The labor market effects of skill-biased technological change in Malaysia ☆

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ABSTRACT

During the last half-century, the evolution of educational attainment in Malaysia has been spectacular, and the current enrollment rates suggest that this progression will continue. Such a transformation of the labor skill composition should bring about macroeconomic effects such as wage compression, sectoral shifts and high skill unemployment, unless compensatory mechanisms exist. Relying on decomposition techniques, we argue that skill biased technological change (SBTC) occurred in Malaysia in recent years, and permitted unemployment figures to remain low and skill premia not to sink. We also develop a dynamic general equilibrium model, simulating the absence of SBTC and limit the number of admissions to higher education. The results are fed to a microsimulation module. They show that the reduction in wage inequalities could have been substantially more important had SBTC not been present. Furthermore, they suggest that the *open-door* higher education policy has contributed heavily to a reduction in wage inequalities.

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1. Introduction

Many countries have experienced sharp increases of enrollment in tertiary education[1] in the last decades, with varying economic and social outcomes. The massification of higher education is sometimes a deliberate policy tool, and sometimes the result of a laissez-faire attitude from policy makers facing increased demand for higher education. Should increased educational attainment, especially at the tertiary level, always be encouraged? Will an exogenous increase in the numbers of tertiary educated be followed by increased demand from firms, in some sort of skill-driven structural change? What is the likely impact of increased enrollment on returns to education and on graduate unemployment?

In the presence of an increasing supply of educated labor, labor market outcomes of educated workers are conditional on the evolution of their demand. An underlying issue here is that of the substitutability between labor categories with different educational attainment. Several authors argue (Goldin and Katz, 1998; Caselli and Coleman, 2006) that this substitutability is imperfect, some countries being better at taking advantage of their skilled workers than others. Caselli and Coleman (2006) argue that countries more abundant in skilled labor will choose technologies best suited to skilled labor, while countries abundant in unskilled labor will choose technologies best suited to unskilled labor, barriers to technology adoption explaining why some countries are unable to make efficient use of their skilled labor. While it would be a stretch to argue that there is consensus on the issue, skill-biased technological change (SBTC) has often been suggested as one of the drivers behind simultaneously rising wage premia and share of skilled workers in the US (Autor et al., 1998). Empirical evidence has also suggested that

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[1] Gross enrolment rates in tertiary education for Upper Middle Income Countries have increased from 8% to 30% in the period 1990–2010. In Malaysia, they have increased from 7% to 37% during the same period.

this is the case in other developed countries. There is some scarce evidence of skill-biased technological change in developing countries (Berman and Machin, 2000), but not many country-specific studies have been carried out. To our knowledge, no one has attempted to study skill biased technical change in Malaysia. We choose to study Malaysia since its spectacular increase in educational attainment has not been accompanied by falling wage premia of tertiary graduates.

The other major labor market adjustment to rising relative quantities of skilled labor is increased unemployment of skilled workers. High public investment in education has been shown to increase unemployment in some contexts, high-skilled unemployment sometimes even being higher than that of low and medium-skilled.[2] The Middle East and North Africa (MENA) region, which has heavily invested in education over four decades[3] serves as a good example of an unsuccessful absorption of young graduates into the labor market (Marouani, 2010; Marouani and Robalino, 2012). However, not only do employment figures matter in their own; it is also important to consider the type of employment facing young graduates. The suggested theoretical links between educational accumulation and growth have sometimes been hard to demonstrate empirically. The arguments put forward range from quality of education to a misallocation problem. Pritchett (1996) argues that one of the reasons education has not been positive for growth is due to inefficient use of graduates, who end up in low productivity sectors such as State-owned enterprises. This could particularly be the case in those contexts where the State acts as a de facto employer of last resort.

An increase in educational attainment implies two things: first of all, a steadily increasing demand for education. Secondly, that this increased demand has been met by an increased supply, either from the government or from private actors. The question is whether this expansion of supply is a deliberate policy choice, or just an expansion to cover what is called the *social demand* for education. Blaug (1967) reflects on this in an early paper, arguing that the spontaneous increase of educational supply faced with increasing demand could find its origin in a belief that something akin to Say's Law operates in the market for professional manpower, i.e. that supply of skilled labor will create its own demand. Thus planners need not fear increasing educational supply in the sense that labor market constraints are unlikely to operate. The topic is however difficult to apprehend: first of all, without a precise picture of the demand for education, it is impossible to know whether supply has been a constraint or not in the evolution of educational attainment. That is, have all those who wished to go into tertiary education been able to do so? If this is the case, have there not been shadow costs associated with the increase, such as increasing rates of exam failure?

Methodological differences and accuracy problems render educational projection exercises notoriously difficult. Blaug (1967) describes the three major methods of forecasting skill requirements, all relying on a number of assumptions and restrictions. Firstly, manpower-forecasts attempt to project sectoral quantities of skilled labor needed to attain certain GDP targets. They rely on labor–output coefficients and education–occupation matrices that are difficult to estimate. Secondly, social demand methods attempt to project the private demand for education, given fixed direct and indirect costs. Finally, rate of return methods are perhaps the most well-known method used by educational planners. Ceteris paribus, the evolution of the rate of return to a certain skill gives an indication of the value the market places on the skill. If this rate is increasing, it means that employers' demand for this particular skill is rising faster than its supply. Rates of return could thus be used

by planners as an indicator of skill gaps to be filled. All three methods however have their weaknesses. In particular manpower planning, which has been largely abandoned in academia since its less than desirable track record was unveiled in Blaug and Ahamad (1974).

Glytsos (1990) argues that severe imbalances between supply and demand for certain skills have been a feature of developed and developing countries alike during the 1970s and 1980s, which tends to confirm the mediocre track record of educational planning before and during this period.[4] Interestingly, he argues that these imbalances have not only been a feature of countries with open enrollment policies, i.e. where quantitative restrictions on the number of students do not exist (perhaps due to social concerns such as equality of access), but also in those countries where admission controls are a fact. We contend that a general equilibrium approach to educational planning permits to overcome some of the most obvious drawbacks of the main methods used to project or forecast educational needs. Notably, manpower forecasts and social demand estimates both consider educational dynamics from one side — that of demand in the case of manpower-forecasts, and that of supply in the case of the "social" demand for education. The evolution, however, is determined jointly by supply and demand factors. Furthermore, the demand and supplies are derived using a constant price-hypothesis. A general equilibrium approach permits prices to vary according to relative supply and demand, but also according to productivity and international demand trend differentials. Also, while manpower forecasting and social demand give target figures, our model permits a simulation of the labor market impacts of educational policy designed to achieve such target figures. Our focus in doing this is on wage premia and unemployment figures.

The higher education policy of the Malaysian government stems from a willingness to increase quickly and significantly the share of skilled labor in the economy (40% enrolment in higher education is a policy target (Guan, 2012)). This article aims to study the impact of this policy on labor market and income distribution outcomes. As explained above, similar policies have proven inefficient in other contexts. Relying on decomposition techniques, we argue that it is thanks to skill biased technological change that expected wage premia have been relatively stable in Malaysia, maintaining a strong social demand for higher education, thereby perpetuating the educational dynamics. We also develop a dynamic general equilibrium model in which we run a retrospective simulation, looking at how unemployment and wages would have reacted had skill biased technological change not been prevalent. Furthermore we simulate the effects of a restriction in the supply of education to understand the impact of recent educational policy in Malaysia. The results are fed to a microsimulation module, addressing distributional concerns.

The rest of the article is organized as follows. Section 2 describes the Malaysian educational expansion of the last two decades and the accompanying labor market adjustments. Section 3 lays out the various blocks of the model, with a particular emphasis on the accumulation of skilled labor. Section 4 presents the data and the calibration of the model. Section 5 lays out the microsimulation module used to analyze wage inequalities. Section 6 presents the simulations and their results. Section 7 concludes.

2. The evolution of Malaysians' educational attainment

Educational attainment in Malaysia has increased remarkably in the last two decades. The two main features of this increase are a big drop in the number of Malaysians with a primary education or less, coupled with a strong increase in the number of secondary and tertiary educated. The second feature has been a clear policy target for the Malaysian

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[2] This is the case for Morocco, (Kabbani and Kothari, 2005).
[3] MENA countries spent around 5% of GDP on education over the period. At similar levels of educational attainment, the MENA region boasts significantly higher unemployment rates of graduates (World Bank, 2008) than other emerging regions. The equivalent spending figure for two groups of Asian and Latin American countries respectively is around 3%.

[4] An alternative to educational planning could have been to let the market regulate supply and demand of educational services, requiring that the total cost of educational services is covered by students. Such a system would however have obvious drawbacks in terms of equality of opportunities.
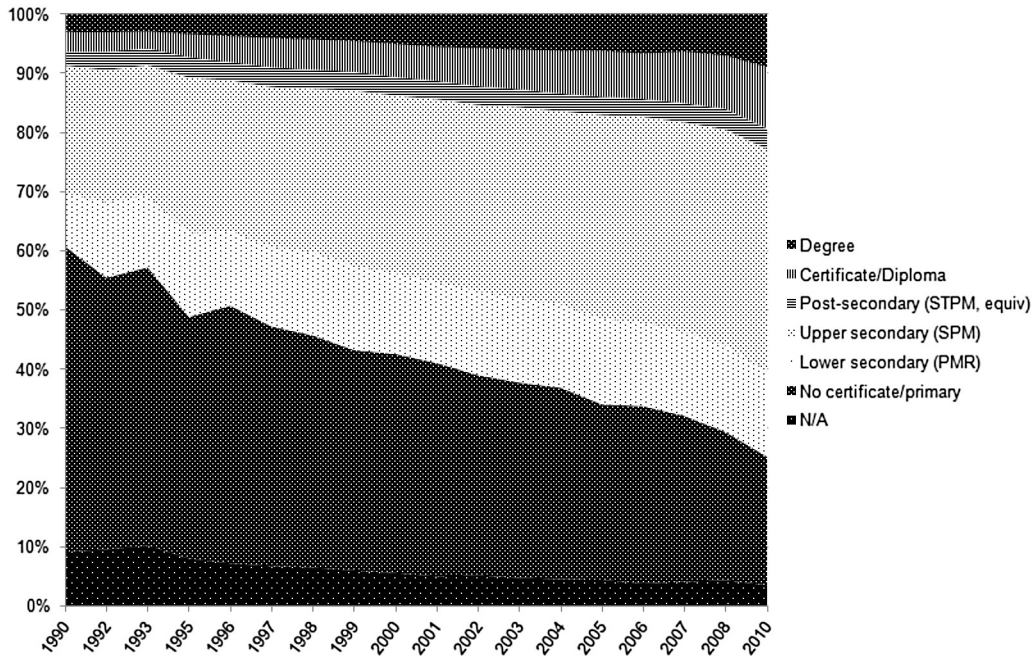
Fig. 1. Educational distribution of the Malaysian Labor Force, 15–64 years old. Note: N/A corresponds to individuals who never went to school.
Source: Labor Force Surveys from 1990 to 2010.

government, desirous to see enrollment rates in higher education of 40% by 2010 (Guan, 2012). The increase in supply of higher education has taken two forms. Firstly, private universities were established in the 1990s (the number of private universities in Malaysia increased from 0 in 1990 to 21 in 2009). Secondly, the number of public universities increased from 7 in 1990 to 20 in 2009. The expansion of tertiary education has not only been a general higher education phenomenon. The creation of *Community Colleges* and the expansion of *Polytechnic* establishments have increased enrollment over the last two decades, and show how the share of highly educated Malaysians has risen sharply and continuously since the early 1990s.

Standard economic theory holds that this important shift in relative quantities should be accompanied – ceteris paribus – by a decrease in the wage premium for educated employees. Fig. 2 shows that average wages in Malaysia have remained relatively constant between 2007 and 2010.[5] An indicator of wage premia can be obtained from studies on returns to education in Malaysia. Chung (2003) looks at the returns to education in Malaysia using a dataset from 1997, and finds that the returns to secondary education are 12% and 15.7% for male and female respectively, while the returns to higher education are 18.1% and 16.4%. Kenayathulla (2013) recently revisited those figures, using Household Income Survey figures from 2007. She finds evidence of a return to secondary education of 16.5% and 27.2% for males and females; the corresponding figures for higher education being 15.5% and 16.1%. This anecdotal evidence thus suggests the presence of some mechanism favorable to skilled labor during the last two decades in Malaysia.

Fully noting that the concept of skill is a multidimensional and complex one, we choose to define skilled labor categories in terms of various levels of education and fields of study. We hereby ignore any skills acquired in the workplace, or any skill endowments independent of schooling.

