Modeling TFP Growth with an Augmented Solow Residual Growth Model

Using Human Capital Measures in Worldwide Panel Data

Brayden Binder

This paper studies the effects of human capital on the growth rate of total factor productivity using worldwide panel data from 1950-2019. The metric of human capital used is a combined metric using both the quantity and quality of education in a country. I use an augmented Solow residual model to study the direct and indirect effects of human capital on TFP growth and look for the appearance of conditional convergence in the model. The estimation results show the positive and statistically significant effect of human capital on 5-year average annual TFP growth rates, and it predicts the convergence of TFP growth rates to that of the technology leader country, the U.S. Evidence for the theory that human capital facilitates TFP growth indirectly through technology diffusion was weak when looking at the marginal effects of human capital on the "catch up" variable. From these results I discuss the necessity for proper investment in education in order to improve the living conditions of a population. Thus, I give empirical input into the contemporary debate regarding the overall role and importance of education for a country.

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I. Introduction

Currently, education policies have been at the forefront of political debate. Many movements have sprung up with a variety of opinions on how to deal with the rising cost of higher education, how to improve our education system, and many differing opinions on how to view higher education. For instance, there has been a recent movement in the U.S. saying that college should not be seen as the be-all end-all for young people. Instead of solely pushing higher education to young adults and adolescents, schools should also put an equal emphasis on vocational schools. Conversely, there has been another movement that puts further emphasis on higher education by stating that the government should make attending public universities tuition-free. Even more questions in regard to education prevail such as: how should charter schools be dealt with, should standardized testing be continued, etc.

As a result, economics literature would benefit all by answering these questions. Further, it would be timely for studies to harken back in on the basic function of education and its effects on the country as a whole. Intuitively, it makes sense that the more educated people are, the more productive workers they become. But what is not straight forward is quantifying the actual relationship between education and productivity. In economics the term used to describe education and its effect on an individual is "human capital". Human capital is the measurement of the relative skills and knowledge of the individual, group, or population. In other words, the more education an individual, group, or population receives, the greater their human capital.

In the past, economists have used two main ways to measure human capital: one computation through quantity, and one through quality. The "quantity" version of human capital is evaluated through looking at the average years of schooling of the relative population. Usually the average years of schooling metric would begin after a certain age in order to capture the skills and knowledge of the actual working population. Each version of human capital comes with advantages and disadvantages and can vastly change the interpretation of the regression results. For instance, take the quantity version of human capital. The biggest advantage in using human capital with this measure is that the data is generally widely available, and the interpretation is clear. When you increase the average years of schooling by X%, it will result in an increase of Y for the dependent variable. However, one drawback of the quantity measure is that it does not take into consideration the quality of the education. It creates a fallacy in saying that one year of education creates the same amount of increase in skills and knowledge (human capital) regardless of location and education system. Therefore, one year of education in Mexico, Norway, Japan, Russia, etc., is equal to one year of education in the United States, Guatemala, England, India, etc.

An advantage of the quality measures of human capital is that they differentiate the quality of the education systems from each other. In other words, they actually show the disparities in the knowledge and skills of different populations. The large drawback, however, is that the data is not widely available, and can become highly subjective. A common way to collect the quality metric is to use international test scores, but the standardized tests have not been around for a long period of time and may not be used by all countries. The subjectivity factor comes into play when one has to decide which tests to use, and how to weigh them if they use multiple. On top of that, the tests most likely are administered to younger children, so the gains in knowledge in the adolescent years may not be captured by the data. Finally, the years of schooling does intuitively matter for human capital. Logically, we do think of graduate students or doctoral students as being more educated individuals than those with a high school diploma, even if we do not know what subjects those students are studying.

I mention these metrics of human capital in order to propose the purpose of this paper. The main goal of this paper is to examine the relationship between human capital on technological progress and diffusion throughout the world, using an augmented Solow residual model. Using a new metric of human capital, I am looking to further establish the relationship between human capital and total factor productivity (TFP) growth. TFP can be defined as productivity growth resulting from changes in technology, i.e., productivity growth due to technological progress and innovation. The model I employ, used by Akhvlediani and Cieślik (2019), is an augmented Solow residual model as it considers the endogenous relationship between technological progress and human capital. This endogenous relationship is observed in a direct effect way, and in an indirect effect way. My hypotheses are as follows:

H_0: Human capital is statistically significant and has a positive effect on total factor productivity growth.

H_1: Human capital is a positive facilitator of technology diffusion.

H_2: There will be a convergence of growth rates in the model.

The dependent variable I will be using is TFP growth, and the independent variables will be human capital, the convergence or catch-up term, and the lagged growth of TFP. As my model has been used before, my paper aims to strengthen the study of human capital by looking at its relationship to TFP growth with an improved measurement. I will be assessing whether the ideas of conditional convergence, technology diffusion, and the new metric of human capital hold up in explaining the Solow residual using worldwide panel data. On top of this, there appears to be a necessity to reestablish what education does, or what role it plays for an economy. In other words, I will explain how exactly education, through human capital, plays into the development—more specifically the technological development—of a nation.

I further the discussion and study of human capital and education in four main ways. First, I will look at the relationship between human capital and total factor productivity. Second, I will assess if there is evidence of technology diffusion. Third, I will explain if the model estimation supports the theory of the conditional convergence of TFP growth rates. Fourth, I will give my interpretation of the results in terms of what it means for education as a whole.

The next sections of this paper are as follows: Section II gives clear explanations of my overall contributions to human capital literature and provides reviews of related economic literature, Section III presents both the economic theory model and the regression model, with explanations, Section IV states the data sources and shows the summary statistics, Section V presents the estimation results and analysis, Section VI includes a robustness check, and finally, Section VII concludes the paper.

