WPS8474

Policy Research Working Paper 8474

Automation and Labor Market Outcomes

The Pivotal Role of High-Quality Education

Raja Bentaouet Kattan
Kevin Macdonald
Harry Anthony Patrinos

WORLD BANK GROUP
Education Global Practice
June 2018

Abstract

Automation will be a boon or a catastrophe depending on whom you listen to. This paper proposes an overlapping-generations model with endogenous school choice in which the quality of a country's education system determines how well skill supply can respond to increased demand from automation and subsequently whether automation will be beneficial or detrimental. In this sense, education quality in the model offers a bridge between the optimistic and pessimistic perspectives on automation. In testing the model's assumptions, the paper finds evidence that educational attainment, cognitive skills, and select noncognitive skills are associated with avoiding automation-prone occupations. Consistent with the model's predictions, census data indicate that countries have historically relied most on these types of occupations at middle-income status. The model and empirical findings suggest that it is middle-income countries that are most vulnerable to automation if their education systems are unable to affect cognitive and noncognitive skills sufficiently. As a result, automation may herald a much different growth model for developing countries: one in which developing these skills is central.

This paper is a product of the Education Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/research. The authors may be contacted at hpatrinos@worldbank.org.

Produced by the Research Support Team

Automation and Labor Market Outcomes: The Pivotal Role of High-Quality Education

Raja Bentaouet Kattan

Kevin Macdonald[1]

Harry Anthony Patrinos

JEL codes: E24, J24, J31, J62, O15, O33

Keywords: Automation, skill-biased technological change, overlapping-generations model

[1] We acknowledge the support of the Korea-World Bank Partnership Facility. We are grateful to Amer Hasan and Andrew Mason for their thoughtful comments and ideas.

INTRODUCTION

Automation, robotics and artificial intelligence will solve all our problems – or end the human race, depending on whom you listen to (Ray Kurzweil (2005) or Stephen Hawking (Cellan-Jones 2014)). Sometime soon, machine intelligence is predicted to surpass human intelligence, a point in time known as "the singularity." Whether the rise of the machines is an existential threat to humankind or not, there is a more mundane issue: robotics are being used to automate production. There are already more than 300,000 industrial robots in operation in Japan and another 200,000 in North America (Hagerty 2015). Brynjolfsson and McAfee (2014) suggest that as computers get more powerful, companies have less need for some kinds of workers. Freeman (2015) argues that robots can be a substitute for even highly skilled professionals. The idea that automation leads to a life of leisure took on new meaning when several jurisdictions started to experiment with basic guaranteed income programs. One of the issues raised is that automation will take so many jobs that too many people will be rendered unemployable. Rather than reduce productivity, the argument is to pay everyone a guaranteed minimum wage because of higher productivity from increased automation. Hawaii, Ontario and India are considering universal basic income programs following trials in Finland, Germany, Kenya, the Netherlands, Scotland, Uganda and the United States (Kentish 2017; Roberts 2017; McFarland 2017; Chapman 2017).

The range of tasks that computers are expected to be able accomplish in the near future has changed considerably since Autor, Levy and Murnane's (2003) routine versus non-routine dichotomy. Computers approach problems in much different ways than humans, for example, by calculating all possible chess move permutations, or learning by using pattern detection in massive data sets (Susskind 2017). Given current trends in machine learning and artificial intelligence, researchers generally point to three types of skills that humans need in order to retain an advantage over and complement technology: (1) social intelligence; (2) creativity; and (3) perception or advanced pattern recognition (Frey and Osborne 2013; Brynjolfsson and McAfee 2011, 2014).

Based on the expected capabilities of machines, many studies have tried to estimate the percent of workers that may be substituted by automation, but these estimates vary considerably, depending on methodology. Elliott (2017) estimates that 62 percent of workers in OECD countries use skills that computers are close to replicating. Frey and Osborne (2013) estimate that 47 percent of U.S. employment is at high risk of automation in the coming decades. Deloitte (2014) finds that 35 percent of workers are in occupations at high risk of automation in the U.K. Manyika (2017) finds that few occupations are fully automatable; about 60 percent of occupations have at least 30 percent of activities that could be automated. Arntz, Gregory and Zierahn (2016) find that only 9 percent of U.S. workers are at high risk of being displaced by automation. For developing countries, Chang and Huynh (2016) estimate the percent of workers in occupations at high risk of automation in East Asian developing countries ranges from 44 percent in Thailand to 70 percent in Vietnam; Asian Development Bank (2015) estimates that a substantially lower proportion are at risk. Hallward-Driemeier and Nayyar (2018:135) applying the method by Arntz, Gregory and Zierahn (2016) estimate 2 to 8 percent of workers are at high risk in low and middle-income countries.

The implications of technology more generally for employment have been studied extensively in the economics literature. This work is motivated by the reduction of the labor share in the U.S. and European labor markets (Karabarbounis and Neiman 2014; Oberfield and Raval 2014) as well as job polarization or the shift from mid-range wage employment to low and high range wage employment (Katz et al. 2006; Autor 2010; Autor and Dorn 2013; Beaudry et al. 2013; Goos et al. 2014). These outcomes are often attributed to skill-biased technological change (Katz and Murphy 1992; Acemoglu 2002); though, some attribute them to other factors including demographic change (Cortes, Jaimovich and Siu 2016) or institutions (Acemoglu and Robinson 2015; Berkowitz, Ma and Nishioka 2017). In developing countries, Maloney and Molina (2016) find little evidence of job polarization.

The "canonical model" of skill-biased technological change involves two labor inputs, low and high skill workers, with technology augmenting one of them (Acemoglu and Autor 2011). For example, if technology augments high-skill workers, then high-skill wages will rise relative to low-skill, and job polarization arises with the addition of a middle-skilled group. This canonical model motivates the pessimism about automation, with automation substituting low or middle skill workers and complementing high-skill workers (e.g., Hemous and Olsen 2014).

Of course, fear of technological change is not new. Frey and Osborne (2013) cite Queen Elizabeth, the first to be concerned that a frame knitting machine would displace knitters' employment. Many would argue that we have historically benefited from technological change, and several models have been proposed in which automation is beneficial and does not perpetuate wage inequality or eliminate employment for low skill individuals (Autor, Levy and Murnane 2003; Acemoglu, Gancia and Zilibotti 2010; Acemoglu and Restrepo 2017).

A key difference between models in which automation and technology are beneficial and those in which they are detrimental is the endogenous shift of individuals from less technology-complementing to more technology-complementing labor categories. In the canonical model, individuals' skill types are innate, and there is generally no possibility for individuals to change their skill, but in Autor, Levy, and Murnane (2003), individuals are born with an innate advantage for task types but are able to shift between them. In Acemoglu, Grancia and Zilibotti (2010) and Acemoglu and Restrepo (2017), individuals' skill categories are innate but as new tasks are endogenously created, older tasks are shifted to lower skill individuals whose skills complement older tasks.

We propose an approach to bridge the optimistic and pessimistic perspectives on automation. In our model, individuals are born with heterogeneous innate ability that determines their skill category in the labor market, but they can attend school and increase their ability and ultimately their skill category. If schooling has a large enough impact on their ability, in other words, is high quality, then those individuals with a low innate ability are able to achieve a high-skill category. In this scenario, individuals can adjust their skills to meet increased demand for high-skill labor resulting in automation being beneficial. However, if schooling is low quality and has a low impact on ability, then it constrains the ability of individuals, especially with lower innate ability, to respond to increased demand for high skill labor. In this latter scenario, automation is detrimental.

We treat automation differently than skill-biased technological change. The difference with—and fear of—automation is that it is not only skill-biased, but it is also skill-replacing: there is some segment of the labor force that automation will render redundant. To capture this, automation in our model's production function reduces the marginal product of lesser-skilled labor while increasing the marginal product of high-skill labor, all things being equal. As a result, automation has a different effect on steady state outcomes than technological change in typical skill-biased technological change models.

The important role of education quality is motivated by education often being the prescribed remedy for automation (Brynjolfsson and McAfee 2011, 2014; Golden and Katz 2008). Given rapid adoption of computing technology in the past 40 years, global demand for education has remained strong with rates of return averaging 9-10 percent (Montenegro and Patrinos 2014; Psacharopoulos and Patrinos 2018), despite substantial increases educational attainment over this period (Barro and Lee 2013). Strong returns are attributed to both increased demand for skills but also restricted supply of quality education (Altinok, Angrist and Patrinos 2018).

Our paper offers several new theoretical and empirical contributions to the literature on the effects of automation on labor market outcomes. Theoretically, we show how, in a general equilibrium, overlapping-generations model, education quality can determine whether automation is beneficial or detrimental, helping to reconcile automation's optimism and pessimism. Second, we provide a definition of automation that differs from skill-biased technological change in an aggregate production function. Third, we show how countries in the midst of development may be most at risk to automation if their education quality is poor. Empirically, we establish the link between skills, educational attainment and the likelihood of an occupation being automated globally. Second, we show that middle income countries tend to have the highest proportion of labor in automation-prone occupations, corroborating our model's prediction. Coupled with evidence from international student assessments showing that low and middle-income countries generally have poor learning outcomes, our findings suggest that middle-income countries are most at-risk to automation. Finally, we show how vocational education programs that offer direct labor market entry while deemphasizing cognitive and non-cognitive skills are especially problematic with automation.

Our paper is structured as follows. We first present an overlapping-generations model in which schooling decisions are endogenous and describe the conditions which place economies at risk of being negatively affected by automation if education quality is poor. Our empirical application follows with a description of the data, methods and results. A discussion of the findings concludes.

THEORY AND MODEL

We develop a general equilibrium, overlapping-generations model with individuals with heterogeneous ability and endogenous schooling choices, drawing on Heckman, Lochner and Taber (1998a; 1998b; 1998c) and Ábrahám (2008). In the initial period, individuals choose their level of schooling which incurs both a direct cost and the opportunity cost of lost wages, but then they reap the rewards with higher earnings in the future. Production in our model arises from a low-productive informal sector that employs low-skill labor and from a high-productive formal sector that employs middle skill labor and high skill labor such that capital affects high-skill labor productivity more than middle-skill labor. The informal sector is a perfect substitute to the formal sector and represents the informal agriculture sector that is a substantial sector of employment in many developing countries. Agents are born with heterogeneous ability that determines their skill type; however, they can attend basic education for one period or higher education for two periods, to increase their ability and become higher skilled workers. Unlike typical technological change, automation reduces the contribution of middle skill labor in the formal sector. If production were fully automated, then middle-skill workers' marginal product is zero; they have no function in the economy as many fear. If schooling is high enough quality, then newly born labor can shift from low to medium to high skill as needed. In this case, automation has a positive effect on steady state output and wages because there is no constraint to skilled labor supply. If schooling is not of sufficient quality, then lower ability individuals who attend school will not graduate with high enough ability to enter the next level of skill category. In this case, the supply of skilled labor can be constrained, and automation can be detrimental to both overall output and low skill wages.

We use this model to study how automation can affect steady state outcomes for countries at different stages of development, derived from differing levels of exogenous capital stock. We define developed countries in our model as having virtually no informal employment while developing countries have a range of employment in the informal sector. This reflects the large proportion of informal workers in developing countries, especially in agriculture.

The model predicts that when skills are constrained by poor education quality, automation will decrease middle skill labor and increase low-skill, informal sector labor. This is a result of automation lowering the marginal product and wages of middle-skill labor; because of the skills constraint, equilibrium cannot be regained by middle-skill labor shifting to high-skill labor, it can only shift to low-skill labor. In this sense, automation reverses the process of development when skills are constrained. Second, if automation would have a positive effect on high-skill labor in absence of a skills constraint, then, with a skills constraint, automation lowers middle-skill wages. By assuming a constant elasticity of substitution production function, the model further predicts that, in economies with a large proportion of middle skill labor, automation reduces total output with a skills constraint and middle-skill wages. Finally, we show that developed countries, defined as those countries with no informal sector, will be less affected than developing countries. This is a result of (1) the informal sector in developing countries presenting a viable alternative to middle-skill labor which is not the case in developed countries and (2) of developing countries, especially those in the middle of development, relying more on middle-skill labor. A simulation of the model using specific functional forms and parameterization is presented which demonstrates that automation can have positive effects on steady state outcomes in absence of a skills constraint, but, with a skills constraint, negative outcomes result and countries close to the threshold of developed-country status are most negatively affected.

Model

Our model economy consists of four inputs to production at time, *t*: unskilled labor, $L_{0,t}$, middle-skilled labor, $L_{1,t}$, high-skilled labor, $L_{2,t}$, and a fixed physical capital stock, K. A single final good, Y_t is produced either directly by low skill labor, representing a low-productive, informal sector or by a formal sector incorporating capital, middle and high skill labor in production function, $Y_t(L_{0,t}, L_{1,t}, L_{2,t}, K)$. We assume the formal sector exhibits diminishing returns to labor, $\frac{\partial^2 Y_t}{\partial^2 L_{i,t}} < 0$ and some complementarity between inputs, $\frac{\partial^2 Y_t}{\partial K \partial L_{i,t}} > 0$, $\frac{\partial^2 Y_t}{\partial L_{j,t} \partial L_{i,t}} > 0$ for $i = 1,2$

and $j = 1,2, i \neq j$, and finally that the marginal product of low-skill labor is equal to β which is an arbitrarily small constant.

Agents live for *n* periods and are born at time *t* with innate ability, $\theta \sim f(\theta)$ with cumulative distribution, $F(\theta)$. In their first period, *t*, they choose a level of schooling, *S*, which can be zero periods (no schooling), one period (basic education) or two periods (higher education) in duration, after which they enter the labor market. One-period schooling increases skills by ϕ_1 and two-period education increases skills by $\phi_1 + \phi_2$. Individuals whose ability, after education, is below Θ_1 are considered as low-skill, between Θ_1 and Θ_2 as middle-skill, and above Θ_2 as high-skill. We assume, for simplicity, that parameters Θ_1, Θ_2, ϕ_1 and ϕ_2 are large enough such that everyone in the middle skill group attended at least 1-period education and everyone in the high skill group attended 2-period education. Wages are determined by the aggregate production function at time, *t*, as $w_{0,t}$, $w_{1,t}$ and $w_{2,t}$, for low, middle and high skill, respectively. Attending one-period education or two-period education incurs cost $c_1(\theta)$ or $c_2(\theta)$ in which costs decline with respect to innate skill level, θ. As there is no saving in this model, maximizing utility is equivalent to maximizing the present discounted value of future wages net of education costs, π_t. The agent's maximizing problem can be described as

$$\max_S \pi_t(S|\theta) = \begin{cases} \sum_{i=0}^{n-1} \delta^i w_{t+i}(\theta) & if\ S = 0 \\ \sum_{i=1}^{n-1} \delta^i w_{t+i}(\theta + \phi_1) - c_{1,t}(\theta) & if\ S = 1 \\ \sum_{i=2}^{n-1} \delta^i w_{t+i}(\theta + \phi_1 + \phi_2) \ - c_{2,t}(\theta) & if\ S = 2 \end{cases} \tag{1}$$

where,

$$w_t(\theta) = \begin{cases} w_{0,t} & if\ \theta \le \Theta_1 \\ w_{1,t} & if\ \theta \in (\Theta_1, \Theta_2) \\ w_{2,t} & if\ \theta \ge \Theta_2 \end{cases} \tag{2}$$

We normalize the number of agents being born at time *t* to 1, and the total population at any given time is *n*. If $U_{0,t}$ and $U_{2,t}$ are the proportions of agents choosing schooling 0 and 2, respectively, then the labor stocks at time *t* can be defined as

$$L_{0,t} = \sum_{i=0}^{n-1} U_{0,t-i}\,, \qquad L_{1,t} = \sum_{i=1}^{n-1} 1 - U_{0,t-i} - U_{2,t-i}\,, \qquad L_{2,t} = \sum_{i=2}^{n-1} U_{2,t-i} \tag{3}$$

Competitive equilibrium

The competitive equilibrium can be defined as an infinite set of wages, $\{\widehat{w}_{0,t}, \widehat{w}_{1,t}, \widehat{w}_{2,t}\}_{t=0}^{\infty}$, labor stocks, $\{\hat{L}_{0,t}, \hat{L}_{1,t}, \hat{L}_{2,t}\}_{t=0}^{\infty}$, and proportions of agents choosing schooling level 0 or 2, $\{\widehat{U}_{0,t}, \widehat{U}_{2,t}\}_{t=0}^{\infty}$. Wages, in equilibrium, are the marginal products of labor for the aggregate production function with $\widehat{w}_{1,t} = \frac{\partial Y_t}{\partial L_{1,t}}(\hat{L}_{0,t}, \hat{L}_{1,t}, \hat{L}_{2,t}, K)$, $\widehat{w}_{2,t} = \frac{\partial Y_t}{\partial L_{2,t}}(\hat{L}_{0,t}, \hat{L}_{1,t}, \hat{L}_{2,t}, K)$, and $\widehat{w}_{0,t} = \beta$.