From Fig. 1, it can be seen that the share of educated Malaysians in the workforce has risen steadily since the early 1990s. The situation is

analogous to the US one in the 1980s–1990s, and merits a closer look. At the aggregate level, a standard CES production function yields the following relative wage when profits are maximized (Sanders and ter Weel, 2000):

$$\omega = \frac{w_S}{w_U} = \left[\frac{\theta_S}{\theta_U}\right]^\rho \left[\frac{L_U}{L_S}\right]^{1-\rho} \tag{1}$$

where w_S and w_U and L_S and L_U are wages and employment of skilled and unskilled workers respectively, θ_S and θ_U the productivity parameters associated with skilled and unskilled labor, and $\frac{1}{1-\rho}$ is the elasticity of substitution between productivity-corrected labor bundles. It thus becomes apparent that in the presence of increasing relative quantities of skilled workers, a decrease in the wage premium of skilled labor can only be avoided if there is an increase in the relative technological efficiency of this labor category. Figs. 1 and 2 would thus suffice to argue for the presence of skill-biased technological change in Malaysia. However, when one considers a sectorally disaggregated production structure, it becomes apparent that sector-biased technological change – if favoring skill-intensive sectors – might in the same fashion increase the demand for skills, counteracting the supply shift and ensuring stable wage premia. Several authors have used translog cost functions to investigate the presence of skill-biased technological change (Machin and Reenen, 1998; Autor et al., 1998; Sanders and ter Weel, 2000). Since we were unable to find R&D data at the industry level in Malaysia, we do not follow this approach. Table 3 however shows the evolution of industry labor shares and industry skilled labor concentrations between 2007 and 2010. Decomposing the aggregate change in the proportion of skilled labor into changes *between* and *within* sectors (Machin and Reenen, 1998; Berman et al., 1998)[6] for Malaysia shows that the lion's share of the upskilling has occurred within industries (74%) rather than between

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[5] Unfortunately we do not have wage data from before 2007.

[6] Following these authors, we decompose the change in the aggregate skill proportion into two components: $\Delta S = \sum S_i E_i + \sum S_i E_i$ where S_i is the share of skilled labor at the industry level, and E_i the employment share of each industry in total employment.
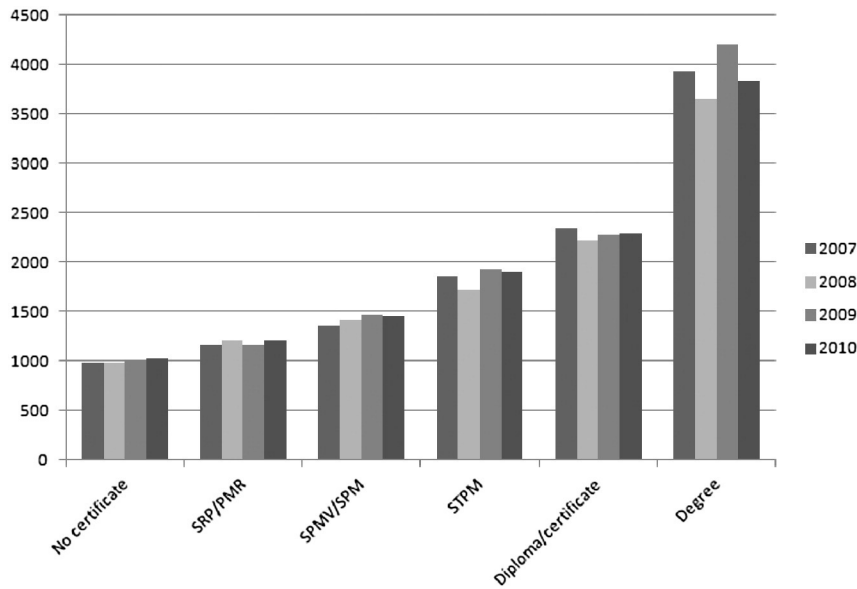
Source: Labor Force Surveys from 2007 to 2010. Wages correspond to average real wages (2007) for 15-64 year old Malaysian out-of-school wage earners.

Fig. 2. Average wage by educational attainment, Malaysian employees (RM). Wages represent average nominal wages for 15–64 year old Malaysian out of school wage earners. Source: Labor Force Surveys from 2007 to 2010.

industries (26%), which leads us to believe that the simultaneous stability of wage premia and high increase of the skill share are associated with skill-biased technical change, rather than a structural change due to a Stolper–Samuelson effect, or any other industry-biased demand alteration. The same analysis was carried out for a period of 20 years (1990 to 2010) at the 3-digit industry level, with the within component of upskilling being equal to 73%. An analysis of labor at the firm level, using the 2005 and 2010 rounds of the Economic census is carried out in World Bank (Forthcoming), and shows that significant upskilling has occurred at the firm level.

Instead of affecting wages, which might be prevented from falling by union activities, it could be that the labor market adjusts to the increase of skilled workers through an increase in unemployment. Looking at unemployment, we see that unemployment of individuals with post-secondary education has only increased slightly (Tables 1 & 2). Degree holders have seen their rate of unemployment increase from 2.1% to 3.6%. The unemployment rate of diploma holders has risen from 2.5% to 3.5%. The *certificates* category, which did not exist in 1990 and corresponds to low-level diplomas representing one year of post-secondary education, is the most severely affected category by unemployment with a 5% unemployment rate in 2011.

The variations are thus minor, relative to the increases in quantities: between 1990 and 2011, the labor force increased by 81%. At the same

time, the number of diploma holders increased by 400% and that of degree holders by 654%. The possibility of unemployment increases as the primary mechanism preserving wage premia facing constant demand thus seems highly unlikely.

3. The model

We develop a dynamic general equilibrium model with a detailed description of the labor market, taking into account jobs across sectors and workers with different ages (youth and non-youth) and levels of education (Marouani and Robalino, 2012). The model also formalizes educational choices and immigration flows. The following section will lay out the main equations of the model. The economy is disaggregated into 23 sectors, with 21 different factors of production, corresponding to labor of 20 different skill types, and physical capital. At the sectoral level, value added is a nested constant elasticity of substitution (CES) function of capital and labor. The labor aggregate is disaggregated into three bundles: a high skilled labor bundle (HS), a medium skilled labor bundle (MS) and a low skilled labor bundle (LS). The nested production structure allows for differentiated elasticities of substitution between various factors of production.

Table 1
Labor Force in 1990, by the highest certificate obtained.
Source: 1990 Labor Force Survey.

Degree	Employed	Unemployed	Total labor force
SRP/PMR	92.7%	7.3%	100.0%
SPMV	89.6%	10.4%	100.0%
SPM	93.4%	6.6%	100.0%
STPM	93.2%	6.8%	100.0%
Diploma	97.5%	2.5%	100.0%
Degree	97.9%	2.1%	100.0%
Not applicable	97.9%	2.1%	100.0%
No certificate	96.2%	3.8%	100.0%
Missing	100.0%	0.0%	100.0%
Total	95.5%	4.5%	100.0%

Table 2
Labor Force in 2011, by the highest certificate obtained.
Source: 2011 Labor Force Survey.

Degree	Employed	Unemployed	Total labor force
UPSR or similar	97.5%	2.5%	100.0%
PMR/SPR or similar	97.3%	2.7%	100.0%
SPM or similar	96.7%	3.3%	100.0%
STPM or similar	96.2%	3.8%	100.0%
Certificate	94.9%	5.1%	100.0%
Diploma	96.5%	3.5%	100.0%
Tertiary degree	96.4%	3.6%	100.0%
No degree	98.4%	1.6%	100.0%
Not applicable	95.8%	4.2%	100.0%
Total	96.9%	3.1%	100.0%

Table 3
Evolution of industry labor shares and proportion of skilled labor by industry, 2007–2010. Source: Labor Force Surveys from 2007 to 2010.

Industry	Δ (labor share)	Δ (skill proportion)
Agriculture	−4%	203%
Oil & gas	67%	54%
Manufacturing food, beverages, tobacco	38%	127%
Manufacturing textile	−26%	92%
Manufacturing wood	−22%	33%
Manufacturing paper & furniture	−3%	13%
Manufacturing chemicals rubber	6%	−3%
Metals, machinery, equipment NEC	−6%	18%
Electronics & electrical	−11%	11%
Manufacturing & transport equipment	−15%	48%
Utilities	4%	34%
Construction	8%	16%
Wholesale & retail	18%	20%
Accommodation & restaurants	15%	4%
Logistics	14%	13%
Post and telecoms	22%	11%
Finance	11%	−2%
Real estate	58%	34%
Business services	−3%	7%
Education	35%	8%
Health	32%	9%
Other services	−2%	63%
Public administration	20%	32%

3.1. The production structure

Value added is a constant elasticity of substitution function of capital and a labor aggregate L[7]:

$$X_t = \left(\alpha_K K_t^{1-\frac{1}{\sigma_1}} + \alpha_L L_t^{1-\frac{1}{\sigma_1}} \right)^{\frac{1}{1-\frac{1}{\sigma_1}}}. \quad (2)$$

The first order conditions imply the following factor demands:

$$K_t = X_t \left(\frac{\alpha_K PVA_t}{R_t} \right)^{\sigma_1} \quad (3)$$

$$L_t = X_t \left(\frac{\alpha_L PVA_t}{PL_t} \right)^{\sigma_1}. \quad (4)$$

At the following nest, L is decomposed into three bundles containing workers with academic degrees, vocationally trained, and secondary school graduates or lower:

$$L_t = A_t \left(\alpha_{HS} HS_t^{1-\frac{1}{\sigma_2}} + \alpha_{MS} MS_t^{1-\frac{1}{\sigma_2}} + \alpha_{LS} LS_t^{1-\frac{1}{\sigma_2}} \right)^{\frac{1}{1-\frac{1}{\sigma_2}}}. \quad (5)$$

Each labor bundle is a CES aggregate of workers of different skill types. The HS bundle contains degree holders of 8 different types, corresponding to eight broad fields of study. The MS bundle contains vocationally trained, in the same 8 broad fields of study. Finally, the LS bundle contains workers of 4 educational categories: primary and less, lower secondary, upper secondary, and pre-university. The choice of a three bundle structure comes from an appreciation of the skill specificity at the different educational levels, ranging from relatively general skills at the lower end of the educational spectrum to relatively profession-specific skills at the higher end. The skill specificity is likely to be inversely related to the substitutability of workers at the given educational level.

$$HS_t = A_{HS,t} \left[\sum_f \beta_f LD_{HS,f,t}^{1-\frac{1}{\sigma_3}} \right]^{\frac{1}{1-\frac{1}{\sigma_3}}} \quad (6)$$

$$MS_t = A_{MS,t} \left[\sum_g \beta_g LD_{MS,g,t}^{1-\frac{1}{\sigma_4}} \right]^{\frac{1}{1-\frac{1}{\sigma_4}}} \quad (7)$$

$$LS_t = A_{LS,t} \left[\sum_l \beta_l LD_{LS,l,t}^{1-\frac{1}{\sigma_5}} \right]^{\frac{1}{1-\frac{1}{\sigma_5}}}. \quad (8)$$

Each of the 20 skill types is composed of local and migrant labor:

$$LD_{lf,t} = \left(\alpha_{loc} LDL_{lf,t}^{1-\frac{1}{\sigma_6}} + \alpha_{mig} MIG_{lf,t}^{1-\frac{1}{\sigma_6}} \right)^{\frac{1}{1-\frac{1}{\sigma_6}}}. \quad (9)$$

And local labor of skill type s is made up of young and old workers:

$$LDL_{lf,t} = \left(\alpha_y LDLA_{y,lf,t}^{1-\frac{1}{\sigma_7}} + \alpha_{ny} LDLA_{ny,lf,t}^{1-\frac{1}{\sigma_7}} \right)^{\frac{1}{1-\frac{1}{\sigma_7}}}. \quad (10)$$

3.2. Labor supply

Each year, workers leave the labor force through death and retirement.[8] New workers enter from the educational system, upon finishing an educational cycle and on deciding not to pursue further education. A skill-specific percentage of graduates (estimated from Labor Force Survey (LFS) data) do not enter the labor force.

