Cultural Values and Productivity

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This paper estimates differences in human capital as country-of-origin-specific labor productivity terms in firm production functions, making it immune to wage discrimination concerns. After accounting for education and experience, estimated human capital varies by a factor of around three between the 90th and the 10th percentile. When I investigate which country-of-origin characteristics most closely correlate with human capital, cultural values are the only robust predictor. This relationship persists among children of migrants. Consistent with a plausible cultural mechanism, individuals whose origin places a high value on autonomy hold a comparative advantage in positions characterized by a low degree of routinization.

I. Introduction

There are very large observed income differences across countries. Quantitative assessments of proximate causes have typically found that at least half of the GDP per capita variation remains unexplained after controlling

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for human and physical capital (Klenow and Rodriguez-Clare 1997; Hall and Jones 1999; Caselli 2005). Recent studies have been able to reduce the unexplained variation by proposing novel measures of human capital, which differ from the traditional ones in that they allow for factors other than observed schooling (Hendricks and Schoellman 2018; Lagakos et al. 2018). These findings underscore the importance of making further progress in estimating human capital differences across countries as well as of identifying determinants of human capital differences other than schooling. This paper contributes to both of those efforts.

My first contribution is to provide a new measure of human capital differences. I exploit unique Swedish administrative data that match employees to their employers, allowing me to estimate firm-level production functions with heterogeneous labor. In particular, I am able to estimate country-of-origin-specific productivity parameters, and I interpret differences in these parameters as cross-country differences in human capital. The labor inputs enter the production function estimation after an adjustment for schooling and experience, so the estimated human capital differences capture factors over and above these "traditional" determinants. I find economically substantial differences in estimated human capital with a 90/10 percentile ratio of three, after accounting for education and experience at the micro level.

What drives these large human capital differences unexplained by schooling? Investigating this question is my second contribution. I regress my estimates of country-of-origin-specific productivity on a large number of country-of-origin characteristics. Several different measures do exhibit explanatory power, such as educational quality and health indicators. However, in a horse race between different factors, only measures of cultural values are economically and statistically significant predictors of human capital.[1] The most powerful predictor is the first principal component from a factor analysis of a large number of answers to questions from the World Values Survey (WVS), as estimated in highly influential work by Inglehart, Baker, and Welzel (Inglehart and Baker 2000; Inglehart and Welzel 2005). A 1 standard deviation change in this cultural measure is associated with roughly a 15 percentage point change in estimated human capital. The cultural dimension that stands out as the strongest underlying driver of this first principal component is a measure of *autonomy* (in contrast to *obedience*).

The influence of culture on human capital proves robust to different specifications of firm production functions and concerns with selection

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[1] By no means do I suggest to interpret this absence of evidence of an impact of education quality, health, and other potentially important factors as evidence of absence of an impact.

into migration or employment; it is replicated in countries other than—and culturally very distinct from—Sweden; and it is not simply proxying for the effect of cultural heterogeneity within a firm's workforce. Corroborating the cultural interpretation is also the fact that differences persist for second-generation migrants, implying that any omitted variables must be not only embodied in the migrants but also susceptible to intergenerational transmission. None of the usual institutional, geographical, or factor-endowment variables can fit these criteria.

The third contribution of this paper is to show that high-autonomy cultural backgrounds hold a comparative advantage in industries and occupations characterized by a lower level of routinization. This is consistent with an intuitive cultural mechanism by which autonomy is more useful in roles with a greater scope for proactivity, independent thinking, and innovation, while it is less useful in heavily routinized roles; a job characterized by obedient execution of narrowly defined tasks leaves limited room for individual initiative cultivated by autonomy.

The early work in the development accounting literature constructed human capital stocks based solely on years of schooling paired with pecuniary returns to schooling. Innovating on this unidimensional measure of human capital, Hendricks (2002) and Hendricks and Schoellman (2018) proposed studying human capital via wages of US immigrants. The idea is that if wage differences among immigrants to the United States—where they are faced with the same institutional and technological environment—are similar to differences among country-of-origin wages, then human capital must be an important determinant of the latter. This approach holds the desirable feature of allowing for differences in every potential dimension of human capital (as measured by labor market returns). However, inferring human capital from wages relies crucially on the assumption that price differences accurately reflect productivity differences. Immigrant wages are potentially (and heterogeneously) affected by ethnic or racial discrimination (Oreopoulos 2011; Booth, Leigh, and Varganova 2012; Neumark 2018), so that a nonnegligible fraction of the wage differentials that Hendricks and Schoellman attribute to human capital could conceivably be caused by differential wage discrimination.

My approach is similar to Hendricks and Schoellman (2018), in that it relies on the same identifying assumption: the only country-of-origin characteristic that affects migrants' productivity is embodied human capital. However, instead of inferring migrant productivity from wages, I directly estimate their contribution to production at the firm level, so that wage discrimination cannot possibly affect my estimates. I also present evidence that my results are robust to other varieties of discrimination. When I hold occupation constant, I do not detect any signs of the reversal in human capital estimates that positional discrimination, via differential selection, would imply. Similarly, restricting attention to workers in occupations with a low level of customer-facing intensity does not significantly alter the results, as a story of large-scale societal discrimination would suggest.

Confronted with evidence of large unexplained residuals in income differences across countries, macroeconomists have tended to gravitate toward explanations based on technology, institutions, geography, or misallocation. My paper suggests that cross-country differences in prevailing cultural attitudes amplify differences in human capital and through these reduce the unexplained component of income differences.[2] The idea that culture influences human capital goes back at least to the classic writings of Max Weber. David Landes (1998), in an influential exposé of the causes of differences in income across countries, highlights the cultural value of autonomy, or "the *autonomy* of intellectual inquiry" (italics his), as one of three key explanations. Landes's propositions are well grounded in the history of economic development, and he provides a multitude of qualitative supportive anecdotes. My findings that autonomy is the strongest predictor of human capital differences and that high-autonomy backgrounds hold a comparative advantage in nonroutinized roles constitute further evidence of his thesis, but of a more systematic kind.

While Landes highlighted autonomy, *religiosity* and *trust* have received more recent attention in the macroeconomics and development literature. Its verdict on the impact of trust is overwhelmingly positive. In contrast, the evidence on religiosity's impact on economic growth is mixed.[3] I do not find a significant role for religiosity once I control for autonomy and trust. Although I do find some support of a positive effect of trust on my baseline human capital measure, the effect is not as robust as for autonomy, and it does not persist among second-generation migrants. Having said that, it is worth stressing that my evidence on trust differs from most of the literature in that it is at the individual level while the typical interpretation of the finding that trust is beneficial for economic activity is that trust facilitates interaction, exchange, and institutional quality.[4] In

[2] As implied by the discussion above, Hendricks and Schoellman also conclude that human capital differences are larger than previously thought, but they are silent on their underlying drivers. Schoellman (2012) suggests educational quality and, e.g., Shastry and Weil (2003) suggest health, but I find no significant explanatory power of these factors once I control for measures of culture. De Philippis and Rossi (2021) show that children of migrants from countries with high Programme for International Student Assessment (PISA) test scores keep performing well even in low-quality schooling systems; they suggest cultural traits as an explanation of this persistence, in line with the cultural interpretation of my findings.

[3] Barro and McCleary (2003), Guiso, Sapienza, and Zingales (2003), McCleary and Barro (2006), and Bryan, Choi, and Karlan (2020) find a positive relationship, while Durlauf, Kourtellos, and Tan (2012) question the robustness of Barro and McCleary's results, and Campante and Yanagizawa-Drott (2015) find a negative relationship.

[4] In that sense, my exercise is closer to Butler, Giuliano, and Guiso (2016)—who look at the relationship between individual trust and individual outcomes—than to many of the other classic references (e.g., Knack and Keefer 1997; Guiso, Sapienza, and Zingales 2004, 2009; Tabellini 2008; Algan and Cahuc 2009, 2010, to name a few).

a similar vein, a societal-level mechanism proposed by Gorodnichenko and Roland (2017), linking *individualism* to economic growth by providing different incentives to innovation across countries, cannot be at play in my data, as I study workers within one country.

The economics literature on autonomy as a cultural trait is more sparse, but one exception is Campante and Chor (2017), who document a significant relationship between (workplace) obedience and the share of exports in a country that can be attributed to heavily routinized industries, consistent with the mechanism I propose for autonomy. In adjacent work, viewing autonomy as a personality trait rather than a cultural value, Nyhus and Pons (2005) find a positive association between earnings and autonomy.[5] Outside of economics, the management literature highlights *proactivity* and *adaptability* as important for worker performance; further validating my way of assessing a mechanism linked to cultural autonomy, Griffin, Neal, and Parker (2007) also propose that the benefits of proactivity and adaptability will vary across organizations as the specific context shapes and constrains which worker characteristics will be most useful. This evidence suggests a natural and plausible interpretation for the role of a culture that values autonomy in affecting human capital, in that an upbringing emphasizing autonomy is likely to forge more proactive, adaptive, and independently thinking individuals.[6]

The remainder of the paper is structured as follows. Section II describes the data. Section III outlines the approach to estimate human capital and how human capital varies across countries. Section IV investigates the main determinants of human capital differences, and section V moves to examine evidence consistent with a plausible mechanism for autonomy. Section VI explores whether something specific to Sweden, or specific to the migrant population, may be driving my results. Section VII concludes.

II. Data

To estimate cross-country differences in human capital, this paper uses administrative individual-level data covering the entire Swedish working-age

[5] Nyhus and Pons investigate the Big Five personality traits' impact on labor market success; it is for male workers with increasing tenure in particular that they find a positive effect. While they include autonomy as one of these traits, most of this literature instead includes *openness (to experience)*. Openness is defined differently; it exhibits a weak but positive association with labor market success (Heckman, Jagelka, and Kautz 2019), and it has also been proposed as a trait with domain-specific productivity (Borghans et al. 2008).

[6] In that sense, the paper overlaps more generally with the literature on noncognitive skills or psychological traits—it shares the focus on characteristics that are distinct from intelligence or education but nevertheless important for labor market success (see, e.g., Heckman, Stixrud, and Urzua 2006), and it shares an emphasis on intergenerational transmission with parents being crucial for, respectively, shaping traits and developing skills or passing down cultural values.

population and the universe of Swedish firms (excluding financial institutions). All individuals have a unique civic registration number that allows for linking information across registers. The Total Population Registry contains basic demographic characteristics, such as year and country of birth, gender, parental country of birth, and so on. Data on educational attainment are from the Education Registry, and the Employment Register provides employment-specific information, such as occupation and income from each individual's main employer(s). These registers cover the most important variables with complete coverage of the population. I also link information from two registers that do not cover the entire population—the Wage Structure Register and the Recruitment Authority. They provide data on, respectively, hours worked for a large representative sample of workers and a measure of cognitive ability for native-born males carried out during the Swedish Military Enlistment test.