From equation (1), an individual's choice of schooling is determined by his or her innate ability conditional on wages. Because schooling is costly, agents will not choose to pursue a level of schooling unless it increases their future wages. It follows that if $S(\theta) = 1$ then $\theta + \phi_1 > \Theta_1$, and if $S(\theta) = 2$, then $\theta + \phi_1 + \phi_2 \ge \Theta_2$. Define $\hat{\theta}_{ij,t}$ as cut-off points for ability where agents with a higher ability prefer schooling level *j* to *i*. In equilibrium, these are defined as

$$\hat{\theta}_{01,t} = max\left\{\theta_{01}: \hat{w}_{0,t} + c_1(\theta_{01}) = \sum_{i=1}^{n-1} \delta^i\left(\hat{w}_{1,t+i} - \hat{w}_{0,t+i}\right), \Theta_1 - \phi_1\right\}$$

$$\hat{\theta}_{12,t} = max\left\{\theta_{12} : \delta\hat{w}_{1,t} + c_2(\theta_{12}) - c_1(\theta_{12}) = \sum_{i=2}^{n-1} \delta^i\left(\hat{w}_{2,t+i} - \hat{w}_{1,t+i}\right), \Theta_2 - \phi_1 - \phi_2\right\} \tag{4}$$

$$\hat{\theta}_{02,t} = \theta_{02} :\ \hat{w}_{1,t} + \delta\hat{w}_{1,t+1} + c_2(\theta_{02}) = \sum_{i=2}^{n-1} \delta^i\left(\hat{w}_{2,t+i} - \hat{w}_{1,t+i}\right)$$

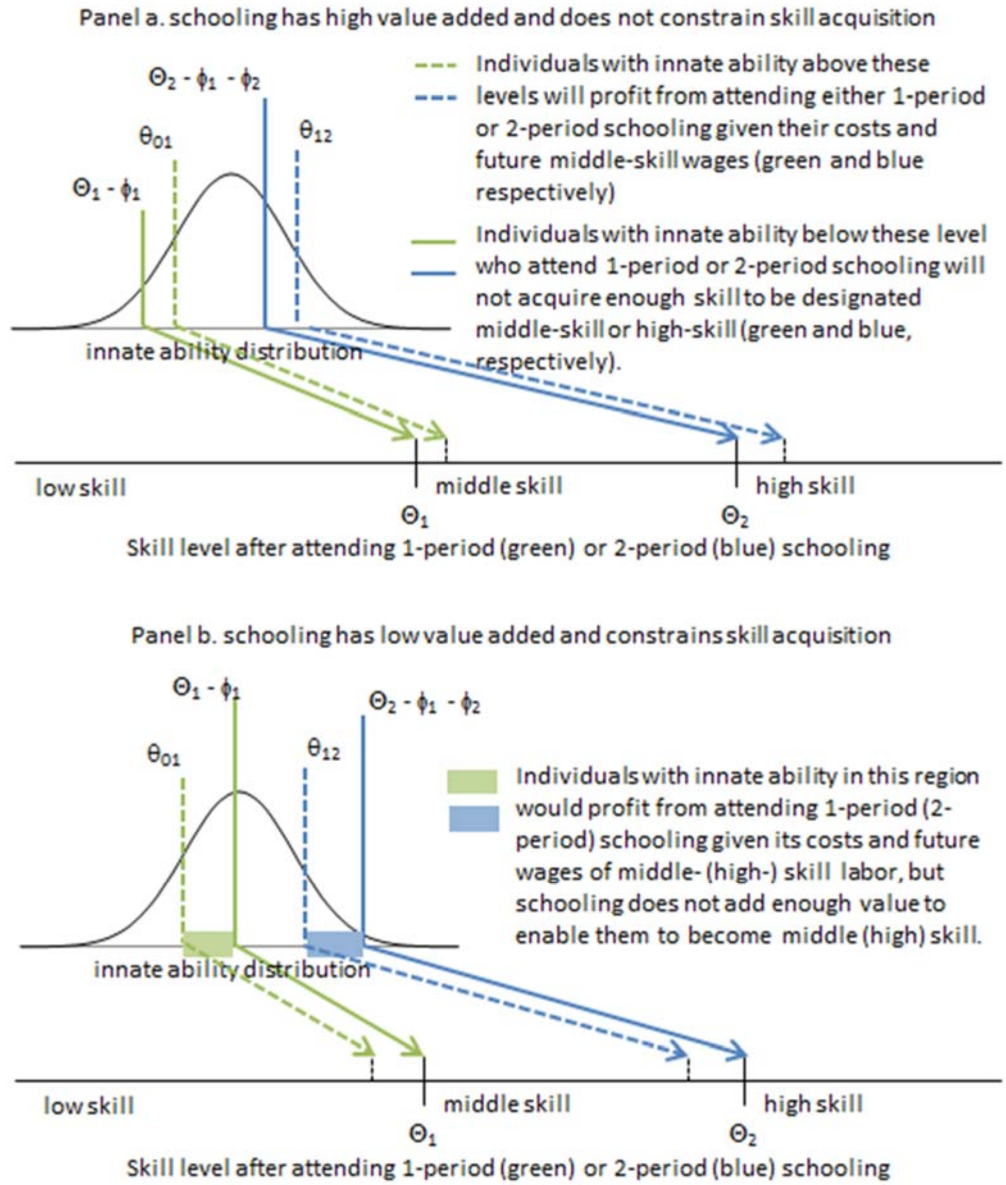
Note that $\Theta_1 - \phi_1$and $\Theta_2 - \phi_1 - \phi_2$ bind agents' schooling decisions; the net present value of future wages may exceed costs, but agents with abilities below these binds would not achieve the higher wages. We limit our analysis to plausible equilibria in which, in absence of these binds, solutions must satisfy $\hat{\theta}_{01,t} \leq \hat{\theta}_{02,t} \leq \hat{\theta}_{12,t}$. These are equilibria where the highest ability individuals would attain 2-period schooling, those with the lowest ability would attend no schooling, and those in between would attend 1-period schooling, in absence of any constraint from school quality. Figure 1 presents a graphical representation of educational choice.

The proportions of low and high skill laborers can then be defined as

$$\hat{U}_{0,t} = F\left(\hat{\theta}_{01,t}\right), \hat{U}_{2,t} = 1 - F\left(\hat{\theta}_{12,t}\right) \tag{5}$$

and the equilibrium labor stocks are defined as in equation (3). Finally, a law of motion can be defined implicitly for $\hat{\theta}_{01,t+1}$ and $\hat{\theta}_{12,t+1}$ given $\hat{\theta}_{01,t-2n+5}, \dots, \hat{\theta}_{01,t}$ and $\hat{\theta}_{12,t-2n+5}, \dots, \hat{\theta}_{12,t}$ as

Figure 1. Graphical depiction of schooling choice



$\hat{\theta}_{01,t+1}, \hat{\theta}_{12,t+1}$:

$$\hat{\theta}_{01,t-n+3} = max\left\{\theta_{01}: \hat{w}_{0,t-n+3} + c_1(\theta_{01}) = \sum_{i=1}^{n-1} \delta^i\left(\hat{w}_{1,t-n+3+i} - \hat{w}_{0,t-n+3+i}\right), \right.$$
$$\left. \Theta_1 - \phi_1 \right\}$$

(6)

$$\hat{\theta}_{12,t-n+3} = max\left\{\theta_{12} : \delta\hat{w}_{1,t-n+3} + c_2(\theta_{12}) - c_1(\theta_{12}) \right.$$
$$\left. = \sum_{i=2}^{n-1} \delta^i\left(\hat{w}_{2,t-n+3+i} - \hat{w}_{1,t-n+3+i}\right), \qquad \Theta_2 - \phi_1 - \phi_2 \right\}$$

Predictions

Our model enables us to study the effect of automation on steady state outcomes for countries with different levels of wealth by varying the capital stock, K. In absence of specific functional forms for production and education costs, a feature of our model is that if higher amounts of capital correspond to high amounts of high skill labor, L_2, then wealthier countries necessarily have lower levels of low skill, informal labor, L_0 (Proposition 1 in Annex 1). We define a "developed" country as having virtually no informal agricultural sector, $F(\theta_{01}) \approx 0$. An implication of this definition is that, among developed countries, wealthier countries are less middle-skill intensive; that is, the ratio between middle skill labor stock and high skill labor, $\frac{L_1}{L_2}$, declines as the capital stock increases in developed countries (Proposition 2). These characteristics of our model are discussed in the empirical section below.

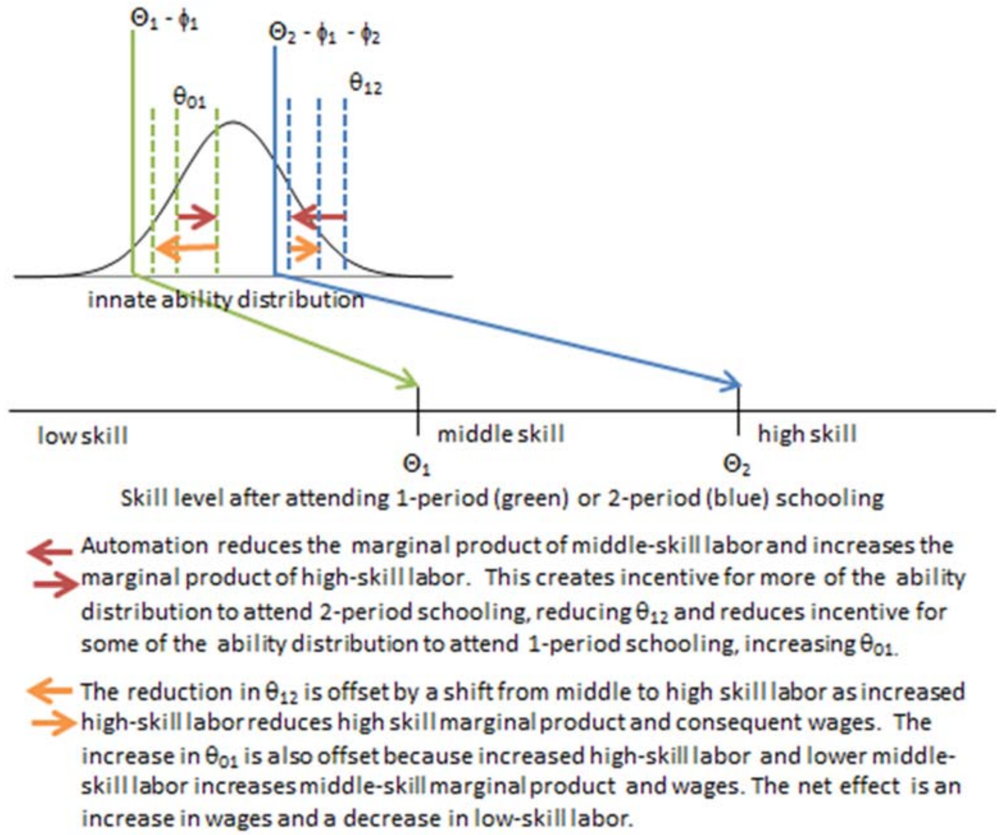
We treat automation as reducing the marginal product of middle-skill labor and increasing the marginal product of high skill labor through parameter, α. The effect of α on the marginal product of middle skill labor reflects the fear of automation: if production becomes fully automated, middle skill labor would have no contribution to the formal sector production.

Automation can be beneficial if education quality is sufficiently high and the labor stock is able to adjust to increased marginal product of high-skill labor. Figure 2 provides a graphical depiction of this scenario which is also demonstrated in the model's simulation discussed below. Automation's positive effect on high-skill wage and negative effect on middle-skill wage induces a shift from middle to high-skill labor by decreasing the ability threshold, θ_{12}, which determines whether an individual attends 2-period instead of 1-period schooling (and becomes high-skill instead of middle-skill). It also induces a shift from middle to low-skill labor by increasing the ability threshold, θ_{01}, which determines whether an individual attends 1-period instead of no schooling. The consequent reallocation of labor offsets these changes in wages, and in the simulation's parameterization, both middle-skill and high-skill wages exhibit a net increase and a net decrease in low-skill labor and higher output.

When the value-added of education is low, individuals with lower ability cannot increase their skill level. This can constrain the supply of skills even when automation increases the demand for skilled labor. To study these effects, we consider the scenario when the value-added of education, ϕ_1 and ϕ_2, are so low that $\theta_{01} = \Theta_1 - \phi_1$ and $\theta_{12} = \Theta_2 - \phi_1 - \phi_2$ in steady state. In this case, the supply of middle and high skill labor cannot increase because it would require increasing the skill level of individuals with lower ability which the education system cannot do.

Automation, coupled with this skills constraint, reduces middle skill labor and increases low skill, informal sector labor (Proposition 3 and Corollary 3.1) essentially reversing development. If, in absence of a skills constraint, automation increases high-skill labor, then the skills constraint is binding and high-skill labor does not change. In this case, automation with a skills constraint decreases middle skill wages (Proposition 4). In a developed country, the ability cut-off for entering the informal, low-skill sector is so low that automation does not affect the allocation of labor (Corollary 4.1) and equilibrium is restored through adjustments in wages alone.

Figure 2. Graphical depiction of the effect of automation in absence of a skills constraint



Further predictions can be obtained under a constant elasticity of substitution production function. Let total output Y_t be specified as

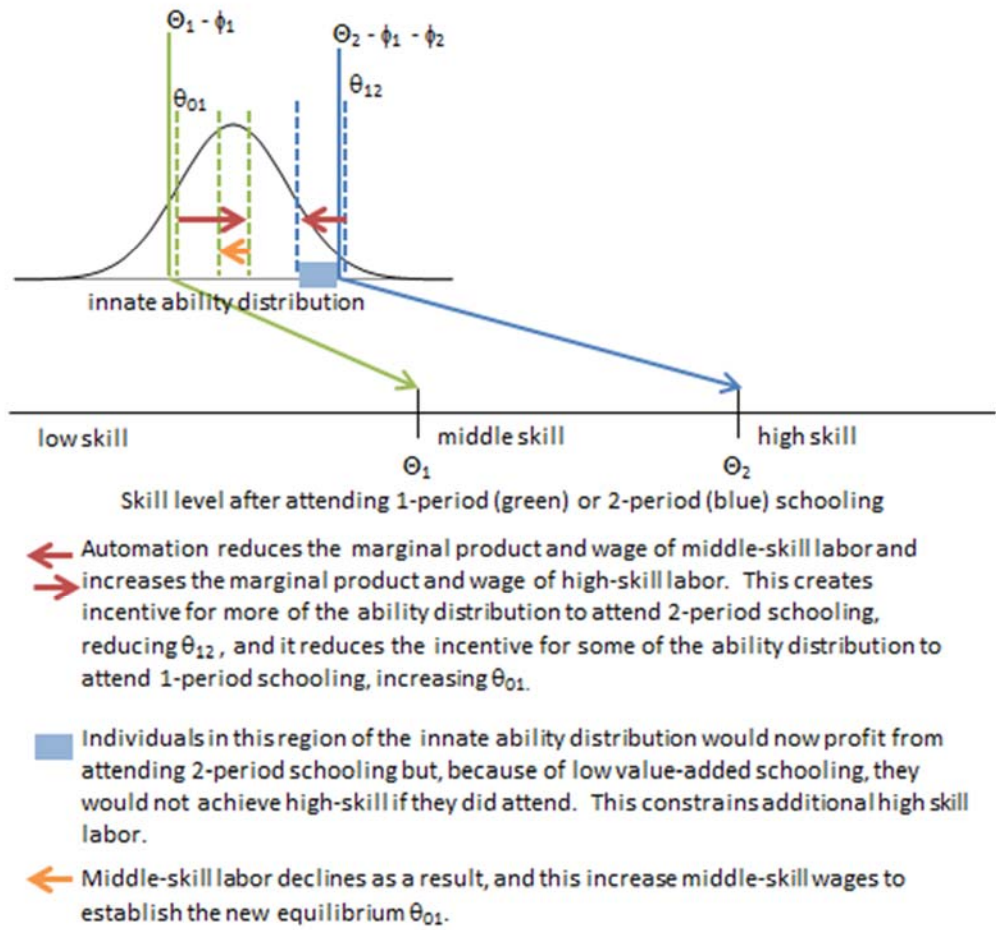
$$Y_t = \beta L_{0,t} + \left((1-\alpha)L_{1,t}{}^{\rho} + \alpha\left(KL_{2,t}\right)^{\rho}\right)^{1/\rho} \tag{7}$$

where the marginal product of low skill labor is small, $\beta \approx 0$, elastic substitution, $\rho \in (0,1)$ and $\alpha \in (0,1)$. There are many ways to model the relationship between capital and high skill labor. We model it as high-skill labor augmenting, much like high-skill biased technology. This is a best-case example for the impact of capital on high skill labor's marginal product, and we choose this model to illustrate the conditions when automation negatively affects outcomes even in this best-case scenario. In addition, it helps differentiate skill-biased technological change, which in this specification is equivalent to an increase in capital, with automation. However, an alternative specification, for example, would be $K^{\gamma}L_{2,t}{}^{(1-\gamma)}$ under which the findings are similar.

