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Dimensions of Human Capital and Technological Diffusion

Zainab Asif
Queensland University of Technology
zainab.asif@hdr.qut.edu.au

Radhika Lahiri
Queensland University of Technology
r.lahiri@qut.edu.au

Abstract

We examine the impact of a comprehensive set of measures of human capital on recently created, direct measures of technology adoption using country-level panel data for the period 1964-2003, covering a wide range of technologies in various sectors of the economy. We consider many dimensions of human capital, using both qualitative and quantitative measures, as well as indirect measures that capture the role of "learning by doing" intrinsic to the process of technological diffusion. Our analysis, which examines the human capital and technological diffusion link more comprehensively relative to previous studies, suggests that the link is a *conditional* one, resting on various aspects of human capital and the nature of the technology in question. Overall, the results suggest that the type of human capital that is formed via the learning-by-doing mechanism may be the most important determinant of technological diffusion, followed by, to a substantially less degree, qualitative determinants such as cognitive skills (measured using test scores) and quantitative or other measures (such as years of schooling and life expectancy). Our conclusions are robust to the inclusion of institutional variables and other factors that determine technological diffusion.

Key words: Cognitive skills, Economic growth, Educational achievements, Educational attainments, Human Capital, Technology

JEL classification: I2, O1, O14, O13

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1. Introduction

A substantial strand of literature on the relationship between education and technological diffusion stems from the work of Nelson and Phelps (1966), who show that human capital accumulation, through its impact on technology adoption and diffusion, influences an economy's ability to catch up with more developed economies. Benhabib and Speigel (1994) extend this approach by emphasizing that human capital not only helps in the adoption of more sophisticated technologies but also facilitates development of new technologies at the frontier through better innovation. They show that the positive link between human capital and economic growth rests critically on both of these mechanisms. Subsequent empirical developments present evidence that is either supportive of this view (as in Barro and Sala-i-Martin, 1995 and Barro, 1998), or supportive with caveats pertaining to the level of development (as in Krueger and Lindahl, 2001) or the measure of human capital used (as in Vandenbussche, 2006; Messinis and Abdullahi, 2010 and Madsen, 2014).

One of the drawbacks of the previously mentioned studies is that they consider changes in total factor productivity as a measure of technological change. However, changes in productivity growth do not properly account for changes in technology (Hulten 2000, Lipsey and Carlaw 2004), given that total factor productivity is a "residual" from growth accounting exercises which can be related not only to technological change, but other unmeasured inputs in the process of production. Moreover, as suggested by Comin and Mestieri (2013), indirect and traditional measures do not distinguish between the *extensive* and *intensive margins* of technology adoption, which should be central to any examination of *mechanisms* through which technology adoption impacts on growth. The intensive margin refers to the intensity of use of a new technology in a given economy while the extensive margin refers to the timing of adoption – i.e whether a particular technology has been adopted at all, and if so at what point in time. The latter is reflected in the time lag in adoption of a technology for the first time relative to the leading adopter of a technology. This concept is termed as *usage lag* was first defined in Comin et al (2008).

If, as the human capital and technology diffusion literature mentioned above suggests, human capital influences growth through its impact on technology adoption and diffusion, the appropriate empirical exercise to address this issue should focus on *direct* measures technology diffusion and how they are impacted by human capital. To comprehensively address this issue it is also important to take a multi-dimensional perspective as human capital comes in various forms. A key objective of this paper, therefore, is to empirically investigate and analyze the link between direct measures technological diffusion as created in the Cross Country Historical Adoption of Technology (CHAT) data set due to Comin and Hobijn (2009) and several measures human capital.[1]

Our human capital measures include educational quality as measured using the recently created data set on cognitive skills (Trends in International Mathematics and Science Study (TIMSS) test scores) due to Hanushek and Woessman (2012), and measures such as life expectancy (Barro, 2013), average years of schooling (Barro and Lee, 2010). We also consider the impact of "learning by doing", which has been emphasized in several theoretical and empirical studies of technology adoption (Parente, 1994; Jovanovic and Nyarko,1996; Conley and Udry, 2010).[2] Our measures of technology diffusion include usage intensity and usage lags of 21 technologies from the CHAT data set.

[1] The Cross Country Historical Adoption of Technology (CHAT) data set captures both the extensive and intensive margins of 104 technologies from 8 sectors for a sample of more than 150 countries, over a period of 1800-2000.

[2] Our paper complements the earlier work by Cinnirella and Streb (2017) who explore the association between different types of quantitative measures of human capital and technological innovation for Prussia in the late nineteenth century, in addition to "training-on-the-job", an aspect which our results suggest is a very important determinant of technological diffusion. In addition, our paper relates to the literature on growth and innovations which employs measures of human capital such as educational attainment and knowledge as among key factors impacting upon the innovation process and growth of economies (Drivas, K., Economidou, C., & Tsionas, E. G. 2018; Dakhli, M., & De Clercq, D, 2004; Barro, R, 2001). In contrast, however, we employ qualitative constructs of human capital such as cognitive skills. Furthermore, our analysis is more comprehensive in scope, looking at various direct measures of technologies over time and across countries.