Firm-level data are from the database Business Economics, compiled by Statistics Sweden (SCB) using mainly data collected by tax authorities. SCB calculates value added as revenue less costs of intermediate inputs. I use the book value of fixed assets and gross investment as the baseline measures of capital and investment. Similar to workers, firms have a unique firm identifier. Measures of labor input for the firm come from the worker-side data—the number of workers (or efficiency units of labor input) per firm is aggregated via this firm identifier. Creating firm-level worker characteristics this way—indirectly via data collected by tax authorities—is useful as it is not sensitive to firms misreporting their labor input.

Data are annual and cover the time period from 2008 to 2014, which is the most recent year for which I have data. I make no sample restrictions on the worker side per se, but workers are indirectly restricted by which firm they are working in—a worker is included only if he or she works for a firm that is included in the sample. On the firm side, the following sample restrictions are made. The baseline sample excludes firms with five or fewer employees. By necessity, I drop firms without information on industry, value added, or capital. That leaves 407,183 firm-year observations; the average firm is included 5.6 out of 7 years. For estimations following the methodology introduced by Olley and Pakes (1996), I can include only firms with nonzero investment data, which further restricts the sample to 270,109 firm-year observations.

Table 1 presents annual average summary statistics for private sector firms, successively adding sample restrictions. The "total" numbers (rows 7–12) are included to illustrate the coverage of the total private sector economy of the different sample restrictions. While I lose the majority of firm observations, first from excluding firms with five or fewer employees (moving from col. 2 to col. 3) and then from excluding firms with missing investment data (from col. 3 to col. 4), I cover a much larger share of the

TABLE 1
Firm Summary Statistics for Different Sample Restrictions

	All Firms (1)	Value Added, Capital >0 (2)	>5 Employees (3)	>0 Investment (Olley and Pakes [1996] Sample) (4)
Average employment	7	9	36	45
Average sales	15	20	88	117
Average fixed assets	12	16	66	89
Average total assets	20	26	107	142
Average investment	.7	1	4	6
Average value added	5	6	25	33
Total employment	2,839,503	2,449,825	2,065,739	1,748,074
Total sales	5,796,226	5,671,858	5,108,392	4,499,723
Total fixed assets	4,535,810	4,450,350	3,860,133	3,415,718
Total total assets	7,625,199	7,117,814	6,230,953	5,497,301
Total investment	243,931	243,426	215,023	215,023
Total value added	1,726,293	1,669,444	1,460,092	1,292,294
Number of firms	431,387	279,075	58,169	38,587

Note.—Values are the yearly average over the pooled sample of firm-year observations (implying, e.g., that the total number of firm-year observations in the Olley and Pakes [1996] sample is $7 \times 38{,}587$). The financial variables are given in units of 1 million SEK. Column 1 includes all private sector firms; in cols. 2–4, I successively restrict the sample to exclude firms without (strictly positive) data on value added and fixed assets, firms with five or fewer employees, and firms lacking investment data, which is the main sample in the paper (each new restriction is in addition to previous restrictions).

actual economy with, respectively, 88% of total sales and 85% of value added (78% and 75% for the Olley and Pakes [1996] sample). This is reflecting the fact that a majority of registered firms are very small, with zero to two employees.

All workers employed by a firm are included as labor input for that firm, but the focus of the analysis is on male workers. In particular, while I split male workers into country-of-origin-specific labor inputs, I split female workers only into foreign- and native-born types. The reason to focus on male workers is the relatively strong relationship between female labor force participation and cultural factors as demonstrated by Fernández (2007) and Fernández and Fogli (2009), among others. Their results from a US context replicate qualitatively in Sweden—female labor force participation, as well as the difference between male and female employment rates across country of origin, are correlated with country-of-origin cultural values. In other words, there is differential selection of females into the labor force, and that differential selection is correlated to the cultural values I study below. There are no analogous results for male labor force participation or indications of strong differential selection into the labor force more generally.[7]

[7] If anything, one would expect labor force participation to increase with the strength of the "male-breadwinner hypothesis"; as I find that employment rates generally are lower for

Table 2 presents summary statistics for male workers aged 25–64 by region of birth. The numbers are annual averages for my sample period. Age, years of education, and hours worked are mean values conditional on being employed by a firm in the main (Olley and Pakes 1996) sample. These conditional means are relatively similar across birth regions (differences in unconditional mean values across origins are somewhat larger). Employment rates, however, differ substantially, with particularly low numbers for African- and Asian-born workers; employment rates are also lower conditional on education and age, indicating that selection into employment (by any sensible mechanism) is positive for these origin regions. This suggests a possible upward bias in my human capital estimates for Africa and Asia. However, in my estimates, African and Asian countries are generally those with the lowest human capital.

Conditional on employment, table 2 does reveal some differential sorting of migrants, especially Asian- and African-born, into cities and firms with a higher share of migrants (conditional on city of residence, the differential selection into firms is smaller than that indicated by the bottom row in table 2). Firm sorting is problematic for my estimates only if it takes place in a discriminatory fashion—that is, if firms fill positions in a way that systematically penalizes certain backgrounds at the expense of firms' financial returns. Summary statistics is a very blunt way of trying to assess whether that is the case. It cannot possibly confirm or rule out its existence, but finding extreme levels of firm sorting, with certain groups of migrants relegated to separate labor markets, would be cause for concern that it may not only take place but also be quantitatively important. However, I do not find any indication of that kind of extreme sorting—a majority of workers from all groups are active in firms with a majority native-born employees and are not confined to firms dominated by employees of similar (non-Swedish) backgrounds.

A key variable for my purposes is country of birth. SCB has historically been very restrictive with releasing data on individuals' (and parents') country of birth at a disaggregated level—to the best of my knowledge, origin information has previously been released only at the continent level or for a short list of selected countries. The data I use contain information on 129 different countries or groups of countries.[8] To obtain the release of country (and parents' country) of birth at a more detailed level than Statistics Sweden normally allows, I have agreed to the condition that no results are presented with individual countries named. Therefore, I will

countries characterized by more traditional gender roles, it does not appear to be something that exacerbates differences in estimated human capital.

[8] SCB merged countries with fewer than 1,000 individuals in Sweden in 2014 into groups of countries, each of which contains at least 1,000 individuals. Of the 129 country groups, all but 18 are individual countries.

TABLE 2
WORKER SUMMARY STATISTICS

	Native-Born Parents	Second-Generation Migrants	Europe	Asia	Africa	North America	South America
Total prime age	1,758,921	241,087	241,168	152,112	45,898	11,581	23,649
Share employed	.84	.81	.65	.54	.50	.63	.70
Share employed in private sector	.68	.66	.54	.45	.38	.48	.54
Share employed in firm included in sample	.48	.46	.37	.28	.29	.33	.41
Share employed in firm included in Olley and Pakes (1996) sample	.42	.40	.31	.24	.25	.28	.34
Age, Olley and Pakes (1996) sample	43.89	41.47	43.98	39.54	40.19	41.35	41.68
Years of education, Olley and Pakes (1996) sample	11.95	12.02	11.32	11.78	11.42	12.77	11.75
% of full-time position, Olley and Pakes (1996) sample	92.74	91.09	92.86	89.56	88.65	91.15	90.92
Hours worked, Olley and Pakes (1996) sample	131.92	127.97	133.52	130.84	127.00	131.43	131.54
Share foreign-born in city, Olley and Pakes (1996) sample	.16	.19	.20	.23	.24	.21	.23
Share foreign-born in firm, Olley and Pakes (1996) sample	.10	.13	.25	.34	.35	.23	.28

NOTE.—This table presents average summary statistics for male workers from 2008 to 2014 by region of birth. "Native-Born Parents" refers to workers born in Sweden with two native-born parents. "Second-Generation Migrants" refers to workers born in Sweden but with at least one foreign-born parent. The other columns refer to workers born outside Sweden. "Total prime age" is a yearly average for 2008–14; other values are for pooled averages over the same time period. In the "sample" are employees in firms with data on value added and fixed assets; the "Olley and Pakes (1996) sample" also requires data on investment. The top five rows are based on all males, 25–64 years of age; the sixth row and below are based only on workers who are employed by a firm in the Olley and Pakes (1996) sample. "% of full-time position" is an alternative measure of average labor supply. For any individual worker, it can theoretically take any number in the range 0–100, where a number below 100 indicates a part-time position whose scope corresponds to the number; the minimum in the sample is five. The two bottom rows are averages of averages. For each individual, I have calculated the average share of foreign-born in that individual's city and firm; the two bottom rows then report the average of those averages by worker category in each respective column.

present only results that are related to country characteristics and never point to specific countries.

III. A New Measure of Human Capital

The main goal of this section is to construct a new measure of human capital differences across countries. The measure complements existing work in that it is robust to discrimination-related issues and by being based on high-quality register data as opposed to survey data that may suffer from misreporting and selection biases. I exploit the feature of the data that employees are matched to their employers to estimate differences in labor productivity via firm-level production functions with heterogeneous labor. I interpret the estimated labor productivity terms as human capital, similar to how past papers have interpreted wage differences.

It is instructive to contrast the measure I suggest below with one based on wages, illustrated in the following standard firm profit-maximization framework. Suppose that firms combine capital K and heterogeneous labor L_c into output Y to solve

$$\max_{L_c} K^{\theta}(AL)^{1-\theta} - \sum_{c=1}^{n}(w_c L_c),\ L = \sum_{c=1}^{n}(\delta_c L_{j,c}), \tag{1}$$

where w_c represents the wage and δ_c represents the human capital level of labor type c. Appealing to competitive markets, so that rental rates of input factors equal their respective marginal product, delivers the key relationship used to obtain human capital as a function of wages:

$$w_c = A^{1-\theta}K^{\theta}L^{-\theta}\delta_c. \tag{2}$$

The unobserved relative human capital level $\delta_c/\delta_{c'}$ is accurately inferred from the observed relative price $w_c/w_{c'}$ if (i) wages indeed equal marginal products and (ii) workers of different types sort into occupations, positions, and firms based on productive capacity, so that A, K, and θ do not vary systematically with type of labor for discriminatory reasons.

