units in the long-run.

4.1.2 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.

Figure 2: Labour efficiency gains for Target 3, EU27



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.

We show that changes in labour efficiency in Figure 2 Here there is a substantial increase in labour efficiency for all countries, this also reflects the increased effect of cognitive skills on overall

human capital levels.

4.1.3 Target 4: Lifelong learning

Currently, the EU average of workers that participated in 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 $\chi^* = 0.158$ ³. Therefore, the EU new average growth rate of OJT will become $\gamma^{EU*} = 0.067 * 0.158 = 1.06\%$ per year. Furthermore, aggregate labour input in the Lisbon scenario will decrease 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 OJT is done without formal training programs. This follows from the assumption that most OJT 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 $\tilde{A} = \frac{\gamma}{\chi} = \frac{0.01}{0.15} = 0.067$. Then, to estimate the gains in γ of increased time in OJT, they use: $\gamma^* = \tilde{A}\chi^* = 0.067 * 0.158 = 1.06\%$. This target implies two changes. First, an increase of $\gamma = 0.01$ to $\gamma_{EU}^* = 0.0106$. Second, the aggregate labour input A will decrease, given that workers will spend 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 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.

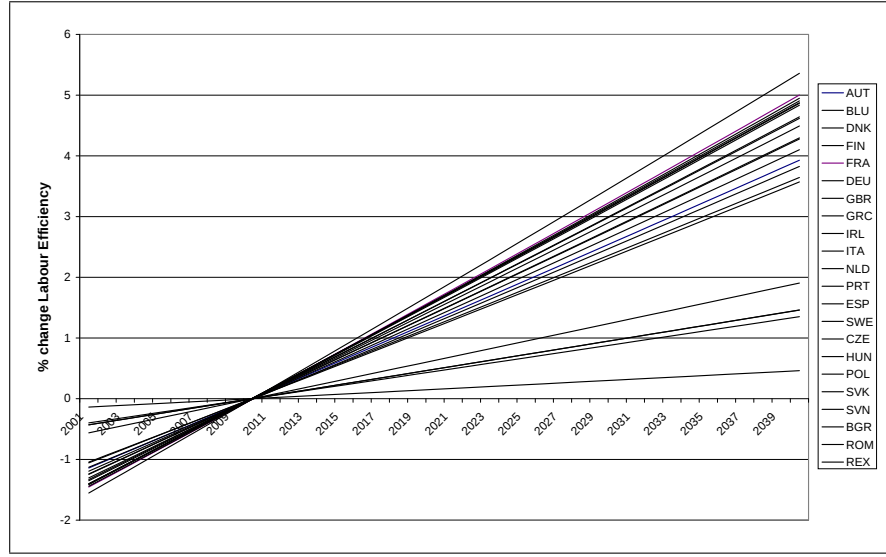
4.1.4 Target 5: Mathematics, science and technology students

This target is achieved assuming that all countries increase by 15% there number of $H3$ workers and decrease $H2$ in the same amount. This is done by changing the graduation rates for η_{rH1} and η_{rH2}

³HRR: It is assumed in the baseline that $\chi = 0.15$ or that 15% for workers time is devoted to OJT. To arrive at $\chi^* = 0.158$, we add the increase in OJT time estimated from ε . $\varepsilon = 2.5\% - 1.7\% = 0.8\% = 0.008$.

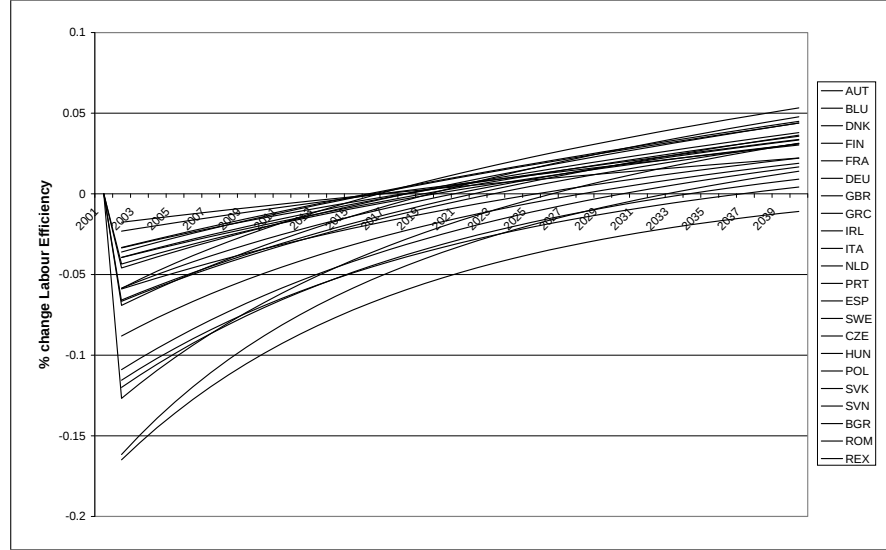
$$\chi^* = \chi + \varepsilon = 0.15 + 0.008 = 0.158$$

Figure 3: Labour efficiency gains for Target 4, EU27



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 4.