The motivation for taking a multi-dimensional approach, in part, stems from this variety of multi-sectoral technologies we are able use from the CHAT data set. This allows us to examine the idea that the mechanisms which transform human capital into output are intrinsically related to the nature of technology in question, an issue that is relatively neglected in this literature. For example, certain technologies require a higher embodiment of skills and educational quality than others, and this is one of the premises of our exploration. This premise is in part inspired by the findings presented in Comin and Hobijn (2004) who explore the link between *quantitative* measures of human capital (such as years of schooling) and technology adoption, and suggest that human capital is an important determinant of the intensity of adoption. However, their regressions pool a large set of technologies into one panel, making it difficult to address this specificity.

Following this idea, we suggest that in an analogous sense, specific types of qualitative measures of human capital may be more or less appropriate or relevant in facilitating adoption depending on the *type* of technology in question. For example, cognitive skills as represented by science scores may be more relevant to the adoption and diffusion of medical technologies, while mathematics scores, which arguably embody analytical skills of a more *generic* nature, could be relevant for a larger set of technologies including medical technologies, computers or digital technologies and technologies relating to transportation. In the analysis to follow, therefore, we prefer to refer to the human capital measure associated with mathematics scores as "generic human capital". The human capital measure associated with science scores is referred to as "specific human capital".[3]

[3] This may be justifiable in the sense that the mathematics test consists of basic mathematical knowledge applied to set of analytical problems. The science test, in contrast, is more knowledge specific rather than analytical. Of course, this may be contentious and the reader may not agree with our interpretation. Our choice of the labels 'specific" and "generic", however proves convenient as well as intuitive in the context of discussing and interpreting the results to follow. Our variable embodying generic skills is a proxy for analytical skills of a very general level.

It is also worthwhile to elaborate further on the learning-by doing aspect we mentioned previously. This aspect of technology adoption stresses the notion that the productivity of technologies depends on the *experience* of using and adapting the technology to local conditions, and the insufficiency of this type of human capital can present barriers to the adoption of such technologies (Basu and Weil, 1998; Acemoglu and Zilibotti, 2001; Lahiri et al 2018). However, while direct measures of this type of human capital are not available in disaggregated technology-specific form, a simple way of capturing this aspect is to examine the impact of past levels of usage intensity and usage lags of the technology in question. In terms of our methodology, we do so by incorporating lags of the dependent variable in our regressions, along with the human capital measures (science and mathematics test scores) based on the TIMSS data set, necessitating the use of dynamic panel techniques due to Arellano and Bond (1991) and Bundell and Bond (2000).[4]

We first consider the regressions of usage-intensity measures on human capital. In the interest of brevity, we defer the detailed discussion of the usage lags and mention only how results differ relative to the usage intensity regressions. In the following, therefore we focus on the broad thrust of usage intensity regressions by elaborating on the case of some technologies and consider the case of usage lags more succinctly.

The results support our premise regarding the technology-specific nature of the link between human capital and technology adoption. For example, our analysis of cognitive skills based on mathematics test scores suggests that the generic type human capital associated with these scores is more likely to have a positive impact on the usage intensity of some technologies we consider,

[4] In addition to our reasoning above Comin et al (2008) suggest that past level of technology adoption is a strong predictor of current levels; as such a dynamic specification is appropriate. In Comin and Hobijn (2004), which to our knowledge is the only other study analyzing the impact of human capital on technology measures based on the CHAT data set, the lagged variable is not considered and the focus is on quantitative measures of human capital such as secondary school enrollment.

particularly in the transportation, tourism and health sectors. We note, however, that not all regressions yield positive and significant coefficients for the human capital variable in these sectors. Furthermore, this type of human capital does not seem to exhibit any clear-cut link with technology adoption in agriculture as regressions based on a variety of technologies in this sector have coefficients of human capital that are either negatively significant or positive but not significant. In our interpretation this does not necessarily suggest that human capital does not matter for the adoption of agricultural technologies. Adoption of technologies in agriculture, for example, may require a different dimension of human capital in the form of "learning by doing" of the type suggested by Foster and Rosenzweig (1995) in the context of technologies such as high-yield varieties of seeds.

Indeed, the lag of the technology (usage intensity) measure, which we interpret as representative of the experiential, learning-by-doing aspect of adoption, is positive and significant not only in the case of agricultural technologies, but highly significant across *all* regressions. This measure remains positive and significant in the regressions based on usage lags of the same technologies, suggesting that shorter time lags in adoption in the past lead to even shorter lags in the present, quickening the pace of adoption as more time has been spent on learning a particular technology.

