Cross Country Income Differences and the Distinction between Cognitive and Non-Cognitive Human Capital

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Abstract

A country’s welfare depends on its ability to accumulate cognitive and non-cognitive human capital. In this paper, we model the productions of cognitive and non-cognitive human capital in general equilibrium. We use revealed comparative advantage to infer countries’ non-cognitive and cognitive productivities without a direct measure for the non-cognitive dimension. Our model also delivers analytical expressions for how non-cognitive and cognitive productivities can be aggregated into a single human-capital index, or HCAP, and how HCAP relates to output per worker.

We find that: 1. many countries with low human capital per worker according to the standard measure have high non-cognitive productivities, and vice versa; 2. the hard-to-measure non-cognitive human capital is important for HCAP; 3. HCAP accounts for over 50% of the cross-country variation in output per worker in most cases, and close to 100% in some cases; 4. international trade matters, theoretically, for HCAP: e.g. the iso-HCAP curve would have a very different shape under free trade. Our model has implications for the importance of specific types of human capital; e.g. excessive attention to test scores may decrease aggregate output.
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.

The failure of the literature to address heterogeneity within human capital has occurred despite the growth of a rich microeconometric literature that has emphasized the distinction between cognitive (hard) skills and non-cognitive (soft) skills (e.g. Heckman and Rubinstein 2001).³ This is problematic, because given the vast difference in the nature of cognitive and non-cognitive skills, it does not require any stretch of the imagination 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 scores are too low; 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

¹We view the concept of educational institutions as broad enough to incorporate opportunities for on-the-job learning.
³Many studies use "soft skills" and "non-cognitive skills" interchangeably. We follow this practice. We also use "hard skills" and "cognitive skills" interchangeably.
Korea declared a 10 pm curfew on private tutoring. The fear is that the educational systems fail to foster non-cognitive skills.\

The multi-dimensionality of human capital poses challenges for researchers; e.g. how to quantify multiple types of human capital, what is the appropriate aggregation, and how much does human capital contribute to 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, non-cognitive human capital, is difficult to quantify, because many non-cognitive skills do not show up in test scores (e.g. Heckman and Kautz 2012). Hanushek and Woessmann (2011) recognize that “the systematic measurement of such skills has yet to be possible in international comparisons”. Lundberg (2017) agrees that "we are far ... from a clear understanding of how to ... measure non-cognitive skills in a way that would allow for meaningful cross-country analysis".

We believe that the neglect of the distinction between cognitive and non-cognitive 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 long overdue. In this paper, we develop a general equilibrium (GE) framework to quantify how countries produce human capital along multiple dimensions. Our model 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 non-cognitive relative to cognitive human capital 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 cognitive dimension. Our model allows us to combine these two elements to infer countries’ productivities for turning resources into both non-cognitive and cognitive human capital. In other words, we can make cross-country comparisons for non-cognitive human capital by combining absolute advantage in cognitive human capital accumulation, measured using standard development accounting techniques, with comparative advantage, revealed by variation in occupational choices across countries.

In our model, aggregate output is produced with labor from non-cognitive and cognitive occupations, which are imperfect substitutes in production. Human capital is produced using

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4For 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).
economic resources, and countries differ in non-cognitive productivity and cognitive productivity, or the efficiencies in turning resources into efficiency-equivalent units of non-cognitive and cognitive human capital. Aggregate stocks of non-cognitive and cognitive 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 occupations, and their comparative advantages in non-cognitive and cognitive skills, as in Willis and Rosen (1979). In the aggregate, the employment shares of non-cognitive and cognitive occupations depend on country-specific non-cognitive and cognitive productivities, and the returns of non-cognitive and cognitive human capital on the labor market. In equilibrium, the returns of human capital are endogenous, and so ultimately, the relative employment share of the non-cognitive occupation varies across countries in the same direction as the ratio of non-cognitive productivity to cognitive productivity.

Our model allows us to aggregate the multi-dimensional differences in non-cognitive and cognitive productivities into a single metric, which we call human-capital accumulation productivity (HCAP) index. We derive the analytical expression for the HCAP index, which shows that the aggregation is through the weighted power mean of non-cognitive and cognitive productivities, the weights being the employment shares of non-cognitive and cognitive occupations. The index depends on three parameters: $\eta$, the elasticity of human capital with respect to resources in human-capital production, $\theta$, the dispersion of workers’ innate abilities, and $\alpha$, the substitution-elasticity across different types of human capital in aggregate production. The ratio of output per worker between any pair of countries can be decomposed into a component due to productivity in accumulating human capital, measured by the HCAP index, and to a component representing residual output TFP. In this sense, HCAP is the ideal index for quantifying human capital.

We then obtain the values of non-cognitive and cognitive productivities and compute HCAP, using publically available data for a sample of mostly high-income countries. Our theoretical and empirical results provide the following new perspectives.

First, countries’ rankings in non-cognitive and cognitive productivities are different from their rankings in standard single-type measures of human capital. This is because institutional productivity along one dimension is only weakly correlated with productivity along the other. For example, many countries with (relatively) low human capital per worker according to the standard measure have high non-cognitive productivities (e.g. Finland and the U.K.), and vice versa (e.g. S. Korea, Slovenia). When we graph the iso-HCAP curve, the combination of cognitive and non-cognitive productivities that generate the same HCAP, we find that countries with imbalanced human-capital productivities tend to have relatively low HCAP.

Second, once multiple types of human capital are properly aggregated, human capital ac-
counts for most cross-country variation in output per worker.\textsuperscript{5} The additional contributions arise for two reasons. One, we augment standard development accounting with non-cognitive human capital by utilizing occupation-employment data. We call this approach development accounting with heterogeneous human capital. Two, we have endogenous human-capital production, and so our model delivers amplification of cross-country differences in cognitive and non-cognitive productivities. We call this the HCAP index approach. For instance, the amounts of human capital account for 5.6\textasciitilde{}16.7\% of the variance in log output per capita in our data, according to the standard development accounting approach, but they explain 20.3\textasciitilde{}42.1\% of the same variance, according to our heterogeneous-human-capital accounting. Once we take into account countries’ efficiencies in turning resources into heterogeneous human capital, using our HCAP index approach, human capital’s contribution increases further, to 39.6\%~89.5\%. When we look at ratios of the 90-10 ratio, we obtain similar, and stronger, results, such that at the end of the day, the HCAP index’s contribution exceeds 50\% in most cases, and approaches 100\% in some cases.

Third, our framework highlights potential policy tradeoffs, because the HCAP index shows how much an increase in the efficiency of accumulating one type of human capital is offset by a decrease in the other. This tradeoff may have useful implications for the discussions of education policies, such as NCLB and RTT in the U.S.\textsuperscript{6} We show that, were the U.S. to trade off non-cognitive productivity for cognitive productivity at the rate that would bring it in the direction of, say, S. Korea, its test score would increase but its output would drop. This message resonates with a large body of applied-micro studies on early childhood intervention programs in the U.S.\textsuperscript{7} 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.”

Fourth, international trade matters. Under free trade, the HCAP index depends only on $\eta$ and $\theta$, but not $\alpha$. With free trade, imbalanced human-capital productivities merely induce countries to specialize, and so they enjoy greater gains from trade. As a result, the iso-HCAP curve would have a very different shape under free trade. Despite these changes, the HCAP

\textsuperscript{5}The contribution of human capital is 10-30\% according to standard development accounting approaches (e.g. Hsieh and Klenow 2010).

\textsuperscript{6}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.”

\textsuperscript{7}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).
index continues to account for most of cross-country variation in output per worker under the free trade equilibrium (e.g. 73.8% of the variance in log output per worker).

Finally, we provide external validations for the values of our non-cognitive and cognitive productivities. For example, we show that the countries with strong comparative advantages for non-cognitive human capital tend to have high normalized net exports of non-cognitive-intensive industries. The countries with high non-cognitive employment shares also tend to have low relative wages for the non-cognitive occupation, for a subset of our countries with available data on wage by occupation. These results are intuitive: non-cognitive and cognitive productivities are about the supply of human capital, and abundance in relative supply shows up in the patterns of trade and relative wages. We also show that our development-accounting results are robust to the values of $\eta$, $\theta$ and $\alpha$.

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, our HCAP index still attributes most of variation in output per worker to human capital.

Caselli and Coleman (2006), Jones (2014) and Malmberg (2017) examine imperfect substitutability among workers with different schooling years, or vertically differentiated human capital, whereas we explore horizontally differentiated human capital. To be specific, these studies abstract away from the production of human capital, and the key parameter there is the substitution elasticity in aggregate production, which corresponds to our $\alpha$. We have endogenous human-capital production and amplification, and the HCAP index depends on all three parameters, $\eta$, $\theta$ and $\alpha$. We also employ different quantification, and our results do not depend on the relative efficiencies of high-skill vs. low-skill workers, the interpretation of which is being debated in this literature (e.g. Caselli and Ciccone 2019, Jones 2019).\footnote{Jones (2014) and Malmberg (2017) show that human capital accounts for most cross-country variation in output per worker if $\alpha$ is around 1.5. Our results are not very sensitive to the value of $\alpha$; e.g. we obtain very similar results with $\alpha = 2$, and under free trade, HCAP does not depend on $\alpha$.}

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.\footnote{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.} We can incorporate the progress these studies have made, by applying their met-
rics to the cognitive dimension and using them as the starting points of our development accounting.

Ohsornge and Treffler (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.\textsuperscript{11}

An applied micro literature examines the formation of cognitive and non-cognitive 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). We take a macro perspective by quantifying the ways in which different countries produce multiple types of human capital, and then clarifying the implications of such differences for aggregate output in a GE model.

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 spells out our theoretical framework and develops the key aggregation techniques. Section 3 explains how we quantify the model and validates key parameter estimates. Section 4 presents the baseline results, discusses their implications for development accounting, and shows that our results are robust to alternative parameter values. Section 5 extends our framework to incorporate international trade, and section 6 concludes.

2 Baseline Model

In this section we develop a stylized model, a key feature of which is that heterogeneous workers optimally choose their investment in both the quantities and types of human capital. Our model delivers an analytical expression for the HCAP index, and shows that it is closely related to output per worker. Following the bulk of the literature, we consider a closed economy environment for now. We will extend the model to allow for international trade in section 5.

\textsuperscript{11}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 non-cognitive and cognitive productivity and HCAP, and abstract away from market frictions and distortion in our model.
2.1 Assumptions

There are $K$ countries, indexed by $k$, each endowed with $L^k$ heterogeneous workers. Workers are endowed with non-cognitive and cognitive attributes $\varepsilon_n$ and $\varepsilon_c$, drawn from the following Frechet distribution:

$$F(\varepsilon_n, \varepsilon_c) = \exp \left( - \left( T_c \varepsilon_c^{-\theta} + T_n \varepsilon_n^{-\theta} \right)^{1-\rho} \right), \quad \theta \equiv \frac{\tilde{\theta}}{1-\rho} > 1. \quad (1)$$

Intuitively, we think about the attributes $n$ and $c$ as two distinct bundles of skills, rather than two individual skills, and these two bundles may have common elements (see note 15 below). In equation (1), $\rho$ determines the degree to which non-cognitive and cognitive packages are correlated, and $\theta$ governs the dispersion of attributes across workers. Higher $\theta$ reduces the dispersion in worker productivity. Note that for the distribution to have finite variance, we require $\theta > 1$. $T_c$ and $T_n$ govern the drifts of the attributes distribution, and we assume that they are common across countries.\(^{12}\)

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

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

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 $\eta$ captures decreasing returns in the production of human capital, and guarantees an interior solution for workers’ optimal choice of $e$. The parameters $h^k_n$ and $h^k_c$ are country $k$’s TFP’s in the production functions of non-cognitive and cognitive human capital, and they capture country $k$’s human capital productivities along these two dimensions, net of resources inputs.