3.2.1. Educational dynamics

Facing the above demands for workers of various skill types, origin and age, the evolution of supply of workers is determined in an educational module calibrated from data from past years. Students move between educational cycles depending on dropout rates, and the willingness to join the labor market at the end of each cycle. For low skill content-cycles, these rates are calculated as averages from the period 2009–2010. The dropout rates are calculated using the following formula:

$$dropout_c = \frac{enrolled_{c,2009} + entrants_{c,2010} - grad_{c,2009} - enrolled_{c,2010}}{enrolled_{2009}}. \quad (11)$$

For each cycle, the dropout rate is calculated as a residual. It corresponds to disappearances from the stock of enrolled between 2009 and 2010, which are not accounted for, relative to the stock of enrolled in 2009. We make the assumption that repetition rates (for which we have no information) are negligible. Graduates deciding not to pursue further education are captured by the parameter *exdip*:

$$exdip_c = \frac{grad_{c,2009} - \sum_c \left(entrants_{c2,2010} \times transmap_{c,c2} \right) \times \frac{grad_{c,2009}}{\sum_c (equiv_{c,c2} \times grad_{c2,2009})}}{grad_{c,2009}} \quad (12)$$

where *transmap* is a mapping parameter between different educational cycles and *equiv* a parameter mapping cycles that are equivalent, in the sense that they can both precede c2. Thus, graduates who choose not to pursue into the next cycles is the residual of the graduates from cycle c, less entrants into the next cycle weighted by the importance of cycle c as a cycle of origin. As such, *exdip* refers to the percentage of graduates who leave a given cycle in 2009 less those who choose to continue into any of the next possible cycles.

$$NEWENR_{c,t} = popent_{c,t} + \sum_c GRAD_{c2,t-1} \times transmap_{c,c2} \times (1 - exdip_{c,t-1}). \quad (13)$$

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[7] Sectoral indices have been omitted in this section for readability.

[8] The mortality and retirement rates were obtained from UNESCO data.

Newly enrolled are equal to children arriving at school age (*popent*) for the primary cycle, plus last year graduates from preceding cycles, less those who choose not to pursue further studies. Thus, the number of enrolled is simply equal to the number of enrolled of the previous year, less graduates and dropouts, plus newly enrolled in the current year.

$$ENR_{c,t} = ENR_{c,t-1} \times (1-dropout_c) - GRAD_{c,t-1} + NEWENR_{c,t} \qquad (14)$$

Furthermore, we assume a stable share of graduates:

$$GRAD_{c,t} = gradrate_c \times ENR_{c,t}. \qquad (15)$$

Students hence move through the educational system cycle by cycle, depending on dropout rates and the willingness to pursue further education; a willingness that is determined by preferences and the expected rate of return to education. At the end of Form 5, students who choose to pursue higher education make a choice of entering pre-university education or seeking vocational training.

3.2.2. Educational choices

The hypothesis that expected wages orient the demand for a certain level of education has been confirmed in numerous studies (e.g. McIntosh (2001) and Canton and de Jong (2005)). Average wages by skill type and field of study have been found to be positively correlated with relative demand for education of a particular skill type and in a particular field of study (Montmarquette et al., 2002; Freeman and Hirsch, 2008; Beffy et al., 2012). In Belgium, Duchesne and Nonneman (1998) find some support for relative wages driving enrollment choices both in university and non-university higher education. The choice between pre-university education and vocational training is thus modeled through a constant elasticity of transformation function (CET) where the first order conditions render the following demands for vocational training and academic degrees respectively[9]:

$$NEWENR_{voc,t} = \alpha_{voc} \times TOTNEWENR_t \times \left[\frac{\frac{\sum_g \left(LD_{g,t} \times (1-Ur_{g,t}) \times avfw_{g,t} \right)}{\sum_g \left(LD_{g,t} \right)}}{\frac{\sum_f \left(LD_{f,t} \times (1-Ur_{f,t}) \times avfw_{f,t} \right)}{\sum_f \left(LD_{f,t} \right)}} \right]^{\sigma_{10}} \qquad (16)$$

$$NEWENR_{deg,t} = \alpha_{deg} \times TOTNEWENR_t \times \left[\frac{\frac{\sum_f \left(LD_{f,t} \times (1-Ur_{f,t}) \times avfw_{f,t} \right)}{\sum_f \left(LD_{f,t} \right)}}{\frac{\sum_g \left(LD_{g,t} \times (1-Ur_{g,t}) \times avfw_{g,t} \right)}{\sum_g \left(LD_{g,t} \right)}} \right]^{\sigma_{10}}. \qquad (17)$$

The demand for vocational training thus increases according to the expected relative mean wage of vocationally trained and degree holders respectively; and with an elasticity of σ_{10}. The total number of students having decided to pursue education after finishing secondary school is thus broken down into two categories: students who continue to vocational training, and students who go on to university. For medium and high skilled, newly enrolled choose different fields of study based on preferences and expected wages in each fields. This choice is again modeled through a constant elasticity of transformation function (CET) which gives an optimal allocation of demand for skills given expected wages. We here assume that workers have myopic expectations and believe the wage distribution by skill to remain constant and equal to that of the previous year. The first order conditions imply the

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[9] See Annex 1 for the initial CET functions. The logic behind the use of a CET function to model educational demands is analogous to that of an income-maximizing firm choosing between exports and the domestic market as an outlet for its production. The representative agent maximizes expected income, subject to the constraint that total endowment in higher education is defined using a constant elasticity of transformation function. This maximization thus gives the optimal allocation of the educational endowment between vocational and general higher education.

following demand for educational services of type *f*, for vocational and university students respectively:

$$NEWENRFIELD_{g,t} = \gamma_g \times NEWENR_{voc,t} \times \left[\frac{avfw_{g,t-1}(1-Ur_{g,t-1})}{avfwtot_{voc,t-1}} \right]^{\sigma_{11}} \qquad (18)$$

$$NEWENRFIELD_{f,t} = \gamma_f \times NEWENR_{deg,t} \times \left[\frac{avfw_{f,t-1}(1-Ur_{f,t-1})}{avfwtot_{deg,t-1}} \right]^{\sigma_{12}} \qquad (19)$$

where $avfwtot_{edu,t-1}$ is the average expected wage of diploma- and degree holding non-youth on the labor market, with $voc,deg \subset edu$. Each year, $NEWENR_{edu,t}$ is fixed and equal to the demand for vocational and university studies respectively. These blocks of equations thereby give us educational demand by skill. These demands are confronted with supply in a sequential fashion: first, fields of study are ranked according to the wage premium associated with each one. Then, desired entrants into that field are confronted with the number of available places in the field. Students not accepted are regrouped with those desiring to enter the second rank field. A second cutoff is carried out, with leftovers going into the third ranked field of study. The mechanism is repeated throughout the list of fields of study, for vocationally trained and degree holders respectively. Any students cut off from the eighth field of study are considered to be secondary school graduates of which a fraction will enter the labor force.

3.2.3. Labor force evolution

Graduates from lower cycles are added to the youth labor force in the following fashion:

$$
\begin{aligned}
LSTA_{lf,y,t} = &\ LSTA_{lf,y,t-1} \times (1-transage_{lf}) \\
&+ \sum_c \left(GRAD_{c,t-1} \times exdip_c \times edumap_{c,lf} \times (1-inact_{lf}) \right) \\
&+ \sum_{c2} \left(ENR_{c,t} \times dropout_c \times (1-inact_{lf}) \right) \\
&\times \sum_c \left(transmap_{c,c2} \times edumap_{c,lf} \right).
\end{aligned} \qquad (20)
$$

That is, the local labor force of skill *lf* equals the previous year's local labor force of skill *lf*, less those workers who flow from the *young* to the *not young* category. Graduates from cycle c who choose not to continue their studies are mapped to a labor skill, and a percentage of them are added to the labor force according to their labor force participation rate. Finally, dropouts from cycles above *c* are added to the relevant labor force category using mapping parameter *transmap*, denoting passages between cycles. For vocational and university students, the logic is the following:

$$
\begin{aligned}
LSTA_{lf,y,t} = &\ LSTA_{lf,y,t-1} \times (1-transage_{lf}) \\
&+ Min \left(CANDID_{lf,t-n}, places_{lf,t-n} \right) \times inact_{lf}.
\end{aligned} \qquad (21)
$$

The labor force holding diplomas and degrees is thus equal to diploma and degree graduates in the labor force the previous year, less those who transit to the *not young* category. Students who were accepted into their desired field of study are added, a percentage being removed depending on the labor participation rate of the category in question. The index n reflects the time it takes to complete a given cycle. We have set *n* to equal 4 years for all degree students, and 2 years for all vocational degrees, reflecting the average duration of these cycles in Malaysia. The inclusion of a delay between entrance in a given field and labor market participation has important implications. During the time of studies, workers are effectively immobilized, such that any increase in the number of students is likely to carry an initial negative impact on growth. In short, instead of being potential low skilled workers these individuals do not contribute directly to production. We thus include a temporal dimension of the efficiency of education policy in the model.

Finally, the evolution of older workers depends on the transit rate between age groups, and the mortality and retirement rates of old workers:

$$LSTA_{lf,ny,t} = LSTA_{lf,ny,t-1} \times (1 - mort_{lf,t} - retir_{lf,t}) + transage_{lf} \times LSTA_{lf,y,t-1}.$$
(22)

3.3. The migrant block

Immigration in Malaysia has increased substantially over the last decades, potentially influencing labor market dynamics. These migrants tend to be low educated, arriving in Malaysia from primarily Indonesia and the Philippines. Various push and pull factors explain the supply of migrants in Malaysia. We model the total supply of migrants using a CET function, where the evolution of the migrant stock at a given skill level depends on the relative wage premium of migration in a given year compared to the relative wage premium in the base year.

$$SMIG_{lf,t} = \sum_{AC} IMMIG_{AC,lf,2005} \times \left(\frac{\frac{avfwm_{lf,t}}{wdom_{lf,t}}}{\frac{avfwm_{lf,2005}}{wdom_{lf,2005}}} \right)^{\sigma_8}.$$
(23)

Furthermore, migrants move between sectors according to relative wages and initial preferences:

$$SMIG_{lf,t} = \sum_{AC} \left[\gamma_{AC,lf} \times IMMIG_{AC,lf,t}^{1+\frac{1}{\sigma_9}} \right]^{\frac{1}{1+\frac{1}{\sigma_9}}}.$$
(24)

Migrants thus make their decision sequentially. First, the decision to migrate is taken based on expected wages and the elasticity of substitution. Once immigrated, they will reallocate between sectors depending on the wage rate and the elasticity of the migrant sectoral supply.

3.4. Labor market adjustments

Migrants and local workers' wages are assumed to be different due to an imperfect substitution by employers (Ozden and Wagner, 2014). It is assumed that the local wage does not clear the labor market, such that there is unemployment among locals. The wage is modeled using a wage curve, reflecting the often observed empirical relationship between wage and unemployment. The local average wage by skill is thus given by:

$$logafw_{lf,t} = \beta_{1,lf} + \beta_{2,lf} \times logUr_{lf,t}.$$
(25)

Sectoral wages are then equal to the average wage, plus an exogenous wage differential:

$$wf_{AC,lf,t} = afw_{lf,t} \times fwdist_{AC,lf}.$$
(26)

Initially, the migrant wage clears the migrant labor market. We thus make the assumption that there is no migrant unemployment. Furthermore, reasonably in line with the regulatory framework, we assume that migrants do not pay social security. Following the minimum wage law passed in Malaysia in 2012, restrictions are imposed on the market wage from 2013. It follows that wages no longer clear the migrant labor market. Since there is no migrant unemployment, the introduction of a minimum wage – supposing it is binding – implies rationing of migrants in Malaysia. The level of the minimum wage is set according to the actual minimum wage introduced, deflated to reflect 2005 prices (since the model is exempt from inflation). The minimum wage is introduced sequentially. First, market wages below the minimum wage level are fixed at the minimum wage rate. The model is then resolved to allow for sectoral adjustments to take place. Any market wage having fallen below the

minimum wage rate is fixed at the minimum wage, and the procedure is repeated. The sequence stops when all wages are equal to or above the minimum wage rate.

3.5. Closure and dynamics

The model has five closures: a macro closure, a government closure, an external balance closure, a labor market closure and a closure of the social security accounts. Concerning the macro closure, it is savings driven (households' marginal propensity to save is exogenous), which means that the level of investment is determined by the level of total available savings in the economy (including foreign savings). Hence as savings increase, the stock of capital and output increase. The government closure chosen consists in fixing government expenditures as a constant share of GDP and tax rates and leaving the government budget balance endogenous. The social security account is modeled separate from the government budget. It earns its income from employers' payroll taxes and pays benefits that are distributed to households. The social security balance is endogenous. The foreign balance closure consists of fixing the exchange rate and leaving the current account balance endogenous. The formal labor market closure consists of a joint determination of unemployment and average local wages through the wage curve described above and no unemployment for foreign workers (wages clear the market).

