IBS WORKING PAPER 15/2015
NOVEMBER 2015

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ibs working paper 15/2015
November 2015

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Abstract

The paper studies the dynamics of college wage premium across OECD countries. It reports that countries which experienced college wage premium growth higher than that of other countries also witnessed a higher growth of the skills supply ten years earlier. Regression results suggest that this pattern could not be explained by the theory of global Directed Technological Change, increase in trade or the fall of trade-unions. However, it can be explained with the model of endogenous technology choices: the growth of skilled workers motivates firms to pick more skill-biased production methods. I calibrate the model using the results of the dynamic panel regression. Endogenous technology choices can explain one third of the total increase in wage inequality in the OECD. One implication is that any policy that affects the supply of skilled workforce at the country level will have an impact on the skill-bias of equilibrium technology and wage inequality dynamics.

Keywords: Technological Change: Choices and Consequences, Skills, Labor Productivity

JEL Codes: O33, J24

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†I am grateful to Arpad Abraham, Fabio Canova, Francesco Caselli, Peter Hansen, Miklos Koren, Ramon Marimon, Jose V. Rodriguez Mora and participants of conferences and seminars in London, Naples, Milan and Florence for their constructive comments and valuable suggestions.

1 Introduction

The second half of the 20th century brought a notable increase in the skill premium - i.e. the relative pay of well educated to low-educated workers - in almost all developed countries. The change has attracted wide interest among researchers and motivated a number of studies aimed to explore its roots. The explanation that wins a growing popularity among researchers is a skill-biased nature of new information and communication technology[1]. The belief is that the new ICT technology platform is by nature ideally matched with highly-skilled workers, thus it has dramatically increased their productivity (relative to the low-skilled workers) and led to higher relative wages.

The empirical finding of this paper suggests that the global technological change has a competitor in explaining the OECD skill-premium raise. I find that countries which experienced college graduate growth higher than that of other countries also witnessed higher growth of college wage premiums a decade later. This cross-country variation suggests that, in addition to the global factors, there must be a local level mechanism that shapes the skill premium dynamics.

Specifically, the local level mechanism which could explain both, the overall increase in skill premia in OECD and its cross-country variation is a simple LeChatelier-style adjustment to the increase in the skill supply. While the first response of the market to an increase in skills supply would be a drop in skill premium, in the second phase, firms would seek opportunities to adjust their production to a new, skill-abundant composition of labour. This adjustment exerts a force, which is counter acting the initial skill premium fall. Furthermore, if the raise in skill supply was unanticipaed, the adjustment phase is delayed and characterized by the observable growth of the skill-premium. Note that this mechanism could explain both, the overall increase in skill premia in OECD and its cross-country variation.

The difference between the change in the nature of the global technology platform (henceforth, "technological change") and choices by individual firms (henceforth "endogenous technology choice") can be better understood with an illustration. Consider two alternative processes for electricity production. Electricity could be generated in coal-fired power plants or with wind turbines. The first alternative requires a significant amount of unskilled labour, particularly in the extraction sector. The second alternative process involves no extraction of resources, but it is based on complex technology requiring skilled labour for design, calibration and maintainance. The wind turbines generation is therefore skill inensive and unskilled labour saving. Therefore, replacing the prodcution based on coal with the one based on wind will shift up the relative demand for skilled workers.

There are two reasons why firms could wish to switch from coal to wind power: the first reason is that the arrival of an ICT global technological platform leads to a greater improvement in wind turbines than in coal extraction and firing. The second reason would be that the number of unskilled workers has reduced, while skills became abundant, generating an interest in an unskilled labour saving, skill intensive production method. This second reason is perhaps even more obvious than the first. It is also not a novel economic theory, rather a simple application of the LeChatelier principle. However it has not been yet explored as a potential cause

[1]The other prominent explanations were the institutional changes (weakening of trade unions - e.g. DiNardo, Fortin and Lemieux (1995)) and globalization (shifting of low-skill-intensive production to less developed countries - e.g. Wood (1995) and Leamer (1995)). The institutional change explanation is questioned because skill premium in the US started to increase before deunionization (Acemoglu (2000)). Although globalization seems to play an important role in the rise (Van Reenen (2011)), it cannot fully explain its pattern (Acemoglu (2000)). I analyze the role of these factors in the empirical investigation in Section 4.

for the 20th century skill-premium outburst[2]. How can we decompose the two effects? How much of the skill premium increase was driven by new technology choices at the local level, and how much due to the global skill-biased technological change? Answering these questions is one of the main purposes of this paper.

It is important to distinguish between the endogenous technology choice hypothesis and the hypothesis in Acemoglu's (1998, 2000, 2007, 2014), often called the directed technology change hypothesis. If we were to classify the two to strands of literature, the latter would be assigned to Hick's (1932) and Samuelson's (1965) induced technology change strand, while the former is contained in the LeChatelier strand of literature initiated with Samuelson (1960) paper. Acemoglu's papers assume that there is only one global technology (a single production method) developed in a profit-maximizing, world scale R&D firm and whose skill bias may be influenced by the relative number of skilled and unskilled workers. Instead, the endogenous technology choice hypothesis assumes that, if there is a world-scale R&D centre, it develops a technology platform that is only a basis for a development of a range of production methods - some being more and some being less skill-biased. The production methods that are chosen depends on individual final-good producers. As a result, while directed technological change predicts that the supply of skills affects technology at the global level, the endogenous technology choice predicts that the skill-bias of the production methods in any country depends on the choices of the firms that are influenced by the local (country-level) skills supply.

Is the distinction between the changing nature of the technology platform and the shift of technology choices important? Firstly, the shift in technology choices does not have to happen during a major technological change. Thus in the future we might observe rapidly a changing skill premium structure, even if we will not observe any change in general purpose technology. Secondly, the technology choice hypothesis implies that the firms' skill bias will respond to any policy that governs the supply of skilled and unskilled labour. For instance, a policy improving early age education or extending the retirement age for less skilled workers can incentivise firms to pay more attention to production methods that favours this kind of workers. Through the effect on technology choices, these policies will have a negative effect on wage inequality. Policy makers may wish to take this effect into account. Finally, the technology choices of firms depend on the local labour market conditions. Thus, the model that incorporates the endogenous technology choice argument might predict a variety of wage inequality dynamics across countries.

There are four parts in the paper: The first step is to present a model which can frame both, the technology change and the technology choice hypothesis. The model is found in section 2. In essence, it is a dynamic extention of the model by Caselli and Coleman (2006).

The second step is to propose an empirical identification strategy to calibrate the theoretical model. The key challenge is determining how to econometrically distinguish the effect of technology choices from the effect of directed technological change. The idea to isolate the two is based on the presumption that the change of the nature of the technology platform must have global consequences (at least if we focus on developed countries). In turn, the technology choice hypothesis involves changes in skill premium as a response to changes in the conditions of local labour market (i.e. the local relative supply of skilled labour). As a result, the technology choice hypothesis predicts an increase in the skill wage premium above the average international

[2]The endogenous technology choice hypothesis appeared in labour economic literature: Peri (2009) uses the hypothesis to explain why immigration has a negative impact on skill-bias of technology and subsequently a very modest effect on low-skilled labour wages in the United States. Caselli and Coleman (2006), who found a positive correlation between the level of country GDP and skill bias of technology, argue that it can be driven by the fact that less developed countries have a higher share of low-skilled labour and thus firms in these countries choose the non skilll-biased technologies (they propose a formal model to describe this argument - the model is used as a basis for the dynamic model presented in section 2). However, to the knowledge of the author, no study has used the hypothesis to explain the dynamics in college wage premium in the second half of 20th century.

increase in countries that have also experienced an above average increase in the skilled labour supply. I devise an empirical model that exploits the cross-section and time-series variation in the data to calibrate the theoretical model. The results implies that approximately one third of the skill premium increase across OECD countries can be explained with the endogenous technology choice hypothesis, while the remaining two third can be exaplined by the skill-biased change in the nature of GPT.

The identification strategy, designed originally for calibration purposes, has in fact uncovered an interesting regularity in the data. The regression results imply that in the period 1970-2005 countries that did experience increases in skilled-labour supply higher than other countries have also witnessed larger increases in skill premium. The coefficient is statistically significant and predicts a 0.22% increase in skill premium after a 1% increase in relative skill supply. This result is interesting on its own and certainly deserves a further investigation. In section 4 I pursue an exploratory econometric analysis. In the empirical section I find that the result is unlikely to be driven by trends in globalization, the fall of trade unions or institutional differences between countries. Finally, I show that reverse causality, if present, should bias the coefficient downward. The endogenous technology choice at a national level is therefore left as the most plausible explanation for the result.

However, there might be other mechanisms that offer similar predictions. I present and formally describe two such mechanisms: the spillover effect (higher density of skilled labour helps each skilled worker to utilize the technology and thus increase her productivity) and the incentive for adoption of ICT effect (more skilled workers implies firms have more incentive to adopt the ICT technology, which is skill biased by nature). I argue that each of these hypothesis is not plausible separately, however, they might compliment well with the endogenous technology choice effect.