The strategy in previous literature has been to measure w_c. The human capital measure in this paper is based on directly estimating the δ on the right-hand side of equation (2) rather than inferring it via wages. This makes the approach immune to concern (1). It does not make it immune to systematic variation between position or firm characteristics and country of origin—a substantial part of section VI is devoted to robustness exercises that investigate whether varieties of discrimination other than through wages might drive estimated human capital differences. Note, though, that the baseline estimation, which controls for capital and proxies for total factor productivity (TFP) differences, already goes further with respect to issues of the latter type than do wage-based measures.[9]

A. *Estimating Production Functions with Heterogeneous Labor*

I estimate firm-level production functions with heterogeneous labor, in the form of

$$\ln(VA_{j,t}) = \alpha_t + \boldsymbol{\kappa}\mathbf{D}_{j,t} + \theta_L \ln\left[\sum_{c=1}^{n}(\delta_c L_{j,c,t})\right] + \theta_K \ln(K_{j,t}) + \omega_{j,t} + \epsilon_{j,t}. \qquad (3)$$

Each firm j produces value added at time t by combining capital $K_{j,t}$ and heterogeneous (but perfectly substitutable) labor inputs $L_{j,c,t}$, where c is a mnemonic for "country of origin."[10] The objects of interest are the country-of-origin-specific productivity terms δ_c. I interpret differences in the δ_c's as differences in human capital. As already implied in the data section, I estimate different δ_c's for male workers by specific birth country, plus a separate δ for native-born female workers and another for foreign-born women. Equation (3) also contains fixed effects for five firm-size bins, industry, and city, contained in the vector $\mathbf{D}_{j,t}$, year fixed effects α_t, a firm-specific productivity level $\omega_{j,t}$, unobserved but known to the firm, and an error term $\epsilon_{j,t}$, containing firm-specific productivity shocks not known by the firm. The error term also captures misspecification in the production technology and potential measurement error.

Since I am interested in variation in the δ's, which capture differences in human capital not accounted for by the standard determinants of education and experience, the country-of-origin labor inputs $L_{j,c,t}$ enter equation (3) with an adjustment for these observables. I now turn to these adjustments.

1. Labor Efficiency-Unit Adjustments

The baseline specification adjusts the number of efficiency units that a worker contributes using relative predicted wages. I run a Mincerian

[9] The outline of wage-based measures here does not bring out the important contribution of Hendricks and Schoellman (2018)—to properly account for selection on unobservable characteristics of migrants. That I am not able to do so is a limitation of this study. Section VI.A discusses and documents selection of several varieties.

[10] It appears reasonable from an a priori perspective to treat workers with the same education and experience level but who are born in different countries as very close substitutes; it also has the advantage that the estimation does not suffer from the identification issue pointed out by Diamond, McFadden, and Rodriguez (1978). I do relax the assumption in several robustness checks. Results are robust, and the estimated elasticity of substitution across labor types is very high.

regression for the reference group, where education enters as dummy variables for nine different educational categories and experience enters as a third-degree polynomial in (potential) years of experience. I then use the coefficients from this regression to generate predicted wages for all workers. Finally, I adjust the number of efficiency units that an individual worker provides by the size of that individual's predicted wage relative to the average predicted wage. If, for example, a worker has a predicted wage that is twice the average, then that worker's contribution to the relevant $L_{j,c,t}$ is two efficiency units. In addition to the efficiency adjustments, I also adjust the labor input based on the average number of hours worked by workers from a given origin.[11]

2. Addressing Endogeneity

There is a large literature on production function estimation. The main challenge faced by this literature is the endogeneity of factor input choices to the unobserved firm-specific productivity level $\omega_{j,t}$. For my parameters of interest, the specific form this concern could take is that the firm uses knowledge about its productivity level when it decides the *composition* of labor types. If so, unobserved productivity biases country-of-origin-specific productivity estimates.[12]

To tackle the problem of endogenous factor input choices, I follow the proxy variable literature. As a baseline, I follow Olley and Pakes (1996). Their basic idea is that (observed) investment decisions are informative of the firm's (unobserved) productivity level.[13] If the choice of investment is a monotonically increasing function of productivity (for a given level of capital), this function can be inverted to get unobserved productivity as a function of investment and capital. The inverted investment function $\omega_{j,t} \approx \phi(k_{j,t}, i_{j,t})$ is unknown so they, and I, approximate it by a third-degree polynomial in investment and capital (including all interactions).

[11] Unfortunately, I have data on hours worked only for a representative sample, not for all workers. However, as my objects of interest are group averages, this should not be a concern. Furthermore, differences are relatively small across origins. The eighth and ninth rows in table 2 show this for continent averages, as I am not allowed to present country-specific numbers. But differences across countries are also small, rarely larger than 5%.

[12] If the firm uses knowledge about its productivity level to decide total labor input but chooses different types of labor at random conditional on total labor input, that would be a problem for estimating the labor share but should not pose a problem for estimating relative productivity levels of different groups of labor.

[13] Unlike papers aiming to estimate firm-level TFP, for my purposes, Olley and Pakes (1996) also alleviates concerns that stem from potential differences in markups across firms correlated to the labor type composition, assuming that investment responds to differences in profit opportunities caused by market power similarly to differences in profit opportunities induced by firm-level TFP.

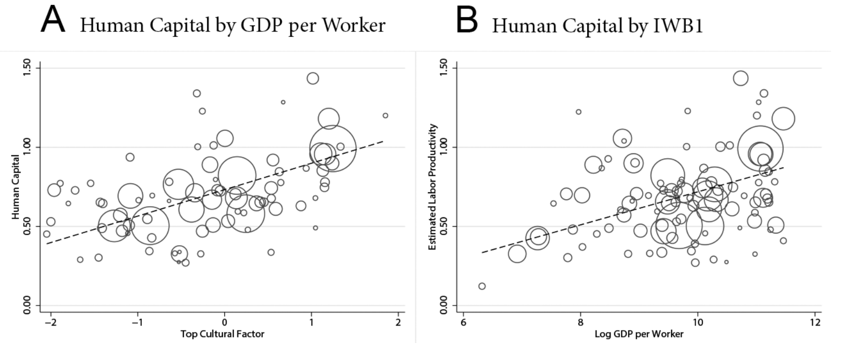

FIG. 1.—Estimated human capital across countries.

B. Results

I estimate equation (3) following the approach outlined above. In general, the production function parameters are plausible, with estimates of returns to scale well in the range of previous micro estimates. The goodness of fit is relatively high, with an adjusted R^2 value of 0.85. A first indication of the results is provided by figure 1*A*, which graphically illustrates the dispersion in labor productivity or human capital across countries by plotting the estimated human capital (the δ's from estimating eq. [3]) against GDP per worker; circle sizes are proportional to the country-of-origin weight in the data. Table 3 gives the corresponding summary statistics.[14] Two immediate lessons emerge: there is significant dispersion in human capital across countries with a 90/10 percentile ratio of 3.2 over and above any dispersion associated with the quantity of schooling and experience, and those residual differences are strongly correlated to GDP per worker. A 1 percentage point increase in estimated human capital is associated with an increase of 10 log points in real GDP per worker. The relationship is statistically significant at the 1% level, both when data are weighted by a country-of-origin weight and when they are unweighted.

The cross-country differences in human capital implied by my estimates are large not only economically but also compared with those based on schooling that have dominated the development accounting literature. For example, the 90/10 percentile ratio in the cross-country average years of schooling distribution is around two, and so is the 90/10 percentile ratio in the human capital stocks calculated by Hall and Jones (1999). Recall that my estimates capture human capital differences other than those induced by the quantity of schooling, so an implication of my

[14] The average estimated human capital is in itself uninformative for my purposes as the native-born act solely as a reference group; I include it to provide a point of reference for the standard deviation and 90/10 ratio.

TABLE 3
Summary Statistics for Estimated Human Capital

Average $\hat{\delta}$ (1)	Average $\hat{\delta}$, Frequency Weighted (2)	Standard Deviation of $\hat{\delta}$ (3)	Standard Deviation of $\hat{\delta}$ Frequency Weight (4)	90/10 Ratio of $\hat{\delta}$ (5)	Regression Coefficient on Log GDP (6)	$\frac{\mathrm{var}[\ln(h_{\mathrm{trad}})]}{\mathrm{var}[\ln(y)]}$ (7)	$\frac{\mathrm{var}[\ln(h_{\mathrm{trad}}\hat{\delta})]}{\mathrm{var}[\ln(y)]}$ (8)
.73	.71	.36	.24	3.2	.097	.066	.35

Note.—This table presents summary statistics for the country-specific measures of human capital $\hat{\delta}_c$ from eq. (3) in the baseline estimation. Standard deviations and the 90/10 ratio quantify the country-of-origin dispersion in human capital estimates. Columns 1–6 are based on 101 observations. The human capital development accounting calculation uses 1995 data (from Caselli 2005). Using data from 2014 from the Penn World Table (v. 10) instead increases the numbers corresponding to cols. 7 and 8 from 6.6% and 35% to 7.6% and 41% and the number of countries those values are based on from 57 to 83.

findings is that factors other than schooling account for more of the overall variation in human capital across countries than schooling itself. Investigating what these factors may be is the focus of the paper starting from the next section.

A brief note on migrant selection is in order, as differential migrant selection on unobservable characteristics has been the predominant issue in the branch of this literature that relies on US data. Hendricks and Schoellman (2018) find that selection on unobservable characteristics explains the discrepancy between their results and the relatively modest human capital differences found by Hendricks (2002); they also document a positive relationship between selection on observable and unobservable characteristics. There is differential selection in Sweden also—immigrants are generally positively selected, and they are relatively more positively selected from countries for which I estimate lower levels of human capital. Together, the positive differential selection on observables and the positive relationship between selection on observable and unobservable characteristics suggest that the human capital differences I estimate, if anything, are attenuated.[15] Section VI.A presents and discusses results related to the various points of selection.

Hendricks and Schoellman (2018) find human capital differentials that are able to account for between half and two-thirds of cross-country income differences, and a back-of-the-envelope calculation from their results suggests a 90/10 percentile ratio in excess of six. Hence, their documented differences are somewhat larger than the 90/10 ratio of 4.9 that I get once I combine my measures of human capital differences

[15] The fact that I nevertheless do detect quantitatively substantial human capital differences suggests that the differential selection on unobservable characteristics for migrating to Sweden is not as strong as it is for migrating to the United States. This would not be surprising given Sweden's relatively compressed income distribution and more comprehensive welfare state and given the stricter restrictions on immigration to the United States.

in excess of schooling with the traditional ones based on schooling. It is also larger than what I can account for in a human capital development accounting exercise where, although my human capital estimates improve radically on the explanatory power of solely using education (from around 7% to 35%–41%), it is still a bit shy of Hendricks and Schoellman's quantitative success.[16] A possible explanation for this difference is that their wage-based measure indeed exaggerates human capital differences because of wage discrimination. However, it is also possible that my estimates underestimate differences in human capital because migrants to Sweden are positively and differentially selected on unobservables. Therefore, the results in this section are complementary rather than contradictory to Hendricks and Schoellman's findings; they rule out (wage) discrimination as the main driver of human capital differences but they do not rule out differences that are quantitatively as large as those that Hendricks and Schoellman (2018) find. In other words, my results imply a narrowing of the interval of plausible human capital differences by adjusting upward the lower bound, but not due to a downward adjustment of the upper bound.