Figure 4: Labour efficiency gains for Target 5, EU27



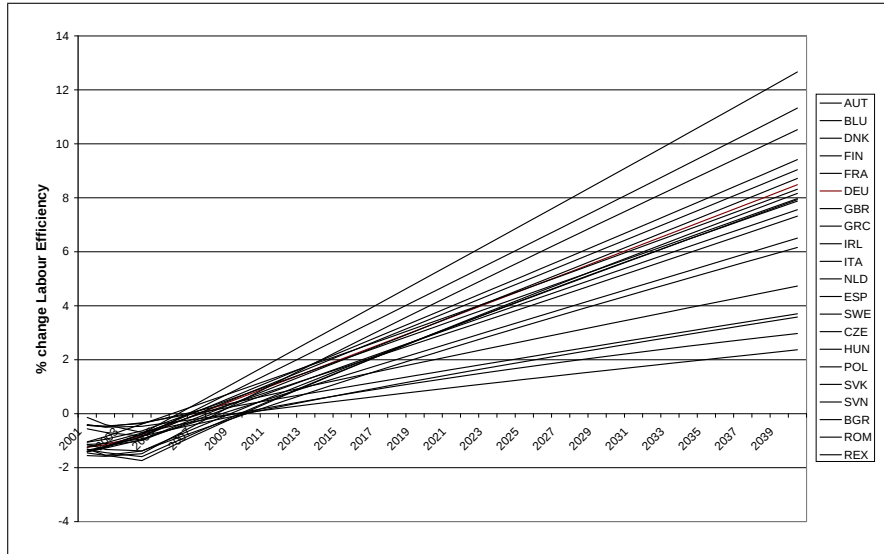
Again we see the pattern of initial decreases with a long-term increase in labour efficiency. However, for this target the positive effects are relatively small. This is because the increase in $H3$ workers that also increases the output of the R&D sector and expands overall output is only

incorporated in the core version of WorldScan. Thus, the full effects of this target are not estimated until we run the full model.

4.1.5 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) shows the results. Two main results emerge. First, there are short-term losses in labour efficiency due to the opportunity costs of extra schooling and formal OJT, however, these losses are more than compensated in the long-term. Secondly, the overall gains in labour efficiency can be substantial from some countries, with an EU average increase of around 7% in 2040.

Figure 5: Labour efficiency gains for all Lisbon targets, EU27



4.1.6 Macroeconomic effects of the skill targets of the Lisbon Agenda

Integrating the satellite model changes in aggregated skills and labour efficiency into the new version of WorldScan produces the macroeconomic outcomes in Table 1. We observe very small or null changes until 2020, but then the long-run impacts are significant. GDP increases by 4.1% with respect to the baseline case and consumption by 3.7%. These changes are significantly higher (4 to 5 times larger) than the previous evaluations from the Lisbon Agenda using the previous version of the satellite model and WorldScan(Gelauff and Lejour, 2006). This results is due to a higher impact of cognitive skills on labour productivity, as well as 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 almost 1%.

Thus, using the new version of WorldScan produces a similar pattern of macroeconomic changes is similar, i.e., a short term reduction in consumption followed by an increase in the long term. However, the new version produces much larger effects due to more complete accounting of the effects of increased human capital and skill formation.

Table 1: Macroeconomic results for all Lisbon targets, % changes from baseline, EU27

	2010	2020	2030	2040
Gross dom. product	0.0	0.1	2.1	4.1
Consumption	0.0	0.1	1.9	3.7
Labour supply	0.0	0.0	0.4	0.7
Employment	0.0	0.0	0.4	0.8
Unemployment	0.0	0.0	0.0	-0.1
Real average wage	0.0	0.1	1.3	2.7
<u>Labour productivity, by sector:</u>				
agriculture, oil, minerals	0.0	0.1	1.4	2.7
energy carriers	0.0	0.1	1.3	2.6
low tech. manufactures	0.0	0.1	1.4	2.7
medium-low tech. manufact.	0.0	0.1	1.4	2.7
medium-high tech. manufact.	0.0	0.1	1.3	2.5
high tech. manufactures	0.0	0.0	1.1	2.0
transport	0.0	0.1	1.4	2.7
commercial services	0.0	0.1	1.5	2.9
government+other services	0.0	0.1	1.6	3.2

5 Summary

We have described the revisions and updates performed on the satellite model of Jacobs (2005). The revised satellite model, in conjunction with the new features of the WorldScan version with human capital, provide a more complete 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 policies and the trade-off between short-term opportunity costs and long-term benefits from increased level of skills within the workforce.

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