Interestingly the effect of lagged skill supply on skill premium starts to vanish at the beginning of the 21st century. I present three possible explanations for this observation: first, as explained in the theoretical section, a delayed response of skill premium to skill supply will take place only if the shock to supply of skills was unanticipated. This could have been true in the 70s, but it becomes less likely in the 90s. The second possible reason is that over time, the labour market between countries became more integrated. Under the mobility of skills, we would expect the skill premium to become more exogenous, less responsive to local demographics and more dependent on global factors. The last reason could be that adjustment of technological choices is easiest to be performed duirng a time of a major technological change - such as a diffusion of information and communication technology in the 80s. Putting this last hypothesis in the context of previous discussion, possibly global technological change is necessary to grease endogenous technological choices.

In the appendix, I return to discussing the theoretical foundations of the endogenous technology choice. The heart of the hypothesis is the presence (at any point in time) of a tradeoff: firms might choose between technologies that assign higher productivity to skilled workers and those that assign higher productivity to unskilled workers. The derivation of this tradeoff is therefore vital for the entire model. In the appendix, I demonstrate how the R&D process in which researchers invent a finite number of production processes might generate the trade-off between two types of technologies.

2 Endogenous Technology Choice Model

In this section, I present a simple dynamic model [3] which illustrates how the labour supply might affect the endogenous technological choice and further, the skill premium. The model sets the basis for the empirical framework introduced in the next section.

Consider an economy with one final product. Suppose that a given technology platform offers a menu of production methods for generating this product, each of them utilizing two inputs - skilled and unskilled labour - but each of them characterized by different productivity parameters. In particular, suppose that production methods i in the menu offered by the platform is characterized with the following production function:

$$F_i = [(A_{is}L_s)^\sigma + (A_{iu}L_u)^\sigma]^{\frac{1}{\sigma}} \tag{1}$$

where L_s and L_u stand for skilled and unskilled labour inputs, and A_{is} and A_{iu} are the productivity parameters for the two types of labour associated with production method i. Apart from choosing the quantities of labour inputs, the firm can also choose a technology from the menu. The menu of production methods is determined by the current GPT (technology platform) and is described by the set of pairs (A_{is}, A_{iu}) that satisfies

$$\frac{1}{\gamma}A_{is}^\omega + A_{iu}^\omega \leq B \tag{2}$$

Since every production method is fully characterized by the (A_{is}, A_{iu}) pair, it can be represented as a point in the A_s, A_u space. Further, the menu of technologies offered by the technology platform may be represented by the set of points satisfying (2). Figure 1 gives two examples of such sets differing in the values of γ.

The key point to be noticed in the figure is that given technology platforms, the firms face a tradeoff between technologies that give highly productive roles to skilled workers and those that assign a highly productive role to unskilled workers.

For simplicity of the argument in the above model, the trade-off between the two productivity parameters at the frontier is explicitly imposed although there are various models in which it will come up naturally. One way to generate the trade-off is to introduce in the model the costs of the adoption of technologies for the firms (in terms of units of their final output). The more advanced the technology it aims to adopt, the higher is the cost of adoption. Suppose there are two types of machines, each assisting different type of labour. Adopting advancements in the machines that assist skilled workers and in the machines that assist unskilled workers has different cost: $\frac{c}{\gamma}$ and c respectively. The firm optimization problem can then be stated as:

$$\max_{L_s, L_u, A_s, A_u} [(A_sL_s)^\sigma + (A_uL_u)^\sigma]^{\frac{1}{\sigma}} - w_sL_s - w_uL_u - \frac{c}{\gamma}A_s^\omega - cA_u^\omega$$

The firm will therefore face the trade-off - it might spend less on the unskilled dimension of the technology but advance more on the skilled dimension of the technology, or vice versa. The trade-off will be rulled by the relative cost of adoption parameter γ. The model in this version is elaborated further in the appendix in the subsection A1.1.

[3] The model presented here is a dynamic extention of the model by Caselli and Coleman (2006)

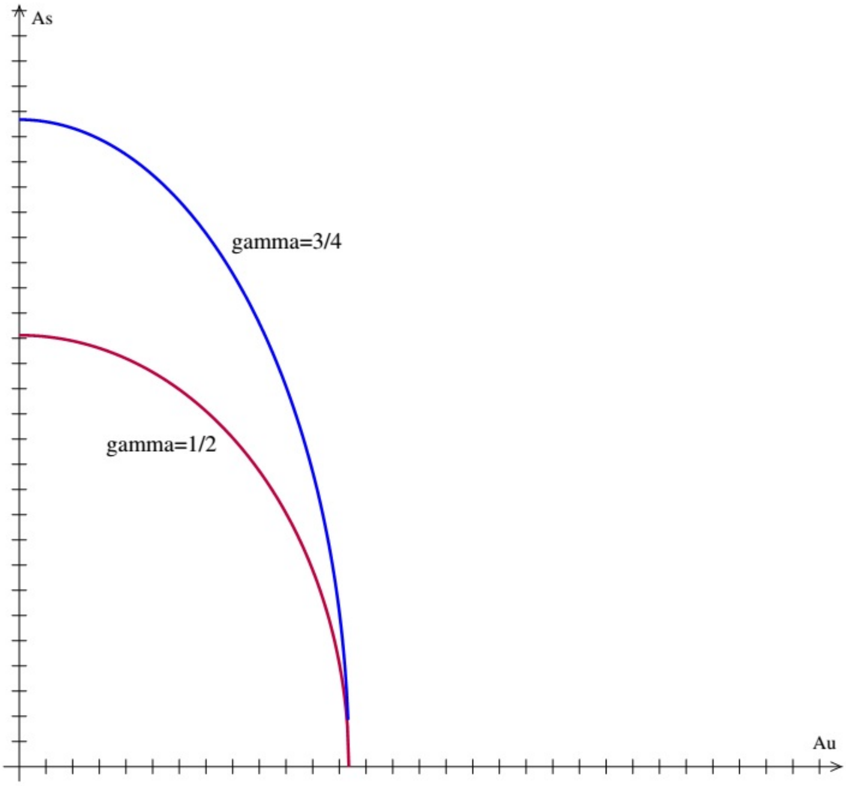

Figure 1: Production methods menu for two different values of gamma.

2.1 Characterization of the equilibrium

The introduction of new GPT (or technology platform) will involve the changes in γ and B parameters and thus the change of the menu of available production methods. If the technology platform becomes more skill-biased, it will offer opportunities of production methods that make very good use of a skilled worker. In the framework presented above, this will involve appearance of possibilities to choose production functions with very high productivity parameters for high-skilled workers. We can capture it in the model as an increase in the γ parameter. Figure 2 illustrates how the menu of available (A_{is}, A_{iu}) pairs changes when the platform becomes more skill-biased (i.e. γ rises).

Since dynamics play important role in the empirical analysis, we shall incorporate them in the theoretical model. I assume that firms cannot immediately switch technology in response to changes in labour market conditions. This reflects the fact that firms first have to spot the change in the labour market, then they have to develop a new strategy, replace the technology (perhaps by replacing capital goods) and train workers until the new production method operates at its full potential. Therefore, I assume that firms can choose technology only for the next period - the current technology of the firm was determined one period before.

The firm's value function is then:

$$V(A_s, A_u, L_s, L_u) =$$
$$\max_{A'_s, A'_u, L_s, L_u} \left\{ [(A_s L_s)^\sigma + (A_u L_u)^\sigma]^{\frac{1}{\sigma}} - w_u L_u - w_s L_s + \beta E\left[V\left(A'_s, A'_u, L'_s, L'_u\right)\right] \right\}$$

subject to $\frac{1}{\gamma} A'^{\omega}_{is} + A'^{\omega}_{u} \leq B$. x' denotes the value of the variable x next period. The first-order conditions for technology choices are

$$\frac{dE\left[V\left(A'_s, A'_u, L'_s, L'_u\right)\right]}{dA'_s} = \lambda \frac{1}{\gamma} \omega A'^{\omega-1}_s$$

$$\frac{dE\left[V\left(A'_s, A'_u, L'_s, L'_u\right)\right]}{dA'_u} = \lambda \omega A'^{\omega-1}_u$$

and the envelope conditions are

$$\frac{dV\left(A_s, A_u, L_s, L_u\right)}{dA_s} = \beta\left[\left(A_s L_s\right)^\sigma + \left(A_u L_u\right)^\sigma\right]^{\frac{1}{\sigma}-1}\left(A_s L_s\right)^{\sigma-1} L_s$$

$$\frac{dV\left(A_s, A_u, L_s, L_u\right)}{dA_s} = \beta\left[\left(A_s L_s\right)^\sigma + \left(A_u L_u\right)^\sigma\right]^{\frac{1}{\sigma}-1}\left(A_u L_u\right)^{\sigma-1} L_u$$

Combining all the above conditions:

$$\frac{E\left[\left[\left(A'_s L'_s\right)^\sigma + \left(A'_u L'_u\right)^\sigma\right]^{\frac{1}{\sigma}-1}\left(A'_s L'_s\right)^{\sigma-1} L'_s\right]}{E\left[\left[\left(A'_s L'_s\right)^\sigma + \left(A'_u L'_u\right)^\sigma\right]^{\frac{1}{\sigma}-1}\left(A'_u L'_u\right)^{\sigma-1} L'_u\right]} = \frac{A'^{\omega-1}_s}{\gamma A'^{\omega-1}_u}$$

Log-linearizing and applying the approximation[4] $\log\left(E[x]\right) = E\left[\log\left(x\right)\right]$:

$$\log\left(\frac{A'_s}{A'_u}\right) = \frac{1}{\omega-\sigma}\log\left(\gamma\right) + \frac{\sigma}{\omega-\sigma} E\left[\log\left(\frac{L'_s}{L'_u}\right)\right]$$

This condition already reflects the fact that the higher the (expected) number of skilled workers is in the economy (relative to number of unskilled), the more skilled-biased technology will be chosen by the firm.