Model dynamics are of the sequential type. Capital accumulation is sectoral. Each year the stock of capital in each sector corresponds to last year's stock plus new investment, minus the depreciation of capital. Sectoral investment has been modeled as a function of the sectoral stocks of capital, sectoral rates of return to capital and capital acquisition costs. As already mentioned, the evolution of the active population by skill is modeled within the education block, which relies on the actual performance rates of the education system and endogenous educational choices in Malaysia. Government and foreign debts increase (decrease) with the yearly level of the net deficit (surplus) of government and foreign savings.

4. Data and calibration

4.1. The database

We build a social accounting matrix using an input–output table of 2005, the base year for the simulations. A social security contributions account has been added, with a fixed percentage of employer and worker contributions being drawn from labor income. Total employment is taken from the 2007 LFS, the first survey for which wages are available. It represents wage earners in each sector, with the exception of the agricultural sector where employment refers to all employed due to the particular nature of this sector (hosting many informally employed workers)[10] and health (where employment corresponds to the estimated amount of wage earners for 2005).

Total value-added (including social security benefits) in each sector is taken from the 2005 input–output (IO) table. Wage related data come from the LFS. In the agriculture, health and education sectors, aggregate wage bills are those of the 2005 I–O tables. In the remaining sectors, wage bills are taken from the LFS 2007 by multiplying mean wages by skill and industry with the number of workers of that skill and industry (the difference between these and the original wage bill is imputed from capital remuneration). Thus, mean wages and wage earners are kept in accordance with the LFS in all except the three sectors mentioned. For those three sectors the standard methodology could not be used since the imputed wage bill would necessitate a negative capital

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[10] The LFS does not include workers in communal housing, which is common among migrant agricultural workers, who are thus likely to be underrepresented.

remuneration. The original wage bill is thus kept, and wages are imputed and not equal to those of the LFS.

Investment by origin is taken from the 2005 IO table and is portioned out to destination sectors. Information from a report titled "National Accounts Capital Stock Statistics" by the Department of Statistics proved very useful for this exercise. Since the data reflect a higher aggregation than the one used for the estimation we assume that investment is equally distributed among our sub-sectors. Ideally, an investment origin–destination matrix would have been used, but such a matrix was not available. The current results will thus fail to accurately capture some subsector dynamics that are due to relatively high or low investment with respect to sector size. World and local growth rates are taken from the World Bank Databank. Data on enrollment, intake and graduates for each cycle were available for 2009 and 2010. This data is used to calculate (for each cycle) the drop out-rates and the share of graduates who move to the next cycle. Enrollment data for the base year are estimated from a dynamic calibration exercise, retracing the evolution of educational outcomes between 2005 and 2010.

Using production and LFS data from 2005 through 2011, we dynamically calibrate the main parameters of the model through an iterative process. The result from this exercise is that the reference scenario is reasonably in line with the survey figures and the evolution of the main variables at the macro and sectoral levels.

4.2. Calibration

Model parameters include initial values of endogenous variables, as well as exogenous parameters. The social accounting matrix provides such values for production and consumption, exports, imports etc. Labor Force Surveys provide us with information on wages and employment status of migrants and locals. Some unobservable parameters can be calculated using initial values obtained from these sources. Others, such as elasticities of substitution, have to be estimated. When possible, we have attempted to estimate these elasticities. When impossible, reasonable values from the literature have been used.

As for the demand elasticity of substitution between high-skilled labor and capital, we follow Card and Lemieux (2001) and derive elasticities of substitution between workers of different age groups, education levels, fields of study as well as elasticities of different labor aggregates of these worker categories. The limited number of years for which we have data on wages sharply limits the regression results, and significant coefficients were not obtained for the full production structure. There are however indications of elasticities decreasing as we move up the production structure. The price-elasticities of demand for migrants with respect to locals have been estimated from LFS data.[11]

We consider the current macroeconomic trends to prevail. As such, the savings rate and the rate of increase of foreign direct investment have been set to values producing reasonable figures, in line with IMF data for the period 2005–2011. Furthermore, we are assuming the government deficit to continue its downward trend, declining to 3% of GDP in 2015, and completely absorbed in 2020.[12]

5. A microsimulation module

A microsimulation module is added to the CGE framework in order to study distributional impacts of SBTC and educational rationing. Since we are focusing on wage inequalities, a micro accounting approach is used, linking model outcomes to micro level data. The LFS

survey contains information on wage earners only, which is why we exclude interest rate variations from our analysis.

We use the most recent exhaustive LFS dataset, that of 2010, to implement factor price variations. Since our simulations produce effects that are likely to be important only in the medium-long-term framework (especially considering educational rationing), we seek to examine the alternative effects by 2020 from our reference scenario and our simulated scenarios. In a sense, we are comparing two counterfactuals. The variation in real wage income between 2010 and 2020 for an individual in industry AC, of skill f and age group a is thus:

$$\Delta W_{2020/2010,AC,f,a} = W_{2010,AC,f,a} \times C_{scen,AC,f,a} \qquad (27)$$

where C is a vector of factor payment variations issued from the various macro model scenarios. Thus, the individual wage impact of a simulation simply amounts to:

$$\Delta W_{AC,f,a} = W_{2010,AC,f,a} \times (C_{sim,AC,f,a} - C_{ref,AC,f,a}). \qquad (28)$$

Since our interest in doing this exercise is to examine how skill-biased technological change and educational policy affect distribution of wage incomes, we look at Gini coefficients and decile ratios, included along with macro results in the following section.

6. Simulations and results

The following section presents the simulations run and their results. Our first simulation assumes the skill-bias of technological change to be zero, i.e. that the overall rate of technological progress, calibrated from the dynamic calibration exercise using exogenous productivity growth rates, is affecting skilled and unskilled labor alike. Secondly, we simulate a rationing in the number of places at institutes of higher learning. For simplicity's sake, we compare an *open-door* policy, considered to be our benchmark scenario, with a scenario where the number of places available is equal to that of 2005, our base year.

In terms of lowering enrolment figures, other educational policies could have been considered, such as increasing fees, which would have an enrolment-reducing effect. The effects in terms of rationing would be similar, although the household share of the cost borne would have increased.[13] Attempting to increase quality rather than quantity is another potential policy candidate. Modeling increases in the quality of education (as measured by the skill endowment of graduates and not the internal efficiency of the educational system) is however not straightforward.
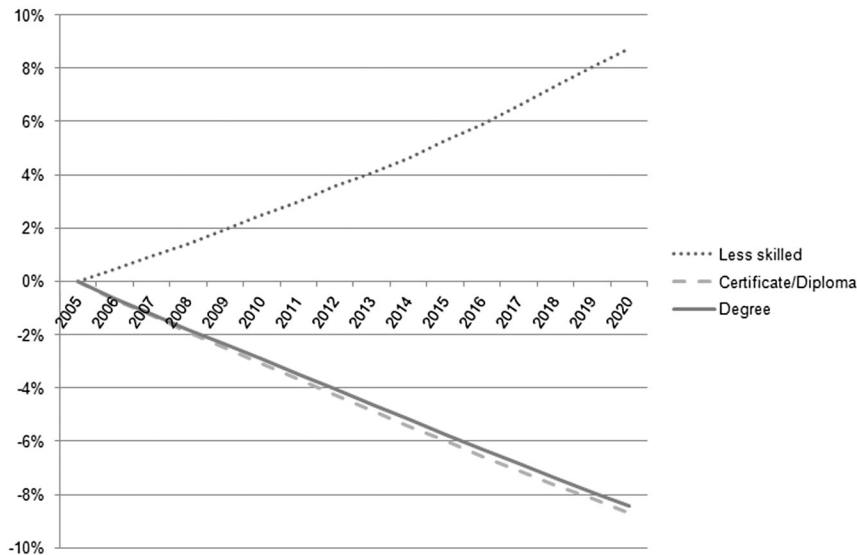
6.1. Malaysia without skill-biased technological change

What would have been the absorption of graduates by the labor market if technological progress in Malaysia were not biased toward skilled labor? How would the wage premia have reacted? We run a two-fold reference scenario, one with and one without skill-biased technological progress, both calibrating overall productivity growth given exogenous sectoral productivity growths and GDP growth rates (using historical figures, then assumed to be 5%). The reference scenario has been calibrated in order to reproduce as closely as possible the evolution of wages, unemployment and other endogenous variables between 2005 and 2011. We have settled on a skill bias of 4% annually for two reasons. Firstly, an estimation of the residual $A = \Delta \frac{\theta_S}{\theta_U}$ from only four data points (the ones for which we have wages) gives us an upper limit of skill-biased technological change of 9%. Choosing roughly

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Source: Authors' calculations using results from the model.

Fig. 3. Evolution of wages of Malaysian wage earners without SBTC.
Source: Authors' calculations using results from the model.

half this figure makes us reasonably sure that we are not overestimating the effect of SBTC. Furthermore, this figure gives us a reference scenario reasonably in line with the evolution of some main macro and sectoral variables.

Our first simulation assumes neutral technological change. Since the global productivity coefficient is calibrated to sectoral productivity growth rates and a GDP target figure, this means that removing the skill bias does not imply modifying aggregate productivity growth. Furthermore, the skill-biased technological change was applied to all tertiary educated, i.e. certificate, diploma and degree holders. As can be seen from Fig. 3, in the absence of skill-biased technological change, less skilled workers would have had a higher wage growth than in the reference scenario. On the other hand, tertiary educated – vocationally and academic alike – would have seen their wages decrease, thus eroding returns to education. Detailed breakdowns by field of study for Diploma holders and degree holders, and by level of education for less skilled can be found in Annex 1. They show that for diploma holders, the biggest winners from SBTC are engineers. For degree holders, those with degrees in agriculture have benefited the most. Fig. 3 shows that the Agricultural sector is the sector who has known the highest upskilling in the period 2007–2010. This large sector has the highest ratio (more than 95%) of unskilled to skilled labor, implying that an important substitution of skilled for unskilled labor needs to take place, significantly affecting wages of the high skilled.

Looking at unemployment (Fig. 4), we see that the tendency is the same as for wages. Had skill-biased technological change not been present, the unemployment rates of tertiary educated would have been around 15–20% higher, while those of less skilled workers would have been 15% lower. Thus, SBTC has clearly had a positive impact on the labor market outcomes of graduates in Malaysia.

The macroeconomic impacts over the period are minor (mainly since the model is calibrated to the same GDP target figures). Unemployment would however have been slightly lower during the period but returning to a very close figure (3.1%) by 2020. Results also show that immigration would have been higher had SBTC not prevailed, since this would have stimulated growth of migrant intensive sectors more than in a scenario with SBTC. Malaysia's immigration in recent years has been important, important enough to spark a concern among the government about its economic and social impact.

Unbiased technological progress, relatively more favorable to low-skill intensive sectors, can thus be seen as increasing the pull factor in the Malaysian context, where the main migration pool is made up of low-skilled Indonesians and Filipinos.[14] Had productivity increases been unbiased, the migrant stock would have been 14% higher by 2020.

Table 4 shows the production growth differentials from 2010 to 2020 in the absence of skill-biased technological change. It suggests that SBTC has led to structural change, benefiting sectors such as business services, finance and certain types of manufacturing, the common denominator of which is a large share of skilled labor. Symmetrically, it has played a role in the relative decline of sectors such as wood or wholesale & retail. Thus, the recent evolution of Malaysia toward a more skill-intensive economy, a policy target, has been facilitated by technical progress biased toward skilled labor.

6.2. Constraining the supply of higher education

Our reference scenario supposes no rationing of supply of educational services in Malaysia. Demand factors alone thus determine the evolution of skilled labor. In this simulation, we restrain the supply of educational services to that of the base year, 2005. Every year, the number of places in each field of study is thus equal to the number of places available in 2005.[15] We here assume the cycle of diploma studies to be two years, and that of degree studies to be four years. An increased enrollment in degree studies would therefore only create an increase in high skilled labor four years later.

Fig. 5 shows the evolution of unemployment of various high-skilled categories when places are kept constant. Unsurprisingly, by 2009, as the effects translate into a lower amount of degree holders than in the reference scenario the unemployment of degree holders starts to

---

[14] According to the 2010 Labor Force Survey, the proportion of employed migrants with at least a diploma or certificate in 2010 stood at less than 4.5%. The equivalent figure for Malaysians is 22%. The bulk of Malaysia's immigrants being low-skilled immigrants, migration responds strongly to variations in low-skilled wages, which are related to the skill bias of technological progress.