The effect of automation on total output is $\frac{dY}{d\alpha} = \frac{\partial Y}{\partial \alpha} + \beta\frac{dL_0}{d\alpha} + \frac{\partial Y}{\partial L_1}\frac{dL_1}{d\alpha} + \frac{\partial Y}{\partial L_2}\frac{dL_2}{d\alpha}$. We define economies as being middle skill intensive if the ratio of middle-skill labor to capital augmented high-skill labor, $\frac{L_1}{KL_2} \geq 1$. For these economies, $\frac{\partial Y}{\partial \alpha} < 0$ in a CES production function; in absence of shifts in labor, automation reduces total output because it lowers the productivity of the dominant labor stock, middle skill labor. As a result, if automation has a positive effect on total output in absence of a skill constraint, then high-skill labor must increase. Output can only increase either as a result of an increase high-skill labor or by an increase in middle-skill labor. If middle-skill labor has an incentive to increase, then high skill labor must also increase in our model (Proposition 5). This suggests that if automation has a positive effect on output in absence of a skills constraint, then with a skill constraint, automation will lower the middle-skill wage (Proposition 4) in addition to the other negative effects described above. Figure 3 graphically represents how a skills constraint affects education choice with automation.

We define developing countries as being middle-skill intensive and discuss this in the empirical section below. Developed countries can also be middle-skill intensive, but our model predicts that the negative effects of automation are lower for developed countries. For developed countries in our model, little shift in labor results from automation because the informal sector is not a viable alternative. The negative effect of automation on output for these countries occurs through $\frac{\partial Y}{\partial \alpha}$ alone; however, under a CES production function, as the ratio of middle-skill to capital-augmented high-skill labor decreases, the negative effect of automation, $\frac{\partial Y}{\partial \alpha}$, decreases in magnitude (Proposition 7). As developed countries become wealthier, their formal sector becomes more sophisticated and this ratio declines (Proposition 2). Hence, for developed countries, this negative effect of automation is maximized at the boundary between developing and developed country status, the negative effect is lower for developed countries. As a result, our model predicts that the country most adversely affected by automation will be a developing country. Note that the negative effect of automation depends on the size of the formal sector as well. The poorest developing countries may be least affected because of a very small formal sector relative to its informal sector. As a result, our model suggests that countries in the middle of development will be most adversely affected.

Figure 3. Graphical depiction of the effect of automation on skill supply with a skills constraint



These general results describe how, in our model, a skills constraint implies that automation negatively affects outcomes. To show that automation can have a positive effect on steady state outcomes in absence of a skills constraint, we present a simulation in Annex 2 with specific functional forms and a reasonable parameterization. We assume a CES production function and linear cost functions, $c_i(\theta) = c_{0i} - c_{1i}\theta$ for $= 1,2$. Parameter values are chosen based on Ábrahám (2008) for those parameters in common. The simulation shows that as the capital stock increases, high skill labor increases and low skill labor decreases; middle skill labor peaks prior to developed country status defined as where low skill labor is essentially zero. Middle-skill labor peaks at the threshold of developing country status. Automation, represented by a large increase in α, increases output and wages for all countries, decreases informal sector labor and middle-skill labor for most countries, when skill acquisition is unconstrained. When skills are constrained, output is negatively affected as are middle skill labor and wages; low-skill, informal agricultural employment increases. Countries just below the threshold for developed country status exhibit the largest negative effects.

The simulation also demonstrates how automation and skill-biased technological change differ in our model. In the CES production function, we explicitly modeled capital to be high-skill labor augmenting in part so that capital, K, is equivalent to skill-biased technological change, as in Ábrahám (2008). Doing so allows us to easily compare automation and a generalized treatment of technological change. First, how their effects on the production function differ becomes clear. Technological change, equivalent to K, increases both middle and high-skill labor marginal products, while automation, α, negatively affects middle-skill labor's marginal product and positively affects high-skill labor's marginal product. For this reason, technological change and automation have different effects on steady state outcomes. In absence of a skills constraint, the effects of automation and technological change are similar with increased output, increased high-skill labor, decreased middle-skill labor and an increased wage differential. For developing countries, they differ as middle-skill labor increases with technological change but decreases with automation, for most countries. With a skills constraint, technological change increases the marginal products of middle and high-skill labor; however, the skills constraint prevents them from adjusting. Automation, however, leads to a decrease in output and, for developing countries, job polarization as the stock of middle-skill labor decreases and shifts to the low-skill sector. Note that in our model skill-biased technological change does not lead to job polarization. For developing countries, this is consistent with Maloney and Molina (2016) who find little job-polarization associated with technological change; job polarization is not possible in developed countries in our model because they have two labor sectors. Hence, in our model, a decrease in total output and job polarization for developing countries is a result of automation but not of skill-biased technological change. This difference in findings ultimately results from what many fear from automation: that there is a segment of the labor force whose marginal product will be reduced by automation.

In our model and simulation, the ability of education systems to add-value and increase the skills for a large proportion of a country's ability distribution determines whether automation has a positive or negative effect. Countries in the middle of development are most at risk if education quality is low because of (1) their reliance on middle-skill labor in a relatively large formal sector and (2) because the informal sector still presents a viable alternative for middle-skill labor to exit. A developed country with poor education quality is less at risk because the informal sector is not a viable alternative to middle-skill labor.

EMPIRICAL APPROACH

Until automation takes hold to the large extent that many expect in the coming decades, we cannot empirically identify how countries will be affected. We can, however, examine the employment characteristics and education quality of countries to identify which countries our model predicts are most likely to be negatively affected and the fears of automation realized.

Our empirical approach is as follows. First, we test the underlying assumption of the model that educational attainment and skills are positively associated with employment that is complementary to automation capital. In doing so, we identify how different types of education and different types of skills associate with this type of employment. Second, we test whether the model correctly predicts the relationship between economic development and the three types of employment in our model: that which is complimentary to automation capital, substitutable by automation capital and informal. Doing this identifies which countries exhibit the employment characteristics which our model predicts are risk factors for automation. Third, we study how international student assessment outcomes relate to these risk factors to identify which countries are most likely to be negatively affected by automation, according to our model. We also examine secondary-level vocational programs which are often viewed in developing countries as an important approach to preparing youth for the labor market.

Identifying automation-substituting and automation-complementing labor sectors

To identify employment that is automation-substituting and automation-complementing, we use the Frey and Osborne (2013) estimates of an occupation's probability of being automated in the coming decades. These authors combine data on the types of tasks involved in occupations in the United States with the opinions of machine-learning experts to determine the probability that an occupation can be automated. They use the Occupational Information Network data set (O*NET) to derive the types of tasks involved for the United States' standard occupational classifications (SOC). For a subsample of 70 occupations, they examined the types of tasks and job descriptions and determined, with a team of machine learning experts, whether all the tasks of a job can "be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment." If so, the occupation was deemed automatable. Then, by modeling the association between key O*NET task variables and whether these 70 occupations are automatable, they predicted the probability that the remaining six-digit occupation classifications are automatable. Their estimated probability that an occupation can be automated is therefore based on the tasks involved in the occupation derived from the O*NET data set and the association of these tasks with whether the original 70 occupations are automatable. They publish the estimated probabilities for 702, six-digit SOC occupational codes. These data are used to estimate the proportion of United States' workers in occupations that are at low, medium and high risk of automation by probability cut-offs of 30 and 70 percent.

Their published data on the automation probabilities of the 702 SOC occupations are used by other researchers to estimate proportions of workers at high risk to automation. Several studies have used mappings between the United States' SOC and International Standard Classification of Occupations (ISCO) to estimate the percent of workers in high risk occupations in other countries. Our methodology most closely resembles that of Chang and Huynh (2016), Asian Development Bank (2015) and Deloitte (2014). We use the publicly available mapping tables of the United States Bureau of Labor Statistics to map the six-digit SOC codes reported Frey and Osborne (2013) with the ISCO-08 coding system used in many census and survey data. We also use publicly available ILO mappings between ISCO-08 and ISCO-88 and the Hendrickx (2004) mapping between ISCO-88 and ISCO-68 to apply the automation probabilities to data sets using these earlier coding systems. In order to calculate the probability of automation for a particular ISCO-08 occupational classification, we take the average of the probabilities of the SOC occupations with a probability of automation that map to it. This same procedure is used to generate the probabilities of automation for the ISCO-88 occupation classifications from the

ISCO-08 occupation classifications and for the ISCO-68 classifications form the ISCO-88 classifications. With the Frey and Osborne estimated probabilities of automation, we classify occupations as being "formal sector, automation-prone" if they are more likely than not to be replaced by automation, in other words, having a probability of automation greater than or equal to 50 percent, and not in the informal agricultural sector defined below. This cut-off provides a broad definition of automation-prone because we are not interested in estimating precisely how many workers will be lose their jobs, but rather who are more likely employed in the formal, automation-substituting sector than not.

In our model, we define an informal sector that is a perfect substitute to the formal productive sector and is unaffected by automation. This captures the informal agricultural sector that comprises a large segment of employment in developing countries. Following Asian Development Bank (2015), we assume these occupations have zero risk of automation. In developing countries, these occupations are unlikely to have access to sufficient capital to adapt automation technology, and they represent default occupations. We define the informal-agricultural sector by occupation classification in order not to require additional variables that some data sets may not have. For the ISCO-88 classification system, these are agriculture, fisheries, and related workers (921), subsistence agricultural and fishery workers (621), fishery workers, hunters and trappers (615), and market gardeners and crop growers (611). For the ISCO-68 classification system, these are mapped to the ISCO-88 occupations: general farmers (611), orchard, vineyard and related tree and shrub crop workers (623), nursery workers and gardeners (627), agricultural and animal husbandry workers not elsewhere classified (629), fishermen (641), and (649) fishermen, hunters and related workers not elsewhere classified.

One limitation with using mappings between SOC and ISCO classification systems is that they assume occupations in different countries involve the same tasks (Arntz, Gregory and Zierahn 2016). Our approach depends on the similarity of the task composition of jobs among mapped occupations between the different classification systems; it also relies on the similarity of the task composition of occupations across countries. For our purposes, these mappings are likely to be sufficient as we are not trying to estimate the exact proportion of workers at risk of losing their jobs to automation technology. Minor differences in the task compositions between mapped occupations are unlikely to change the overall findings of our analysis.

Data

Four data sets are used in our analysis. These are the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), World Bank's Skills Towards Employability and Productivity (STEP), the Integrated Public Use Microdata Series (IPUMS-I) by the Minnesota Population Center (2017), and the OECD's Programme for International Student Assessment (PISA).

Both the PIAAC and STEP data are household surveys that collect data on individuals' occupations (coded using ISCO-08) and measure individuals' literacy achievement. STEP also measures non-cognitive skills including the "Big 5" personality traits of extraversion, conscientiousness, openness to experience, emotional stability and agreeableness. Both data sets also include data on educational attainment, gender and age. We apply the Frey and Osborne (2013) automation probabilities to the occupation coding as described above using the ISCO-08 occupation classifications included in the data set. These data are used to test the underlying assumption of the model that educational attainment and skills are positively associated with non-automation-prone occupations and to understand how educational attainment, cognitive skills (as measured by literacy achievement) and non-cognitive skills associate with being in a non-automation-prone occupation. For PIAAC data, post-secondary education is labeled as vocational if it is in the ISCED B track (whose graduates are normally destined for direct entry to the labor market). Also, those in ISCED levels 4A and 4B are grouped with general upper secondary while those in 4C are grouped with vocational upper secondary. For STEP data, a variable denoting ISCED level and orientation is used to define vocational and general programs for each level of education. STEP's non-cognitive skill variables are standardized to mean 0 and standard deviation of 1. PIAAC data sets for 21 countries and STEP data sets for 7 countries have the necessary variables for our analysis. PIAAC surveys were conducted between 2008 and 2016 while STEP surveys were collected between 2011 and 2013.

From the IPUMS data collection, we select any country that has data available from 1990 onward with ISCO occupation classifications, and, of these countries, we apply the Frey and

Osborne (2013) estimate of an occupation's probability of automation using the ISCO classification mapping described above. This provided us with data on 41 countries and 73 data sets, of which 57 of these data sets contained the ISCO-88 classification of occupations, and 16 contained the ISCO-68 classifications. For each data set, we estimate the proportion of workers in automation-prone occupations, non-automation-prone occupations, and the informal agricultural sector. For our analysis, we only compare proportions derived from the same ISCO coding system. Finally, estimates use sample weights when data are not self-weighted.

The fourth data set used is the OECD's Programme for International Student Assessment (PISA). The 2015 data for 70 economies are used in this analysis; economies without GDP per capita data are not shown in the plots with GDP per capita. These data are representative of 15-year-old students in grades 7 or higher and include internationally comparable measures of student achievement on literacy, program of study (including vocational), grade, gender, an index of economic, social and cultural status (ESCS), and an index of a student's value of cooperating with others. We use this latter measure as a measure of non-cognitive skills. We use the PISA data to compare education quality of countries and to compare the cognitive and non-cognitive skills across countries and to examine how being in a non-academic track (which we refer to as vocational) versus an academic track program associates with cognitive and non-cognitive skills.

Empirical models and estimation methods

To test the model's assumption of the association of being in a non-automation-prone occupation with educational attainment and skills in the STEP and PIAAC data, two logistic regression models are estimated. Let a_i be a binary variable denoting whether individual i is in an automation prone occupation, $\boldsymbol{s}_i$ be a binary vector denoting his or her highest level of schooling excluding general post-secondary, l_i denote his or her literacy achievement, f_i be a binary variable denoting whether individual i is female, and y_i denote his or her age. The first model is

$$ln\left(\frac{P\{a_i = 1\}}{P\{a_i = 0\}}\right) = \beta_0^1 + \boldsymbol{\beta}_1^1\boldsymbol{s}_i + \beta_2^1 l_i + \beta_3^1 f_i + \beta_4^1 y_i \qquad (8)$$

For STEP countries, we add the "Big 5" non-cognitive skills, denoted by vector $\boldsymbol{b}_i$,

$$ln\left(\frac{P\{a_i = 1\}}{P\{a_i = 0\}}\right) = \beta_0^1 + \boldsymbol{\beta}_1^1\boldsymbol{s}_i + \beta_2^1 l_i + \beta_3^1 f_i + \beta_4^1 y_i + \boldsymbol{\beta}_4^1\boldsymbol{b}_i \quad (9)$$

To estimate the association of being in a vocational program with literacy achievement in PISA, two linear regression models are estimated. Let v_i be a binary variable denoting whether student i is in a vocational program, g_i denote his or her grade level, f_i denote whether the student i is female, h_i denote his or her household's economic, socio and cultural status, r_i denote whether his or her school is located in an urban area, and e_i denote a residual. The first regression model is defined as

$$l_i = \beta_0^1 + \beta_1^1 v_i + \beta_2^1 g_i + \beta_3^1 f_i + \beta_4^1 h_i + \beta_4^1 r_i + e_{1,i} \quad (10)$$

In the second model, the dependent variable is the student's enjoyment of cooperation with others, x_i.

$$x_i = \beta_0^1 + \beta_1^1 v_i + \beta_2^1 g_i + \beta_3^1 f_i + \beta_4^1 h_i + \beta_4^1 r_i + e_{1,i} \quad (11)$$

Models for all three data sets are estimated using the 10 multiple imputations of literacy achievement (plausible values). For PIAAC data, standard errors are jackknifed following the OECD's guidance, and, for STEP data, they are estimated using a cluster-robust method.

For PISA, estimates utilize the 10 multiple imputations of literacy achievement (plausible value) and standard errors are robust to intra-school correlation using the Balanced Repeated Replicate method as suggested by the OECD. These estimates as well as those for PIAAC and STEP are implemented using routines by Macdonald (2008).

EMPIRICAL FINDINGS

With these data and methods, we examine two hypotheses raised by the model. First, using

PIAAC and STEP data, we test the underlying assumption that educational attainment and skills are positively associated with being in a non-automation-prone occupation. Our logit model estimates suggest that post-secondary education and literacy achievement are associated with being in non-automation-prone occupations in most countries. Two non-cognitive skills, openness and extraversion, are also found to be positively associated in some countries. These findings are consistent with the assumption underlying our model but also help us identify the types of skills and schooling to best complement automation-capital. Second, using the IPUMS data, we find that the relationship between GDP per capita and the proportions of workers in the three labor categories follows the patterns predicted by our model and presented in our simulation. These findings suggest that middle-income countries exhibit the employment characteristics that our model predicts are indicative of automation having a negative impact if education quality is too low.

Based on this first set of findings, we use PISA data to first show that developing countries including many middle-income countries have low levels of student achievement. Given the employment characteristics of middle income countries described above, we conclude that middle income countries are the most at risk of being negatively affected by automation. We then turn to secondary vocational programs. In the PIAAC and STEP data sets, vocational secondary programs generally do not offer any benefit for avoiding automation-prone occupations and in many countries increase the likelihood of being in such occupations. These programs generally focus on technical skills and deemphasize cognitive and non-cognitive skills. Using PISA data, we show that they tend to attract individuals with lower cognitive and non-cognitive skills; the skills that the PIAAC and STEP data suggest are needed to mitigate the effect of automation.