We treat $h^k_n$ and $h^k_c$ 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.\(^{13}\) In many East Asian countries, the national exam has

\(^{12}\)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.

\(^{13}\)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).
been a cornerstone of the educational institution for over 1,000 years.\footnote{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).} 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 $\rho$, $\theta$, and $\eta$ do not vary across countries.

Both non-cognitive and cognitive tasks are needed to produce the final good. When a worker chooses task $i$, or occupation $i$, her output is

$$h_i(e)\varepsilon_i, \ i = n, c$$

(3)

where $h_i(e)$ is the quantity of the worker’s human capital, accumulated according to the technology (2), and $\varepsilon_i$ her attribute, drawn from the distribution in (1).\footnote{Equation (3) assumes that occupation $i$ uses skill $i$. In section 4 we have both occupations use both skills, with occupation $i$ being more intensive in skill $i$, and obtain very similar results.} The educational and occupational choices made by workers lead to aggregate supplies of non-cognitive and cognitive human capital in country $k$ of $L_n^{kS}$ and $L_c^{kS}$ (hence the $S$ superscript), respectively.

The representative firm hires workers in both non-cognitive and cognitive occupations to maximize output

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

(4)

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

The key prices in country $k$ are the price of an effective unit of cognitive human capital, $w_c^k$, the price of an effective unit of non-cognitive 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

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

(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, \textit{ceteris paribus}.

All markets are perfectly competitive. The timing happens as follows. First, workers choose how much and what type (cognitive or non-cognitive) 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

We first analyze individual workers’ optimal choices for the quantity and type of human capital accumulation. We then aggregate across individuals to obtain the aggregate supplies of non-cognitive and cognitive human capital in country $k$, and bring in the demand side and characterize the equilibrium.

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

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

and so the optimal choice of human capital investment is

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

In equation (6), $e(\varepsilon_i)$ is the quantity of human capital investment. 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 $i$,

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

Equation (6) and (7) show that net income, $I_i(\varepsilon_i)$, is proportional to human-capital spending, $e_i(\varepsilon_i)$. In addition, (6) and (7) show that the final-good price index, $P^k$, has the same effects on $e(\varepsilon_i)$ and $I_i(\varepsilon_i)$ for both occupations, and so does not affect individuals’ occupational choices.

Equation (7) implies that the worker chooses occupation $n$ if and only if $w^k_w h^k_w \varepsilon^k_w \leq w^k_n h^k_n \varepsilon^k_n$. Using the Frechet distribution (1), we show that the employment share of occupation $i$ equals (Theory Appendix 1)

$$p^k_i = \frac{T_i(w^k_i h^k_i)^\theta}{T_c(w^k_c h^k_c)^\theta + T_n(w^k_n h^k_n)^\theta}, \quad i = c, n. \quad (8)$$

Equation (8) says that the non-cognitive employment share, $p^k_n$, is high, if non-cognitive skills have a high relative return in the labor market (high $w^k_n/w^k_c$), or country $k$ has a
strong comparative advantage in fostering non-cognitive human capital \((h_n^k/h_c^k)\). In (8), \(\theta\) plays the important role of governing the elasticity of labor supply. As \(\theta\) 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.

To solve the model, we start by calculating the average net income of non-cognitive and cognitive workers. Analytically, this involves taking the expected value of equation (7), with respect to \(\varepsilon_i\), conditional on type \(i\), \(i = n, c\). In Theory Appendix 2, we show that the average net income is the same for non-cognitive and cognitive workers; i.e.

\[
I_n^k = I_c^k = \gamma(1 - \eta)\eta^{\frac{n}{\gamma - 1}} \left[ T_c \left( \frac{w_c^k}{P^k h_c^k} \right)^\theta + T_n \left( \frac{w_n^k}{P^k h_n^k} \right)^\theta \right]^{\frac{1}{\gamma(1 - \eta)}}, \quad (9)
\]

where \(\gamma = \Gamma \left( 1 - \frac{1}{\theta(1 - \rho)(1 - \eta)} \right)\).

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). \(\Gamma(\cdot)\) is the Gamma function and so \(\gamma\) is a constant.

Equations (8) and (9) imply that the average educational expenditure is equalized for non-cognitive and cognitive workers:

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

By equation (10), we now use \(E^k\), without an occupation subscript, to denote the average educational spending in country \(k\). Equation (10) will prove useful in pinning down \(\eta\), the elasticity of the output of human capital with respect to input. To see this, consider the following proposition:

**Proposition 1** Country \(k\) spends fraction \(\eta\) of its aggregate output on education; i.e.

\[
E^k L^k = \eta Y^k. \quad (11)
\]

**Proof.** By equations (9) and (10), \(w_i^k L_i^k = L_i^k p_i^k E^k/\eta\), and so \(\eta \left( \sum_i w_i^k L_i^k \right) = L^k E^k \left( \sum_i p_i^k \right) = E^k L^k\). In our model aggregate output equals aggregate income, and so \(\eta \left( \sum_i w_i^k L_i^k \right) = \eta Y^k\).

As shown in Theory Appendix 2, the aggregate supply of human capital of type \(i\), \(L_i^{kS}\), \(i = n, c\), is given by

\[
L_i^{kS} = L_i^k p_i^k E(h_i^k e^\eta | Occp, i) = \frac{L_i^k p_i^k}{w_i^k} \left( \eta^{\eta(P^k)^{1 - \eta}} \left( T_c \left( \frac{w_c^k}{P^k h_c^k} \right)^\theta + T_n \left( \frac{w_n^k}{P^k h_n^k} \right)^\theta \right)^{\frac{1}{\gamma}} \right)^{\frac{1}{1 - \eta}} \gamma. \quad (12)
\]
Equation (12), together with $w^k_L c + w^k_L n = P^k Y^k$, implies that the income shares of cognitive and non-cognitive workers are given by

$$\frac{w^k L^k S}{P^k Y^k} = p^k_i. \tag{13}$$

To complete our characterization of the supply side of the economy, we use equations (8) and (12) to derive the relative supply of non-cognitive human capital, which is given by

$$\frac{w^k n}{w^k c} \frac{L^k n}{L^k c} = \frac{p^k_n}{p^k c} \text{ where } \frac{p^k n}{p^k c} = \left( \frac{w^k h^k n}{w^k h^k c} \right)^\theta \frac{T_n}{T_c}. \tag{14}$$

Equation (14) says that the relative supply of non-cognitive labor, $L^k n / L^k c$, is increasing in the comparative advantage of that country in non-cognitive human capital, $h^k n / h^k c$, and the relative return of non-cognitive human capital, $w^k n / w^k c$. As foreshadowed by our discussion of equation (8), it is clear from equation (14) that $\theta$ is the supply elasticity: as workers’ skills become more homogeneous, a given change in $h^k n / h^k c$ or $w^k n / w^k c$ affects the occupational choices of more workers, and so solicits a larger response in $L^k n / L^k c$.

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

$$s^k_i = \frac{(A_i)^\alpha (w^k_i)^{1-\alpha}}{(A_c)^\alpha (w^k c)^{1-\alpha} + (A_n)^\alpha (w^k n)^{1-\alpha}}. \tag{15}$$

It follows immediately that the relative demand for non-cognitive human capital is given by

$$\frac{w^k n}{w^k c} \frac{L^k D n}{L^k D c} = s^k n \quad \frac{s^k n}{s^k c} \text{ where } \frac{s^k n}{s^k c} = \frac{(A_n)^\alpha (w^k n)^{1-\alpha}}{(A_c)^\alpha (w^k c)^{1-\alpha}}. \tag{16}$$

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

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

$$L^k i = L^k S i, i = n, c \tag{17}$$

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

$$\frac{w^k n}{w^k c} = \left[ \frac{T_c}{T_n} \left( \frac{h^k c}{h^k n} \right)^\theta \left( \frac{A_n}{A_c} \right)^\alpha \right]^{\frac{1}{\phi}}, \phi \equiv \theta + \alpha - 1 > 0. \tag{18}$$

Given these relative factor prices, all the other endogenous variables of interest can be solved.
2.3 Key Decomposition Results

We now clarify the connections between $h^k_c$ and $h^k_n$ and income differences across countries. We derive an analytical expression that decomposes the differences in output per worker into a component that reflects differences in human-capital productivities, and another that reflects differences in output TFP. This analytic expression will guide our quantitative analyses below. We then explicitly compare our framework with the development-accounting literature, and discuss why heterogeneous human capital is important for development accounting.

2.3.1 Human Capital Accumulation Productivity (HCAP) Index

Differences across countries in output per worker is either due to variation in the stock of productive inputs available to workers, or to 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. This stock depends on the reward to accumulating skills, which is driven in part by output TFP, and in the efficiency with which resources can be turned into human capital, which depends on the productivity of the educational institution. We now show how efficiencies for non-cognitive and cognitive human capital can be aggregated to produce a single index of Human Capital Accumulation Productivity, or HCAP (Theory Appendix 3):

Proposition 2 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; i.e.

$$\frac{Y^k}{Y^0} = \left( \frac{\Theta^k}{\Theta^0} \Omega^k \right)^{\frac{1}{1-\eta}},$$  \hspace{1cm} (19)

where $\text{HCAP} = (\Omega^k)^{\frac{1}{1-\eta}}$ is related to the ratios of non-cognitive and cognitive productivities and the occupation employment shares of country $0$:

$$\Omega^k \equiv (\Omega^k)^{\frac{1}{1-\eta}} = \left( p^0_c \left( \frac{h^k_c}{h^0_c} \right)^{\frac{\theta(a-1)}{\sigma}} + p^0_n \left( \frac{h^k_n}{h^0_n} \right)^{\frac{\theta(a-1)}{\sigma}} \right)^{\frac{1}{\sigma(a-1)}} \right)^{\frac{1}{1-\eta}}.$$  \hspace{1cm} (20)

Equation (19) shows how variation in output per worker across countries can be decomposed into a component that stems from variation in output TFP across countries, $(\Theta^k/\Theta^0)^{\frac{1}{1-\eta}}$, and a component that stems from variation in how efficiently resources are used in the production of human capital, $(\Omega^k)^{\frac{1}{1-\eta}}$, which we have called the HCAP index.