In the usage intensity regressions, it is interesting to note that the "generic" human capital measure associated with mathematics scores yields a positive and significant impact on usage intensity in only 10 out of the 21 technologies we consider. In the case of usage lags evidence regarding the hypothesis that human capital facilitates adoption by reducing adoption lags is substantially weaker; only 3 regressions yield a negatively significant coefficient for the variable representing human capital. The evidence based on the "specific" measure of science further reinforces this point. In this case, the human capital measure has the hypothesized impact on usage intensity in only 5 out of the 21 regressions. Likewise, we find that the coefficient of the human capital variable in the usage lag regressions is negative and significant only for 4 of these technologies. The lagged technology measure, however, remains positive and significant across all regressions, as was the case in the usage intensity regressions, signifying robust and clear-cut evidence to suggest that the learning-by-doing aspect associated with technology adoption matters.

Furthermore, we consider several robustness exercises. We include in our regressions variables that have been considered relevant in related literature such as GDP lags (Comin et. al 2008), foreign direct investment (Sinani and Myer, 2004; Branstetter, 2006; Herzer, 2011) and measures of institutional quality such as political rights and civil liberties (Acemoglu et al, 2005). We further consider pooling all of the technologies into a single panel to get a composite view of the impact of human capital on technology in an overall sense. Further, we split the pooled sample into developed and developing economies to assess if there are any threshold effects pertaining to levels of development.

We find that our broad conclusions are robust to these exercises. We find, specifically, that the most important determinant of technology adoption is the past level of technology, reinforcing the importance of the learning-by-doing aspect of technology adoption. Likewise, the evidence in relation to other measures of human capital is mixed, as was the case in baseline regressions. The magnitude of the learning-by-doing is even more important in the context of developed economies, suggesting that, as development takes place the importance of various measures of human capital changes to shifting to a further degree in favour of human capital that is created in on-the-job training.

The remainder of this paper is organized as follows: Section 2 outlines the main features of theoretical and empirical framework relevant to our paper. In section 3 we summarize results analyzing the role of cognitive skills in the process of technology adoption. Section 4 examines this role from the perspective of diffusion of technologies within and across selected sectors. Section 5 presents the results for panel pooled analysis for usage intensity and usage lags of technologies. Lastly section 6 presents our conclusions.

II. Empirical Methodology

In what follows we provide a brief review of our measures of adoption and diffusion of technology and cognitive skills. We also present the econometric specifications examining the role of cognitive skills in the process of adoption and diffusion of technologies.

A. Measures of Technology Adoption and Diffusion

Our measures of technology adoption and diffusion are borrowed from Comin et al (2008).[5] As mentioned previously, they consider two measures: usage intensity and usage lags, which we describe in further detail in this section. The former is relatively simple and captures the intensity with which each adopter uses the technology-i.e. the intensive margin of adoption.[6] In our paper usage intensity is measured as the number/magnitude of technological units employed at a particular point in time scaled by the population in a country.[7] Therefore, the usage intensity of