If we combine this result with the first-order conditions for labour choices, we find that

$$\log\left(\frac{w_s}{w_u}\right)\Big|_t = -\left(1-\sigma\right)\log\left(\frac{L_s}{L_u}\right)\Big|_t + \sigma\log\left(\frac{A_s}{A_u}\right)\Big|_t =$$

$$-\left(1-\sigma\right)\log\left(\frac{L_s}{L_u}\right)\Big|_t + \frac{\sigma}{\omega-\sigma}\log\left(\gamma\right)\Big|_{t-1} + \frac{\sigma^2}{\omega-\sigma} E_{t-1}\left[\log\left(\frac{L_s}{L_u}\right)\Big|_t\right]$$

The first term is the standard effect associated with diminishing returns to each type of labour: if we increase the number of skilled workers (relative to unskilled), the skilled workers will become (relatively) less productive and earn smaller skill premiums.

The second effect is associated with exogenous change in the nature of the technology platform: If the technology platform becomes more skill-biased (γ increases), the menu of available production methods will

[4]This approximation is correct if the variance of the relative supply of skilled labour, $\log\left(\frac{L_s}{L_u}\right)$, is small and firms before time t do not expect any rapid changes in relative skilled labour supply. If we focus on the optimization problem of firms in the early 70s, this is exactly what would be expected: until then the number of skilled workers grew steadily in a constant trend, and the deviations from this trend were marginal. At the beginning of the 70ss firms could have believed the variance of relative skilled labour is very low. Later, it turned out that they were wrong, since the supply growth increased. The unexpected change in the variation is important for the identification, as explained later, in section 3.1.

now include numerous production processes that involve a high productivity of skilled workers. The firms will respond to this change in opportunities with a shift of opimal production method choices towards the ones that favour skilled workers. This will in turn increase their relative productivity and skill premium.

Finally, the third term captures the key mechanism of the endogenous technology choice hypothesis: a higher (expected) number of skilled workers gives an incentive for firms to choose the production method that fits skilled workers better. As a result, their relative productivity increases and so does the skill premium.

To close the model we should model the supply side of the labour market. For simplicity of the analysis, I assume that the relative supply of skilled workers is exogenous and follows a random walk with drift process:

$$\log\left(\frac{L_s}{L_u}\right)\bigg|_t = \log\left(\frac{L_s}{L_u}\right)\bigg|_{t-1} + \mu + \xi_t$$

where ξ_t is an iid disturbance term. The assumption on the exogeneity of the skills supply is discussed in the empirical section.

We could also model firms' expectations about next period's relative supply of skilled labour. Given that relative supply of skills follows a random walk with drift, firms base their expectations on the current relative supply of skills:

$$E_{t-1}\left[\log\left(\frac{L_s}{L_u}\right)\bigg|_t\right] = \log\left(\frac{L_s}{L_u}\right)\bigg|_{t-1} + \mu$$

Collecting all these conditions, we find that the equilibrium skill wage premium is determined as:

$$\log\left(\frac{w_s}{w_u}\right)\bigg|_t = -(1-\sigma)\log\left(\frac{L_s}{L_u}\right)\bigg|_t + \frac{\sigma}{\omega-\sigma}\log(\gamma)\bigg|_{t-1} + \\ + \frac{\sigma^2}{\omega-\sigma}\left(\log\left(\frac{L_s}{L_u}\right)\bigg|_{t-1} + \mu\right) \quad (3)$$

The skill wage premium depends therefore on the exogenous changes in current relative supply of skilled labour, the skill-bias of the global technological platform and last period relative supply of skills, since the latter was used by the firms' last period to form predictions about the current relative supply of skills. The relative supply of skills at time t, $\log\left(\frac{L_s}{L_u}\right)\big|_t$ is going to be correlated with firms' prediction, $\left[\log\left(\frac{L_s}{L_u}\right)\big|_{t-1} + \mu\right]$. The size of the correlation depends on the size of the unexpected shock to the relative supply of skills, ξ_t.

3 Calibration of the Model

In this section, I design and estimate the empirical model to determine the extent to which new technology choices (motivated by a skilled labour supply increase) could have contributed to the overall increase in skill premium. In section 4 I investigate whether there is evidence for the causal impact of the relative skill supply on national-level technology choices and thus on the skill premium.

The empirical model can be directly derived from equation (3). The equation is restated below:

$$\log\left(\frac{w_s}{w_u}\right)\bigg|_t = -(1-\sigma)\log\left(\frac{L_s}{L_u}\right)\bigg|_t + \frac{\sigma}{\omega-\sigma}\log(\gamma)\bigg|_{t-1} +$$

$$+\frac{\sigma^2}{\omega-\sigma}\left(\log\left(\frac{L_s}{L_u}\right)\Big|_{t-1}+\mu\right) \tag{4}$$

3.1 Identification

The callibration of this model involves two identification problems: first, we have to isolate the effect of the actual increase in the relative skills supply (the first term in the equation above will decrease skill premium due to diminishing returns to skilled labour) and the effect of the expected increase in the relative skills supply (the last term in the equation above will increase the college wage premium as firms wish to adjust their technology choices based on a higher expected number of skilled workers). If the expectation is exactly the same as the actual change, the identification of the two effects would not be possible. According to the model, the firms, however, cannot perfectly forecast the future supply of skills, and this fact can be exploited for the identification.

Notice that if this assumption is violated and firms were able to forecast the supply of skills for next decade, then the coefficient on past supply of skills will be equal to zero, even if firms do adjust their technology choices. In this case, the regression coefficient will underestimate the role of endogenous technology choices in shaping wage inequality dynamics.

The second identification problem is to isolate changes in the global technological platform from new choices of technologies driven by the increasing number of skilled workers. For this purpose, we are going utilize the fact that the growth in the number of skilled workers varied across countries. Thus we can use a cross-section of the data to isolate the role of technology choices from the role of global technological change. The assumption that is required for identification is that, within OECD, all countries face the same technology platform – i.e. that access to all available production methods is free among all developed countries. Therefore, the parameter γ will be considered as global and will be indexed by the time but not by the country index. [5]

The model should take into account that some countries might have traditionally different productivities of skilled and unskilled labour, perhaps due to the differences in educational systems and the skilled workers' productivity, relative to unskilled workers' productivity in some countries is lower than in others. To account for this fact, I include country fixed effects in the empirical model.

The above observations and assumptions forms the following empirical model:

$$w_{it} = \alpha_1 l_{it} + \alpha_2 l_{it-5} + \alpha_3 l_{it-10} + d_t + c_i + \varepsilon_{it}$$

where $w_{it} = \log\left(\frac{w_s}{w_u}\right)$, $l_{it} = \log\left(\frac{L_s}{L_u}\right)$ in country i at time t and d_t and c_i are time and country fixed effects. [6].

Because the country fixed effect might be potentially correlated with skills supply (e.g. a more egalitarian

[5] In fact the assumption might be much less restrictive: countries technology platforms might be characterized (see equation (2)) by different B parameter (thus we allow some countries to have higher overall productivity). Furthermore given that the estimation uses a first difference regression (as described later) at any moment of time the countries might face different γ parameter (that captures the skill-bias of technological platform, the menu of available production methods, see equation (2)). In fact the only restriction needed is that the change of γ parameter should be uncorrelated with the country growth of relative skills supply.