Robustness variations.—There are several potential concerns one may have with the approach here to estimate human capital. Two broad categories of issues are (i) misspecification of the production function and (ii) the empirical data that I use not precisely mapping to the corresponding model variables.[17] To assess the robustness of my results, I try a host of variations of both different production functions and varying the underlying data (e.g., changing measures of capital and investment, excluding young migrants, or including "time in Sweden" when estimating labor efficiency units). To very briefly summarize the results of the robustness variations, the range of 90/10 ratios is 2.1–4.3 (with a median of 2.95)—that is, its lower bound is slightly above the years-of-schooling ratio of two. The appendix (available online) lists the variations and corresponding results.

C. Human Capital Persistence

Whether differences in human capital across origins persist over generations is informative for discriminating between determinants of those differences. Unfortunately, the number of second-generation migrants is

[16] The human capital development accounting calculation uses the same 1995 data as Caselli (2005), as that year comes very close to the average immigration year for workers in my sample. Using more recent data instead—e.g., 2014 (the last year included in my micro data)—from the Penn World Table (v. 10) increases the explained variation from 6.6% and 35% to 7.6% and 41%, and the number of countries included increases from 57 to 83.

[17] Two other major concerns are that the sample of workers included may not be representative of their respective country populations and that there may be "unfair" sorting into firms, industries, or occupations that bias country estimates of human capital (as outlined in the beginning of sec. III). I defer a discussion of these two concerns to sec. VI.

not large enough to produce country-specific estimates in the same way as I do for the baseline human capital measure.[18] To assess the persistence of human capital, I instead estimate an alternative labor aggregator that allows the productivity of second-generation migrants to be a weighted average of the productivity of their parents' origins on the one hand and of natives' origins on the other.[19] That is, I estimate the convergence parameter ϕ in a labor aggregator of the form

$$L = \sum_{c=1}^{n}(\delta_c(L_{c,1} + \phi L_{c,2}) + (1 - \phi)L_{c,2}),$$

where subscript c denotes country, numerals 1 and 2 respectively refer to first- and second-generation migrants, and there is an implicit $\delta_{\mathrm{Nat}} = 1$ in front of the $(1 - \phi)L_{c,2}$ term. The estimated $\hat{\phi} = 0.48$ (with a standard error of 0.07) indicates a relatively high degree of persistence, suggesting that a major component of human capital differences remains when potentially important factors, such as schooling and health care access, converge for second-generation migrants.

IV. Determinants of Human Capital

The findings in section III suggest that human capital differences are substantially larger than what is captured by direct measures of years of schooling. This section aims to investigate what the key determinants of those differences are. It consists of two broad parts. Section IV.A explores the explanatory power of different country-of-origin characteristics on the migrant-based human capital measure from section III; with the result that cultural values are its best predictor, section IV.B then turns to studying second-generation migrants to provide a cleaner test of culture as a driver of human capital differences.

A. What Predicts Human Capital Differences?

This section explores the predictive power of different country-of-origin characteristics on estimated human capital differences in ordinary least squares (OLS) regressions. Although the regressions below at first glance look like standard cross-country regressions, they are not. The dependent variable in these regressions is a country's human capital as estimated from workers operating in Sweden, which greatly diminishes the risk of relevant omitted variables. Any country-of-origin omitted variable must have followed the worker in his or her move to Sweden, and I believe my

[18] When I do try, the standard errors for most countries are at least an order of magnitude greater than point estimates.

[19] I thank an anonymous referee for this suggestion.

regressions exhaust the possibilities that plausibly fit this requirement. In fact, since (as I show below) my results are robust to using second-generation migrants, omitted variables must be not only embodied in the migrants but also susceptible to intergenerational transmission. None of the usual institutional, geographical, or factor-endowment variables can fit these criteria.

Due to the nature of my human capital estimate, following the above reasoning, in my baseline analysis I restrict attention to characteristics that could plausibly have a direct impact on transportable human capital. The characteristics I consider fall into the broad categories of *education*, *health*, and *cultural values*. First, I examine these categories separately (I relegate the within-category regression output to the appendix). Then, I compare the statistically most successful predictors of human capital differences from each category. From the education category, education quality as measured by pupil performance in standardized test scores is the strongest and only robust predictor—perhaps unsurprisingly, as several papers find evidence that it is an important driver of human capital and the human capital measures already account for individual-level quantity of education.[20] From the health category, life expectancy and the fertility rate are the strongest predictors.[21]

Within the cultural values category, to avoid data-mining issues with the long list of possible cultural measures from the WVS data (Inglehart et al. 2014), I restrict attention to those values that previous literature has suggested as important for labor productivity, economic growth, or development. These are measures of religiosity (e.g., McCleary and Barro 2006; Campante and Yanagizawa-Drott 2015), measures of attitudes toward cooperation, women, legal norms, the market, thriftiness (suggested by Guiso, Sapienza, and Zingales 2003), and individualism (Gorodnichenko and Roland 2017). I also include a measure due to Ronald Inglehart, Wayne Baker, and Christian Welzel (e.g., Inglehart and Baker 2000; Inglehart and Welzel 2005) that has been very influential in political science and sociology. They extract the top two factors from an underlying set of answers to WVS questions by means of factor analysis. Below I refer to the two variables as IWB factors after the original authors; they in turn refer to the top cultural factor (IWB1) as *traditional versus secular-rational* and the second factor (IWB2) as *survival versus self-expression* values. It is this top cultural factor, IWB1, that turns out to be the variable with strongest explanatory power; figure 1*B* shows graphically its close correlation with human capital estimates.

[20] Its contenders within the category are country-of-origin measures of spending on education, teacher/pupil ratios, and quantity of education.

[21] Contenders here are measures of mortality under age 5, mental health (proxied by suicide rate), measles immunization, and low birth weight.

TABLE 4
Human Capital and Country Characteristics

	(1)	(2)	(3)	(4)
IWB1 (cols. 1, 2)/autonomy (cols. 3, 4)	.150***	.149***	.110**	.111**
	(.0393)	(.0397)	(.0493)	(.0496)
IWB2 (cols. 1, 2)/trust (cols. 3, 4)	.0463	.0495	.0542	.0546
	(.0438)	(.0460)	(.0343)	(.0344)
Hanushek and Woessman (2012) education quality	.0441	.0490	.0421	.050
	(.0537)	(.0588)	(.0555)	(.0661)
Fertility rate	.00379	.00394	−.000584	.000146
	(.00916)	(.00915)	(.00784)	(.00837)
Life expectancy at birth	−.00882	−.00716	−.00919	−.00646
	(.00902)	(.0105)	(.00705)	(.0101)
Log GDP per worker		−.0182		−.0242
		(.0668)		(.0751)
Observations	62	62	62	62
Adjusted R^2	.494	.486	.490	.482

Note.—OLS regressions are used. Robust standard errors are shown in parentheses. The dependent variable throughout is the human capital measure across countries, $\hat{\delta}_c$, retrieved from estimating eq. (3). Independent variables included are those with the strongest predictive power from each respective category of health and fertility, education, and cultural values. Education quality is from Hanushek and Woessman (2012) and based on test score results from international assessments. The top two rows show the cultural variables; in cols. 1 and 2, these are IWB1 and IWB2, following the work of Inglehart, Welzel, and Baker, and in cols. 3 and 4 these are substituted for autonomy and trust, coded Y003 and A165 in the WVS. Cultural variables and education quality are normalized to have a cross-country standard deviation of one.
** $p < .05$.
*** $p < .01$.

With one or two statistically significant predictors from each category, I turn to comparing these across categories. Table 4 elucidates the result previewed above, that the top cultural factor is the explanatory factor with the most robust and quantitatively strongest relationship with human capital—a 1 standard deviation change is associated with roughly 15 percentage points higher labor productivity in units of the reference group (or a change of roughly 20% of the average estimated δ_c). No other explanatory variable is robustly related to human capital differences.

Including GDP per capita as an explanatory variable is questionable—after all, one purpose of the paper is to explain differences in income via human capital. Seeing as it is the most frequently included variable in cross-country regressions, I nevertheless try including it. As I show in section III, it is strongly correlated to the measure of human capital on its own. Here, after controlling for human capital determinants, it lacks predictive power. The dependent variable is constructed to capture human capital, and independent variables are chosen to explain human capital differences as well as possible. Therefore, it is reassuring that GDP, a variable that is a combination of TFP and human and physical capital, does not add explanatory power, both for the choices of potential human capital determinants and for the identifying assumption that the migrant-based measure reflects human capital levels of origin countries but not TFP or physical capital. The key takeaway from table 4 (as from the extensive list of robustness exercises I have carried out) is that the one country characteristic that remains strongly statistically and economically related to estimated human capital is the top cultural factor, IWB1.[22]

Having said that, I am not suggesting this as evidence of absence of an effect of these other factors on human capital. The positive impact of certain cultural values may well work to some extent via other factors, such as higher-quality education. It is also likely that societies use their educational system partly to try and teach, preserve, or amplify certain values, and as suggested by Campante and Chor (2017), industrial composition could well interact in a similar two-way fashion with cultural values. However, the remarkably robust statistical relationship between IWB1 (or autonomy) and my measure of human capital is not the only piece of evidence that leads me to favor cultural values over other factors. The results on a persistent effect for children of migrants and differential sorting and productivity in nonroutinized occupations are both supportive of an independent role for cultural values; I find no similar consistent set of results that favors education quality or health factors.[23]

Using the IWB factors relies on the knowledge and judgment of these authors to construct measures that summarize "culture" reasonably well. The results indicate that culture generally, or secular-rational as opposed to traditional values in particular, is an important determinant of human capital. The drawback is that it is difficult to give a more detailed interpretation of why cultural values affect human capital based on the factor (although underlying factor loadings can give some guidance). Therefore, in columns 3 and 4 of table 4, I substitute IWB1 (and IWB2) for the strongest underlying driver(s) of the relationship between IWB1 and labor productivity: autonomy as opposed to obedience (and trust).[24] Also in this version of comparing cultural values with the strongest health and education contenders, it is the cultural measure that stands out as the

[22] Bootstrapping standard errors by resampling the dependent variable δ_c from $N(\hat{\delta}_c, \mathrm{SE}_{\hat{\delta}_c})$ substantially improves the statistical significance of IWB1 and does not change the relative importance across different potential human capital determinants. Therefore, the regressions presented here are likely conservative in terms of statistical significance. Since estimating eq. (3) requires around 24 hours, bootstrapping standard errors by resampling starting from the "first stage" is computationally infeasible even for one of the human capital determinant comparisons.

