Cross Country Income Differences and the Distinction between Hard and Soft Skills in Human Capital*

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Abstract

A country's stock of human capital is a composite of hard and soft skills obtained by its people. Because hard skills are easily measured while soft skills are not, existing estimates of human capital stocks are biased against countries that excel at fostering soft skills. To overcome the lack of direct measures of soft skills, we model the productions of hard and soft skills in general equilibrium. Our model shows how to use occupation-based revealed comparative advantage to infer a country's ability to foster soft skills and delivers an index for aggregate human capital. Relative to existing measures, ours delivers much more dispersion of human capital across countries, has unique policy implications, and accounts for most cross-country variation in output per worker in a generalized-development-accounting framework.

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1 Introduction

A country's stock of human capital is the productive value of the aggregate stock of heterogeneous skills that is embedded in its workforce. To what extent is the huge variation in the value of output per worker across countries due to variation in the per capita stock of human capital? While the importance of this question is self-evident, it is difficult to answer due a thicket of measurement problems. At root of these measurement problems is the question of how to value and to aggregate the heterogeneous educational and experiential investments of heterogeneous individuals. These individuals differ along at least four dimensions. They differ (1) in their intrinsic ability, (2) in the time and resources spent acquiring skills, (3) in the *average* quality of their countries' educational institutions in accumulating different types of skill, and (4) in the *heterogeneity across* skill types in the effectiveness of their countries' educational institutions.[1] A large literature has tackled measurement issues (1)-(3) by either carefully modeling the educational decisions and international test score outcomes of individuals or by using careful microeconometric analysis of worker-level data on education and test score to guide aggregation.[2] The remaining problem that the effectiveness of a country's educational system may differ dramatically across skill types has not been addressed in the literature despite the growth of a rich microeconometric literature that has emphasized the distinction between hard and soft skills (e.g. Heckman and Rubinstein, 2001; Kuhn and Weinberger, 2005; Deming, 2017).

An important way that hard and soft skills differ is in the ease with which they can be measured in a population. "Hard" skills are those skills for which hard evidence can easily be gathered that the skills have been obtained by an individual (e.g. the ability to solve for a first-order condition or to parse a sentence). These skills are readily measurable on formal exams, such as PISA. "Soft" skills, such as the ability to mediate interpersonal conflicts or to organize teams to a common end, are more like experience goods in the sense that there is no quick and easy way to measure their presence in an individual. Both types of skills can be fostered by education. While rote "drill and kill" instruction can help individuals to master many hard skills, such as integration by parts, soft skills can be obtained in a formal educational setting through group projects that require interaction, through activities such as group projects, school plays, or through participation in student organizations. Different

[1] We view the concept of educational institutions as broad enough to incorporate opportunities for on-the-job learning.

[2] e.g. Mankiw, Romer and Weil 1992, Barro and Sala-i-Martin 1995, Klenow and Rodriguez-Clare 1997, Hall and Jones 1999, Bils and Klenow 2000, Hendricks 2002, Shastry and Weil 2003, Caselli 2005, Caselli and Coleman 2006, Erosa, Koreshkova and Restuccia 2010, Schoellman 2012, Jones 2014, Manuelli and Seshadri 2014, Malmberg 2017. The focus on a single type of human capital is also common for other literatures, such as the studies on how international trade affects skill acquisition (e.g. Findlay and Kierzkowski 1983, Atkin 2016, Li 2016, Blanchard and Olney 2017).

fields of study vary dramatically in the relative importance of hard and soft skills.

The failure of the literature to address heterogeneity within human capital between hard skills and soft skills is problematic, because the vast difference in the nature of hard and soft skills means that an educational system that is efficient in fostering one type of skill may be deficient in fostering the other. Indeed, a number of countries with low international test scores are concerned that their low scores indicate an inability to foster hard skills; e.g. the U.S. implemented No Child Left Behind (NCLB) in 2001 and Race To the Top (RTT) in 2009. In contrast, many countries whose students excel in international exams worry that their test scores are *too high*! e.g. the Education Ministry in China declared a ban on homework assignments for young children in 2013, and South Korea declared a 10 pm curfew on private tutoring. The fear is that these educational systems overemphasize hard skills at the expense of soft skills.[3]

The multi-dimensionality of human capital poses challenges for researchers; e.g. how to quantify multiple types of human capital, how to aggregate these skills appropriately, and how to assess the role of variation in human capital in cross-country differences in output per worker. If the policy implication is to increase human capital, which type to increase? On top of these, the second dimension, the soft skill component of human capital, is difficult to measure, precisely because these skills do not show up in test scores (e.g. Heckman and Kautz, 2012; Deming 2017). Hanushek and Woessmann (2011) recognize that "the systematic measurement of such skills has yet to be possible in international comparisons".

We believe that the neglect of the distinction between hard and soft skills in the construction of country-level measures of human capital limits the value of these measures in accounting for variation in output per capita, and that a proper accounting for this heterogeneity in skills is overdue. In this paper, we develop a methodology for aggregating heterogeneous types of human capital accumulated by heterogeneous workers to a single country-wide measure. Output is produced with labor from occupations that are imperfect substitutes in production, and these occupations differ in the extent to which they entail hard versus soft skills. Human capital is produced using economic resources, and countries differ in their efficiencies in turning resources into efficiency-equivalent units of hard and soft-skill human capital.

Aggregate stocks of hard and soft-skill human capital are determined by heterogeneous workers' optimal decisions about which types of human capital to invest in, and how much. These decisions, in turn, are driven by individual workers' innate abilities at different occu-

[3] For example, the Wall Street Journal reports that "A typical East Asian high school student often must follow a 5 a.m. to midnight compressed schedule, filled with class instruction followed by private institute courses, for up to six days a week, with little or no room for socializing" (February 29, 2012), and that "many students prepare for [the national college] entrance exams from an early age, often studying up to 16 hours a day for years to take these tests" (November 10, 2011).

pations, and their comparative advantages in performing hard and soft skills, as in Willis and Rosen (1979). In the aggregate, the employment shares of hard and soft skill occupations, which can readily be identified using O*net characteristics, depend on country-specific productivities in fostering these skills, and the returns to hard and soft skills in their local labor markets. In equilibrium, the returns of human capital are endogenous, and so ultimately, the relative employment share of the soft skill occupation varies across countries in the same direction as the ratio of soft skill productivity to hard skill productivity.

This framework allows us to aggregate the multi-dimensional differences in hard and soft-skill accumulation productivities into a single metric that we call human-capital accumulation productivity (HCAP) index. For any pair of countries, the relationship between the ratio of output per worker and the HCAP index can be condensed into a single analytical equation, in which the output-per-worker ratio monotonically increases with the HCAP index. There are two mechanisms embedded in the HCAP index. First, the HCAP index has an amplification mechanism that exists because the production of human capital requires human capital in our framework, and so the cross-country differences in soft and hard-skill accumulation productivities are amplified. The magnitude of amplification depends on the elasticity of human capital with respect to resources in human-capital production, η.

The HCAP index also has a heterogeneity mechanism. The HCAP index is the weighted power mean of hard and soft-skill accumulation productivities, where the weights are the employment shares of hard and soft skill occupations in a base country, and the power coefficients depend on the dispersion of workers' innate abilities, θ, and the substitution-elasticity across different types of human capital in aggregate production, α. This feature of the HCAP index contrasts with the standard treatment of human capital measurement that we refer to as "single-type" models of human capital because they abstract from heterogeneity in human capital.

Our quantification of the HCAP index is based on two simple premises. The first is that peoples' occupational choices reveal information about their skills at different types of tasks. For example, a manager issues directions and guidance to subordinates, while an engineer uses the knowledge in math and science to solve problems. Intuitively, this allows us to infer a country's comparative advantage in fostering soft skills relative to hard skills from occupational choice data. The second premise is that the standard measures for a single type of human capital (e.g. Caselli 2005), based on schooling years and test scores, can be applied to the hard-skill dimension because by definition hard skills as those for which objective quantiative measures are readily available. We combine these two elements to infer countries' productivities for turning resources into both hard-skill and soft-skill human capital. In other words, we can make cross-country comparisons for soft-skill human capital by combining absolute advantage in hard-skill human capital accumulation, measured using standard development accounting techniques, with comparative advantage, revealed by variation in occupational choices across countries. Our quantification provides a solution to the difficult problem of systematic measures of soft skills for cross-country comparison, and allows us to incorporate into the HCAP index the advances in the measures of single-type human capital in the literature.

We use the methodology of the HCAP index for two quantitiative applications. In the first all workers are assumed to have access to education and we use data for high-income countries. We explore the quantitative differences between the HCAP index and previous measures of human capital in the literature, draw out the unique policy implications of the HCAP index, and perform external validations of our quantification. In the second, we allow for unequal access to education across a country's citizens. This extension makes our framework comparable to the generalized-accounting literature (e.g. Jones 2014, Caselli and Ciccone 2019, or CC 2019), and allows us to perform development accounting using data for both high- and low-income countries.

In the first application, we show that the HCAP index delivers substantially larger dispersions of human capital than existing single-type measures, and both the amplification and heterogeneity mechanisms contribute to the increase in dispersion. If an advance in measurement leads to larger dispersions of human capital in a single-type setting, it does so with the HCAP index as well. For example, the variance of log human capital (per capita) is small, according to the standard single-skill measure. When we take the heterogeneity of hard and soft skills into account, the variance of log human capital increases by a factor of 2.4, and when we use the HCAP index, with both heterogeneity and amplification, it increases by a factor of 5.7. When we incorporate Schoellman (2012)'s improved measure of homogeneous human capital into the HCAP index, the variance of log human capital increases by a factor of 2 relative to Schoellman (2012)'s metric, and by a factor of 12 relative to the standard single-type metric. At this point, the variance of log human capital exceeds the variance of log output per worker. Our results are robust to the parameter values of α, θ, and η.

We also show that, relative to existing single-type measures, the HCAP index delivers unique policy implications, because it takes soft skills into account. For example, countries' soft-skill productivities, an important component of the HCAP index, are but weakly correlated with their PISA scores, and many countries with high PISA scores (e.g. S. Korea, Hong Kong) have low soft-skill productivities and so low HCAP indices. In other words, the concern in S. Korea and some East Asian countries about the efficiency of their educational systems in fostering soft skills may be well grounded. In addition, the HCAP index provides one way to quantify the overall proficiency of a country's educational system and to evaluate the potential tradeoffs between hard-skill and soft-skill accumulation efficiencies. This tradeoff may have useful implications for the discussions of education policies, such as

NCLB and RTT in the U.S.[4] We show that, were the U.S. to trade off soft-skill for hard-skill productivity at the rate that would bring it in the direction of S. Korea, its test score would increase but its HCAP index, and output, would drop. This message is consistent with a large body of applied-micro studies on early childhood intervention programs in the U.S.[5] Here, a common finding is that the programs boost participants' adult outcome (e.g. higher wages), but have little long-term effects on their test scores. Quoting Chetty et al. (2011), the results "suggest that policy makers may wish to rethink the objective of raising test scores and evaluating interventions via long-term test score gains." In comparison, previous measures of human capital are silent on these fronts, because they do not distinguish between hard and soft skills.

Because hard and soft-skill accumulation productivities are not directly observable, we use correlation patterns in the cross-country macro and trade data to validate our estimates. We show that countries that score well on international tests tend to have a large percentage of their population working in hard-skill occupations. In addition, immigrants to the United States tend to have occupation employment rates that reflect their source country rather than those of the U.S., the countries with high soft-skill employment shares also tend to have low relative wages for the soft-skill occupation, and the countries with strong comparative advantages for soft-skill human capital tend to have high normalized net exports of soft-skill-intensive industries. These results suggest that differences in occupational employment shares across countries reflect relative supply of human capital, rather than relative demand.

In our second application, we show that the expression for the ratio of human capital per capita in our model is similar to the generalized-accounting literature, with the HCAP index playing the role of skilled labor's relative efficiency. As a result, the HCAP index offers one answer to CC (2019)'s call to provide specific mechanisms for skilled labor's relative efficiency to vary across countries. Meanwhile, the HCAP index also meets Jones (2014)'s vision about the importance of human capital in development accounting. For example, when we incorporate Schoellman (2012)'s metric into the HCAP index, we find that human capital accounts for most of the cross-country variation in output per worker, as long as the substitution elasticity between skilled and unskilled labor, ρ, is not too low ($\rho \geq 2$). If this elasticity is higher ($\rho \geq 3$), human capital's contribution approaches 100%. For even higher elasticity values ($\rho \geq 5$), human capital per capita has more dispersion across countries than

[4] For example, the National Education Association states that, in response to NCLB and RTT, "We see schools across America dropping physical education ... dropping music ... dropping their arts programs ... all in pursuit of higher test scores. This is not good education."

[5] For the Head Start program, see Garces, Thomas and Currie (2002), Ludwig and Miller (2007), Deming (2009), and U.S. DHHS 2010. For Perry, see Schweinhart et al. (2005) and Heckman et al. (2010). For Star, see Chetty et al. (2011). Recent surveys include Duncan and Magnuson (2013) and Heckman and Kautz (2013).

output per worker.

We now place our contribution in the context of the literature. Erosa et al. (2010), Manuelli and Seshadri (2014) and Cubas et al. (2016) model the production of one type of human capital, making the point that human-capital production can amplify small differences in output TFP. We model the production of multiple types of human capital and obtain an analytical expression for the HCAP index. While the magnitude of amplification in our model is substantially smaller than in these studies,[6] our HCAP index still attributes most of variation in output per worker to human capital.

In the generalized-accounting literature (e.g. Jones 2014, Malmberg 2017, CC 2019, Jones 2019, and Rossi 2021), the main mechanism is the variation of the relative efficiency of skilled labor across countries, and these studies abstract away from the production of human capital. We have endogenous human-capital production in our general-equilibrium (GE) model, and so the HCAP index, derived from our GE model, has amplification.

Klenow and Rodriguez-Clare (1997), Hendricks (2002), Shastry and Weil (2003), Schoellman (2012), and Lagakos et al. (2019) refine the standard single-type measure of human capital.[7] We can incorporate the progress these studies have made, by applying their metrics to the hard-skill dimension and using them as the starting points of the HCAP index.

Ohsornge and Trefler (2007), Lagakos and Waugh (2013), Burnstein, Morales and Vogel (2016), Lee (2017) and Hsieh, Hurst, Jones and Klenow (2018) model heterogeneous workers making optimal choices across occupations (or industries). While the models used in these studies share common elements with our model, they do not examine how human capital contributes to cross-country variation in output per worker.[8]

An applied micro literature examines the formation of hard and soft skills using worker-level data from a single country (e.g. Kuhn and Weinberger 2005, Cunha, Heckman and Schennach 2010, Jackson, Johnson and Persico 2015), but has made limited progress in measuring soft skills for cross-country comparison. We use occupation employment data to back out countries' comparative advantages in fostering soft skills, quantify different countries' efficiencies in producing hard-skill and soft-skill human capital, and summarize

[6] Manuelli and Seshadri (2014) show that human capital accounts for most cross-country variation in output per worker if the amplification elasticity exceeds 5. This elasticity is 1.37 in our main specification.

[7] Hendricks and Schoellman (2018) show that, if measured as the residual, human capital accounts for most cross-country variation in output per capita. We measure human capital directly. Bils and Klenow (2000) explore experiences in the measurement of human capital, and a specification where human capital affects output TFP, which has some flavor of amplification.

[8] These studies also abstract away from the production of human capital, except for Hsieh et al. (2018). Hsieh et al. (2018) and Hsieh and Klenow (2009) investigate how market frictions for capital, final goods and labor distort resource allocation and output, using micro data from China, India, and the U.S. We focus on cross-country comparisons of soft-skill and hard-skill accumulation productivities and HCAP, and abstract away from market frictions and distortion in our model.

these differences into the HCAP index.

More broadly, the ways countries produce their human capital are related to their educational systems, which often have deep historic roots and so are an important part of their institutions. We thus also contribute to the institutions literature (e.g. Acemoglu, Johnson and Robinson 2001) by quantifying key characteristics of the educational institution and their implications for aggregate output.

For the remainder of our paper, section 2 derives the analytical expression of the HCAP index using a model with two types of labor, soft skilled and hard skilled, and clarifies the theoretical differences between the HCAP index and previous measures of human capital. Section 3 presents our first quantification application with data for high-income countries. Section 4 extends our model to have three types of labor, unskilled, hard-skilled, and soft-skilled, and presents our second quantification application with data for both high- and low-income countries. Section 5 concludes.

2 The HCAP Index: Theory

In this section, we derive the analytical expression for the HCAP index, develop its intuition, and highlight its theoretical differences with previous measures of human capital in the literature. In order to stay focused on the HCAP index, we adopt a stylized model in which heterogeneous skilled workers optimally choose their investment in both the quantities and types of human capital. We will allow for unskilled labor in section 4 below.

2.1 Assumptions

We start with a closed economy setting, and consider international trade in sub-section 2.6. There are K countries, indexed by k, each endowed with L^k heterogeneous workers. Workers are endowed with soft-skill and hard-skill attributes ε_n and ε_c, drawn from the following Frechet distribution:

$$F(\varepsilon_n, \varepsilon_c) = \exp\left(-\left(T_c \varepsilon_c^{-\theta} + T_n \varepsilon_n^{-\theta}\right)^{1-\upsilon}\right), \; \theta \equiv \frac{\widetilde{\theta}}{1-\upsilon} > 1. \tag{1}$$

We think about the attributes n and c as two distinct packages of skills, rather than two individual skills, and these packages may have common elements (see sub-section 2.5 below). In equation (1), υ determines the degree to which soft and hard packages of skills are correlated in the population of workers, and $\theta > 1$ governs the dispersion of attributes across workers. Higher θ reduces the dispersion in worker productivity. The parameters T_c and T_n govern the central tendencies of the attributes distribution, and are assumed to be common across countries.[9]

Following Hsieh et al. (2018), we specify the following production function for human capital of type i, $i = n$ (soft) or c (hard)

$$h_i(e) = h_i^k e^{\eta},\ i = c, n. \tag{2}$$

In equation (2), e is an individual worker's spending on human capital accumulation, in units of the final good (we specify its production below). The parameter η captures decreasing returns in the production of human capital, and guarantees an interior solution for workers' optimal choice of e. The parameters h_n^k and h_c^k are country k's TFP's in the production functions of soft skills and hard skills, and they capture the efficiency of country k's educational system along these two dimensions, net of resources inputs.

We treat h_n^k and h_c^k as exogenous, because the educational institution, an important contributor to human capital production, has deep historic roots in many countries. For example, in the U.S., private universities and colleges are a main feature of the educational institution, and their legal rights and status were enshrined by the Supreme Court in 1819 in Dartmouth-College-vs-Woodward.[10] In many East Asian countries, the national exam has been a cornerstone of the educational institution for over 1,000 years.[11] We capture, and quantify, such cross-country differences in educational institutions as h_n^k and h_c^k, and so we place no restriction on their values. On the other hand, we follow the literature and assume that ρ, θ, and η do not vary across countries.

Both soft and hard-skill tasks are needed to produce the final good. When a worker chooses task i, or occupation i, the quantity of her labor inputs, in efficiency equivalent units, equals

[9] This assumption says that genetic differences across countries have no significant effects on birth talents. We also assume away severe malnutrition, which might affect the T's. While the importance of nutrition for human capital development has been established for specific countries, its contribution to variation in income per capita remains an open question. In related work, Shastry and Weil (2003) show that anemia explains a small portion of the log variance of output per worker.