[6] I use both, five and ten years lags since it is difficult to assume apriori how long is the adjustment time for technology

education system that decreases the skill premium might also discourage higher education, affecting the skills supply), it might potentially bias the estimates. One way to remove this problem is to look at the above equation through first differences:

$$\triangle w_{it} = \alpha_1 \triangle l_{it} + \alpha_2 \triangle l_{it-5} + \alpha_3 \triangle l_{it-10} + \hat{d}_t + \triangle \varepsilon_{it} \tag{5}$$

Perhaps we can gain an additional clarity if the above equation is rearranged into:

$$(\triangle w_{it} - \triangle w_t) = \alpha_1 (\triangle l_{it} - \triangle l_t) + \alpha_2 (\triangle l_{it-5} - \triangle l_{t-5})$$
$$+\alpha_3 (\triangle l_{it-10} - \triangle l_{t-10}) + \triangle \epsilon_{it}$$

where b_t is the cross-country average of variable b at time t and $\epsilon_{it} = \varepsilon_{it} - \varepsilon_t$.

Therefore, the effect that we actually meassure with the coefficients α_2 and α_3 is the impact of the deviation of skill supply growth from the average international growth on the deviation of the growth in college wage premium from its globally-observed growth. Putting it differently, we can examine if countries that experienced growth in the number of college graduates higher than that of other countries also experienced higher growth of college wage premiums a decade later. If this did occur, there must be some country-level mechanism that generates this dependence. In this section, I will attribute this dependence to endogenous technology choices. The estimation of the parameters will therefore serve to determine a possibility result on how large the role of the adjustment of technology choices in shaping the dynamics of wage inequality was.

In section 4, I will discuss other potential local-level mechanisms that could explain the dependence of skilled premium growth on past skill supply growth. However, it turns out that it is difficult to explain the result with any explanation other than the endogenous technology choice hypothesis.

3.2 Data

The source of the data is the EU KLEMS dataset, 2008 release, covering annual data between 1970 and 2005 for 23 countries (although the panel is not balanced). 2008 release is the last release of EU KLEMS that cotains panel data on total hours worked and total compensation for three groups of employees: highly-skilled (those with at least a tertiary education), medium-skilled (those with a secondary education) and low-skilled (those with at most a primary education)[7].

To simplify the analysis and maintain clarity I merge the low-skilled and medium skilled worker groups into one group of “unskilled” workers. Because the hours of medium-skilled work might be worth more than the hours of low-skilled work in the computation of unskilled labour supply, I use the standard approach to weight the medium-skilled workers’ hours by their productivity, relative to the low-skilled workers’ productivity. Hence unskilled labour supply is computed as $L_u = L_l + (w_m/w_l)L_m$. As a result, the labour supply of unskilled work is measured in terms of low-skilled hours equivalents.

To avoid potential problems with cyclicality, I use only the datapoints in 1970, 1975, 1980, 1985, 1990, 1995 and 2005 and meassure the differences over 5-year periods. Obviously the 5-year difference is effectively an

[7]the WIOD dataset provides data on hours and compensations by education group for the period from 1995 to 2009. I decided not to merge the two datasets because there are significant differences between the data in the overlapping period 1995-2005.

	(1)	(2)	(3)
skills supply growth {t}	-0.804***	-0.825***	-0.803***
	(0.125)	(0.133)	(0.126)
skills supply growth {t-5}	-0.255*	-0.224	-0.253*
	(0.144)	(0.154)	(0.145)
skills supply growth {t-10}	0.218**	0.217**	0.225**
	(0.09)	(0.097)	(0.092)
d85		-0.006	
		(0.05)	
d90		-0.03	
		(0.048)	
d95		0.013	
		(0.038)	
d00		0.013	
		(0.037)	
year			0.001
			(0.002)
constant	0.167***	0.163***	-1.466
	(0.026)	(0.033)	(4.181)
Rsquare:	0.5803	0.5887	0.5816

Table 1: The dependent variable is five years change of college wage premium (in logs). The independent variables are the 5 year change in the ratio of college graduates to remaining part of labour force (in logs), its 5 and 10 years lags and dummy variables for each year (or linear trend). All estimations comes from Random Effect regressions.

average of the annual differences in a 5-year period.

3.3 Regression Results

The results from the random effect regression are presented in table 1, column 2. As predicted by the model, the coefficient on the current change in skills supply is negative; this reflects the diminishing returns to skilled labour. The effect is substantial (the 10% increase in relative skill supply is associated with the 8% drop in skill premium), though very close to the estimates obtained by Katz and Murphy (1992) in the similar regression of the skill premium series on the skill supply series using US data. Nevertheless, as mentioned above, this result should not be taken as a causal effect due to the likely reverse causality.

The results also show a significant positive effect of past increases in the relative supply of skilled labour. The effect is also substantial in economic terms: a 10% increase in the relative skill supply involves a 2.2% increase in the skill premium. Interestingly, the time needed for the change in relative labour supply to be reflected in the change in skill premium is rather long: the coefficient is positive and significant only for the relative skill supply lagged by 10 years. The coefficient on the five year lag is not significantly different from zero and in fact negative.

An important remark on the regression result is a warning that the positive coefficient on the lagged skill supply *does not* imply that the increased supply of skills brings in the long run an increase in skill premium. If we take the Katz and Murphy estimates of the slope of demand (reconfirmed later by the more careful instrumental variable estimates in Ciccone and Peri (2005) and by the results of regression in Table 1), an increase in relative skill supply leads first to an approximately 7% drop in skill premium. If we use estimates from the regression results, we will expect the skill premium to rebound in a decade and increase by approximately 2%. This means that the initial level of skill premium will not be restored, and the long run effect of skill supply on skill premium will be a 5% drop.

At this stage we can calibrate the model from section 2 and calculate the contribution of an endogenous technology choice in the total increase in skill premium. Since a number of countries do not have observations before 1980, I will consider the period of 1990-2005. Over these 15 years, the relative skill supply in 12 OECD countries (that have data for entire period) increased by 32%. Using Katz and Murphy estimates of demand curve, that should translate into an 18% drop in skill premium. Instead, the skill premium in this period increased by 28%. This leaves a 56% of unexplained wage increase (0.193 log points). In the period of 1980-1995, the relative skills supply increased by 90%. This, according to the model and the estimates above, should lead to a 15% (0.062 log points) increase in skill premium due to the endogenous technology choice between 1990 and 2005. The residual increase left is then 35% (0.131 log points), which can be probably attributed to skill-biased technology changes. This leads to the conclusion that endogenous technology choice can explain 32% (0.062 out of 0.193 log points) of the increase in skill premium that could not be explained in the standard demand-supply (Katz and Murphy model) framework.

4 Empirical Investigation

The empirical results presented above indicate that skill premium dynamics are not explained solely by global factors (such as the nature of general purpose technology), but are also shaped by mechanisms operating in local labour markets. For some readers, the observation that countries which experienced a higher growth of skill premium have also witnessed a higher growth of skill supply a decade earlier could be the most interesting result of this paper. In section 2, I have shown one possible explanation for this correlation: changes in the labour market might change the optimal production method choice from the set of available technologies. In subsections 4.1 - 4.3, I present several alternative explanations, and I discuss whether they could be supported by the regression results. In subsection 4.4, I investigate whether the effect is stable over time. Interestingly, the correlation between the growth of skill premium and the lagged growth of skills supply weakens over time. I discuss several explanations for this finding.

4.1 Endogeneity

Operating in the context of labour market equilibrium, it is important to keep in mind that the relative productivity and relative wage will impact the relative skills supply. Although this should bias the estimated effect of the current skills supply on the current skill premium, it is not obvious why it would drive a correlation between *past* skill supply and *current* skill premium. It is not likely that workers can predict that the growth of college wage premiums in their country will be higher than in other countries in a decade. Second, even if they could predict this, it is not obvious why the *change* in relative skill supply should depend on the growth of the college wage premium a decade later. If workers who consider attending college in 1990 predict that in their countries the college premiums will grow substantially, they may be more keen to attend college. However, the same is true for workers in 1985 and earlier.

However, the endogeneity could bias the results if the error terms in the regression are serially correlated. Suppose that one country experienced an exogenous positive shock that increased the skill premium both in the 70s and 80s. Since the change in skill supply may depend on the current changes in skill premium, a country will witness an increase in skills in the 70s. Hence the same exogenous shock could lead to skills accumulation in the 70s and skill-premium growth in the 80s.

To illustrate this logic more formally, assume that the innovation for the *level* of skill wage premium (in deviation from the international level) follows the IMA(1,1) process:

$$w_{it} - w_t = X\alpha + \epsilon_{it}$$

where X is the set of controls in the regresssion and

$$\epsilon_{it} = \eta_{it} + \beta\eta_{it-10} + \epsilon_{it-10}$$

It follows that the change in the innovation can be expressed as:

$$\Delta\epsilon_{it} = \eta_{it} + \beta\eta_{it-10} \tag{6}$$

The source of the upward bias of the results might be the MA component in the innovation in the skill premium. The MA components are associated with the factors that impact the increase (or decrease) of the skill premium (relative to an international increase) over the 5 year period (the time period of the observation). This might be due to a change in the labour or tax policies or a change in the education system that leaves a permament impact on the skill premium. Most of these factors are unlikely to lead to a further increase in skill premium a decade later (it is difficult to imagine a tax policy reform that would lead to an increase of the skill premium in the 80s and another increase in the 90s). The exceptions might be globalization and a decreasing importance of trade unions (we could imagine globalization or trade unions collapse will lead to an increase in the college wage premium over 20-30 years).