II. Literature review

Overall, my contributions to human capital literature mainly come from using the best metric of human capital to date, and by using worldwide panel data with a longer time period to obtain more robust results from the model. In other words, I use the models employed by Akhvlediani and Cieślik (2019), and study if the various theories and overall model holds up when looking globally. The results will show the relationships more precisely not only due to having more years of data to work with, but because I am using data from 183 countries in that time period. Further, this different than many other empirical papers, who have mostly looked at their metrics of human capital in a certain section of the world. For instance, the researchers may only look at

OECD nations or European nations. Thus, I am testing a theory in the most widespread way possible, in order to see if theory really does predict reality. The goal is to look empirically at the various theories for the case of the whole world, not to create a counter theory. From this empirical basis, I will then talk about some of the original issues surrounding education to more clearly present education's purpose in an economy.

What should be considered the biggest contribution of this paper to human capital literature is the use of the new form of human capital with the old theory. As stated before, human capital usually has two metrics: quantity or quality. The metric for human capital I use for my data considers both quantity, based on average years of schooling, and quality, based on the returns to education. This is a very new measure of human capital and is revolutionary for the study overall. Originally, studies had to make the subjective choice whether quantity or quality was a better metric of human capital, and future studies will not have to do that anymore. Now, what could be called the "combined" human capital can be altered, fixed, and improved by future studies. By using this combined version of human capital, the disadvantages incurred from choosing one of the specific forms go away, leaving only their advantages. In other words, this combined version of human capital incorporates the quality of quantity of education into one internationally comparable index without the past drawbacks. This not only makes logical sense that both forms of human capital matter and is demonstrated through empirical evidence in this paper.

Nonetheless, past studies researching human capital still have some very interesting and strong findings even with the earlier versions of human capital. For instance, Hanushek and Woessmann (2012) studied the causal relationship between the relative "cognitive skills", or educational achievement, of a country's citizens with GDP growth. They aimed to strengthen human capital research using their metric of "cognitive skills", while criticizing past studies that used average years of schooling as the base metric of human capital. Instead, their metric was constructed using panel data consisting of 64 countries looking at their relative math, reading, and science test scores from 1960-2000. Since Hanushek and Woessmann (2012) use test scores as their metric of human capital, they are not measuring human capital through the quantity of education, they purely look at the education's quality.

The theoretical model they employed was: $H = \lambda F + \phi(qS) + \eta A + \alpha Z + v$, where H represents the skills of workers, or human capital, F stands for family inputs, qS stands for the quantity (q) and quality (S) of inputs provided by schools, A stands for individual ability, Z represents other relevant factors, and v is the error term. Hanushek and Woessmann (2012) found a direct causal relationship between cognitive skills and economic growth while controlling for other country-specific factors. They found that the more skilled the labor force is, the more rapid is the adoption of new technologies, leading to further technological diffusion and growth. Through regression analysis they found that a one standard deviation increase in a country's cognitive skills results in a 2% higher annual GDP per capita growth rate.

In addition, Hanushek used another quantity metric of human capital in a later, more comprehensive study than their previous research. Hanushek et al. (2017) were able to calculate the economic gains relative to U.S. states as well as for the whole U.S. as a whole resulting from different education policies. They began their article by emphasizing the incompleteness of other education studies which used average years of schooling as their metric of human capital. Instead, they introduced their metric of what they call "human knowledge capital", which is a quality measurement of human capital. Using panel data from 1970-2010, they created a regression model analyzing the effect that average test scores had on the annual growth of state

GDP per capita. The data Hanushek et al. (2017) used was from the National Assessment of Education Progress (NAEP). They found that a one-standard-deviation—or 100 points—increase in scores resulted in a 1.31% faster annual growth rate for state GDP. They use this as the basic relationship between human knowledge capital and annual GDP growth rates and extrapolate their model to analyze different education policies.

The first policy explored was a 0.25 standard deviation improvement for all states' test scores, and Hanushek et al. (2017) found this led to an average discounted increase of 5.2% for state GDP in 2095, or a discounted value of $43,561 billion for the whole U.S. Their second policy involved bringing all states up to the level of the best test-score-performing state. Their model predicted this policy to result in an average increase of 8.3% state GDP in 2095, or $69,697 billion if implemented for the whole U.S. Their third policy was to have each state reach the test score level of the best performing state in their region and resulted in an increase on average of 3.9% state GDP, a discounted value of $32,810 billion for the U.S. Their last policy was to set a minimum skill level on the tests, and it resulted in an increase of 3.5% of state GDP on average, or $29,738 billion. These economic gains are massive, and to be clear, these percentage increases in GDP are gains above what the 2095 GDP is expected to be in their model if the current U.S. education system and policies stay the same. One implication of this study is that education is long-term investment, its effects are not seen until those included in the new policies become a larger portion of the labor market with the retirement of the pre-policy workers.

In contrast to these past two studies, Akhvlediani and Ceiślik (2019) used a quantity metric of human capital in their research. They studied the effect of human capital—measured through average years of schooling—on technological progress, technology diffusion, and convergence of TFP growth rates for all countries in Europe. Using panel data from the PWT 9.0 for TFP growth rates from 1950-2014 in 5-year averages and human capital measures, they found positive and statistically significant effects of human capital on TFP growth and technology diffusion. Akhvlediani and Cieślik (2019) used the Nelson-Phelps augmented Solow-growth model, which instead of treating human capital as a factor of production, treats human capital as a facilitator of technological progress and growth.

Through their estimation results, they found that if human capital increases by 10%, the TFP growth rate would increase by 0.35%. However, they found that this increase in TFP growth rates could range from 0.23% to 0.7%, depending on how close the country i is to the leader country in the catch-up ratio. On top of looking at the direct effect of human capital, Akhvlediani and Cieślik (2019) also had insights into the indirect effect of human capital on TFP growth through technology diffusion. They found a negative relationship between the catch-up term in the model, which implies verification of conditional convergence. If in my model the catch-up term is also negative, H_2 will be further verified. More will be said regarding their theoretical and regression models in the next section, as I employ both models in this research paper. The research from Akhvlediani and Cieślik (2019) is the most instrumental for my paper, as it was the original inspiration for me to search for more complete versions of human capital, and attempt to verify the effects of human capital using global data.