[10] In 1816, New Hampshire enacted state law to convert Dartmouth College from a private institution to a state institution. The case went to the U.S. Supreme Court, the legal issue being whether Dartmouth's original charter with the King of England should be upheld after the American Revolution. In 1819, the Supreme Court sided with Dartmouth, and this decision also guaranteed the private status of other early colonial colleges, such as Harvard, William and Mary, Yale, and Princeton (e.g. Webb, Metha, and Jordan 2013).

[11] China used archery competitions to help make promotion decisions for certain bureaucratic positions before 256 B.C.E., and established the imperial examination system as early as 605 A.D., which remained in use for over 1,000 years. In this system, one's score in the national exam determines whether or not he is appointed as a government official, and if so, his rank. Through trade, migration, and cultural exchanges, China's imperial examination system spread to neighboring countries; e.g. Korea established a similar system in 958 A.D. (Seth, 2002).

$$h_i(e)\varepsilon_i,\ i = n, c \tag{3}$$

where $h_i(e)$ is the quantity of the worker's human capital, accumulated according to the technology (2), and ε_i her attribute, drawn from the distribution in (1).[12] The educational and occupational choices made by workers lead to aggregate supplies of soft-skill and hard-skill human capital in country k of L_n^{kS} and L_c^{kS} (the S superscript indicates supply). The representative firm then hires workers in both soft-skill and hard-skill occupations to maximize output:

$$Y^k = \Theta^k \left(A_c \left(L_c^{kD} \right)^{\frac{\alpha-1}{\alpha}} + A_n \left(L_n^{kD} \right)^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1}}. \tag{4}$$

In equation (4), Θ^k is country k's output TFP, and A_c and A_n common technological parameters. The parameter $\alpha > 0$ is the substitution elasticity between soft and hard skills. L_n^{kD} and L_c^{kD} are the aggregate levels of soft and hard human capital demanded (the D superscript indicates demand) by final goods producers in country k.

The key prices in country k are the price of an effective unit of hard-skill human capital, w_c^k, the price of an effective unit of soft-skill human capital, w_n^k, and the price of the final output, P^k. Given cost minimization of the perfectly competitive final goods producers, the price of the final good (4) is given by

$$P^k = \frac{1}{\Theta^k} \left((A_c)^\alpha \left(w_c^k \right)^{1-\alpha} + (A_n)^\alpha \left(w_n^k \right)^{1-\alpha} \right)^{\frac{1}{1-\alpha}}. \tag{5}$$

Equation (5) says that P^k varies across countries because w_c^k and w_n^k may vary across countries. In addition, a country with high output TFP tends to enjoy low price of the final good, *ceteris paribus.*

All markets are perfectly competitive. The timing happens as follows. First, workers choose how much and what type (hard or soft-skill) of human capital to obtain. Second, final goods producers choose how many workers of each type to employ. Finally, all markets clear.

2.2 Equilibrium

In this sub-section, we characterize our model's equilibrium. We first solve for workers' optimal choices for the quantity and type of human capital given anticipated wages by occupation and the cost of education. These decisions determine the aggregate supply of each type of skilled labor. We then solve the firm's cost minimization problem in order to derive demand for each type of labor. Labor market clearing determines the equilibrium wages.

[12] Equation (3) assumes that occupation i uses skill i. We relax this assumption in sub-section 2.5.

Recall that human capital investment is in terms of final output. This means that the proper maximization problem facing an individual that will choose occupation i is

$$\max_{e} \left\{ w_i h_i^k e^{\eta} \epsilon_i - P^k e \right\},$$

and so the optimal choice of human capital investment is

$$e(\epsilon_i) = \left(\eta \frac{w_i^k}{P^k} h_i^k \epsilon_i \right)^{\frac{1}{1-\eta}}. \tag{6}$$

In equation (6), $e(\epsilon_i)$ is the quantity of human capital investment that includes a wide range of resources as in Haveman and Wolfe (1995). Equation (6) says that gifted individuals make large quantities of human capital investment whatever occupation they choose. In addition, individuals invest more in accumulating skills when real wages are high.

We substitute worker's optimal choice in (6) into her maximization problem to obtain the following expression for her optimal net income in occupation i,

$$I_i(\varepsilon_i) = (1-\eta)\eta^{\frac{\eta}{1-\eta}} \left(\frac{w_i^k}{P^k} h_i^k \varepsilon_i^k \right)^{\frac{1}{1-\eta}}. \tag{7}$$

Equation (7) show the potential income that a worker would obtain by pursuing occupation i, and we can use it to solve for the share of the workers who choose occupation i because it yields the highest level of income. Equation (7) implies that the worker chooses occupation n if and only if $w_c^k h_c^k \varepsilon_c^k \leq w_n^k h_n^k \varepsilon_n^k$.[13] Using the Frechet distribution (1), we show that the employment share of occupation i equals (Theory Appendix 6.1)

$$p_i^k = \frac{T_i (w_i^k h_i^k)^{\theta}}{T_c (w_c^k h_c^k)^{\theta} + T_n (w_n^k h_n^k)^{\theta}}, \; i = c, n. \tag{8}$$

Equation (8) says that the soft-skill occupation employment share, p_n^k, is high, if soft skills have a high relative return in the labor market (high w_n^k / w_c^k), or country k has a strong comparative advantage in fostering soft-skills (high h_n^k / h_c^k). In (8), θ plays the important role of governing the elasticity of labor supply. As θ rises and workers become more homogeneous, given changes in w_i^k or h_i^k lead to bigger shifts in the proportion of workers that opt to work in different occupations.

We now derive other aggregate outcomes that are determined by country characteristics and equilibrium prices. First, it is straightforward to show that the average net income is

[13] (6) and (7) show that the final-good price index, P^k, has the same effects on $e(\epsilon_i)$ and $I_i(\varepsilon_i)$ for both occupations, and so does not affect individuals' occupational choices.

the same for soft and hard-skill workers; i.e.

$$\begin{aligned} I_n^k &= I_c^k = \gamma(1-\eta)\eta^{\frac{\eta}{1-\eta}} \left[T_c \left(\frac{w_c^k}{P^k} h_c^k \right)^{\theta} + T_n \left(\frac{w_n^k}{P^k} h_n^k \right)^{\theta} \right]^{\frac{1}{\theta(1-\eta)}}, \\ \text{where } \gamma &= \Gamma\left(1 - \frac{1}{\theta(1-\rho)(1-\eta)}\right). \end{aligned} \tag{9}$$

Equation (9) is a common feature of the solution to discrete choice problems with Frechet distribution and homothetic demand (e.g. Eaton and Kortum 2002). In (9), the term in the square brackets is proportional to the denominator of the employment-share expression, (8). $\Gamma(.)$ is the Gamma function and so γ is a constant. Similarly, we can show that equations (8) and (9) imply that the average educational expenditure is equalized for workers in both occupations:

$$E_n^k = E_c^k = \gamma \left[\eta \left(T_c \left(\frac{w_c^k}{P^k} h_c^k \right)^{\theta} + T_n \left(\frac{w_n^k}{P^k} h_n^k \right)^{\theta} \right)^{\frac{1}{\theta}} \right]^{\frac{1}{1-\eta}}. \tag{10}$$

By equation (10), we now use E^k, without an occupation subscript, to denote the average educational spending in country k. These expressions imply that country k spends fraction η of its aggregate output on education;[14] i.e.

$$E^k L^k = \eta Y^k. \tag{11}$$

We now solve for the aggregate supply of human capital of type i, L_i^{kS}, $i = n, c$, and obtain (Theory Appendix 6.2):

$$L_i^{kS} = L^k p_i^k E(h_i^k e^{\eta} | Occp.i) = \frac{L^k p_i^k}{w_i^k} \left(\eta^{\eta} (P^k)^{1-\eta} \left(T_c \left(\frac{w_c^k}{P^k} h_c^k \right)^{\theta} + T_n \left(\frac{w_n^k}{P^k} h_n^k \right)^{\theta} \right)^{\frac{1}{\theta}} \right)^{\frac{1}{1-\eta}} \gamma. \tag{12}$$

Equation (12), together with $w_c^k L_c^k + w_n^k L_n^k = P^k Y^k$, implies that the income shares of hard-skill and soft-skill workers are given by

$$\frac{w_i^k L_i^{kS}}{P^k Y^k} = p_i^k. \tag{13}$$

To complete our characterization of the labor supply side of the economy, we use equations (8) and (12) to derive the relative supply of soft skills, which is given by

$$\frac{w_n^k}{w_c^k} \frac{L_n^{kS}}{L_c^{kS}} = \frac{p_n^k}{p_c^k}, \text{ where } \frac{p_n^k}{p_c^k} = \left(\frac{w_n^k h_n^k}{w_c^k h_c^k} \right)^{\theta} \frac{T_n}{T_c}. \tag{14}$$

[14] In section 4 below, we show that when we add unskilled labor into our model, high-income countries spend larger fractions of their output on education than low-income countries (e.g. equation (35) and Table 8).

Equation (14) says that the relative supply of soft-skill labor, L_n^{kS}/L_c^{kS}, is increasing in the availability of raw talent in the country, the comparative advantage of that country in soft-skill human capital, h_n^k/h_c^k, and the relative return of soft-skills, w_n^k/w_c^k. As foreshadowed by our discussion of equation (8), it is clear from equation (14) that θ is the supply elasticity: as workers' skills become more homogeneous, a given change in h_n^k/h_c^k or w_n^k/w_c^k affects the occupational choices of more workers, and so solicits a larger response in L_n^{kS}/L_c^{kS}.

We now turn our attention to the demand side. Cost minimization by final goods producers facing technology (4) determines the demand for hard and soft skills, implying that the cost share of input $i = c, n$ is given by

$$s_i^k = \frac{(A_i)^\alpha \left(w_i^k\right)^{1-\alpha}}{(A_c)^\alpha \left(w_c^k\right)^{1-\alpha} + (A_n)^\alpha \left(w_n^k\right)^{1-\alpha}}. \tag{15}$$

It follows immediately that the relative demand for soft skills is given by

$$\frac{w_n^k}{w_c^k}\frac{L_n^{kD}}{L_c^{kD}} = \frac{s_n^k}{s_c^k} \text{ where } \frac{s_n^k}{s_c^k} = \frac{(A_n)^\alpha \left(w_n^k\right)^{1-\alpha}}{(A_c)^\alpha \left(w_c^k\right)^{1-\alpha}} \tag{16}$$

Equation (16) is a standard relative demand equation where the demand elasticity is given by α.

Combining the supply and demand side of the economy, we obtain

$$L_i^{kD} = L_i^{kS}, i = n, c \tag{17}$$

We are now in a position to define the equilibrium of our model.

Definition 1 *An equilibrium to our model is a set of factor prices w_c^k and w_n^k that imply quantities of factors supplied, given by (14), and factors demanded, given by (16). These quantities clear domestic factor markets, given by (17), in conjunction with (12).*

Finally, using equations (8) and (14)-(17), we can solve for relative wages:

$$\frac{w_n^k}{w_c^k} = \left[\frac{T_c}{T_n}\left(\frac{h_c^k}{h_n^k}\right)^\theta \left(\frac{A_n}{A_c}\right)^\alpha\right]^{\frac{1}{\phi}}, \phi \equiv \theta + \alpha - 1 > 0. \tag{18}$$

Given the solution, to (18), occupational shares (8), labor supplies (12), and aggregate outputs (4) can be calculated.

2.3 Human Capital Accumulation Productivity (HCAP) Index

Differences across countries in output per worker are due to variation in the stock of productive inputs available to workers, conditional on the efficiency with which those inputs are used (output TFP). Our focus in this paper is on the stock of skills endogenously accumulated by workers, and this stock depends on the efficiency with which resources can be turned into human capital, as captured by countries' hard and soft-skill accumulation productivities. We now show how these productivities can be aggregated to produce a single index of Human Capital Accumulation Productivity, or HCAP (Theory Appendix 6.3):

Proposition 1 *Output per worker in country k relative to the base country 0 can be decomposed into the ratio of output TFP and the HCAP index according to.*

$$\frac{Y^k/L^k}{Y^0/L^0} = \left[\frac{\Theta^k}{\Theta^0}\right]^{\frac{1}{1-\eta}} HCAP^k, \tag{19}$$

where $HCAP^k$ is related to the ratios of soft-skill and hard-skill accumulation productivities and the occupation employment shares of country 0:

$$HCAP^k \equiv (\Omega^k)^{\frac{1}{1-\eta}},\ \Omega^k = \left(p_c^0 \left(\frac{h_c^k}{h_c^0}\right)^{\frac{\theta(\alpha-1)}{\phi}} + p_n^0 \left(\frac{h_n^k}{h_n^0}\right)^{\frac{\theta(\alpha-1)}{\phi}} \right)^{\frac{\phi}{\theta(\alpha-1)}}. \tag{20}$$

Equation (20) shows that the HCAP index has two main elements, amplification and heterogeneity. The first element, amplification, is expressed by the exponent $\frac{1}{1-\eta}$. Intuitively, $HCAP^k$ depends on η because we have endogenous human-capital production; i.e. high human-capital productivities imply large quantities of human capital and so high output, which is also used as inputs in producing human capital. In this round-about production, the differences in human-capital productivities, h_c^k/h_c^0 and h_n^k/h_n^0, are amplified, the magnitude of which depends on η, the degree of diminishing returns in human-capital production. The larger is η, the lower is diminishing returns, and so the larger is amplification.

The second element of the HCAP index, heterogeneity, shows up in the expression for Ω^k. This expression says that country k's HCAP index (relative to country 0) depends on the weighted power mean of the ratios of soft-skill and hard-skill accumulation productivities, where the weights are the occupational employment shares of the base country 0 and the power coefficients are determined by θ and α. As both θ, $\alpha \to \infty$, Ω^k goes to the maximum of h_c^k and h_n^k. This is intuitive, as workers become equally capable at both perfectly substitutable tasks. In this case, being strong in producing one type of human capital but weak in producing the other type has few consequences for the HCAP index. As $\alpha \to -\infty$, however, the aggregate production function becomes Leontief, Ω^k goes to the minimum of h_c^k and h_n^k, and excelling along a single dimension in human-capital production does little good for the HCAP index. For the more empirically relevant case found in our data (see below), Ω^k is reasonably well approximated as a geometric mean, where the relative importance of soft and hard-skill accumulation productivities is determined by the occupational shares. In this case, both productivities are important, and so a country with high productivity along one dimension but low productivity along the other tends to have low $HCAP^k$.[15]

Combining these two elements, the HCAP index summarizes the multi-dimensional differences in soft and hard-skill accumulation productivities into a single numerical value. Unlike L_c^{kS} and L_n^{kS}, the aggregate quantities of country k's human capital (in efficiency equivalent units), the HCAP index is a relative metric, and captures the overall efficiency of country k's human-capital production relative to country 0.

Finally, equation (19) shows that the ratio of output per worker can be decomposed into the HCAP index and a component that is related to the ratio of output TFP, and highlights the theoretical importance of the HCAP index to the variation of output per worker across countries. Later, in section 4, when we introduce additional model elements, the HCAP index continues to play an important role for output per worker, and the expression of the HCAP index, equation (20), remains unchanged.

2.4 HCAP Index and Previous Measures of Human Capital: Theory

In this sub-section, we relate the HCAP index to previous measures of human capital in the literature. We first discuss the relationship of the HCAP index to the standard measure of human capital, by using equations (19) and (20) to construct the following intermediate metric of human capital

$$\frac{Y^k/L^k}{Y^0/L^0} = \underbrace{\frac{\Theta^k}{\Theta^0}}_{\text{output TFP}} \times \underbrace{HHC^k}_{\text{Heterogeneous Human Capital}}, \qquad HHC^k = \underbrace{\frac{L_c^{kS}/L^k}{L_c^{0S}/L^0}}_{\text{Standard Measure}} \times \underbrace{\left(\Omega^k\right)^{\frac{\theta\alpha}{\phi}} \left(\frac{h_c^k}{h_c^0}\right)^{-\frac{\theta\alpha}{\phi}}}_{\text{Our correction}}. \tag{21}$$

In equation (21), the metric of heterogeneous human capital, HHC^k, has two components. The first component, $\frac{L_c^{kS}/L^k}{L_c^{0S}/L^0}$, is the average hard-skill human capital per capita. Since the measurement of hard skills is straightforward, we can apply the standard measure of human capital in the literature, based on schooling years and international test scores, to measure $\frac{L_c^{kS}/L^k}{L_c^{0S}/L^0}$. We think of this component as country k's *absolute advantage* in fostering hard skills.

Expression (21) makes clear that the standard measure is missing the component of human capital that reflects the existence of multiple types of skills. This shows up in our correction in (21) that contains country k's *comparative advantage* in accumulating soft skills. As we show in the next section, while it is difficult to directly measure countries'

[15] Note that as α becomes smaller (i.e. hard and soft-skill human capital become less substitutable in aggregate production), equation (20) assigns a bigger penalty for given imbalances in hard and soft-skill accumulation productivities.

soft skills, comparative advantage can be indirectly observed through a country's labor force occupational composition: countries with a large labor force working in soft-skill occupations are revealed to have a comparative advantage in fostering these skills. This second component of comparative advantage is the main difference between the standard measure of human capital and the metric of heterogeneous human capital, HHC^k.

Comparing HHC^k with the HCAP index, HHC^k takes existing stocks of human capital as given, whereas the HCAP index delivers equilibrium stocks from deeper model parameters, and so the value of η plays no role in HHC^k. In this sense, HHC^k is conceptually similar to the standard approach to human capital measurement, but extends this approach to account for heterogeneity. The HCAP index goes deeper, and recognizes that the existing stocks of human capital are produced, in general equilibrium, from the underlying fundamentals of hard and soft skill accumulation productivities. As a result, the cross-country differences of both productivities are magnified by the round-about structure of human capital accumulation.

The HCAP index thus incorporates the contribution of both heterogeneity of human capital and the amplification implied by its endogenous accumulation, and so is conceptually similar to the amplification literature, such as Erosa et al (2010), Manuelli and Seshadri (2014) and Cubas et al (2016). This literature focuses on the amplification of the cross-country differences in output TFP, and the mechanisms that affect the degree of amplification, such as demographics, the complementarity between physical capital and human capital, and whether human capital is produced using time, physical goods, or services. In comparison, the HCAP index incorporates heterogeneous human capital, and the amplification works on the efficiencies of their production, h_c^k and h_n^k. The role for amplification is smaller in our setting, however, because we have abstracted away from many of the mechanisms proposed there.[16]

Finally, Klenow and Rodriguez-Clare (1997), Hendricks (2002), Shastry and Weil (2003), Schoellman (2012), and Lagakos et al. (2018) refine the standard single-type measure of human capital. These studies complement ours, because we can apply their metrics to the measurement of hard-skill human capital, as we show in section 3 below.