Skills, educational attainment and automation-prone occupations

In our model, automation replaces middle skill workers and complements high skill workers, and individuals who attend 2-period schooling versus 1-period schooling, in equilibrium, become high-skill rather than middle-skill. That education and skills determine whether an individual is replaceable by automation or not is motivated by the automation research looking at trends in machine learning and artificial intelligence which view education and skills as essential for humans to be complementary to machines. Our assumption implies, empirically, that individuals employed in occupations that are complementary to automation should have better levels of educational attainment and skills; however, an unresolved question is what types of skills complement automation and, subsequently, what types of educational attainment provide these skills? For example, Frey and Osborne (2013) and Brynjolfsson and McAfee (2011, 2014) find that non-cognitive skills including creativity, social-intelligence as well as advanced perception will be humans' comparative advantage over machines given current technological trends.

We test several hypotheses about which types of skills and educational attainment are positively associated with being in a non-automation-prone occupation. First, we test the hypothesis, more general than the automation literature, that cognitive skills and non-cognitive skills are positively associated with non-automation-prone occupations. In the PIAAC and STEP we use literacy achievement as a measure of cognitive skills. In the STEP data, we use the "Big 5" personality traits. Second, we test whether general education versus vocational or technical education is positively associated with non-automation-prone occupations. Finally, we test whether post-secondary general education is better than general secondary programs. In doing so we validate the underlying assumptions of the model but also better define what types of skills associate with employment that is complementary to automation and which types of education programs best promote these skills.

Estimates of logit model (8) applied to 21 PIAAC country data sets are presented in Table 1, and 7 STEP country data sets are presented in Table 2. In this model, the dependent variable is being in an automation-prone occupation; positive coefficients imply that a variable is positively associated with being in an automation-prone occupation. First, in all countries, there is a positive and statistically significant difference in the likelihood of being in an automation-prone occupation between those with general upper secondary education and those with general post-secondary education. Second, there is a negative and statistically significant difference between those in general upper secondary and those in vocational upper secondary in 9 countries and a positive association in 1 country, but in the remaining 15 countries (which have a vocational upper secondary track), there is no statistically significant association. Third, in half of the countries, literacy achievement has a statistically significant and negative association with being in an automation-prone occupation; in the other half, no statistically significant association is found.

Table 1. Logit model (eq. 8) estimates PIAAC countries

country	Belgium	Chile	Cyprus	Czech Rep.	Denmark	Spain
literacy achievement	-0.09	-0.1	-0.06	-0.11	-0.16***	-0.16**
	(0.06)	(0.1)	(0.06)	(0.09)	(0.05)	(0.07)
educational attainment (relative to general post-secondary)						
none	3***	4.34***	n.a.	n.a.	2.37	2.02***
	(0.89)	(0.71)			(1.66)	(0.36)
primary	2.26***	3.74***	1.88***	n.a.	2.97***	2.03***
	(0.3)	(0.46)	(0.2)		(0.73)	(0.17)
lower secondary	2.23***	3.43***	1.49***	2.58***	2***	1.86***
	(0.2)	(0.38)	(0.2)	(0.36)	(0.15)	(0.13)
vocational upper secondary	2.03***	n.a.	n.a.	2.2***	1.45***	1.58***
	(0.18)			(0.2)	(0.12)	(0.29)
general upper secondary	1.73***	3.04***	1.49***	1.34***	1.3***	1.52***
	(0.14)	(0.35)	(0.12)	(0.17)	(0.12)	(0.13)
technical post-secondary	0.64***	1.89***	0.86***	0.55**	0.34***	1.43***
	(0.12)	(0.33)	(0.14)	(0.27)	(0.12)	(0.12)
age	-0.01**	-0.02***	-0.01**	-0.01	-0.02***	-0.01**
	(0)	(0.01)	(0)	(0.01)	(0)	(0)
female	0.28***	-0.05	0.55***	0.43***	-0.17**	0.27***
	(0.1)	(0.15)	(0.1)	(0.11)	(0.07)	(0.1)
constant	-0.97***	-0.93*	-0.78***	-0.79***	-0.18	-0.52**
	(0.19)	(0.52)	(0.21)	(0.26)	(0.13)	(0.2)
observations	3083	3428	2496	3419	4547	3157
gen - voc upper secondary	-0.301**	n.a.	n.a.	-0.865***	-0.153	-0.064
	(0.139)			(0.16)	(0.111)	(0.269)

Authors' calculations using OECD PIAAC data. Standard errors denoted in parentheses. Statistical significance at the 1, 5, and 10 percent levels denoted by ***, **, *, respectively.

Table 1, cont'd

country	France	UK	Greece	Israel	Italy	Japan
literacy achievement	-0.22***	-0.18***	-0.09	-0.28***	-0.1	-0.17***
	(0.04)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)
educational attainment (relative to general post-secondary)						
none	2.88***	1.65***	0.84	1.88***	3.12	n.a.
	(0.65)	(0.22)	(1.88)	(0.37)	(3.15)	
primary	2.12***	n.a.	2.12***	1.92***	2.45***	n.a.
	(0.2)		(0.26)	(0.26)	(0.38)	
lower secondary	1.86***	0.83	1.75***	1.82***	1.91***	1.3***
	(0.12)	(0.6)	(0.2)	(0.18)	(0.16)	(0.19)
vocational upper secondary	1.72***	1.39***	1.5***	1.68***	1.42***	1.35***
	(0.09)	(0.14)	(0.17)	(0.13)	(0.2)	(0.13)
general upper secondary	1.35***	0.84***	1.45***	1.6***	1.41***	1.16***
	(0.1)	(0.13)	(0.17)	(0.13)	(0.12)	(0.11)
technical post-secondary	1.04***	0.32**	0.75***	1.11***	0.79	0.51***
	(0.1)	(0.15)	(0.19)	(0.14)	(0.48)	(0.11)
age	-0.02***	-0.02***	-0.01**	-0.01***	-0.02***	-0.02***
	(0)	(0)	(0.01)	(0)	(0.01)	(0)
female	0.16***	-0.38***	0.2*	0.17**	0.22*	0.54***
	(0.06)	(0.1)	(0.12)	(0.08)	(0.11)	(0.09)
constant	-0.35**	-0.08	-0.37	-0.98***	-0.15	0.35**
	(0.14)	(0.21)	(0.27)	(0.18)	(0.27)	(0.15)
observations	4306	3884	2225	3211	2577	3640
gen - voc upper secondary	-0.37***	-0.553***	-0.054	-0.076	-0.013	-0.19
	(0.086)	(0.142)	(0.168)	(0.13)	(0.17)	(0.128)

Table 1, cont'd

country	Korea, Rep.	Lithuania	Netherlands	New Zealand	Poland	Russia
literacy achievement	-0.16***	-0.09	-0.08	-0.14***	-0.17***	-0.11
	(0.06)	(0.07)	(0.06)	(0.05)	(0.06)	(0.07)
educational attainment (relative to general post-secondary)						
none	2.52***	n.a.	2.53***	n.a.	n.a.	2.61
	(0.6)		(0.44)			(3.72)
primary	2.28***	2.05***	2.5***	1.68***	1.36***	1.34
	(0.25)	(0.66)	(0.2)	(0.47)	(0.48)	(1)
lower secondary	1.58***	2.94***	2.02***	1.52***	2.14***	1.04**
	(0.15)	(0.3)	(0.12)	(0.16)	(0.22)	(0.42)
vocational upper secondary	1.28***	2.32***	1.77***	1.3***	2.16***	n.a.
	(0.13)	(0.53)	(0.15)	(0.11)	(0.15)	
general upper secondary	1.34***	2.01***	1.49***	1.47***	1.48***	0.92***
	(0.12)	(0.12)	(0.11)	(0.14)	(0.12)	(0.1)
technical post-secondary	0.65***	0.89***	0.88***	0.58***	0***	0.64***
	(0.12)	(0.19)	(0.21)	(0.12)	(0)	(0.17)
age	-0.02***	-0.01***	-0.02***	0***	-0.01***	0.01***
	(0)	(0)	(0)	(0)	(0)	(0)
female	-0.27***	0.32***	-0.06	-0.04	0.28***	-0.65***
	(0.07)	(0.11)	(0.08)	(0.07)	(0.09)	(0.11)
constant	0.8***	-0.8***	-0.65***	-0.83***	-0.37**	-0.53***
	(0.18)	(0.22)	(0.18)	(0.1)	(0.16)	(0.17)
observations	4236	2858	3737	3407	4879	1663
gen - voc upper secondary	0.065	-0.313	-0.279*	0.162	-0.68***	n.a.
	(0.132)	(0.524)	(0.146)	(0.125)	(0.129)	

Table 1, cont'd

country	Slovak Rep.	Slovenia	Turkey
literacy achievement	-0.07	-0.22***	-0.06
	(0.06)	(0.06)	(0.09)
educational attainment (relative to general post-secondary)			
none	0***	n.a.	1.45***
	(0)		(0.42)
primary	3.68***	3.14***	1.75***
	(0.95)	(0.7)	(0.2)
lower secondary	2.41***	3.37***	1.55***
	(0.26)	(0.25)	(0.17)
vocational upper secondary	2.08***	2.93***	1.43***
	(0.12)	(0.15)	(0.18)
general upper secondary	1.36***	1.94***	1.43***
	(0.11)	(0.13)	(0.19)
technical post-secondary	0***	0.89***	1***
	(0)	(0.15)	(0.2)
age	-0.01***	-0.01	-0.02***
	(0)	(0)	(0.01)
female	0.21***	0.41***	0.14
	(0.07)	(0.09)	(0.15)
constant	-0.74***	-1.46***	-0.2
	(0.16)	(0.22)	(0.24)
observations	3130	2873	1984
gen - voc upper secondary	-0.725***	-0.988***	-0.004
	(0.115)	(0.122)	(0.187)

Table 2. Logit model (eq. 8) estimates STEP countries

country	Armenia	Bolivia	Colombia	Georgia	Ghana	Kenya	Vietnam
literacy achievement	0.04	-0.29***	-0.08	-0.05	-0.35***	-0.16*	-0.21***
	(0.09)	(0.11)	(0.11)	(0.09)	(0.1)	(0.08)	(0.07)
educational attainment (relative to general post-secondary)							
none	1.56	2.28***	1.5***	0***	2.52***	1.45***	2.16***
	(1.31)	(0.36)	(0.44)	(0)	(0.4)	(0.3)	(0.33)
primary	1.29	2.81***	2.15***	1.6	2.26***	1.39***	1.65***
	(1.25)	(0.63)	(0.36)	(1.12)	(0.42)	(0.23)	(0.2)
lower secondary	1.83***	2.44***	1.69***	1.03**	1.93***	0.99***	1.31***
	(0.45)	(0.28)	(0.41)	(0.44)	(0.36)	(0.22)	(0.15)
vocational upper sec.	1.41***	1.92***	1.74***	1.42***	1.97***	0.55**	0.45
	(0.29)	(0.25)	(0.39)	(0.36)	(0.41)	(0.24)	(0.29)
general upper sec.	1.13***	2.06***	1.46***	0.88***	1.3***	0.82***	0.95***
	(0.2)	(0.25)	(0.29)	(0.26)	(0.32)	(0.17)	(0.13)
technical post-sec.	0.93***	1.28***	0.94***	1.28***	0.79**	-0.92**	n.a.
	(0.2)	(0.26)	(0.28)	(0.23)	(0.39)	(0.37)	
age	0.01*	0	0	0	0	0.01**	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0)
female	-0.26*	-0.07	0.13	-0.41**	0.27*	0.2*	0.18*
	(0.15)	(0.13)	(0.17)	(0.19)	(0.14)	(0.11)	(0.11)
constant	-0.95***	-0.93***	-0.63	-0.42	-0.94**	-0.58***	0.19
	(0.3)	(0.34)	(0.39)	(0.36)	(0.42)	(0.22)	(0.21)
observations	956	1760	1702	888	2094	2340	2305
gen - voc upper secondary	-0.284	0.14	-0.278	-0.535	-0.663*	0.272	0.503*
	(0.297)	(0.26)	(0.335)	(0.391)	(0.356)	(0.194)	(0.287)

Authors' calculations using World Bank STEP data. Standard errors denoted in parentheses. Statistical significance at the 1, 5, and 10 percent levels denoted by ***, **, *, respectively.

Non-cognitive skill measures are available for the 7 STEP countries; estimates of model (9) are presented in Table 3. Openness to experience is found to have a negative, statistically significant association with being in an automation-prone occupation in three countries; extraversion is found to have a positive statistically significant association in one country and a negative statistically significant association in one country, and conscientiousness has a negative association in one country.

Table 3. Logit model (eq. 9) estimates STEP countries with non-cognitive skill

country	Armenia	Bolivia	Colombia	Georgia	Ghana	Kenya	Vietnam
extraversion	0.03	0.01	-0.02	0.07	0	0.1*	-0.17***
	(0.08)	(0.08)	(0.08)	(0.09)	(0.1)	(0.05)	(0.05)
conscientious	0.12	0.2**	-0.09	0.05	-0.03	-0.04	-0.11**
	(0.09)	(0.09)	(0.1)	(0.09)	(0.11)	(0.06)	(0.05)
openness to exper.	-0.14*	0.01	-0.1	-0.32***	0.02	0.06	-0.12**
	(0.08)	(0.09)	(0.09)	(0.1)	(0.09)	(0.06)	(0.06)
emot. stability	0.01	-0.03	-0.08	-0.09	0.01	0.01	0.03
	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.06)	(0.05)
agreeableness	-0.04	0.13	-0.02	-0.11	0.06	0.03	-0.04
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.06)	(0.05)
literacy achievement	0.03	-0.31**	-0.06	0.03	-0.39***	-0.15*	-0.18**
	(0.09)	(0.12)	(0.11)	(0.11)	(0.12)	(0.08)	(0.08)
educational attainment (relative to general post-secondary)							
none	1.63	2.5***	1.39***	0***	2.08**	1.29***	2.1***
	(1.43)	(0.39)	(0.46)	(0)	(0.84)	(0.31)	(0.35)
primary	1.05	3.04***	2.11***	1.1	2.7***	1.3***	1.58***
	(1.37)	(0.66)	(0.37)	(1.13)	(0.52)	(0.24)	(0.2)
lower secondary	1.76***	2.74***	1.6***	0.9*	1.63***	0.89***	1.26***
	(0.46)	(0.32)	(0.41)	(0.46)	(0.38)	(0.23)	(0.15)
vocational upper sec.	1.35***	2.11***	1.72***	1.17***	1.87***	0.49**	0.45
	(0.3)	(0.31)	(0.4)	(0.38)	(0.46)	(0.24)	(0.3)
general upper sec.	1.07***	2.35***	1.44***	0.8***	1.27***	0.78***	0.98***
	(0.2)	(0.26)	(0.29)	(0.27)	(0.33)	(0.17)	(0.14)
technical post-sec.	0.92***	1.57***	0.91***	1.23***	0.71*	-1.04***	0***
	(0.2)	(0.26)	(0.27)	(0.24)	(0.4)	(0.38)	(0)
age	0.01*	0	0	0	0	0.01**	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0)
female	-0.24	-0.12	0.09	-0.32	0.21	0.21*	0.18*
	(0.15)	(0.14)	(0.19)	(0.2)	(0.19)	(0.11)	(0.11)
constant	-0.92***	-1.15***	-0.59	-0.4	-0.9**	-0.49**	0.18
	(0.29)	(0.38)	(0.38)	(0.37)	(0.46)	(0.23)	(0.22)
observations	953	1641	1702	832	1019	2267	2303

Authors' calculations using World Bank STEP data. Standard errors denoted in parentheses. Statistical significance at the 1, 5, and 10 percent levels denoted by ***, **, *, respectively.

That those with upper-secondary education are more likely than those with post-secondary education to be in an automation-prone occupation is consistent with our model's assumption. In all countries, post-secondary education appears to provide skills that enable individuals to be employed in non-automation-prone occupations. While the data are less unanimous on what these skills are, some important insights emerge. First, those with general rather than vocational upper secondary are more likely to be in a non-automation-prone occupation for those countries in which there is a statistically significant difference, with one exception. In the countries without a statistically significant difference, this at least suggests that vocational programs, which typically focus on technical skills and deemphasize cognitive and non-cognitive skills, offer no clear advantage to avoiding automation-prone occupations. Second, there is clear evidence that literacy achievement, as a measure of cognitive skills, tends to be positively associated with being in a non-automation-prone occupation. Third, we see some evidence that the non-cognitive skill of openness to experience is positively associated with being in a non-automation-prone occupation. This is consistent with the automation literature's finding that creativity is a determinant of being complementary to automation as openness to experience has been found to correlate with creativity in the psychology literature (Furnham 1999).

Automation-prone occupations and stage of development

Our model assumes that the proportion of labor in the automation-complementing sector (equivalent to high-skill labor) is higher for wealthier countries, and it predicts that wealthier countries will have lower proportions of informal sector (low-skill) labor. Our simulation predicts that the proportion of employment in the automation-substituting (middle-skill) labor peaks at the cusp of developed country status. Applying our definitions of automation-prone occupations to the IPUMS-I data shows that this pattern is generally correct.

Figure 4 presents estimates of the proportion of workers in informal agricultural occupations, automation-prone occupations and non-automation-prone occupations, plotted against real GDP per capita. The figure includes only countries' latest data since 1990 and those data sets that use the ISCO-88 classification of occupations. Similar to the model's simulation presented in Annex 1 Figure 1, the proportion of automation-prone occupations peaks just around the point where the informal sector disappears which corresponds closely to the high-income status threshold.