[23] Attributing measured human capital differences to a factor formed before migration (e.g., cultural values) is in line with the results due to Lagakos et al. (2018).

[24] That autonomy and (to a lesser extent) trust are the strongest underlying drivers is based on various model-selection algorithms as well as pairwise OLS comparisons; I defer the details of these exercises to the appendix. The measures of autonomy and trust are the variables coded Y003 and A165, respectively, in the WVS.

strongest predictor of human capital—a 1 standard deviation of the extent to which societies emphasize autonomy or independence, in contrast to obedience, is associated with an increase in estimated human capital of 11 percentage points. Finding that autonomy can account for most of the explanatory power of IWB1 also serves as motivation to move toward investigating a cultural mechanism, which I do in section V.

1. The Quantitative Impact of Cultural Differences

An important motivation to study the determinants of human capital differences is the very large unexplained TFP variation across countries. To assess whether the culturally related differences in human capital are quantitatively important for income differences as well, I carry out a relatively standard development accounting exercise with the modification that I adjust human capital stocks based on the main determinant of residual human capital (net of education and experience) according to section IV—cultural values. This is done by regressing the estimated productivity parameters from section III on IWB1 and IWB2, taking the predicted values of that regression, and using it to adjust aggregate human capital stocks across countries in the same multiplicative way as the δ_c's enter the firm-level production function. What I find is that a culture-augmented version of human capital stocks improves the amount of income differences that can be accounted for by around 15 percentage points (or close to 50%) starting from either "traditional" development accounting that constructs human capital stocks using only quantity of education and experience or a version that also includes a quality-of-schooling adjustment. In contrast, adding the quality-of-schooling adjustment to the traditionally calculated human capital stock improves the explanatory power by roughly 2.5 percentage points, or less than one-fifth of the improvement achieved with the cultural adjustment factor.[25]

The improvement due to the culture adjustment is economically substantial and adds further credibility to the conclusion that culture matters for productivity and income differences. Note also that since the adjustment derives solely from a *direct* impact of cultural values on human capital stocks, it neglects the potential role of culture for technological or institutional differences, or differences in factor accumulation; this makes it a conservative estimate for the broader question of "the impact of culture."

[25] Both the traditional and the quality-of-schooling-adjusted versions follow Caselli (2005). I use the midpoint of Caselli's cited estimates of returns to quality of schooling; even moving to the upper bound of that range only marginally changes the numbers presented here.

2. Robustness Variations

The same potential issues as described in "Robustness Variations" in section III.B also apply for investigating its determinants. Therefore, I use the alternative δ estimates from the same variations of the production function and underlying data as the dependent variable in regressions analogous to those presented in table 4. In addition, there may be important omitted variables in the table 4 regressions, leading me to try all of the country characteristics suggested by Sala-i-Martin (1997). The relationship with IWB1 as the best predictor of human capital differences is remarkably robust and remains statistically significant at a 1% level; the quantitative relationship generally lies within 11%–17% of a native-born labor unit per 1 standard deviation change in IWB1. The appendix lists the variations and corresponding IWB1 coefficient from a regression analogous to column 1 in table 4.

B. Human Capital Determinants in the Second Generation

While I argue that the regressions above are not standard cross-country regressions, as the standard explanatory factors of differences in labor productivity—technology, institutional quality, geography—do not apply since differences are measured in one and the same country, one may still worry that the cultural values are a proxy for some other dimension of human capital. For example, it may be that schooling quality is measured imperfectly by the test-based scores, and cultural values happen to capture some other important aspect of education that I misinterpret as culture. Therefore, studying human capital differences via the second generation of migrants is a cleaner way of separating the impact of cultural values from education quality and health. These individuals have grown up in the same country, been through the same schooling system, and had access to the same health care but differ in inherited cultural values; indeed, this is the reason why a substantial literature has pursued this "epidemiological" approach to study the persistent effects of culture (a good survey is provided in Fernández 2011).[26] For the same reason, transferability of skills is also not an issue for the second generation.

Section III.C provides a first piece of evidence that an important part of human capital differences persists via intergenerational transmission. To more directly demonstrate an increasing relationship with IWB1 (or autonomy) in the second generation of migrants as well, I follow three

[26] As argued by, among others, Bisin and Verdier (2001), Guiso, Sapienza, and Zingales (2008), Tabellini (2008), Algan and Cahuc (2010), Dohmen et al. (2012), and Ek (2021), people's beliefs and values are determined partly by their contemporaneous environment and partly by beliefs and values inherited from previous generations.

separate routes.[27] The first approach is to estimate firm-level production functions very similar to equation (3) but where labor types are defined by country-of-origin IWB1 bin instead of country of birth. With three separate second-generation bins, estimated labor productivity is monotonically increasing in the (parental) IWB1 value. Estimated productivity levels for, respectively, a low-, medium-, and high-IWB1 bin are 0.79, 0.89, and 0.92. This approach, in addition to demonstrating a clear persistence of quantitatively substantial human capital differences into the second generation of migrants, also allows me to compare the direct estimates of labor productivity by IWB1 bin with average earnings by the same bin, to argue that earnings reflect productivity relatively well at the group level. Using earnings as a proxy for labor productivity is the second approach.

Labor productivity proxied by earnings.—While issues such as transferability of skills and imperfectly measured quantity or quality of education can arguably be ruled out as issues for the estimates based on the second generation, there may be other noncultural candidate explanations. A key concern highlighted by the literature on intergenerational mobility is socioeconomic status correlated with parental country of birth. Another is inheritability of health conditions, such as mental health problems (e.g., due to the stress inflicted by migration). To control for parental characteristics at a more detailed level, I move to study human capital differences via wages. An individual-level outcome variable enables me to include individual characteristics at a level of detail that would render the number of distinct labor types unmanageable for production function estimation.

I already alluded to the result that in my data, at the group level, earnings do reflect differences in estimated productivity well.[28] The precise quantitative relationship between estimated productivity and wages differs slightly across specifications, but the data always reject a zero relationship and cannot reject the fact that average marginal productivity moves one-for-one with average wages (I defer the empirical basis of this claim to the appendix). With this result as motivation, I look at worker earnings as the outcome, instead of firm-level value added, and run regressions on the following form:

$$\ln(w_{i,c}) = \alpha + \rho P_i + \psi D_i + \beta X_i + \gamma C_c + \varepsilon_{i,c}. \tag{4}$$

Here P includes the parental characteristics of education, income, age at which the income was earned, and sick-leave compensation as a proxy for health status; D includes dummies for city and a dummy for having at

[27] Unfortunately, I do not have enough observations to estimate country-specific human capital for the second generation.

[28] The result that earnings reflect productivity across groups merely serves an instrumental purpose for this paper. Nevertheless, it is far from something that can be taken for granted or projected onto other settings (e.g., the US labor market).

least one foreign-born parent; and X includes individual characteristics of education, age, and in one specification a mandatory ability test administered by the military. The key variables of interest are the group-level characteristics associated with the parental countries of birth, here captured by C.

The results of these regressions, presented in table 5, echo those for the first generation in table 4—the top cultural factor (IWB1) remains strongly positively related to earnings as I successively add controls for parental wages and education, sick-leave as a proxy of parental health, individual education, and the ability test score, suggesting that inherited cultural values matter for productivity over and above any relationship they may have with parental income and education, inheritable components of health status, and individual education and ability. Quantitatively, a 1 standard deviation change in IWB1 is related to an 8–10 log point decrease in earnings. The results corroborate the cultural interpretation and are inconsistent with socioeconomic stories of explaining lower estimated productivity of certain second-generation migrants with low parental earnings, education, or health issues. To the extent that parental

TABLE 5
Regression of Individual Log Earnings on Parental Characteristics and Characteristics of Parental Country of Birth

	(1)	(2)	(3)	(4)	(5)
IWB1	.0907**	.105***	.0966***	.101***	.0813***
	(3.04)	(5.12)	(4.95)	(5.38)	(3.61)
IWB2	−.00855	−.0318	−.0298	−.0258	−.0262
	(−.77)	(−1.79)	(−1.72)	(−1.55)	(−1.53)
Autonomy	.097***	.058*	.058*	.063*	.052*
	(4.11)	(2.05)	(2.06)	(2.27)	(2.09)
Trust	.000	.01	.007	.009	−.010
	(.02)	(.72)	(.40)	(.53)	(−.10)
Earnings (E); education (Ed); sick leave (S)		E	E; Ed	E; Ed; S	E; Ed; S
Individual education (I-Ed); ability test (A)				I-Ed	I-Ed; A
GDP per worker, education quality Quantity, suicide rate	No	Yes	Yes	Yes	Yes

Note.—OLS regressions are used. The dependent variable is individual log gross earnings; both individual and parental earnings are averaged over 4 years. Each column includes either IWB1 and IWB2 or autonomy and trust; these two variable pairs are never included in the same specification. The bottom three rows indicate which other control variables are included, with successive inclusion of parental earnings, parental education, parental sick leave, individual education, and individual ability test score. For characteristics associated with the individual's parents' countries of birth, I use the average value of the two birth countries and set the value to zero if both parents are born in Sweden. Standard errors are clustered at the parental country of birth level. t statistics are shown in parentheses.

* $p < .1$.
** $p < .05$.
*** $p < .01$.

wages vary due to culturally related productivity factors, which my results above indicate, the results here are conservative, as some fraction of the explanatory power attributed to parental wages should be attributed to the cultural measure.

In slight table abuse, the "Autonomy" and "Trust" rows show the results when I substitute IWB1 and IWB2 for autonomy and trust. That is, these variables are *not* included in the same regressions; rather, they show the results for autonomy and trust instead of IWB1 and IWB2 and with the same control variables as each respective column specifies. These results indicate a persistent labor productivity effect of cultural autonomy. For trust, I do not find evidence of a persistent effect for the second generation, rendering the cultural interpretation for trust as having a direct individual labor productivity–enhancing effect substantially weaker.

A third way of studying second-generation human capital differences is to include the cultural characteristics directly when estimating firm-level production functions. Section V.B.2 presents results of following that approach, again similar to those already presented with a persistent effect of autonomy for second-generation migrants.