2.5 Packages of Hard and Soft Skills

In this sub-section, we elaborate on our earlier claim that h_n^k and h_c^k can be thought of as packages of skills. To do so, we extend equation (3) such that occupations require both skills, but differ in the soft-skill intensity. To be specific, suppose that the workers accumulate

[16] In the literature, the amplification elasticity is between 2 and 3 in Erosa et al. (2010) and Cubas et al. (2016), and ranges from 5.7 to 9 in Manuelli and Seshadri (2014). Our amplification elasticity, $1/(1-\eta)$, is 1.37, given our η estimate of 0.27 (see section 3 below).

human capital for occupation i, $i=1,2$, according to

$$\begin{aligned} l_i^k &= h_c(e)^{\beta_i} h_n(e)^{1-\beta_i}\varepsilon_i, \\ h_c(e) &= h_c^k e^{\eta}, h_n(e) = h_n^k e^{\eta} \end{aligned} \tag{22}$$

In this expression, β_i captures the hard-skill intensity of occupation i, and h_c^k and h_n^k are the hard and soft skill accumulation productivities. Let $\beta_1 > \beta_2$; i.e. occupation 1 is hard–skill-intensive, and let $\widetilde{h}_i^k = \left(h_c^k\right)^{\beta_i}\left(h_n^k\right)^{1-\beta_i}, i=1,2$. We show in Theory Appendix 6.4 that the expression for the HCAP index is now

$$HCAP^k = \left(p_1^0\left(\frac{\widetilde{h}_1^k}{\widetilde{h}_1^0}\right)^{\frac{\theta(\alpha-1)}{\phi}} + p_2^0\left(\frac{\widetilde{h}_2^k}{\widetilde{h}_2^0}\right)^{\frac{\theta(\alpha-1)}{\phi}}\right)^{\frac{\phi}{\theta(\alpha-1)}\frac{1}{1-\eta}}.$$

In other words, equation (20) continues to hold, with h_n^k and h_c^k re-interpreted as countries' efficiencies in producing packages of soft and hard-skill human capital, $\widetilde{h}_1^k$ and $\widetilde{h}_2^k$.

2.6 International Trade

So far we have maintained the closed-economy setting. We now introduce international trade into our model, by assuming that the individuals can sell the services of their human capital as intermediate inputs around the globe. Countries can costlessly export intermediates to an international clearinghouse for factor content and import intermediates at iceberg trade cost τ^k from this clearinghouse. On the other hand, we assume that the final good itself is non-tradeable, because it is used as inputs in the production of human capital. Let $x_i^k = \frac{L_i^{kS}-L_i^{kD}}{L_i^{kS}}, i=c,n$, denote net exports of hard and soft skill labor.[17] We show in Theory Appendix 6.5 that the expression for the HCAP index is now

$$HCAP^k = \left(p_c^0\left(\left(\frac{p_c^0(1-x_c^0)}{p_c^k(1-x_c^k)}\right)^{\frac{1}{\alpha-1}}\frac{h_c^k}{h_c^0}\right)^{\theta} + p_n^0\left(\left(\frac{p_n^0(1-x_n^0)}{p_n^k(1-x_n^k)}\right)^{\frac{1}{\alpha-1}}\frac{h_n^k}{h_n^0}\right)^{\theta}\right)^{\frac{1}{\theta}\frac{1}{1-\eta}}. \tag{23}$$

Equation (23) says that the HCAP index remains a weighted power mean involving the ratios of soft and hard skill accumulation productivities, but it also involves country k's trade and occupation employment shares. It turns out as an empirical matter that Equation (20), derived under the closed-economy setting, provides a reasonable approximation to equation (23), because the factor content of trade, x_c^k and x_n^k, is small in the data (see sub-section 3.4 below).

[17] For example, if $x_c^k = -0.5\%$, country k imports cognitive human capital, the quantity of which is 0.5% of its aggregate supply.

On the other hand, international trade could potentially affect educational policy trade-offs, in theory, if it is free. In this case, the expression for the HCAP index would be

$$HCAP^k = \left(p_c^0 \left(\frac{h_c^k}{h_c^0} \right)^\theta + p_n^0 \left(\frac{h_n^k}{h_n^0} \right)^\theta \right)^{\frac{1}{\theta} \frac{1}{1-\eta}} . \tag{24}$$

The key difference between equations (24) and (20) is that the power coefficients do not include α under free trade, as local labor market demand does not have to equal local labor market supply. This has the effect of increasing the size of these power coefficients relative to the closed economy case; i.e. as if $\alpha \to \infty$ in equation (20).

3 The HCAP Index: Quantification

In the previous section, we developed the intuition of the HCAP index and compared it with other measures of human capital. In this section, we implement the quantification of the HCAP index. An important component of the HCAP index is countries' soft skill accumulation productivity, and the quantification of soft-skill human capital for cross-country comparisons has been difficult for previous studies. We show that the use of revealed comparative advantage provides a solution to this difficult problem, and provide external validations for our quantification. We focus on high-income countries, for which access to education is widespread, as we hypothesized in the previous section. We find that the use of the HCAP index leads to substantially wider dispersion of human capital than previous measures and provides unique policy implications.

3.1 Methodology

We start by explaining how we measure countries' hard and soft skill accumulation productivities, h_c^k and h_n^k, relative to a base country 0, as functions of the model's equilibrium conditions, occupational data, and an auxiliary assumption over the measurement of hard skills.

3.1.1 Absolute Advantage

We begin by backing out a country's absolute advantage in producing human capital. Combining equations (8), (10), (12) and (13), we obtain the following expression for country k's average hard-skill human capital (in efficiency equivalent units), relative to a base country 0 (Theory Appendix 6.6):

$$\frac{L_c^{kS}/L^k}{L_c^{0S}/L^0} = \left(\frac{Y^k/L^k}{Y^0/L^0} \right)^\eta \left(\frac{p_c^k}{p_c^0} \right)^{1-\frac{1}{\theta}} \left(\frac{h_c^k}{h_c^0} \right) \tag{25}$$

Given a measurement of the stock of hard-skill human capital in country k, L_c^{kS}/L^k, the country's efficiency at developing hard skills, h_c^k, can be backed out using equation (25). Intuitively, the first term on the right-hand side of equation (25) captures the effects of resources inputs, Y^k/L^k.[18] Resources are raised to the power of η because the production technology of human capital, (2), is subject to diminishing returns. The second term, which involves p_c^k, captures the effects of incentives and selection. To see these effects, suppose that many choose the hard-skill occupation in country k; i.e. p_c^k is high. This means that the hard-skill occupation is an attractive career choice, and so individuals have strong incentives to accumulate hard skills. This incentive effect implies high average hard-skill human capital for country k, and its magnitude is raised to the power of 1. On the other hand, workers are heterogeneous, and so a high p_c^k implies that many individuals with low innate hard-skill abilities have self-selected into the hard skill occupation. Their presence tends to lower the average hard-skill human capital. The magnitude of this selection effect is p_c^k raised to the power of $-1/\theta$.[19] Finally, hard-skill accumulation efficiency, h_c^k, soaks up all the other reasons why average hard skill per capita is high for country k, net of the effects of resources, and incentives minus selection.

To measure the efficiency units of hard skills in the population, L_c^{kS}/L^k, we lean on the standard single-type measure of human capital from the literature, ST^k, where

$$ST^k = b\exp[f(S^k)]g(t^k). \tag{26}$$

In equation (26), $f(.)$ and $g(.)$ are increasing functions, S^k and t^k denote, respectively, average schooling years and measures of human-capital quality (e.g. test scores) for country k, and b is a constant. We apply this approach to the hard-skill dimension and assume that

$$\frac{L_c^{kS}}{L^k} = b\exp[f(S_c^k)]g(t_c^k), \tag{27}$$

where $f(.)$, $g(.)$ and b are the same as in equation (26), and S_c^k and t_c^k are average schooling years and human-capital-quality measures for the hard-skill occupation. By following previous studies on single-type measures and applying their specifications of the functions $f(.)$ and $g(.)$, we incorporate the progress made in this literature into the absolute advantage of the HCAP index. Note that, because ST^k is for all human capital and L_c^{kS}/L^k is for hard-skill human capital only, the numerical value for ST^k, obtained from (26), exceeds L_c^{kS}/L^k, obtained from (27).[20] Our approach is natural given that test scores are effective at measuring hard skills but are less informative about soft skills.

[18] Recall that Y^k/L^k is proportional to E^k by equation (11).

[19] Note that, because $\theta > 1$, the incentive effect always dominates.

[20] Like L_c^{kS}/L^k, the right-hand-side variables in equation (27) are also unconditional means, and smaller than their counterparts in equation (26); e.g. S_c^k is the number of hard-skill-occupation schooling years averaged over all the workers in country k.

3.1.2 Comparative Advantage

Conceptually, we *could* measure the level of soft-skill human capital by using the counterpart of equation (25) for soft-skilled human capital, if a direct measure *were* available. The lack of such a measure lies at the heart of our quantification approach.

To see the problem, consider conscientiousness. It has positive correlation with wages across individuals within the same country, and is one of the "Big Five" non-cognitive traits in psychology (e.g. Lundberg 2017) that are often associated with soft skills. In cross-country survey data, however, conscientiousness has *negative* correlation with per capita GDP (e.g. Schmitt et al. 2007). Depending on how conscientiousness is scaled, the correlation coefficient is either -0.21 (p-value = 0.13) or -0.68 (p-value $<$ 0.05). The top nations for conscientiousness turn out to be Ethiopia and the Democratic Republic of Congo, while the bottom ones include Japan and S. Korea. Schmitt et al. (2007)'s interpretation is that cultural norms matter, and so respondents rate their conscientiousness relative to their peers within the same country. Many direct measures of such skills are survey based, just like conscientiousness,[21] and so they are likely to be country specific, too. While this does not affect the variation of these measures across individuals within the same country, it makes cross-country comparisons very difficult.

In the development-accounting literature, direct measures are often important for quantification; e.g. Schoellman (2012) use immigrants data to measure the quality of schooling, and Cubas et al. (2017) use PISA scores to quantify the endogenous production of skills. The problem that we face is that no such direct measure exists of soft-skill human capital. Our revealed-comparative advantage approach to which we now turn provides one solution to this very difficult problem.

Equations (8) and (18) imply that, relative to a base country 0,

$$\frac{h_c^k/h_n^k}{h_c^0/h_n^0} = \left(\frac{p_c^k/p_n^k}{p_c^0/p_n^0}\right)^{\frac{\phi}{\theta(\alpha-1)}}, \ \phi \equiv \theta + \alpha - 1 > 0. \tag{28}$$

Equation (28) has the flavor of revealed comparative advantage: we can back out a country's comparative advantage for accumulating soft-skill human capital, h_n^k/h_c^k, using the data and parameter values on the right-hand side of (28). This term captures the effects of the endogenous choices of workers and the optimal hiring decisions of the final goods producers. If we observe, in the data, that many have chosen the hard-skill occupation in country k, we can infer that country k has a strong comparative advantage for hard-skilled human capital.

Equation (28) also delivers the values of soft-skill accumulation productivity, h_n^k, given that we have the values of hard-skill accumulation productivity, h_c^k, from equations (25) and (27). These h_n^k values compare countries' efficiencies in producing soft-skill human capital.

[21] See Deming (2017b) for the difficulty of constructing more objective measures of non-cognitive skills.

In other words, equation (28) says that, even without a direct measure for soft skills across countries, we can still make cross-country comparisons for the soft skill dimension, by leaning on the measure we have for the hard-skill dimension, and revealed comparative advantage.[22]

It is worth pointing out that the identification assumption behind equation (28) is that relative demand for soft-skills, A_c/A_n, is common across countries. We will provide empirical evidence in sub-section 3.3 below that supports the assumption that it is the relative supply, h_c^k/h_n^k, rather than relative demand, that drives the cross-country variation of p_c^k/p_n^k in the data. The use of (28) also relies on our earlier assumptions of $\theta > 1$ and $\alpha > 1$. We provide empirical evidence consistent with these assumptions in the next sub-section.

We now turn to the specifics of the parameterization of the model, and the data we use to measure h_c^k, h_n^k, and the HCAP index.

3.2 Data, parameter values, and metrics

In this sub-section, we explain how we classify occupations into soft-skill and hard-skill categories to obtain values of p_c^k and p_n^k. We also explain the publically available sources of the remaining data and how we obtain the values of the parameters of θ, η, and α.

3.2.1 Soft-skill and Hard-skill Occupations

We classify occupations on the basis of their emphasis on tasks that can be identified as requiring hard versus soft skills. We follow much of the task based literature and use the O*NET database to identify the characteristics that are important to each occupation.[23] As soft skills largely involve interpersonal relationships and leadership, we classify occupations on the basis of the first principal component of eight O*NET characteristics of leadership, such as guiding and directing subordinates, and leadership in work style. If the principal component is important for an occupation, we classify this occupation as a soft-skill occupation, and we classify all the other occupations as hard-skill occupations (see Data Appendix 7.1 for more details).

[22] Note that our model implicitly determines the level of soft-skill human capital, L_n^{kS}/L^k, once we have the value of h_n^k, because $\frac{L_n^{kS}/L^k}{L_c^{0S}/L^0} = \left(\frac{Y^k/L^k}{Y^0/L^0}\right)^\eta \left(\frac{p_n^k}{p_n^0}\right)^{1-\frac{1}{\theta}} \left(\frac{h_n^k}{h_n^0}\right)$, which is the counterpart of equation (25) for soft-skill human capital. This computation, however, is unnecessary, because L_n^{kS}/L^k has already been embedded into the HCAP index.

[23] Examples of soft skills include communications (e.g. Hummels, Jorgensen, Munch and Xiang 2014), grit (e.g. Almlund, Duckworth, Heckman and Kautz 2011), leadership (e.g. Kuhn and Weinberger 2005), self-esteem (e.g. Heckman and Rubinstein 2001), and social skills (e.g. Deming 2017). Recent surveys include Heckman and Kautz (2013) and Lundberg (2017). A common approach in this literature is to use surveys or occupation-characteristics data to measure soft skills, and provide empirical evidence that these measures are distinct from hard skills. This is the approach we follow.

To be clear, we are not proposing leadership as *the* measure of soft skills. Rather, we demonstrate that leadership is *a* useful measure; i.e. it captures some skills that are not well measured by test score, a common measure for hard-skills. To do so, we draw on the well-established correlation between individuals' wages and their AFQT (Armed Force Qualification Test) scores (e.g. Neal and Johnson 1996, Altonji and Pierret 2001, Deming 2017), and that between wages and the Rotter-Rosenberg (RR) scale of control and self-esteem, a measure of traits often associated with soft-skills (e.g. Heckman et al. 2006). We use this framework to show that the wages of leadership occupations are less correlated with test scores but more correlated with RR scales than those of the other occupations.[24]

The data used in Table 1 is the 1979 NLSY (National Longitudinal Survey of Youth). The dependent variable is the log of individuals' wages in 1991, and the main explanatory variable is their AFQT score in 1980, before they enter the labor force. Column 1 shows that the coefficient estimate of AFQT score is positive and significant, and this result replicates Neal and Johnson (1996).[25] Columns 2 and 3 show that AFQT score has a smaller coefficient estimate for the subsample of occupations that we have classified as soft-skill than for the subsample of occupations that we have classified as hard-skill.[26] To show this pattern more rigorously, we pool the data in column 4 and introduce the interaction between AFQT score and the soft-skill-occupation dummy. The coefficient estimate of this interaction term is negative and significant.[27] This result continues to hold in column 5, where we control for the college dummy. In column 6, we add the RR scale into our regression, and obtain a positive and significant coefficient estimate. This result is consistent with Heckman et al. (2006). In column 7, we augment our regression further with the interaction of the RR scale and the soft–skill-occupation dummy. While the coefficient of the RR scale is no longer significant for the hard-skill occupations (0.162, p-value = 0.103), it remains significant for the soft-skill occupations (0.285, p-value = 0.044).[28]

Our model is based on the premise that all occupations require human capital, and one may wonder whether there are occupations in our data for which human capital is not relevant. Column 5 of Table 1 shows that the coefficient estimate of test score remains

[24] We have experimented with classifying occupations using the single O*NET characteristic of guiding and directing subordinates, and obtained similar results, as shown in Data Appendix 7.1. In this appendix, we also examine additional O*NET characteristics as candidates for occupation classification, and show that they do not exhibit the correlation patterns in Table 1.

[25] We include both men and women in Table 1, while Neal and Johnson (1996) do the estimation separately for men and women. We have experimented with this and obtained very similar results. We also use the same sample cuts as Neal and Johnson (1996) (Data Appendix 7.1).

[26] The coefficient estimates for AFQT square are not significant.

[27] Note that we have included the soft-skill-occupation dummy itself, whose coefficient estimate is positive and significant.

[28] It is the coefficient of the RR scale plus that of the RR-scale-soft-skill-occupation interaction.

positive and significant after we control for the college dummy. Kuhn and Weinberger (2005) show that men with leadership positions in high school tend to have higher wages, consistent with the results presented in column 6 of Table 1, and that the marginal effect of leadership is as strong for low-education individuals as for high-education ones.

We next bring in employment data by 3- or 4-digit occupations from the International Labor Organization (ILO) (more details are in Data Appendix 7.2) to show that countries differ in the extent to which their workforces have accumulated soft and hard skills. We keep only the countries whose raw data are in ISCO-88 (International Standard Classification of Occupations), because O*NET occupations can be easily mapped into ISCO-88 occupations but the mappings among other occupation codes are scarce (e.g. we cannot find the mapping between Canadian and U.S. occupation codes). In order to keep our focus on the HCAP index, we keep high-income countries, where access to education is widespread, as hypothesized in our model in section 2. This leaves us with a cross-section of 26 countries, and most of the observations are for the year 2000. Using these detailed occupational data, we compute the employment shares of the hard and soft skill occupations by country, the variables p_c^k and p_n^k in our model. Figure 1 plots the histogram of p_n^k across countries, and the upper panel of Table 2 reports its summary statistics ($p_c^k = 1 - p_n^k$). Table 3 lists the countries and years in the sample.

With over 100 ISCO-88 occupations, each occupation typically accounts for a small share of total employment, and no single occupation drives the cross-country variation in p_c^k and p_n^k. In our data, the mean employment share, across countries and occupations, is 0.88% for soft-skill occupations and 0.96% for hard-skill occupations. Examples of large soft-skill occupations include managers of small enterprises (1310) (cross-country mean = 3.8%) and nursing and midwifery professionals (3230) (cross-country mean = 1.5%). Examples of large hard-skill occupations include finance and sales professionals (3410) (mean = 2.7%) and secretaries (4110) (mean = 2.3%). There is also substantial cross-country variation for a given occupation. For example, the employment share of occupation 1310 exceeds 5% in Hong Kong, the Netherlands and Spain, but not in the U.K. or Belgium; the 25th percentile of its distribution is 2.0% but its 75th percentile is 5.4%. We provide the full list of hard and soft-skill occupations and their summary statistics in Data Appendix 7.2.

3.2.2 Other Data

We obtain the rest of our data from standard public sources. We briefly describe these sources below, and leave more detailed discussions in Data Appendix 7.2. For aggregate output, Y^k, we strip capital from GDP, obtained from Penn World Tables, by assuming a Cobb-Douglas production function between capital and aggregate labor and using the parameter values of Klenow and Rodriguez-Clare (1997). We do so because we do not have physical capital in our model.[29] We obtain data on schooling years from Barro and Lee (2013), and PISA math scores from the official PISA website.[30]

To implement equation (27), we need data on employment at the level of occupation-by-education[31] that is available from EuroStat for a subset of our sample countries. We show that these employment shares, occupation by education, are highly correlated with the corresponding shares for the U.S. immigrants born in these countries (our data on immigrants comes from 2000 U.S. Census). We then use this correlation and the immigrants' shares to extrapolate the data for the countries not covered in EuroStat,[32] and combine these data with the Barro-Lee schooling-years data to compute average schooling years for the hard-skill occupation.

Our data on employment occupation-by-education show that our occupational classification is distinct from the high-skill-low-skill classification. For the median country with non-missing data from EuroStat, most college-educated workers (55.9%) are in the hard-skill occupation, and most workers in the soft-skill occupation (55.5%) have below-college education.