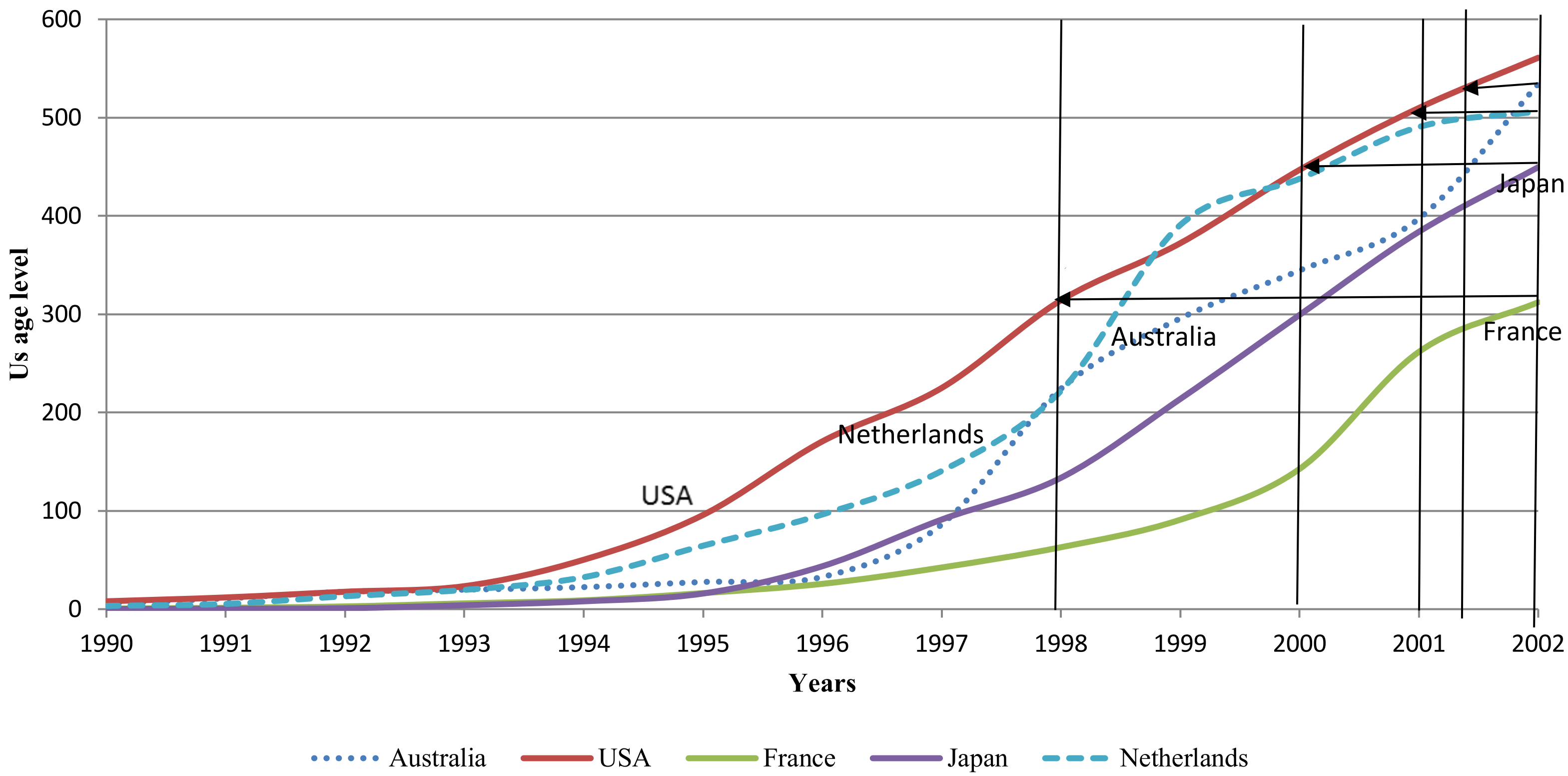
[5] Comin and Hobijn (2009) refer to the definition of "technology" in Merriam-Webster's Collegiate Dictionary. It defines technology as "a manner of accomplishing a task especially using technical processes, methods, or knowledge". Given this definition the basic idea behind technological measures in CHAT is to cover these various aspects of technology. For example, it includes the quantity of capital goods required to achieve a specific task (e.g. number of sail ships (measured in tonnage) in use in a country), amounts of times a specific task that have been completed (e.g. metric tonnes of steel produced) and the number of users of a the specific manner in which the task was accomplished (e.g. number of subscribers of cable TV in a household).
[6] Comin and Mestieri (2013) use a different theoretical construct for intensive margin of technology in their theoretical framework.
[7] Comin and Mestieri (2013) suggest use of population or Gross Domestic Product as scaling factors.

technology conceptually measures the per capita usage of technology instead of measuring technology adoption simply as the number of units of a particular technology available in an economy for each year in our analysis. However, the latter measure, i.e. usage lags is more complex. In what follows we discuss this concept in a fashion very similar to Comin et al (2008).[8] However, we believe that the discussion is worthy of reiteration for the sake of reader's convenience. We simply present the intuitive explanation here; the formal mathematical expression of this concept, also identical to that of Comin et al 2008) is presented in part A of the online supplementary appendix to this paper.

To provide an intuitive explanation for the concept of technology usage lag, we plot the usage levels for internet for Australia, US, France, Japan and Netherlands in Figure 3.1, and perform an exercise similar to Comin et al (2008). Specifically, we ask the question: how many years before the year 2002 did the United States last have the usage level that Japan had in 2002? As is visible from Figure 1, US last passed Japan's 2002 usage level in 2000, 2 years before 2002. Similarly we can perform this exercise for other countries in our sample to find that in 2002 US led Australia by a few months, France by 4 years and Netherlands by a year.

[8]As indicated earlier our sample includes a set of 50 countries and includes both developed and developing countries. Here the choice of countries to illustrate the concept of technological lags is motivated purely by the ease of graphical presentation.

Figure 1 Graphical Representation of Technology Usage Lags.



Using the aforementioned measures of technology adoption and diffusion we estimate usage intensity of technology and usage lags for 14 technologies in six sectors given in the CHAT data set.[9] Table 1 below presents the list of technologies used in estimations.[10]

[9] We have 21 technologies in our sample, but the tables in the paper include results for 14 technologies while regressions for other technologies are presented in the online appendix. The technologies used are selected from the Comin and Hobijn (2009) paper.

[10] For a detailed description of these technologies please refer to Comin and Hobijn (2009) or part A of the supplementary online appendix to this paper.