Figure 4. Percent of workers by sector by GDP per capita

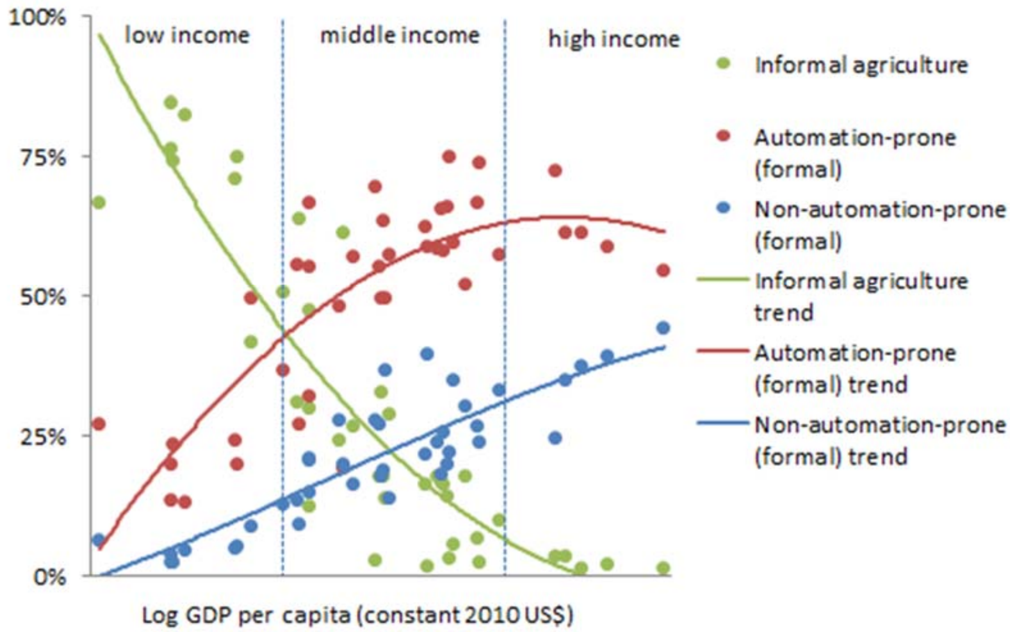
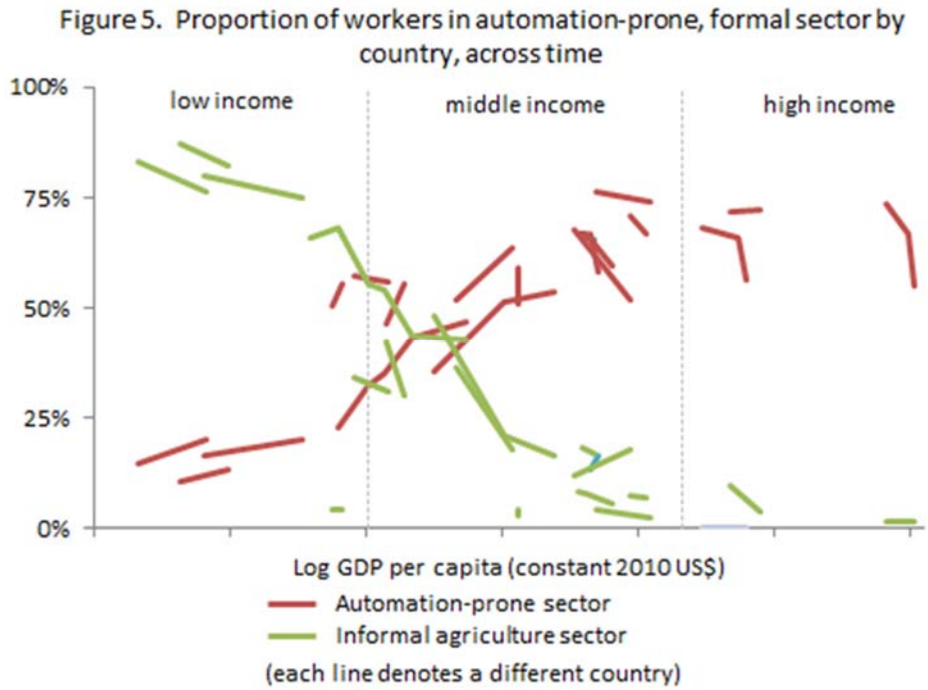


Figure 5 plots the proportion of workers in the informal agricultural sector and the automation-prone formal sector for countries with data at more than one point in time. Low and middle-income countries tend to exhibit decreasing informal agricultural employment and increasing automation-prone employment; upper middle-income countries exhibit declines in automation-prone employment as labor begins to shift to the non-automation-prone sector. Countries tend to rely more on automation-prone occupations around upper middle-income status.



In addition to testing a prediction of our model, the IPUMS-I data also help identify which countries may be most at-risk to automation if their education systems do no provide sufficient skills. According to our model and simulation, the countries that are most at risk have high proportions of middle-skill, automation-substituting labor and a non-trivial informal sector. Consistent with our simulation, the middle-income countries exhibit these characteristics in the IPUMS-I data.

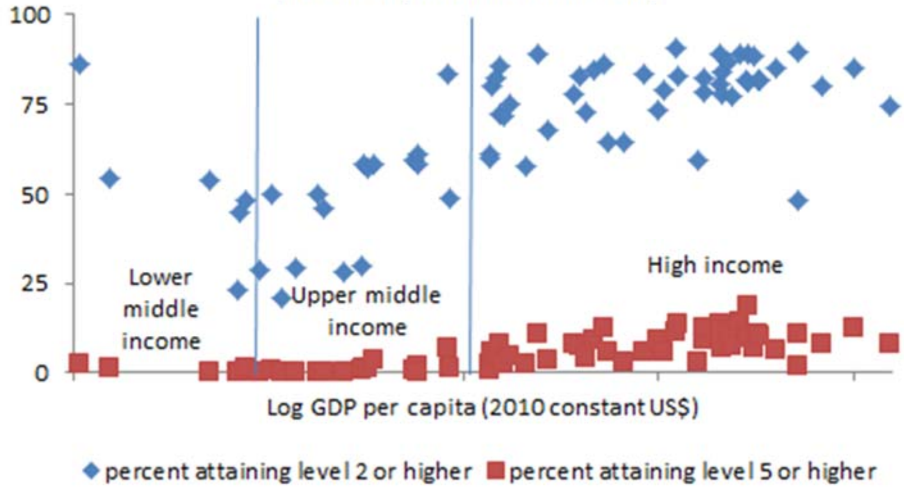
How robust are these findings? First, the IPUMS-I data provide nationally representative data on occupations but, being typically derived from census data, some data points are old, with some data points dating back to 1990. As a result, we also applied our definition of occupations to the latest data on occupational composition of workers provided by ILO-STAT. A limitation with the ILO-STAT data set is that it only provides data on select occupations which cover approximately 60 percent of the workforce. None of these occupations are informal agricultural occupations by our definition. However, we find the same pattern with respect to GDP per capita: automation-prone occupations tend to decline. Second, the Frey and Osborne (2013) estimates of the proportion of U.S. workers at high risk of automation tend to be high compared to other studies. However, the Frey and Osborne (2013) estimates are currently the only ones that can be applied to a wide range of countries and GDP per capita. For our purposes, the magnitude of the proportion of laborers in automation-prone employment is less important than identifying which countries have the highest proportions. Different results than ours are found by Ahmed and Chen (2017) in Hallward-Driemeier and Nayyar (2018:135) who apply the Frey and Osborne (2013) probabilities to STEP countries following Arntz, Gregory and Zierahn (2016). In this study, they find that the high-income countries in PIAAC have a higher proportion of workers at high risk of automation than the middle-income countries in STEP. Similar to our results, however, lower middle-income countries have a lower proportion of workers at high risk. Even if high-income countries have a higher proportion of workers in automation-prone employment, our main findings to do not change. First, high income countries lack a viable informal sector which mitigates potential negative effects of automaton. Second, what matters in our model is the quality of education systems, and as discussed in the next section, middle income education outcomes tend to be worse than those in high income countries.

Learning outcomes of education systems

Our model and simulation as well as our analysis of the IPUMS-I data suggest that automation can be beneficial to middle income countries, but if their education systems are not sufficiently high quality, then automation will be the most detrimental for them. Research on learning outcomes for low and middle-income countries finds, in general, quite poor learning outcomes. For example, Graham and Kelly (2018) find very low proportions of primary school students can read a simple sentence with ease and comprehension. Banerji et al. (2010) suggest that most students in middle income countries are functionally illiterate. The OECD PISA data provide an instructive comparison. It categorizes reading achievement into proficiency levels. In their assessment, minimum reading proficiency is defined at Level 2 in which students can infer information from a text, recognize the main idea of a text, and make comparisons. Students at the advanced level of reading proficiency, Level 5 or higher, can retrieve deeply imbedded information from and critically evaluate a text (OECD 2016b:162). Figure 6 presents the proportion of 15-year-old students attaining minimum proficiency and advanced proficiency in PISA, for the 67 participants that have GDP per capita data available. As shown, the proportion of students attaining minimum proficiency ranges between 20 to 60 percent with the exception of

Vietnam at 86 percent. Very few students achieve advanced proficiency in the middle-income countries.

Figure 6. Percent of 15 year-olds attaining minimum and advanced proficiency in PISA 2015 literacy



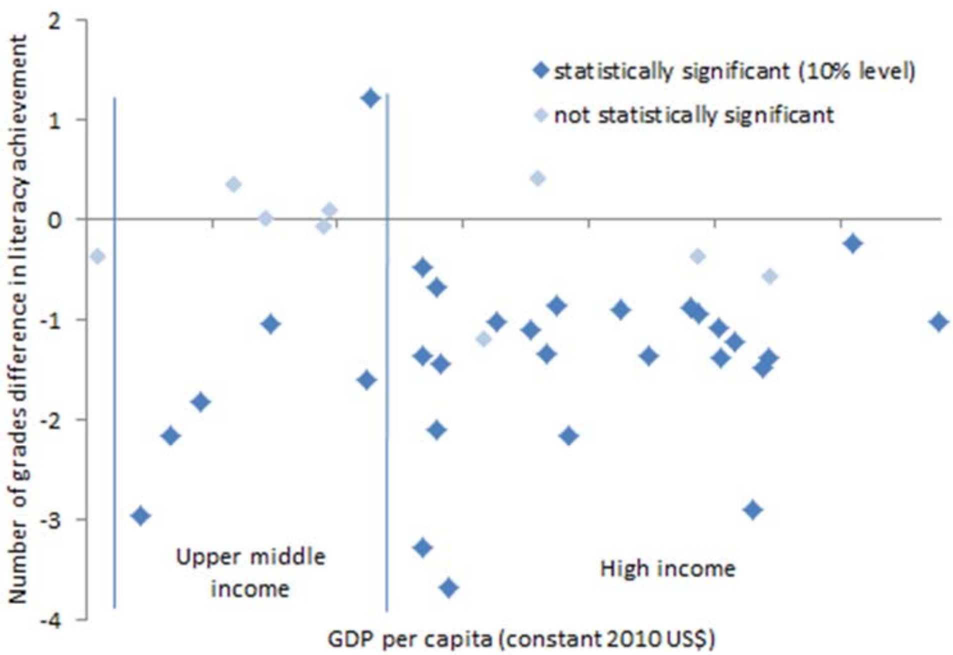
Source: OECD PISA 2015

Our findings paint a bleak picture for middle income countries in the face of automation. They exhibit the characteristics that our model predicts as indicative of being most negatively affected by automation if their education quality is not sufficient. The PISA data and other studies suggest that these countries have poor learning outcomes. Together, these findings suggest that the fears of automation are justified in many middle-income countries; however, at the same time, several middle-income countries have very high learning outcomes, including Vietnam, which suggest they will benefit from automation because they will be able to provide the skills needed to adapt.

Vocational education and skills associated with automation-prone occupations

Many countries rely on vocational upper secondary programs to prepare youth for direct labor market entry, but many of these programs deemphasize cognitive skills which we find evidence of being associated with non-automation-prone employment and non-cognitive skills that the automation literature believes are important. Figure 7 presents the coefficient for literacy achievement estimated with model (10). Differences in literacy achievement are shown in terms of the average difference between grades for 15-year-old students. For 32 countries, 15-year-olds in vocational education programs have lower literacy achievement than their peers in general programs, controlling for the background variables. These differences are substantial, with many ranging between 1 to 2 years of schooling. Only in Brazil is a positive difference found. For the 9 countries with vocational education, no statistically significant difference is measured.

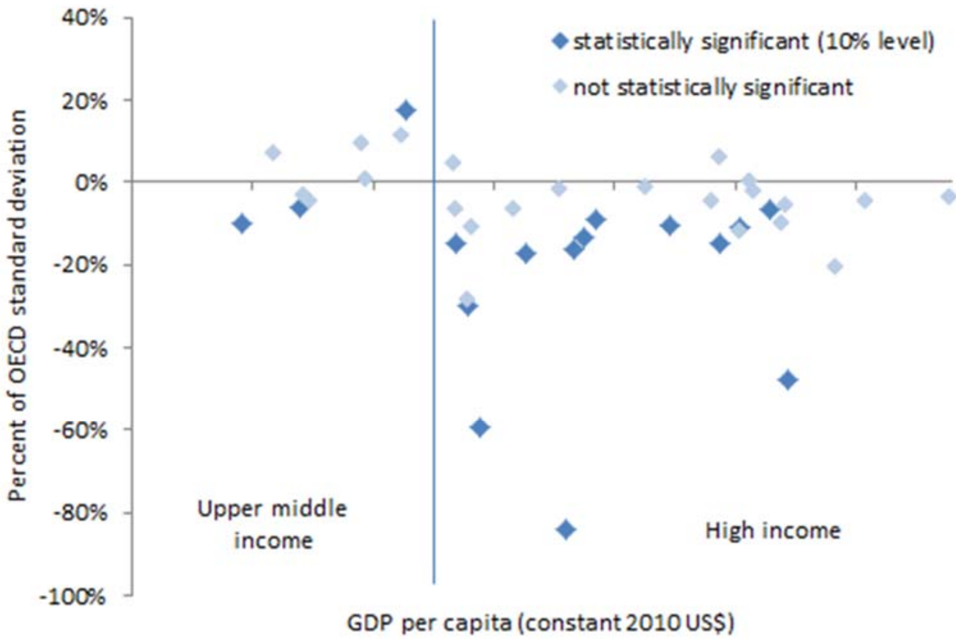
Figure 7. Summary of regression model (eq. 10) estimates: coefficient for being in a vocational programme by country



Source: authors' calculations using PISA 2015 data

Figure 8 presents the association between vocational education and the index of enjoying cooperation estimated with model (11). This indicator is chosen because it most closely matches social intelligence that the automation literature suggests complements automation technology. The figure is expressed in terms of the percent of a standard deviation different from the OECD mean. Vocational students are less likely to enjoy cooperation compared to their peers in 15 countries, more likely in one country, and no statistically significant difference is found for the remaining 23 countries.

Figure 8. Summary of regression model (eq. 11) estimates: coefficient for being in a vocational programme by country



Source: authors' calculations using PISA 2015 data

In Tables 1 and 2, vocational programs were found to provide no advantage in obtaining a non-automation-prone occupation, with one exception. These programs tend to emphasize technical skills over cognitive and non-cognitive skills, but in doing so, they deemphasize the skills that education systems are likely to provide to youth to reduce their vulnerability to automation. As presented in Figures 7 and 8, these students often lag far behind their peers in cognitive skills and in many countries, social skills.

DISCUSSION

We find that upper middle-income countries may be at most risk to automation because they exhibit (1) the largest automation-prone employment sectors, (2) non-trivial informal agricultural sectors, and (3) generally low education outcomes. Having a large automation-prone sector and a non-trivial informal sector, according to our model, amplifies the negative effects of automation resulting from poor education quality. However, if education quality is sufficiently high, then middle-income countries can benefit from automation as well.

We also find that cognitive skills and the non-cognitive skills of openness to experience are positively associated with non-automation-prone occupations. As an initial, empirically-grounded benchmark, this is instructive. Vocational programs that are seen as an important piece of developing countries' industrialization deemphasize these types of skills for the youth that lag furthest behind in them. In the labor force survey data, they rarely provide an advantage to general secondary education in avoiding automation-prone occupations.

Our model suggests countries will be negatively affected by automation unless their education systems are of high enough quality to allow even those with relatively low innate ability to acquire higher skills. For developing countries, this poses a significant challenge. Increasing educational attainment further, especially to higher education, is quite costly. While we see educational attainment associated with avoiding non-automation prone occupations, if they are of low quality and unable to increase the skills of lower innate ability students, then increasing attainment may not be effective.