Equation (20) says that country $k$’s HCAP index (relative to country $0$) depends on the weighted power mean of the ratios of non-cognitive and cognitive productivities, with the weights being the occupational employment shares of the base country $0$. This index summarizes the multi-dimensional differences in non-cognitive and cognitive productivities.
into a single numerical value. Unlike $L^k_c$ and $L^k_n$, 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.

Intuitively, the HCAP index depends on $\eta$ 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, $h^k_c/h^0_c$ and $h^k_n/h^0_n$, are amplified, the magnitude of which depends on $\eta$, the degree of diminishing returns in human-capital production. The larger is $\eta$, the lower is diminishing returns, and so the larger is amplification.

Meanwhile, $\theta$ and $\alpha$ determine the power coefficients of the HCAP index in (20). As both $\theta, \alpha \to \infty$, workers become equally capable at perfectly substitutable tasks, and so $\Omega^k$ goes to the maximum of $h^k_c$ and $h^k_n$. In this case, being strong in producing one type of human capital but weak in producing the other type does not affect a country’s well-being. As $\alpha \to -\infty$, however, the aggregate production function becomes Leontief, $\Omega^k$ goes to the minimum of $h^k_c$ and $h^k_n$, and excelling along a single dimension in human-capital production does little good for national well-being. For the more empirically relevant case found in our data (see below), $\Omega^k$ is reasonably well approximated as a geometric mean, where the relative importance of non-cognitive and cognitive productivities is determined by the occupational shares. In this case, both non-cognitive and cognitive productivities are important, and so a country with high productivity along one dimension but low productivity along the other tends to have low HCAP.

In section 3, we show how the HCAP index can be measured using readily available data. Doing so will allow us to quantify the share of variation in output per capita that can be attributed to differences across countries in their educational efficiencies as captured by the HCAP index. Before proceeding with quantification, though, we explicitly compare our framework with the development-accounting literature.

### 2.3.2 Development Accounting with Heterogeneous Human Capital

We first recast our decomposition, (19), in terms of the standard development accounting approach, which does not distinguish between cognitive and non-cognitive human capital. We obtain, from (19),

$$\frac{Y^k}{Y^0} = \frac{\Theta^k}{\Theta^0} \times \frac{L^k_{Sc}/L^k}{L^0_{Sc}/L^0} \times \left(\Omega^k\right)^{\frac{\theta}{\alpha}} \times \left(\frac{h^k}{h^0}\right)^{-\frac{\theta}{\alpha}}. \quad (21)$$

In equation (21), the term $L^k_{Sc}/L^k$ is the average cognitive human capital per capita, and it is similar to the measure of human capital in standard development accounting, based on
Mincerian regressions (see section 3.2). Meanwhile, the term \( (\Omega^k)^{\frac{\theta_k}{\eta}} (\frac{h^k_c}{h^0_c})^{-\frac{\theta_c}{\eta}} \) captures the contribution of heterogeneity within human capital to cross-country differences in output per worker, and it would reduce to the value of 1 under standard development accounting. Expression (21) then makes clear that standard development accounting is missing the potentially important contribution due to the existence of multiple types of skills.

Although decompositions (21) and (19) are theoretically equivalent, they represent different accounting exercises in practice, and they get at different conceptual questions. Equation (21) takes as given existing stocks of human capital, and sheds light on how much our heterogeneous-human-capital accounting, which recognizes the variation in countries’ stocks of non-cognitive human capital, improves on standard accounting, which lumps cognitive and non-cognitive human capital into a single type. In this exercise, the value of \( \eta \) plays no role. Equation (19) goes deeper, and focuses on cognitive and non-cognitive productivities, the underlying fundamentals that give rise to variation in human capital stocks across countries. It directly addresses the portion of the underlying productivity heterogeneity across countries that is due to differences in the efficiency of its institutions in producing cognitive and non-cognitive human capital. The cross-country differences of both cognitive and non-cognitive productivities are magnified by the round-about structure of human capital accumulation.

We call the development accounting by (21) heterogeneous-human-capital accounting, and that by (19) the HCAP index accounting. We implement both accounting exercises in section 4.

2.3.3 Discussion

The development-accounting literature has made much progress relative to the standard accounting approach, and we now place our work in the context of the progress that has been made. First, as in Erosa et al (2010), Manuelli and Seshadri (2014) and Cubas et al (2016), we endogenize human capital accumulation as a function of underlying productivity differences across countries, and so our HCAP index analysis, based on (19), is conceptually similar to the accounting exercises in these studies. We differ in that the human capital being accumulated involves two very different types of skills, while these studies have a single type. To see how our model relates to this literature, we set \( p^n_k = 0 \) and \( p^c_k = 1 \), and obtain (using equations (19) and (20))

\[
\frac{Y^k}{Y^0} / L^k / L^0 = \left[ \frac{\Theta^k}{\Theta^0 \Omega^k} \right]^{\frac{1}{1-\eta}}, \Omega^k = \frac{h^c_k}{h^c_0}, \tag{22}
\]

and

\[
\frac{L^k_{c,S}}{L^0_{c,S}} / L^k / L^0 = \left( \frac{\Theta^k}{\Theta^0} \right)^{\frac{1}{1-\eta}} \left( \Omega^k \right)^{\frac{1}{1-\eta}}. \tag{23}
\]
Equations (22) and (23) show that holding $\Theta^k$ fixed, a country that produces cognitive human capital well (high $h^k_c$) also has a lot of it and high output per worker. In other words, the distinction between the quantity of cognitive human capital (in efficiency equivalent units), $L_c^{kS}/L^k$, and its TFP, $h^k_c$, is not important, and there is a monotonic relationship between this quantity and output per worker. In this one-dimensional world, there is no comparative advantage so that the HCAP index simplifies to $h^k_c$.

Equations (22) and (23) also show that we are using two parameters, $\Theta^k$ and $h^k_c$, for absolute advantage, and so one is redundant. Setting $h^k_c = h^0_c$ for all $k$, we obtain

$$\frac{Y^k/L^k}{Y^0/L^0} = \left[\frac{\Theta^k}{\Theta^0}\right]^{1-\eta} \frac{L_c^{kS}/L^k}{L_c^{0S}/L^0} = \left(\frac{\Theta^k}{\Theta^0}\right)^{1-\eta}$$

This expression says that a country with high output TFP (high $\Theta^k$) has a large quantity of cognitive human capital and so high output per worker.\textsuperscript{16} In addition, a given difference in output TFP can be amplified through human-capital production. This explains why in the human-capital production literature, the focus is on 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, we abstract from many amplification mechanisms to focus on horizontally differentiated human capital accumulation. Our interest is in quantifying how variation in the efficiency with which countries turn resources into human capital, captured by the HCAP index, can account for variation in output worker. Hence, when we find that the HCAP index explains most of the variation in output per worker, we do so with relatively weak amplification.\textsuperscript{17} Furthermore, we quantify three productivity parameters, cognitive productivity, non-cognitive productivity, and output TFP, while this literature focuses on output TFP alone. Therefore, our amplification works on the efficiencies of human-capital production, and we come closer to understanding why some country’s human capital stock is low.

Second, 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 cognitive human capital (section 4.3). Our development accounting with heterogeneous human capital, (21), then adds to these metrics the contributions of

\textsuperscript{16}Erosa et al (2010) and Manuelli and Seshadri (2014) measure the quantity of human capital (in efficiency equivalent units) using spending, while Cubas et al (2016) use average PISA score.

\textsuperscript{17}It 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 $\eta$ estimate of 0.27 (see section 4).
non-cognitive human capital. Our HCAP index analysis, (19), goes one step further, and shows the results under the assumption that these metrics are endogenous to the underlying production technology of human capital, $h^k_c$ and $h^n_k$.

Finally, our aggregate production function, (4), has human capital differentiated across occupations. This feature of differentiation bears some resemblance to Caselli and Coleman (2006), Jones (2014) and Malmberg (2017), where workers with different schooling years are imperfect substitutes in aggregate production. These studies, however, abstract away from the production of human capital, and so the results depend on the substitution elasticities of the aggregate production, which correspond to our $\alpha$. The results also depend on the relative efficiencies of workers with different schooling years, which are backed out from data on relative quantities and relative wages. This literature, however, has not reached a consensus about how to interpret the relative efficiencies.

In comparison, we have taken a different path. In terms of modeling, we have endogenous human-capital production and occupational choices. As a result, we have amplification, and in (20), the HCAP index depends on three parameters: $\alpha$, the substitution elasticity in aggregate production, $\theta$, which is like a substitution elasticity in human-capital production, and $\eta$, which governs the magnitude of amplification. We also show, in section 5, that under free trade, the HCAP index would depend on $\theta$ and $\eta$, but not on $\alpha$. In terms of quantification, accounting for multiple types of human capital is straightforward in our setting. We measure cognitive human capital by following the standard practice in the literature, and measure non-cognitive human capital using data on occupation employment shares (section 3). In addition, our results are not very sensitive to the value of $\alpha$ (section 4.4).

### 3 Calibration

In this section, we obtain measures of country-level cognitive and non-cognitive productivities. We first show how the model’s equilibrium conditions can be used to measure countries’ absolute and comparative advantages given model parameters, observable country charac-

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18 We abstract away from imperfect substitutability within a given type of human capital, and compute the aggregate supply (in efficiency equivalent units) by summing across workers in equation (12). Conceptually, we can think about embedding this literature in our framework by replacing $L^{KD}_c$ and $L^{KD}_n$ in equation (4) with, say, CES aggregates of workers with different schooling years. However, data for wages by occupation by education are hard to obtain. In addition, in our sample of mostly high-income countries, illiteracy is uncommon.

teristics, and occupational choice shares by country. We then explain how occupations can be classified into either cognitive or non-cognitive and provide empirical support for this classification. After briefly describing the data and our choice of values for the key elasticities, we present the estimates of human capital production efficiencies for cognitive and non-cognitive skills, and provide external validations that these estimates are reasonable.

3.1 Identifying Comparative Advantage

We begin by backing out a country’s comparative advantage in human capital production. Equations (8) and (18) imply that, relative to a base country 0,

\[
\frac{h^k_c}{h^n_c} / \frac{h^0_c}{h^n_0} = \left( \frac{p^k_c}{p^n_c} / \frac{p^0_c}{p^n_0} \right)^{\frac{\phi}{\theta (\alpha - 1)}} \quad \text{, } \phi \equiv \theta + \alpha - 1 > 0. \tag{24}
\]

Equation (24) has the flavor of revealed comparative advantage: we can back out a country’s comparative advantage for cognitive human capital, \(h^k_c/h^n_c\), using the data and parameter values on the right-hand side of (24). 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 cognitive occupation in country \(k\), we can infer that country \(k\) has a strong comparative advantage for cognitive human capital.

Equation (24) also delivers the values of non-cognitive productivity, \(h^k_n\), if we have the values of cognitive productivity, \(h^k_c\). These \(h^k_n\) values compare how well different countries produce non-cognitive human capital, and provide a solution to a major challenge for the literature on non-cognitive human capital. To put our results into the context of this literature, we note that while there are direct measures to compare cognitive human capital across countries, such as test score, no such measure is available for non-cognitive human capital. Our discussions in Introduction suggest that it could be difficult to come up with such a measure.\(^{20}\) Equation (24) says that even without such a measure, we can still make cross-country comparisons for the non-cognitive dimension, by leaning on the measure we have for the cognitive dimension, and revealed comparative advantage.