The differences in exposure to globalization across countries could indeed be a factor that explains the result: countries that quickly becomes exposed to globalization might experience a quicker growth of demand for educated workers. This will encourage more workers to become skilled. If in the next decade the same country continues to become exposed to globalization more than other countries, the demand for educated workers might shift further, increasing the skill premium. This would generate a spurious correlation between an increase of the college premium today and growth of the college workforce ten years ago. To control for the change in exposure to globalization, I include in the regression the change of the ratio of export to GDP. The results are reported in the second column (regression number (4)) in Table 2. The positive coefficient on the past growth of the skill supply remains significant. Furthermore, it appears that once the past growths of the skill supply are controlled for, the increase in export to GDP ratio has no effect on the change in the skill premium. Although not reported in the table, I have also included the level (rather than growth) of the ratio of export to GDP. Again, this does not affect the results.

Another possibility is that the results are driven by the collapse of trade-unions: if the number of unskilled workers drops significantly, this might undermine the bargaining power of trade-unions and lead to an increase in wage inequality. Moreover, this effect is likely to be delayed. Nevertheless, inclusion of the change in trade union density does not change the results, as reported in the second column (regression number (4)) of Table 2. It seems that trade unions do not have a significant impact on the college wage premium in OECD countries.

	(2)	(4)	(5)	(6)
skills supply growth {t}	-0.825***	-0.822***	-0.793***	-0.786***
	(0.133)	(0.138)	(0.132)	(0.137)
skills supply growth {t-5}	-0.224	-0.222	-0.242	-0.242
	(0.154)	(0.158)	(0.151)	(0.155)
skills supply growth {t-10}	0.217**	0.213**	0.191**	0.183*
	(0.097)	(0.101)	(0.096)	(0.1)
d85	-0.006	-0.007	-0.018	-0.021
	(0.05)	(0.052)	(0.05)	(0.051)
d90	-0.03	-0.028	-0.034	-0.031
	(0.048)	(0.052)	(0.048)	(0.051)
d95	0.013	0.015	-0.001	0.000
	(0.038)	(0.042)	(0.038)	(0.042)
d00	0.013	0.013	0.006	0.003
	(0.037)	(0.043)	(0.036)	(0.042)
supply of skills (level)			-0.041*	-0.042*
			(0.024)	(0.025)
change in union density		-0.034		-0.053
		(0.145)		(0.142)
change in export to gdp ratio		-0.006		0.004
		(0.089)		(0.087)
constant	0.163***	0.161***	0.274***	0.272***
	(0.033)	(0.036)	(0.072)	(0.075)
Rsquare:	0.5887	0.5894	0.6143	0.6156

Table 2: The dependent variable is the five-year change of the college wage premium (in logs). The independent variables are the 5-year change in the ratio of college graduates to the remainder of the labour force (in logs), its 5- and 10- year lags, dummy variables for each year, the proportion of skilled labour in total labour (lagged 10 years), 5- year change in ratio of exports to GDP (in logs), and 5- year change in trade union density (in logs). All estimations come from random effect regressions.

The argument that the results are unlikely to be biased by the autocorrelation of changes in the college wage premium also comes from the the inspection of the data. In almost all countries, the period of raising the relative skill supply comes first, and only after certain time can the beginning of an upward trend in skill premium be seen.

Another possibility is that the result is driven by the differences in the potency to adopt ICT across countries. Specifically, countries which experienced high growth of skilled labour a decade earlier are able to faster adopt new technologies which happened to be skill-biased. A large change in the skill supply results in a higher stock of skilled labour, including engineers and scientists. This might translate into a higher capacity to adopt technologies that were just developed - like the ICT in the 80s. If the new technologies are (by nature) skill-biased, a higher increase in skill premium in these countries will be observed.

To check for this possibility, we can include in the regression a control for the stock of highly-skilled labour (total hours worked) 10 years ago [8]. The column (5) in Table 2 shows that inclusion of this control does not change the results significantly - the effect of a change in the skill supply on the change in the skill premium is still siginificant at the 5% confidence level, and the coefficient has dropped marginally to 0.19. The

[8] the lag seems to be necessary since we need to allow a time before the decision to adopt a new technology and a point at which the effect of adoption will be reflected in wage data

regression shows also that the stock of skilled labour does not matter for the increase in the skill premium. The coefficient is significant only at a 10% level, and in fact it is negative. Almost exactly the same results are obtained if instead of controlling for the stock of skilled labour lagged 10 years, I control for the stock lagged 5 years and 15 years.

4.2 Spillover effect

The presence of spillover might be responsible for translating a higher skill supply into a higher skill premium. Suppose that how well a skilled worker uses a technology depends on how many other skilled workers are around. This might be because operating the technology requires a certain degree of experimentation, and sharing experience can facilitate the process and improve the outcome.

An illustrative example of such system of information exchange (although in the context of depeloped countries) is presented in the work of Bandiera and Rasul (2006). They studied the adoption of new crop varieties (a newly introduced technology) among farmers in Northern Mozambique and found that the output of the farmer depends crucially on the interaction with other farmers.

The effect does not have to be immediate - indeed it could be expected to take time before new workers establish connections with the old ones, before they trust each other, find a common language and learn how to utilize each other's experiences. Therefore, I would predict that the increase in the skilled workers supply first drives down their productivity due to diminishing returns to skills, but after a while the additional workers might contribute in knowledge sharing and increase the productivity of every skilled worker. Thus, the spillover effect can explain the pattern observed in the data.

To illustrate this line of thought, one might consider a formal model that includes the spillover effect. The productivity of skilled workers (how well they utilize the technology that is devoted to them) depends positively on the density of skilled workers in the economy, which is approximated with the ratio $\frac{L_s}{L_u}$ [9]. With the amended production function, the profit maximization for the firm i in country j is then:

$$\max_{L_{ijs}, L_{iju}} P_{ij} \left[\left(\left(\frac{L_{js}}{L_{ju}} \right)^{\beta} A_{is} L_{ijs} \right)^{\sigma} + \left(A_{iju} L_{iju} \right)^{\sigma} \right]^{\frac{1}{\sigma}} - w_{js} L_{ijs} - w_{ju} L_{iju}$$

The combination of the two first-order conditions then gives:

$$\left(\frac{L_{ijs}}{L_{iju}} \right)^{\sigma - 1} \left(\frac{L_{js}}{L_{ju}} \right)^{\sigma\beta} \left(\frac{A_{ijs}}{A_{iju}} \right)^{\sigma} = \frac{w_{js}}{w_{ju}}$$

And denoting $l_{ij} = \log \left(\frac{L_{ijs}}{L_{iju}} \right)$, $l_j = \log \left(\frac{L_{js}}{L_{ju}} \right)$, $a_{ij} = \log \left(\frac{A_{ijs}}{A_{iju}} \right)$ and $w_j = \log \left(\frac{w_{js}}{w_{ju}} \right)$:

$$(\sigma - 1)\, l_{ij} + \sigma\beta l_j + \sigma a_{ij} = w_j$$

Adding the time indices (that take into account that the effect of spillover is not immediate):

$$(\sigma - 1)\, l_{it} + \sigma\beta l_{jt-1} + \sigma a_{ijt} = w_t \tag{7}$$

[9] I do not include a similar effect for unskilled workers since spillover in their case is less likely. Nevertheless, inclusion of spillover for unskilled workers would not change the result.

If firms are symmetric in the sense that they face the same a_{ijt} and the same p_{ijt}, then the firm indices can be dropped:

$$(\sigma-1)\, l_{jt} + \sigma\beta l_{jt-1} + \sigma a_{jt} = w_{jt}$$

Therefore, the spillover model predicts that, following the increase in the relative skill supply, the drop of the skill premium due to diminishing returns to the skill supply is first observed; later, its increase is observed, due to the spillover effect.

The problem with this hypothesis is that it cannot explain the long time lag (10 years) between changes in skill supply and changes in skill premium. Although, as argued before, establishing connections and learning how to share experiences might take some time, it is not plausible that some part of this effect would not be observed in five years. Yet, the data show no positive dependence of the skill premium on relatvie skills lagged five years.

The spillover effect might however play an important role if it is augmented with the endogenous technology choice effect: suppose that the firm knows about the spillover effects and it knows that a higher number of skilled workers implies that new technology directed to skilled workers will be used more efficiently. This creates additional incentive for the firm to shift towards such technology. More formally, this logic can be placed in the model that follows.