V. Toward a Cultural Mechanism

Although it is difficult to reconcile the robust relationship between country-of-origin cultural values and labor productivity with noncultural stories given that it persists for children of migrants, this relationship says little about a potential mechanism. To move toward support for a cultural mechanism, I ask whether the comparative advantage of workers with different cultural backgrounds varies across industries and occupations in a predictable manner. Specifically, I investigate whether the advantage of autonomy varies with the degree of routinization that characterizes an industry or occupation. The intuitive idea is that proactivity, autonomous thinking, and initiative in a heavily routinized role with precisely defined tasks cannot contribute as much as in a less routinized environment with defined (individual or organizational) goals rather than narrow tasks. Monitoring an assembly line is one example of a job where obedience and executing instructions without questioning is likely beneficial, while there is a whole different scope for autonomy to be useful in less routinized roles—for example, via proactivity or minor process innovation (even before going as far as actual innovation roles where autonomous thinking is a basic requirement). The economics literature on autonomy is sparse, but one notable exception is Campante and Chor (2017), who document evidence of a relationship between (workplace) obedience and the share of exports in a country that can be attributed to heavily routinized industries, consistent with the mechanism I propose. There is also evidence outside the economics literature that supports heterogeneous productivity benefits of autonomy. Griffin, Neal, and Parker (2007) document an impact on worker performance of proactivity and adaptability that varies depending on the nature of the organization; one example is that in more uncertain environments, the importance of adaptability is greater.

I investigate two intuitive implications of the idea that a high-autonomy background is associated with a comparative advantage in nonroutinized roles. First, whether autonomy increases *sorting into* occupations and industries characterized by a low level of routinization, and second, whether autonomy affects *productivity differentially* across occupations and industries.[29] To evaluate these two predictions, I go back to the micro-level data and make use of the task-based measures of occupations constructed by Autor, Levy, and Murnane (2003). I combine different task-based measures T_o^{xx} of occupation o into one measure of nonroutine task intensity, as $\mathrm{NR}_o = \ln(T_o^{nr,ca}) + \ln(T_o^{nr,m}) - \ln(T_o^{r,c}) - \ln(T_o^{r,m})$, where *(n)r* denotes (non)routine, *c(a)* denotes cognitive (analytical), and *m* denotes manual.[30]

A. *Sorting*

With a measure of occupational nonroutineness (NR) at hand, I split workers into percentiles based on where in the distribution of employed workers they are, so that $\mathrm{NR}_{i,o}^{\mathrm{PC}} \in \{1, \ldots, 100\}$, and regress the percentile $\mathrm{NR}_{i,o}^{\mathrm{PC}}$ of individual i on education, experience, time in Sweden, and the cultural measure of autonomy. Table 6 presents the results of this exercise. Individuals from an origin country that places a higher value on autonomy tend to work in less routinized occupations. This is true of both the first (cols. 1–3) and the second (cols. 4–6) generation of migrants; on average, a 1 standard deviation increase in autonomy is associated with moving up 3.4–4.9 percentiles for migrants and roughly 1–2 percentiles for children of migrants, in the nonroutineness distribution of occupations. Quantitatively, this effect is comparable to an additional year of schooling, which is associated with a 3.5 percentile move in the distribution. To avoid picking up some version of heterogeneous interpersonal discrimination in customer-facing roles, in columns 2 and 3 and 5 and 6, I control for interpersonal

[29] I leave out trust in this section because (i) there is neither the same kind of intuitive case for why trust would be especially important in nonroutine jobs nor the existing literature suggesting that this may be the case and (ii) its much weaker predictive power for the second-generation diminishes the argument for trust as a persistent human-capital-enhancing cultural characteristic.

[30] This is very similar to how Campante and Chor combine the task-based measures but differs slightly in that I exclude the measure of nonroutine cognitive *interpersonal* task intensity; because mine is a migrant-based study, I exclude it to minimize the impact on results from heterogeneous interpersonal treatment across different migrant groups. Including it has a negligible impact on the results, generally toward making them quantitatively stronger.

TABLE 6
Nonroutinized Occupations and Autonomy

	First Generation			Second Generation		
	(1)	(2)	(3)	(4)	(5)	(6)
Autonomy (Y003)	4.730***	4.897***	3.425***	.990***	1.921***	1.605***
	(.782)	(.633)	(.503)	(.327)	(.469)	(.469)
ITI		12.20***	12.18***		11.98***	11.98***
		(.0897)	(.0985)		(.105)	(.105)
GDP per worker			4.046***			.615
			(.779)			(.431)
Adjusted R^2	.177	.288	.285	.176	.288	.288

Note.—OLS regressions are used. The dependent variable throughout is the percentile rank of an individual's occupation routinization following Autor, Levy, and Murnane (2003). Throughout, the specifications include controls for education, (potential) experience, year and city fixed effects, a dummy and a second-degree polynomial for time in Sweden for first-generation migrants, and a dummy for second-generation migrants. "Autonomy" is question Y003 from the WVS, constructed following the work of Inglehart, Baker, and Welzel; this and "GDP per worker" are attributed based on country of origin. "ITI" is from Sevinc (2019). Robust standard errors are shown in parentheses.

*** $p < .01$.

task intensity (ITI) due to Sevinc (2019), constructed specifically to measure customer interaction. Columns 3 and 6 include GDP per worker as a test of whether the results are merely capturing the fact that individuals from more "advanced" economies work in more "advanced" occupations; this does not appear to be the case.

One limitation of looking specifically at occupations is that any individual can be associated with only one occupational code; in the event that proactive individuals take on additional tasks or broader roles, potentially spanning more than one occupation code, this is not captured. With the additional assumption that this kind of employee mindset is more valuable in industries characterized by a generally low level of routinization, I have also looked at sorting into industries. I quantify the industry-NR measure by calculating the average routinization of employees in each industry at the four-digit level and then sort industries into percentiles. Regressions analogous to those presented in table 6 but with the dependent variable substituted for industry-NR percentile look very similar.

B. *Productivity Differences*

If sorting into industries and occupations were perfect, or if the hypothesis that autonomy is particularly useful in occupations and industries characterized by a low level of routinization is false, then I should find no differential impact of autonomy across industries or occupations. If, alternatively, the hypothesis is true and sorting is not perfect, that implies differential effects of autonomy. I investigate this in four separate ways, with two different routes each for the industry and occupation comparison.

1. Production Functions with the Baseline Labor Aggregator

The first route follows the baseline production function specification in equation (3) but estimates separate country-specific productivity measures for workers in high- and low-routinization industries (and similarly across occupations). Specifically, I split firms into two groups based on whether their industry is above or below the NR median and estimate equation (3) separately for the two groups of firms. This produces two country-specific estimates of human capital, one based on workers in high-routinization industries and one based on workers in low-routinization industries. I then regress each of these human capital measures on autonomy to see whether human capital varies more strongly with autonomy in less routinized industries. Columns 1 and 2 in table 7 present the results for highly routinized industries, and columns 3 and 4 present the results for low routinization. Comparing these two indicates a clear

TABLE 7
Human Capital and Country Characteristics by Degree of Routinization

	Low-NR Industries		High-NR Industries		Low-NR Occupations		High-NR Occupations	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Autonomy (Y003)	.0855*	.128**	.271***	.258***	.096**	.137***	.262***	.186***
	(.0437)	(.052)	(.040)	(.043)	(.040)	(.050)	(.054)	(.057)
GDP per worker		−.0709		.0261		−.0726		.157***
		(.0533)		(.0516)		(.0526)		(.0585)
Adjusted R^2	.102	.123	.399	.391	.115	.135	.342	.402

Note.—OLS regressions are used. The dependent variable in cols. 1–4 is $\hat{\delta}_c$, retrieved from estimating eq. (3) in the same way as the baseline measure of human capital but with the following firm sample restrictions. In cols. 1 and 2, firms included are those in industries above the median in terms of routinization; cols. 3 and 4 instead include firms below the routinization median. The dependent variable in cols. 5–8 is based on a different alteration of eq. (3). Here labor types are defined by both country of origin and an occupation with an above- or below-median level of routinization. The human capital measure in cols. 5 and 6 is based on the high-routinization (or low-NR) labor type; in cols. 7 and 8, the measure is based on the low-routinization type. Autonomy's impact is statistically significantly stronger in less routinized industries and occupations when comparing the specifications in cols. 1 and 3, 2 and 4, and 5 and 7 but not when comparing cols. 6 and 8. Robust standard errors are shown in parentheses.

* $p < .1$.
** $p < .05$.
*** $p < .01$.

differential effect—the point estimate for autonomy in low-routinization industries is more than two times that of its high-routinization analogue; they are statistically significantly different at, respectively, a 1% (col. 1 vs. col. 3) and a 5% (col. 2 vs. col. 4) level.

Separating workers based on the routinization intensity of their occupation rather than industry paints a similar picture. Columns 5 and 6 in table 7 present the results for high-routinization occupations, and columns 7 and 8 present the results for low routinization. Here, instead of splitting firms in two halves and estimating equation (3) twice, I split occupations directly based on whether they are above or below the routinization median and estimate equation (3) once, but with separate labor types for high- and low-routinization occupations. Since this exercise requires twice as many types of labor, parameter estimates are considerably less precise, and in contrast to the split by industry routinization, the impact of autonomy is statistically significantly different across routinization categories only when I exclude the GDP control. However, the overall pattern remains, with a stronger quantitative relationship between autonomy and human capital in high-NR occupations.

2. Production Functions with Autonomy as a Labor Characteristic

The preceding results suggest that autonomy is a useful characteristic in production and that it is more useful in industries and occupations characterized by a lower level of routine task intensity. As an alternative to allowing labor types to vary by country-of-origin fixed effects, I include autonomy as a fundamental worker characteristic directly in the labor aggregator when estimating production functions. While this has the disadvantage that it relinquishes the agnosticism concerning what drives cross-country differences, it is a more direct way of assessing the production function suggested by the interpretation that autonomy is a fundamental characteristic in human capital. Furthermore, it allows for imperfect substitutability specifically between “autonomy units” and regular efficiency units of labor, and it allows me to test second-generation differences in labor productivity without binning workers or going via earnings.[31]

Concretely, I estimate production functions that are identical to the baseline version in equation (3) but modify the labor aggregator in two separate ways. In the first version, to make comparisons across industries, firm j at time t combines efficiency units $L_{j,t,c}$ and autonomy units $A_{j,t,c}$ from country of origin c into a total labor input $L_{j,t}$ according to

[31] I thank an anonymous referee for the suggestion to include cultural characteristics directly in the labor aggregator.

$$L_{j,t} = \left[\left(\sum_{e\in E}\delta_e L_{j,t,e}\right)^{\rho} + \left(\sum_{c\in C}\psi_a A_{j,t,c}\right)^{\rho}\right]^{1/\rho}, \tag{5}$$

where $L_{j,t,e}$ represents the number of efficiency units that are, respectively, natives, foreign-born, and second-generation migrants (with natives as the reference group, $\delta_{\text{Nat}} = 1$).[32] The variable $A_{j,t,c}$ is the autonomy value associated with country c multiplied by the number of efficiency units employed by firm j at time t from that same country of origin c. I then estimate equation (3) with the modified labor aggregator and do this separately for firms in industries in the top and the bottom half of the NR distribution, where that distribution is defined as above.