[15] An important caveat here is that we do not actually know the number of places in 2005, only the number of enrolled in each field of study. It is possible that more places were available in some fields.
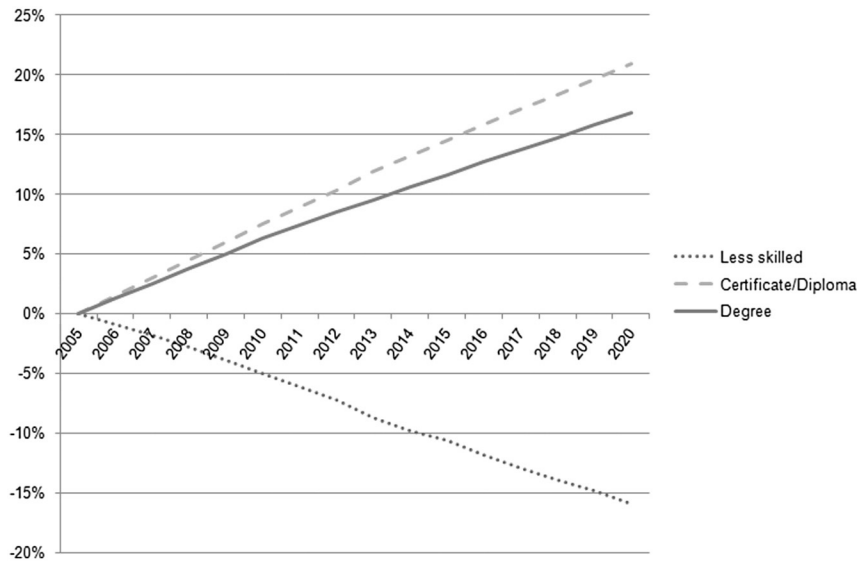
Source: Authors' calculations using results from the model.

Fig. 4. Evolution of unemployment of Malaysian wage earners without SBTC.
Source: Authors' calculations using results from the model.

decrease. At the end of the period, unemployment rates are 35% to 50% lower than in the reference scenario. The effect is also felt on wages, which would have been up to 20% higher by the end of the period (see Annex 1). By constraining access to higher education, a rent is created and awarded to those in possession of a tertiary education. For diploma holders, there is more variation in unemployment decreases and wage increases (see Annex 1). Some fields of study experience large increases while others get relatively minor ones. In particular, diploma holders in health do not benefit much from the rationing. This is partially due to the fact that the demand for health diplomas was falling in the reference scenario. Rationing actually creates a slight increase in the long term supply of health diploma graduates, since some of those diploma students that are cut out from more desirable fields due to rationing end up joining health programs as a fall back option.

Table 4
Sectoral production growth differentials 2010–2020 without SBTC (private sectors).
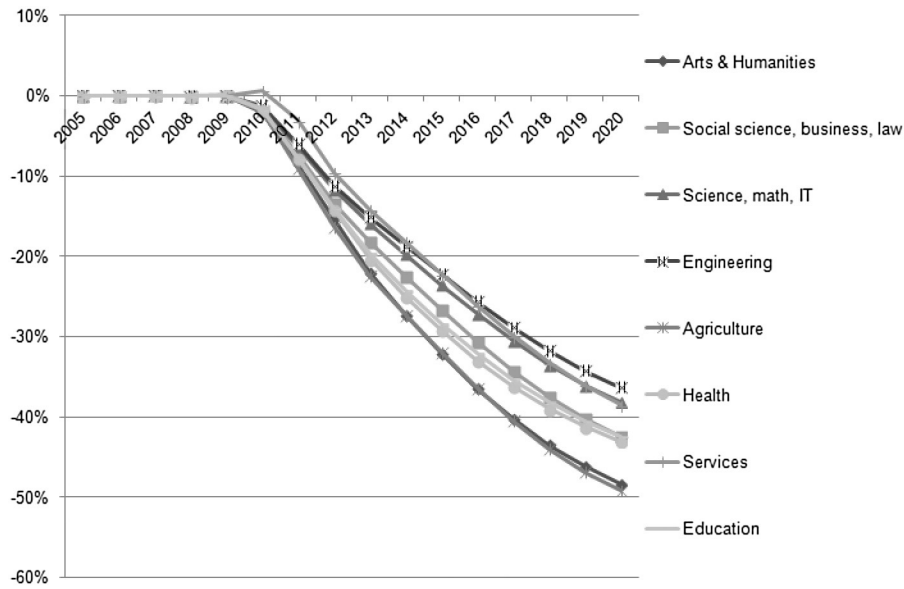Source: Authors' calculations using results from the model.

Agriculture	11%
Oil & gas	3%
Manufacturing food, beverages, tobacco	10%
Manufacturing textile	2%
Manufacturing wood	12%
Manufacturing paper & furniture	3%
Manufacturing chemicals rubber	−1%
Metals, machinery, equipment NEC	0%
Electronics & electrical	−2%
Manufacturing & transport equipment	−1%
Utilities	1%
Construction	1%
Wholesale & retail	8%
Accommodation & restaurants	5%
Logistics	4%
Post and telecom	0%
Finance	−1%
Real estate	0%
Business services	−10%

Looking at sectoral production growth differentials over the decade 2010–2020, we find disparate results across sectors (See Table 5). Several mechanisms are at play. Firstly and most intuitively, rationing increases the relative cost of skilled labor. Sectors who are relatively intensive in unskilled labor will thus benefit. The most unskilled labor-intensive sectors (agriculture, wood, wholesale & retail trade) are therefore those where production increases the most. Symmetrically, the most skill-intensive sectors (business services, finance and manufacturing of transport equipment) see their production decrease. Secondly, a variation of wage costs affects most those sectors who are relatively labor intensive. This explains why manufacturing of wood benefits more than agriculture from the rationing, agriculture being more capital-intensive. Among the relatively skill-intensive sectors, the most capital-intensive sectors such as finance are less hurt by the rationing than relatively labor-intensive ones such as business services.

Looking at Figs. 15–17 in Annex 1 provides insight into the determinants of wage shifts and their sensitivity to variations in these determinants. Skill biased technological change is indeed a strong one, as has been shown in the previous results. However, the magnitude of the bias sharply correlates to the subsequent wage loss (gain) of more (less) skilled workers. Furthermore, the elasticity of substitution between the three main labor bundles is also a strong determinant of the distributional effects of skill-biased technological change and educational rationing. We feel that our main hypotheses are reasonable. Our main variable, the skill shifter, is at 4% although the residual estimated stood at 9%. The elasticity of substitution between skilled labor bundles is also conservatively set at 1.5. As a matter of comparison, Katz and Murphy (1992) find an elasticity of supply between high school and college labor of 1.4 for the United States. They do not however implicitly account for substitutability within these two labor aggregates. When doing so, Card and Lemieux (2001) find estimates ranging between 2 and 2.5 in the UK and US.

6.3. Distributional results

The micro accounting exercise shows that the scenarios considered have substantially different impacts on Gini coefficients and interdecile

Source: Authors' calculations using results from the model.

Fig. 5. Evolution of unemployment of degree holding wage earners with a restriction in places.
Source: Authors' calculations using results from the model.

Table 5
Sectoral production growth differentials 2010–2020 with rationing (private sectors).
Source: Authors' calculations using results from the model.

Agriculture	3.6%
Oil & gas	1.4%
Manufacturing food, beverages, tobacco	3.0%
Manufacturing textile	1.1%
Manufacturing wood	4.5%
Manufacturing paper & furniture	1.4%
Manufacturing chemicals rubber	−0.1%
Metals, machinery, equipment NEC	0.1%
Electronics & electrical	0.1%
Manufacturing & transport equipment	−0.5%
Utilities	0.5%
Construction	0.4%
Wholesale & retail	4.8%
Accommodation & restaurants	2.2%
Logistics	1.9%
Post and telecom	0.2%
Finance	−0.4%
Real estate	0.1%
Business services	−5.1%

ratios (See Table 6). Overall, however, the massification of higher education together with SBTC bring about a decrease in overall wage inequality, as confirmed by the decrease in the Gini coefficient in our reference scenario. The same holds true for the interdecile measures, which are lower than in the 2010 LFS, and the Atkinson index. The Atkinson index allows inequality at the lower end of the distribution to affect the index more than inequality at the upper end, and the more so the higher the inequality aversion parameter e.[16]

As stated above, the reference scenario corresponds to skill-biased technological change and an *open-door* educational policy. This is what we consider to be the path Malaysia is currently on. The increased educational attainment of Malaysians will lead to a wage compression, substantially reducing wage inequality (almost a 3 point drop in the Gini coefficient).

When comparing the reference scenario with a situation without SBTC (simulation 1), maintaining the educational policy, the corresponding drop in the Gini is about 1.1. Skill-biased technological change thus prevented a reduction in wage inequality over the period. Similarly, both interdecile ratios would have been lower, had SBTC not been present.

Turning to educational policy, the second simulation shows the counterfactual Gini coefficient and interdecile ratios in a situation with SBTC and with educational rationing. Thus, the Gini coefficient would have been 1.6 points higher had the number of educational places been maintained at their 2005 level. The open-door policy of the Malaysian government has thus contributed to a decrease in wage inequality. It should be noted that even in this scenario, the counterfactual Gini coefficient for 2020 is 1.3 points lower than the one computed from the 2010 LFS data. This is due to two other things: firstly, demographic factors (older workers are more often of lower skill, such that the rate of destruction of the lower skilled category is higher than the rate of destruction of other skill categories) push the share of skilled labor upwards even in the presence of educational rationing. Secondly, the minimum wage introduced in 2013 is inequality-reducing in itself. Thus far empirical evidence of the minimum wage effects in Malaysia is scant, but Saari et al. (2016) who investigate the impact of the minimum wage on poverty across ethnic groups in Malaysia, find that it reduces poverty in all ethnic groups, but that the effect on Indians is substantially higher than that of other ethnic groups. They however do not consider employment effects. The latest available time series data for Malaysia[17] clearly shows that if any adverse employment

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[16] As long as $e > 0$, the sensitivity to inequality in the lower end of the distribution is increasing in e. We have chosen to set $e = 1$ in the simulation.

[17] Department of Statistics, accessed on April 11th, 2016.

Table 6
Summary of distributional indices from micro accounting exercise.
Source: Authors' calculations using results from the model.

	2010 LFS	Ref.	Sim. 1	Sim. 2	Sim. 3
		SBTC, no rationing	No SBTC, no rationing	SBTC, rationing	No SBTC, rationing
Gini coefficient	0.40743	0.3782	0.36686	0.39393	0.38078
Atkinson index (1)	0.24532	0.2143	0.20306	0.23019	0.21683
p90/p10	6.415	5.66	5.458	6.133	5.695
p90/p50	2.52	2.399	2.301	2.559	2.425

effects were to result from the introduction of the minimum wage, they have yet to manifest themselves: the labor force participation rate is steadily increasing from 2010 through 2014, and increased even after the introduction of the minimum wage act of January 2013. Furthermore, unemployment is decreasing from 3.3% to 2.9% over the same period, decreasing by 0.2 p.p. following the year of introduction of the minimum wage. We thus believe that a secular decrease in wage inequality is a reasonable result for Malaysia even in the absence of SBTC and with educational rationing.

Turning to simulation 3 (no SBTC, rationing), it shows that the impact of rationing is lower, but not far from that of SBTC. It thus seems that the open-door educational policy has counteracted the inequality maintaining effect of skill-biased technological change in Malaysia.

The full story of educational impacts on inequality should mention social returns to education. While private returns have largely been the focus of the literature (although a sizeable literature on social returns to education exists), externalities of educational accumulation might impact the distribution of income in indirect ways. Primarily, there is an evident link between education and the innovation process, likely to impact technical progress directly. The impact of this nexus on the relative productivity bias is however uncertain and we therefore assume the absence of such an effect. Secondly, spillover effects in worker productivity might be expected. It is plausible that an individual in training will increase not only his or her productivity, but also that of his or her coworkers, for example by introducing new ideas or forms of organization of the workplace. This is perhaps the most relevant type of externality for our purposes. Acemoglu and Angrist (1999) try to estimate social returns using variations in compulsory schooling laws in U.S. states. They find little evidence of a higher social than a private return. Furthermore, to our knowledge there are no studies trying to estimate the social returns to education in Malaysia. Again, we are unable to ascertain any impact on the skill bias of technological change from these mechanisms.

6.4. The hypothesis of exogenous SBTC

A major drawback of the canonical model of skill-biased technological change (Acemoglu and Autor, 2011) is that it says nothing about the origin of SBTC. Could it not be that the increase of skilled labor has provoked the direction taken by technical bias? Acemoglu (1998, 2002) creates a model in which a marketplace for innovation exists, and firms can choose to develop technologies suited to one factor of production rather than the other. He shows that whatever the elasticity of substitution between factors, an increase in the relative abundance of one creates some amount of technical change biased toward that factor. This however relies on profit incentives as the main source of the direction of technological bias. While arguing that innovation might indeed not be driven by profits, the direction of innovation somehow is. No clear explanation is given as to why this would be the case.