As for non-cognitive skills, currently very little is known about how to promote them, especially social intelligence and creativity which the automation literature believes is crucial to future employment. For social intelligence, the evidence is limited but emerging. Social and behavioral skills tend to be most malleable in adolescence (Almlund et al. 2011). Several programs target social skills including youth programs in Latin America that tie socio-emotional learning with technical skills (Sanchez Puerta, Valerio and Bernal 2016). Creativity, on the other hand, is a much more amorphous concept. Much of the psychology literature on creativity focuses on definitions and theory; there is little consensus on whether creativity should be considered as a general skill or a skill specific to a field or domain (see Baer and Kaufman 2005). Several instruments have been developed to measure creativity, especially in terms of divergent thinking (Plucker and Makel 2010). Only a small body of empirical literature so far exists on how to stimulate or improve creativity (Grigorenko et al. 2008); the only consensus is that education systems, as they are designed now, do not integrate or promote much creativity and how to do so is also not well understood (Beghetto and Kaufman 2014).

Finally, our model suggests that automation when skill acquisition is constrained by poor quality schooling will not yield the same output per capita for a given level of capital. This has important implications for industrialization and growth models in the future. The East Asian growth model involved substantial domestic and foreign investment but was coupled with high quality basic level education that enabled the supply of what or model perhaps would call middle-skills to respond to rapidly increased demand (World Bank 1993). Our model and findings suggest that, to achieve the same growth with automation, the same levels of capital investment would need to be coupled with much higher levels of cognitive skills as well as non-cognitive skills. Automation will usher in a much different type of growth model where cognitive skills and non-cognitive skills including social intelligence and creativity are fundamental. Given what we know about producing these types of skills, this requires a significant shift in our approach to research on growth and development.

References

Acemoglu, D. 2002. "Technical change, inequality, and the labor market." *Journal of Economic Literature* 40(1): 7-72.

Acemoglu, D. and P. Restrepo. 2017. "Robots and Jobs: Evidence from US Labor Markets." NBER Working Paper No. 23285.

Acemoglu D. and J. Robinson. 2015. "The Rise and Decline of General Laws of Capitalism." *Journal of Economic Perspectives* 29(1):3-28.

Agars, M. D., Kaufman, J. C., and Locke, T. R. 2008. "Social influence and creativity in organizations: A multilevel lens for theory, research, and practice." In M. Mumford, S. T. Hunter, and K. E. Bedell-Avers (Eds.), *Multi-level issues in organizational innovation (Multi-level issues series)* (pp. 3–62). Amsterdam: JAI Press.

Almeida, R., Corseuil, C., and Poole, J. 2017a. "The Impact of Digital Technologies on Routine Tasks: Do Labor Policies Matter?" World Bank Group Policy Research Working Paper.

Almeida, R., Fernandes, A., and Viollaz, M. 2017b. "Does the Adoption of Complex Software Impact Employment Composition and the Skill Content of Occupations? Evidence from Chilean Firms." World Bank Group.

Almlund, M., A. L. Duckworth, J. Heckman and T. Kautz. 2011. "Personality Psychology and Economics." In: Hanushek, E. A., S. Machin and L. Woessmann (Eds.) *Handbook of the Economics of Education*, 1-181. Amsterdam: Elsevier.

Altinok, N., N. Angrist and H.A. Patrinos. 2018. Global data set on education quality (1965-2015). World Bank Policy Research Working Paper No. 8314.

Arntz, M., T. Gregory and U. Zierahn (2016), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", *OECD Social, Employment and Migration Working Papers*, No. 189, OECD Publishing, Paris. http://dx.doi.org/10.1787/5jlz9h56dvq7-en

Asian Development Bank (2015). Special chapter: A smarter future. Skills, education and growth in Asia. *Key Indicators for Asia and the Pacific, 2015, 46th Edition.* Manila: Asian Development Bank

Autor, D. 2010. "The polarization of job opportunities in the us labor market: Implications for employment and earnings." Center for American Progress and The Hamilton Project.

Autor, D. and Dorn, D. 2013. "The growth of low-skill service jobs and the polarization of the us labor market." *American Economic Review* 103(5):1553-1597.

Autor, D., D. Dorn, and G. Hanson. 2013. "Untangling Trade and Technology: Evidence from Local Labor Markets." NBER Working Paper Series 18938.

Autor, D., Levy, F. and Murnane, R.J. 2003. "The skill content of recent technological change: An empirical exploration." *The Quarterly Journal of Economics* 118(4): 1279-1333.

Autor, D. 2015. "Why are there still so many jobs? The history and future of workplace automation." *Journal of Economic Perspectives* 29(3): 3-30.

Baer, J., and Kaufman, J. C. 2005. "Bridging generality and specificity: The Amusement Park Theoretical (APT) Model of creativity." *Roeper Review* 27: 158-163.

Banerji, A., W. Cunningham, A. Fiszbein, E. King, H. Patrinos, D. Robalino, J.P. Tan. 2010. *Stepping up skills for more jobs and higher productivity*. Washington, D.C.: The World Bank.

Barro, R. and J.W. Lee. 2013. "A new data set of educational attainment in the world, 1950–2010." *Journal of Development Economics* 104: 184-198.

Beaudry, P., D.A. Green and B.M. Sand. 2013. "The Great Reversal in the Demand for Skill and Cognitive Tasks," NBER Working Paper No. 18901.

Beghetto, R. A., and Kaufman, J. C. 2014. "Classroom contexts for creativity." *High Ability Studies* 25: 53-69.

Berkowitz, D., H. Ma, and S. Nishioka. 2017. "Does Capital-Labor Substitution or Do Institutions Explain Declining Labor Shares." University of Pittsburgh, Department of Economics, Working Paper Series No. 17/004.

Brynjolfsson, E. and A. McAfee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York and London: W.W. Norton & Company.

Cellan-Jones, R. 2014. "Stephen Hawking warns artificial intelligence could end mankind." BBC News (http://www.bbc.com/news/technology-30290540).

Chapman, Ben. 2017. "Finnish citizens given universal basic income report lower stress levels and greater incentive to work." *The Independent* (Wednesday 21 June 2017).

Chang, J.-H. and P. Huynh (2016) *ASEAN in transformation. The future of jobs at risk of automation*. Geneva: ILO

Cortes, G. M., N. Jaimovich, H. E. Sui. 2016. "Disappearing Routine Jobs: Who, How, and Why?" NBER Working Paper 22918.

Deloitte (2014). *London Futures. Agiletown: the relentless march of technology and London's response.* London: Deloitte, LLP

Deming, D. 2015. "The growing importance of social skills in the labor market." National Bureau of Economic Research Working Paper w21473.

Eden, M. and P. Gaggl. 2015. "On the welfare implications of automation." World Bank Policy Research Working Paper 7487.

Elliott, S. 2017. "Computers and the Future of Skill Demand." Centre for Educational Research and Innovation (http://dx.doi.org/10.1787/9789264284395-en).

Federation of Indian Chambers of Commerce and Industry (FICCI) and Ernst & Young LLP (EY). 2016. "Future of jobs and its implications on Indian higher Education."

Freeman, R. 2015. "Who owns the robots rules the world." IZA World of Labor.

Frey, C. B. and M. Osborne 2013. *The future of employment*. Oxford Martin Programme on Technology and Employment.

Furnham, A. 1999. "Personality and creativity." *Perceptual and Motor Skills* 88: 407-408.

Gaggl, P. and G.C. Wright. 2016. "A Short-Run View of What Computers Do: Evidence from a UK Tax Incentive." *American Economic Journal: Applied Economics* Forthcoming.

Goldin, C. and L Katz. 2009. *The race between education and technology*. Harvard.

Goos, M., Manning, A., and Salomons, A. 2014. "Explaining job polarization: Routine biased technological change and offshoring." *American Economic Review* 104(8): 2509-26.

Graham, J. and S. Kelly. 2018. How Effective Are Early Grade Reading Interventions? World Bank Policy Research Working Paper No. 8292.

Gregory, T., A. Salomons and U. Zierahn. 2016. "Racing with or Against the Machine? Evidence from Europe." ZEW - Centre for European Economic Research Discussion Paper No. 16-053.

Grigorenko, E. L., L. Jarvin, M. Tan and R. J. Sternberg. 2008. "Something new in the garden: assessing creativity in academic domains." *Psychology Science Quarterly* 50: 295-307.

Hagerty, J. 2015. "Meet the New Generation of Robots for Manufacturing." *Wall Street Journal* June 2.

Hallward-Driemeier, M. and G. Nayyar. 2018. *Trouble in the Making? The Future of Manufacturing-Led Development*. Washington, DC: World Bank.

Hanushek, E., Schwerdt, G., Wiederhold, S., and Woessmann, L. 2017. "Coping with change: International differences in the returns to skills." *Economics Letters* 153: 15-19.

Heckman, J. 2000. "Policies to foster human capital." *Research in Economics* 54(1): 3-56.

Hendrickx, J. (2002). ISKO: Stata module to recode 4 digit ISCO-88 occupational codes, *Statistical Software Components* S425802, Boston College Department of Economics, revised 20 Oct 2004. <https://ideas.repec.org/c/boc/bocode/s425802.html>

Katz, L.F. and Murphy, K.M. 1992. "Changes in relative wages, 1963–1987: supply and demand factors." *The Quarterly Journal of Economics* 107(1): 35-78.

David, H., L.F. Katz and M.S. Kearney. 2006. "The polarization of the US labor market." *American economic review* 96(2): 189-194.

Kentish, B. 2017. "Hawaii considering universal basic income after positive trials in Europe." *The Independent* (Tuesday 5 September 2017).

Kurzweil, R. 2005. *The singularity is near: When humans transcend biology*. Penguin.

Macdonald, K. (2008). PV: Stata module to perform estimation with plausible values, *Statistical Software Components* S456951, Boston College Department of Economics, revised 12 Feb 2014. <https://ideas.repec.org/c/boc/bocode/s456951.html>

Maloney, W. and C. Molina. 2016. "Are automation and trade polarizing developing country labor markets, too?" World Bank Policy Research Working Paper Series No. 7922.

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., and Dewhurst, M. 2017. *A Future that Works: Automation, Employment, and Productivity*. McKinsey Global Institute.

McFarland, K. 2017. "Current Basic Income Experiments (and those so called): An Overview." The McFarland Report (http://basicincome.org/news/2017/05/basic-income-experiments-and-those-so-called-early-2017-updates/).

Michaels, G., A. Natraj and J. Van Reenen. 2014. "Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years." *Review of Economics and Statistics* 96(1):60-77.

Minnesota Population Center (2017). *Integrated Public Use Microdata Series, International: Version 6.5* [data set]. Minneapolis: University of Minnesota. http://doi.org/10.18128/D020.V6.5.

Morin, M. 2016. "Computer Adoption and the Changing Labor Market." Working paper, Cambridge University.

Montenegro, C. and H. Patrinos. 2014. "Comparable estimates of returns to schooling around the world." World Bank Policy Research Working Paper 7020.

OECD 2016a. *Skills Matter. Further results from the survey of adult skills.* Paris: OECD.

OECD 2016b. *PISA 2015 Results. Excellence and equity in education. Volume 1*. Paris: OECD.

Plucker, J.A. and M.C. Makel. 2010. "Chapter 3 – Assessment of Creativity." In: Kaufman, J. C. and R. J. Sternberg (Eds.) *The Cambridge Handbook of Creativity*. Cambridge University Press.

Psacharopoulos, G. and H.A. Patrinos. 2018. "Returns to Investment in Education: A Decennial Review of the Global Literature." World Bank Policy Research Working Paper No. 8402.

Psacharopoulos, G. and H. Patrinos. 2004. "Returns to investment in education: a further update." *Education Economics* 12(2): 111-134.

Roberts, R. 2017. "Indian politicians consider universal basic income following successful trials." *The Independent* (Friday 28 July 2017).

Sanchez Puerta, M. L., A. Valerio and M. G. Bernal. 2016. *Taking Stock of Programs to Develop Socio-emotional Skills: A Systematic Review of Program Evidence*. Washington, D.C.: The World Bank.

Susskind, D. 2017. "Re-Thinking the Capabilities of Machines in Economics." Oxford Department of Economics Working Paper Series No. 825.

Tinbergen, J. 1975. *Income distribution: Analysis and policies*.

vom Lehn, Christian. 2015. "Labor Market Polarization, the Decline of Routine Work, and Technological Change: A Quantitative Analysis." Working paper, Brigham Young University.

World Bank. 1993. *The East Asian Miracle*. Washington, D.C.: World Bank

World Bank. 2017. *World Development Indicators*. Washington, D.C.: The World Bank.

World Economic Forum. 2017. "Realizing Human Potential in the Fourth Industrial Revolution An Agenda for Leaders to Shape the Future of Education, Gender and Work." http://www3.weforum.org/docs/WEF_EGW_Whitepaper.pdf

Annex 1. Model assumptions and propositions[2]

Model features

The capital stock differentiates wealthier and poorer countries. When investment increases steady state high skill labor (consistent with our empirical findings) then low skill, informal agricultural employment decreases (Proposition 1). We define a "developed" country as having virtually no informal agricultural sector. In these countries the ratio of middle skill labor to high skill labor decreases (Proposition 2).

Assumption 1 (production function properties): $\frac{\partial^2 Y}{\partial K \partial L_i} > 0, \frac{\partial^2 Y}{\partial^2 L_i} < 0$ (diminishing returns), and $\frac{\partial^2 Y}{\partial L_j \partial L_i} > 0$ for $i = 1,2$ and $j = 1,2, i \neq j$. w_0 is constant and small.

Assumption 2 (capital complements high skill labor more): $\frac{\partial w_2}{\partial K} / \frac{\partial w_1}{\partial K} > 1 + \frac{1}{\sum_{i=1}^{n-2} \delta^i}$

Assumption 3: education cost functions c_1 and c_2 must satisfy the existence of c_d: $c_d(\theta) = c_2(\theta) - c_1(\theta)$ and where c_d has an inverse which is differentiable and $\frac{\partial c_d}{\partial \theta} < 0$, higher ability lowers the difference in costs of schooling.

Assumption 4 (developed country characterization): $F(\theta_{01}) \approx 0, f(\theta_{01}) \approx 0, L_0 \approx 0$, a developing country has virtually no informal agricultural sector.

Proposition 1: $\frac{dL_2}{dK} > 0$ implies $\frac{dL_0}{dK} < 0$, if higher steady-state capital increases high-skill labor, then it also decreases low skill labor

Proposition 2: In developed countries, the ratio of middle-skill labor to capital-augmented high skill labor, $\frac{d}{dK}\frac{L_1}{L_2} < 0$, decreases as the capital stock increases

[2] Proofs in Annex 3

Effects of automation on skills and wages

We assume automation, all things being equal, reduces the marginal product of middle-skill labor and increases the marginal product of high-skill labor (Assumption 5). When skill supply is constrained due to low quality-schooling (Definition 1), automation decrease middle-skill labor and increases low-skill labor (Proposition 3 and Corollary 3.1). In countries where automation increases high skill labor, a skills constraint binds high skill labor and no change occurs. This implies that automation will decrease middle-skill labor wages in the presence of a skills constraint (Proposition 4) and, in in developed countries, middle-skill labor will not change (Corollary 4.1).

Assumption 5 (effect of automaton on production): α is a parameter of the extent of automation where $\frac{\partial}{\partial\alpha}\frac{\partial Y}{\partial L_1} < 0$ and $\frac{\partial}{\partial\alpha}\frac{\partial Y}{\partial L_2} > 0$.

Definition 1 (skill constraint): $\theta_{01} = \Theta_1 - \phi_1$ and $\theta_{12} = \Theta_2 - \phi_1 - \phi_2$

Proposition 3: $\frac{dL_1}{d\alpha} < 0$ with skill supply constraint

Corollary 3.1: $\frac{dL_0}{d\alpha} < 0$ with skill supply constraint

Proposition 4: if $\frac{dL_2}{d\alpha} > 0$ in absence of a skills constraint, then $\frac{dw_1}{d\alpha} < 0$ with a skills constraint

Corollary 4.1: in developed countries in which $\frac{dL_2}{d\alpha} > 0$ in absence of a skills constraint, $\frac{dL_1}{d\alpha} \approx 0$.

Automation's effect on output and why developing countries are most at risk

Under a CES production function (Assumption 6), if automation has a positive effect on middle-skill intensive economies' output (Definition 2), then it must have a positive effect on the high-skill labor stock (Proposition 5). It follows that middle skill wages will be negatively affected

(Proposition 4). The effect of automation on total output in countries that are middle-skill intensive will be unambiguously negative when skills are constrained (Proposition 6). For developed countries that are middle-skill intensive where automation has a positive effect, the magnitude of the negative effect declines implying that that largest negative effect would be in middle-skill intensive developing countries (Proposition 7).