The line of the logic is best protrayed in the version of the model in which the firm has to pay (in the units of its final output) for the adoption of technology. Moreover, the adoption of the technology that assists skilled workers and the adoption of the technology that assists unskilled workers have different costs: $\frac{c}{\gamma}$ and c respectively. Then, the profit maximization is given by:

$$\max_{L_{ijs},L_{iju},A_{ijs},A_{iju}} \left[\left(\left(\frac{L_{js}}{L_{ju}}\right)^{\beta} A_{ijs}L_{ijs}\right)^{\sigma} + \left(A_{iju}L_{iju}\right)^{\sigma}\right]^{\frac{1}{\sigma}}$$
$$-w_{js}L_{ijs} - w_{ju}L_{iju} - \frac{c}{\gamma}A_{ijs}^{\omega} - cA_{iju}^{\omega}$$

Combining two first-order conditions with respect to A_{ijs} and A_{iju}, we obtain:

$$\left(\frac{A_{ijs}}{A_{iju}}\right)^{\sigma-1}\left(\frac{L_{ijs}}{L_{iju}}\right)^{\sigma}\left(\frac{L_{js}}{L_{ju}}\right)^{\sigma\beta} = \frac{1}{\gamma}\left(\frac{A_{ijs}}{A_{iju}}\right)^{\omega-1}$$

Again changing the notation, as above, and adding the time indices[10]:

$$(\sigma-1)\, a_{ijt} + \sigma l_{ijt-2} + \sigma\beta l_{jt-2} = -\ln\left(\gamma_{t-2}\right) + (\omega-1)\, a_{ijt}$$

Rearranging:

$$a_{ijt} = \frac{\ln\left(\gamma_{t-2}\right) + \sigma l_{ijt-2} + \sigma\beta l_{jt-2}}{(\omega-\sigma)} \tag{8}$$

and referring back to the first condition (7):

[10]The choice of production method is based on the information from two periods back.

$$(\sigma-1)\,l_{ijt}+\sigma\beta l_{jt-1}+\sigma\frac{\ln(\gamma_{t-2})+\sigma l_{ijt-2}+\sigma\beta l_{jt-2}}{(\omega-\sigma)}=w_{jt}$$

$$(\sigma-1)\,l_{ijt}+\sigma\beta l_{jt-1}+\frac{\sigma}{\omega-\sigma}\ln(\gamma_{t-2})+\frac{\sigma^2}{\omega-\sigma}l_{ijt-2}+\frac{\beta\sigma^2}{\omega-\sigma}l_{jt-2}=w_{jt}$$

Dropping the firm indices in the equilibrium (however, not merging the terms in order to ease interpretation):

$$(\sigma-1)\,l_{jt}+\sigma\beta l_{jt-1}+\frac{\sigma}{\omega-\sigma}\ln(\gamma_{t-2})+\frac{\sigma^2}{\omega-\sigma}l_{jt-2}+\frac{\beta\sigma^2}{\omega-\sigma}l_{jt-2}=w_{jt}$$

As in the previous model (without the endogenous choice of technology), there is a direct effect of spillover on skill premium (represented in the second term) taking place after first period (that may be 5 years). However, if β is small, this effect may be very limited and even improperly reflected in the data. In addition to the direct effect, the spillover also has an indirect effect: since the returns to investing in the skill-biased technology depends positively on how well this technology is utilized and this depends in turn on the density of skilled workers, the increase in the relative skill supply will incentivise firms to invest more in skill-biased technology, thus providing an additional factor that shifts the skill premium. However, this effect will be introduced only in the second period since two periods are required before the firm spots the increase in the relative skill supply and then implements the new technology. Moreover, the indirect effect of spillover (through incentivising a skill-biased technology choice) might be stronger than the direct effect. If ω is not large and σ is not too far from unity, the effect of spillover might appear only after second period.

4.3 Endogenous adoption of skill-biased technology.

Suppose that the technology choice mechanism does not work, and each technological paradigm offers only one new production method and firms cannot choose between various production methods). Now imagine that new technology paradigm (e.g. information and communication technology) and the (single) production method it offers guarantees higher productivity for both skilled and unskilled workers; however, compared to the previous technology it is clearly skill-biased in the sense that it benefits skilled workers much more than the unskilled. Suppose that the adoption of this technology is very costly (e.g. involves temporary loss of overall productivity) and not all countries want to immediately jump to the new production methods. One would expect that the first countries to adopt the new technology (and consequently move to a higher skill-premium) were the countries that can benefit most, i.e. those with a high stock of skilled labour. This could potentially explain the empirical results: countries with a high growth of skilled labour supply could have accumulated a high stock of skills. Those countries would adopt the new, skill-biased production method more rapidly and thus increase their skill-premium more than other countries.

Furthermore, the story may be continued beyond the first two periods: next period, another new technology (even more skill-biased) may appear and again countries that will adopt it first will be those with the biggest stock of skilled workers.

This hypothesis is in fact testable: it would imply that the skill premium increase should depend positively not only on the growth of skill supply but also on the level of skill supply. Yet, this is disproved by the regression in column (5) of Table 2: there is no evidence that such positive association exist. The hypothesis would not be also able to explain the experience of Korea, which has reported a decline of relative skill supply and a decline of skill premium.

Nevertheless, elements of these mechanisms can be incorporated into the endogenous technology choice model. It may be that the new technology platform offers a range of production methods that boost skilled workers' productivity and only a few methods that improve unskilled workers' productivity (in the mode,l this is simply captured by the increase in γ and modest increase in B) - indeed, it is very likely in case of ICT. All countries in such case will shift towards more skill-biased technologies. However, the countries that have large numbers of skilled workers and which before and after the change were operating relatively skill-biased technologies will witness a large jump away from the old technology (since there are so many new opportunities in the corner for skill-biased technologies) and, analogously, will experience a high degree of adoption of new technology. Conversely, countries that had a high number of unskilled workers, and which always positioned themselves at the unskilled corner of technolgy choices, will only move slightly away from their previous positions (although they might move towards more skill-biased technologies, they will still remain closer to the corner of unskill-biased technologies where not many new opportunities had been offered by the new technology platform).

Yet, the model does not predict the effect of the stock of skills on the change in skill premium - this is because countries with high stocks of skilled workers were already using more skill-biased technology; therefore, if the technology platform nature becomes more skill-biased itself, this will not have a higher effect on skill premium in these countries than in any other countries.

4.3.1 Stability of the effect

Interestingly, the positive effect of the supply of skills on future skill premiums seems to be diminishing in recent decades. Column (8) in Table 3 reports the results of the regression if the observations for years 2000 and 2005 are excluded. Comparing these results to the original regression (column (2) in Table 3) indicates that the coefficient on lagged growth of skills supply has almost doubled. If in addition observations for year 1995 are excluded, the coefficient increases further. In column (7), I also report the regression (for the full sample) which includes an interaction between lagged growth of skills supply and the time trend. The interaction term is negative and highly significant.

There are three possible explanations for these observations: first, as explained in the theoretical section, a delayed response of the skill premium to the skill supply will take place only if the shock to the supply of skills was unanticipated. This could have been true in the 70s, but it becomes less likely in 90s. The second possible reason is that over time, the labour market between countries became more integrated. Under mobility of skills, skill premium would be expected to become more exogenous, less responsive to local demographics and more dependent on global factors. The last reason could be that the adjustment of technological choices is easiest to be performed during a time of a major technological change - like a diffusion of information and communication technology in the 80s. Putting this last hypothesis in the context of the previous discussion, possibly global technological change is necessary to grease endogenous technological choices.

	full sample (2)	full sample (7)	before 2000 (8)	before 1995 (9)
skills supply growth {t}	-0.825***	-0.679***	-0.874***	-0.729*
	(0.133)	(.108	(0.139)	(0.387)
skills supply growth {t-5}	-0.224	-0.313***	-0.132	-0.103
	(0.154)	(0.122	(0.236)	(0.547)
skills supply growth {t-10}	0.217**	83.598***	0.415***	0.461**
	(0.097)	(15.617)	(0.106)	(0.236)
d85	-0.006	-0.214***	-0.05	-0.016
	(0.05)	(0.056)	(0.035)	(0.071)
d90	-0.03	-0.134***	-0.053	
	(0.048)	(0.043)	(0.035)	
d95	0.013	-0.054*		
	(0.038)	(0.032)		
d00	0.013	-0.015		
	(0.037)	(0.029)		
skills growth {t-10} X year		-0.042***		
		(0.008)		
constant	0.163***	0.241***	0.126***	0.035
	(0.033)	(0.03)	(0.030)	(0.073)
Rsquare	0.5887	0.7504	0.8458	0.7747

Table 3: The dependent variable is a five-year change of the college wage premium (in logs). The independent variables are the 5-year change in the ratio of college graduates to remained of the labour force (in logs), its 5- and 10- year lags, dummy variables for each year, and the interaction term for the interaction between the time trend and the 5-year change in the ratio of college graduates to remained of the labour force lagged 10 years (in logs). All estimations come from random effect regressions.

