Horizontal Differentiation: An Improvement Upon the Human Capital Stock Index in Growth Accounting*

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Abstract

In the development growth accounting of cross-country income variation, the human capital stock index has become an increasingly important explanatory factor. At the same time, its value is very sensitive to measurement decisions, making accurate proxies for human capital essential for reliable accounting. The existing literature has progressed to quantify human capital through stratifying by level of educational attainment and weighting each level by its marginal productivity. As explored in the microeconomic literature, however, increased college participation in the past 30 years has made "field of study" increasingly important in the determination of life outcomes and earnings. Drawing on a recently published data set containing college graduates by field of study in 45 countries, I am able to differentiate college educational attainment horizontally, that is by field of study. My newly developed human capital stock index increases the explanatory power of observables in cross-country income variation relative to the previous index by 48 percent, with more conservative but consistently positive increases in alternative accounting measures. This study helps to recognize the importance of horizontal differentiation in education and calls for more macroeconomic research in the topic.

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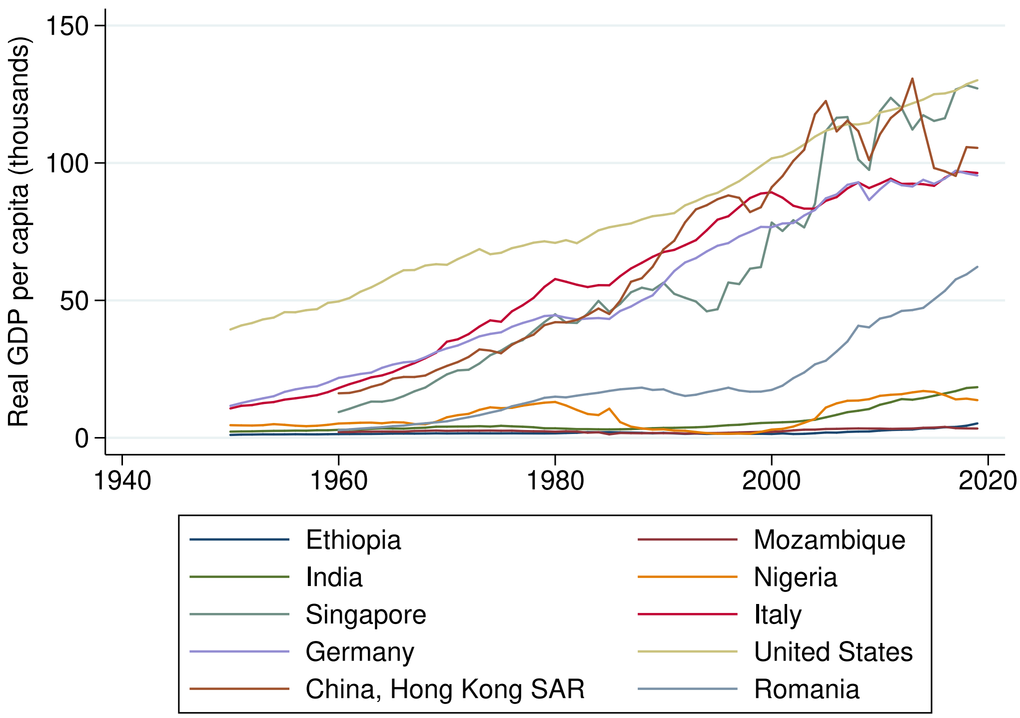
1 Introduction

Economists have long been concerned with the reasons for inequality between countries. Understanding the nature of these disparities can help promote greater global equity in the future. As shown from just a handful of nations in Figure 1 below, cross-country income inequality has grown over the past 70 years by a significant degree. These issues of global inequality are of the utmost importance and demand focus in macroeconomic research.[1]

Figure 1: Real GDP Per Capita



In this paper, I improve upon the existing accounting of country output growth by incorporating horizontal differentiation into the human capital stock index. Using a newly released dataset of college graduates by field of study for over 40 countries, I create a weighted sum human capital index that accounts for varying degrees of productivity by field of study at the bachelor degree level. Including this differentiation in the index increases the explanatory power of the Solow growth model by 48 percent.

Growth development accounting is an important aspect of macroeconomic research, as is evident in the wealth of literature that concerns the topic.[2] Growth development accounting saw its most solid foundations in Robert Solow's "A Contribution to the Theory of Economic Growth" (Solow, 1956). This paper set up the broad model that many

[1] Note that the focus within this context is *between* country inequality, not *within* country inequality. While *within* country disparities are certainly another important focus in economic literature, this study will focus solely on *between* country disparities.

[2] For a good survey of this literature, including a discussion of the three main determinants of cross country income variation (human capital, physical capital, and TFP), see Hsieh and Klenow's "Development Accounting" (Hsieh and Klenow, 2010).

growth development economists have been using since. Solow's theory attributes the output per capita of countries to 1) their physical capital stock to output ratio, 2) the size of their labor force, and 3) an all encompassing residual value that contains a country's productivity as well as any other omitted factors. In response to this paper, economists have been adding to this model in an attempt to reduce the size of the unexplained Solow residual.[3] One of the most successful works in this respect was published by Mankiw, Romer, and Weil (MRW). In "A Contribution to the Empirics of Economic Growth," the authors make a groundbreaking addition to the Solow growth model, incorporating human capital stock alongside the physical capital stock for the first time (Mankiw, Romer, Weil, 1992). This work increased the explanaotry power of the Solow model to 78 percent.

While a seminal work in the evolution of human capital growth accounting, MRW had a somewhat rudimentary measure for human capital stock investment: the percentage of the 12 to 17 year olds in a country in secondary school. More recent works have confirmed the importance of schooling in cross-country income variation accounting (Bils and Klenow, 1998; Benhabib and Spiegel, 1994). Some more technical works have underlined the importance of human capital in explaining these variations, and particularly the sensitivity of this accounting in regards to how the human capital stock is measured (Jones, 2008). For that reason, many economists since the MRW paper in growth development accounting have focused on how the human capital stock is measured, attempting for more comprehensive accounting constructions. This has included accounting for variations in the quality of schooling by country (Angrist et. al., 2019; Kaarsen, 2014). An extremely important addition to the MRW human capital stock index is vertical differentiation in education, or accounting for level of educational attainment. This practice was put forward in a paper by Peter Klenow and Andres Rodriguez-Clare, which incorporated primary and tertiary education into the existing MRW dataset (Klenow and Rodriguez-Clare, 1997). This significantly reduced the explanatory power of human capital in the Solow growth accounting model, indicating that the previous measure was likely not representative of actual human capital.