Furthermore, the quantity metric of human capital has been used by many other researchers. Panda (2017) studied TFP growth for 48 US states using panel data covering 1980-2010. Panda wanted to contribute to TFP growth literature through divergence from the neoclassical model of TFP growth created by Robert Solow. In contrast to Robert Solow's "primal TFP growth" equation, Panda used the "dual accounting" model of TFP growth. The dual accounting growth method sees TFP as a function of both real wage growth rates and real user cost growth rates, while accounting for the after-effect TFP has on the factors as well. As Panda states, an increase in the two factors increases TFP, which increases output, which then increases overall prices, including real wages and real user costs. The dual accounting model employed by Panda (2017) was: $TFPG_{s,t} = \bar{\alpha}_{L,s}\widehat{w}_{s,t} + \bar{\alpha}_{K,s}\hat{r}_{K,t}$, where $\bar{\alpha}_{L,s}$ and $\bar{\alpha}_{K,s}$ represent the two-period average shares of labor income and capital income, respectively, and $\widehat{w}_{s,t}$ and $\hat{r}_{K,t}$ represent the state-specific real wage growth and real user cost growth rates, respectively. Panda found that the real user cost had a slightly stronger effect on state variations in TFP growth rates than real wage growth.

In the second part of the paper, Panda (2017) used the dual accounting model of TFP growth, and looked at the quantity effect of years of college education and years of high school education on TFP growth using model: $g_{s,(t,t+10)} = \alpha_t + \gamma Schooling_{s,t} + \delta Log(Labor\ productivity)_{s,t} + \beta'^{X_{s,t}} + \epsilon_{s,t}$. They found that a one-year increase in college education per worker raised the annual state growth rate by 0.452 percentage points, or 4.52% over a decade, but found no significant association between TFP growth and high school education.

The original theoretical study by Nelson and Phelps (1966) was instrumental in the study of human capital and TFP growth. Not only did Akhvlediani and Cieślik (2019) and Hanushek and Woessmann use their theoretical model to study various aspects of human capital and TFP growth, but Vandenbussche et al. (2006) also employed their model. Specifically, Vandenbussche et al. (2006) studied the relationship between human capital and technology diffusion. Using panel data from 19 OECD countries from 1960-2000, they studied through many regression models how technology diffusion occurred in these nations. In all models, they found that skilled labor (attained through tertiary education), with unskilled human capital held constant, had a higher TFP or economic growth spurring effect the closer the country was to the technology frontier. The technology frontier is the idea proposed by Nelson and Phelps (1966) that rich countries are the closest to the technology frontier, or even may be the leader country, as they are producing or using more advanced technologies. The closer a country is to the frontier, the more innovative and progressive they are with their available technologies.

Vandenbussche et al (2006) found that most if not all of OECD countries would benefit from a larger fraction of their workforce being skilled as they are generally closer to the technology frontier. Due to this, they analyzed how educational attainment in countries closer to the frontier effected TFP growth. Not surprisingly, they found that the closer a country is to the technology frontier, given a level of tertiary education, the more negatively primary/secondary educated individuals contribute to TFP growth. We can interpret many things from their study, but one main takeaway should be that the closer a country is to the technology frontier, the more it relies on skilled labor for TFP growth. In other words, the more educated the people are in a technologically progressive country, the more TFP growth and thus economic growth for that country.

Most of these studies, if not all, were in some way influenced by the work of Nelson and Phelps (1966). They paved the way for human capital with a theoretical model that includes an endogenous relationship between human capital and technological progress and diffusion. For my paper I use the new metric of human capital, used in the PWT 10.0, which is a combined version of human capital. Using the data from the PWT 10.0, I will attempt to verify if the Nelson-Phelps augmented theoretical Solow residual model of TFP growth holds true. I will contribute to the literature by looking in the most expansive way possible, testing to see if human capital with worldwide data still has a positive effect on TFP growth or technological progress, and technology diffusion. Further, as this is a verification of an augmented neoclassical model, I am looking for the appearance of conditional convergence within the estimation results through the variable representing the endogenous nature of technology progress and human capital.

III. Modeling procedures

Many economists have taken the original theory by Nelson and Phelps (1966) and tested it by creating an equivalent regression equation. Their original theory transformed into an equation is as such:

$$\varDelta a_{it} = b + (g + c)h_{it} - c(h_{it})\left(\frac{A_{it}}{A_{mt}}\right) + \xi_i + \varepsilon_{it} \qquad (Eq. 1)$$

where $\varDelta a_{it}$ is the annual growth rate of total factor productivity (TFP) of country i at time t, b is the constant technological progress, g is the growth rate of TFP based on the level of human capital, c is the "catch up term" defining technology diffusion, h_{it} is the human capital level of country i at time t, $\left(\frac{A_{it}}{A_{mt}}\right)$ is the ratio between country i's TFP level and the leader country's level, ξ_i is the time invariant fixed-country effect, and ε_{it} is the error term.

In the theoretical equation, $(g + c)h_{it}$ represents the direct effect that human capital, h_{it}, has on TFP growth, a_{it}. This shows the direct relationship because when the model is transformed again into a regression equation, the changes in a_{it} occur due solely to changes in h_{it}. In past studies, one quantity metric for h_{it} was average years of schooling for country i at time t. As such, the interpretation of the model would be such that a 1% increase in average years of schooling would increase TFP growth by a certain amount. Conversely, if the researcher used a quality metric of human capital, the interpretation would be based on how the increases in standard deviations of test score points effected TFP growth or other metrics like GDP growth. As such, $(g + c)h_{it}$ models the direct relationship between human capital and TFP growth.