Assumption 6 (CES production function): $Y = \beta L_0 + \left((1-\alpha){L_1}^{\rho} + \alpha(KL_2)^{\rho}\right)^{1/\rho}$ such that $\beta \approx 0$ and $\rho \in (0,1)$

Definition 2: In middle skill intensive economies, $\frac{L_1}{KL_2} \geq 1$

Proposition 5: For middle skill intensive economies, if $\frac{dY}{d\alpha} > 0$ in absence of a skills constraint then $\frac{dL_2}{d\alpha} > 0$

Proposition 6: For middle skill intensive economies, $\frac{dY}{d\alpha} < 0$ when skills are constrained

Proposition 7: $\frac{d}{dK}\frac{dY}{d\alpha} < 0$ in developed countries

Annex 2. Model Simulation

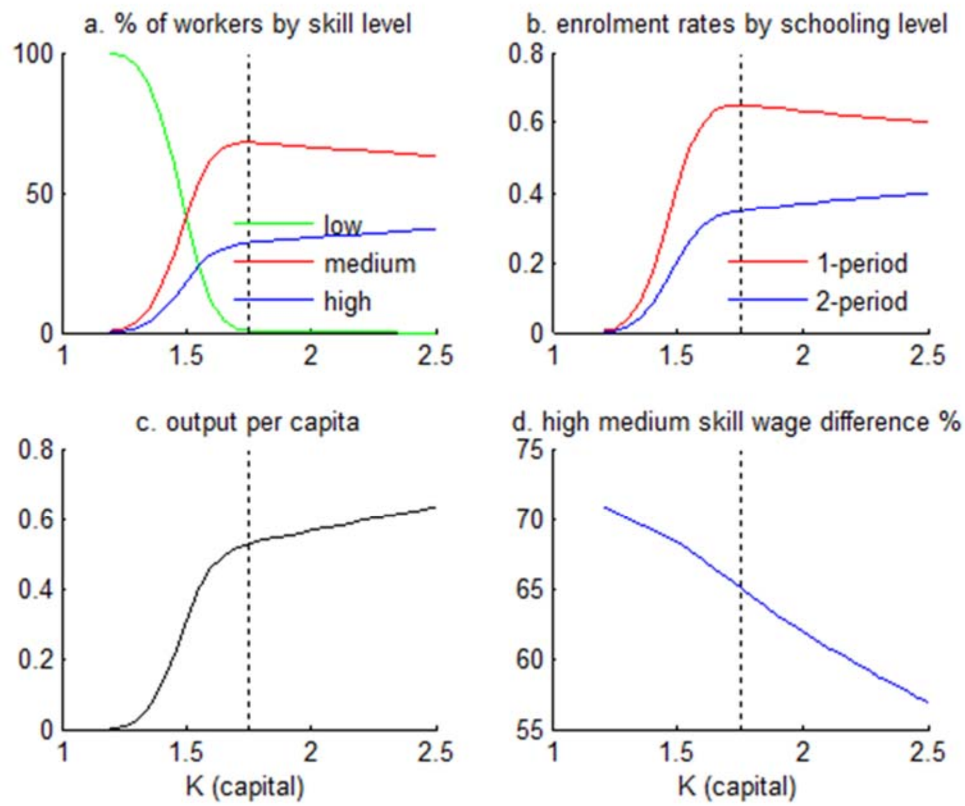
To understand empirical predictions of the model, we calculate steady state values of the variables for different levels of capital to represent countries at different levels of development. Steady state outcomes are computed by solving equation (4) for $\hat{\theta}_{01,t} = \theta_{01}^{*} \forall t$ and $\hat{\theta}_{12,t} = \theta_{12}^{*} \forall t$. In this simulation, we assume that the innate ability distribution is normal with mean μ and standard deviation, σ and parameterize the model as in Annex 2 Table 1. Note that we use the same values as Ábrahám (2008) for those parameters which we have in common. We choose ability bounds for medium and high skill labor and the value-added of 1- and 2-period such that they do not constrain the solutions for θ_{01}^{*} or θ_{12}^{*}.

Annex 2 Table 1. Parameterization of model simulation

Preferences and periods			
n	δ		
9	0.96		
Innate ability distribution			
μ	σ		
0.2	0.1		
Skill level cut-offs and impacts of schooling			
Θ_1	Θ_2	ϕ_1	ϕ_2
0.51	2.06	1.45	1.45
Production			
β	α	ρ	ξ
0.4	0.45	0.29	0
Schooling cost function			
c_{01}	c_{11}	c_{02}	c_{11}
0.3	1	1.8	1.3

The steady state outcomes for various levels of capital which define differing levels of economic development are presented in Annex Figure 1. As the stock of capital increases, the steady state stock of unskilled labor employed in the informal sector drops to zero. The stock of medium-skill workers peaks at the same point and declines thereafter, while the stock of high skill labor continues to grow. We define the point when the informal sector employment reaches zero as the boundary between developed and developing countries. This is depicted with a vertical dashed line. Enrollment rates in 1-period and 2-period schooling increase until developed status, when 1-period enrollment declines and 2-period enrollment increases. Finally, the wage differential which is the percent difference between high and middle skill workers declines as capital grows.

Annex 2 Figure 1. Simulated steady state variables (baseline parameterization)



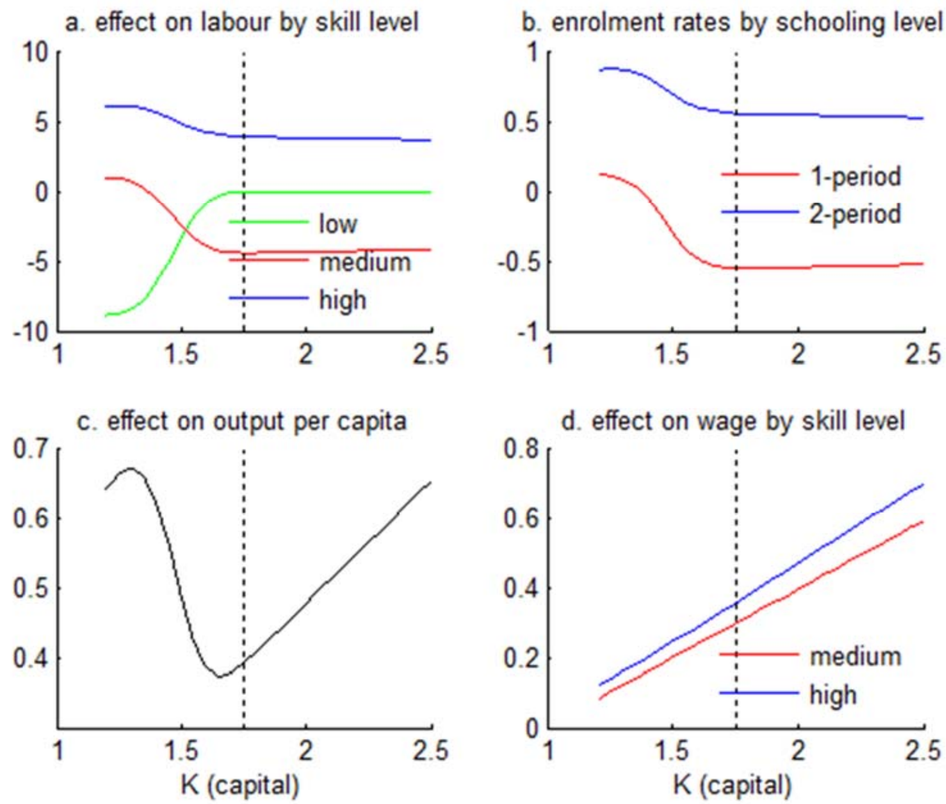
Our model closely resembles the canonical model of skill-bias technological change where normally technology, not capital, is high-skill labor augmenting. By allowing labor to shift between skill-levels through schooling, the wage differential declines rather than increases. Also, at around the point when the low-skill labor stock reaches zero, the growth in high-skill labor declines, which has been observed empirically by Mishel, Shierholz and Schmitt (2013) and Beaudry, Green and Sand (2014). The predictions of our model, however, can be easily reconciled with the canonical model. If the impact of schooling ϕ_1 and ϕ_2 were lowered to 0.83 and 0.99, respectively, then high and middle skill labor would be constrained at a level of capital just above developed country status, and, as capital (or technology) increases past this point, the wage differential would increase and not decrease.

Effect of automation

The fear of automation is that it will render workers unemployable. In our model, this would translate into the marginal product of middle skill labor to become zero. We assume that the informal sector will continue to exist, for example as informal agriculture serves as a default occupation in developing countries. Our approach to modeling automation is a change in parameter, α. If production is fully automated, α would be 1, and the marginal product of middle-skill labor would be zero: middle-skill labor would have no contribution to formal production. To demonstrate the effect of automation in our model when skill supply is unconstrained, Annex Figure 2 presents effects on steady state outcomes by increasing α from 0.45 to 0.85; this is an arbitrary choice to illustrate how steady state outcomes would change. As Annex 2 Figure 2 demonstrates, the effects of automation are positive for countries at all stages of development. Output per capita increases for all countries; though, it has the lowest increase for countries just prior to developed-country status. Wages increase for both medium and high skill, with high skill wages increasing faster implying a higher wage differential.

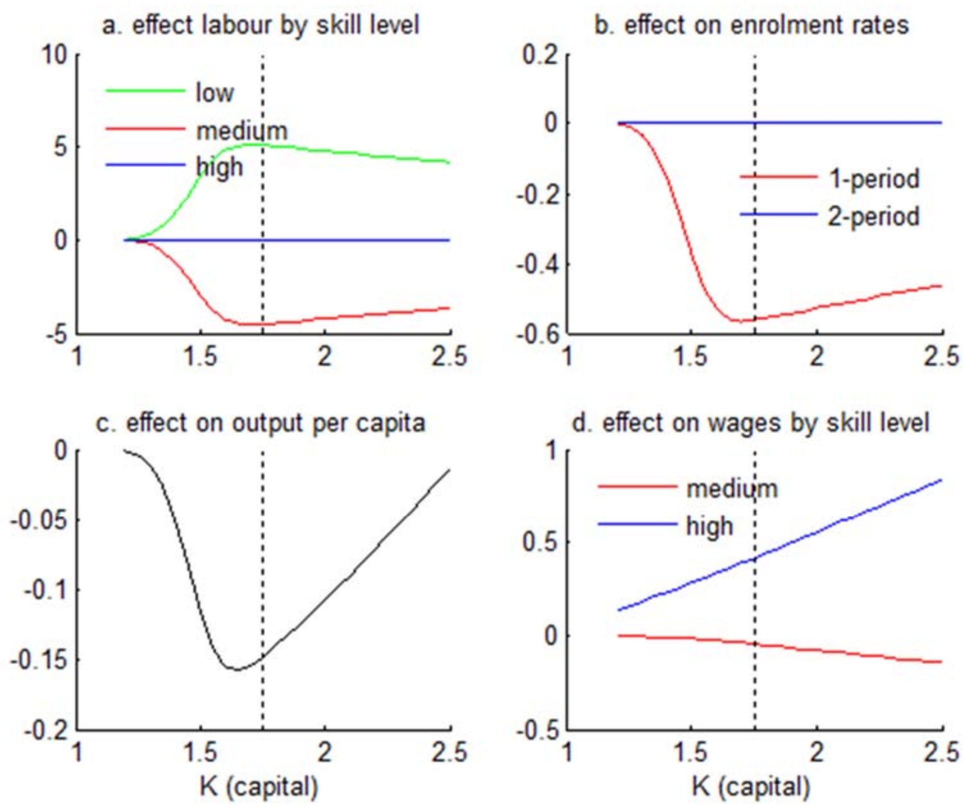
Increased automation, through an increase in α, reduces the formal sector's reliance on lower productive middle-skill labor in favor of higher productive, high-skill labor, resulting in an overall increase in output and wages. This also incentivizes workers to attend a higher level of schooling and attain higher skills. The proportion of low-skill workers declines for developing countries as does the proportion of medium-skill workers except for the poorest countries. Schooling enrollment rates reflect the same pattern. This scenario represents the best-case: capital is high-skill labor augmenting meaning that it increases the productivity of all high-skill workers, regardless of the number, and there is no constraint on skill production. Under this scenario, automation unequivocally has positive effects for both developed and developing countries.

Annex 2 Figure 2. Simulated effect of automation on steady state variables (no constraints to skill acquisition)



The opposite extreme is when schooling quality is poor and has low value-added to individual skills; for example, when ϕ_1 and ϕ_2 are so low in a country that the supply of middle and high-skill workers cannot increase. For this example, the enrollment rates in Annex Figure 1 are assumed to be the upper bounds; the resulting levels of ϕ_1 and $\phi_2$would differ by country accordingly. Annex 2 Figure 3 presents the effect of automation when enrollment rates are bounded above at the level presented in Annex 2 Figure 1. Output per capita declines for all countries (except for those with extreme capital stock sizes not shown in the figure), and the largest decrease is countries just prior to developed-country status. Wages for high skill individuals increase because they rely less on medium-skill workers, and medium skill workers' wages decrease as their contribution to formal sector production declines. This results in a shift of workers from medium-skill to low-skill and a resulting decrease in the 1-period enrollment rate. The high-skill labor stock and enrollment rates do not change because of the bound imposed by schooling's limited value-added. There is strong incentive for more individuals to attend 2-period schooling and become high-skill, but because schooling has low value added, these individuals would not attain the skill level necessary to become high-skill. In this case, the education system is unable to respond to demand for high skill labor. Note that this can arise either from low ϕ_1 (value added of 1-period or basic education) or from low ϕ_2 (value added of 2-period or higher education).

Annex 2 Figure 3. Simulated effect of automation on steady state variables (skill supply constrained at baseline model level)



Annex 3: Proofs of propositions

Proposition 1: $\frac{dL_2}{dK} > 0$ implies $\frac{dL_0}{dK} < 0$, if higher capital increases high-skill labor, then it also decreases low skill labor

Proof of proposition 1: From equations (3) and (5), $L_0 = nF(\theta_{01})$, by differentiation $\frac{dL_0}{dK} = n\frac{\partial F(\theta_{01})}{\partial \theta_{01}}\frac{d\theta_{01}}{dK}$. Let c_1^{-1} be the inverse of c_1. and where $\theta_{01} = c_1^{-1}(c)$. From equation (4) in equilibrium,

$$\theta_{01} = c_1^{-1}\left(\left(\sum_{i=1}^{n-1}\delta^i\right)(w_1 - w_0) - w_0\right)$$

Let $\Delta_1 = \sum_{i=1}^{n-1}\delta^i$ and $c_{01} = \Delta_1(w_1 - w_0) - w_0$, then $\frac{d\theta_{01}}{dK} = \frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\frac{dw_1}{dK}$. Differentiation of w_1 yields $\frac{dw_1}{dK} = \frac{\partial w_1}{\partial K}\frac{dK}{dK} + \frac{\partial w_1}{\partial L_1}\frac{dL_1}{dK} + \frac{\partial w_1}{\partial L_2}\frac{dL_2}{dK}$. Substituting the above together,

$$\frac{dL_0}{dK} = nf(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\left(\frac{\partial w_1}{\partial K}\frac{dK}{dK} + \frac{\partial w_1}{\partial L_1}\frac{dL_1}{dK} + \frac{\partial w_1}{\partial L_2}\frac{dL_2}{dK}\right)$$

$L_1 = (n-1)\left(1 - \frac{L_2}{n-2} - \frac{L_0}{n}\right)$ implying $\frac{dL_1}{dK} = -\frac{n-1}{n-2}\frac{dL_2}{dK} - \frac{n-1}{n}\frac{dL_0}{dK}$. Substituting the above together yields,

$$\frac{dL_0}{dK} = nf(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\left(\frac{\partial w_1}{\partial K}\frac{dK}{dK} - \frac{\partial w_1}{\partial L_1}\frac{(n-1)}{n-2}\frac{dL_2}{dK} - \frac{\partial w_1}{\partial L_1}\frac{(n-1)}{n}\frac{dL_0}{dK} + \frac{\partial w_1}{\partial L_2}\frac{dL_2}{dK}\right)$$

Solving for $\frac{dL_0}{dK}$,

$$\frac{dL_0}{dK} = \frac{nf(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\left(\frac{\partial w_1}{\partial K}\frac{dK}{dK} + \left(-\frac{\partial w_1}{\partial L_1}\frac{(n-1)}{n-2} + \frac{\partial w_1}{\partial L_2}\right)\frac{dL_2}{dK}\right)}{1 + nf(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\frac{\partial w_1}{\partial L_1}\frac{(n-1)}{n}}$$

Let

$$C_0 = nf(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\frac{\partial w_1}{\partial K}$$

$$C_1 = nf(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\left(\frac{\partial w_1}{\partial L_2} - \frac{\partial w_1}{\partial L_1}\frac{n-1}{n-2}\right)$$

$$C_2 = nf(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\frac{\partial w_1}{\partial L_1}\frac{n-1}{n}$$

Then,

$$\frac{dL_0}{dK} = \frac{C_0 + C_1\frac{dL_2}{dK}}{1 + C_2}$$

Note that $\frac{\partial c_1^{-1}}{\partial c} < 0$ as schooling costs and ability, θ, are inversely related. Because, $f(\theta_{01}) > 0$, $n > 2$, $\Delta_1 > 0$, by Assumption 1, $\frac{\partial w_1}{\partial K} > 0$, $\frac{\partial w_1}{\partial L_1} < 0$, $\frac{\partial w_1}{\partial L_2} > 0$, it follows that $C_0 < 0$, $C_1 < 0$, and $C_2 > 0$. Hence, $\frac{dL_2}{dK} > 0 \Rightarrow \frac{dL_0}{dK} < 0$.