The microeconomic literature has been engaging in its own work with education, and in ways that have become relevant for growth accounting. Many of these papers have started from the stylized fact that collegiate attendance in the US has risen significantly in the past 50 years, and they explore what this means for field of study (i.e., choice of major). Some works are in more of a theoretical framework, showing major choice decisions to be highly sensitive to expected future earnings (Berger, 1988; also see Manuelli and Seshadri, 2014). Many quantitative pieces have found that as a result of increased college attendance, the variance in lifetime outcomes by field of study has grown, and the choice of college major has become increasingly important in determining these effects (Kim et. al., 2015; Thomas, 2000; Altonji et. al., 2015).

Tying this individual-level research into macroeconomic development growth accounting provides new insight

[3] In one work, social infrastructure such as governmental policies and institutions are cited as another reason for these global disparities in income (Hall and Jones, 1999).

relevant to improving the growth accounting approach. With the growing importance of field of study for lifetime outcomes, this could imply a greater dispersion in the marginal productivities of fields of study, and something that should be accounted for in the growth model.[4] One paper notes the narrowing of the gap in average educational attainment between countries as a result of overall educational growth (Lee and Lee, 2016). This coupled with the fact that cross country incomes are not converging implies the measurement of human capital stock that only accounts for vertical differentiation (different levels of educational attainment) is losing its explanatory power in development growth accounting.

Figure 2 confirms this through an accounting process at 5 year intervals, running the Solow Growth model regression from 1950 to 2010, with the human capital stock index that only accounts for level of educational attainment. There is a clear decline in the explanatory power of the human capital stock index past 1985. [5] What this basic accounting exercise shows, and as is supported by developing microeconomic literature, is that field of study is becoming more important in determining productivity, relative to a general indicator of bachelor's educational attainment. Continuing to implement a human capital stock index that only accounts for levels of educational attainment has decreased in explanatory power over the last 30 years.

Horizontal differentiation that accounts for varying productivity by field of study are now essential in maintaining an accurate proxy for the human capital stock index. This research incorporates newly tabulated data to account for varying productivity by field of study and observes the effects in the accounting model. It calls for further research in the topic with updated data on field of study productivities by country and a consideration for the social benefits by field of study.

2 Data and Methods

2.1 Data

This study draws from the findings of multiple datasets. For information on wages in the US by field of study, I use data from the American Community Survey (Ruggles et. al., 2020). This data is collected on an individual basis, and I collect variables on sex, age, race, educational attainment, field of bachelor's degree, usual hours worked per week, total income, and weeks worked in the year. Figure 3 below shows the average yearly hours worked (for full time workers) by field of study. Note the lowest annual hours are for those who completed only high school and less than high school in education, while the largest average hours are from those with degrees in engineering and agriculture.

[4] Indeed, work is already underway in incorporating field of study in cross country comparisons. One such study compares the labor outcomes in 22 different countries, finding the differences in labor market outcomes by field of study have grown as more students generally graduate from Universities (Reimer et. al., 2008)

[5] I run this accounting exercise with marginal productivities for each level of educational attainment over time constant, at their current values. If these were to change over time as well, the decreased explanatory power of the human capital stock index would be even more severe because the returns to college education were lower in the past.

Figure 2: Solow Growth Model R-Squared Values, 1950-2010

I also utilize a recently published OECD dataset on the raw number of college graduates from 45 different countries, partitioned by the field of study they majored in (OECD, 2019). This information was available for the year 2005 and the years 2010 to 2017. Figure 4 displays the distribution of college graduates shares by field of study in the US in both 2010 and 2017. Between these two periods the biggest changes are a large drop in humanities and large increases in engineering, health, and STEM shares. This may be a result of the Great Recession and individuals' choices to enter into majors with higher salaries and job security.

Figure 5 shows the shares of college graduates, averaged from 2010 to 2017, in Math and the Natural Sciences for each country in the sample. Countries with the largest shares in STEM include Canada, India, and the United Kingdom while the smallest shares include countries such as Luxembourg, Argentina, and Colombia.

Figure 6 compares the shares of college graduates for each field of study between Russia and the United States. The biggest observable differences between shares are in business and law, engineering, fine arts, health, humanities, STEM, Services, and the Social Sciences, of which the US has greater shares in all.

Figure 3: Average Annual Hours Worked by Field of Study (US)