In a second version, to investigate the advantage of autonomy across occupations, I add an occupation layer above the aggregator in equation (5). Firms then combine efficiency units and autonomy units in high-NR (h) and low-NR (l) occupations and then combine the total high- and low-NR units in a separate constant elasticity of substitution (CES) layer according to

$$\begin{aligned} L_{j,t,o} &= \left[\left(\sum_{e\in E}\delta_e L_{j,t,e}\right)^{\rho_o} + \left(\sum_{c=1}^{n}\psi_a A_{j,c,t}\right)^{\rho_o}\right]^{1/\rho_o}, \; o \in \{h, l\}, \\ L_{j,t} &= [\alpha L^{\sigma}_{j,t,h} + (1-\alpha)L^{\sigma}_{j,t,l}]^{1/\sigma}, \end{aligned} \tag{6}$$

where I also allow the substitutability parameter between efficiency and autonomy units (ρ_o) to vary across high- and low-NR occupations.[33]

To account for the nonlinear labor aggregator and complementarities between autonomy and efficiency units, instead of simply comparing ψ_a parameter estimates, I quantify the comparative advantage of autonomy units as the marginal contribution to value added in units of native-born efficiency units (evaluated at average values).[34] That is what table 8 presents, comparing industries with the labor aggregator according to equation (5) in columns 1–3 and according to equation (6) in columns 4 and 5, where I compare occupations. Again, autonomy is beneficial for productivity on average (a 1 standard deviation increase is associated with 10% of a native-efficiency-unit improvement, quantitatively very similar to the results from table 4), but more so in the lower half of the industry routinization distribution (15% vs. 8%). The same pattern also holds

[32] I include the fixed effects δ_x so as to not have results driven by migrants vs. native-born. Leaving out those fixed effects makes results here quantitatively substantially stronger.

[33] The way of allowing for differences in substitutability here in practice is very different from doing so in eq. (3); here there are only two different types of units (efficiency and autonomy), while in the baseline there are more than 100, and the structure forces the substitutability to be constant across labor types with high and low levels of autonomy. Hence, it is not surprising that I can get estimates of ρ here deviating substantially from one at the same time as it is estimated as very close to one in eq. (3).

[34] This coincides with quantifications in the baseline specification, as the δ_c's are also measured in native-born efficiency units.

TABLE 8
Estimating Production Functions with Autonomy as a Labor Characteristic

	All Industries (1)	Low-NR Industries (2)	High-NR Industries (3)	Low-NR Occupations (4)	High-NR Occupations (5)
Autonomy	.097***	.079***	.15***	.063***	.12***
	(.008)	(.011)	(.014)	(.0068)	(.012)
Autonomy, second generation	.044***	.002	.10***	.13***	.25***
	(.013)	(.06)	(.025)	(.016)	(.013)
ρ	.57	.55	.58	.99	.57
	(.043)	(.074)	(.047)	(.085)	(.026)

Note.—This table presents results from estimating production functions with autonomy included as a characteristic of workers directly in the labor aggregator, following the specifications in eqq. (5) and (6). The first and second rows present the marginal contribution to value added (in native efficiency units) of an additional unit of autonomy. The third row gives the point estimate of the substitutability parameter, with $\rho = 1$ corresponding to perfect substitutability.
*** $p < .01$.

across occupations (12% vs. 6.3%), as well as for the second generation of migrants, across both industries and occupations. Interestingly, the comparative advantage of autonomy across occupations is due to a greater complementarity between efficiency and autonomy units in high-NR occupations, consistent with the idea that autonomy can play a fundamentally different role in nonroutinized jobs.[35] Across industries, there is no estimated significant difference in complementarity, and the greater productivity advantage of autonomy in high-NR industries is due to a higher estimated ψ_a parameter.

That high-autonomy backgrounds both sort into and hold a relatively greater productivity advantage in less routinized industries and occupations is suggestive of an autonomy mechanism at play. This comparative advantage of autonomy, which is robust to different production function specifications and remains for second-generation migrants, further limits the scope for competing alternative hypotheses and corroborates the cultural explanation of human capital differences that this paper has argued in favor of.

VI. Alternative Explanations

The main results in this paper are based on Swedish data and driven by differences across migrant groups. I have interpreted these results as being explained by cultural differences across origins. However, there may exist explanations of the documented data regularities that have more to do with the specifics of the environment or the group of workers that this study is mainly built on, rather than some fundamental characteristic

[35] High- and low-NR occupations are estimated as perfect substitutes—i.e., $\sigma = 1$.

that is more universally beneficial for human capital. In this section, I investigate three alternative explanations related to those specifics—*selection*, (nonwage) *discrimination*, or it being a *Sweden-specific story* lacking in external validity.[36]

A. *Selection*

In the context of migrants, selection typically refers to the fact that which individuals decide to leave their home country generally is not random. Empirically, migrants to high-income countries are predominately positively selected, and they are more positively selected from low-income countries.[37] The same is true for Swedish immigrants—they are positively selected and more strongly positively selected from countries with lower estimated human capital. I assess this by calculating the ratio of years of education of the workers in my sample to the average number of years of education in their respective countries of origin, so that a higher number implies stronger positive selection, and I look at how this ratio covaries with estimated human capital, IWB1 values, and GDP per worker. Column 1 in table 9 quantifies this relationship with regression coefficients; a negative coefficient implies that individuals in my sample are relatively less positively selected for countries with higher values of each of the relevant country characteristics.[38]

Differential selection across origin countries of who comes to Sweden is not the only point of potential selection; a second is that immigrants can remigrate, and who decides to stay in the country is unlikely to be random. Generally, I find that those who remigrate are doing worse in the labor market than those who remain.[39] To assess differential remigration selection, I estimate country-specific "leaver" fixed effects relative to "remainers" and regress these fixed effects on my country characteristics. The positive regression coefficients in column 2 of table 9 indicate that leavers are relatively less negatively selected from countries with higher estimated human capital, meaning remainers are less positively selected from these countries—again a pattern that attenuates my results.

[36] Readers who do not worry about any of these alternative explanations can skip this section, as the results are more robustness checks than leading to any additional conclusion.

[37] Theoretically, the canonical Roy model would predict negative selection from poorer countries as Sweden's income distribution is relatively compressed. See, e.g., Grogger and Hanson (2011) for an empirical documentation of positive selection from poorer to richer countries, as well as a modification of the Roy model that predicts positive selection.

[38] As I control for education, the relevant selection would in fact be individuals' human capital conditional on education. Hendricks and Schoellman (2018) provide a concrete piece of evidence that selection on observable and unobservable productivity factors are positively correlated. As long as this positive relationship between selection on observable and unobservable characteristics is not reversed, selection into Sweden attenuates the comovement between IWB1 and human capital.

[39] This finding mirrors Lubotsky's (2007) result for (re)migrants in the United States.

TABLE 9
MEASURES OF SELECTION

	Migration Selection	Remigration Selection	Selection into Employment
Estimated human capital	−.5	.21	.06
	(.17)	(.13)	(.035)
IWB1	−.19	.097	.017
	(.036)	(.034)	(.0082)
GDP per worker	−.35	.12	.041
	(.040)	(.027)	(.010)

NOTE.—This table presents the coefficients (and standard errors) from nine separate regressions, each combination of selection measure and relevant country-of-origin characteristics. The coefficients paint a consistent picture of differential selection of workers in my sample being more strongly positive for countries with low estimated human capital, with a low IWB1 value, and with lower GDP per worker.

Third, there is selection into employment. As my human capital estimates are based solely on employed individuals, selection into employment affects those estimates. Column 3 in table 9 presents the coefficients from regressing employment rates on country characteristics. Employment rates are lower for low human capital and for low IWB1 countries. Assuming that attaining a job is positively associated with productive capacity, employment selection is more strongly positive for these countries.

In summary, there is differential selection of who immigrates, remains in the country, and finds employment, but it appears to overwhelmingly be in the direction of dampening the relationship between IWB1 values (or autonomy) and human capital, relative to a relationship absent of selection.

B. *Occupational Discrimination*

The baseline approach is immune to wage discrimination. However, being paid less for the same position is only one type of discrimination. It may be that occupations are allocated in a discriminatory way, with high-productivity positions more difficult to obtain for certain groups of workers.[40] Analogous to Becker's model of taste-based discrimination, employers could be prepared to take a cut in value added generating capacity to avoid granting high-productivity (and likely highly paid) positions to workers from groups that they are averse to. Then, for a given position, those belonging to groups suffering from discrimination would

[40] Separating the productivity level of worker and occupation is highly unrealistic. That is the reason why I do not do it as a baseline (just as studies of wage convergence among immigrants do not include occupation fixed effects) and why I worry specifically about discriminatory sorting where workers of certain backgrounds need to be *better* on average to obtain occupations where they get closer to realizing their full potential.

(on average) need to be superior in productive capacity to acquire that position—it is a story of discrimination that implies differential selection conditional on occupation.[41]

To address the concern of occupational discrimination, I first alter the baseline approach in section III and estimate labor productivity conditional on occupation. I hold occupation constant either by including occupation fixed effects at the most detailed four-digit level when I estimate labor-input efficiency units or by adding an occupational layer in the labor aggregator so that the labor input is a function of four imperfectly substitutable occupational types. The results, presented in columns 1–4 of table 10, are similar to the baseline results and inconsistent with a story of estimated human capital differences being driven mainly by occupational sorting.

While the slightly smaller magnitude is consistent with sorting driving some part of estimated differences, it is not a clear indication of discriminatory sorting. If low-IWB1 backgrounds needed to be more productive to "qualify" for each respective occupation, that amounts to a higher occupation-specific δ for those backgrounds. Then, averaging across occupations should plausibly lead to a $\delta_{\mathrm{lowIWB1}} < \delta_{\mathrm{highIWB1}}$ and a negative coefficient on IWB1 in table 10.