3.2.3 Metrics for Human Capital and Parameter Values

We use two metrics for human capital, and they correspond to different specifications of $f(.)$ and $g(.)$ in equations (26) and (27). Metric 1 is the standard single-type measure (e.g. Caselli 2005, Hanushek et al. 2017). The function $f(.)$ is piecewise linear with slopes of 0.134, 0.101 and 0.068 for, respectively, schooling years below 4, between 4 and 8, and above 8, and $g(.) = \exp(0.002t^k)$, where t^k is test score.[33] Denote this measure by ST_1^k. Metric

[29] We experimented with labor income, or compensation of employees from National Income and Product Account, which is similar to the approach taken in Hsieh et al (2018). The aggregate output of this second approach has a correlation of 0.9994 with our main output variable.

[30] We use PISA scores because they are widely reported in the media, and have influenced education policies in many countries. In addition, PISA samples students in a nationally representative way, covers many countries, and controls qualities of the final data (e.g. the 2000 UK scores and 2006 US reading scores are dropped because of quality issues). Finally, while PISA scores are for high-school students, they are highly correlated with the scores of adult tests (e.g. Hanushek and Zhang 2009). Compared with PISA, adult tests cover substantially fewer countries (they would cut our sample size by at least 25%) and also have lower response rates (e.g. Brown et al. 2007). See also Data Appendix 7.2.

[31] This level of aggregation is finer than the data for p_c^k and p_n^k, which is by occupation.

[32] This extrapolation is for the variable s_c^k in equation (27), not for p_c^k and p_n^k, whose data come directly from the ILO and do not require extrapolation.

[33] We do not observe the average PISA score for the cognitive occupation in the data, and we assume it is the same as the national average. We have experimented with alternative assumptions (e.g. dropping test score) and obtained similar results. In the specification of $g(.)$, the coefficient is 0.002 per point of PISA score, with mean 500 and standard deviation 100. This is similar to Hanushek et al.(2017), where test score also has mean 500 and standard deviation 100, and the coefficient is 0.17 per standard deviation.

2 follows Schoellman (2012), with $f(.) = \exp(0.2S^k)$ and $g(.) = 1$. Relative to ST_1^k, the coefficient of 0.2 magnifies variation in schooling. The reasoning is that average schooling years measure both quantity and quality of human capital, and so test score is no longer needed. We denote this measure ST_2^k.

We now move on to our parameter values. By equation (11), η is the ratio of aggregate educational spending, $E^k L^k$, to aggregate output, Y_k. Haveman and Wolfe (1995) show that the total spending on human capital in the U.S. (including both public and private spending) is 15.5% of GDP. This implies that aggregate educational spending is 27% of U.S. output according to our output measure. We choose $\eta = 0.27$ for our main results, and experiment with $\eta = 0.22$ and $\eta = 0.33$. We also provide additional validation for η in section 4 below (e.g. Table 8).

We next obtain the value of θ, which measures the dispersion of innate abilities across workers. A recent Roy-model literature has estimated θ using a variety of data sources and identification strategies, and reached a consensus about the range of its value. This range is 1.5 to 2.5 in Hsieh et al (2019), 1.78 to 2.62 in Burnstein et al. (2019), and 1.48 to 2.5 in Lee (2020).[34] We also do our own estimation of θ, by relating our model's prediction of income distribution to the data. Briefly speaking (the details are in Data Appendix 7.2), our model says that the distribution of gross income is Frechet. We interpret our model's gross income as life-time labor earnings in the data, and use the U.S. PSID[35] to construct the distribution of this variable. In our main specification, our model's prediction accounts for over 70% of the variation in the distribution of life-time labor earnings in the data, and we obtain $\theta = 2.2$. This is consistent with our assumption of $\theta > 1$, and not statistically different from $\theta = 2$, the mid point of the range reported in the Roy-model literature. We thus use $\theta = 2$ for our main results, and experiment with $\theta = 1.5$ and $\theta = 3$.

For α, the substitution elasticity between occupations in aggregate production, we draw on Burnstein et al. (2019), where aggregate production is also CES across occupations. They use cross-section and over-time variations in occupational wages and employment in micro data from the U.S., and obtain $\alpha = 1.78$. We also produce our own estimate for α. Briefly speaking (see Data Appendix 7.2), our model says that the cross-country relationship between output normalized by hard-skill human capital and the relative quantity of soft-skill human capital depends on α. We measure hard-skill human capital using (27), and show that the relative quantity of soft-skill human capital can be related to relative employment shares. Under our main specification, we obtain $\alpha = 1.73$, which is consistent with our assumption of $\alpha > 1$. Since our α estimate is not statistically different from Burnstein et al.

[34] Lagakos and Waugh (2013), whose model has industries and not occupations, obtain $\theta = 2.7$ for the non-agricultural sector.

[35] PSID has a larger sample size than NLSY79.

(2019)'s, we use $\alpha = 1.78$ for our main results,[36] and experiment with $\alpha = 1.4$ and $\alpha = 2$.

3.3 External Validation

In this sub-section, we provide external validations for our quantification. More details are in Data Appendix 7.3.

3.3.1 Evidence for Occupation Classification in Macro Data

We first validate our classification of hard-skill and soft-skill occupations using cross-country macro data. If, as we have asserted, an individual's mastery of hard-skill can be quantified using test scores, then countries with high average PISA test scores should be those that excel in developing hard skills and so should have a large portion of their workforce choosing to work in hard-skill occupations as we have defined them. Motivated by equation (25), we examine whether the log of normalized test scores, $\ln\left(\frac{S^k}{\left(Y^k/L^k\right)^\eta}\right)$, has positive correlation with the log of hard-skill employment shares, $\ln(p_c^k)$.

We report the results from this regression in Table 4. Table 4 provides evidence that our occupation classification, based on the correlation patterns in the U.S. micro data in Table 1, is consistent with cross-country macro data. The upper panel has PISA math scores, the lower panel has PISA science scores, and all columns have aggregate output as weights.[37] Column 1 uses raw PISA scores, whose mean is standardized to 500 and standard deviation to 100, while columns 2 and 3 use the scaled PISA scores of $(S^k)^\delta$, where $\delta > 0$ is a scaling factor. To obtain an estimate for δ, we go back to the wage-AFQT regressions of Table 1, re-standardize AFQT to have mean 500 and standard deviation 100, and use the log of this score in the estimation. We obtain an estimate of 0.912 for the elasticity of wage with respect to PISA-scaled AFQT score, and report the results with $\delta = 0.912$ in column 2.[38] In column 3, we re-estimate the wage-AFQT regression using the log of raw AFQT score, and find that the wage elasticity is now 0.150. We then standardize the PISA scores in macro data to have the same mean (38.6) and standard deviation (27.8) as the raw AFQT scores, and use $\delta = 0.150$ for the re-standardized PISA scores. In all specifications, the coefficient

[36] $\alpha = 1.78$ is also used in Atalay et al (2017).

[37] Size varies a lot across countries in our sample (e.g. the U.S. and Switzerland).

[38] In our model, the quantity of an individual's cognitive human capital (in efficiency equivalent units) is given by equations (2) and (3). These choices of units imply that across individuals, wage moves one-for-one with the quantity of cognitive human capital. In the literature, Cubas et al (2016) also consider the specification $(S^k)^\delta$, but assume that $(S^k)^\delta$ maps into the location of the talent distribution (which is like T_c in our model). The other aspects of their model are also different from ours. As a result, they obtain a different value for δ.

estimates of $\ln(p_c^k)$ are positive and significant.[39] Countries in which workers are clustered in hard-skill occupations tend to score well on international tests (normalized by resources inputs) and formal tests measure primarily hard-skill achievement.

3.3.2 Occupation Employment Shares: Relative Supply or Relative Demand?

A key identification assumption that is implicit in equation (28) is that relative demand for hard skills is not driven by cross-country variation in A_c/A_n. We now address this threat to our quantification by showing that the data are consistent with relative supply, h_c^k/h_n^k, driving the cross-country variation of the relative employment share, p_c^k/p_n^k. We note that, according to equations (8) and (18), relative demand affects country-k workers' occupational choices, p_c^k/p_n^k, only through the relative wage, w_c^k/w_n^k, and it has no direct effect on p_c^k/p_n^k.

Suppose, first, that there is no variation in hard and soft-skill accumulation productivities, h_c^k and h_n^k, across countries, and that occupational employment shares, p_c^k and p_n^k, are completely determined by relative demand. Consider, in this scenario, the occupational choices of country k's emigrants in the U.S., and let $p_c^{k,0}$ denotes the share of country k's emigrants who choose the hard-skill occupation in the U.S. Then, $p_c^{k,0}/p_n^{k,0}$ depends on the relative wage in the U.S., w_c^0/w_n^0, which does not depend on country k's relative demand. Thus, we obtain the prediction that, in this scenario, country k's relative employment share, p_c^k/p_n^k, is uncorrelated with their U.S.-emigrants' relative employment share, $p_c^{k,0}/p_n^{k,0}$.[40]

We use the 2000 U.S. Census to investigate this prediction. We follow the literature (e.g. Hendricks 2002, Schoellman 2012) and focus on the adult immigrants who arrived in the U.S. after their expected graduation dates. Figure 2 plots country-k U.S. emigrants' relative employment shares in soft-skill occupations, $p_n^{k,0}/p_c^{k,0}$, against country-k workers' relative employment shares, p_n^k/p_c^k. It shows a clear positive correlation (0.582, p-value = 0.0045), and provides evidence against the hypothesis that the cross-country variation of employment shares, p_c^k and p_n^k, is completely determined by relative demand.

Next, suppose that both relative demand and relative supply matter for occupational employment shares, p_c^k and p_n^k, and that relative demand dominates, such that w_n^k/w_c^k is high where p_n^k/p_c^k is high (see equation (18)). We examine this prediction for a subset of our sample countries, by combining EuroStat data on their average annual earnings by occupation[41] with our ILO data on occupational employment, to compute w_n^k/w_c^k by country.

[39] The magnitudes of these estimates are also consistent with equation (25), because they are between 0 and 1.

[40] This prediction is based on the assumption that across countries, the relative restrictiveness of U.S. immigration policies, between hard-skill and soft-skill types, is uncorrelated with country k's relative demand. See Theory Appendix 6.7 for more details.

[41] The OWW data covers many countries, but the occupation codes there closely follow industry classification (e.g. forestry, oil-and-gas, furniture) (Oostendorp 2012), and it is unclear how to map these codes to

We find that w_n^k/w_c^k and p_n^k/p_c^k have a negative correlation of -0.437 (p-value = 0.048). This negative correlation provides evidence against the hypothesis that the cross-country variation of employment shares is driven by relative demand.[42]

One might be concerned about our measurement of w_n^k/w_c^k; e.g. the average earnings are not adjusted for hours, and the treatment of benefits may differ across countries. We then move to the next piece of evidence, based on the following prediction of our open-economy model: if relative demand dominates, the countries with observed relative abundance (high p_n^k/p_c^k) are net importers of soft-skill-intensive products, because w_n^k/w_c^k is high, and vice versa if relative supply dominates.

We investigate this prediction by following the trade literature (e.g. Nunn 2007, Bombardini, Gallipoli and Pupato 2012) and examining the correlation between the patterns of trade and the interactions between relative factor abundance and factor-use intensities. To measure trade patterns, we calculate net export divided by the sum of import and export by industry by country. For each country, we measure its relative abundance in soft-skill human capital, physical capital and skilled labor as, respectively, the ratio of h_n^k to h_c^k, the ratio of physical capital stock to population, and the fraction of college-educated labor force. For each industry, we measure the intensities of soft-skill human capital, physical capital and skilled labor using U.S. data. We control for industry fixed effects and country fixed effects.

Table 5 reports the results. Column (1) includes only the interaction for soft-skill human capital. We add the interaction for physical capital in column (2), and then the interaction for skilled labor in column (3). In column (3), the interaction for skilled labor is positive and significant, consistent with the regularity in macro data that skill premia tend to be low in skilled-abundant countries. Meanwhile, the interaction for soft-skill human capital has positive and significant coefficient estimates in all specifications. This result provides additional evidence against the hypothesis that the cross-country variation of employment shares is driven by relative demand. It also suggests that our h_c^k and h_n^k values are useful for explaining the variation of trade patterns by industry by country, even though we did not use such variation to obtain them.

In the literature, Rossi (2021) uses immigrants' wage data in multiple host countries to back out the relative demand for skilled vs. unskilled workers, by assuming homogeneity within skill groups and abstracting away from endogenous production of human capital. In comparison, we lack a direct measure of soft-skill, and address this difficult problem by de-

ISCO 88.

[42] To place this correlation into context, the correlation between the relative supply of skilled labor and skill premium in the widely used data of Caselli and Coleman (2006) is -0.337 (p-value = 0.015). Caselli and Coleman (2006) compute skill premia using Mincer wage returns, from Bils and Klenow (2000), and duration of schooling years from Barro-Lee. We cannot implement this approach because the Barro-Lee data does not break down schooling by occupation.

veloping a GE model with worker heterogeneity and human capital production, and making the identification assumption that A_c/A_n does not vary across countries in our quantification. Given the potential importance of soft-skill human capital and the absence of direct measures for its cross-country comparison, our quantification provides a useful first step. If data become feasible for A_c/A_n by country in future research, it will be straightforward to incorporate this progress into our theoretical and quantification framework.

3.4 HCAP Index vs Previous Measures of Human Capital: Data

In this sub-section, we compare our measures of human capital with measures that have been proposed in the literature. We begin by discussing the results for countries' hard and soft-skill accumulation productivities, h_c^k and h_n^k. We then compare the distribution of human capital stocks implied by the HCAP index to those implied by previous measures.

Table 3 lists the rankings of our countries in their hard and soft-skill accumulation productivities, h_c^k, h_n^k, and standard measures of human capital per worker, ST_1^k, as well as these countries' schooling years and PISA math scores. To better visualize how hard-skill efficiencies compare to standard measures of human capital, we plot h_c^k against ST_1^k in Figure 3. Unsurprisingly, the rankings in h_c^k and ST_1^k are highly correlated (0.77). This is expected because our measure of hard-skill accumulation productivies, (27), is derived in part from the standard measure, (26).[43]

Figure 4 shows that the rankings in soft-skill accumulation productivities, h_n^k, are substantially different from the rankings in the standard measure of human capital per worker, ST_1^k. For example, Belgium, Finland, and the U.K. all have low human capital per worker (outside of top 10), according to ST_1^k. However, our model says that the standard measure fails to take into account high employment shares of the soft-skill occupation in these countries, which suggest strong comparative advantages for producing soft-skill human capital. Once we quantify the comparative advantages, using (28), these countries turn out to have high soft-skill accumulation productivities (within top 5). Meanwhile, the opposite is true for S. Korea, Switzerland and Slovenia. These examples show that the soft-skill accumulation productivity, h_n^k, opens up a new dimension for cross-country comparison. The different rankings of h_n^k and ST_1^k also suggest that after correctly adjusting for soft-skill human capital, the variance in human capital stocks across countries increases. In the rest of this sub-section, we describe the change in dispersion from the standard measure to ours, and

[43]Figure 3 also shows that these two rankings are quite different for a number of countries. For example, the standard measures of human capital per capita, ST_1^k, are low for Poland and Hungary, but these countries have high cognitive efficiencies, h_c^k. This is because cognitive efficiencies correct for low output per worker in these countries, and so limited resources for human capital production. This also explains why the U.S. has high ST_1^k but low h_c^k.

clarify the intuition of this change. We show how this change in dispersion helps account for the cross-country differences in output per worker in section 4 below (e.g. Figure 7).

The upper panel of Table 6 reports the variance of the logarithm of measures of human-capital, and the lower panel reports the 90-10 ratios of these measures. In our sample, the log of output per worker has variance of 0.13, and output-per-worker has the 90-10 ratio of 2.23. The first measure of human capital that we report is the standard, homogenous measure calculated according to metric 1, ST_1^k. The variance of $\log(ST_1^k)$ is 0.013, and the 90-10 ratio of ST_1^k is 1.33. These results are consistent with the previous findings in the literature that the standard measures of human capital have limited variation across countries.

In the heterogeneous-human-capital measure of equation (21), our measure of hard-skill human capital, $L_c^{kS} L^0 / L^k L_c^{0S}$, is similar to, but has smaller variation than, metric 1, but we add the variation associated with heterogeneous human capital differentiated across soft-skill and hard-skill occupations. The addition of our adjustment due to heterogeneity increases the variance of log human capital by a factor of 2.4, to 0.032, and it increases the 90-10 ratio of human capital by a factor of 1.2, to 1.58. These results show that taking the hard-to-measure soft-skill human capital into account leads to larger dispersion of human capital across countries.

Finally, we calculate the HCAP index of equation (20) directly. Relative to the heterogeneous-human-capital measure, the HCAP index amplifies the differences in hard and soft-skill accumulation efficiencies through the input-output loop. This addition of the variation due to the amplification mechanism leads to another substantial increase in the dispersion of human capital across countries. The variance of log human capital increases by a factor of 5.7 relative to ST_1^k, to 0.074. The 90-10 ratio of human capital increases by a factor of 1.6 relative to ST_1^k, to 2.10. These results show that the HCAP index leads to substantially larger dispersion of human capital across countries than the standard measure.

We now move on to Schoellman (2012)'s improved measure of homogeneous human capital, metric 2. The variance of $\log(ST_2^k)$ is 0.077, and the 90-10 ratio of ST_2^k is 1.82. These results echo Schoellman (2012), and suggest that human capital stocks show more dispersion across countries than under metric 1. As this additional variance is also present in our framework, it also increases the overall variance of our quantifications of (26) and (27), relative to metric 1.

When we take heterogeneous human capital into account by using HHC^k, the variance of log human capital is 0.068 and the 90-10 ratio of human capital is 1.80. While these are higher than under HHC^k with metric 1, they are lower than under ST_2^k. The latter happens because the dispersion of human capital decreases as we apply the single-type measure of ST_2^k, in (26), to hard-skill human capital, in (27), and this decrease dominates the correction of heterogeneity given in (21). In other words, our quantifications of (28)

~(27) do not mechanically produce larger dispersions for the heterogeneous-human-capital measure of HHC^k relative to the single-type measure that HHC^k starts with. When we take into account both heterogeneity and amplification by using the HCAP index, however, we obtain larger dispersion than ST_2^k. The variance of log human capital is 0.16, a two-fold increase relative to metric 2, and a factor-12 increase relative to metric 1. The 90-10 ratio of human capital is 2.70, a factor-1.5 increase relative to metric 2, and a two-fold increase relative to metric 1. In other words, once the input-output loop is allowed to play a role, the dispersion of human capital exceeds the dispersion of output per worker.

In Table 7, we show the variance of $\log(HCAP^k)$ with metric 1 under alternative values of η, θ, and α. Column (1) re-iterates our results from Table 6, and the values of η, θ, and α that we used there. In columns (2) and (3), we report the variance in the log of the HCAP index when constructed using the alternative values of η, θ, and α.[44] The results in columns (2)-(3) are similar to column (1), suggesting that the HCAP index is robust to alternative values of η, θ, and α. Intuitively, this is because all three parameters enter into the expression for the HCAP index, and so the change of a single parameter has more limited effects.