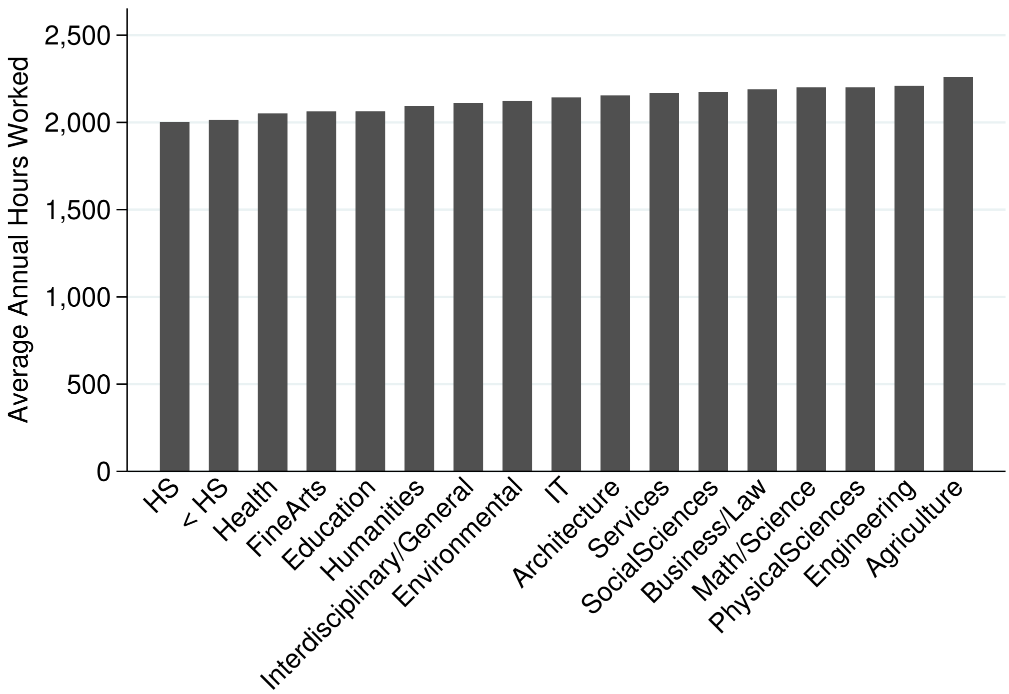


Figure 4: US College Graduates by Field of Study, 2010 and 2017

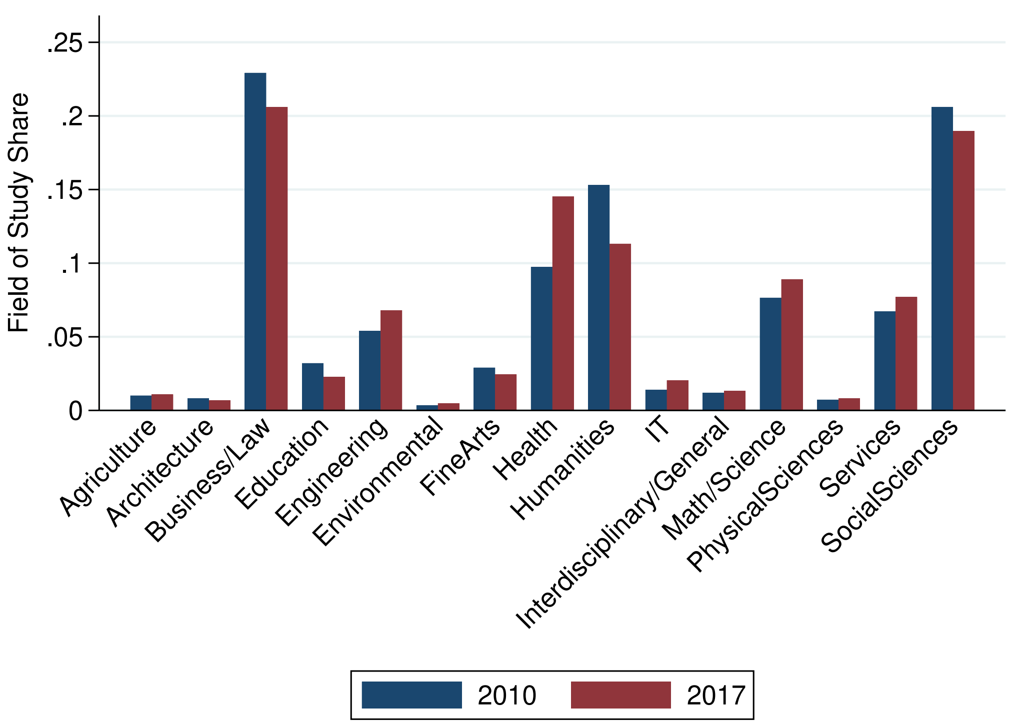


Figure 5: College Graduates in STEM by Country (2010-2017 average)

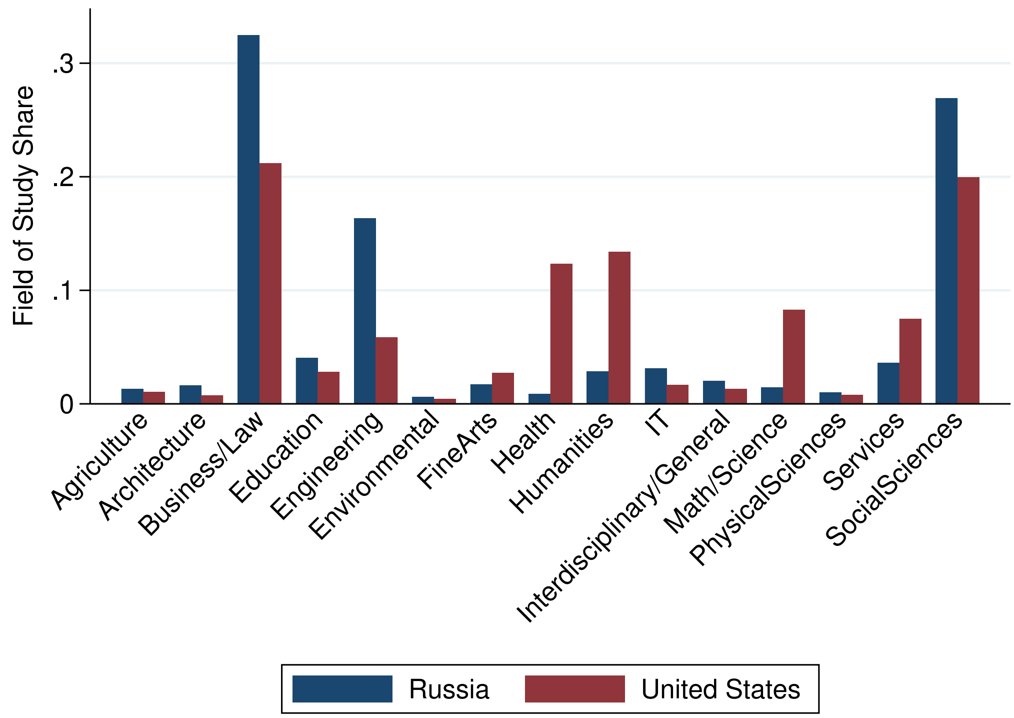
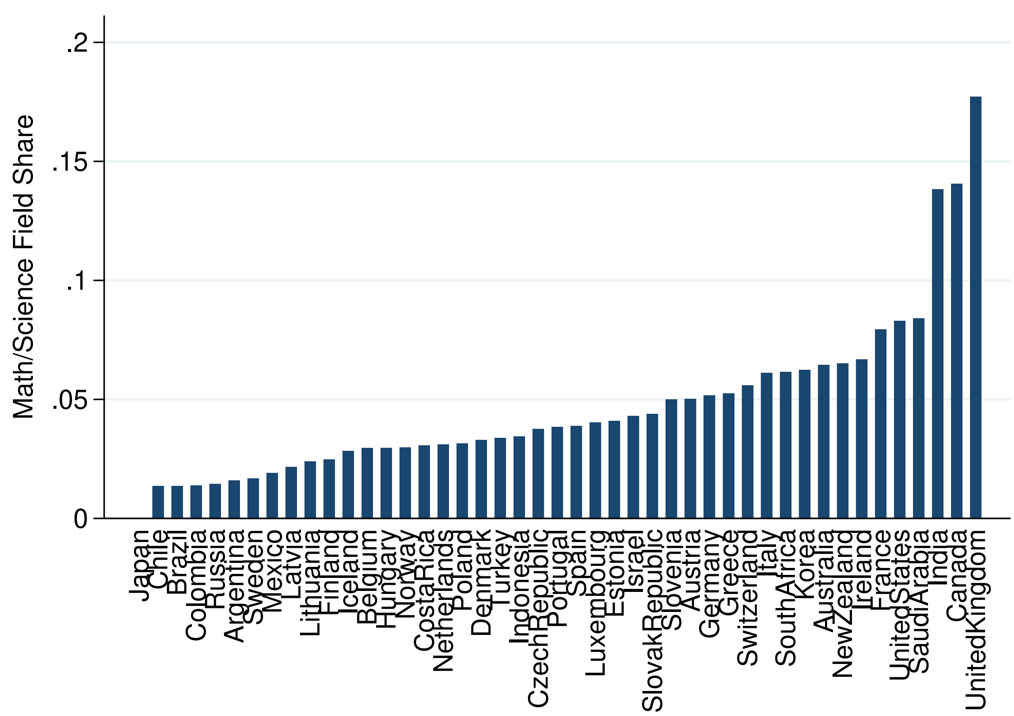