Meanwhile, $c(h_{it})\left(\frac{A_{it}}{A_{mt}}\right)$ represents the indirect effect of human capital on TFP growth through the neoclassical idea of conditional convergence. Due to this, there is a minus sign in front of this term. The basic idea of conditional convergence, created by Robert Solow in the original Solow model of growth, is that as countries approach the leader country in terms of the value of the human capital and amount of technology present, growth rates slow down. Logically, this makes sense as it is difficult for bigger and more technologically advanced countries to make huge gains in TFP as they are the main drivers of TFP in the world. In other words, they are the leaders in technological innovation and progress. It is difficult for nations that already have the best measures of TFP and human capital in the world to make larger gains. It would seem improbable that a population that is already the most skillful and knowledgeable in the world would in a span of five, ten years, become five percent smarter and more skillful than they were in the past. The model predicts, however, that this amount of growth it possible for smaller nations who are "catching up" with those technological leader countries.

As such, $c(h_{it})\left(\frac{A_{it}}{A_{mt}}\right)$ represents the indirect effect of human capital because it shows the effect of human capital on technological progress through technology diffusion. In order to adopt new technologies, the labor force needs to have the skills and knowledge, or human capital, necessary to use them. Thus, human capital indirectly effects TFP growth as it allows for technology diffusion to occur. The model suggests that the more human capital present in an economy, the easier the country can adopt new technologies in order to catch up to the leader country. Human capital is then considered in this model to be a facilitator of technological adoption. Consequentially, human capital is most adequately defined in this part of the equation to have an indirect effect on TFP growth as it allows for countries far from the technological frontier to “catch up” to the leader nation. In the process of catching up to the technological progressive leader country, human capital stock will grow, making it harder and harder to make impressive gains in TFP growth. This model of TFP growth heavily differs from the original model of the Solow residual, or TFP growth. The original model of TFP growth rates is shown by Panda (2017) to be:

$$\hat{A} = \hat{Y} - \alpha_K \hat{K} - \alpha_L \hat{L} \qquad (Eq. 2)$$

where, TFP growth, $\hat{A}$, is the residual of an economy’s output, $\hat{Y}$, after subtracting the weighted shares of the $\hat{K}$ growth rate of capital, and $\hat{L}$ growth rate of labor. Hence, it is the residual of output growth that cannot be explained by changes in capital or labor, therefore called the Solow residual.

Moving forward to my actual regression model, I use the same model that Akhvlediani and Cieślik (2019) use, which is the transformed version of the Nelson and Phelps (1966) theoretical model into a regression model. The model employed is as follows:

$$growthtfp_{collapsed} = \beta_0 + \beta_1 loghc + \beta_2 hcratio + \xi + \varepsilon \qquad (Eq. 3)$$

where $growthtfp\_collapsed$ is the five-year average growth rate of TFP, β_0 is the constant, $loghc$ is the level of human capital in log format, $hcratio$ is the catch-up term, and ξ is the fixed effects for the given country. The dependent variable $loghc$ represents the direct effect of human capital on TFP growth rates, $(g + c)h_{it}$ in the theoretical model. The dependent variable $hcratio$ represents the indirect effects of human capital on TFP growth, or $c(h_{it})\left(\frac{A_{it}}{A_{mt}}\right)$ from the theoretical model. I predict that β_1 will be positive, seen in H_0, and β_2 will be negative, seen in

H_2. The second hypothesis, H_2, will only be verifiable when looking at the marginal effects of $loghc$ in the $hcratio$ variable.

IV. Data and Data Analysis

All of the data for my research paper comes from the newest form of the PWT, the PWT 10.0. One of the largest changes from the PWT 9.0 to the PWT 10.0 is the appearance of the new combined metric of human capital. Thus, the PWT 10.0 instead employs the combined quality and quantity version of human capital, based on both average years of schooling and returns to education. Past versions of the PWT used the quantity measurement of human capital, average years of schooling in the adult population. The data for the dependent variable of TFP growth rates came from the PWT variable called "rtfpna", representing the measure of TFP for the respective country at constant national prices (with 2017=1). Then, $growthtfp\_collapsed$ was created in Stata by averaging the growth rates in TFP for the countries in five-year averages from 1950-2019.

The data for the independent variable $loghc$ came from the PWT variable called "hc". The original theoretical model uses human capital in its normal form, but in the regression version of the model human capital needs to be transformed into log(hc) for every measure of human capital, as then researchers and I can interpret changes in TFP growth rates through percentage changes in human capital.

The independent variable $hcratio$ is created by multiplying $loghc$ by the variable in the PWT called "ctfp", representing the TFP level at current purchasing power parities. The ctfp variable is the catch-up term for developing countries, with the U.S.=1 as the U.S. is considered by PWT to be the technological leader country for the entire world. In other words, the U.S. is the most innovative and technologically progressive country in the world. The variable $hcratio$ does represent $c(h_{it})\left(\frac{A_{it}}{A_{mt}}\right)$ adequately as $loghc$ represents $c(h_{it})$, and ctfp represents $\left(\frac{A_{it}}{A_{mt}}\right)$ as it is the fraction of the relative country's TFP level to that of the leader country, which is the U.S. in the data set.