Proposition 2: In developed countries, the ratio of middle-skill labor to capital-augmented high skill labor, $\frac{d}{dK}\frac{L_1}{L_2} < 0$, decreases as the capital stock increases

Proof of Proposition 2: From equations (3) and (5), $L_2 = (n-2)\big(1 - F(\theta_{12})\big)$. Differentiating yields $\frac{dL_2}{dK} = -(n-2)\, f(\theta_{12})\frac{d\theta_{12}}{dK}$. With Assumption 3 and equilibrium condition equation (4), $\theta_{01} = c_d^{-1}(\Delta_2 w_2 - \Delta_1 w_1)$, where $\Delta_2 = \sum_{i=2}^{n-1}\delta^i$. Let $c_{12} = \Delta_2 w_2 - \Delta_1 w_1$. Then, by differentiating wages,

$$\frac{d\theta_{12}}{dK} = \frac{\partial c_d^{-1}}{\partial c_{12}}\left(\Delta_2\left(\frac{\partial w_2}{\partial K} + \frac{\partial w_2}{\partial L_1}\frac{dL_1}{dK} + \frac{\partial w_2}{\partial L_2}\frac{dL_2}{dK}\right) - \Delta_1\left(\frac{\partial w_1}{\partial K} + \frac{\partial w_1}{\partial L_1}\frac{dL_1}{dK} + \frac{\partial w_1}{\partial L_2}\frac{dL_2}{dK}\right)\right)$$

Let,

$$B_0 = f(\theta_{12}) \frac{\partial c_d^{-1}}{\partial c_{12}} \left(\Delta_2 \frac{\partial w_2}{\partial K} - \Delta_1 \frac{\partial w_1}{\partial K} \right)$$

$$B_1 = f(\theta_{12}) \frac{\partial c_d^{-1}}{\partial c_{12}} \left(\Delta_2 \frac{\partial w_2}{\partial L_1} - \Delta_1 \frac{\partial w_1}{\partial L_1} \right)$$

$$B_2 = f(\theta_{12}) \frac{\partial c_d^{-1}}{\partial c_{12}} \left(\Delta_2 \frac{\partial w_2}{\partial L_2} - \Delta_1 \frac{\partial w_1}{\partial L_2} \right)$$

Then,

$$(1 + (n-2)B_2) \frac{dL_2}{dK} = -(n-2) \left(B_0 + B_1 \frac{dL_1}{d\alpha} \right)$$

$L_1 = (n-1)\left(1 - \frac{L_2}{n-2} - \frac{L_0}{n}\right)$ and $\frac{dL_1}{dK} = -\frac{n-1}{n-2}\frac{dL_2}{dK} - \frac{n-1}{n}\frac{dL_0}{dK}$. By Assumption 4, a developed country has $\frac{dL_0}{dK} \approx 0$; hence, $\frac{dL_1}{dK} = -\frac{n-1}{n-2}\frac{dL_2}{dK}$.

$$(1 + (n-2)B_2) \frac{dL_2}{dK} = -(n-2) \left(B_0 - B_1 \left(\frac{n-1}{n-2} \frac{dL_2}{dK} \right) \right)$$

$$(1 + (n-2)B_2 - (n-1)B_1) \frac{dL_2}{dK} = -(n-2)B_0$$

$$\frac{dL_2}{dK} = \frac{-(n-2)B_0}{1 + (n-2)B_2 - (n-1)B_1}$$

By Assumption 2, $\frac{\partial w_2}{\partial K} / \frac{\partial w_1}{\partial K} > 1 + \frac{1}{\sum_{i=1}^{n-2} \delta^i}$ which implies $\Delta_2 \frac{\partial w_2}{\partial K} > \Delta_1 \frac{\partial w_1}{\partial K}$ and $B_0 < 0$. By Assumptions 1 and 5, $B_1 < 0$, and $B_2 > 0$. Hence $\frac{dL_2}{dK} > 0$, from Proposition 1, $\frac{dL_1}{dK} < 0$ which implies that $\frac{d}{dK}\frac{L_1}{L_2} < 0$.

Proposition 3: $\frac{dL_1}{d\alpha} < 0$ with skill supply constraint

Proof of Proposition 3: By Assumption 5, $\frac{\partial}{\partial\alpha}\frac{\partial Y}{\partial L_1} < 0$ and $\frac{\partial}{\partial\alpha}\frac{\partial Y}{\partial L_2} > 0$. Because wages in equilibrium are equal to the marginal products of labor, $\frac{\partial w_1}{\partial\alpha} < 0$ and $\frac{\partial w_2}{\partial\alpha} > 0$. By definition 1, a skills constraint implies $\theta_{01} = \Theta_1 - \phi_1$ and $\theta_{12} = \Theta_2 - \phi_1 - \phi_2$; labor stocks of middle and high skill labor cannot increase, it follows that $\frac{dL_1}{d\alpha} \leq 0$ and $\frac{dL_2}{d\alpha} \leq 0$. $L_1 = (n-1)\big(F(\theta_{12}) - F(\theta_{01})\big)$. As above, $\theta_{01} = c_d^{-1}(\Delta_2 w_2 - \Delta_1 w_1)$, and let $c_{12} = \Delta_2 w_2 - \Delta_1 w_1$. By differentiation of wages and substitution,

$$\frac{dL_1}{d\alpha} = (n-1)\left(f(\theta_{12})\frac{\partial c_d^{-1}}{\partial c_{12}}\left(\Delta_2\left(\frac{\partial w_2}{\partial\alpha} + \frac{\partial w_2}{\partial L_1}\frac{dL_1}{d\alpha} + \frac{\partial w_2}{\partial L_2}\frac{dL_2}{d\alpha}\right)\right.\right.$$
$$\left. - \Delta_1\left(\frac{\partial w_1}{\partial\alpha} + \frac{\partial w_1}{\partial L_1}\frac{dL_1}{d\alpha} + \frac{\partial w_1}{\partial L_2}\frac{dL_2}{d\alpha}\right)\right)$$
$$\left. - f(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\left(\left(\frac{\partial w_1}{\partial\alpha} + \frac{\partial w_1}{\partial L_1}\frac{dL_1}{d\alpha} + \frac{\partial w_1}{\partial L_2}\frac{dL_2}{d\alpha}\right)\right)\right)$$

Let

$$A_0 = f(\theta_{12})\frac{\partial c_d^{-1}}{\partial c_{12}}\left(\Delta_2\frac{\partial w_2}{\partial\alpha} - \Delta_1\frac{\partial w_1}{\partial\alpha}\right) - f(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\frac{\partial w_1}{\partial\alpha}$$

$$A_1 = f(\theta_{12})\frac{\partial c_d^{-1}}{\partial c_{12}}\left(\Delta_2\frac{\partial w_2}{\partial L_1} - \Delta_1\frac{\partial w_1}{\partial L_1}\right) - f(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\frac{\partial w_1}{\partial L_1}$$

$$A_2 = f(\theta_{12})\frac{\partial c_d^{-1}}{\partial c_{12}}\left(\Delta_2\frac{\partial w_2}{\partial L_2} - \Delta_1\frac{\partial w_1}{\partial L_2}\right) - f(\theta_{01})\frac{\partial c_1^{-1}}{\partial c_{01}}\Delta_1\frac{\partial w_1}{\partial L_2}$$

then,

$$\frac{dL_1}{d\alpha} = \frac{(n-1)\left(A_0 + A_2\frac{dL_2}{d\alpha}\right)}{1-(n-1)A_1}$$

From Assumption 3, $\frac{\partial c_d}{\partial\theta} < 0$, and because $\frac{\partial w_1}{\partial\alpha} < 0$, $\frac{\partial w_2}{\partial\alpha} > 0$ and $\frac{\partial c_1^{-1}}{\partial c_{01}} < 0$, $A_0 < 0$. From

Assumption 1, $A_1 < 0$ and $A_2 > 0$, and, because $\frac{dL_2}{d\alpha} \leq 0$, it follows that $\frac{dL_1}{d\alpha} < 0$.

Corollary 3.1: $\frac{dL_0}{d\alpha} < 0$ with skill supply constraint

Proof of Corollary 3.1: $L_0 = n\left(1 - \frac{L_1}{n-1} - \frac{L_2}{n-2}\right)$; $\frac{dL_0}{d\alpha} = n\left(-\frac{1}{n-1}\frac{dL_1}{d\alpha} - \frac{1}{n-2}\frac{dL_2}{d\alpha}\right)$. From Assumption, $\frac{dL_2}{d\alpha} \leq 0$ and, from Proposition 3, $\frac{dL_1}{d\alpha} < 0$, it follows that $\frac{dL_0}{d\alpha} > 0$.

Proposition 4: if $\frac{dL_2}{d\alpha} > 0$ in absence of a skills constraint, then $\frac{dw_1}{d\alpha} < 0$ with a skills constraint

Proof of Proposition 4: As above, a skills constraint implies $\frac{dL_2}{d\alpha} \leq 0$. If $\frac{dL_2}{d\alpha} > 0$ in absence of the constraint, the constraint will be binding and $\frac{dL_2}{d\alpha} = 0$. In this case, $\frac{dL_1}{dK} = -(n-1)\frac{\partial F(\theta_{01})}{\partial \theta_{01}}\frac{d\theta_{01}}{d\alpha}$, and following the above notation,

$$\frac{dL_1}{d\alpha} = \frac{-(n-1)f(\theta_{01})\frac{\partial c_1^{-1}}{\partial c}\Delta_1\frac{\partial w_1}{\partial \alpha}}{1 + (n-1)f(\theta_{01})\frac{\partial c_1^{-1}}{\partial c}\Delta_1\frac{\partial w_1}{\partial L_1}}$$

Because $\frac{dL_2}{d\alpha} = 0$, $\frac{dw_1}{d\alpha} = \frac{\partial w_1}{\partial \alpha} + \frac{\partial w_1}{\partial L_1}\frac{dL_1}{d\alpha}$. It follows that $\frac{dw_1}{d\alpha} < 0$ if and only if $\frac{\partial w_1}{\partial \alpha} < -\frac{\partial w_1}{\partial L_1}\frac{dL_1}{d\alpha}$.
By substitution

$$\frac{\partial w_1}{\partial \alpha} < -\frac{-(n-1)f(\theta_{01})\frac{\partial c_1^{-1}}{\partial c}\Delta_1\frac{\partial w_1}{\partial L_1}}{1 + (n-1)f(\theta_{01})\frac{\partial c_1^{-1}}{\partial c}\Delta_1\frac{\partial w_1}{\partial L_1}}\frac{\partial w_1}{\partial \alpha}$$

which is true because

$$0 < \frac{(n-1)f(\theta_{01})\frac{\partial c_1^{-1}}{\partial c}\Delta_1\frac{\partial w_1}{\partial L_1}}{1+(n-1)f(\theta_{01})\frac{\partial c_1^{-1}}{\partial c}\Delta_1\frac{\partial w_1}{\partial L_1}} < 1$$

Corollary 4.1: in developed countries in which $\frac{dL_2}{d\alpha} > 0$ in absence of a skills constraint, $\frac{dL_1}{d\alpha} \approx 0$.

Proof of Corollary 4.1: By Assumption 4, $f(\theta_{01}) \approx 0$ in developing countries. By definition of $\frac{dL_1}{d\alpha}$ in Proposition 4, $f(\theta_{01}) \approx 0$ implies $\frac{dL_1}{d\alpha} \approx 0$.

Proposition 5: For middle skill intensive economies, if $\frac{dY}{d\alpha} > 0$ in absence of a skills constraint then $\frac{dL_2}{d\alpha} > 0$

Proof of Proposition 5: $L_2 = (n-2)\big(1-F(\theta_{12})\big)$. Following the notation above, let

$$B_0 = f(\theta_{12})\frac{\partial c_d^{-1}}{\partial c_{12}}\left(\Delta_2\frac{\partial w_2}{\partial \alpha} - \Delta_1\frac{\partial w_1}{\partial \alpha}\right)$$

then,

$$\frac{dL_2}{d\alpha} = \frac{-(n-2)\left(B_0 + B_1\frac{dL_1}{d\alpha}\right)}{1+(n-2)B_2}$$

As above, $B_1 < 0$, and $B_2 > 0$. By Assumption 5, $\frac{\partial w_2}{\partial \alpha} > 0$ and $\frac{\partial w_1}{\partial \alpha} < 0$; hence, $B_0 < 0$. As a result, if $\frac{dL_1}{d\alpha} > 0$, then $\frac{dL_2}{d\alpha} > 0$. Next, $\frac{dY}{d\alpha} = \frac{\partial Y}{\partial \alpha} + \beta\frac{dL_0}{d\alpha} + \frac{\partial Y}{\partial L_1}\frac{dL_1}{d\alpha} + \frac{\partial Y}{\partial L_2}\frac{dL_2}{d\alpha}$. By definition 2, middle skill intensive economy implies $\frac{L_1}{KL_2} \geq 1$. By Assumption 6,

$$\frac{\partial Y}{\partial \alpha} = \frac{1}{\rho}\big((1-\alpha)(L_1)^{\rho} + \alpha(KL_2)^{\rho}\big)^{\frac{1}{\rho}-1}\left((KL_2)^{\rho} - {L_1}^{\rho}\right)$$

If follows that $\frac{\partial Y}{\partial \alpha} < 0$. Because, $\beta \approx 0$, $\frac{dY}{d\alpha} > 0$ requires either $\frac{dL_2}{d\alpha} > 0$ or $\frac{dL_1}{d\alpha} > 0$, but $\frac{dL_1}{d\alpha} > 0$ implies $\frac{dL_2}{d\alpha} > 0$.

Proposition 6: For middle skill intensive economies, $\frac{dY}{d\alpha} < 0$ when skills are constrained

Proof of Proposition 6: $\frac{dY}{d\alpha} = \frac{\partial Y}{\partial \alpha} + \beta \frac{dL_0}{d\alpha} + \frac{\partial Y}{\partial L_1}\frac{dL_1}{d\alpha} + \frac{\partial Y}{\partial L_2}\frac{dL_2}{d\alpha}$. From Proposition 3, a skills constraint implies $\frac{dL_2}{d\alpha} \leq 0$ and as a result $\frac{dL_1}{d\alpha} < 0$ and $\frac{dL_0}{d\alpha} > 0$. Because $\beta \approx 0$, $\frac{dY}{d\alpha}$ is unambiguously negative when $\frac{\partial Y}{\partial \alpha} \leq 0$. By Assumption 6,

$$\frac{\partial Y}{\partial \alpha} = \frac{1}{\rho}\big((1-\alpha)(L_1)^\rho + \alpha(KL_2)^\rho\big)^{\frac{1}{\rho}-1}\ ((KL_2)^\rho - {L_1}^\rho)$$

and $\frac{\partial Y}{\partial \alpha} \leq 0 \Leftrightarrow KL_2 \leq L_1$ which is true by definition of middle-skill intensive.

Proposition 7: $\frac{L_1}{KL_2} \geq 1 \Rightarrow \frac{d}{dK}\frac{dY}{d\alpha} < 0$ in developed countries when skills are constrained.

Proof of Proposition 5: As above, $\frac{dY}{d\alpha} = \frac{\partial Y}{\partial \alpha} + \beta \frac{dL_0}{d\alpha} + \frac{\partial Y}{\partial L_1}\frac{dL_1}{d\alpha} + \frac{\partial Y}{\partial L_2}\frac{dL_2}{d\alpha}$. By Assumption 4, $L_0 \approx 0$, Definition 1 and Corollary 4.1, $\frac{dL_1}{d\alpha} \approx 0$ and $\frac{dL_2}{d\alpha} = 0$, it follows that $\frac{dY}{d\alpha} = \frac{\partial Y}{\partial \alpha}$ for developed countries. Let K^d be the threshold for development, such that countries with $K > K^d$ are developed. Let $x = \frac{L_1}{L_2 K}$ which, by Proposition 2, is decreasing for $K > K^d$. By Assumption 6 and definition of x,

$$\frac{\partial Y}{\partial \alpha} = \frac{1}{\rho}\big((1-\alpha)(xKL_2)^\rho + \alpha(KL_2)^\rho\big)^{\frac{1}{\rho}-1}(((KL_2)^\rho - xKL_2)^\rho)$$

It suffices to show that $\frac{d}{dx}\frac{\partial Y}{\partial \alpha} \leq 0$.

$$\frac{d}{dx}\frac{\partial Y}{\partial \alpha} =$$

$$(1-\alpha)\left(\frac{1}{\rho}-1\right)\frac{1}{\rho}\left((1-\alpha)(xKL_2)^{\rho}+\alpha(KL_2)^{\rho}\right)^{\frac{1}{\rho}-2}((KL_2)^{\rho}-(xKL_2)^{\rho})\rho(KL_2)^{\rho}x^{\rho-1}$$

$$-\frac{1}{\rho}(\alpha(xKL_2)^{\rho}+(1-\alpha)(KL_2)^{\rho})^{\frac{1}{\rho}-1}\rho(KL_2)^{\rho}x^{\rho-1}$$

$\frac{L_1}{KL_2} \geq 1 \Rightarrow x \geq 1$ which implies $((KL_2)^{\rho}-(xKL_2)^{\rho}) \leq 0$ and $\frac{d}{dx}\frac{\partial Y}{\partial \alpha} \leq 0$.