Figure 6: Russia and US College Graduates by Field of Study (2010-2017 average)



I also use data from the Barro Lee Distributions (Barro and Lee, 2013). This contains information at the country level for various educational characteristics. For the purposes of this paper, I pull information on the percentage of country populations whose highest educational attainment was less than high school, high school, and some college. Information in this dataset spans from 1950 to 2010 at 5 year intervals.

The last dataset I consult is the Penn World Tables (summary statistics in Table 1 below; Feenstra et. al., 2015). This source contains information on various national economic indicators for different countries, including income, output, and productivity, and particularly contains information on all the variables used in the Solow Growth model. I draw upon the variables for labor share of output, gdp, labor force, and capital stock for the growth model regressions.

Table 1: Penn World Table Summary Statistics (2010-2017)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Per-Capita Expenditure-side real GDP	1,449	19,733.74	20,481.6	600.779	153,458.3
Per-Capita Output-side real GDP	1,449	18,599.44	19,531.7	606.867	151,928.3
Population (in millions)	1,449	39.338	144.284	0.005	1409.517
Employed (in millions)	1,372	18.486	72.911	0.043	792.575
Average Annual Hours Worked	528	1875.211	261.696	1353.887	2455.551
Household/Government Consumption	1,449	401,050.7	1,288,226	106.558	1.484e+07
Capital Stock	1,433	2,383,583	7,877,208	1672.296	1.058e+08
TFP	934	0.633	0.253	0.161	2.364

2.2 Methods

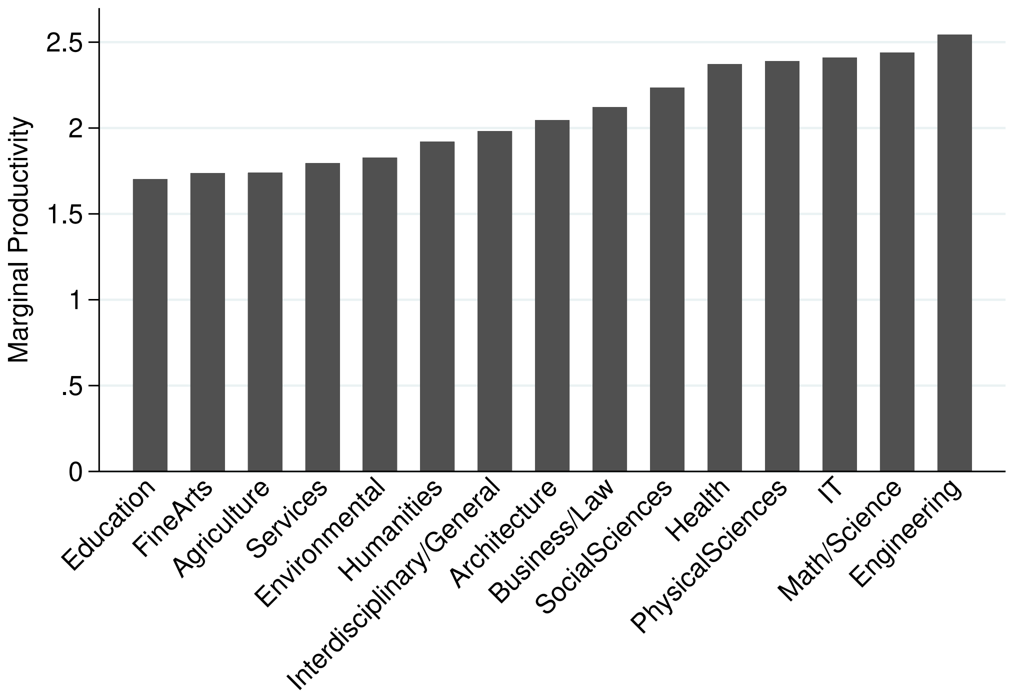
The first portion of methodology derives the marginal productivities of each collegiate field of study. Going off of the assumption that workers are paid their marginal productivity, I utilize the ACS data to derive the marginal wage gains of each major relative to the base case group, those individuals with educational attainment of less than a high school degree. As shown in equation 1, I run a regression with each field of study contained as a dummy variable, along with a series of controls and the other levels of educational attainment.[6] The second term is a summation of field of study dummy indicators. I also control for vertical educational attainment, age, squared age, gender, race, and year-fixed effects. As a regression with the outcome being the natural log of wage and the independent variables being dummy variables, I interpret these coefficients on the field of study variables as expressed in Equation 2. The marginal productivity of each field is equivalent to e raised to the power of the coefficient on the average college (Bachelors) coefficient plus the particular field coefficient. The results of each field's marginal productivity is included in figure 7 below.