3.2 Cognitive Human Capital Efficiencies

We now turn to backing out a country’s absolute advantage in producing human capital from data. We start by combining equations (8), (10), (12) and (13), to obtain the following expression for country \(k\)’s average cognitive human capital (in efficiency equivalent units), relative to a base country 0 (Theory Appendix 4):

\[
\frac{L^k_{cS}}{L^n_{cS}} / \frac{L^k_0}{L^n_0} = \left( \frac{Y^k}{Y^n / L^n} \right)^{\eta} \left( \frac{p^k_c}{p^n_c} \right)^{1-\frac{1}{\eta}} \left( \frac{h^k_c}{h^n_c} \right) \tag{25}
\]

\(^{20}\)See also Deming (2017b).
On the right-hand side of equation (25), the first term captures the effects of resources inputs, \( Y^k / L^k \). \(^{21}\) \( Y^k / L^k \) is raised to the power of \( \eta \) because the production technology of human capital, (2), is subject to diminishing returns.

The second term in (25) captures the effects of incentives and selection. To see these effects, suppose that many choose the cognitive occupation in country \( k \); i.e. \( p^c_k \) is high. This means that the cognitive occupation is an attractive career choice, and so individuals have strong incentives to accumulate cognitive human capital. This incentive effect implies high average cognitive 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 cognitive abilities have self-selected into the cognitive occupation. Their presence tends to lower the average cognitive human capital. The magnitude of this selection effect is \( p^c_k \) raised to the power of \(-1/\theta\). \(^{22}\)

Finally, cognitive productivity, \( h^c_k \), soaks up all the other reasons why average cognitive human capital is high for country \( k \), net of the effects of resources, and incentives minus selection. Equation (25) makes it clear that we need the values of average cognitive human capital, \( L^c_kS/L^k \), in order to back out \( h^c_k \).

To obtain these values, we follow the development-accounting literature. In this body of work, the standard approach to measure (a single type of) human capital is to use average years of schooling, and this metric is often augmented by test scores (e.g. Caselli 2005, Hanushek et al. 2017); i.e.

\[
H^k = b \exp[f(s^k)]g(t^k), \tag{26}
\]

where \( f(.) \) and \( g(.) \) are increasing functions, \( s^k \) and \( t^k \) denote, respectively, average schooling years and test scores for country \( k \), and \( b \) is a constant. We apply this approach to the cognitive dimension and assume that

\[
\frac{L^c_kS}{L^c_k} = b \exp[f(s^c_k)]g(t^c_k), \tag{27}
\]

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 test scores for the cognitive occupation. We will follow the development-accounting literature and use the coefficients of Mincer-wage regressions to specify the functions \( f(.) \) and \( g(.) \), in section 3.3 below, for equations (26) and (27). Because \( H^k \) is for all human capital and \( L^c_kS/L^k \) is for cognitive human capital only, the numerical value for \( H^k \), obtained from (26), should exceed \( L^c_kS/L^k \), obtained from (27).

\(^{21}\)Recall that \( Y^k / L^k \) is proportional to \( E^k \) by Proposition 1.

\(^{22}\)Note that, because \( \theta > 1 \), the incentive effect always dominates.
3.3 Data, parameter values, and metrics

In this section, we explain how we classify occupations into non-cognitive and cognitive. We also explain the sources of our other data, all of which are publically available, and how we obtain the values of the parameters of $\theta$, $\eta$, and $\alpha$.

3.3.1 Non-Cognitive and Cognitive Occupations

A large literature has examined many soft, or non-cognitive, skills. While there has not been a consensus about which should be the standard measure(s), a common approach has emerged: use surveys or occupation-characteristics data (e.g. the U.S. O*NET) to proxy for non-cognitive skills, and provide empirical evidence that these measures are different from the measures of hard, or cognitive, skills.

We follow this approach, and use leadership to measure non-cognitive occupations. To be specific, we classify occupations on the basis of the first principal component of the following 8 O*NET characteristics of leadership: guiding and directing subordinates; leadership in work style; coordinating the work and activities of others; developing and building teams; coaching and developing others; recruiting and promoting employees; monitoring and controlling resources and spending; and coordinate or lead others in work. If the principal component is important for an occupation, we classify this occupation as a non-cognitive occupation, and we classify all the other occupations as cognitive occupations (see Data Appendix 1 for more details).

To be clear, we are not proposing leadership as the measure for non-cognitive human capital. 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 cognitive human capital. To do so, we draw on a large literature showing that individuals’ AFQT (Armed Force Qualification Test) scores are strongly correlated with their wages (e.g. Neal and Johnson 1996, Altonji and Pierret 2001). We use this framework to show that the wages of leadership occupations are less correlated with test scores than those of the other occupations.

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). Columns 2 and 3 show that AFQT score has a smaller coefficient

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23Examples 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).

24We include both men and women in Table 1, while Neal and Johnson (1996) do the estimation separately.
estimate for the subsample of non-cognitive occupations than for the subsample of cognitive occupations.  

To show this pattern more rigorously, we pool the data in columns 4 and 5, and introduce the interaction between AFQT score and the soft-skill-occupation dummy. The coefficient estimates of this interaction term are negative and significant.

So far we have used the numerical values of occupation characteristics to classify occupations, and we experiment with using ratios of these values, following the approach of Autor, Levy and Murnane (2003). These alternative measures are qualitatively similar to the measure we use, but their coefficient estimates in the wage-AFQT regressions are not statistically significant (Data Appendix 1).

We next bring in employment data by 3- or 4-digit occupations from the International Labor Organization (ILO) (more details are in Data Appendix 2) to show that countries differ in the extent to which their workforces have accumulated cognitive vs non-cognitive human capital. 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 very scarce (e.g. we cannot find the mapping between Canadian and U.S. occupation codes). This leaves us with a cross-section of 32 countries, and most of the observations are for the year 2000. Examples of non-cognitive occupations include business professionals (ISCO-88 code 2410), managers of small enterprises (1310), building frame and related trades workers (7120), nursing and midwifery professionals (3230), etc. Examples for cognitive occupations include architects, engineers and related professionals (2140), finance and sales professionals (3410), secretaries (4110), motor vehicle drivers (8320), etc. We show the variation of the employment share of non-cognitive occupations across our sample countries by plotting its histogram in Figure 1, and report the summary statistics of this variable in Table 2.

Our model is based on the premise that both non-cognitive and cognitive 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 positive and significant after we control for the college dummy. Kuhn and Weinberger (2005) report that the marginal effect of leadership skills is as strong 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 1).

\[ \text{Note that the coefficient estimates for AFQT square are not significant.} \]

\[ \text{Column 5 includes the college dummy and its interaction with AFQT score as additional controls.} \]

\[ \text{The literature has used both approaches. Examples of numerical values include Hummels et al. (2014) and Deming (2017). Examples of ratios include Ebenstein, Harrison, McMillan and Phillips (2014). Autor, Levy and Murnane (2003) use both.} \]

\[ \text{One may also be concerned that the O*NET occupation scores are noisy and that their values are ordinal but not cardinal. This is why we focus on the dichotomy between the non-cognitive group and the cognitive group.} \]
low-education individuals as for high-education ones. When we tabulate the distribution of average schooling years across occupations using the 2000 US Census, we find that this distribution is compressed in the left; e.g. the median is 12.8 years while the 5th percentile is 10.9 years. These results are intuitive, because the U.S. is a high-income country, where illiteracy, subsistence farming and the informal sector are not salient features of the economy.\footnote{Caselli and Coleman (2006) make a similar point, classifying primary-school completion as skilled labor in the benchmark specification.} We therefore present results separately for the narrow sample of 26 high-income countries and for the full sample, which includes the middle-income countries of Bulgaria, Estonia, Latvia, Lithuania, Romania and Thailand. The countries in our narrow (full) sample account for 41.8% (43.0%) of world GDP in 2000.

### 3.3.2 Other Data

Table 2 reports the summary statistics of both samples, and Table 3 lists the countries and years in the narrow sample. 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 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.\footnote{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.} We obtain data on schooling years from Barro and Lee (2013), and PISA math scores from the official PISA website.\footnote{PISA reading and science scores yield similar results. We use PISA data because they are widely used and cover many countries. They are also highly correlated with the scores of adult tests (e.g. Hanushek and Zhang 2009), for the countries that have both PISA and adult scores.} To implement quantification (27), we need data on employment by occupation by education, which is available from EuroStat and IPUMS for a subset of our sample countries. We show that these employment shares, by 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 or IPUMS, and combine these data with the Barro-Lee schooling-years data to compute average schooling years for the cognitive occupation.

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

### 3.3.3 Parameter Values and Metrics for Human Capital

We start with \( \theta \), which measures the dispersion of innate abilities across workers. A recent Roy-model literature has estimated \( \theta \) using a variety of data sources and identification strategies, and reached a consensus about the range of its value. To be specific, this range is 1.5 to 2.5 in Hsieh et al (2018), 1.78 to 2.62 in Burnstein et al. (2016), and 1.48 to 2.5 in Lee (2016). Lagakos and Waugh (2013), whose model has industries and not occupations, obtain \( \theta = 2.7 \) for the non-agricultural sector. We thus pick \( \theta = 2 \), the mid point of the range reported in this literature, for our main results, and experiment with \( \theta = 1.5 \) and \( \theta = 3 \) in section 4 below.

For \( \alpha \), the substitution elasticity between occupations in aggregate production, we draw on Burnstein et al. (2016), 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 \( \alpha = 1.78 \), and this is the value we use for our main results.\(^{32}\)

We experiment with \( \alpha = 1.4 \) and \( \alpha = 2 \) in section 4.

By equation (11), \( \eta \) 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 thus choose \( \eta = 0.27 \) for our main results, and experiment with \( \eta = 0.22 \) and \( \eta = 0.33 \) in section 4.

We use three metrics for human capital, and they correspond to different specifications of \( f(.) \) and \( g(.) \) in equations (26) and (27). In metric 1, \( f(.) \) is a piecewise linear function with slopes of 0.134, 0.101 and 0.068 for, respectively, schooling years below 4, between 4 and 8, and above 8, and \( g(.) = \exp(0.002 t^k) \).\(^{33}\) Metric 2 has \( f(.) \) as a linear function with slope 0.10.\(^{34}\) We then estimate the relationship between log wage and log AFQT score (which is scaled to have the same mean and standard deviation as PISA) using the U.S. NLSY79 data, and obtain the coefficient of 0.75 for log AFQT. We thus specify \( g(t^k) = (t^k)^{0.75} \) in metric 2.

\(^{32}\)\( \alpha = 1.78 \) is also used in Atalay et al (2017).

\(^{33}\)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.