Table 1 Summary Statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
hcratio	6,412	0.552	0.342	0.00381	2.323
loghc	8,637	0.673	0.359	0.00701	1.471
growthtfp_collapsed	1,268	0.00434	0.0278	-0.186	0.185

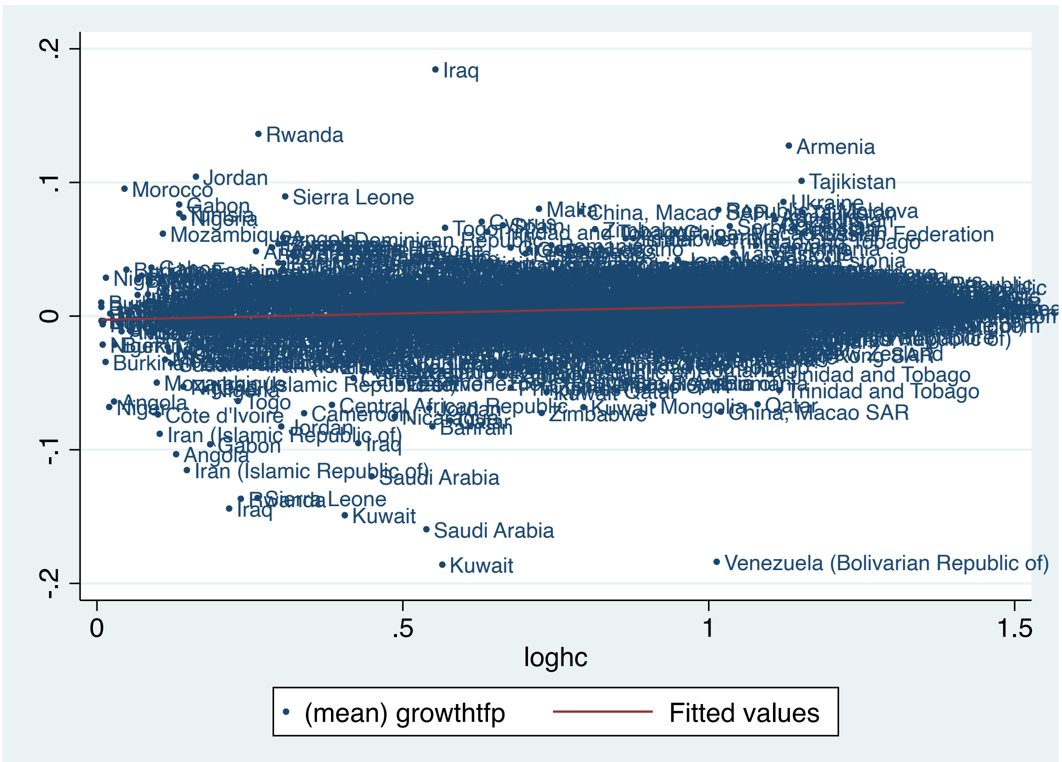
The number of observations for $hcratio$ are 6,412, with a mean of 0.552, standard deviation of 0.342, min value of 0.00381, and max value of 2.323. The minimum value for $hcratio$ is held by Niger in 1969. The maximum value for $hcratio$ is held by China in 2012. The number of observations is good for this term, and as standard deviation is low, there is a low chance of a large number of outliers from the mean in the data. This observation is verified by the min and the max values being decently close to each other.

Moving on, the independent variable $loghc$ has a very good number of observations, at 8,637, with a mean of 0.673, standard deviation of 0.359, min value of 0.00701, and max value 1.471. The minimum value of $loghc$ is held by Burkina Faso in 1960. The maximum value of $loghc$ is held by Singapore in 2019. This variable has by far the highest number of observations in the data, which means that the regression results for this variable will be by far the most precise. The standard deviation of 0.359 is just above the standard deviation for $hcratio$ but is very small still. Thus, there is a small chance there are outliers from the mean in the data, verified by the min and max values being close to each other.

Finally, the dependent variable $growthtfp\_collapsed$ has 1,268 observations, a mean of 0.00434 or 0.434%, standard deviation of 0.0278, min value of -0.186, and max value of 0.185. The minimum value of $growthtfp\_collapsed$ is held by Kuwait in 1980. The maximum value of $growthtfp\_collapsed$ is held by Iraq in 1995. This means that Kuwait had the lowest TFP growth in any five-year period out of all other countries, occurring in the 1980-1984 period. Meanwhile, Iraq had the greatest TFP growth rate out of all other countries for any five-year period, occurring in the 1995-1999 period. Naturally, $growthtfp\_collapsed$ has the least number of observations due to it being the average 5-year growth rates of TFP. As the data has been collapsed so much, the number of observations will be the lowest, but 1,268 is still a good amount. Further, the standard deviation is very low, meaning that there is a very low chance of there being a large number of outliers from the mean in the data. What is interesting is that the min and max growth rates for this variable have almost the exact same absolute values.

An interpretation of the growth rates shows that over all 5-year periods, the least TFP growth by a country was -18.6%, with the most being 18.5%. As the mean 5-year annual TFP growth rate is 0.434%, this shows that this high of a TFP growth rate at 18.5% is very hard to sustain. In fact, it seems logically improbable as once a country becomes more technologically progressive, there are less and less new technologies to adopt. Unless the citizens in the country become the most innovative populace in the world, creating massive amounts of new technologies every year, TFP growth logically needs to decrease. There are less technologies to adopt as they progress, and technological progress itself does not occur within a short amount of time. This is because it takes time to research and develop, then sell the technology, then have a portion of the population learn how to use the new technology and fully adopt it.

Figure 1 Scatterplot of loghc and growthtfp_collapsed



What we can see in figure one is a scatter plot showing the relationship between the variables $loghc$ and $growthtfp\_collapsed$. In order to see the relationship, the line of best fit—colored in red—is included in the scatter plot graph. Looking at the line of best fit, one can see that there is a positive relationship between $loghc$ and TFP growth, albeit a somewhat slight one. This slight positive relationship between $loghc$ and TFP is most likely due to the low numbers actually involved in the data with both human capital measurements and the TFP growth rates, but also due to human capital being in log format. As such, the scatter plot is more specifically showing the relationship between a 1% change in human capital, and the resulting change in the TFP growth rate.