[6]The population of this study is limited to full time workers only, which is defined as anyone who worked at least 1200 hours in the calendar year

$$lnw_i = \beta_0 + \Sigma_{j=1}^{n} \beta_j field_{i,j} + \beta_{n+1} HighSchool_i + \beta_{n+2} SomeCollege_i + \beta_{n+3} Bachelors_i + \beta_{n+4} Masters_i$$
$$+\beta_{n+5} Doctoral_i + \beta_{n+6} age_i + \beta_{n+7} age_i^2 + +\beta_{n+8} female_i + \beta_{n+9} race_i + \beta_{n+10} year_t + \varepsilon_i \quad (1)$$

$$MargProd_j = e^{Coeff_{college} + Coeff_j} \quad (2)$$

Figure 7: Marginal Productivities by Field of Study



With each field's marginal productivity now derived, I next derive the shares of graduates by field of study in the OECD data. To remain consistent with traditional methods of growth accounting, I calculate these shares relative to the size of each country's labor force. Due to the fact that the field of study data is only for new graduates and not the aggregate, I divide by the change in the labor force for that year. I then create a variable for the marginal productivity and entered the values derived by the wage regression and Equation 2. With this variable, I then weight each share of college graduates by field according to their marginal productivity. I then sum all the weighted shares together for each country to develop a horizontally-differentiated college level human capital stock. Equation 3 shows the formula for this methodology. The bachelor's level human capital stock index *HC* of each country *i* is equivalent to the sum Σ of graduate shares π by field of study j, weighted by the marginal productivity of each field, δ.

$$HC_i = \Sigma_{j=1}^{n} \delta_j \pi_{i,j} \tag{3}$$

Table 2: Educational Attainment Shares Summary Statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
Labor Force (Millions)	45	32.39	80.69	0.183	517.7
LessHighSchoolShare	45	0.535	0.136	0.264	0.814
HighSchoolShare	45	0.211	0.0807	0.0822	0.398
SomeCollegeShare	45	0.155	0.0769	0.0386	0.408
BachelorShare	41	0.0413	0.0393	0.00128	0.199
DoctoralShare	41	0.00174	0.00232	2.19e-05	0.0108
MastersShare	41	0.0204	0.0269	0.000250	0.133

Note that, to construct the Human Capital Stock index as described, a few assumptions must be made. First, there must be perfectly competitive factor markets. This allows for the assumption that workers are paid their marginal productivity. This is a somewhat constrictive assumption, and one that only measures the private benefit of college degrees as opposed to the overall social benefit, and a point I will talk about more in the dicussion. Second, we must assume that individuals are perfect substitutes across all types of labor. This allows the summation of each type of labor into a uniform value without consideration for spillover effects or frictions between markets. This is a highly restrictive assumption as well, and one that is likely not similar to real labor substitution phenomena. It is, however, a standard assumption made in the existing growth development literature.

As this horizontal differentiation only accounts for college level educational attainment, I derive the other levels of educational attainment in the standard (aggregate) method to complete my human capital stock index. The OECD data also contains total bachelors, masters, and doctoral graduates by country, so the sum of these weighted shares are acquired in the same process as for field of study (See Table 6 in Appendix). For the lower education levels, I utilize the Barro Lee Distribution dataset. The methodology follows as described before, although for this dataset I derived the weighted shares for educational attainments of less than high school, high school, and some college (Also included in Appendix Table 6).

To summarize, the methods engaged through these datasets derive weighted educational shares at the less than high school, high school, some college, college, masters, and doctoral levels. For the college level, I derive both the general bachelors weighted share as well as a share of each individual field of study at the bachelor level. From these level shares, I then construct two human capital stock indices, the first being a baseline model that only accounts for

Table 3: Field of Study Shares Summary Statistics

VARIABLES	(1) Countries	(2) mean	(3) sd	(4) min	(5) max
ArchitectureShare	45	0.0158	0.00946	0	0.0325
EnvironmentalShare	45	0.00270	0.00232	0	0.00944
PhysicalSciencesShare	45	0.00687	0.00505	0	0.0185
SocialSciencesShare	45	0.133	0.0680	0	0.374
ServicesShare	45	0.0429	0.0280	0	0.0888
InterdisciplinaryGeneralShare	45	0.0229	0.0372	0	0.166
ITShare	45	0.0229	0.00977	0	0.0468
HealthShare	45	0.117	0.0813	0	0.330
EngineeringShare	45	0.119	0.0477	0.0466	0.238
EducationShare	45	0.0862	0.0566	0.0113	0.262
FineArtsShare	45	0.0190	0.0140	0	0.0513
BusinessLawShare	45	0.254	0.0875	0	0.458
HumanitiesShare	45	0.0945	0.0894	0.0149	0.517
AgricultureShare	45	0.0167	0.0132	0.00322	0.0743
MathNaturalSciencesShare	45	0.0475	0.0339	0	0.164

vertical differentiation (less high school, high school, some college, bachelors, masters, doctoral) while the second index included an extension that accounts for horizontal differentiation (by field of study) at the bachelor level.