In our computations we have chosen to work with the closed economy setting, because the measured factor content of trade in the years in which our data were generated are known to be small. In Data Appendix 7.4 we report the HCAP index using the absolute values of the factor-contant-of-trade flows, x_c^k and x_n^k in equation (23). As expected, the results generated by the closed economy framework are a good approximation for a framework that allows for trade between countries.

In summary, the HCAP index starts from existing single-type measures of human capital, and delivers substantially larger dispersions of human-capital stocks than these measures. If an advance in measurement leads to larger dispersions of human capital under the single-type setting, it tends to do so under our multiple-type setting as well. In this sense, the HCAP index is complementary to the literature on single-type measures of human capital.

3.5 Policy Implications of the HCAP Index

The HCAP index summarizes countries' efficiency at turning resources into human capital, and we discuss its policy implications for high-income countries in this sub-section. International test scores, such as PISA scores, are often used to evaluate countries' educational systems. Even if PISA scores accurately reflect countries' hard-skill accumulation efficiencies, they are not informative about soft-skill accumulation efficiencies, h_n^k, because the data

[44] We have chosen $\eta = 0.33$ because it implies an amplification elasticity of 1.49, an often-used benchmark in the amplification literature, and chosen $\theta = 1.5$ and 3 because they are the end points of the range of estimates reported in the Roy-model literature. The other parameter values in Table 5 are more ad hoc. In our computation, we have updated the h_c^k and h_n^k values using the alternative values of η, θ, and α.

in Table 3 show that the correlation between PISA scores and h_n^k is 0.14 (p-value = 0.45). This overlook is a serious issue for the use of PISA scores, because soft-skill accumulation efficiencies are an important component of the HCAP index.

Figure 5 plots the value of h_c^k against h_n^k, and serves as our canvas for the iso-HCAP curve, the combinations of h_c^k and h_n^k that yield a constant level of the HCAP index. We draw the iso-HCAP curve through the U.S., our benchmark country with $h_c^{US} = h_n^{US} = 1$. In Figure 5, the countries with high productivity along one dimension but low productivity along the other (e.g. Germany) lie below the iso-HCAP curve, meaning that they have lower overall human-capital productivity than the U.S.

In our Introduction, we discussed the concern in S. Korea and many East Asian countries that their educational systems may be inefficient for developing soft skills. Our results suggest that this concern may be well founded. While South Korea and Hong Kong are top performers in PISA score, they rank at the bottom in terms of soft-skill accumulation productivity (Table 3), and lie below the U.S. iso-HCAP curve in Figure 5. Meanwhile, PISA scores understate the U.S. soft-skill accumulation efficiency (Table 3), and the overall proficiency of the U.S. educational system, as measured by the HCAP index, is similar to Norway and Denmark (Figure 5). This result resonates with the argument in the U.S. discussions of education policy against focusing exclusively on test scores.

Test scores are also often used to evaluate education policies and programs (e.g. Figlio and Loeb 2011, Duncan and Magnuson 2013). This is also problematic, following our discussions above, because changes in test scores likely miss changes in soft skills and so may misrepresent the change in the overall proficiency of the educational system. To illustrate this point, we construct an iso-PISA score curve by treating our estimates of h_c^k and h_n^k as data and regressing PISA scores on h_c^k and h_n^k. We obtain a positive coefficient estimate for h_c^k, 82.6 (p = 0.02), and a negative one for h_n^k, -11.9 (p = 0.20) (more details in Data Appendix 7.5).[45] We then trace out the combinations of h_c^k and h_n^k values that produce the same predicted PISA math score as the U.S., and add this iso-PISA score curve into Figure 5.[46] By comparing the Iso-PISA score curve and the Iso-HCAP curve in Figure 5, we can illustrate the trade-offs that the United States might face were it to emulate the educational systems of different countries.[47] For instance, were the United States to trade off h_n^k for h_c^k at the

[45] These correlation patterns are consistent with our model, because an increase in h_c^k tends to increase average hard-skill human capital, by equation (25), and a decrease in h_n^k tends to push workers away from choosing the soft-skill occupation, by equation (8), and so create stronger incentives to accumulate hard skills.

[46] We have experimented with deriving the changes in test scores in response to changes in h_c^k and h_n^k using our model, under the additional assumption that the year of schooling remains unchanged. This approach produces a qualitatively similar iso-PISA score curve (Theory Appendix 6.7).

[47] Such emulation shows up in policy discussions from time to time. e.g. in February 2014, Elizabeth Truss, the U.K. education minister, visited Shanghai, China, whose test score is much higher than the U.K.'s, to

rate that would bring it in the direction of South Korea, it would improve its test scores but at the cost of having a lower HCAP index. Hence, its output would fall, by equation (19). One the other hand, many of the highest performing countries in terms of producing human capital in general feature very high h_n^k relative to h_c^k (e.g. Belgium, the Netherlands). Emulating these countries could lead to higher HCAP index and higher output per worker, but might come at the expense of lower test scores.

These results resonate with the literature on early childhood intervention programs in the U.S. This literature shows that these programs tend to have little long-term effects on participants' test scores, but positive effects on their adult outcome, such as higher wages, and lower probabilities of poverty and crime, and also makes the inference that the intervention programs primarily boost participants' soft skills. In other words, our macro framework and this body of applied-micro studies share the same policy implication: a real outcome, such as aggregate output or wage, is a better objective for education policies than test scores.

We have shown earlier (e.g. equation (24)) that free trade could affect educational policy trade-offs, in theory. We now illustrate this point by computing the (counterfactual) free-trade equilibrium. We assume that the data we observe (e.g. L^k, Y^k, p_c^k and p_n^k) are well approximated by our closed-economy equilibrium, and use the full set of closed-economy parameter values. We then recompute the implied free-trade iso-HCAP curve, using equation (24), and plot it in Figure 6.[48] Figure 6 has the same underlying values of soft and hard-skill accumulation productivities as Figure 5, and the U.S. occupation employment shares under free trade are similar to their closed-economy values. However, the iso-HCAP curve bends toward the origin in Figure 6, in contrast to Figure 5. Intuitively, in a free-trade world countries could fully exploit their comparative advantages, and so having a high efficiency in creating one-type of human capital would be more important than having more balanced hard and soft-skill accumulation efficiencies; i.e. under free trade, imbalance would be a source of strength. The data, however, suggest that the world is closer to autarky than it is to free trade (e.g. sub-section 3.4). Thus for the moment at least, educational institutions that focus on one type of human capital to the great detriment of another result in low HCAP indices; i.e. imbalance is a source of weakness.

In summary, the use of test scores for education policies is potentially misleading, since test scores are un-informative about soft skills. The HCAP index takes soft skills into account, and provides one way to quantify the overall proficiency of a country's educational system and to evaluate the potential tradeoffs between hard and soft-skill accumulation efficiencies (e.g. reduced rote learning in favor of open-ended experimentation). The previous measures of human capital are silent on these fronts, because they do not distinguish between

"learn a lesson a math".

[48] Details about the trading environment can be found in the Theory Appendices 6.5 and 6.7.3.

hard and soft-skill human capital.

Looking back at section 3, we have highlighted the quantitative differences between the HCAP index and previous measures of human capital in the literature, using data for high-income countries. In particular, we find no correlation between countries' soft-skill accumulation productivities and their human capital per worker according to the standard measure, and the hard-to-measure soft-skill human capital. In addition, the HCAP index provides substantially larger dispersions of human capital than the standard measure, delivers additional policy implications compared with the standard measure and incorporates the advances in the single-type measures of human capital in the literature. Still, one may be concerned about the quantitative relevance of the HCAP index for the larger differences in output per worker between low- and high-income countries, and that we have not addressed how the HCAP index relates to the generalized accounting framework of Jones (2014), where skilled labor is differentiated from unskilled labor. We address these concerns now.

4 The HCAP Index: Development Accounting

In this section, we embed the HCAP index into a model where access to education is uneven among a country's citizens. In addition to the differentiation between hard-skilled workers and soft-skilled workers summarized in the HCAP index, we allow for the additional differentiation between unskilled labor and the skilled-labor composite, following Jones (2014). Because we have fully developed the intuition of the HCAP index previously, we now focus on its interactions with the other elements of the model, and its contribution to the differences in output per worker between low- and high-income countries. Our model continues to deliver an analytical expression relating the HCAP index to output per worker, and we show that, with the use of the HCAP index, human capital accounts for most of the cross-country variation in output per worker if the substitution elasticity between skilled and unskilled labor is not too low. For medium and high values of this elasticity, the contribution of human capital approaches 100%.

4.1 Additional Model Elements

In this sub-section, we explain how we incorporate the standard building blocks of the generalized-accounting literature into our model. The first element is the differentiation between unskilled labor, the quantity of which we denote by L_u^k, and the skilled-labor composite, denoted by H^k, in the production of the final good, Y^k:

$$Y^k = \Theta^k \left(B_u^k \left(L_u^k \right)^{\frac{\rho-1}{\rho}} + B_s^k \left(H^k \right)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} . \tag{29}$$

In equation (29), Θ^k is country k's output TFP, and H^k, the composite skilled labor input, consists of hard skilled and soft-skilled labor, as in sections 2 and 3. B_u^k and B_s^k are the efficiencies of the two types of labor, and ρ is the elasticity of substitution between them.

Following the standard approach in the generalized-accounting literature, we normalize $B_u^k = 1$, and interpret B_s^k as the exogenously given relative efficiency of skilled labor. As we show below, our general-equilibrium model also endogenously delivers relative efficiency of skilled labor. To highlight this contribution relative to the literature, we set $B_s^k = B_s^0$ for all k, as in CC (2019). We will discuss how our approach relates to the generalized-accounting literature in sub-section 4.3 below.

Of the L^k workers in country k, we assume that the fraction λ^k are unskilled. The parameter λ^k is exogenous, and reflects the differences in access to education and human-capital production across countries. We also assume, following the literature (e.g. CC 2019), that skilled workers are restricted to skilled jobs, and likewise for unskilled workers. These assumptions make the key measurement implications of our model, the analytical expression relating human capital to output per worker, comparable to the expressions used in the generalized-accounting literature.

4.2 The Rest of the Model

The rest of the model follow section 2 closely, and so we highlight the key elements in this sub-section, and relegate the details to Theory Appendix 6.8. The composite skilled labor input, H^k, is constructed from soft and hard-skilled labor:

$$H^k = \left(A_c \left(L_c^{kD} \right)^{\frac{\alpha-1}{\alpha}} + A_n \left(L_n^{kD} \right)^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1}} . \tag{30}$$

Equation (30) is similar to our production function (4) from section 2, and so the aggregate production function (29) extends our analysis there, by differentiating between stocks of skilled (L_c^{kD} and L_n^{kD}) and stocks of unskilled labor (L_u^k). Meanwhile, p_c^k and p_n^k are now conditional employment shares of the hard-skill and soft-skill occupations, with $p_c^k + p_n^k = 1$ continuing to hold, and E^k is now educational spending per skilled worker.

In our economy, all markets are competitive, and the timing happens as follows. First, workers receive draws for access to education. The fraction $1 - \lambda^k$, who are skilled, receive talent draws given by (1), accumulate human capital according to (2), and obtain the outputs specified by (3). The skilled workers then choose the soft-skilled or hard-skilled occupations in the same way as in section 2. Next, skilled and unskilled workers join the labor force, and the labor markets clear. Finally, all other markets clear.

We assume that the inputs into human-capital production are in terms of the skilled labor composite, H^k. This implies that there are two sectors in our economy, the final-goods sector of (29), plus the sector that produces human capital. In terms of national accounting, then, the nominal value of the total output of our economy, G^k, exceeds the nominal value of the final good, P^kY^k. We show in Theory Appendix 6.8 that $G^k = P^kY^k(1+\frac{\eta}{1-\eta}\pi^k)$, where π^k is the income share of skilled labor in the final-goods sector of (29). Let Q^k denote the quantity of total real output, defined as $Q^k = G^k/P^k$. We show that

Proposition 2 *Output per worker in country k relative to the base country 0 can be decomposed into the ratio of output TFP and human capital per capita, HC^k; i.e.*

$$\frac{Q^k/L^k}{Q^0/L^0} = \frac{\Theta^k}{\Theta^0}\frac{HC^k}{HC^0}, \tag{31}$$

where HC^k/HC^0 is related to the HCAP index given by (20), $HCAP^k$

$$\frac{HC^k}{HC^0} = \frac{1+\frac{\eta}{1-\eta}\pi^k}{1+\frac{\eta}{1-\eta}\pi^0}\left(\left(1-\pi^0\right)\left(\frac{\lambda^k}{\lambda^0}\right)^{\frac{\rho-1}{\rho}} + \left(\pi^0\right)\left(\frac{1-\lambda^k}{1-\lambda^0}HCAP^k\right)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}. \tag{32}$$

Intuitively, the first term on the right hand side of equation (32) reflects the difference between total output and final-goods output, as we discussed above, and the second term reflects final-goods output per worker. In our data, the cross-country differences of the first term are relatively small (see sub-section 4.4 below), and the second term is the main driver for the differences in human capital per capita across countries. This second term consists of the weighted power mean of the relative supply of unskilled labor, λ^k/λ^0, and that of skilled labor, $(1-\lambda^k)/(1-\lambda^0)$, where the weights are the two types of labor's income shares, and the power coefficient depends solely on the substitution elasticity, ρ. The relative supply of skilled labor is then augmented by the HCAP index. As compared with section 2, although we have incorporated additional elements into the model (e.g. three types of labor), the relationship between output and human capital per capita can still be condensed into a single analytical expression. In this expression, the HCAP index remains unchanged, and continues to play an important role.

4.3 Relation to Current Literature

To further clarify the role of the HCAP index in equation (32), we now compare our approach with the generalized-accounting literature. We first discuss the approaches of the literature, and then compare them to ours.

We first show that CC (2019)'s approach can be expressed as (Theory Appendix 6.9)

$$\frac{HC^k_{CC}}{HC^0_{CC}} = \left(\left(1-\pi^0\right)\left(\frac{\lambda^k}{\lambda^0}\right)^{\frac{\rho-1}{\rho}} + \left(\pi^0\right)\left(\frac{1-\lambda^k}{1-\lambda^0}RE^k_{CC}\right)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}, RE^k_{CC} = 1, \tag{33}$$

where RE^k is the relative efficiency of country k's skilled labor relative to country 0. Like equation (32), equation (33) uses the weighted power mean of the relative supplies of unskilled and skilled labor. Given the power coefficient of $(\rho - 1)/\rho$ and the weights that depend on π^0, equation (33) says that country k's relative supplies of unskilled and skilled labor are both important for its relative human capital per capita. The economic intuition of this result is that the increase in the relative supply of skilled labor runs into diminishing returns, because the substitution elasticity between skilled and unskilled labor is finite, and the relative efficiency is the same for all countries. This is a main point emphasized by CC (2019).

Jones (2014)'s approach can be expressed as

$$\frac{HC^k_{Jones}}{HC^0_{Jones}} = \left(\left(1-\pi^0\right) \left(\frac{\lambda^k}{\lambda^0}\right)^{\frac{\rho-1}{\rho}} + \left(\pi^0\right) \left(\frac{1-\lambda^k}{1-\lambda^0} RE^k_{Jones}\right)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, RE^k_{Jones} = [\frac{SP^k(\frac{1-\lambda^k}{\lambda^k})^{\frac{1}{\rho}}}{SP^0(\frac{1-\lambda^0}{\lambda^0})^{\frac{1}{\rho}}}]^{\frac{\rho}{\rho-1}}, \tag{34}$$

where SP^k is the skill premium of country k, and the relative efficiency, RE^k_{Jones}, is inferred from three pieces of data: skill premium, relative supply of skilled labor, and the value of ρ. The crucial difference between equations (34) and (33) is the term RE^k_{Jones}, and it plays an important role in offsetting the diminishing returns that are prominent in CC's formulation. An increase in the relative supply of skilled labor may imply larger inferred relative efficiency of skilled labor, given the values of the substitution elasticity and skill premia. This offsets the effects of diminishing returns, and allows skill abundant countries to produce with relatively more skill intensive technologies. This means that Jones's framework could generate larger variation in human capital per worker across countries for given variation in the relative supply of skilled labor than CC's, ceteris paribus.

Conceptually, several factors cause the relative efficiency of skilled labor to vary across countries. Jones (2014)'s approach uses all these factors, and RE^k_{Jones}, in equation (34), varies with both the relative supply of skilled labor and substitution elasticity. Meanwhile, CC (2019)'s approach sets the relative efficiency to one, and and so RE^k_{CC}, in equation (33), summarizes CC (2019)'s message that a specific mechanism for the relative efficiency needs to be proposed or quantified.

Equations (32) - (34) all use the same weighted power mean between the relative supplies of unskilled labor and skilled labor, and they differ in the specification of the relative efficiency (note that the relative efficiency is $HCAP^k$ in equation (32)). These equations clarify that our approach has some of the flavor of Jones (2014). By equation (32), the relative efficiency of skilled labor is high in skilled-labor abundant countries in our approach. Intuitively, this is because skilled labor is used in the production of human capital in our general-equilibrium model, and the round-about production of human capital is one channel for skilled-labor abundant countries to have high relative efficiency of skilled labor. This helps offset some of the diminishing returns with skill abundance.

Our approach also has some of the flavor of CC 2019. In equations (32) and (33), the relative efficiency does not depend on the substitution elasticity, ρ, but in equation (34), it does. Intuitively, diminishing returns are strong when ρ is small. Jones (2014)'s approach counters this by using all the factors for relative-efficiency differences so that the expression of relative efficiency depends on ρ. Our approach focuses on the specific contributions of the HCAP index, which does not depend on ρ. As a result, our approach shares in common with CC 2019's, in that all countries are assumed to work with the same exogenous technology parameter (i.e. $B_s^k = B_s^0$ for all k), and as such, variation in skilled labor's relative supply is subject to large diminishing returns when ρ is small.

Our approach is distinct from, and complementary to, Rossi (2021). Rossi (2021) breaks RE_{Jones}^k into a worker component ("human capital") and a country component ("technology") using a theoretical framework comparable to Jones (2014). In this framework, if ρ is large, the relative importance of the worker component within RE_{Jones}^k is large, but the overall size of RE_{Jones}^k becomes small. In our GE model human capital production is endogeneous and we compute the relative efficiency of skilled labor directly from $HCAP^k$. $HCAP^k$ does not depend on ρ (e.g. Table 9), and reflects institutional differences across countries in producing heterogeneous human capital (as captured by h_c^k and h_n^k). The conceptual exercise of (32) is to consider the counter-factual long-run equilibrium outcome were we to give country 0 country k's human-capital institutions.

Finally, CC (2019)'s approach, in (33), is akin to the standard single-type measure of human capital with a finite substitution elasticity.[49] Thus the difference between equations (32) and (33) echoes the main theme of our discussions in sections 2 and 3: that multiple types of skilled labor, differentiated by occupation and summarized by the HCAP index, amplify the relative efficiency differences across countries. We will show, below (sub-section 4.5), how this increase in dispersion helps account for the cross-country differences in output per worker (e.g. Figure 7).

4.4 Data, Parameter Values, and Quantification

In section 3, we discussed the values of the parameters of η, α and θ, and showed that the HCAP index is robust to alternative values of these parameters. We use the main specification from section 3; i.e. $\eta = 0.27$, $\alpha = 1.78$, and $\theta = 2$.

We augment our sample from section 3 with the countries for which IPUMS data are available for 3-digit ISCO-88 occupations, many of which are low-income countries (e.g. Cambodia, Vietnam). This increases our sample size to 53. We obtain the data on private and public educational spending from the UNESCO Global Education Digest of 2007 (see

[49] CC (2019)'s measure approaches the standard measure when ρ approaches infinity.