\(^{34}\)The motivation for \( f(.) \) in metric 1 is that Mincer wage returns may be lower in rich countries than in poor countries. In metric 2, the motivation is that they are similar across countries. Both specifications are common in the literature; e.g. see Hall and Jones (1999) and Caselli (2005) for the specification in metric 1, and Banerjee and Duflo (2005) and Manuelli and Seshadri (2014) for that in metric 2.
For metric 3, we estimate the Mincer wage regression with both schooling years and AFQT scores in the estimation.\textsuperscript{35} We obtain 0.068 for schooling years and 0.57 for log(AFQT), and specify $f(.)$ and $g(.)$ accordingly. For each metric, we compute the standard single-type measure of human capital, $H^k$, using (26), and average cognitive human capital, $L^{cS}/L^k$, using (27). Our $H^k$ values exceed $L^{cS}/L^k$ values since $s^k$, the average schooling years, exceeds $s^c$, the average schooling years for the cognitive occupation (see Table 2).

Finally, we normalize the values of $H^k$ and $L^{cS}/L^k$ relative to the U.S. We then use the values of $\eta$, $\theta$ and cognitive human capital in equation (25) to compute cognitive productivities, $h^k_c$. We use the values of $\theta$ and $\alpha$, plus data on occupational employment shares, in equation (24) to compute the comparative advantage for cognitive human capital, $h^k_h/h^k_n$. We combine these values with $h^k_c$ to back out non-cognitive productivity, $h^k_n$. The $h^k_c$ and $h^k_n$ values are both relative to the U.S.

\subsection*{3.4 Estimates}

We have three sets of values for $h^k_c$, $h^k_n$ and $H^k$, since we have three metrics for human capital. In this sub-section, we show the values associated with metric 1, and in section 4, we show the results based on all three metrics.

Table 3 lists the rankings of our narrow-sample countries in $h^k_c$, $h^k_n$ and $H^k$, as well as these countries’ schooling years and PISA math scores. Although both schooling years and PISA scores contribute to the cross-country variation in $H^k$, schooling years contribute more. On the other hand, Figures 2 and 3 plot the rankings in $h^k_c$ and $h^k_n$ against the rankings in $H^k$.

Figure 2 shows that the rankings in $h^k_c$ and $H^k$ are highly correlated (0.77), since our measure of cognitive human capital, (27), is very similar to the standard measure, (26). Figure 2 also shows that these two rankings are quite different for a number of countries, and we highlight the differences using the 45 degree line. Consider, first, Poland and Hungary. They have relatively low human capital per worker, according to the standard measure, and rank outside of top 10. However, our model says that this outcome should be viewed in the context of low output per worker in these countries, and so limited resources for human capital production. Once we correct for resources inputs, using (25), their cognitive productivities rank within the top 10. Meanwhile, it is the opposite for the U.S.; i.e. the U.S. has low cognitive productivity (outside of top 15) despite high human capital per worker (within top 5), because of high output per worker and so abundant resources. These examples

\textsuperscript{35}The constants in metric 1 are based on the coefficient estimates of schooling years and test scores reported in the literature, but it is unclear if these studies include both schooling years and test scores in the same Mincer regressions. In metric 2, we obtain the coefficient 0.10 for schooling years and 0.75 for log AFQT when schooling years and log AFQT enter the regression separately.
echo our discussions in sub-section 2.3.3: in our model with multiple types of human capital, a country with a large amount of human capital may not produce it well.

Figure 3 shows that the rankings in non-cognitive productivity, $h^k_n$, are substantially different from the rankings in the standard measure of human capital per worker, $H^k$. Consider, first, Belgium, Finland, and the U.K. They have low human capital per worker (outside of top 10), according to $H^k$. However, our model says that the standard measure fails to take into account high employment shares of the non-cognitive occupation in these countries, which suggest strong comparative advantages for producing non-cognitive human capital. Once we quantify the comparative advantages, using (24), these countries turn out to have high non-cognitive productivities (within top 5). Meanwhile, it is the opposite for S. Korea, Switzerland and Slovenia; i.e. these countries have low non-cognitive productivities (outside of top 15) despite high standard measures of human capital (within top 10), because of low employment shares of the non-cognitive occupation and so weak comparative advantages. These examples illustrate our contribution relative to the standard measure with a single type of human capital: our non-cognitive productivity, quantified using data on occupation employment shares, opens up a novel dimension for cross-country comparison.

This novel dimension may also have useful policy implications. Comparing the countries’ rankings in PISA scores and $h^k_n$ in Table 3, we see that PISA scores are not informative about the proficiencies of the educational systems in producing non-cognitive human capital (correlation = 0.14, p-value = 0.45). Specifically, while South Korea, Hong Kong and Switzerland are top performers in PISA score, they rank at the bottom in terms of non-cognitive productivity. In our Introduction, we discussed the concern in S. Korea and many East Asian countries that the educational systems may be inefficient for developing non-cognitive skills. Our non-cognitive productivity quantifies this concern and suggests that it may be well grounded. Meanwhile, Table 3 shows that PISA scores substantially understate the proficiency of the U.S. in fostering non-cognitive human-capital. This result resonates with the argument in the U.S. discussions of education policy against focusing exclusively on test scores.

The countries’ rankings in $h^k_c$ and $h^k_n$ in Table 3 also suggest that if education-policy makers would like to choose some countries to emulate, Finland, Netherlands and Belgium might be better candidates than, say, South Korea and Hong Kong, because these countries have high rankings in both cognitive and non-cognitive productivity. We will revisit these policy implications in section 4.1, where we relate non-cognitive and cognitive productivity to output per worker.

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36For example, 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 “learn a lesson a math”.
3.5 External Validation: I

In this sub-section, we present the results of three external validations for our model and quantification. More details are in Data Appendix 3. The first one speaks to the concern that the occupational classifications used to compute non-cognitive and cognitive productivities, $h_n^k$ and $h_c^k$, were derived from U.S. data, and so may not be appropriate for other countries. We have implicitly assumed that occupations have similar rankings across countries in terms of the importance of leadership.\(^{37}\) This assumption implies that the type of human capital a worker has acquired in her birth country will also be useful were she to emigrate to the US. Hence, we should observe a positive correlation between countries’ comparative advantages for non-cognitive human capital, $h_n^k / h_c^k$, and the fractions of their U.S. emigrants in non-cognitive occupations.\(^{38}\) 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. We find a strong positive correlation (0.634 with p-value = 0.0015), which is consistent with our assumption that occupational requirements for skills are similar across countries.

Second, we compute countries’ output TFP, $\Theta^k$, using HCAP and equation (19), and check the correlation coefficients between $\Theta^k$ and the output-TFP estimates reported in the literature. They are all positive and significant, ranging from 0.55 (Klenow and Rodriguez-Clare 1997) to 0.69 (Hall and Jones 1999). They are also comparable to the correlation coefficients among the literature’s estimates.

For our third validation exercise, we note that our estimates of $h_n^c$ and $h_c^k$ reflect countries’ relative abundance in non-cognitive human capital, a source of comparative advantage. It follows that the countries that are relatively abundant in non-cognitive human capital ought to have low relative wage for the non-cognitive occupation, $w_n^k / w_c^k$ (equation (18)). We check this prediction for a subset of the countries in our narrow sample by combining EuroStat data on average annual earnings by occupation\(^{39}\) with our ILO data on occupational employment. We find a negative correlation (-0.459, p-value = 0.036). To place this correlation in context, the correlation between the relative supply of skilled labor and the skill premium in the widely used skill-premium data of Caselli and Coleman (2006) is -0.337 (p-value = 0.015).\(^{40}\)

\(^{37}\)This assumption is necessary because for most countries, occupation-characteristic data is not available. As a result, many studies use the same approach as we do (e.g., Hummels, Munch and Xiang 2018 provide a recent survey).

\(^{38}\)We do not expect this correlation to be perfect; e.g. the restrictiveness of U.S. immigration policy may vary across countries and across occupations.

\(^{39}\)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 ISCO 88.

\(^{40}\)Caselli and Coleman (2006) compute skill premia using Mincer wage returns, from Bils and Klenow
4 Main Results

In this section, we provide estimates of the HCAP index, discuss its policy implications, and show that it can account for most of the variation in output per capita in our data. We then show that our framework complements the literature that refines the standard development accounting approach, and that our results are robust to alternative parameter values.

4.1 Human Capital Accumulation Productivity

The HCAP index summarizes countries’ efficiency at turning resources into human capital. It is of immediate interest to assess the cross country variation in the HCAP index and the individual components from which it is constructed. Figure 4 plots the value of $h^k_c$ against $h^k_n$, and provides a 2-dimensional illustration of the differences in $h^k_c$ and $h^k_n$ across our narrow-sample countries. It also serves as our canvas for the iso-HCAP curve, the combinations of $h^k_c$ and $h^k_n$ that yield a constant level of the HCAP index. We draw the iso-HCAP curve through the U.S., our benchmark country with $h^k_{US} c = h^k_{US} n = 1$. This curve illustrates the countries whose HCAP’s are similar to the U.S. (e.g. Norway), those with higher HCAP’s relative to the U.S. (e.g. Finland), and those with lower HCAP’s (e.g. Italy).

The curvature and shape of the iso-HCAP curve are determined by equation (20), and they tell us the trade-offs of increasing cognitive productivity for non-cognitive productivity. Intuitively, given the values of $\alpha$ and $\theta$, equation (20) says that both non-cognitive and cognitive productivities are important in HCAP. We see, in Figure 4, that the countries with high productivity along one dimension but low productivity along the other (e.g. Germany and S. Korea) lie below the iso-HCAP curve, meaning that they have lower overall human-capital productivity than the U.S. This is because the imbalance of their productivities holds down their HCAP, which echoes our discussions in sub-section 2.3.1. There is also a silver lining for the countries with imbalance: it would be a useful asset under free trade, as we show in section 5.

We now further explore the policy implications of the HCAP index. As we have just seen in Figure 4, countries have very different mixtures of efficiencies in the accumulation of cognitive and non-cognitive human capital. To the extent that changes in a country’s educational system might result in tradeoffs between the two types of efficiencies (e.g. reduced rote learning in favor of open-ended experimentation), the iso-HCAP curve allows us to assess which trade-offs are potentially worthwhile, in terms of output per worker. Meanwhile, test scores are often used to evaluate education policies and programs (e.g. Figlio and Loeb 2011, Duncan and Magnuson 2013). To relate our model to these studies and discussions,

(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.
we construct an iso-PISA score curve in the following way (more details in Data Appendix 2).