With the baseline and extension human capital stock indices constructed, I then run standard growth development accounting techniques to evaluate whether horizontal differentiation reduces the size of the Solow residual. Using the World Penn Tables, I calculate output per capita (y), capital output ratios ($\frac{K}{Y}$), and the labor share coefficient ($\frac{\alpha}{1-\alpha}$) for each country (i) and run Solow Growth model regressions with both the Baseline (h_{base}) and Extension (h_{ext}) human capital stock indices (For the production function, see Equation 4; Equations 5 and 6 are those from which I derived the regressions). I explore multiple measures of success in evaluating the extent to which horizontal differentiation improves growth development accounting.

$$y_i = A_i h_i (\frac{K_i}{Y_i})^{\frac{\alpha_i}{1-\alpha_i}} \tag{4}$$

$$ln(y_{base}) = ln(A) + ln(h_{base}) + \frac{\alpha}{1-\alpha} ln(\frac{K}{Y}) \tag{5}$$

$$ln(y_{ext}) = ln(A) + ln(h_{ext}) + \frac{\alpha}{1-\alpha} ln(\frac{K}{Y}) \tag{6}$$

One last important feature to note is that the regression implemented herein is not a time linear trend, which is the methodology used by MRW and many other preceding growth development papers. This is a simplification due to data limitations. The data on field of study graduates is not in stock levels, but just for 2010 to 2017 flows. I did not want to make any assumptions or statements about the lagged effects of college degrees on productivity, so I decided not to implement a linear time trend. This may also be a reason for the limited R-squared value observed in the next section.

3 Results

There are multiple measures of success when evaluating the improvement of input factor measurement in an accounting exercise, of which I explored a few. Much of these methods are implemented in an accounting overview paper by Caselli (Caselli, 2004; also see Hendricks and Schoellman, 2017 and Klenow and Rodriguez-Clare, 1997).

The first and most basic technique I implement entails running two Solow growth model regressions, the first with the Baseline Human Capital Stock Index and the second with the Extended Human Capital Stock Index (Equations 5 and 6). The baseline regression yields an R-squared value of 0.0075, while the extension regression yields an R-squared value of 0.0144. This implies that horizontally differentiating the human capital stock index by field of study increases the explanatory power of the Solow growth model by about 48 percent. Note that the R-squared values of both regressions are significantly lower than the findings in previous accounting literature such as MRW or Bils and Klenow. Part of this is likely due to the fact that this study only drew from OECD countries, which yield lower explanatory power in the other studies as well, as the income per capita between the wealthier group of countries are likely due to more nuanced characteristics. Additionally, the lowest level of educational attainment is delineated as anyone obtaining less than high school education, which lumps together a lot of variation at that level. Regardless, this exercise looks to simply isolate the relative improvement of the model from the baseline to extended human capital stock index, so the explicit magnitudes are less pertinent than their relative difference.

A second measure for success (from Caselli) involves comparing the relative differences of variance in the actual output (Equation 7) and two counterfactuals with TFP held constant, for the baseline and extended human capital stocks (Equations 8 and 9). The success measure in this exercise is defined as the ratio of the variance of the counterfactual to the variance of actual output (Equation 10). The success measure calculated for the baseline model is 0.073, while the success measure calculated for the extended model is 0.080, a 9 percent increase.

$$ln(y) = ln(A) + ln(h) + \frac{\alpha}{1-\alpha} ln(\frac{K}{Y}) \tag{7}$$

$$ln(y_{cf,base}) = ln(h_{base}) + \frac{\alpha}{1-\alpha} ln(\frac{K}{Y}) \tag{8}$$

$$ln(y_{cf,ext}) = ln(h_{ext}) + \frac{\alpha}{1-\alpha} ln(\frac{K}{Y}) \tag{9}$$

$$success_1 = \frac{var[ln(y_{cf,base})]}{var[ln(y)]}, \frac{var[ln(y_{cf,ext})]}{var[ln(y)]} \tag{10}$$

Yet another measure of success compares the variance of the country in the 90th percentile to the variance of the country in the 10th percentile and takes the ratio of the counterfactual scenario described above to the actual output (Equation 11). In this specification, the baseline model yields a success measure of 0.802 and the extension model's success measure is 0.908, a 12 percent increase in success.

$$success_2 = \frac{y^{90}_{cf,base}/y^{10}_{cf,base}}{y^{90}/y^{10}}, \frac{y^{90}_{cf,ext}/y^{10}_{cf,ext}}{y^{90}/y^{10}} \tag{11}$$

Hendricks and Schoellman implement another approach in their decomposition analysis to really isolate the added effects of human capital (Equation 13). They do this by constructing a model z_c that contains all factors of the Solow growth model excluding human capital (Equation 12) and then comparing that to human capital alone to see the share breakdown in total accounting (shares because the two terms are set equal to 1 in equation 13). In the baseline model, human capital share (the second term in equation 13) was, on average, 0.112, while in the extended model, the human capital share averaged 0.081, a 38 percent decrease.[7] This is a puzzling outcome in comparison to the other success measures. This horizontally differentiated measure is still highly imperfect, in that it only uses US field of study marginal productivities. It could be that this particular method of measuring success is especially sensitive to this simplified measure, and acquiring field of study marginal productivities for each country could make this method

[7] To see the specific share breakdowns for each country, see Table 7 in the Appendix.

more in line with the results of the others.

$$z_c = (\frac{K}{Y})^{\frac{\alpha}{1-\alpha}} A_c \tag{12}$$

$$1 = \frac{ln(z_c) - ln(z_{c'})}{ln(y_c) - ln(y_{c'})} + \frac{ln(h_c) - ln(h_{c'})}{ln(y_c) - ln(y_{c'})} \tag{13}$$

Klenow and Rodriguez-Clare use yet another method to account for the covariance between TFP and human capital (Equation 14). The baseline model success using this formula is -0.634, while the extension model's success is -0.683, a 7 percent improvement. This is a difficult measure to interpret because one would expect the covariance terms to be positive. Data measurement limitations may once again be the reason for this. Interpreting it as a positive value, this is in line with the results from most of the previous exercises and once again point to an improvement in the development accounting.

$$success_{KR} = \frac{var[ln(y_{cf,base})] + cov[ln(A), ln(y_{cf,base})]}{var[ln(y)]}, \frac{var[ln(y_{cf,ext})] + cov[ln(A), ln(y_{cf,ext})]}{var[ln(y)]} \tag{14}$$

Table 4 summarizes the success measures for each of the preceding accounting equations. The success measures increase for all but the accounting measure that decomposes human capital from other factors and compares to a base country (the US), suggesting a lack of direct precision in the current measurement of the horizontally differentiated human capital stock index, which could be improved with wage data by country for country-specific marginal productivities.[8]

Table 4: Success Measure Outcomes

Equation	Base Success	Extension Success	% Improvement
4	0.0075	0.0144	47.917
10	0.073	0.080	9.356
11	0.802	0.908	11.662
13	0.112	0.081	-38.272
14	-0.634	-0.683	7.174

[8]For more information on the values of particular parameters in the above equations, see Table 5 in the Appendix.