Data Appendix 7.6 for more details). The lower panel of Table 2 reports the summary statistics for our expanded sample.

For λ^k, the employment share of unskilled labor, we include those with primary schooling or less, which is the standard practice in the generalized-accounting literature. Subsistence farming is a common occupation for the low-income countries in our sample, but it is absent from the U.S., whose data we use to classify hard skilled and soft skilled occupations, and so we also count those in subsistence farming as unskilled labor. As we discussed earlier, for equation (30), p_c^k is now the share of skilled labor in hard-skill occupations, and p_n^k is the share of skilled labor in soft-skill occupations.

We follow the generalized-accounting literature and compute the earnings of skilled and unskilled labor using Mincer regression returns and the duration of primary, secondary and tertiary schooling.[50] We then use these earnings to obtain the values for SP^k, skill premium (used in the Jones (2014)'s approach given by equation (34)), and β_s^k, skilled-labor's observed income share in total output. Our model says that π^k, skilled-labor's income share in final-good production, is related to β_s^k as in $\pi^k = (1-\eta)/(1/\beta_s^k - \eta)$ (Theory Appendix 6.8), and we use this expression to compute π^k. The values of π^k and β_s^k are similar, with means of 0.66 and 0.71, respectively, and a correlation coefficient of 0.997.

The relationship between educational spending and total output becomes

$$EdShare^k = \eta \beta_s^k, \tag{35}$$

where $EdShare^k$ is country k's share of educational spending in total output. Equation (35) extends equation (11), and says that countries spend fraction η of their skilled-labor's income, $\beta_s^k G^k$, on education. Equation (35) implies that high-income countries, where β_s^k is large, spends a larger fraction of their total output on education, as compared with low-income countries.

In order to obtain reduced-form empirical evidence for equation (35), we regress several measures of $EdShare^k$ from our data on β_s^k, and report our results in Table 8. We use total output as weights in the regressions, as in section 3 and Table 4. In column 1, the dependent variable is the UNESCO data of private plus public spending on education as shares of GDP. In column 2, the dependent variable is the ratio of private plus public educational spending to total output.[51] Because the ratio of U.S. private plus public educational spending to U.S. GDP is 8% in the UNESCO data, lower than Haveman and Wolfe (1995)'s 15.5%, we scale the dependent variable in column 2 by 1.94 (=15.5%/8%), to obtain back-of-the-envelope data of spending on human capital as shares of total output,[52] and use this variable as the

[50] We rely heavily on CC (2019)'s codes, and have been able to replicate their main results, such as Table 1.

[51] We discussed how we constructed total output in sub-section 3.2.2 above.

[52] As far as we know, the types of computations in Haveman and Wolfe (1995) have not been done for EU

dependent variable in column 3.

The coefficient estimate of β_s^k is positive and statistically significant in all the three columns of Table 8, and its magnitude is 0.269 in column 3, similar to our parameter value of $\eta = 0.27$. It is also noteworthy that the constant is statistically insignificant in all three columns.

Turning to the computation of the HCAP index, we continue to use equation (28) for comparative advantage. For absolute advantage, we use the following counterpart of equation (25):

$$\frac{L_c^{kS}/(L^k(1-\lambda^k))}{L_c^{0S}/(L^0(1-\lambda^0))} = \left(\frac{E^k}{E^0}\right)^{\eta} \left(\frac{p_c^k}{p_c^0}\right)^{1-\frac{1}{\theta}} \left(\frac{h_c^k}{h_c^0}\right). \tag{36}$$

Equation (36) is the same as equation (25), except that the left-hand side involves hard-skill human capital per skilled worker, $L_c^{kS}/(L^k(1-\lambda^k))$, and the first term on the right-hand side has real educational spending per skilled worker, E^k. For $L_c^{kS}/(L^k(1-\lambda^k))$, we apply metric 1 and metric 2 from equation (27) to skilled labor, with the caveat that a number of low- and middle-income countries in our sample do not have PISA-score data. This prevents us from including test scores in metric 1, but does not affect metric 2. For E^k, we first compute nominal private plus public educational spending from the UNESCO data, and then deflate it using the 2005 ICP price for education.

We next follow the same steps as in section 3, to compute the HCAP indices based on metrics 1 and 2, and then use the HCAP indices to compute relative human-capital per capita, HC^k/HC^0, according to equation (32). We also calculate the relative human-capital measures of equations (34) and (33). Following the generalized-accounting literature, we choose the benchmark country, 0, as a poor country, the one at the 10th percentile of the output-per-worker distribution in our data, and examine our results with different values of ρ.[53] The low values of $\rho = 1.5$ and 2 are emphasized in Jones (2014), the high value of $\rho = 5$ is the lower-bound estimate from Hendricks and Schoellman (2018), and the limiting case of $\rho = \infty$ is discussed in CC 2019. Finally, we obtain the ρ value that minimizes the root square distance between our model's predictions of the ratios of skill premia, SP^k/SP^0, and those from the data (Theory Appendix 6.10). This results in an estimate around the medium value of $\rho = 3$, which is also the upper bound of the micro-data estimates surveyed in Katz and Autor (1998).

countries.

[53] The first term in equation (32), $(1+\frac{\eta}{1-\eta}\pi^k)/(1+\frac{\eta}{1-\eta}\pi^0)$, has the mean of 1.15 and standard deviation of 0.075.

4.5 Results

In this sub-section, we first illustrate our results graphically, in Figure 7, and then perform development accounting, in Table 9.

Figure 7 plots the logs of our sample countries' relative human capital against the log of their output per worker (relative to the same benchmark country 0). Both panels show CC (2019)'s measure, of (33) (in "+"), and Jones (2014)'s measure, of (34) (in triangles). The left (right) panel shows our HCAP-based measure with metric 1 (metric 2), both in dots. All relative human-capital measures are computed with $\rho = 3$ (we discuss the results with other ρ values in Table 9 below). Figure 7 shows that, while all human capital measures have similarly strong correlation with output per worker,[54] they differ substantially in dispersion. As a result, we focus on comparing the dispersions of human-capital measures, as suggested by Caselli (2005).

Figure 7 illustrates the trade-off between Jones (2014)'s approach and CC (2019)'s: while the former has much larger dispersion, it does not specify a specific mechanism for the relative efficiency of skilled labor to differ across countries. Figure 7 also illustrates our contributions to this literature. Intuitively, CC (2019)'s measure is akin to the standard one-type measure of human capital with a finite substitution elasticity, relative to which our HCAP-based measure adds both heterogeneity (between soft and hard skills) and amplification (from endogenous human-capital production). Earlier, in section 3, we saw that both additional elements increase dispersion. Now, from Figure 7, we see that this increase in dispersion preserves the strong correlation with output per worker. Relative to Jones (2014)'s measure, the HCAP index provides one specific mechanism for the relative efficiency of skilled labor to vary across countries, and Figure 7 shows that our measures have comparable dispersion to Jones (2014)'s. We also see that, as we move from metric 1 to metric 2 for our HCAP-based measure, we obtain more dispersion, which is consistent with our results in section 3. Figure 7 clarifies that this increase in dispersion, again, preserves the strong correlation with output per worker.

Table 9 shows our results for development accounting, where we choose country k, a rich country, as the one at the 90th percentile of the distribution of output per worker. The first panel shows country k's relative efficiency of skilled labor, relative to country 0's, and the second panel shows country k's human capital per capita relative to country 0's. The third panel shows the ratio of the human-capital measure of the second panel to the 90-10 ratio of output per worker. The last panel shows the variance ratio of human capital relative to output per worker; i.e. the variance of the log of human capital per capita divided by the variance of the log of output per worker.

[54] The correlation coefficient with output per worker is 0.56 for CC (2019)'s measure, 0.37 for Jones (2014)'s, and 0.65 (0.64) for ours with metric 1 (metric 2).

Table 9 reproduces the key point in the debate between CC (2019) and Jones (2019). According to CC (2019)'s approach, given in equation (33), country k's relative efficiency of skilled labor is 1, and human capital makes small contributions to the cross-country variation in output per worker, especially when ρ is small, because of strong diminishing returns; e.g., when $\rho = 2$, human capital accounts for 15% of the 90-10 ratio of output per worker, and 3% of the variance of log output per worker. In contrast, according to Jones (2014)'s approach, given in equation (34), the contribution of human capital is large when ρ is small, because country k's relative efficiency is large.[55] With $\rho = 2$, human capital accounts for 65% of the 90-10 ratio of output per worker, and 148% of the variance of log output per worker. This implies that under Jones (2014)'s approach, human capital's contributions are 1.47 and 3.84 log points larger than under CC (2019)'s approach.

We now move on to our approach with the HCAP index, given in equation (32), where the HCAP index is based on metric 1. Country k's relative efficiency is now 4.41. This increase in relative efficiency (relative to CC (2019)'s approach) echoes our results from section 3 that the use of the HCAP index to measure human capital delivers larger dispersions than the standard single-type measure. Now the contribution of human capital is sizeable when the value of ρ is medium or high. For example, when $\rho = 3$, human capital accounts for 73% of the 90-10 ratio of output per worker and 47% of the variance of log output per worker, and when $\rho = 5$, human capital's contribution becomes 94% and 66%, respectively.

In the context of the generalized-accounting literature, the HCAP index is firmly grounded in our general-equilibrium model, and so provides one answer to CC (2019)'s call for specific elements of skilled labor's relative efficiency. On the other hand, the sizeable contribution of human capital under the HCAP index is consistent with Jones (2014)'s vision about the importance of human capital. Table 9 shows that, as we move from CC (2019)'s approach to ours, taking into account of the contribution of the HCAP index to skilled labor's relative efficiency, the gap with Jones (2014)'s results shrinks. For example, when $\rho = 2$, human capital's contribution to the 90-10 ratio of output per worker is 50% under our approach, a gap of 0.27 log points vs. Jones (2014)'s approach. This is 82% smaller than the gap between CC (2019) and Jones (2014).

Finally, when we construct the HCAP index using metric 2, which is based on Schoellman (2012)'s measure, country k's relative efficiency increases further, to 6.24. This corroborates our results from section 3 that the HCAP index is complementary to the advances in the single-type measures of human capital. Human capital now accounts for most of the cross-country variation in output per worker for most of the ρ values in Table 9. When $\rho = 2$, for example, human capital accounts for 65% of the 90-10 ratio of output per worker, and 49% of the variance of log output per worker. Human capital's contributions increase to 99% and

[55] When ρ is large, however, the relative efficiency becomes small, and so does human capital's contribution.

87%, respectively, when $\rho = 3$, the value that minimizes the differences between our model's predicted values of skill premia and the data of skill premia. For higher values of ρ in Table 9, the variation of human capital per capita across countries exceeds the variation of output per worker.

In summary, our development-accounting results show that, with the use of the HCAP index, human capital accounts for most of the cross-country variation in output per worker, as long as the substitution elasticity between skilled and unskilled labor is not too low ($\rho \geq 2$). If this elasticity is higher ($\rho \geq 3$), human capital's contribution approaches 100%. For even higher elasticity values ($\rho \geq 5$), human capital per capita has more dispersion across countries than output per worker. In addition, the HCAP index satisfies CC (2019)'s demand by offering a specific way for skilled labor's relative efficiency to vary across countries, and also meets Jones (2014)'s vision by implying that human capital is very important in accounting for the cross-country differences in output per worker.

Discussion Manuelli and Sesadri (2014), Jones (2014), Malmberg (2017) and Hendricks and Schoellman (2018) all show that human capital accounts for most cross-country variation in output per worker. While the results in these studies are similar to ours, the mechanisms are different. Our results are due to the following elements of the HCAP index that we discussed in detail in section 3: the differentiation of skilled labor into soft-skill and hard-skill types, the round-about production of human capital, and the incorporation of the advances in single-type measures of human capital. The results in Manuelli and Sesadri (2014) hold with an amplification elasticity of 5.7, much larger than ours. The quantification in Jones (2014) and Malmberg (2017), as we discussed above, makes use of all the factors for relative-efficiency differences, and the results hold for very low values of ρ. Finally, Hendricks and Schoellman (2018) measure the contribution of human capital as the residual, and we measure it directly.

5 Conclusion

We have developed a GE framework, in the spirit of Roy (1951), to model the productions of nsoft and hard-skill human capital. Our stylized model allows us to use revealed comparative advantage to infer countries' soft and hard-skill accumulation productivities without a direct measure for the soft-skill dimension. Our model also delivers analytical expressions for how soft-skill and hard-skill accumulation productivities relate to the HCAP index, and how the HCAP index relates to output per worker.

We used the HCAP index for two quantiative applications. In the first, we considered a set of mostly high-income countries that appear on the surface to be relatively similar in their educational obtainment. We show that standard, single-type measures of human capital substantially understate the differences across countries in the stock of human capital and that even the rankings of absolute stocks are mis-measured. The mis-measurement arises because many countries with a strong absolute advantage providing hard skills have an absolute disadvantage producing soft skills.

Our analysis demonstrated that the assessment of a country's educational systems is partially dependent on the extent of globalization. In an autarkic environment, unevenness in the efficiency of the provision of soft and hard skills is a weakness while in a world of globalization it can be a strength. Our data suggest that the world is closer to autarky than it is to free trade and so this informs the tradeoffs of efficiency in one dimension at the expense of the other. Policy reforms that *increase* a nation's test scores may nonetheless *reduce* aggregate output. This points to the importance of spelling out the impacts of education policies on aggregate output when we formulate their objectives and conduct cost-benefit analyses. Here, our model provides a potentially useful tool.

In our second quantiative application, we adapt our quantiative framework to allow countries to vary in the access to education that they confer on their citizens. The adapted model nests our HCAP into the generalized developing accounting setting. In such a setting, uneducated and educated workers are imperfect substitutes, and this implies decreasing returns to the accumulation of human capital. We show that the overall quality of human capital accumulated, as captured by the HCAP index, helps to offset these decreasing returns.

In our computations, we find that, with the use of the HCAP index, human capital accounts for most of the cross-country variation in output per worker if the substitution elasticity between skilled and unskilled labor is not too low. Relative to the recent work of CC (2019), our model with heterogeneous human capital with amplification assigns a much larger role to human capital in development accounting. Moveover, our framework is less sensitive to the assumptions over the substitutability of skilled and unskilled workers than the approach of Jones (2014).

With respect to future work, it would be desirable to identify the particular educational institutions that are associated with soft-skill accumulation efficiencies. In this paper, these efficiencies were treated as exogenous parameters that can be observed through the lens of a model. Our motivation was to quantify these parameters and to draw out their implications for the HCAP index and output per worker, given that previous estimates of their values do not exist. Could policies affect the values of soft and hard-skill accumulation productivities? If so, what policies? How much resources do these policies require? Could there be optimal policies, and how might they vary in closed vs. open economies? We leave these questions for future research.

References

[1] Acemoglu, Daron, Simon Johnson, and James A. Robinson. "The Colonial Origins of Comparative Development: An Empirical Investigation." *American Economic Review* 91.5 (2001): 1369-1401.

[2] Almlund, M., Duckworth, A. L., Heckman, J., & Kautz, T. (2011). Personality psychology and economics. In *Handbook of the Economics of Education* (Vol. 4, pp. 1-181). Elsevier.

[3] Atkin, David, 2016. "Endogenous Skill Acquisition and Export Manufacturing in Mexico", *American Economic Review* 106(8), 2046-2085.

[4] Autor, David H., Frank Levy and Richard J. Murname, 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration", *Quarterly Journal of Economics* 118(4).

[5] Banerjee, Abhijit V., and Esther Duflo. "Growth theory through the lens of development economics." *Handbook of Economic Growth* 1 (2005): 473-552.

[6] Barro, Robert J. and Sala-i-Martin, Xavier. Economic Growth. New York: McGraw-Hill, 1995.

[7] Bils, Mark, and Peter J. Klenow. "Does schooling cause growth?." *American economic review* 90.5 (2000): 1160-1183.

[8] Blanchard, Emily and William Olney, 2017. "Globalization and Human Capital Investment: Export Composition Drives Educational Attainment", *Journal of International Economics*, 106, 165-183.

[9] Bombardini, Matilde, Giovanni Gallipoli, and Germán Pupato. "Skill dispersion and trade flows." *American Economic Review* 102.5 (2012): 2327-48.

[10] Burnstein, Ariel, Eduardo Morales and Jonathan Vogel, 2019. "Changes in Between-Group Inequality: Computers, Occupations and International Trade", *American Economic Journal: Macroeconomics* 11(2): 348-400.

[11] Card, David, and Thomas Lemieux. "Can falling supply explain the rising return to college for younger men? A cohort-based analysis." *The Quarterly Journal of Economics* 116.2 (2001): 705-746.

[12] Caselli, F. 2005. "Accounting for Cross-Country Income Differences." in Handbook of Economic Growth.

[13] Caselli, Francesco, I. I. Coleman, and Wilbur John. "The world technology frontier." *American Economic Review* 96.3 (2006): 499-522.

[14] Caselli, Francesco, and Antonio Ciccone. (2019) "The Human Capital Stock: A Generalized Approach. Comment," *American Economic Review.*

[15] Chetty, Raj, John N. Friedman, Nathaniel Hilger, Emmanuel Saez, Diane W. Schanzenbach, and Danny Yagan. 2011. "How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project STAR." *Quarterly Journal of Economics*, 126(4): 1593 –1660.

[16] Costinot, Arnaud and Andrés Rodríguez-Clare, 2014. "Trade Theory with Numbers: Quantifying the Consequences of Globalization", in *Handbook of International Economics*, edts. Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, vol. 4, chapter 4.

[17] Cubas, German, B Ravikumar, and Gustavo Venture. (2016) "Talent, labor quality, and economic development" 2016.Review of Economic Dynamics 21 (2016) 160–181.

[18] Cunha, Flavio, James Heckman and Susanne Schennach. "Estimating the Technology of Cognitive and Non-cognitive Skill Formation", *Econometrica* 78(3), May 2010, 883-931.

[19] Davis, Donald R., and David E. Weinstein. "An account of global factor trade." *American Economic Review* 91.5 (2001): 1423-1453.

[20] Deckle, Jonathan Eaton, and Samuel Kortum. 2008. "Global Rebalancing with Gravity." *International Monetary Fund Staff Papers* 55: 511-540

[21] Deming, David. 2009. "Early Childhood Intervention and Life-Cycle Skill Development: Evidence from Head Start." *American Economic Journal: Applied Economics* 1(3): 111–34.

[22] Deming, David J. "The growing importance of social skills in the labor market." *The Quarterly Journal of Economics* 132.4 (2017): 1593-1640.

[23] Deming, David J. "The value of soft skills in the labor market." NBER Reporter 4 (2017): 7-11.

[24] Duncan, Greg J., and Katherine Magnuson. "Investing in preschool programs." *Journal of Economic Perspectives* 27.2 (2013): 109-32.

[25] Eaton, Jonathan and Samuel Kortum, 2002. "Technology, Geography and Trade", *Econometrica*, 70(5), 1741-1779.

[26] Ebenstein, A., Harrison, A., McMillan, M., Phillips, S. Estimating the impact of trade and offshoring on American Workers Using the Current Population Surveys. *Review of Economics and Statistics* 96(4): 581–595.

[27] Erosa A., T. Koreshkova, and D. Restuccia (2010). "How important is human capital? A quantitative theory assessment of world income inequality." *Review of Economic Studies* 77(4): 1421-1449.