Table 1: Description of Technologies

Sector	Technology	Description
Transportation	Aviation pkm/ Air	Civil aviation passengers' kilometer traveled. Invention year 1903
	Shipton Steam motor/Sea	Gross tonnage (above a minimum weight) of steam and motor ships in use. Invention year 1788
Health	Transplant liver	Number of liver transplants performed. Invention year 1963
	Transplant lung	Number of lung transplants performed.
	Transplant Bone marrow	Number of bone marrow transplants performed.
Telecommunications & Information	Telephone	Number of telegrams sent. Invention year 1876
	Cell phones	Number of users of portable cellphones. Invention year 1973
	Cable TV	Number of household subscriptions to multichannel television.
	Mail	Number of items mailed/received, cross-border and internally. Invention year 1840
	Internet	Number of people with access to the worldwide network. Invention year: 1983
	Computers	Number of self-contained computers designed for use by one per- son. Invention year: 1973
Agriculture	Fertilizers	Metric tons of fertilizers consumed. Invention year 1910
	Harvesters	Number of machines that reap and thresh in one operation. Invention year 1912
Tourism	Visitor Beds	Number of visitor beds available in hotels.
Electricity		Gross output of electric energy [inclusive of electricity consumed in power stations) in KwHr. Invention year 1882

B. Measures of Cognitive Skills

Following Hanushek and Woessmann (2012) we use measures of educational quality to incorporate one of the dimensions of human capital in our model. Educational quality reflects educational achievement measured as "cognitive skills" which are averages of all observed mathematics and science scores for international tests conducted during the time period (1964-2003) for a set of more than 50 countries.[11] Hanushek and Woessmann (2012) develop this metric by standardizing the performances of students to make it comparable across time. This metric takes US as the benchmark country, as it is the only country that has participated in all the international tests. Given the time series evidence on test score performance for students from US, the metric scales the current level of each International Student Achievement Test (ISAT) relative to the known previous comparable performance of students.[12] Similar to usage lags of technologies these standardized test scores also use United States as the benchmark country.

C. Econometric Methodology

This section explains the empirical methodology used to examine the link between technological diffusion and human capital. The specifications are shown in equations (1) and (2) below.

$$T_{c,t}^{i} = \alpha_c + \gamma T_{c,t-1}^{i} + \beta_1 CS_{c,t} + \beta_2 AS_{c,t} + \beta_3 X_{c,t} + \mu_{c,t} \quad (1)$$

$$Lag_{c,t}^{i} = \theta_c + \Phi Lag_{c,t-1}^{i} + \Omega Y_{ct-s} + \beta_4 CS_{c,t} + \beta_5 AS_{c,t} + \beta_6 X_{c,t} + \varepsilon_{c,t} \quad (2)$$

[11] The measure developed in Hanushek and Woessmann (2012) is an extension of Hanushek and Kimko (2000). Details for countries and tests are present in Hanushek and Woessmann (2012). The observations for mathematics and science test scores are sporadically spread across the time period 1963-2003. This is because, firstly, the tests are not conducted every year. Secondly, the countries may not participate in every test that is conducted. Hence, we have missing observations for mathematics and science test scores in our data set. In order to extrapolate observations for these years we use averages of the available test scores for the countries in our sample.

[12] Details of this qualitative measure of education, from Hanushek and Woessmann (2012), are also presented in part A of the online supplementary appendix.

In equation (1), T is the usage intensity of technology, CS represents cognitive skills, AS is average of schooling, X is a set of control variables and $\mu_{c,t}$ is the error term. The subscripts i, c, t denote a specific technology i, country c and year t respectively. In equation (2) Lag is the usage lag of technological diffusion and the rest of the variables are the same as equation (1). The dynamics of technology and the dimension of "learning by doing" are introduced as $T^{i}_{c,t-1}$ and $Lag^{i}_{c,t-1}$ to denote the lag of the dependent variables in period 1 in equation (1) and (2) respectively. Here, we expect the sign of $\gamma > 0$. This implies a positive association between previous period's usage intensity and current period's usage intensity of technology. In equation (2) we expect the sign of $\Phi > 0$. This suggests a positive association between previous period's usage lag of technology with current period's usage lag of technology.

To further capture the dynamics of technology, in equation (2) we follow Comin et al (2008) and introduce Y_{ct-s} which is the per capita income or GDP lag of a country. It is measured in analogous fashion to technology usage lags, i.e. how far behind a country c is in GDP at time t compared to the GDP leader s in the world. In this case the leader in the context of both GDP and technology is the United States.[13] We expect the sign of $\Omega>0$ which implies that reduced income lags are associated with shorter technology usage lags.

While estimating these equations there is a possibility of the error term being correlated with any of the explanatory variables in the model or with the lagged dependent variable. To address this we employ the dynamic GMM estimator of Arellano and Bond (1991). This estimator takes

[13] It is possible that there are some technologies where other countries could be leaders. However, US leads in most cases and is hence chosen for consistency, as well as comparability with the Comin et al (2008) approach to measure usage lags of technologies.

into account the dynamic nature of the model and correlation (with the error term) generated due to the introduction of the lag of the dependent variable.[14]

In our analysis cognitive skills are a measure of human capital and educational quality. In addition, we include a quantitative measure of human capital as average years of schooling based Barro and Lee (2010). In equation (1) we therefore expect that $\beta_1 > 0$ and $\beta_2 > 0$. In equation (2) we expect $\beta_4 < 0$ which implies that better skills result in reducing timing of adoption of a given technology Likewise, we expect $\beta_5 < 0$ indicating that higher educational attainments reduce the timing of adoption of technologies.