However, the fact that the estimated relationship does not reverse does not completely rule out some level of occupational discrimination. The average estimated human capital for a given background is not only a function of occupation-specific productivity levels but also the relative share of workers in different occupations; different shares of workers in different occupations and heterogeneous productivity differences across occupations could mask occupational discrimination somewhere in the distribution, in spite of a positive relationship between IWB1 and estimated human capital. To move closer to a direct test of occupational discrimination than the results presented in table 10, I have also estimated country-specific productivity based on one occupation at a time, so that the estimated δ parameters are driven by the average productivity level conditional on a given occupation and not by the relative shares of workers sorting into different occupations. Reassuringly, I still find no indications of occupational discrimination; IWB1 coefficients remain positive and statistically significant for all four occupation categories that I try.[42]

[41] It need not be taste-based discrimination. A model where search is costly for risk-averse employers and where it is more costly to extract accurate information on workers from certain groups would have the same prediction—that workers from those groups would need to be on average "better" (from a value added generating perspective) to acquire a given position.

[42] A weakness of this is that occupation categories are relatively broad; they need to be to maintain a reasonable level of precision in productivity parameter estimates. To further alleviate any residual concern, two additional results are indirectly indicative of an absence of occupational discrimination. The first is the documented differential productivity in

C. External Relevance

Although it is a clear advantage of this paper to hold labor market institutions, technology, and the like constant when studying human capital differences, there is also a potential downside—certain cultural traits detrimental for productivity in the Swedish labor market need not necessarily be so elsewhere. I have tried two separate ways to address this concern. A first route is to estimate country-of-origin-specific labor productivity in other countries, culturally distinct from Sweden; in a second approach, I alter the baseline estimation to control for (within-firm) or remove (outside-of-firm) cultural frictions.

1. Non-Swedish Evidence

Unfortunately, I do not have access to the kind of data in other countries that would allow me to replicate the same exercise. Instead, I am forced to rely on the assumption of competitive labor markets as the literature has relied on and use wages or labor income as a proxy for productive capacity. I study the relationship between inherited cultural values and productivity by first estimating Mincerian regressions with country-of-origin fixed effects according to

$$\ln(w_{h,o,i}) = \alpha_h + \beta_h \mathrm{Ed}_{h,o,i} + \sum_o \mathbf{1}(o_i \neq h_i, o_i = o)\delta_o + \gamma X_{h,o,i} + \varepsilon_{h,o,i}, \quad (7)$$

where subscripts h and o indicate the respective host and origin country of the individual worker. Returns to education, captured by β_h, and intercepts α_h are both host-country specific.[43] The parameters of interest are the country-of-origin-specific intercepts in equation (7), captured by the δ_o parameters. Under the assumption of competitive labor markets, so that the marginal product of labor equals the wage rate, the δ_o parameters in equation (7) estimate a country-of-origin-specific labor productivity (or human capital) that is equivalent to the δ_c parameters in equation (3).

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nonroutine occupations; as these occupations are typically better paid and of higher productivity, the differential results that I document are inconsistent with low-autonomy backgrounds needing to pass a higher productivity bar to acquire those occupations. A second result (not included in this paper) is when I quantify labor input by wage bill and look at whether wage bill input units differ in productivity by IWB1 background. If low-IWB1 backgrounds were discriminated against, they should then be of higher productivity for a given wage bill. I find that the opposite is true. While the second result really speaks to (a lack of) wage discrimination, it seems reasonable to believe that discriminating business owners/managers, hypothetically requiring higher productivity from certain workers for them to obtain a given position, would also require higher productivity from those workers for a given level of monetary compensation.

[43] I restrict attention to male workers and exclude unemployed, as I do in Sweden. Education (Ed) enters as dummy variables by category of education; it is the detailed version of eddattain, which includes 14 different categories that I interact with host-country fixed effects. X includes a third-degree polynomial in age and fixed effects for marital status.

TABLE 10
COUNTRY CHARACTERISTICS AND HUMAN CAPITAL

	Occupation Fixed Effects		Occupation Layer		IPUMS Wages		IPUMS Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IWB1	.0834***	.105***	.0820***	.0941**	.231***	.327***	.239***	.247***
	(.0195)	(.0350)	(.0241)	(.0421)	(.0647)	(.0781)	(.0584)	(.0871)
IWB2	.00984	.0245	.000860	.0227	.111	.150	.151	.152
	(.0183)	(.0269)	(.0186)	(.0249)	(.130)	(.107)	(.117)	(.109)
Hanushek and Woessman (2012)								
education quality		.0448		.00797		−.972***		−.613*
		(.0663)		(.0672)		(.284)		(.316)
Life expectancy at birth		−.00939		−.0106		.0288		.00542
		(.00814)		(.00753)		(.0243)		(.0267)
Fertility rate		.00476		−.00114		−.0485*		−.0480
		(.00807)		(.00842)		(.0243)		(.0334)
Observations	62	62	62	62	50	49	57	56
Adjusted R^2	.225	.251	.246	.253	.243	.616	.274	.504

NOTE.—The dependent variable in cols. 1–4 is the human capital measure across countries, $\hat{\delta}_c$, retrieved from estimating eq. (3) by nonlinear least squares, but where labor efficiency units are calculated based on predicted wages that include occupation fixed effects at the four-digit level in cols. 1 and 2 and an occupation CES layer in cols. 3 and 4. The dependent variable in cols. 5–8 is based on fundamentally different data, from IPUMS instead of Swedish administrative data. The dependent variable there is the $\hat{\delta}_c$ from estimating eq. (7), using wages in cols. 5 and 6 and earnings in cols. 7 and 8. Explanatory variables are as previously defined. Note that the countries listed in the text are host countries, while the number of observations in cols. 5–8 are origin countries. Standard errors are shown in parentheses.

* $p < .1$.
** $p < .05$.
*** $p < .01$.

I make use of data from Integrated Public Use Microdata Series (IPUMS) International to estimate equation (7) and include as many host countries as data availability permits. Columns 5–8 in table 10 present the results of regressing the country-of-origin-specific relative wages (the estimated δ parameters) on country-of-origin characteristics. The results in columns 5 and 6 are based on a restricted sample where data exist for both labor earnings and hours worked, while in columns 7 and 8 the dependent variable is based on total labor income rather than hourly wages.[44] The restricted sample includes data from Brazil, Canada, Mexico, Puerto Rico, and Venezuela; the wider sample also contains the Dominican Republic, Panama, South Africa, and Trinidad and Tobago. Since the paper's main results on determinants of human capital pertain to cultural values, it is of particular interest to investigate the same relationship in countries that are culturally distinct from Sweden. All of the host countries included here (to the extent that they are included in the WVS) have IWB1 values below the global average and are hence characterized by significantly more traditional (or less autonomy-oriented) values than Sweden. As is clear from table 10, the strong, positive relationship between estimated human capital (as proxied by their wage) and IWB1 remains; there are no indications that this relationship varies systematically with the cultural values of the host country. The fact that the relationship persists in countries whose ethnic composition also deviates from that in Sweden should further alleviate any remaining concern that it could be traced to some version of ethnic discrimination.

2. Accounting for Cultural Differences

This paper has proposed the interpretation of the results that it is the level of certain cultural values that explains differences in estimated human capital. An alternative interpretation is that it is not about the level of cultural values but how migrants' cultural values differ from those of the majority population's. This is a particular concern because Sweden is an outlier in terms of the cultural factors—I cannot simply control for both the level and the difference, as they are virtually perfectly collinear. As a complement to the results based on IPUMS data, I also try to address the issue of cultural differences at the micro level in the Swedish data. Since I estimate human capital differences across countries through migrants, those estimates are in principle a function both of the direct level of all of the skills, knowledge, health, attitudes, values, and so on that any one migrant brings and of how those skills and values interact with the host society.

[44] Hours worked are not significantly correlated to the origin country characteristics that I study; thus, for my purposes, this approximation appears justifiable.

That interaction takes place both within the firm and within the broader society, mainly via customers of the firm. I try and isolate the human capital related to the level of cultural values by altering the baseline production function estimation in two ways to address the two respective types of interactions.

First, I control for the cultural dispersion within the firm when I estimate human capital (this dispersion is calculated as the within-firm standard deviation of employees' IWB values).[45] Second, I split the sample of workers based on the degree of customer-facing intensity of an individual worker's occupation (as above, based on data from Sevinc 2019) so that a worker type is defined by both country of birth and whether the occupation is above or below the median ITI value.

The idea with these two alterations is that, by accounting for within-firm cultural differences in the production function and focusing on workers with very limited interaction outside the firm, I isolate the level effect of cultural values. Reassuringly, the results for non-customer-facing workers are similar to the baseline, as well as similar to those having more customer-facing jobs. This approach also constitutes a further robustness check against results being driven by some version of societal-level discrimination.

VII. Conclusion

This paper provides a new measure of human capital. In contrast to previous migrant-based studies, the measure is immune to wage discrimination and robust to other types of discrimination. I find large differences in human capital net of education and experience. In that sense, I reach the same conclusion as other recent migrant-based measures of human capital—that years of schooling and experience are insufficient to properly account for human capital differences across countries—but in my case, these differences cannot be explained by differential discrimination.

Large differences in human capital over and above differences in education and experience beg the question of what determines those differences. The data in this paper support cultural values as a key determinant. Secular-rational as opposed to traditional values, or autonomy, are the strongest and most robust predictors of human capital. The conclusion receives support from both direct estimates of production functions with heterogeneous labor and Mincerian regressions, using data from countries culturally distinct from Sweden. Key pieces of evidence

[45] There is indeed a literature on diversity, suggesting that diversity could be both advantageous and harmful for firm-level output. See, among others, Williams and O'Reilly (1998), Alesina and La Ferrara (2005), Ottaviano and Peri (2006), and Parrotta, Pozzoli, and Pytlikova (2014).

relate to the second generation of migrants: the relationship with productivity persists, so that neither differences in schooling quality nor transferability of skills can account for productivity differences. These differences also remain after controlling for parental characteristics, rendering stories of socioeconomic background as the main driver implausible. Furthermore, several robustness exercises demonstrate that (noncultural) channels related to discrimination—a first-order concern when studying migrants—do not appear to drive the results.

Consistent with a cultural mechanism, high-autonomy backgrounds hold a comparative advantage in roles that are less routinized; they both sort into and have a quantitatively larger productivity advantage in occupations and industries characterized by lower levels of routinization. Again, this comparative advantage is robust to different production function specifications, and it persists into the second generation of migrants.

I consider the estimated impact of culture on cross-country differences in human capital and income conservative. First, there are several points of selection that attenuate the productivity estimates' relation to the cultural values. Second, I estimate only the direct impact on labor productivity and ignore any potential indirect channel, such as the impact of cultural values on institutions, on average educational attainments, on technological progress, or on capital accumulation. These indirect channels, as well as further evidence on autonomy's precise mechanism, are exciting avenues for future research.

Data Availability

Code for replication and information about the data used in this article can be found in the Harvard Dataverse, https://doi.org/10.7910/DVN/BCLL4I (Ek 2023).

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