Due to this, we can look at a specific point, say the Tajikistan point at the top right of the scatter point, and intuit it. For this year in Tajikistan, it had loghc about equal to 1.2, and a TFP annual growth rate in the five-year span of almost exactly 0.10 or 10%. This means that a 1% increase in human capital for this year roughly resulted in a 12% increase in the TFP growth rate. It should be noted, however, that this scatter plot only shows the relationship between $loghc$ and the resulting TFP growth rate of that year. That means that it does not take into consideration the other variables and their effects on TFP growth for that year. Overall, the scatter plot does clearly show the positive relationship between $loghc$ and the five-year average TFP growth rate.

V. Model Estimation and Analysis

In this section I report the regression results from the models employed. The same overall regression model was used in all three models, what varied were the controls and the change to show the interaction term which produced $hcratio$. First, I will discuss the estimation results in all three models. Second, I will discuss what the results show about the relationship between human capital and TFP growth. Third, I will discuss what this means for the theoretical models overall.

In order to clearly show the effects of human capital on TFP growth rates, I ran three different models. All were fixed effects models that were run using the Stata command xtreg as the data is longitudinal. The estimation results are all shown in Table 2.

Table 2 Estimation Results

VARIABLES	(1) fe-model1	(2) fe-model2	(3) fe-model3
loghc	0.0234***	0.0216*	0.0216*
	(0.00611)	(0.0111)	(0.0111)
hcratio	-0.0506***	-0.0393***	
	(0.00656)	(0.00652)	
L.growthtfp	0.0264	0.0192	0.0192
	(0.0163)	(0.0161)	(0.0161)
1965.year		-0.00626	-0.00626
		(0.00441)	(0.00441)
1970.year		-0.00511	-0.00511
		(0.00434)	(0.00434)
1975.year		-0.0148***	-0.0148***
		(0.00448)	(0.00448)
1980.year		-0.0303***	-0.0303***
		(0.00463)	(0.00463)
1985.year		-0.0133***	-0.0133***
		(0.00484)	(0.00484)
1990.year		-0.0175***	-0.0175***
		(0.00519)	(0.00519)
1995.year		-0.0105*	-0.0105*
		(0.00553)	(0.00553)
2000.year		-0.00139	-0.00139
		(0.00584)	(0.00584)
2005.year		-0.0117*	-0.0117*
		(0.00619)	(0.00619)
2010.year		-0.0103	-0.0103
		(0.00650)	(0.00650)
2015.year		-0.0192***	-0.0192***
		(0.00682)	(0.00682)
c.ctfp#c.loghc			-0.0393***
			(0.00652)
Constant	0.0145***	0.0217***	0.0217***
	(0.00357)	(0.00595)	(0.00595)
Observations	1,150	1,150	1,150
R-squared	0.061	0.154	0.154
Number of Countries	118	118	118

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Column (1) shows the results of the base regression model. Column (2) presents the same regression model but with added year dummy variables. Column (3) shows the same regression model as column (2), yet instead of $hcratio$ shows the interaction term producing $hcratio$. This interaction term, as stated in the data section of this paper, is c.ctfp#c.loghc, with the "c." in front of the two terms as they are both continuous variables, not being made up of binary data. The "#" is to show that the two terms are being multiplied.

As one can see, the coefficients of the interaction term and $hcratio$ are exactly the same, meaning all other results for coefficients will be the same as well. The purpose of showing the interaction term is to show that $hcratio$ is the indirect effect of human capital on TFP growth through technology diffusion, and to be able to later talk about the marginal effects of human capital on TFP growth.

Throughout all three models, human capital has a positive and statistically significant effect on total factor productivity growth. In the first most basic model, $loghc$ is statistically significant at the 1% level of significance, and at the last two models it is statistically significant at 10%. Further, $hcratio$, or the equivalent interaction term, is statistically significant at 1% in all of the models and has a negative effect on TFP growth.

Due to the signs of both $hcratio$ and $loghc$ are as expected, the first and third hypotheses cannot be rejected. Thus, the estimation results show that human capital has a positive effect on technological progress, and that conditional convergence does effect TFP growth rates. In other words, the model does predict a convergence of TFP growth rates.

In order to test hypothesis two, I must look at the marginal effect of human capital in the interaction term. In Table 3, I show the marginal effects of human capital on technology diffusion, otherwise known as the indirect effect of human capital on TFP growth. Therefore, given a fixed distance away from the technology leader country—that being the United States—I see what effect human capital has on the "catching up" of a nation. This is all to test whether or not the hypothesis that human capital is a positive facilitator of technology diffusion or not can be rejected.

Table 3 Marginal Effects of Loghc on TFP in hcratio (Indirect Effect)

	(1)
VARIABLES	margins
1. ctfp at (0.0)	0.0216*
	(0.0111)
2. ctfp at (0.1)	0.0177
	(0.0110)
3. ctfp at (0.2)	0.0138
	(0.0109)
4. ctfp at (0.3)	0.00986
	(0.0108)
5. ctfp at (0.4)	0.00593
	(0.0107)
6. ctfp at (0.5)	0.00200
	(0.0107)
7. ctfp at (0.6)	-0.00193
	(0.0108)
8. ctfp at (0.7)	-0.00586
	(0.0109)
9. ctfp at (0.8)	-0.00979
	(0.0110)
10. ctfp at (0.9)	-0.0137
	(0.0111)
11. ctfp at (1.0)	-0.0176
	(0.0113)
Observations	1,150

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

While looking at the indirect effects of human capital, I fixed the distance from the technology leader country at certain amounts, beginning at 0.0, then increasing to 1.0 in 0.1 increments. Quite interesting results appear when looking at these marginal effects. Firstly, there is only one statistically significant marginal value, significant at the 10% level. This statistically significant occurs at ctfp=0, meaning where the country is very far from the technological frontier, or the technology leader country. Second, the effect becomes negative after ctfp=0.5. However, these marginal effects are all statistically insignificant, so they can be overlooked. As such, the only usable results from looking at the marginal effects is the one value at ctfp=0. This means that though the evidence is not very large, I cannot reject the second hypothesis as no statistically significant negative relationships are present in the results. As the one significant value is positive, the model shows that human capital is a positive facilitator of technology diffusion.