The control variables in our analysis include health and foreign direct investment (FDI) as facilitators to technology adoption and diffusion. We include health as a second dimension of human capital as it has gained importance in economic growth literature since the early 1990s. Many studies suggest that health is one of the main components of human capital formation which contributes to economic growth as it facilitates the acquisition of skills and adds to productivity (Ainsworth and Over, 1994; Jamison et al, 1998; Barro, 2013). However, there is a dearth of studies that examine the role of health in technology diffusion and adoption from the human capital perspective. We therefore add life expectancy in order to incorporate the health dimension of human capital borrowing from Barro (2013).[15]

[14] In this estimation procedure we instrument current variables at time t by their past lags, which eliminates correlation between explanatory variables and the error term. Furthermore, in our GMM estimations the use of these past lags as instruments may (effectively) control for the possible endogeneity of human capital acquisition employed as explanatory variable for adoption and diffusion of technology. However, we do not explicitly control for endogeneity of human capital due to our assumption that it is strictly exogenous, as per the assumptions underlying the difference-GMM approach. Given that the left-hand-side variable is a microeconomic, sectoral variable while our human capital measures are macroeconomic in flavor we believe this is a reasonable assumption. However, we perform robustness checks based on various diagnostic tests and use the system GMM approach of Blundell and Bond (2000) for all cases. The results for these are presented in part B of the online appendix.

[15] We obtain data for life expectancy for the years 1964-2003 from World Development Indicators (WDI) of the World Bank (2015). It is measured as life expectancy at birth in total years. See www.worldbank.org for details.

The literature on technology adoption also suggests that FDI inflows may contribute to spillovers and affect domestic industries and firms (Sun, 2011). However, the empirical evidence in relation to FDI affecting technology diffusion and adoption remains mixed (Aitken and Harrison, 1999; Li et al, 2001; Sun, 2011). Nevertheless, based on empirical support for the positive impact of FDI as a determinant of technology adoption (Meyer and Sinani, 2009), we use it as control variable in our analysis. The measure for FDI is drawn from the WDI of the World Bank (2015) data for the years 1964-2003 and measured as net inflows of FDI as percentage of Gross Domestic Product.

An additional robustness check we perform involves pooling the data on individual technologies to create panels that include the dimensions country, technology and time and estimating the following counterparts of equations (1) and (2):

$$T_{ic,t} = \alpha_{ic} + T_{ic,t-1} + \beta_1 CS_{ic,t} + \beta_2 AS_{ic,t} + \beta_3 X_{ic,t} + \mu_{ic,t} \quad (1a)$$

$$Lag_{ic,t} = \theta_{ic} + \Phi Lag_{ic,t-1} + \beta_4 CS_{ic,t} + \beta_{54} AS_{ic,t} + \beta_{64} X_{ic,t} + \varepsilon_{ic,t} \quad (2a)$$

In the above, the notations are analogously described as in equations (1) and (2), but the cross-sectional dimension is now a technology-country pair, indexed respectively by i and c. Pooling the data in this manner has the advantage that a larger set of observations, and consequently greater degrees of freedom in the estimations. This also enables us to split the data into categories of developed and developing economies and estimate the above equations for these groups to gain further insights on the link between human capital and technological diffusion.[16]

[16] We thank two anonymous referees for these suggestions.

III. Empirical Evidence on Measures of Human Capital and the Usage Intensity of Technologies

We begin by estimating equation (1) to examine the association between human capital of different types and technology diffusion as measured by usage intensity. We consider a larger set of 21 technologies; however, 14 are presented here as described in Table 1. These include technologies considered in Comin et al (2008), and in the interest of a more detailed analysis, some other technologies that were not included in that paper.[17] We present estimates of equation (1) for the selected technologies in tables 2 and 3.[18] Table 3 includes results of cognitive skills based on mathematics test scores and usage intensity of technologies. Table 4 presents results of cognitive skills based on science test scores and usage intensity of technologies.

A key finding of our empirical analysis is that the lagged dependent variable has a coefficient that is positive and significant across almost all of the regressions we consider. As mentioned earlier we consider the lagged dependent variable as reflective of the "learning-by-doing" dimension of human capital. We stress that this is only our interpretation of the result; the caveat applies that such dimensions of human capital are hard to measure directly.

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[17] Comin et al (2008) include technologies such as; electricity production, internet, personal computers, telephones, cell phones, cars, trucks, passenger and cargo planes and tractors. We consider a larger set from the updated data set in Comin and Hobijn (2009)

[18] A complete sector-wise overview of these results including a larger set of technologies is available on request. The more succinct presentation of these results in the form of tables in the paper does not affect the overall findings and interpretation of the analysis.