[28] Figlio, David and Susanna Loeb, 2011. "School Accountability", in *Handbook of the Economics of Education*, Volume 3, Edited by Eric Hanushek, Stephen Machin and Ludger Woessmann, Elsevier North-Holland: Amsterdam, 383-421.

[29] Findlay, Ronald and Henryk Kierzkowski, 1983. "International Trade and Human Capital: A Simple General Equilibrium Model", *Journal of Political Economy*, 91(6), 957-978.

[30] Garces, Eliana, Duncan Thomas, and Janet Currie. 2002. "Longer-Term Effects of Head Start." *American Economic Review* 92(4): 999 –1012.

[31] Hall, Robert E. and Charles I. Jones. (1999) "Why Do Some Countries Produce So Much More Output per Worker than Others?", *Quarterly Journal of Economics* 114: 83-116.

[32] Hanushek, E. .(2008) "Education Production Functions", *The New Palgrave Dictionary of Economics.*

[33] Hanushek, Eric A., and Dennis D. Kimko. "Schooling, labor-force quality, and the growth of nations." *American Economic Review* 90.5 (2000): 1184-1208.

[34] Hanushek, Eric and Lei Zheng (2009). "Quality-Consistent Estimates of International Schooling and Skill Gradients." *Journal of Human Capital* 3(2): 107-143.

[35] Hanushek, Eric, and Ludger Woessman. 2011. "How Much do Educational Outcomes Matter in OECD Countries?" *Economic Policy* 26(67): 427-491.

[36] Haveman, Robert, and Barbara Wolf (1995). "The Determinants of Children Attainments: A Review of Methods and Findings." *Journal of Economic Literature* 33(4): 1829-1878.

[37] Heckman, James J., Seong Hyeok Moon, Rodrigo Pinto, Peter Savelyev, and Adam Yavitz. 2010. "A New Cost–Benefit and Rate of Return Analysis for the Perry Preschool Program: A Summary." NBER Working Paper 16180.

[38] Heckman, James J., and Tim Kautz. "Hard evidence on soft skills." *Labour economics* 19.4 (2012): 451-464.

[39] Heckman, James J., and Tim Kautz. Fostering and measuring skills: Interventions that improve character and cognition. No. w19656. National Bureau of Economic Research, 2013.

[40] Heckman, James J. and Yona Rubinstein. 2001. "The Importance of Noncognitive Skills: lessons from the GED Testing Program", *American Economic Review* Papers & Proceedings 91(2): 145-149.

[41] Hendricks, Lutz. "How important is human capital for development? Evidence from immigrant earnings." *American Economic Review* 92.1 (2002): 198-219.

[42] Hsieh, Chang-Tai, and Peter J. Klenow. "Misallocation and manufacturing TFP in China and India." *The Quarterly Journal of Economics* 124.4 (2009): 1403-1448.

[43] Hsieh, Chang-Tai, Erik Hurst, Charles Jones and Peter Klenow. (2019) "The Allocation of Talent and U.S. Economic Growth." *Econometrica* 87: 1439-1474..

[44] Hummels, D., Jørgensen, R., Munch, J., & Xiang, C. (2014). The wage effects of offshoring: Evidence from Danish matched worker-firm data. *American Economic Review*, 104(6), 1597-1629.

[45] Hummels, David, Jakob R. Munch, and Chong Xiang. "Offshoring and Labor Markets." *Journal of Economic Literature*.

[46] Jackson, Kirabo , Rucker C. Johnson, and Claudia Persico. 2016. "The Effects of School Spending on Educational and Economic Outcomes: Evidence from School Finance Reforms," *The Quarterly Journal of Economics* 131(1): 157-218.

[47] Jones, Benjamin. 2014. "The Human Capital Stock: A Generalized Approach." *American Economic Review* 104(11): 3752-3777.

[48] Jones, Benjamin. 2019. "The Human Capital Stock: A Generalized Approach. Reply." *American Economic Review*.

[49] Klenow, Peter, and Andres Rodriquez-Clare. 1997. "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" NBER Working paper.

[50] Kuhn, Peter, and Catherine Weinberger. 2005. "Leadership Skills and Wages." *Journal of Labor Economics* 23(3): 395-436.

[51] Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman. 2018. "Life Cycle Wage Growth across Countries." *Journal of Political Economy* 126(2): 797-849.

[52] Lagakos, David, and Michael E. Waugh. "Selection, agriculture, and cross-country productivity differences." *American Economic Review* 103.2 (2013): 948-80.

[53] Lee, Eunhee, 2020. "Trade, Inequality, and the Endogenous Sorting of Heterogeneous Workers." *Journal of International Economics* 125.

[54] Li, Bingjing, 2016. "Export Expansion, Skill Acquisition and Industry Specialization: Evidence from China", mimeo, National University of Singapore.

[55] Ludwig, Jens, and Douglas L. Miller. 2007. "Does Head Start Improve Children's Life Chances: Evidence from a Regression Discontinuity Design." *Quarterly Journal of Economics* 122(1): 159 –208.

[56] Lundberg, Shelly. "Non-cognitive skills as human capital." Education, Skills, and Technical Change, and Future US GDP Growth. University of Chicago Press, 2017.

[57] Malmberg, Hannes. 2017. "Human Capital and Development Accounting Revisited." mimeo Institute for International Economic Studies.

[58] Manuelli, Rodolfo E., and Ananth Seshadri. "Human capital and the wealth of nations." *American economic review* 104.9 (2014): 2736-62.

[59] Neal, Derek A., and William R. Johnson, "The Role of Premarket Factors in Black – White Wage Differences", *Journal of Political Economy* 104 (5), October 1966, 869-895.

[60] Nunn, Nathan. "Relationship-specificity, incomplete contracts, and the pattern of trade." *The Quarterly Journal of Economics* (2007): 569-600.

[61] Ohnsorge, Franziska and Daniel Trefler, "Sorting it Out: International Trade and Protection with Heterogeneous Workers." *Journal of Political Economy* 115(5) (2007): 868-892.

[62] Rossi,Federico. 2021. "The Relative Efficiency of Skilled Labor Across Countries: Measurement and Interpretation." forthcoming *American Economic Review.*

[63] Roy, Arthur. 1951. "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers* 3(2): 135-146.

[64] Seth, Michael J. Education fever: Society, politics, and the pursuit of schooling in South Korea. University of Hawaii Press, 2002.

[65] Schmitt, D. P., Allik, J., McCrae, R. R., & Benet-Martínez, V. (2007). The geographic distribution of Big Five personality traits: Patterns and profiles of human self-description across 56 nations. *Journal of cross-cultural psychology*, 38(2), 173-212.

[66] Schoellman, Todd. "Education quality and development accounting." *The Review of Economic Studies* 79.1 (2011): 388-417.

[67] Schweinhart, Lawrence J., Jeanne Montie, Zongping Xiang, W. Steven Barnett, Clive R. Belfield, and Milagros Nores. 2005. Lifetime Effects: The HighScope Perry Preschool Study through Age 40. Monographs of the HighScope Educational Research Foundation,14. Ypsilanti, MI: HighScope Press.

[68] Shastry, Gauri Kartini, and David N. Weil. "How much of cross-country income variation is explained by health?." *Journal of the European Economic Association* 1.2-3 (2003): 387-396.

[69] Trefler, Daniel. "The case of the missing trade and other mysteries." *The American Economic Review* (1995): 1029-1046.

[70] US Department of Health and Human Services, Administration for Children and Families. 2010. Head Start Impact Study: Final Report. Washington, DC.

[71] Webb, L. Dean, Arlene Metha, and Kenneth Forbis Jordan. Foundations of American education. Merrill, 2013.

[72] Willis, Robert and Sherwin Rosen. "Education and Self-Selection", J*ournal of Political Economy* 87(5), October 1979, S7-S36.

Figure 1 Histogram of Employment Share of Soft-Skill Occupations

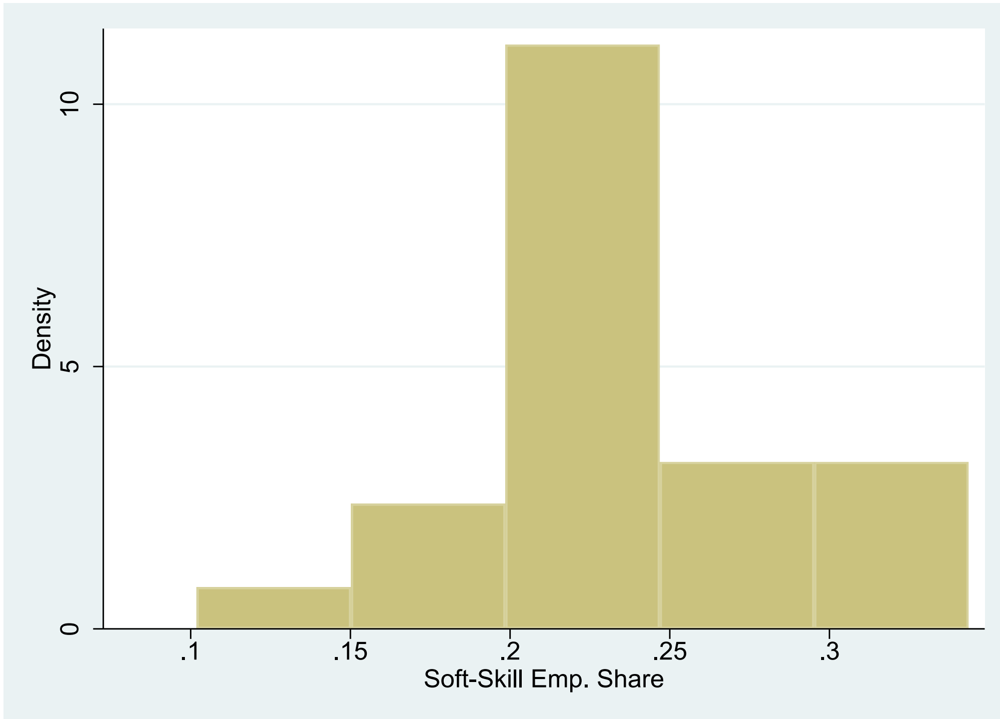

Figure 2 Relative Employment Shares of Country-k's U.S. Emigrants and Country-k's Workers