We treat our estimates of $h_k^c$ and $h_k^n$ as data, and summarize their cross-country correlation with PISA math scores by regressing the PISA scores on $h_k^c$ and $h_k^n$. We obtain a positive coefficient estimate for $h_k^c$, 82.6 ($p = 0.02$), and a negative one for $h_k^n$, -11.9 ($p = 0.20$). These correlation patterns are consistent with our model, because an increase in $h_k^c$ tends to increase average cognitive human capital, by equation (25), and a decrease in $h_k^n$ tends to push workers away from choosing the non-cognitive occupation, by equation (8), and so create stronger incentives to accumulate cognitive human capital. We then trace out the combinations of $h_k^c$ and $h_k^n$ values that produce the same predicted PISA math score as the U.S., add this iso-PISA score curve into Figure 4, and obtain Figure 5. Note that our iso-PISA score curve has been chosen to pass through the observation for the United States.\(^{41}\)

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. For instance, were the United States to trade off $h_k^n$ for $h_k^c$ at the rate that would bring it in the direction of South Korea, it would improve its test scores but at the cost of having an educational system that was less effective at producing an appropriate mixture of skills. Hence, its output would fall. The same would be true if the United States were to emulate either Switzerland or Germany. One the other hand, the tradeoff of $h_k^n$ for $h_k^c$ that would be implied by emulating an educational system such as Denmark or Sweden would raise test scores and also improve output per capita as well. It is also worth noting that many of the highest performing countries in terms of producing human capital in general feature very high $h_k^n$ relative to $h_k^c$ (e.g. Belgium, the Netherlands). Emulating these countries would carry potentially high payoffs in terms of output per worker, but might come at the expense of lower test scores.

These observations could be relevant for several early childhood intervention programs in the United States. A large body of work shows that these programs tend to have little long-term effects on program participants’ test scores, but positive effects on their adult outcome, such as higher wages, and lower probabilities of poverty and crime (see the Introduction). This body of work also makes the inference that the intervention programs primarily boost the participants’ non-cognitive skills. It follows, then, that 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.

\(^{41}\) We have experimented with deriving the changes in test scores in response to changes in $h_k^c$ and $h_k^n$ 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 5).
4.2 Development Accounting

We now spell out the connections between HCAP and output per worker, by performing development accounting. The upper panel of Table 4 reports the variances of the logs of measures of human capital relative to the variance of $\log(Y^k/L^k)$ for our full sample.

We start with the standard measure with one type of human capital, computed using equation (26). Under metric 1, human capital accounts for 8.7% of the cross-country variation in $\log(Y^k/L^k)$. The contribution of human capital is slightly higher under metric 2, at 11.7%, but slightly lower under metric 3, at 5.6%. These results are in line with the development-accounting literature.

We next perform heterogeneous-human-capital accounting, using equation (21). In this approach, our measure of cognitive human capital is similar to, and smaller than, the standard measure, but we add heterogeneous human capital differentiated across non-cognitive and cognitive occupations. This addition substantially increases the contribution of human capital, relative to the benchmark standard measure, to 27.0% under metric 1, 28.8% under metric 2, and 20.3% under metric 3.

We now move on to the HCAP index analysis using equations (19) and (20). Relative to the heterogeneous-human-captial accounting, we lean more heavily on our model and turn on the amplification mechanism. This approach leads to another substantial increase in the contribution of human capital. The HCAP index accounts for 49.3% of the cross-country variation in $\log(Y^k/L^k)$ under metric 1, 54.5% under metric 2, and 39.6% under metric 3.

We can also see that the contribution of human capital, under our model, varies in the same way across metrics 1-3 as under the standard single-type measure. They are highest under metric 2, followed by metric 1, and then metric 3. This result is intuitive: both our accounting procedures use the standard measure as the foundation.

The lower panel of Table 4 reports the results for our narrow sample, where the variance of $\log(Y^k/L^k)$ is smaller than for the full sample. By the standard single-type measure, the contributions of human capital are slightly higher than for the full sample, ranging 7.9%~16.7%. By our development accounting with heterogenous human capital, the contributions increase to 30.0%~42.1%, again higher than for the full sample. By the HCAP index approach, the contributions of human capital increase further, to 63.7%~89.5%.

Table 5 reports the 90-10 ratios of human-capital measures relative to the 90-10 ratio of $Y^k/L^k$. Overall, the contributions of human capital are higher than in Table 4, while the other aspects of the results are similar to Table 4. By the standard single-type measure, the contribution of human capital is 35.9%~39.7% (full sample) or 57.0%~63.4% (narrow sample). By our heterogeneous-human-captial accounting, the contribution increases to 50.4%~56.4% (full sample), or 76.3%~86.9% (narrow sample). By the HCAP index, the

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42 We have obtained similar results for the 75-25 ratio, which are available upon request.
contribution goes up further, to 63.6%–64.7% (full sample), or 94.7%–98.2% (narrow sample).

In summary, according to our framework, human capital accounts for a much larger fraction of cross-country variations in output per worker than the standard single-type measure. The additional contributions arise for two reasons. First, we have multiple types of human capital and utilize occupation-employment data, as can be seen in our heterogeneous-human-capital accounting. Second, we have endogenous productions of all types of human capital and so our model has amplification. Our analytical expression for the HCAP index provides a clean summary of these elements. At the end of the day, according to the HCAP index, the contribution of human capital exceeds 50% in most cases, and approaches 100% in some cases.

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. The quantification in Jones (2014) and Malmberg (2017) works through the relative efficiencies of high- vs low-skill workers, and the results hold if $\alpha$ is around 1.5. Our occupational cut of non-cognitive vs cognitive is distinct from high-vs-low skill (section 3.3.2), and our quantification does not use relative efficiencies. We also obtain very similar results with $\alpha = 2$ (section 4.4), or under free trade, when the HCAP index does not depend on $\alpha$ (section 5.5). The results in Manuelli and Sesadri (2014) hold with an amplification elasticity of 5.7. Our amplification elasticity is $1/(1 - \eta) = 1.37$, and we obtain similar results with even smaller amplification (section 4.4). Finally, Hendricks and Schoellman (2018) measure the contribution of human capital as the residual, and we measure it directly.

4.3 Alternative Metrics for Human Capital

We have obtained our results in the previous sub-section by applying the standard single-type measure of human capital to the cognitive dimension. A literature has made progress on single-type measures, as we discussed in sub-section 2.3. We illustrate the complementarity between this literature and our framework in this sub-section, by applying the measure of Schoellman (2012) to the cognitive dimension. We call this metric 4.

Briefly speaking, the idea behind metric 4 is that schooling years indicate both quantity and quality of human capital, and so the standard single-type measure understates the contribution of human capital. Using Schoellman (2012)’s preferred specification, we have $f(.) = \exp(0.1s/0.5)$, $s = s^k$ or $s^c$, and $g(.) = 1$, in equations (26) and (27); i.e. the

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43Jones (2014) and Malmberg (2017) classify low-skill as primary schooling or below and the rest as high-skill. Since this high-skill classification encompasses most workers in our data, we classify high-skill as college or above.
coefficient for schooling is effectively 0.2, and test score is no longer used.

In the top panel of Table 4, we see that under metric 4, human capital accounts for 34.9% of the variance of $\log(Y^k/L^k)$ for our full sample, which is substantially higher than under metrics 1-3. This result echoes Schoellman (2012). This rising tide also lifts our results, because our quantification is built upon the measures developed for a single type of human capital, as can be seen in (26) and (27). When we take heterogeneous human capital into account, the contribution of human capital increases to 58.4%. Once we turn on amplification using the HCAP index approach, human capital accounts for all the variation in $\log(Y^k/L^k)$, at 115.0%. Meanwhile, the top panel of Table 5 shows that the single-type measure of human capital accounts for 51.3% of the 90-10 ratio of $Y^k/L^k$ for our full sample, under metric 4. The contribution of human capital increases to 67.5% with heterogenous-human-capital accounting, and 94.9% with the HCAP index approach. We obtain similar results for the narrow sample (lower panels of Tables 4 and 5).

This exercise shows that it is straightforward to incorporate into our framework the advances in the single-type measure of human capital. If these advances imply higher contributions of human capital under the single-type setting, using them in our multiple-type setting tends to imply bigger roles of human capital.

4.4 Alternative Parameter Values

In this sub-section, we explore the sensitivity of our development-accounting results to alternative values of $\eta$, $\theta$, and $\alpha$, and report our results in Table 6. We focus on the HCAP index approach, given by (19) and (20), and the ratio of variance for the full sample, to keep our discussions compact. Column (1) of Table 6 re-iterates our results from Table 4, and the values of $\eta$, $\theta$, and $\alpha$ that we used there.

In Panel A, we experiment with the $\eta$ values of 0.22 and 0.33. We picked 0.22 because it is the mid point between 0.27, our main specification, and 0.155, the share of human-capital spending in U.S. GDP reported in Haveman and Wolfe (1995). We chose 0.33, on the other hand, because it implies an amplification elasticity of 1.49, an often-used benchmark value in the human-capital-production literature. Columns (2) and (3) show that the larger is $\eta$, the larger is amplification, and so the larger is the contribution of the HCAP index. This result is consistent with the human-capital-production literature. On the other hand, the magnitude of the HCAP index’s contribution in columns (2) and (3) is overall similar to column (1). In particular, with the smaller amplification of 1.28, under $\eta = 0.22$, the contribution of the HCAP index remains substantial, at 43%.

In Panel B, we experiment with the $\theta$ values of 1.5 and 3, the end points of the range of estimates reported in the Roy-model literature. Columns (2) and (3) show that we obtain very similar results to column (1).
In Panel C, we explore the $\alpha$ values of 1.4 and 2, which are often used in the skill-differentiation literature. Columns (2) and (3) show that lower $\alpha$ values imply larger contributions for the HCAP index, which is consistent with the skill-differentiation literature. However, unlike in that literature (e.g. Caselli and Ciccone 2019, Jones 2019), the HCAP index’s contribution does not change much as we increase the value of $\alpha$ from 1.4 to 2.\footnote{As we discussed in sub-sections 2.3 and 4.2, the results in this literature depend on the relative efficiencies of workers with different skills. In quantification, these values are sensitive to the substitution elasticity because they come from data on relative quantities and relative wages. In comparison, we take a different approach to quantification, and so our results are less sensitive to the value of $\alpha$.} In particular, the contribution of the HCAP index remains at 48\% when $\alpha = 2$.

So far, we have held non-cognitive and cognitive productivities, $h^k_c$ and $h^k_n$, fixed, as we change $\eta$, $\theta$, and $\alpha$. We now update the values of $h^k_c$ and $h^k_n$ along with $\eta$, $\theta$, and $\alpha$, using the same procedure outlined in section 3, and report the results in columns (4) and (5). The results are very similar to columns (2) and (3).

In summary, our development-accounting results are robust to alternative values of $\eta$, $\theta$, and $\alpha$. Intuitively, this is because all three parameters enter into the expression for the HCAP index, (19) and (20), and so the change of a single parameter has more limited effects. Before we explore how the expression for the HCAP index changes in the open-economy setting in the next section, we note that we have done the following robustness exercise, and obtained similar results. We extend equation (3) such that occupations require both cognitive and non-cognitive skills, but differ in the non-cognitive intensity. Our results continue to hold for countries’ efficiencies in producing packages of non-cognitive and cognitive human capital (Theory Appendix 6).