Table 2 Usage Intensity of Technologies, Mathematics Skill Panel Estimations.

Variables	Aviation pkm/ Air	Shipton Steam motor/ Sea	Transplant Liver	Transplant Lung	Transplant Bone marrow	Cable TV	Mail
Lagged dependent variable	0.889*** (0.032)	0.955*** (0.027)	0.7933*** (0.077)	0.2136 (0.1171)	0.817*** (0.06)	0.8615*** (0.03)	0.9075*** (0.028)
Cognitive Skills	0.00087*** (0.0003)	-0.00005 (0.0004)	0.000012** (0.000006)	0.000026*** (0.000006)	0.0000052 (0.00001)	0.1072*** (0.03)	0.000122** (0.00004)
Years of Schooling	-0.138*** (0.02)	0.0056 (0.003)	0.00069 (0.0005)	-0.00089** (0.0003)	-0.00056 (0.001)	1.529 (2.61)	0.00048 (0.003)
Life Expectancy	0.0413*** (0.013)	0.00011 (0.001)	-0.000303 (0.0002)	0.0004*** (0.0001)	0.0014 (0.0009)	0.0402 (1.5)	-0.0022 (0.001)
FDI	0.0136 (0.011)	0.00111 (0.001)	-0.000012 (0.00004)	0.000002 (0.00002)	-0.00003 (0.0001)	-1.113*** (0.31)	0.0033** (0.001)
Observations	170	111	83	68	106	212	163
Sargan test: p-val	0.232	0.000	0.813	0.245	0.82	0.0001	0.089

Standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively. Sargan-Hansen test to check for over-identifying restrictions; p values mentioned in the last row. In the cases where the test identifies issues of endogeneity we perform system GMM technique to cater for this issue. The results for system GMM are presented in Appendix B.

Table 2 (continued): Usage Intensity of Technologies, Mathematics Skill Panel Estimations.

Variables	Computers	Internet User	Telephone	Cell phones	Visitor beds	Harvester	Fertilizer
Lagged dependent variable	1.0137*** (0.015)	0.945*** (0.03)	1.0002*** (0.025)	1.001*** (0.018)	0.7342*** (0.054)	0.8828*** (0.02)	0.834*** (0.03)
Cognitive Skills	0.1891*** (0.057)	0.449* (0.25)	-0.0666 (0.04)	-0.158* (0.08)	0.011*** (0.003)	-0.0009** (0.0004)	-0.040*** (0.01)
Years of Schooling	7.331** (3.57)	7.018 (10.009)	0.514 (2.63)	11.365*** (6.35)	-0.584 (0.211)	0.032 (0.037)	-3.24*** (1.12)
Life Expectancy	3.0355 (2.20)	24.95*** (6.44)	1.926 (1.23)	21.265*** (4.27)	-0.794 (0.13)	-0.0084 (0.019)	3.099*** (0.64)
FDI	0.2325 (0.4)	0.591 (1.02)	2.753 (0.70)	2.473*** (0.93)	-0.687 (0.03)	-0.011 (0.007)	-0.133 (0.21)
Observations	178	150	190	258	157	287	293
Sargan test: p val	0.000	0.000	0.000	0.000	0.131	0.765	0.002

Standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively. Sargan-Hansen test to check for over-identifying restrictions; p values mentioned in the last row. In the cases where the test identifies issues of endogeneity we perform system GMM technique to cater for this issue. The results for system GMM are presented in Appendix B.

Table 3 Usage Intensity of Technologies, Science Skill Panel Estimations.

Variables	Aviation pkm air	Shipton Steam motor/ sea	Transplant Liver	Transplant Lung	Transplant Bone marrow	Cable TV	Mail
Lagged dependent variable	1.0220*** (0.03)	0.81053*** (0.06)	0.6794*** (0.08)	0.40465*** (0.104)	0.7417*** (0.062)	0.89391*** (0.02)	0.9496*** (0.31)
Cognitive Skills	-0.000028 (0.0001)	0.00003*** (0.000005)	-0.000006*** (0.000002)	-0.000005*** (0.000001)	0.000017** (0.000007)	0.0184* (0.01)	-0.000046** (0.00001)
Years of Schooling	-0.0681** (0.03)	0.0037*** (0.001)	0.00031 (0.0004)	-0.00124*** (0.0003)	-0.0021 (0.001)	-0.6624 (2.23)	-0.00052 (0.004)
Life Expectancy	0.28313* (0.016)	-0.00154*** (0.0005)	0.000401 (0.0002)	0.00023 (0.0001)	0.00115 (0.0007)	0.39457 (1.38)	0.00581*** (0.001)
FDI	0.00299 (0.109)	-0.00074*** (0.0002)	0.000032 (0.00003)	-0.0000024 (0.00002)	-0.00007 (0.0001)	-0.9187*** (0.26)	0.00237 (0.001)
Observations	162	88	90	72	109	253	153
Sargan test: p-val	0.007	0.000	0.773	0.42	0.731	0.000	0.289

Standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively. Sargan-Hansen test to check for over-identifying restrictions; p values mentioned in the last row . In the cases where the test identifies issues of endogeneity we perform system GMM technique to cater for this issue. The results for system GMM are presented in Supplementary Appendix B.