5 Concluding Remarks and Policy Implications

The purpose of this paper was to decompose the increase in the college premium growth across OECD countries into the growth caused by global forces (such as skill-biased changes in the global technological paradigm, the new ICT) and the growth driven by local (national-level) forces related to the supply of the college workforce. I propose an empirical model which uses both the cross-section and the cross-time variation in the data to separate global from local factors. I find that countries with a higher growth of the college workforce experience a substantially higher college wage premium growth a decade later. Given that the independent variable of interest is lagged ten years, it is unlikely that the result is driven by reverse causality. The results of the regression which includes various control variables suggest that the dependence is not caused by a decreasing importance of trade unions, globalization forces, or the endogenous adoption of ICT technology. In this light, the most plausible candidate to explain this result is the endogeneity technology choice: if the number of college workers increases, firms have an incentive to choose the production methods (technologies) that are better suited for skilled workers. This, after some time, drives up the demand for educated workers and thus leads to an increase in the college wage premium. Using the results of the regression, I might conclude that a national-level mechanism driven by the supply of skilled workers (most likely endogenous technology choice at the local level) can explain 30% of the increase of the college premium in OECD countries.

To draw a policy implication, I need to consider all effects predicted by the model. The framework presented in section 1.2 (and supported by empirical evidence from section 1.3) predicts that the increase in the college workforce will first lead to the fall of the college wage premium (due to diminishing returns to skilled labour) and later (approximately in a decade) to its growth (due to the fact that technology choices of firms will be adjusted to a higher supply of skilled workers). The latter growth will be smaller than the initial drop, thus the net effect of the college workers' supply on their relative wages will be negative.

One important lesson policy makers can learn from the model is that a negative effect of the increase of the skill supply on wage inequality is smaller than predicted by the previous studies based solely on the short-term analysis. The second implication is that any unexpected increase in the college workforce will produce a substantial fluctuation of the college wage premium (it will first drop, then grow later). Such fluctuations might lead to suboptimal educational choices of workers. A suggestion for the policymakers might be therefore to implement policies increasing the number of college graduates gradually rather than rapidly.

In the theoretical part I explore the microeconomic foundations of the endogenous technology choice. The heart of the hypothesis is the presence (at any point in time) of a tradeoff: firms might choose between technologies that assign higher productivity to skilled workers and those that assign higher productivity to unskilled workers. The derivation of this tradeoff is therefore vital for entire model. I present a model that demonstrates how the R&D process in which researchers invent a finite number of production processes might generate the trade-off between two types of technologies.

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APPENDIX: Tradeoff in Production Methods Menu.

In this section, I elaborate in more detail the ideas drafted in section 1.2.1 - I present and formally discuss two arguments on why the tradeoff between technologies that assign high productivity to skilled workers and technologies that assign high productivity to unskilled workers can be expected. The first argument is based on the presumption that the adoption of each technology might be costly - a firm might not find it optimal to adopt technologies that increase productivity of unskilled workers if there are very few unskilled workers. The second argument is that the random nature of production method discoveries might generate the trade-off itself. Both arguments are described with formal models.

A1.1. Costly adoption

One implicit, though potentially problematic, assumption in the analysis presented so far is that technology is taken to be a single object associated with some productivities for skilled and unskilled workers. Instead, in the real world, technologies devoted to skilled workers and technologies devoted to unskilled workers might exist separately. Mathematically, this would imply that each technology is no longer characterized by a vector (A_s, A_u), but by scalars: technologies for skilled workers are characterized by scalar A_s, technologies for unskilled workers are characterized by a scalar A_u. In such case, firms will simply take the best technology available for skilled workers (buy the fastest available PCs, apply best practices for HR management etc., i.e. maximize A_s) and take the best available technology for unskilled workers (purchase the most productive machines, apply best practices in production line organization etc. i.e., maximize A_u). Why would the purchase of better computers necessarily involve a necessity to use poorer production machinery?

Such trade-off might arise if firms face adoption costs. Suppose that the more advanced the technology is that the firm aims to adopt, the higher the cost of adoption. Moreover, progressing on the advancement of technologies devoted to skilled workers and technologies devoted to unskilled have different costs: $\frac{c}{\gamma}$ and c respectively. The firm's optimization problem can then be stated as:

$$\max_{L_{is}, L_{iu}, A_{is}, A_{iu}} [(A_{is}L_{is})^{\sigma} + (A_{iu}L_{iu})^{\sigma}]^{\frac{1}{\sigma}} - w_s L_{is} - w_u L_{iu} - \frac{c}{\gamma} A_{is}^{\omega} - c A_{iu}^{\omega}$$

subject to $A_s \leq \bar{A_s}$ and $A_u \leq \bar{A_u}$ where $\bar{A_s}$ and $\bar{A_u}$ are the frontier technologies.

Of course firms might hit the frontier for both technologies. However, if the costs are high enough, this will not happen and firms will not find it optimal to adopt technologies that increase productivity of unskilled workers if there are very few unskilled workers. In fact, if a firm is not choosing frontier technologies, the first order condition will be exactly the same as before, with γ ruling the tradeoff between the optimal choices of A_s and A_u.

Another possibility is that firms face the credit constraints for adoption of technologies. In such a scenario, a firm's optimization will be given by

$$\max_{L_{is}, L_{iu}, A_{is}, A_{iu}} [(A_{is}L_{is})^{\sigma} + (A_{iu}L_{iu})^{\sigma}]^{\frac{1}{\sigma}} - w_s L_{is} - w_u L_{iu} - \frac{c}{\gamma} A_{is}^{\omega} - c A_{iu}^{\omega}$$

subject to $A_s \leq \bar{A_s}$ and $A_u \leq \bar{A_u}$ and $\frac{c}{\gamma} A_{is}^{\omega} + c A_{iu}^{\omega} \leq B$, where B is the borrowing constraint for the firm. As long as B is not high enough, the firm will not be able to adopt the best technologies for either skilled and unskilled workers, and it will face a tradeoff between investing in the two types of technologies. In such case, the first-order conditions will be exactly the same as before.

A1.2. Random Discoveries

The purpose of this subsection is to demonstrate that if one is ready to assume that each technology is associated with a pair of productivities: for skilled and unskilled workers (rather than some technologies determining technologies for skilled workers and other technologies ruling productivity of unskilled workers), then the tradeoff can be derived easily by allowing these pairs to be random draws from a bivariate distribution. A similar framework in the context of capital-augmenting and labour-augmenting technology parameters has been proposed by Jones (2005) and developed in Growiec (2008, 2013).

Before proceeding, I should first consider if the assumption of a single technology for both unskilled and skilled workers is defendable. It is hard to justify the assumption if the roles of skilled and unskilled workers are clearly defined and separated and when technologies are only used to help workers perform their duties better. Two types of technologies would probably be observed - one devoted to skilled workers and one devoted to unskilled workers - and the two types are unlikely to be negatively correlated.

However, what happens if the roles of unskilled and skilled workers are not independent of technology? If technology (especially if it is defined broadly, including management strategies and organization of production) itself determines the roles and their division between two types of workers, it has to be treated as a unitary object - firms cannot choose technologies for skilled and unskilled workers separately and independently.

The logic above suggests that if the tasks of workers are predefined and technology determines the division of these tasks between skilled and unskilled workers, the trade-off between skill-biased and unskill-biased technologies appears immediately: firms have to decide to adopt technology where skilled workers assist unskilled workers (key roles in production go to the unskilled) or the technology with unskilled workers assisting the skilled (the key roles go to skilled). However, what if the set of roles is not predetermined but defined by technology? The technology might determine the duties for skilled workers independently of duties for unskilled. The model below captures this idea and shows how random generation of technology might explain the trade-off that is essential for the endogenous technology choice hypothesis.

Imagine a Central Science University that has just devised a new civilizational milestone (such as steam power, semi-conductors, or radioactive decay). The finding has been passed to Central Engineering University, which will try to determine how to combine the new scientific disovery and two types of labour inputs to generate a final good. In fact, they might have various ideas on how to do it, and each idea will involve some degree to which the newly discovered law of nature can compliment the work of skilled and unskilled humans. Thus each idea can be represented with the production function (1) with parameters (A_{is}, A_{iu}).