5 Open Economy

We have shown, in our closed-economy setting, that imbalance in human-capital productivities tends to imply low HCAP index. With trade, however, this imbalance may help countries specialize and enjoy gains from trade. In this section, we extend our model to incorporate trade, and show how the expression and value for the HCAP index change. We then conduct an additional external validation using data on trade patterns, and perform development accounting using the new HCAP index values. To keep our exposition concise, we focus on the main equations and their intuition, and the main results of quantification. We relegate additional equations and derivations to Theory Appendix 7, and details about data to Data Appendix 4.
5.1 Assumptions

To introduce trade into our model, we assume that the individuals can sell the services of their human capital as intermediate inputs around the globe. The services of cognitive and non-cognitive labor are embodied in traded intermediates. Countries can costlessly export intermediates to an international clearinghouse for factor content and import intermediates at iceberg trade cost $\tau^k$ from this clearinghouse. In order to relate the aggregate quantities of non-cognitive and cognitive human capital to trade and occupation employment shares, we define net exports as quantity ratios

$$x_i^k = \frac{I_i^{kS} - I_i^{kD}}{I_i^{kS}}, \ i = c, n.$$ (28)

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, we assume that the final good itself is non-tradeable, because it is used as inputs in the production of human capital.

With trade, equations (6) through (16) still hold. However, factor market clearing in country $k$ is now

$$\frac{L_n^{kD}}{L_n^{kD}} = \frac{L_n^{kS} 1 - x_n^k}{L_n^{kS} 1 - x_c^k}.$$ (29)

Equation (29) says that the total quantities of country $k$’s human capital, $L_n^{kS}$ and $L_c^{kS}$, can be different from the quantities used in aggregate production, $L_n^{kD}$ and $L_c^{kD}$, because of trade, $x_n^k$ and $x_c^k$.

5.2 Open Economy HCAP Index

Equation (19) still holds, but the expression for the HCAP index is now

$$\left(\Omega^k\right)^{\frac{1}{\eta - 1}} = \left( p_c^0 \left( \frac{p_c^0 (1 - x_c^0)}{p_c^k (1 - x_c^k)} \right)^{\frac{1}{\eta - 1}} \, \frac{h_c^k}{h_c^0} \right)^{\theta} \left( p_n^0 \left( \frac{p_n^0 (1 - x_n^0)}{p_n^k (1 - x_n^k)} \right)^{\frac{1}{\eta - 1}} \, \frac{h_n^k}{h_n^0} \right)^{\theta} \left( \frac{1}{\theta} \frac{1}{\eta - 1} \right).$$ (30)

Equation (30) says that the HCAP index remains a weighted power mean involving the ratios of non-cognitive and cognitive productivities. However, it also involves country $k$’s trade and occupation employment shares, all of which are endogenous variables for $k$. To clearly show the intuition, we consider the case of free trade, where there is a single global price per unit of non-cognitive and cognitive human capital (i.e. $w_c^k = w_c$ and $w_n^k = w_n$ for all $k$), and equation (30) simplifies to

$$\left(\Omega^k\right)^{\frac{1}{\eta - 1}} = \left( p_c^0 \left( \frac{h_c^k}{h_c^0} \right)^{\theta} + p_n^0 \left( \frac{h_n^k}{h_n^0} \right)^{\theta} \right)^{\frac{1}{\theta}} \left( \frac{1}{\eta - 1} \right).$$ (31)
The key difference between equations (31) and (20) is in the power coefficients in the construction of the power mean. These coefficients do not include $\alpha$ under free trade, as local labor market demand does not have to equal local labor market supply, by equation (29). 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). As a result, being relatively inefficient at producing one type of human capital is less of a drag on the HCAP index.

Equation (30), then, represents an intermediate case between (20) and (31). Intuitively, if trade flows have small values, (30) is more similar to (20).

The expression for comparative advantage is now

$$
\frac{h^k_c/h^k_n}{h^0_c/h^0_n} = \left( \frac{p^k_c/p^k_n}{p^0_c/p^0_n} \right)^{\frac{1}{\bar{\gamma}+\frac{1}{\bar{\alpha}}}} \left( \frac{1 - x^k_c}{1 - x^k_n} \right)^{\frac{1}{\alpha - 1}}. 
$$

(32)

The first term on the right-hand side of equation (32) is the same as equation (24). The second term in (32) captures the effects of international trade. If we observe, in the data, that country $k$ imports, in the net, the service of cognitive human capital (i.e. $x^k_c < 0$), we can infer that country $k$ has a stronger comparative advantage for cognitive human capital than its employment shares suggest, because the cognitive workers in $k$ have chosen their occupation despite import competition.

Finally, equation (11) continues to hold under open economy, and so we have the same value for $\eta$ for our quantification in sub-section 5.4 and 5.5. We use the same values for $\theta$ and $\alpha$, too.

5.3 External Validation: II

Our open-economy setting allows us to examine the following implication of comparative advantage on trade patterns: non-cognitive abundant countries should be net exporters of the industries that use non-cognitive human capital intensively. This prediction speaks to whether our $h^k_n$ and $h^k_c$ estimates reflect relative supply or relative demand, like the negative correlation between the relative abundance of non-cognitive human capital and its relative wage we document in sub-section 3.5, and we can include all the countries in our sample.

We follow the literature\textsuperscript{e.g. Nunn 2007, Bombardini, Gallipoli and Pupato 2012.} and examine 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 non-cognitive human capital, physical capital and skilled labor as, respectively, the ratio of $h^k_n$ to $h^k_c$, the ratio of physical capital stock to population, and the fraction of college-educated labor force. For each industry, we measure the intensities of non-cognitive human capital, physical capital
and skilled labor using U.S. data. We control for industry fixed effects and country fixed effects.

Table 7 reports the results. Column (1) includes only the interaction for non-cognitive human capital. We add the interaction for physical capital in column (2), and then the interaction for skilled labor in column (3). The upper panel is for the narrow sample, and the lower panel the full sample. 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 non-cognitive human capital has positive and significant coefficient estimates in all specifications. These results suggest that our $h^k_c$ and $h^k_n$ values are useful for the variation of trade patterns by industry by country, even though we did not use such variation to obtain them. In addition, the $h^k_c$ and $h^k_n$ values mainly reflect the supply of (not demand for) human capital, because the countries with high $h^k_n/h^k_c$ tend to have large net exports (not imports) of non-cognitive intensive industries.

5.4 HCAP Index with Observed Factor-Content Trade

We now explore the quantitative contributions of human capital under the open-economy setting. We first use observed data of factor-content trade, in this sub-section, and then consider the counterfactual scenario of the free-trade equilibrium, in the next sub-section. To keep our discussions concise, we focus on the contribution of the HCAP index to cross country variation in output per worker.

For the trade flows, $x^k_c$ and $x^k_n$, we calculate the numbers of cognitive and non-cognitive workers embedded in the net export flows relative to the numbers of these workers in country $k$’s labor force. Table 2 shows that the absolute values of these trade flows are small, consistent with the findings of the trade literature.

We report the contribution of the open-economy HCAP index in Tables 4 and 5. The lower panel of Table 4 shows that this contribution is similar to our previous results for the narrow sample, which is intuitive, given that the trade flows are small in magnitude. We obtain similar results in the upper panel of Table 4, when we look at the full sample, and in Table 5, when we look at the 90-10 ratio.

---

46 Our motivations for this world-is-flat counterfactual are as follows. First, free trade might be more useful for regional differences within countries, complementing the economic geography literature (e.g. Krugman 1991, Davis and Weinstein 2002, Redding and Sturm 2008, Allen and Arkolakis 2014). Second, internationally, while service trade has been growing faster than goods trade (e.g. wto.org), it has seen less liberalizations than goods trade, and so has more scope for further liberalization. Finally, new technology may decrease the cost of service trade.

47 e.g. Treffer (1995), Davis and Weinstein (2001), and Costinot and Rodriguez-Clare (2014).
5.5 HCAP Index with Free Trade

To compute 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.\footnote{Note that we are unable to apply the standard techniques of Deckle, Eaton and Kortum (2008), or DEK 2008, because $x_c^k = x_n^k = 0$ under closed economy. However, our computation still has the flavor of DEK 2008, in that we do not need to make additional assumptions about unidentified parameters.} We also use metric 1 and the narrow sample.\footnote{We add Japan and China into the computation, to get more changes for the U.S. We do so by assuming that Japan has the same cognitive and non-cognitive productivities as S. Korea, and that China has the same values as Hong Kong. We obtain similar results without Japan and China.} This counterfactual exercise shows that the iso-HCAP curve changes dramatically from closed economy to free trade. We plot the free-trade iso-HCAP curve in Figure 6. Figure 6 has the same values of non-cognitive and cognitive productivities as Figure 4, and the U.S. occupation employment shares under free trade are also similar to their closed-economy values. However, the iso-HCAP curve bends towards the origin in Figure 6, in contrast to Figure 4. Intuitively, this is because under free trade, the countries that have imbalanced productivities in human-capital production benefit from being able to specialize in the occupations in which they excel. To help visualize this intuition, we plot the changes in the HCAP index against non-cognitive and cognitive productivities in Figure 7. In this 3D plot, the countries in the middle, who have balanced non-cognitive and cognitive productivities, have limited changes in the HCAP index. However, changes in the HCAP index are large for the countries on the edges of the figure, who have strong comparative advantages in either cognitive or non-cognitive human capital. For example, S. Korea would see a 17.6% increase in the HCAP index, the Netherlands 27.5%, and Belgium 26.0%.

We now perform development accounting for our free-trade equilibrium, and quantify the contribution of the HCAP index, \eqref{eq:31}, to the cross-country variation in output per worker. The variance of $\log(Y^k/L^k)$, 0.28, and the 90-10 ratio of $Y^k/L^k$, 3.63, are both larger than our previous results for the narrow sample, 0.13 and 2.23. Despite these changes, the HCAP index has a similar contribution under free trade vs. closed-economy: the variance of $\log(\text{HCAP})$ is 73.8% of $\log(Y^k/L^k)$, and the 90-10 ratio of the HCAP index is 83.4% of $Y^k/L^k$.

To make sense of these results, we note that the changes in the HCAP index, from closed economy to free trade, are closely related to output changes. Let $\hat{z}$ denote the value of variable $z$ at the subsequent equilibrium relative to its value at the initial equilibrium; i.e. $\hat{z} = z'/z$. Equation \eqref{eq:19} implies that

$$\hat{Y}^k = \hat{Y}^0(\hat{\Omega}^k)^{1/n}.$$  \label{eq:33}

Equation \eqref{eq:33} says that country $k$’s gains from trade is equal to the change in its the HCAP
index multiplied by the base country’s (here the U.S.) gains from trade.\textsuperscript{50} \textsuperscript{51}

With the help of (33), we see that we have more cross-country variation in $Y_k^*/L_k^*$ under free trade, because gains from trade are unevenly distributed across countries (Figure 7). Human capital accounts for a similar fraction of cross-country variation in output per worker under free trade, because the output changes are primarily driven by changes in the HCAP index.

6 Conclusion

We have developed a GE framework, in the spirit of Roy (1951), to model the productions of non-cognitive and cognitive human capital. Our stylized model allows us to use revealed comparative advantage to infer countries’ non-cognitive and cognitive productivities without a direct measure for the non-cognitive dimension. Our model also delivers analytical expressions for how non-cognitive and cognitive productivities relate to the HCAP index, and how the HCAP index relates to output per worker. Using publically available data for a sample of mostly high-income countries, our quantification exercises show that hard-to-measure non-cognitive human capital is important for the HCAP index, and the HCAP index is important for output per worker. To be specific, the HCAP index accounts for over 50\% of the cross-country variation in output per worker in most cases, and close to 100\% in some cases.