4 Discussion/Conclusion

The findings of this study confirm the importance of horizontal differentiation by field of study in growth development accounting. This human capital stock measure continues to be highly imperfect, however, as shown in the differentiation exercise. One of the main assumptions I make in this paper, and one that restricts a lot of its findings, is that the marginal productivities by field of study are uniform between countries for each field of study. Due to data limitations, with only wage data corresponding with field of study in the US, I applied the assumption that all countries have the same marginal productivities by field os study as observed in the US. This is a highly restrictive assumption, as it is likely the case that some countries will specialize in particular fields, and would have physical capital stock that is more conducive to the productivity of one field over another. Studies have already found that the quality of education varies significantly across countries, so accounting only for attainment, even when horizontally differentiated, is not a comprehensive proxy (Kaarsen, 2014). Additionally, there may be a feedback process in countries whereby the increased productivity in a field attracts more graduates for that major, and increasing the majors in a field could have multiplicative effects for that field's productivity. Obtaining wage information with field of study for each country in the regression would yield more accurate results in the process and develop an even more accurate indicator for the human capital stock index. Still, this study showcases the importance in horizontal differentiation in general. In restricting the study to US marginal productivities, the exercise can be considered a decomposition counterfactual analysis that isolates the effects of major distribution shares by country, holding marginal productivity fixed.

Another implicit assumption made when conducting this study is that the marginal productivity of fields of study is equivalent to wages. This assumption only calculates the private benefit of these fields of study; many studies have come to find that education has spillover effects that benefit others and create a social benefit larger than the private gains.[9] One such study explores this phenomenon in cities, and finds that college graduates help to improve the productivity of nonskilled workers around them (Moretti, 2003). The methods of that study could be extended and differentiated to the field of study level to see if majors vary significantly in their spillover effects and overall social benefit. An example of one hypothetical flaw in only examining private gain could be that although a humanities major has a significantly lower marginal wage gain than a STEM major, the soft skills developed in the humanities relating to social skills and communication abilities may have more productive effects in a spillover context. Under this theory, the private gain would be significantly underestimating the overall marginal productivity of a humanities major.

A next big step in this area of research would be to explore the causal mechanisms driving field of studies distributions in countries. The exercise herein asserted the topic's importance; further research is necessary to explore causality. A confounding conclusion to draw from this research would be that countries should redirect their citizens into more productive fields of study to improve their income per capita. Some studies have grappled with the issue of

[9] This notion is rooted in a theoretical model of the human capital stock index developed by Ben Jones that incorporates a multiplier value over all units of labor from an additional unit of skilled labor (Jones, 2014)

selection bias, whereby individuals with higher skill sets will direct themselves toward more lucrative majors, thereby endogenizing ability into the productivity gains of field of study (Kinsler and Pavan, 2015). The relative wage of skilled workers is also not exclusively determined by their own attributes, and instead can be influenced by technology, institutions, and other features of the economic environment (Caselli and Ciccone, 2019). Additionally, future earnings are not the only considerations individuals have in making their major choice decisions. Levels of lifetime satisfaction vary significantly by major choice, for example, and fields of Arts and Humanities have significantly higher levels of satisfaction than other fields while exhibiting a lower marginal wage gain (Wolniak, 2005). There are many other considerations in choosing a field of study that wage gains do not capture.

Another interesting extension of this research, and one that can already be undertaken with the data in this study is accounting explicitly for horizontal differentiation by gender. If one were to derive field of study marginal productivities by field of study, and within each field of study by gender, and applied these to the shares of college graduates by field of study and gender, explanations in the growth accounting could significantly increase. The intuition behind this importance would be that countries are on different paths of development in regard to female access to the labor market. In countries where women are less able to earn a degree and work, there are likely significant misallocations of talent within that nation's economy that hinders their overall income levels and growth.[10] Studies have found that the returns to education are greater for women than for men, so countries that restrict female ability to obtain higher education are losing these gains (Psacharopoulos, 1994). Additionally, studies show that college major choice decisions vary significantly by gender, where men decide more on external career advancement, job opportunities, and level of compensation, while women are more concerned about their own aptitude within a subject (Malgwi, 2005). Accounting for these differences in the growth accounting could significantly increase the explanatory power of the human capital input.

Generally speaking, the findings of this study open a lot more avenues for discussion and research within the field of growth development accounting. Human capital is an extremely transient variable that will likely always need adjustments in its measurement, and exploring these nuances of human capital can help to greatly improve that measure.

[10] For more information on the misallocation of talent, see (Hsieh et. al., 2019).

5 Appendix

Table 5: Values for Success Measures

Statistics	Values	Countries
var[ln($y_{cf,base}$)]	0.019	N/A
var[ln($y_{cf,ext}$)]	0.021	N/A
var[ln(y)]	0.265	N/A
$y^{90}_{cf,base}$	7.737	Indonesia
$y^{10}_{cf,base}$	2.597	Canada
$y^{90}_{cf,ext}$	7.721	Indonesia
$y^{10}_{cf,ext}$	2.287	Canada
y^{90}	106,849.2	Switzerland
y^{10}	28,774.09	Brazil
ln(z'_{base})	11.564	United States
ln(z'_{ext})	11.619	United States
ln(h'_{base})	0.061	United States
ln(h'_{ext})	0.007	United States
ln(y')	11.626	United States
cov[ln(A_{base}), $ln(y_{cf,base})$]	-0.187	N/A
cov[ln(A_{ext}), $ln(y_{cf,ext})$]	-0.202	N/A