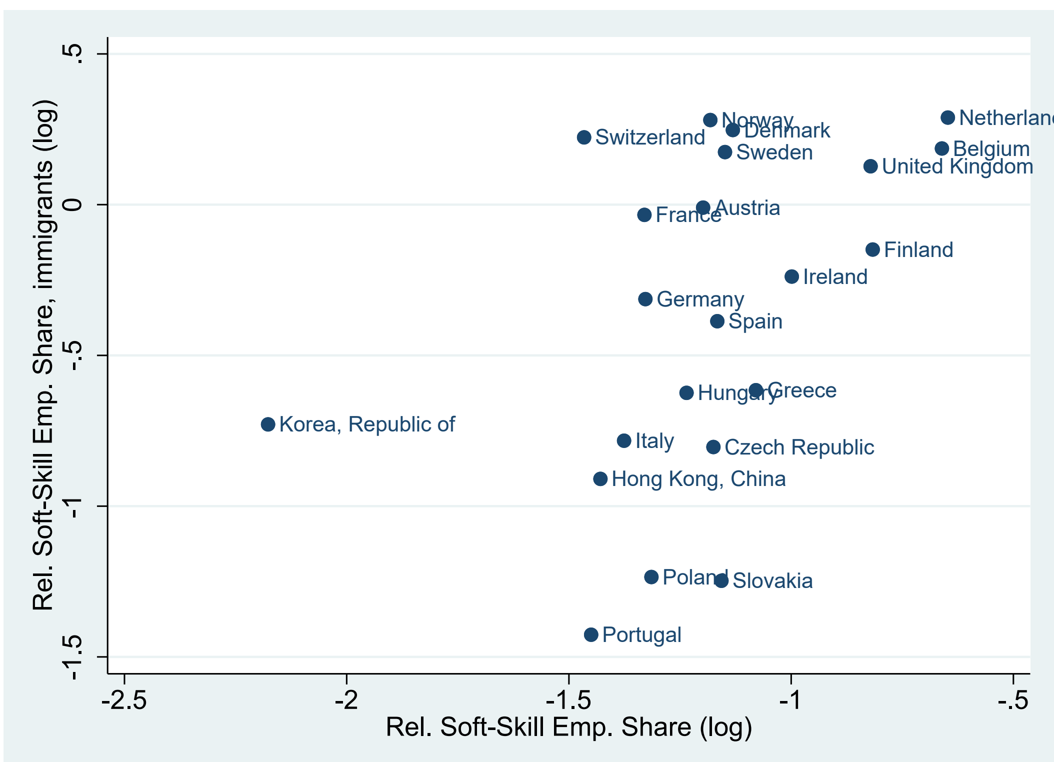

Figure 3 Rankings of Hard-Skill Productivity & Standard Human-Capital Measure

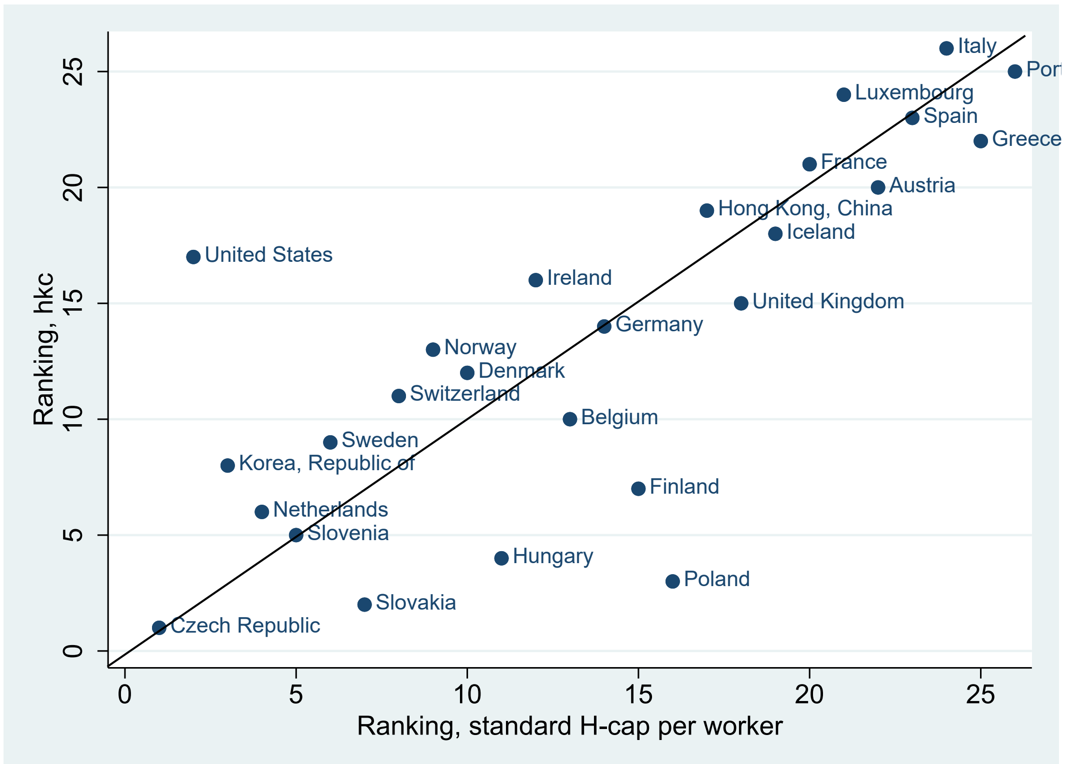

Figure 4 Rankings of Soft-Skill Productivity & Standard Human-Capital Measure

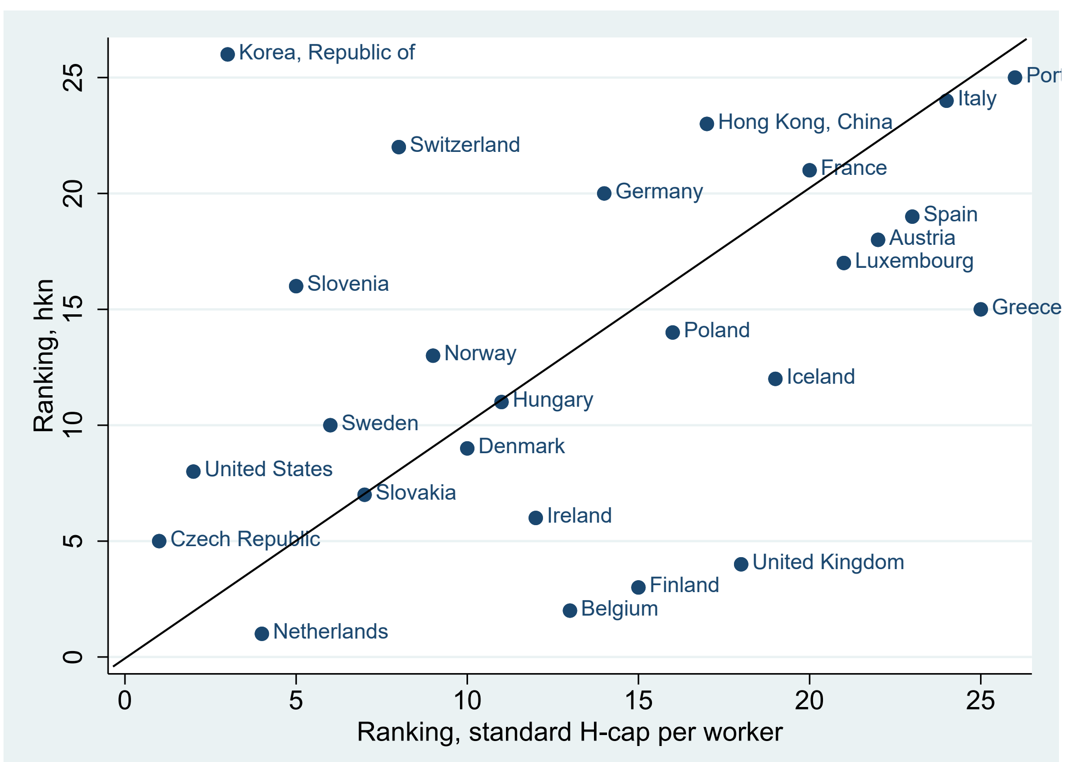

Figure 5 Iso-HCAP and Iso-PISA curves

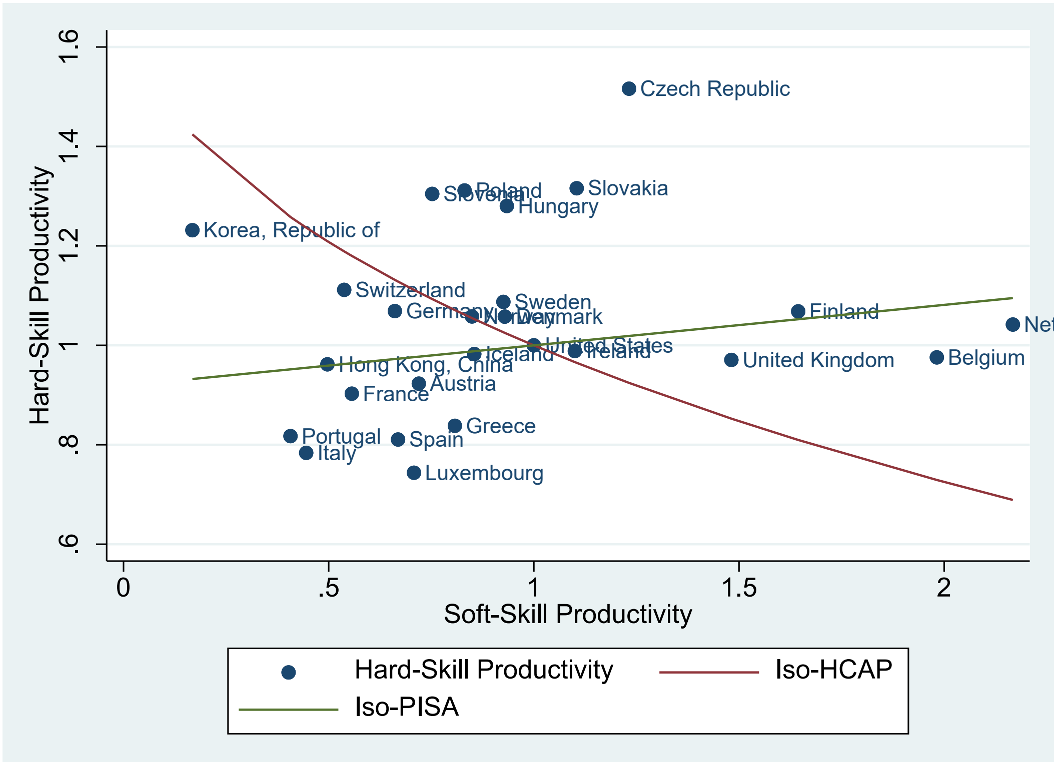

Figure 6 Iso-HCAP, Free-trade

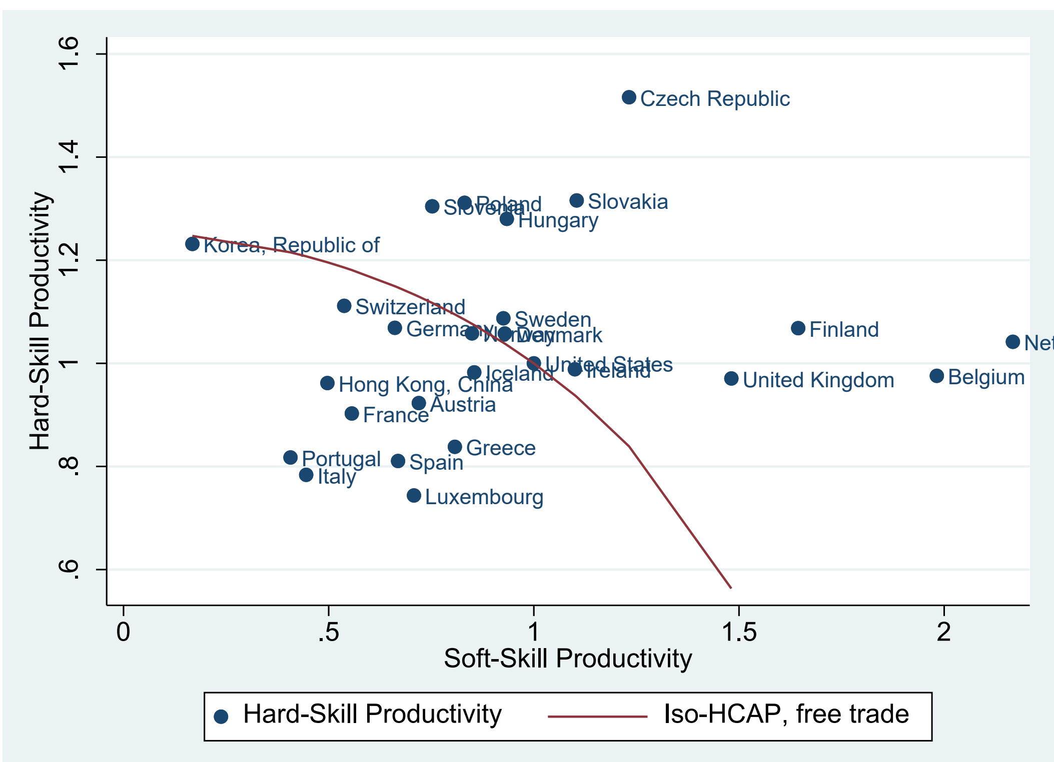

Figure 7 Human Capital Measures and Output per Worker

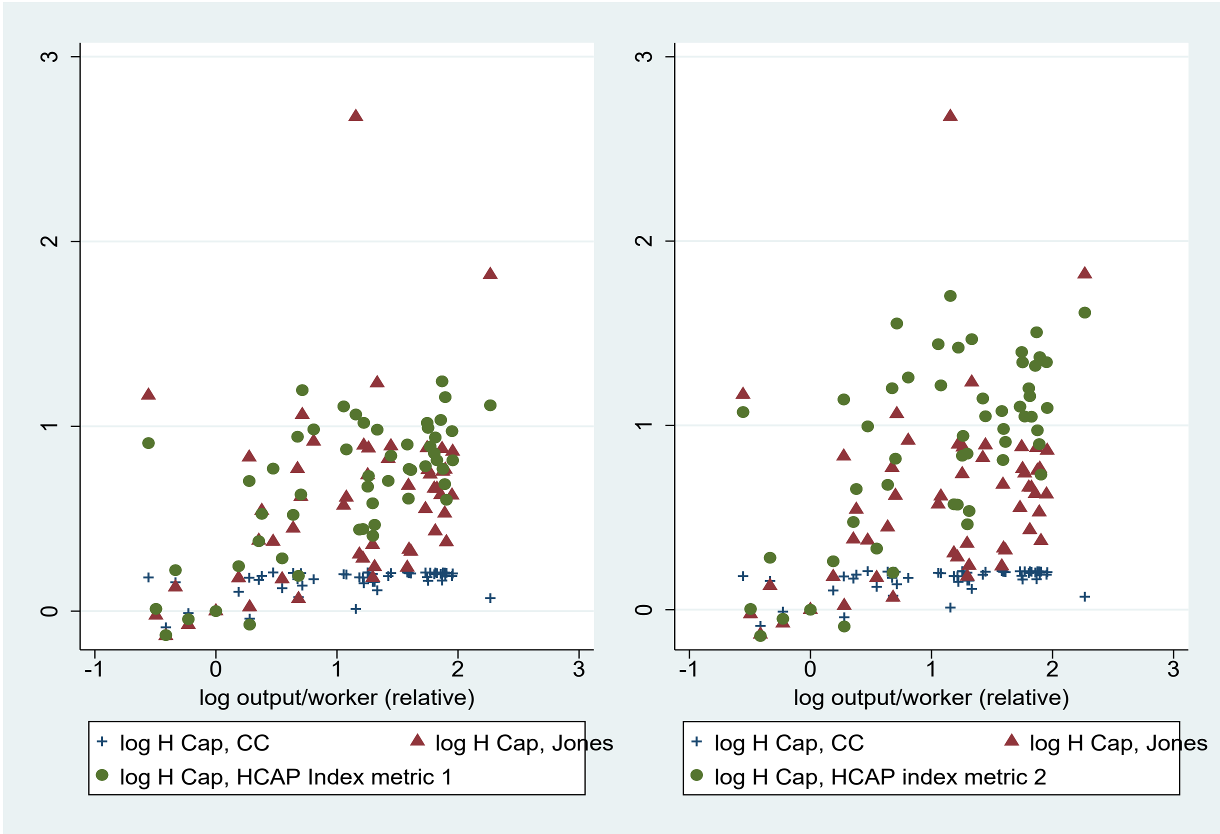

Table 1 Soft-Skill and Hard-Skill Occupations

VARIABLES	(1) Replicate	(2) Soft-Skill SubSample	(3) Hard-Skill SubSample	(4) Interaction	(5) Add College	(6) Add Rotter-Rosenberg (RR)	(7) RR Interaction
Black	-0.0537***	-0.0740**	-0.0462**	-0.0544***	-0.0656***	-0.0797***	-0.0796***
	(0.0196)	(0.0355)	(0.0230)	(0.0193)	(0.0191)	(0.0199)	(0.0199)
Hispanics	0.0425**	0.0276	0.0455*	0.0401*	0.0424**	0.0465**	0.0464**
	(0.0211)	(0.0375)	(0.0251)	(0.0208)	(0.0205)	(0.0212)	(0.0212)
Age	0.0349***	0.0465***	0.0286***	0.0342***	0.0320***	0.0338***	0.0337***
	(0.00708)	(0.0126)	(0.00839)	(0.00698)	(0.00687)	(0.00708)	(0.00708)
Soft-Skill Occp.				0.156***	0.131***	0.124***	0.124***
				(0.0163)	(0.0163)	(0.0165)	(0.0165)
College					0.179***	0.188***	0.189***
					(0.0265)	(0.0269)	(0.0270)
AFQT	0.183***	0.146***	0.183***	0.183***	0.140***	0.139***	0.139***
	(0.00964)	(0.0179)	(0.0114)	(0.0107)	(0.0115)	(0.0119)	(0.0119)
$AFQT^2$	-0.0130	-0.0185	-0.00453	-0.00919	-0.0356***	-0.0322***	-0.0324***
	(0.00802)	(0.0140)	(0.00971)	(0.00797)	(0.00948)	(0.00977)	(0.00977)
AFQT x Soft-Skill				-0.0397**	-0.0541***	-0.0509***	-0.0509***
				(0.0161)	(0.0160)	(0.0161)	(0.0161)
AFQT x College					0.0582**	0.0475*	0.0478*
					(0.0245)	(0.0251)	(0.0251)
Rotter-Rosenberg (RR)						0.0202**	0.0162
						(0.00813)	(0.00989)
RR x Soft-Skill							0.0123
							(0.0172)
Constant	6.233***	6.178***	6.276***	6.197***	6.218***	6.196***	6.197***
	(0.112)	(0.199)	(0.133)	(0.110)	(0.109)	(0.112)	(0.112)
Obs. No.	3,210	973	2,237	3,210	3,210	3,047	3,047
R^2	0.168	0.130	0.167	0.192	0.217	0.220	0.220

Notes: The dependent variable is log wage, and the sample is NLSY 79. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2 Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
High-Income Countries					
Labor Force Size	26	12764.77	23915.90	156.43	120464.70
Soft-Skill Emp. Share	26	0.24	0.05	0.10	0.34
Total Output ($000)	26	4.92E+08	1.23E+09	4196242	6.32E+09
Schooling Years	26	10.22	1.39	6.70	12.93
Sch. Yrs., Hard-Skill Occp.	26	8.52	1.58	4.95	12.16
PISA Math Score	26	502.79	22.76	455.80	553.40
High- and Low-Income Countries					
Labor Force Size	53	9317.01	17886.27	156.43	120464.70
Soft-Skill Emp. Share Within Skilled	53	0.25	0.06	0.10	0.39
Total Output ($000)	53	2.75E+08	8.83E+08	2.65E+06	6.32E+09
Schooling Years, Skilled	53	8.18	2.48	1.85	12.58
Private & Public Edu Spending/GDP	53	0.06	0.02	0.02	0.11
Sch. Yrs., Skilled & Hard-Skill Occp.	53	6.06	1.75	1.49	9.45

Notes: The set of high-income countries is listed in Table 3 below, and the set of low-income countries listed in Data Appendix 7.6.

Table 3 High-Income Countries, Years and Rankings

Country	Year	Sch. Yrs.	PISA Math	Std. H-Cap. Rank	Hard-Skill Prod Rank	Soft-Skill Prod Rank
Austria	2000	9.04	505.54	22	20	18
Belgium	2000	10.2	519.86	13	10	2
Czech Republic	2000	12.91	504.52	1	1	5
Denmark	2000	10.73	507.66	10	12	9
Finland	2000	9.32	537.98	15	7	3
France	2000	9.53	499.53	20	21	21
Germany	2000	10.51	508.27	14	14	20
Greece	2000	8.57	455.80	25	22	15
Hong Kong, China	2001	8.8	553.40	17	19	23
Hungary	2000	11.24	487.04	11	4	11
Iceland	2000	9.45	505.03	19	18	12
Ireland	2000	10.84	498.24	12	16	6
Italy	2000	8.58	473.90	24	26	24
Korea, Republic of	2000	10.59	547.42	3	8	26
Luxembourg	2000	9.68	490.53	21	24	17
Netherlands	2000	10.98	529.32	4	6	1
Norway	2000	11.21	493.09	9	13	13
Poland	2000	10.42	499.49	16	3	14
Portugal	2000	6.7	476.53	26	25	25
Slovakia	2000	11.52	492.15	7	2	7
Slovenia	2000	11.57	502.35	5	5	16
Spain	2000	8.89	483.22	23	23	19
Sweden	2000	11.42	495.98	6	9	10
Switzerland	1990	10.29	530.28	8	11	22
United Kingdom	2000	9.86	493.93	18	15	4
United States	2000	12.93	481.50	2	17	8

Notes: The year is for the ILO employment data, and the data for average schooling years come from Barro and Lee (2013). The standard human-capital rankings are based on the variable ST_1^k, as discussed in sub-section 3.2.

Table 4 Normalized PISA Scores and Hard-Skill Employment Shares

	Raw Score	Scaled Score	
	(1)	(2) AFQT to PISA	(3) PISA to AFQT
PISA Math			
$\ln(p_c^k)$	0.819**	0.800**	0.817**
	(0.354)	(0.346)	(0.371)
Constant	3.562***	3.014***	-2.084***
	(0.101)	(0.0989)	(0.106)
Obs. No.	26	26	26
R^2	0.182	0.182	0.168
PISA Science			
$\ln(p_c^k)$	0.677**	0.671**	0.669**
	(0.328)	(0.323)	(0.341)
Constant	3.543***	2.997***	-2.108***
	(0.0937)	(0.0922)	(0.0973)
Obs. No.	26	26	26
R^2	0.151	0.153	0.138

Notes: The dependent variable is the log of PISA scores normalized by output per worker to the power of 0.27. Column (1) uses raw PISA scores, column (2) uses PISA scores to the power of 0.912, and column (3) standardizes PISA scores to have mean 38.6 and standard deviation 27.8 and then raises these scores to the power of 0.150. Columns (1)-(3) are discussed in sub-section 3.3.

Table 5 Normalized Net Exports & Relative Abundance in Soft-Skill Human Capital

Dep. Var. = Revealed Comp Advantage

	(1)	(2)	(3)
Soft-Skill abundance x soft-skill intensity	1.556***	1.555***	0.962**
	(0.44)	(0.43)	(0.43)
Cap abundance x cap intensity		0.000	0.000
		(0.00)	(0.00)
Skill abundance x skill intensity			9.231***
			(1.99)
industry FE	yes	yes	yes
country FE	yes	yes	yes
R^2	0.353	0.353	0.387
Obs. No.	1103	1103	1103

Notes: The dependent variable is net export value divided by the sum of import and export values, by industry by country. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6 Dispersions of Human Capital among High-Income Countries

	Metric 1	Metric 2
Variance of log Human Cap		
Single-type Measure	0.0130	0.0773
Our Model		
Heterogeneous Human Cap	0.0319	0.0679
HCAP Index	0.0745	0.1558
90-10 Ratio of Human Cap		
Single-type Measure	1.3281	1.8211
Our Model		
Heterogeneous Human Cap	1.5786	1.7961
HCAP Index	2.0945	2.6961

Notes: The sample consists of 26 high-income countries, as listed in Table 3 above. The single-type measure of human capital is given in equation (27), the heterogeneous-human-capital measure in equation (21), and the HCAP index in equation (20). The variance of log output per worker is 0.13, and the 90-10 ratio of output per worker is 2.23. Metrics 1 and 2 are discussed in sub-section 3.2.

Table 7 Variance of log HCAP Index under Alternative Parameter Values

	Benchmark	Alt. Par. Values	
	(1)	(2)	(3)
A. η			
Value	0.27	0.22	0.33
Implied amplification	1.37	1.28	1.49
Var. of ln($HCAP^k$)	0.074	0.065	0.088
B. θ			
Value	2.00	1.50	3.00
Var. of ln($HCAP^k$)	0.074	0.074	0.074
C. α			
Value	1.78	1.40	2.00
Var. of ln($HCAP^k$)	0.074	0.076	0.074

Notes: In each panel, the row "Value" shows the values of the corresponding parameter. The row "Var. of ln($HCAP^k$)" shows var[ln($HCAP^k$)], computed using metric 1 of human capital. In Panel A, "implied amplification" equals $1/(1-\eta)$. Column (1) shows the main parameter values and results from Table 6 above. Columns (2) and (3) show the alternative parameter values and alternative results.

Table 8 Share of Educational Spending and Share of Skilled Labor's Income

	(1)	(2)	(3)
	Edu Spending/GDP	Edu Spending/Output	H-Cap Spending/Output
β_s^k	0.0738***	0.139***	0.269***
	(0.00937)	(0.0158)	(0.0306)
Constant	0.00433	0.00279	0.00541
	(0.00818)	(0.0138)	(0.0267)
Obs. No.	53	53	53
R^2	0.549	0.603	0.603

Notes: The dependent variable is $EdShare^k$ in equation (35). In column (1), $EdShare^k$ is the share of private plus public educational spending in GDP from UNESCO. In column (2), $EdShare^k$ is the ratio of private plus public educational spending to total output. In column (3), $EdShare^k$ is the ratio of spending on human capital to total output. The sample consists of both high- and low-income countries. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9 Development Accounting

ρ (sub-elasticity, skilled & unskilled)	1.5	2	3	5	∞
1. Relative Efficiency, 90-10					
Previous Studies					
CC 2019	1.00	1.00	1.00	1.00	1.00
Jones 2014	112.54	7.94	1.98	1.09	0.56
Our Framework with					
HCAP Index with Metric 1	4.41	4.41	4.41	4.41	4.41
HCAP Index with Metric 2	6.24	6.24	6.24	6.24	6.24
2. Human Cap per Capita, 90-10					
Previous Studies					
CC 2019	0.80	0.99	1.21	1.42	1.75
Jones 2014	17.57	4.33	2.08	1.52	1.07
Our Framework with					
HCAP Index with Metric 1	2.12	3.28	4.82	6.23	8.43
HCAP Index with Metric 2	2.62	4.29	6.55	8.62	11.82
3. Ratio of 90-10 ratio					
Previous Studies					
CC 2019	0.12	0.15	0.18	0.21	0.26
Jones 2014	2.65	0.65	0.31	0.23	0.16
Our Framework with					
HCAP Index with Metric 1	0.32	0.50	0.73	0.94	1.27
HCAP Index with Metric 2	0.39	0.65	0.99	1.30	1.78
4. Variance Ratio					
Previous Studies					
CC 2019	0.13	0.03	0.01	0.02	0.07
Jones 2014	5.68	1.48	0.37	0.12	0.02
Our Framework with					
HCAP Index with Metric 1	0.09	0.24	0.47	0.66	0.91
HCAP Index with Metric 2	0.18	0.49	0.87	1.14	1.47

Notes: The rows "CC 2019" are based on equation (33), "Jones 2014" on (34), and the rows with "HCAP Index" are based on equation (32). Panel 1 reports the 90-10 ratios of the variable $HCAP^k$ in equation (32), and those of the variables "*RE*" in equations (33)-(34). Panel 2 reports the 90-10 ratios of the relative human-capital-per-capita in equations (32)-(34). Panel 3 reports the ratios of the numbers in Panel 2 to the 90-10 ratios of output per worker. Panel 4 reports the ratios of the variance of the log of relative human-capital-per-capita to the variance of log output per worker. The sample consists of both high- and low-income countries.