The standard policy implication of the development-accounting literature is about the importance of human capital in general. Because our model incorporates multiple types of human capital, our results have the additional implications about the importance of specific types of human capital. Many countries that have high human capital per worker according to the standard measure have low productivities on non-cognitive human capital, and vice versa. In addition, policy reforms that increase test score 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.

\textsuperscript{50}(33) is a conservative estimate of gains from trade, because we abstract away from product differentiation and intra-industry trade, which have been extensively studied in the trade literature (e.g. Costinot and Rodriguez-Clare 2012, or ACR 2012).

\textsuperscript{51}We show that equation (33) can be re-written as $1/\tilde{Y}_k = (p_k^c (1-x_k^c))^{\sigma/\sigma-1} + p_k^a (1-x_k^a))^{\sigma/\sigma-1} \left( \frac{1}{\eta} \right)^{\sigma/\sigma-1} \frac{1}{\gamma}$. It is the counter-part of the ACR-2012 formula for our model, because all the variables on the right-hand side are observables at the initial equilibrium. Relative to ACR 2012, this expression extends the results beyond one single input, and says that the cognitive and non-cognitive contents of trade should be weighed, respectively, by cognitive and non-cognitive employment shares. We also show that a country must gain from trade as long as it is a net importer of at least one type of factor service (i.e. $\tilde{Y}_k > 1$ if $x_i^k < 1$ for at least one $i$).
Here, our model provides a potentially useful tool.

While we show that globalization and associated trade in factor services are critical, theoretically, in assessing a country’s overall productivity in human capital, the data suggest that the world is closer to autarky than it is to free trade. For the moment at least, educational institutions that focus on one type of human capital to the great detriment of another are the source of lower income per capita; i.e. imbalance is a source of weakness. However, the countries with imbalanced human-capital productivities would reap substantial output gains if countries were to engage in free trade of the services of human capital; i.e. under free trade, imbalance would be a source of strength.

We now discuss additional caveats. First, the different ways in which countries produce human capital may provide incentives for immigration; e.g. those educated in high relative-cognitive-productivity countries (e.g. S. Korea) may have incentives to migrate to where such relative productivities are low (e.g. the U.S.). This intuition for immigration is similar to trade, which we have in our model. In addition, in our model, the individuals who migrate at young ages are not distinguishable from native-borns, and it is unclear whether data for immigrants show how much human capital they accumulate in their birth countries. If such data is available for future research, it will be interesting to explore the implications of the cross-country differences in non-cognitive and cognitive productivities for the welfare gains of immigration.

In addition, we have taken non-cognitive and cognitive productivities as exogenous parameters. Our motivation is 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 non-cognitive and cognitive 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


Figure 1 Histogram of Employment Share of Non-cognitive Occupations

Figure 2 Cognitive-Productivity Ranking vs. Human-Capital Ranking
Figure 3 Non-Cognitive-Productivity Ranking vs. Human-Capital Ranking

Figure 4 Iso-HCAP Curve
Figure 5: Iso-HCAP and Iso-PISA curves

Figure 6: Iso-HCAP, Free-trade
Figure 7 Changes in HCAP, Autarky to Free Trade
Table 1 AFQT Score and Wages of Non-cognitive and Cognitive Occupations

<table>
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<th>VARIABLES</th>
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<th>(3) Interaction</th>
<th>(4) Add College</th>
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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

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Notes: The narrow sample consists of 26 high-income countries, and they are listed in Table 3 below. The full sample is the narrow sample plus Bulgaria, Estonia, Latvia, Lithuania, Romania and Thailand. Net exports of cognitive and non-cognitive human capital are, respectively, \( x_c^k \) and \( x_n^k \) in our model, and they are discussed in sub-sections 5.1 and 5.4.
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<th>Std. H-Cap. Rank</th>
<th>Cog Prod Rank</th>
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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 $H^k$, discussed in sub-sections 3.2 and 3.3.
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<th>Metric 2</th>
<th>Metric 3</th>
<th>Metric 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full Sample</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-type Human capital</td>
<td>0.0866</td>
<td>0.1165</td>
<td>0.0559</td>
<td>0.3491</td>
</tr>
<tr>
<td>Our Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heterogeneous Human Capital</td>
<td>0.2703</td>
<td>0.2876</td>
<td>0.2034</td>
<td>0.5842</td>
</tr>
<tr>
<td>HCAP Index</td>
<td>0.4929</td>
<td>0.5447</td>
<td>0.3959</td>
<td>1.1504</td>
</tr>
<tr>
<td>HCAP Factor-Content Trade</td>
<td>0.6558</td>
<td>0.7122</td>
<td>0.5668</td>
<td>1.3340</td>
</tr>
<tr>
<td><strong>Narrow Sample</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-type Human capital</td>
<td>0.1003</td>
<td>0.1665</td>
<td>0.0785</td>
<td>0.5963</td>
</tr>
<tr>
<td>Our Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heterogeneous Human Capital</td>
<td>0.3672</td>
<td>0.4211</td>
<td>0.2986</td>
<td>1.0207</td>
</tr>
<tr>
<td>HCAP Index</td>
<td>0.7613</td>
<td>0.8946</td>
<td>0.6369</td>
<td>2.1052</td>
</tr>
<tr>
<td>HCAP Factor-Content Trade</td>
<td>0.7359</td>
<td>0.8680</td>
<td>0.6218</td>
<td>2.0545</td>
</tr>
</tbody>
</table>

Notes: This table reports the ratios of the variances of the logs of measures of human capital, to the variance of ln($Y^k/L^k$). Metrics 1-3 are discussed in sub-section 3.3.3, and metric 4 in sub-section 4.3.
Table 5 90-10 Ratio Relative to Output per Worker

<table>
<thead>
<tr>
<th></th>
<th>Metric 1</th>
<th>Metric 2</th>
<th>Metric 3</th>
<th>Metric 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full Sample (90-10 ratio of $Y^k/L^k = 3.553$)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-type Human capital</td>
<td>0.3878</td>
<td>0.3971</td>
<td>0.3591</td>
<td>0.5125</td>
</tr>
<tr>
<td>Our Model</td>
<td>0.5176</td>
<td>0.5639</td>
<td>0.5043</td>
<td>0.6747</td>
</tr>
<tr>
<td>Heterogeneous Human Capital</td>
<td>0.6356</td>
<td>0.6466</td>
<td>0.6381</td>
<td>0.9494</td>
</tr>
<tr>
<td>HCAP Index</td>
<td>0.6875</td>
<td>0.7183</td>
<td>0.7115</td>
<td>1.0214</td>
</tr>
<tr>
<td>HCAP Factor-Content Trade</td>
<td>0.6875</td>
<td>0.7183</td>
<td>0.7115</td>
<td>1.0214</td>
</tr>
<tr>
<td><strong>Narrow Sample (90-10 ratio of $Y^k/L^k = 2.226$)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-type Human capital</td>
<td>0.5967</td>
<td>0.6335</td>
<td>0.5695</td>
<td>0.8183</td>
</tr>
<tr>
<td>Our Model</td>
<td>0.7742</td>
<td>0.8692</td>
<td>0.7633</td>
<td>1.0773</td>
</tr>
<tr>
<td>Heterogeneous Human Capital</td>
<td>0.9823</td>
<td>0.9821</td>
<td>0.9468</td>
<td>1.5159</td>
</tr>
<tr>
<td>HCAP Index</td>
<td>1.0084</td>
<td>1.0115</td>
<td>1.0130</td>
<td>1.4818</td>
</tr>
<tr>
<td>HCAP Factor-Content Trade</td>
<td>1.0084</td>
<td>1.0115</td>
<td>1.0130</td>
<td>1.4818</td>
</tr>
</tbody>
</table>

Notes: This table reports the ratios of the 90-10 ratios of measures of human capital, to the 90-10 ratio of $Y^k/L^k$. Metrics 1-3 are discussed in sub-section 3.3.3, and metric 4 in sub-section 4.3.
Table 6 Alternative Parameter Values

<table>
<thead>
<tr>
<th></th>
<th>Benchmark</th>
<th>$h^k$ &amp; $h^n$ fixed</th>
<th>change $h^k$ &amp; $h^n$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>A. $\eta$</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value</td>
<td>0.27</td>
<td>0.22</td>
<td>0.33</td>
</tr>
<tr>
<td>amplification</td>
<td>1.37</td>
<td>1.28</td>
<td>1.49</td>
</tr>
<tr>
<td>Ratio of Var. HCAP</td>
<td>0.49</td>
<td>0.43</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>B. $\theta$</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value</td>
<td>2.00</td>
<td>1.50</td>
<td>3.00</td>
</tr>
<tr>
<td>Ratio of Var. HCAP</td>
<td>0.49</td>
<td>0.50</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>C. $\alpha$</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value</td>
<td>1.78</td>
<td>1.40</td>
<td>2.00</td>
</tr>
<tr>
<td>Ratio of Var. HCAP</td>
<td>0.49</td>
<td>0.52</td>
<td>0.48</td>
</tr>
</tbody>
</table>

Notes: In each panel, the row “Value” shows the values of the corresponding parameter. The row “Ratio of Var. HCAP” shows $\text{var}[\log(HCAP)]/\text{var}[\log(L^k)]$ for the full sample, computed using metric 1 of human capital. In Panel A, “amplification” equals $1/(1 - \eta)$. 
Table 7 Normalized Net Exports & Relative Abundance in Non-cognitive Human Capital

Dep. Var. = Revealed Comp Advantage

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Narrow Sample</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-cog abundance x non-cog intensity</td>
<td>1.556***</td>
<td>1.555***</td>
<td>0.962**</td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.43)</td>
<td>(0.43)</td>
</tr>
<tr>
<td>Cap abundance x cap intensity</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
</tr>
<tr>
<td>Skill abundance x skill intensity</td>
<td>9.231***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.99)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>industry FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>country FE</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>R²</td>
<td>0.353</td>
<td>0.353</td>
<td>0.387</td>
</tr>
<tr>
<td>Obs. No.</td>
<td>1103</td>
<td>1103</td>
<td>1103</td>
</tr>
</tbody>
</table>

| **Full Sample**     |              |              |              |
| Non-cog abundance x non-cog intensity | 1.708***     | 1.693***     | 1.002**      |
|                     | (0.43)       | (0.42)       | (0.42)       |
| Cap abundance x cap intensity | 0.000        | 0.000        |              |
|                     | (0.00)       | (0.00)       |              |
| Skill abundance x skill intensity | 9.053***     |              |              |
|                     | (1.92)       |              |              |
| industry FE         | yes          | yes          | yes          |
| country FE          | yes          | yes          | yes          |
| R²                  | 0.32         | 0.321        | 0.375        |
| Obs. No.            | 1508         | 1508         | 1472         |

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.