Table 6: Total (Weighted Sums) and Levels of Educational Stock

Country	>HS	HS	SomeCollege	Bachelors	Doctoral	Masters	HCBase	HCExt
Argentina	0.724	0.186	0.070	0.015	0.000	0.002	1.065	1.040
Australia	0.401	0.215	0.231	0.050	0.002	0.016	1.088	1.003
Austria	0.582	0.249	0.102	0.021	0.002	0.023	1.100	1.064
Belgium	0.493	0.196	0.185	0.042	0.002	0.032	1.118	1.046
Brazil	0.721	0.156	0.072	0.103	0.001	0.003	1.184	1.009
Canada	0.340	0.192	0.296	0.081	0.003	0.022	1.157	1.019
Chile	0.600	0.228	0.118	0.013	0.000	0.003	1.054	1.033
Colombia	0.660	0.126	0.112	0.009	0.000	0.004	0.983	0.968
Costa Rica	0.688	0.096	0.112	0.112	0.000	0.014	1.173	0.982
Czech Republic	0.463	0.398	0.092	0.030	0.002	0.021	1.151	1.100
Denmark	0.468	0.241	0.175	0.087	0.004	0.044	1.240	1.092
Estonia	0.395	0.272	0.198	0.011	0.001	0.005	1.012	0.993
Finland	0.569	0.138	0.199	0.199	0.011	0.096	1.570	1.232
France	0.558	0.224	0.146	0.066	0.004	0.072	1.293	1.182
Germany	0.442	0.326	0.139	0.018	0.002	0.012	1.070	1.039
Hungary	0.473	0.313	0.112	0.018	0.001	0.009	1.040	1.009
Iceland	0.585	0.145	0.163	0.012	0.000	0.006	1.007	0.987
India	0.744	0.148	0.065	0.038	0.000	0.009	1.089	1.024
Indonesia	0.789	0.130	0.048	0.001	0.000	0.000	1.009	1.006
Ireland	0.419	0.134	0.265	0.032	0.002	0.014	1.023	0.969
Israel	0.384	0.199	0.251	0.017	0.001	0.007	1.001	0.972
Japan	0.468	0.237	0.177	0.012	0.002	0.003	1.016	0.995
Korea	0.394	0.192	0.221	0.034	0.001	0.008	0.994	0.936
Latvia	0.537	0.273	0.113	0.071	0.001	0.023	1.182	1.061
Lithuania	0.433	0.292	0.163	0.054	0.001	0.018	1.127	1.035
Luxembourg	0.509	0.166	0.195	0.002	0.000	0.002	0.974	0.971
Mexico	0.688	0.102	0.121	0.015	0.000	0.002	1.002	0.976
Netherlands	0.482	0.229	0.174	0.100	0.002	0.043	1.252	1.082
New Zealand	0.567	0.087	0.231	0.030	0.001	0.004	1.043	0.992
Norway	0.451	0.265	0.187	0.020	0.001	0.010	1.071	1.036
Poland	0.501	0.316	0.110	0.100	0.001	0.050	1.296	1.126
Russia	0.272	0.149	0.408	0.037	0.003	0.133	1.360	1.297
Saudi Arabia	0.684	0.162	0.092	0.015	0.000	0.001	1.025	0.999
Slovak Republic	0.469	0.382	0.097	0.022	0.002	0.025	1.141	1.103
Slovenia	0.463	0.323	0.128	0.060	0.011	0.038	1.219	1.118
South Africa	0.627	0.332	0.039	0.009	0.000	0.001	1.081	1.066
Sweden	0.462	0.273	0.159	0.012	0.001	0.010	1.041	1.020
Switzerland	0.398	0.284	0.191	0.032	0.002	0.015	1.081	1.026
Turkey	0.796	0.100	0.063	0.019	0.000	0.002	1.035	1.002
United Kingdom	0.478	0.253	0.162	0.037	0.003	0.022	1.108	1.045
United States	0.264	0.213	0.340	0.033	0.001	0.015	1.063	1.007

Table 7: Equation 12 Measures

country	eq12_base	eq12_ext	eq12_basehshare	eq12_exthshare
Argentina	1.000	1.000	0.002	0.027
Australia	1.000	1.000	0.096	0.021
Austria	1.000	1.000	0.110	0.157
Belgium	1.000	1.000	0.173	0.144
Brazil	1.000	1.000	0.068	0.002
Canada	1.000	1.000	0.184	0.039
Chile	1.000	1.000	0.011	0.029
Colombia	1.000	1.000	0.054	0.027
Costa Rica	1.000	1.000	0.069	0.020
Czech Republic	1.000	1.000	0.095	0.104
Denmark	1.000	1.000	0.279	0.200
Estonia	1.000	1.000	0.062	0.018
France	1.000	1.000	0.322	0.299
Germany	1.000	1.000	0.023	0.094
Hungary	1.000	1.000	0.028	0.003
Iceland	1.000	1.000	0.125	0.047
India	1.000	1.000	0.011	0.008
Indonesia	1.000	1.000	0.031	0.000
Ireland	1.000	1.000	0.137	0.138
Israel	1.000	1.000	0.121	0.070
Japan	1.000	1.000	0.105	0.027
Latvia	1.000	1.000	0.098	0.054
Lithuania	1.000	1.000	0.064	0.033
Luxembourg	1.000	1.000	0.383	0.157
Mexico	1.000	1.000	0.055	0.029
Netherlands	1.000	1.000	0.281	0.181
New Zealand	1.000	1.000	0.036	0.029
Norway	1.000	1.000	0.036	0.149
Poland	1.000	1.000	0.189	0.128
Republic of Korea	1.000	1.000	0.130	0.140
Saudi Arabia	1.000	1.000	0.183	0.053
Slovakia	1.000	1.000	0.086	0.106
Slovenia	1.000	1.000	0.145	0.119
South Africa	1.000	1.000	0.015	0.049
Sweden	1.000	1.000	0.080	0.044
Switzerland	1.000	1.000	0.207	0.223
Turkey	1.000	1.000	0.064	0.010
United Kingdom	1.000	1.000	0.094	0.086

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