Putting everything together, the results show that human capital has both a direct positive effect on TFP growth and an indirect positive effect on TFP growth. This indirect effect of human capital on TFP growth is shown in Table 3 as $loghc$ has a positive effect on $hcratio$. As a result, $loghc$ is a positive facilitator of technology diffusion, meaning human capital positively effects a country's ability to "catch up" to the leader country. The coefficient on $hcratio$ is negative, meaning that conditional convergence is present in the model. Specifically, when a country catches up to the leader nation in TFP level, the growth rates begin to converge, and the developing country's TFP growth rate decreases. This follows with the original idea of conditional convergence, that when approaching a set steady state, developing nations will grow faster than developed nations. Therefore, the theory of conditional convergence in terms of total factor productivity growth rates is backed up by my model.

The estimation results show that when human capital increases by 1%, total factor productivity growth rates will increase by 0.0234%, as shown in column (1). Furthermore, an increase of 10% would increase TFP growth by 0.234%. When the developing nation is very far away from the TFP level of the leader country (ctfp almost 0.0), the contribution of a 10% increase human capital to TFP growth could be upwards of 0.45%. Therefore, the model predicts that a 10% increase in human capital over the 5-year period could increase the annual average TFP growth rate by 0.234% to 0.45%. Although, this high estimate may be very improbable to occur as the TFP level of the developing nation would have to almost be or be at 0. Looking at this logically, it means that there needs to be almost no technology present in the developing nation, very unlikely to occur in reality.

Combining the intuitions together, human capital has a positive and statistically significant relationship with TFP growth. A 1% increase in human capital results in the 5-year annual average TFP growth rate to increase by 0.0234% directly, and if the developing nation is incredibly far away from the leader country, increases TFP growth by 0.0216% indirectly, for a combined range of 0.045%. However, the closer the country gets to the leader country in terms of TFP level, conditional convergence is verified by the model, so TFP growth rates decrease. Other studies find that the indirect effects are greater the closer the country is to the technology frontier, but as Table 3 shows, my results cannot verify this finding. Table 3 does show evidence that human capital is a positive facilitator of technology diffusion, however.

These findings verify that there still is a positive relationship between human capital and TFP growth or technological process when human capital is calculated using both the combined quantity and quality metrics. The theoretical model predicts conditional convergence, which presents itself in the model through the negative sign of $hcratio$, yet the regression model cannot specify the indirect relationship between human capital and technological progress through technology diffusion. While human capital does appear to help the spreading of technology, and logically so, the evidence is not abundantly clear. Therefore, none of the three hypotheses can be rejected.

VI. Robustness Check

Table 4 Robust Results

VARIABLES	(1) fe-model1
loghc	0.0234**
	(0.00977)
hcratio	-0.0506***
	(0.0110)
L.growthtfp	0.0264
	(0.0417)
Constant	0.0145***
	(0.00397)
Observations	1,150
Number of Country_new	118
R-squared	0.061

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As the robust regression model results show, $loghc$ and $hcratio$ stay statistically significant at 5% level of significance and at 1%, relative. Due to this, there is no evidence that the model suffers from heteroskedasticity.

VII. Conclusion

In this paper, I used the combined version of human capital to study its role in technological progress and technology diffusion using worldwide panel data from 1950-2019. I employed the model used by Akhvlediani and Cieślik (2019), whose regression model was derived from the Nelson and Phelps (1966) theoretical model. Therefore, this paper used the newest and most accurate form of human capital to verify human capital's positive effect on total factor productivity growth and the spreading of technology. The model passed a robustness check, and the estimation results show that human capital has a statistically significant and positive effect on technological progress. The evidence for human capital indirectly facilitating TFP growth through technology diffusion is weak, yet the evidence for the convergence of TFP growth rates with the leader country, the United States, is very strong.

The results are clear, the main purpose of education in a country is to increase the amount of human capital present to make living conditions improve through the making and adoption of new technologies. While college does not need to be seen as an "be all and end all", education needs to be encouraged and supported in order for a country to be able to develop. This holds true for both developing and developed nations, as the results show that if a nation stops increasing its population's overall human capital, technological progress will slow down. If you lower the average year of schooling of a population, or lessen the quality of education, technological progress will slow, and living conditions will not improve as quickly. Education plays an incredible role in improving the lives of a nation's population overall, and political leaders should view it under this level of importance. The living conditions of a people will improve if a country encourages more years of schooling and constantly invests in the quality of its education as well. Education is necessary for your people to not only be innovative themselves but also to adopt new technologies.

In sum, technological progress does not occur in a void, it requires more and more investments to keep occurring. Education through human capital should be seen by policymakers as a clear way to improve the overall living conditions of the population through technological progress. Future studies should now use the combined version of human capital; however, work should be done to get a clearer picture of the indirect effects of human capital on TFP growth. The evidence of greater indirect effects, or greater technological adoption, as a nation approaches the technology frontier was not found when looking at the worldwide data. Due to this, the indirect side of the regression model and thus theoretical model may need to be augmented to consider more variables to see the marginal effects of human capital. None of my hypotheses could be rejected, yet the evidence of the second hypothesis is weak, and future studies should work to correct this part of my study.