How the ideas look (what are the pairs (A_{is}, A_{iu}) that engineers could come up with) depends partly on chance and partly on the nature of the fundamental scientific discovery made in Central Science University. Therefore, one might think about each idea, or rather a pair (A_{is}, A_{iu}), that characterizes it as a draw from the bivariate distribution whose parameters depend on the nature of discovery (some fundamental scientific discoveries might be skill-biased by nature in the sense that the explored law of nature compliments ideally with the effort of educated workers - then engineers have much higher chances of discovering production methods with very high A_s). Engineers have n ideas and thus n production methods (with n associated

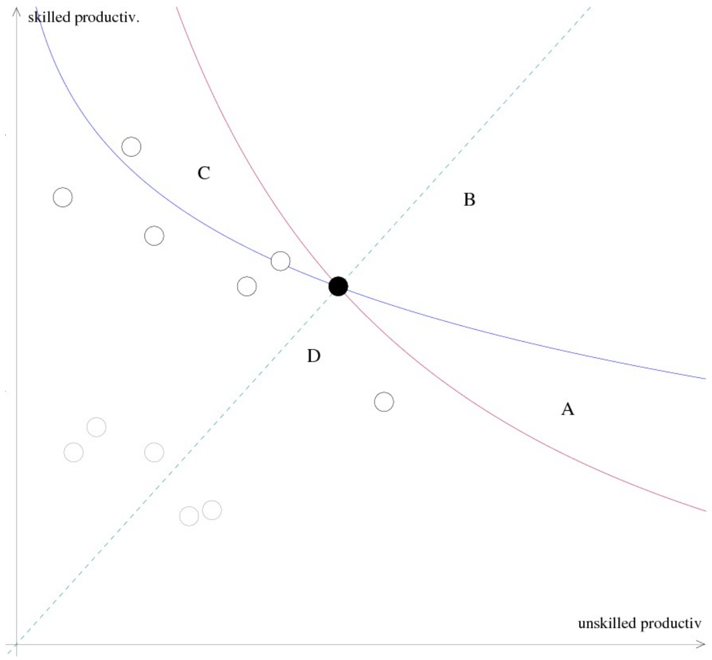


Figure 2: Optimal Choices of Technologies under changing relative supply of skills

(A_{is}, A_{iu}) pairs) appear as possibilities to be picked up by firms.

As in the other parts of the paper, the production function is assumed to take a CES from for all available technologies:

$$F_i = [(A_{is}L_s)^\sigma + (A_{iu}L_u)^\sigma]^{\frac{1}{\sigma}}$$

Suppose that it is known that a representative firm uses the technology represented by a solid point on Figure 3. An isoquant going through this point indicates that in areas A and B there must not be any available technology (otherwise firm did not choose the optimal technology). Suppose now that the skilled and unskilled labour supply has changed - in particular relative to the number of unskilled workers the number of skilled workers has increased. This makes the isoquant flatter, as illustrated on the graph. I know for certain that a firm will not jump to technologies in areas A and B because there are no available technologies there. It also do not choose technology from area D because it is suboptimal - it is better to stay with the current technology (represented with a solid dot). The only possibility is then that a firm might find other available technologies in area C - then it will decide to shift. There will be no jump to the technologies that lay below the dotted line. The proposition follows:

Proposition 1. Upon a relative increase in the supply of one of the types of labour, the representative firm will never jump to technologies that disfavour this type of labour.

In fact we can tell much more about the changes of optimal choices of the company if we consider a particular bivariate distribution of technologies. We might assume that this distribution is a bivariate normal distribution with no correlation between A_s and A_u (to form a production method engineer first draws A_s from a normal distribution, then draw A_u from another normal distribution (but independent of the value of the first draw) and then puts the two draws together). With this assumption, another proposition can be developed:

Proposition 2. If a pair (A_s, A_u) is drawn from the bivariate normal distribution with no correlation between

A_s and A_u, then the most likely ex ante (i.e. before the realization of the draws) choice of technology (the mode of the optimal technology choice distribution) has to satisfy:

$$\log\left(\frac{A_s}{A_u}\right) = \frac{1}{2-\sigma}\log(\gamma) + \frac{\sigma}{2-\sigma}\log\left(\frac{L_s}{L_u}\right)$$

Proof: With the bivariate normal distribution with no correlation the equidensity contours in the (A_s, A_u) space takes the form $A_s^2 + \gamma A_u^2 = B$. Each contour is associated with some density level π (i.e. if point (A_s, A_u) lays on the contour k, the probability (or probability density) that a random draw from the distribution will be (A_h, A_l) is equal to π^k)

Suppose that there are n independent draws of inventions (and so n points (A_s, A_u) a firm can select from). Each draw will be indexed by i. Further, let $F^j = \left(\left(A_s^i L_s^j\right)^\sigma + \left(A_u^i L_u^j\right)^\sigma\right)^{1/\sigma}$ be the output of firm j if it picks the draw i.

Take any point in the (A_s, A_u) space, call it point P. The probability (or probability density) that this point ex-ante (before the realization of the draws) is the optimal point for firm j is given by the probability that the first draw happens to be at point P multiplied by the probability that the first draw is optimal for firm j among all the other draws plus the probability that the second draw will happens to be at point P multiplied by the probability that the second draw is best etc.

$$\Pr\left(\left(A_s^P, A_u^P\right) \text{ is selected by country } j\right) =$$

$$= \sum_i \Pr\left(\left(A_s^i, A_u^i\right) = \left(A_s^P, A_u^P\right)\right) *$$

$$*\Pr\left(\left(A_s^P, A_u^P\right) \text{ is optimal for } j \text{among all the draws}\right)$$

If the point $\left(A_s^P, A_u^P\right)$ lays on the contour k then probability that a draw is exactly equal to $\left(A_s^P, A_u^P\right)$ is given by π^k . The probability that draw i is optimal for country j among all the other draws is in turn equal to probability that the use of any other technologies that popped out will give smaller output:

$$\Pr\left(\left(A_s^P, A_u^P\right) \text{ is optimal for } j \text{among all the draws}\right) =$$

$$= \prod_{s \neq i} \Pr\left(F^j\left(A_s^s, A_u^s\right) < F^j\left(A_s^P, A_u^P\right)\right)$$

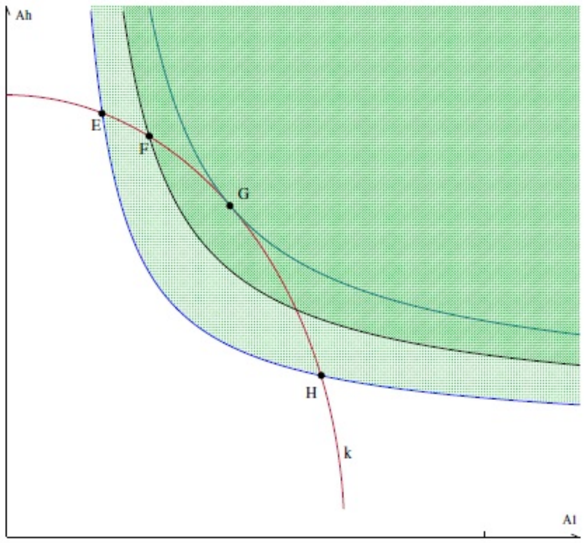
Now consider particular point E that lays on the contour k depicted on figure 4. Probability that a draw happens to be exactly at point E is π^k. Probability that this draw is the best option among all the other draws is the probability that no other draw appears in the shaded area above the isoquant passing through point E - if it does, then selection of that alternative draw (and the associated production function) would result in a higher output and selection of point E would be suboptimal. Observe that point H has exactly the same probability that it will appear as an optimum as point E: it lays on the same contour k and it has exactly the same probability that no other draw will give higher output (i.e. the probability that the shaded area remains empty). Now notice that if we consider any point on the contour k between points E and H, say point F, again they have exactly the same probability they will be drawn in one of the draws (they lay on the same contour) but they have strictly higher probability that no other draw will give higher output. This is because and isoquants.jpg and isoquants.bb 

Figure 3: Derivation of density distribution of optimal technology choices

the probability that there exist other draw that will give better output than point F is the probability that this draw will appear in the double shaded area. This area is strictly contained within the single shaded area. Thus the probability that poin E is outperformed has to be higher than the probability that point F is outperformed. The only point on the contour k that for which we cannot find a point with higher probability of being and optimum (among other points on contour k) is point of tangency of the contour with the isoquant. Therefore point G has the maximum probability of being chosen among all the points on contour.

A simple algebra - analogous to the one from Caselli and Coleman model - shows that the point of tangency between equidensity contours and isoquants has to satisfy

$$\left(\frac{A_h}{A_l}\right)^{2-\sigma} = \gamma \left(\frac{L_h}{L_l}\right)^{\sigma}$$

Notice that this condition does not depend on which contour we consider. This means that the mode - the point in (A_h, A_l) space that is most likely to be selected has to satisfy this condition. The condition might be rearranged to the form in the proposition. □

Now consider a bivariate distribution of optimal choices of technologies (ex ante - i.e. before we know which technologies are available to firms). Since proposition 1 tells us that none of the firms will move towards technologies disfavouring skilled workers after they became more numerous (relative to unskilled) and proposition 2 tells us that at least some mass of the distribution of optimal technology choices has to move towards choices that favour more abundant factor we arrive to the final proposition of the paper:

Proposition 3. Consider a bivariate distribution of optimal choices of technologies (ex ante - i.e. before we know which technologies are available to firms). The expected optimal choice must shift towards more skill-biased technologies after an increase in the supply of skilled labour

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