If SBTC results from firm responses to modifications of factor proportions, then this type of mechanism should be the most prevalent in countries which carry out a lot of innovation domestically, such as

high-income economies. To our knowledge, only one paper has tested for endogeneity of SBTC, in the German context (Bogliacino and Lucchese, 2015). Using the influx of East Germans as a source of exogenous variation in the proportion of skilled labor, they conclude on the absence of a demand pull effect on skill biased technological change. The experience of MENA countries and their record-high unemployment rates for tertiary graduates can also be raised as an argument for the absence of a demand pull effect. The considerable increases in quantities witnessed by these countries have not been followed by job creation suited to their qualifications.

In an era of openness and globalization, innovation travels fast. Berman et al. (1998), using data from 12 countries, show that skill-biased technological change such as the one observed in the US has been pervasive, occurring simultaneously in all countries. Berman and Machin (2000) further show that this pervasiveness extends to middle-income countries (of which Malaysia is one) in the 1980s, whose skill upgrading is correlated with that of the US. Since the world has not ceased to be a globalized place, it is likely that the same kind of pervasiveness of SBTC is at least as evident today as three decades ago. The hypothesis of SBTC through imports of goods which embody skill bias has been tested by Conte and Vivarelli (2011), who find evidence of such a mechanism on a set of 23 low- and middle income countries in the period 1980–1991. Eaton and Kortum (2001) show that the production of capital goods is highly concentrated among seven OECD countries which provide the main source of imports of capital goods for the rest of the world.

Cross-country regressions and the little evidence testing directly the demand-pull hypothesis thus suggest that SBTC is at least partly unrelated to the proportion of skilled labor in the economy. In the Malaysian case in particular, being a middle-income country relying on imports of capital goods to a larger extent than high income countries (and in particular, high technology countries such as Germany), there is reason to believe that much of the technological bias experienced is embodied in imported technology.

If SBTC is to a large extent exogenous with respect to skill proportions, the results of our simulations are valid. Should a significant share of SBTC be due to the increase in skilled labor, this would nuance some of the results obtained, but would not change their rank order. Simulation 1 would slightly overestimate the drop in the skill premia and subsequently the reduction in the inequality measures. Simulation 2 would slightly underestimate the increase in skill premia and subsequently the reduction in the inequality measures.

7. Conclusion

This article has looked at the labor market impacts of two alternative scenarios; a neutral technological change, and a rationing of places available in tertiary education. We develop a dynamic general equilibrium framework in which we extensively model educational choices both on the demand and the supply side, while taking into account immigration decisions. We are thus able to fully endogenize labor supply dynamics in the Malaysian context.

Our results show that in the absence of skill-biased technological change, relatively skilled wage earners should have expected lower wages and higher unemployment, while unskilled labor would have been able to expect higher wages and lower unemployment. The absence of SBTC would also have meant increased migration. We also show that skill-biased technological change has led to structural change, benefiting sectors with a large share of skilled labor, such as business services. Furthermore, our model does not take into account geography. A limitation of the study is thus that territorial inequalities or geographical shifts of production linked to internal migration of relatively more/less demanded skills across administrative divisions are ignored.

With rationing of the supply of higher education, we find that rents are created for high skilled workers, who would have seen their wages increase and unemployment decrease. At the sectoral level, we identify two mechanisms affecting sectoral production growth: Relatively less expensive unskilled labor, benefiting low skill-intensive sectors; and substitution effects among high skill-intensive sectors favoring the more capital-intensive sectors. These macro effects translate into distributional effects in the micro accounting module. We show that skill-biased technological change and rationing of educational services both have adverse effects on wage inequalities in the medium-term (their presence generates a Gini index of 0.394 in 2020 compared to 0.367 in their absence), although even with both mechanisms in play we would expect wage inequalities to drop. It seems therefore that the expansive educational policy adopted in Malaysia has counteracted some of the increase in inequalities expected from skill-biased technological change. The presence of skill-biased technological change in Malaysia thus constitutes a case for continued open enrollment policies to reduce wage inequalities.

In this paper we assume that total factor productivity and skill-bias are unrelated, to be able to isolate the effect of skill bias on the evolution of skill-specific unemployment and wage rates. Further research should be aimed at understanding in depth the linkages between skill-biased technological change and total factor productivity.

Annex 1

Table 7
Variables used in the CGE model.

$X_{AC,t}$	Composite production by sector AC in year t
$K_{AC,t}$	Capital stock by sector
$L_{AC,t}$	Aggregate labor bundle
$PVA_{AC,t}$	Value added price
$R_{AC,t}$	Interest rate
$PL_{AC,t}$	Price of aggregate labor bundle
$HS_{AC,t}$	High-skilled labor bundle
$MS_{AC,t}$	Medium-skilled labor bundle
$LS_{AC,t}$	Low-skilled labor bundle
$LD_{AC,f,t}$	High-skilled labor bundle of type f
$LD_{AC,g,t}$	Medium-skilled labor bundle of type g
$LD_{AC,l,t}$	Low-skilled labor bundle of type l
$LDL_{AC,lf,t}$	Local labor bundle of skill type lf
$MIG_{AC,lf,t}$	Migrant labor of skill type lf
$LDLA_{a,lf,t}$	Local labor of age a and skill type lf
$ENR_{c,t}$	Enrolled by educational cycle
$GRAD_{c,t}$	Graduates by educational cycle
$NEWENR_{edu,t}$	Newly enrolled in cycles voc or deg
$TOTNEWENR_t$	Newly enrolled in tertiary education
$NEWENRFIELD_{lf,t}$	Newly enrolled in tertiary education
$avfw_{lf,t}$	Average wage of labor of skill type lf
$Ur_{lf,t}$	Unemployment rate of labor of skill type lf
$CANDID_{lf,t-n}$	Successfully accepted candidates by labor skill type
$avfwm_{lf,t}$	Average wage of migrant labor of skill type lf
$SMIG_{lf,t}$	Total migrant supply by skill type
$IMMIG_{AC,lf,t}$	Sectoral demand for migrant labor of skill type lf
$wf_{AC,lf,t}$	Sectoral wage of local labor of skill type lf
$afw_{lf,t}$	Average wage of local labor of skill type lf

Table 8
Parameters used in the CGE model.

$A_{AC,t}$	Labor augmenting productivity parameter
$\alpha_{AC,K}$	Share parameter of capital
$\alpha_{AC,L}$	Share parameter of labor
$\alpha_{AC,HS}$	Share parameter of high-skilled labor
$\alpha_{AC,MS}$	Share parameter of medium-skilled labor
$\alpha_{AC,LS}$	Share parameter of low-skilled labor
$A_{HS,AC,t}$	High-skilled labor productivity parameter
$A_{MS,AC,t}$	Medium-skilled labor productivity parameter
$A_{LS,AC,t}$	Low-skilled labor productivity parameter
β_f	Share parameter of high-skilled labor type f
β_g	Share parameter of medium-skilled labor type g
β_l	Share parameter of low-skilled labor type l
$\alpha_{AC,loc,lf}$	Share parameter of local labor
$\alpha_{AC,mig,lf}$	Share parameter of migrant labor
$\alpha_{y,lf}$	Share parameter of young local labor

Table 8 (continued)

$\alpha_{ny,lf}$	Share parameter of older local labor
$dropout_c$	Dropout rate by educational cycle
$enrolled_{c,t}$	Enrolled by educational cycle (historical figure used in calculations)
$entrants_t$	New entrants by educational cycle (historical figure used in calculations)
$grad_{c,t}$	Graduates by educational cycle (historical figure used in calculations)
$exdip_c$	Share of graduates pursuing further studies, by cycle
$transmap_{c,c2}$	Mapping parameter relating different educational cycles
$equiv_{c,c2}$	Equivalency parameter denoting cycles which are similar in the educational hierarchy
$gradrate_c$	Graduation rate, by cycle
α_{voc}	Share parameter of vocational students
α_{deg}	Share parameter of academic students
γ_f	Share parameter of field of study f in academic degrees
γ_g	Share parameter of field of study g in vocational degrees
$transage_{lf}$	Transition rate between age categories, by skill type
$edumap_{c,lf}$	Mapping parameter between educational cycles and labor skill types
$inact_{lf}$	Inactivity rate by skill type
$places_{lf,t}$	Number of places by field of study (tertiary cycles only)
$mort_{lf}$	Mortality rate by labor skill type
$retir_{lf}$	Retirement rate by labor skill type
$wdom_{lf,t}$	Domestic country wage rate by skill type
$\beta_{1,lf}$	Wage curve intercept parameter
$\beta_{2,lf}$	Wage curve elasticity parameter
$fwdist_{AC,lf}$	Exogenous sectoral wage differentials by skill type

Table 9
Elasticity parameters used in the CGE model.

$\sigma_{1,AC}$	Elasticity of substitution between aggregate labor and aggregate capital
$\sigma_{2,AC}$	Elasticity of substitution between high-skilled, medium-skilled and low skilled labor
$\sigma_{3,AC}$	Elasticity of substitution between high-skilled labor bundles
$\sigma_{4,AC}$	Elasticity of substitution between medium-skilled labor bundles
$\sigma_{5,AC}$	Elasticity of substitution between low-skilled labor bundles
$\sigma_{6,AC,lf}$	Elasticity of substitution between migrant and local labor
$\sigma_{7,AC}$	Elasticity of substitution between younger and older labor
$\sigma_{8,AC,lf}$	Elasticity of transformation of migrant supply
$\sigma_{9,lf}$	Elasticity of transformation of migrants between sectors
$\sigma_{10,lf}$	Elasticity of transformation between vocational and academic studies
$\sigma_{11,lf}$	Elasticity of transformation between vocational degrees
$\sigma_{12,lf}$	Elasticity of transformation between academic degrees

Table 10
CET equations used to derive educational demands.

The maximization problem at hand is:
$$Max(\sum_{edu}[avfw_{edu,t} \times NEWENR_{edu}])$$

subject to $TOTNEWENR_t = [\alpha_{voc} \times NEWENR_{voc,t}^{\rho_{10}} + \alpha_{,deg} \times NEWENR_{,deg,t}^{\rho_{10}}]^{\frac{1}{\rho_{10}}}$.

For the choice of field of study, the following CET functions were used:
For general higher education:
$$Max \left(\sum_f [avfw_{f,t} \times NEWENRFIELD_{f,t}]\right)$$

subject to $NEWENR_{,deg,t} = [\gamma_f \times \sum_f NEWENRFIELD_{f,t}^{\rho_{12}}]^{\frac{1}{\rho_{12}}}$

For vocational higher education:
$$Max(\sum_g [avfw_{g,t} \times NEWENRFIELD_{g,t}])$$

subject to $NEWENR_{voc,t} = [\gamma_g \times \sum_g NEWENRFIELD_{g,t}^{\rho_{12}}]^{\frac{1}{\rho_{12}}}$

Table 11
Evolution of industry labor shares and proportion of skilled labor by industry, 1990–2011.
Source: Authors' calculations from the 1990 and 2011 LFS.

Industry	Δ(labor share)	Δ(skill share)
Agriculture	−13.6%	2.1%
Oil & gas	0.0%	27.0%
Manufacturing food, beverages, tobacco	−0.2%	8.9%
Manufacturing textile	−2.3%	7.0%
Manufacturing wood	−0.4%	2.7%
Manufacturing paper & furniture	0.4%	10.7%
Manufacturing chemicals rubber	0.4%	16.2%
Metals, machinery, equipment NEC	−0.1%	12.3%
Electronics & electrical	4.1%	16.5%
Manufacturing & transport equipment	0.4%	16.0%
Utilities	−1.5%	23.2%
Construction	2.9%	11.2%
Wholesale & retail	2.1%	10.3%
Accommodation & restaurants	2.1%	6.3%
Logistics	1.4%	11.7%
Post and telecom	0.9%	59.6%
Finance	0.7%	33.7%
Real estate	0.2%	30.6%
Business services	3.8%	15.8%
Education	0.7%	20.9%
Health	0.9%	44.0%
Other services	−2.3%	6.8%
Public administration	−0.6%	23.0%
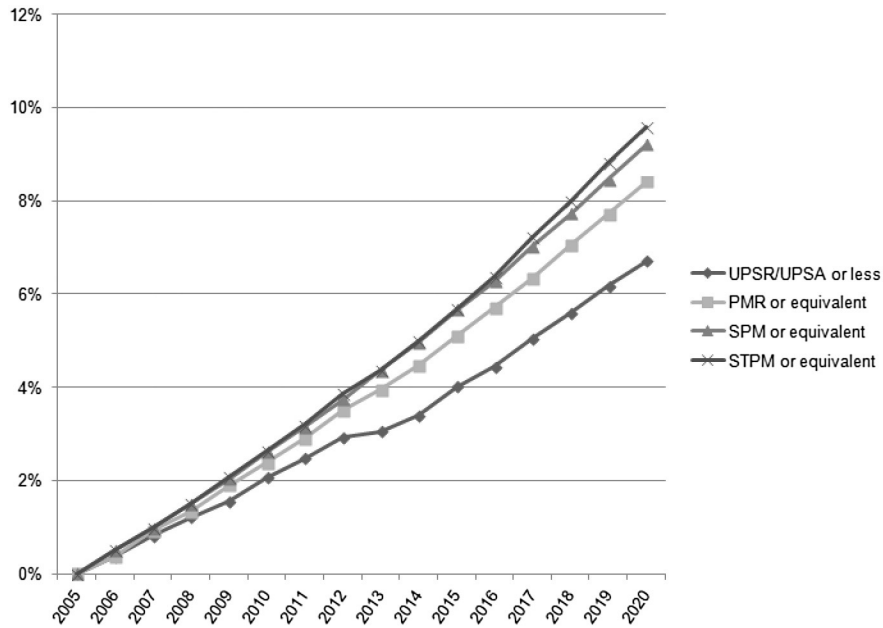
Source: Authors' calculations using results from the model.