VIII. Appendix (All Figures and Tables)

$$\Delta a_{it} = b + (g + c)h_{it} - c(h_{it})\left(\frac{A_{it}}{A_{mt}}\right) + \xi_i + \varepsilon_{it} \qquad (Eq. 1)$$

$$\hat{A} = \hat{Y} - \alpha_K \hat{K} - \alpha_L \hat{L} \qquad (Eq. 2)$$

$$growthtfp_{collapsed} = \beta_0 + \beta_1 loghc + \beta_2 hcratio + \xi + \varepsilon \qquad (Eq. 3)$$

Figure 1 Scatterplot of loghc and growthtfp_collapsed

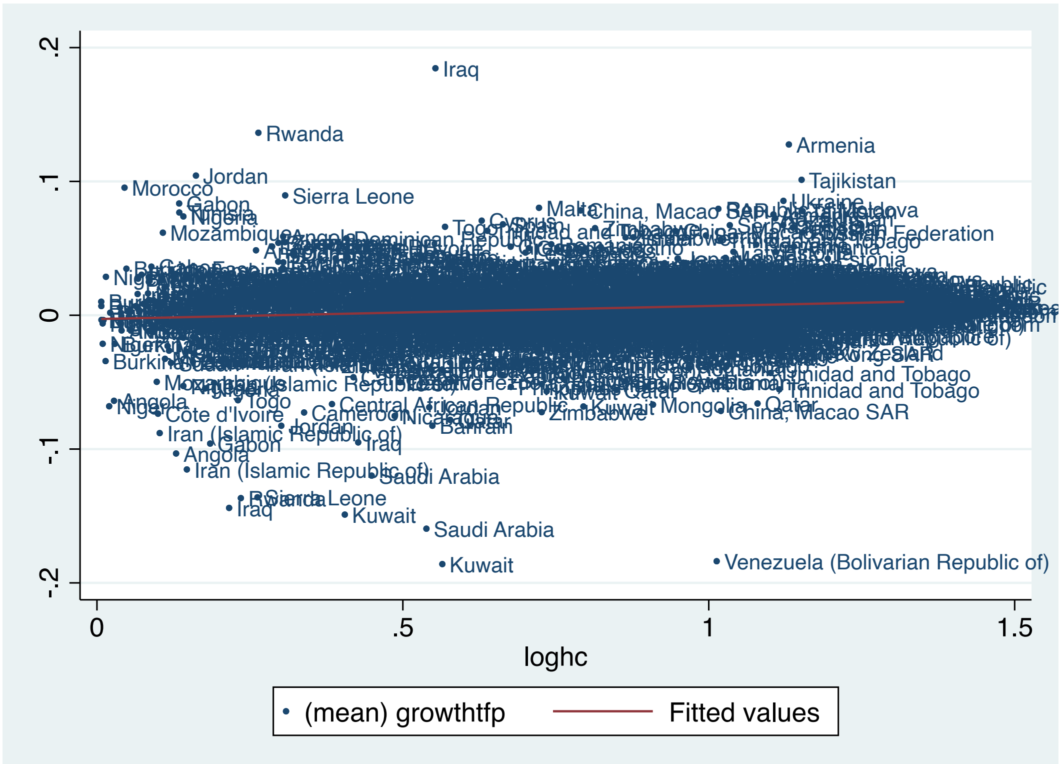


Table 1 Summary Statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
hcratio	6,412	0.552	0.342	0.00381	2.323
loghc	8,637	0.673	0.359	0.00701	1.471
growthtfp_collapsed	1,268	0.00434	0.0278	-0.186	0.185

Table 2 Estimation Results

VARIABLES	(1) fe-model1	(2) fe-model2	(3) fe-model3
loghc	0.0234***	0.0216*	0.0216*
	(0.00611)	(0.0111)	(0.0111)
hcratio	-0.0506***	-0.0393***	
	(0.00656)	(0.00652)	
L.growthtfp	0.0264	0.0192	0.0192
	(0.0163)	(0.0161)	(0.0161)
1965.year		-0.00626	-0.00626
		(0.00441)	(0.00441)
1970.year		-0.00511	-0.00511
		(0.00434)	(0.00434)
1975.year		-0.0148***	-0.0148***
		(0.00448)	(0.00448)
1980.year		-0.0303***	-0.0303***
		(0.00463)	(0.00463)
1985.year		-0.0133***	-0.0133***
		(0.00484)	(0.00484)
1990.year		-0.0175***	-0.0175***
		(0.00519)	(0.00519)
1995.year		-0.0105*	-0.0105*
		(0.00553)	(0.00553)
2000.year		-0.00139	-0.00139
		(0.00584)	(0.00584)
2005.year		-0.0117*	-0.0117*
		(0.00619)	(0.00619)
2010.year		-0.0103	-0.0103
		(0.00650)	(0.00650)
2015.year		-0.0192***	-0.0192***
		(0.00682)	(0.00682)
c.ctfp#c.loghc			-0.0393***
			(0.00652)
Constant	0.0145***	0.0217***	0.0217***
	(0.00357)	(0.00595)	(0.00595)
Observations	1,150	1,150	1,150
R-squared	0.061	0.154	0.154
Number of Countries	118	118	118

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 Marginal Effects of Loghc on TFP in hcratio (Indirect Effect)

VARIABLES	(1) margins
1. ctfp at (0.0)	0.0216*
	(0.0111)
2. ctfp at (0.1)	0.0177
	(0.0110)
3. ctfp at (0.2)	0.0138
	(0.0109)
4. ctfp at (0.3)	0.00986
	(0.0108)
5. ctfp at (0.4)	0.00593
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6. ctfp at (0.5)	0.00200
	(0.0107)
7. ctfp at (0.6)	-0.00193
	(0.0108)
8. ctfp at (0.7)	-0.00586
	(0.0109)
9. ctfp at (0.8)	-0.00979
	(0.0110)
10. ctfp at (0.9)	-0.0137
	(0.0111)
11. ctfp at (1.0)	-0.0176
	(0.0113)
Observations	1,150

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4 Robust Results

	(1)
VARIABLES	fe-model1
loghc	0.0234**
	(0.00977)
hcratio	-0.0506***
	(0.0110)
L.growthtfp	0.0264
	(0.0417)
Constant	0.0145***
	(0.00397)
Observations	1,150
Number of Country_new	118
R-squared	0.061

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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