Fig. 6. Evolution of wages of low-skilled Malaysians without SBTC.
Source: Authors' calculations using results from the model.

Source: Authors' calculations using results from the model.
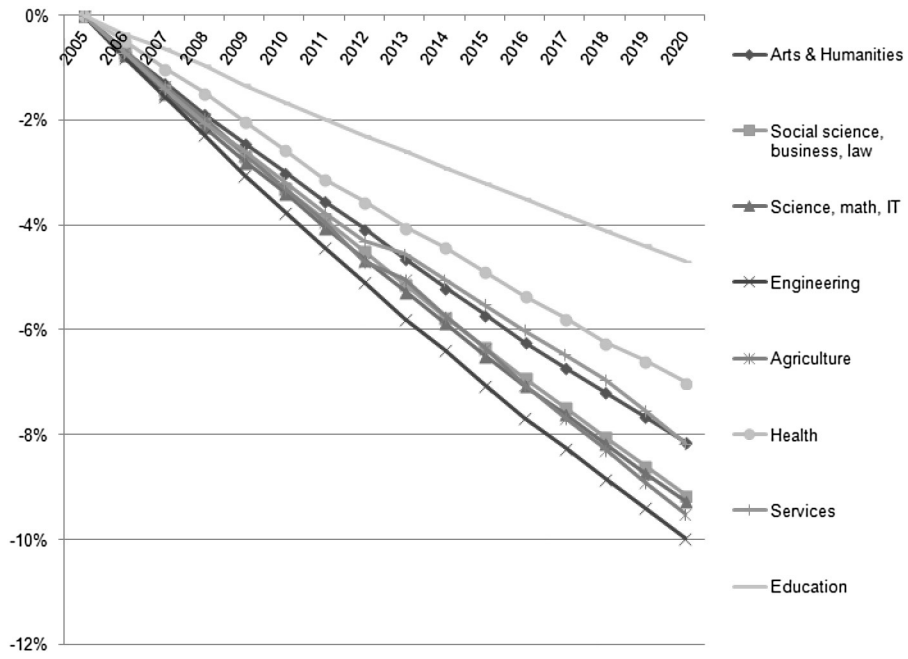
Fig. 7. Evolution of wages of diploma holders without SBTC.
Source: Authors' calculations using results from the model.

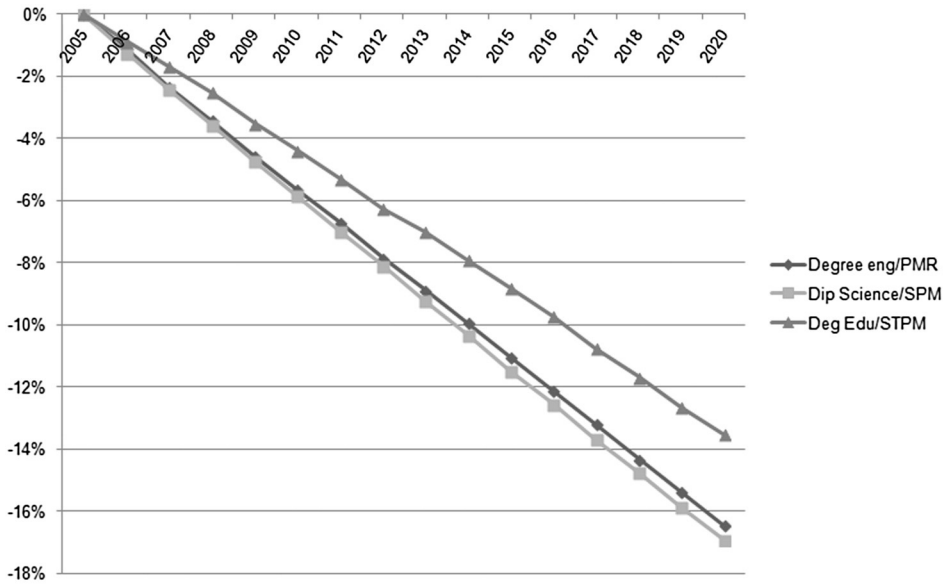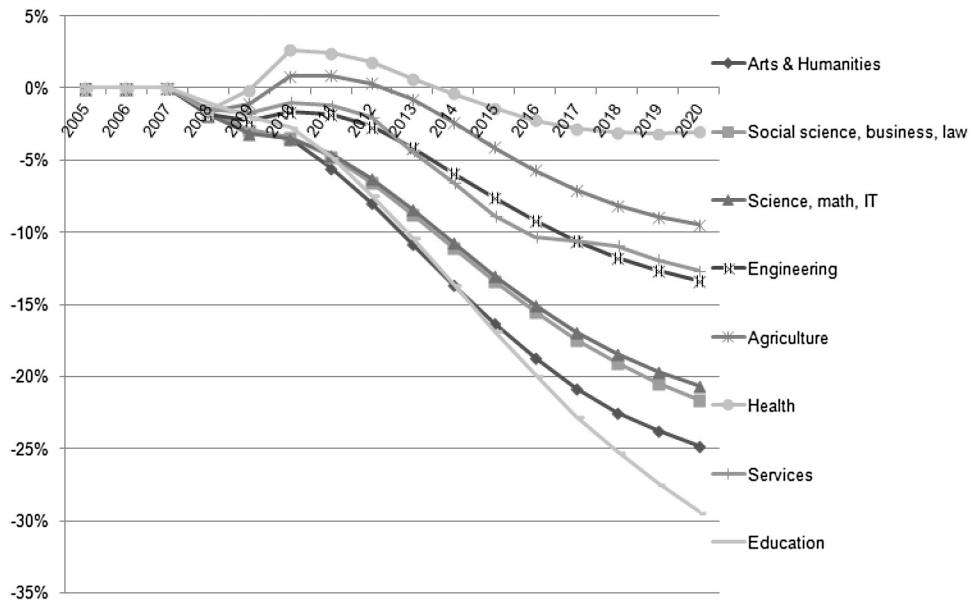Source: Authors' calculations using results from the model.
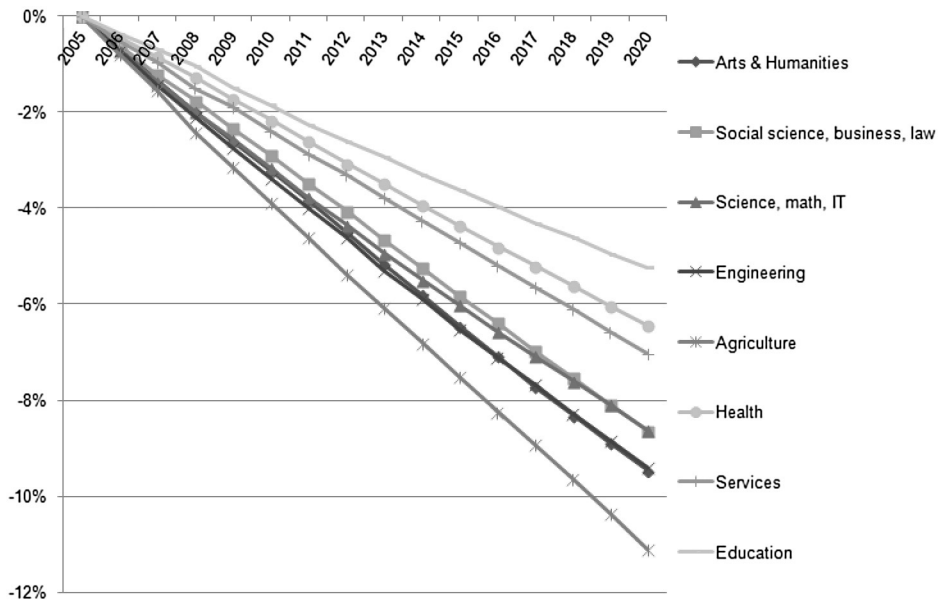
Fig. 8. Evolution of wages of degree holders without SBTC.
Source: Authors' calculations using results from the model.

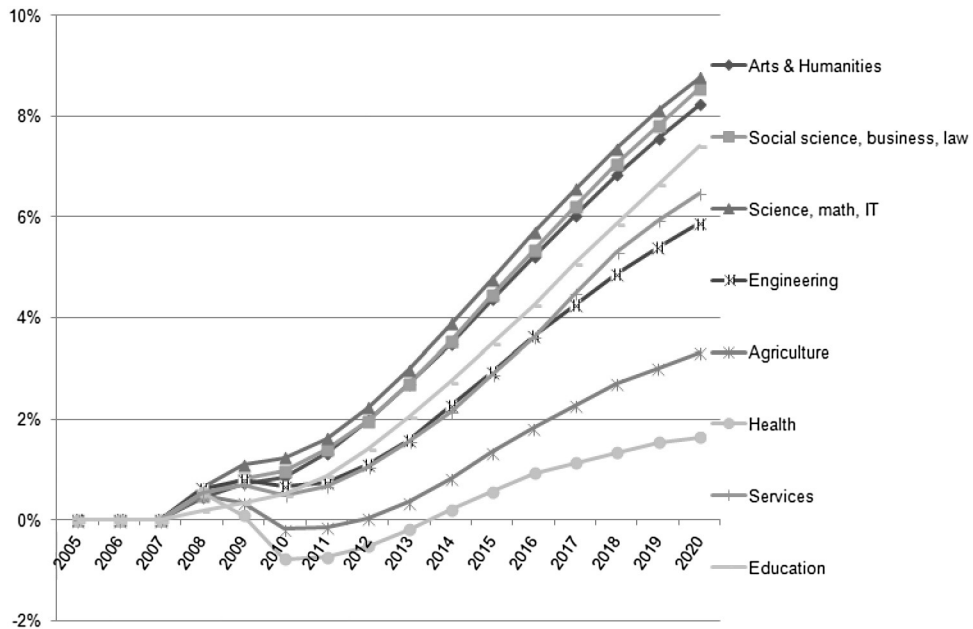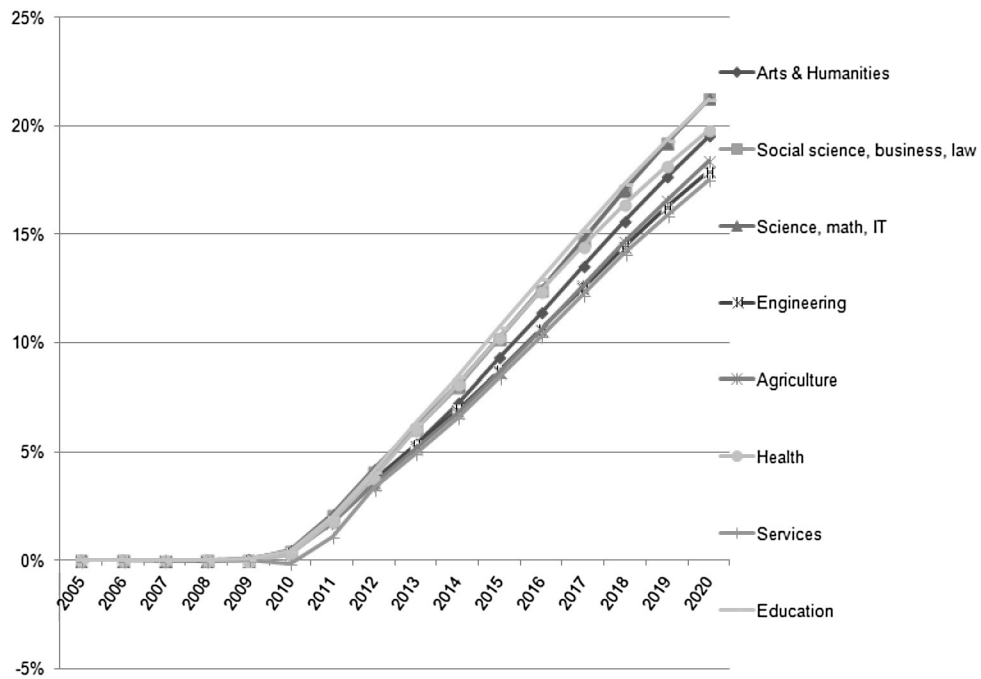Source: Authors' calculations using results from the model.

Fig. 9. Evolution of selected wage differentials without SBTC.
Source: Authors' calculations using results from the model.

Source: Authors' calculations using results from the model.

Fig. 10. Evolution of unemployment of diploma holding wage earners with rationing.
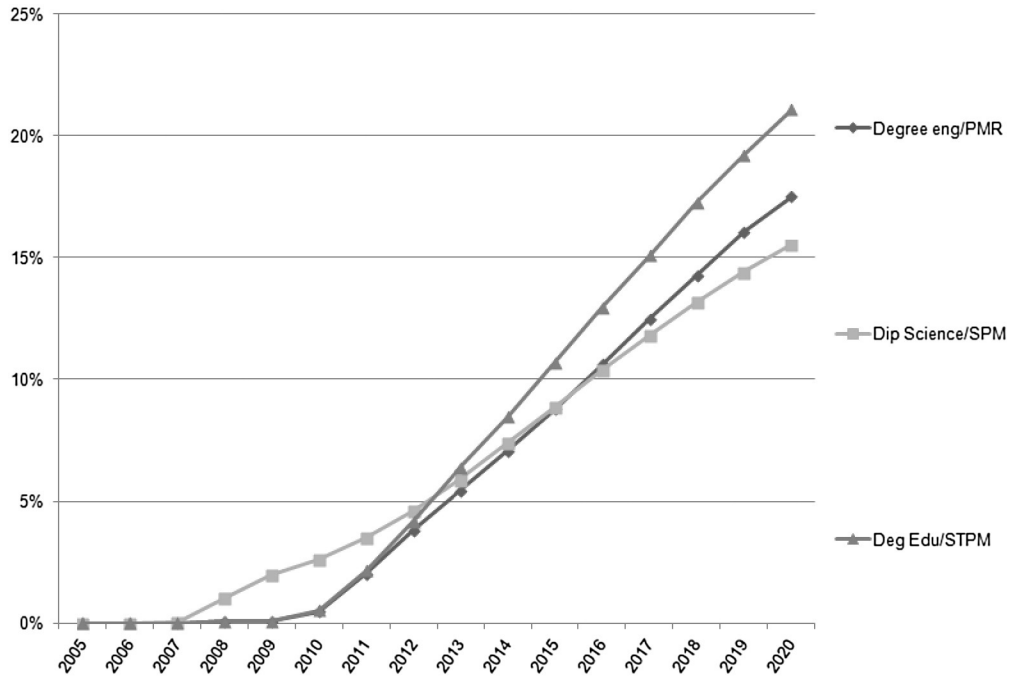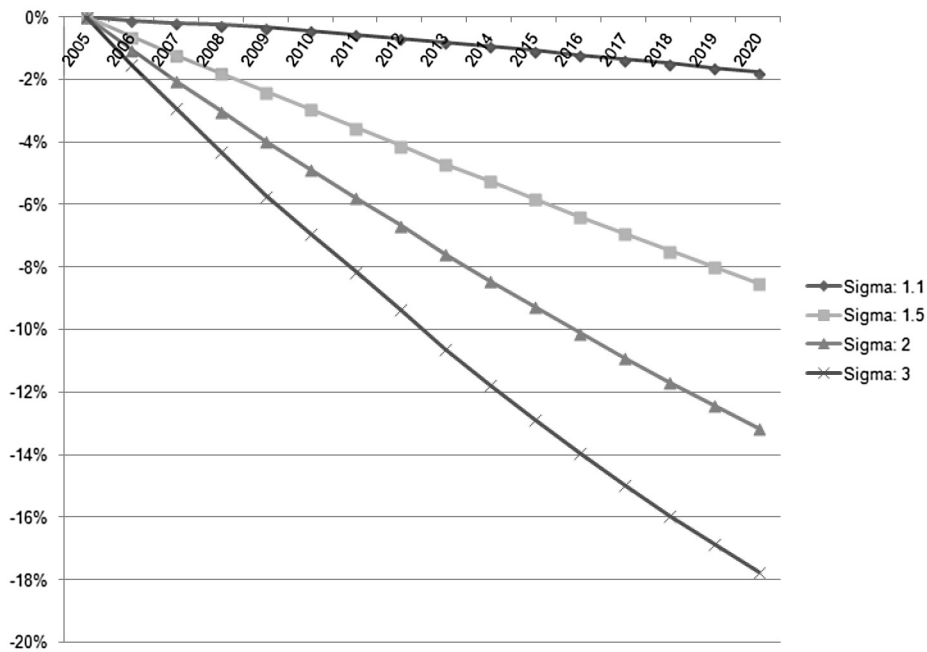Source: Authors' calculations using results from the model.

Source: Authors' calculations using results from the model.

Fig. 11. Evolution of wages of diploma holders with rationing.
Source: Authors' calculations using results from the model.

Source: Authors' calculations using results from the model.

Fig. 12. Evolution of wages of degree holders with rationing.
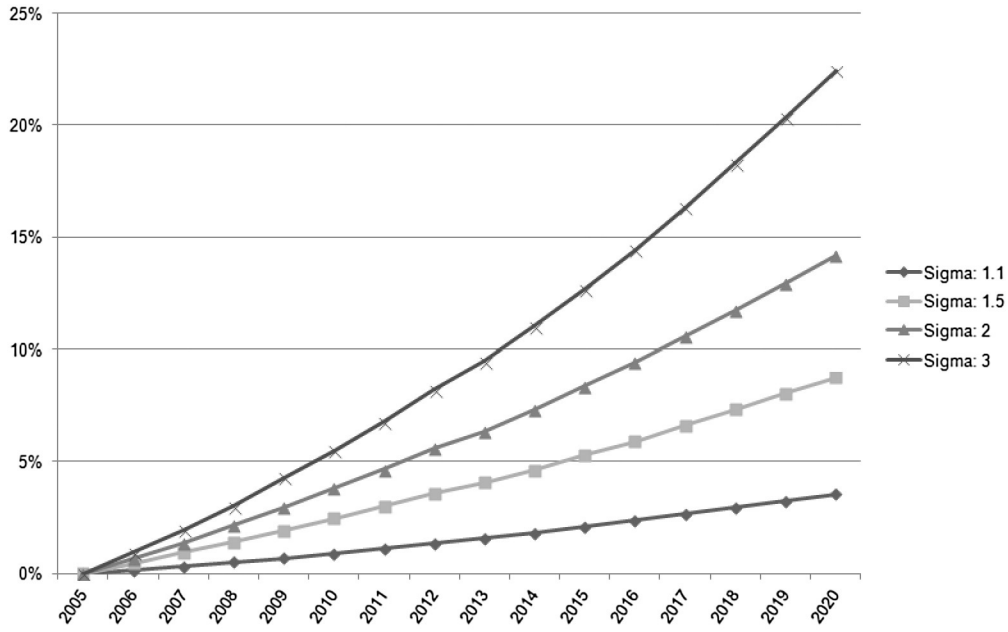Source: Authors' calculations using results from the model.

Source: Authors' calculations using results from the model.

Fig. 13. Evolution of selected wage differentials with rationing.
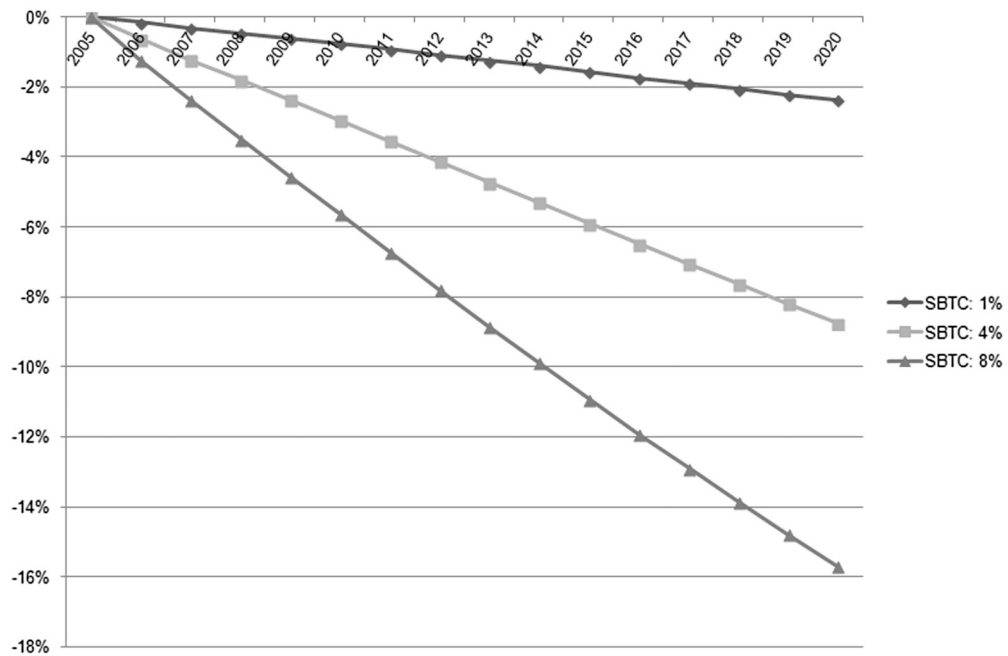Source: Authors' calculations using results from the model.

Source: Authors' calculations using results from the model.

Fig. 14. Evolution of degree holders' wages without SBTC (4%) for various elasticities of substitution.
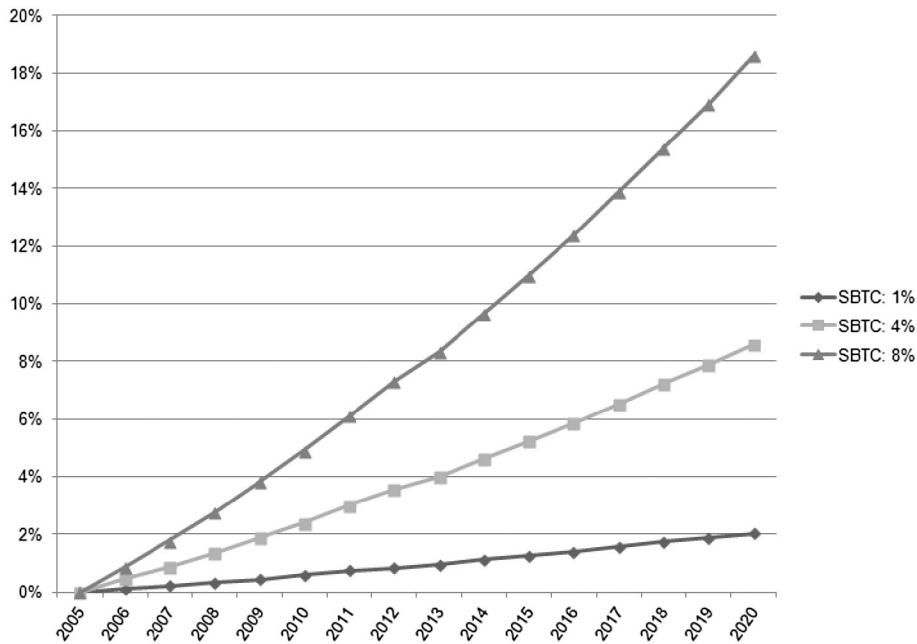Source: Authors' calculations using results from the model.

Source: Authors' calculations using results from the model.

Fig. 15. Evolution of wages of less skilled workers without SBTC (4%) for various elasticities of substitution.
Source: Authors' calculations using results from the model.

Source: Authors' calculations using results from the model.

Fig. 16. Evolution of degree holders' wages for various levels of SBTC (Sigma: 1.5).
Source: Authors' calculations using results from the model.

Fig. 17. Evolution of wages of less skilled workers for various levels of SBTC (Sigma: 1.5).
Source: Authors' calculations using results from the model.

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