Table 3 (continued): Usage Intensity of Technologies, Science Skill Panel Estimations.

Variables	Computers	Internet user	Telephone	Cell phones	Visitor rooms	Harvester	Fertilizers
Lagged dependent variable	1.0159*** (0.13)	0.92361*** (0.028)	0.9379*** (0.02)	1.0266*** (0.015)	0.85242*** (0.033)	0.83778*** (0.02)	0.08068*** (0.027)
Cognitive Skills	0.01487 (0.01)	0.07052 (0.061)	-0.00452 (0.01)	0.00006 (0.027)	0.00185** (0.007)	-0.00049** (0.0001)	-0.00746 (0.005)
Years of Schooling	6.4531** (3.14)	2.3008 (8.45)	-1.026 (2.63)	19.439*** (5.77)	0.11308 (0.13)	0.0342 (0.366)	-2.5538*** (0.98)
Life Expectancy	5.0570** (1.97)	33.118*** (6.36)	2.414 (1.634)	17.655*** (3.67)	-0.082805 (0.077)	-0.00816 (0.016)	2.2730 (0.46)
FDI	0.35111 (0.37)	0.3104 (0.94)	2.3892*** (0.58)	1.9098** (0.81)	-0.01549 (0.02)	-0.000841 (0.007)	-0.219 (0.18)
Observations	215	177	162	304	269	288	305
Sargan test: p-val	0.000	0.000	0.000	0.000	0.809	0.609	0.000

Standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively. Sargan-Hansen test to check for over-identifying restrictions; p values are mentioned in the last row. In the cases where the test identifies issues of endogeneity we perform system GMM technique to cater for this issue. The results for system GMM are presented in Supplementary Appendix B.

In contrast to learning-by-doing, the qualitative dimensions of human capital exhibit a relatively weak association with usage intensity of technologies. For instance, a review of the results in Table 2 reveals that the cognitive skills based on mathematics test scores – which we interpret as "generic" in nature - have a positive and significant association with 8 out of 14 technologies such as aviation pkm/air, transplant liver, transplant lung, cable TV, mail, computers, internet users and visitor beds. Furthermore, in Table 3 the evidence based on science scores – which we interpret as reflective of specific skills (i.e. knowledge of science) – is weaker. The coefficient of the qualitative measure of human capital is now positive and significant in only 4 out of 14 regressions for technologies such as shipton steam motor/sea, transplant bone marrow, cable TV and visitor rooms.[19]

Overall, our interpretation is that a workforce equipped with generic in contrast to specific skills may serve as a more appropriate channel to enhance technological diffusion. However, the results also suggest that the evidence is weak relative to previous literature examining the contribution of human capital in facilitating technology adoption. Given the significance of the lagged dependent variables in all regressions, we again suggest that more important drivers of technology adoption and diffusion are to be found in other, less measurable dimensions of human capital, such as those developed via learning-by-doing.

Furthermore, our results reveal that embodiment of a certain skill is not positively associated with adoption of *all* technologies within a sector. For example, in Table 2 the first four columns include results for technologies from the telecommunications and information sector. As can be

[19] In the sector-wise analysis, presented in the online appendix, we have 21 technologies each in the mathematics and science panels. The coefficient of mathematics and science skills is significant in 10 and 5 intensity of usage of technologies respectively. Hence, we could suggest that in a broad sense a labor force embodied with mathematics skills is more suitable for improving the adoption of technology relative to on embodied with science skills. However, there are obvious caveats to such an interpretation as we would expect specialized skills, more directly measured, to impact in sectors where they were relevant. We discuss this caveat in further detail at the end of this section.

seen that the association of mathematics (i.e. generic) skills is positive and significant for computers and internet, it is certainly not the case for telephone and cell phone of technologies.[20] A possible interpretation is that the link between a particular type of human capital and technology is a *conditional* one which rests on various aspects of human capital as well as the nature of the technology in question.

Some remarks are in order in relation to the counter-intuitive results we find in the context of a few technologies. Interestingly results for mathematics (i.e. generic) and science (i.e. specific) cognitive skills are *significant* in majority of technologies in agriculture but the association is *negative*. This is visible in the last two columns of tables 2 and 3, where the coefficient for these skills is negative and significant for usage intensities of harvester and fertilizer technologies. While these results are hard to interpret, they still connect with earlier empirical evidence by Foster and Rosenzweig (1995) who suggest that agricultural technologies are associated to a greater degree with "learning by doing" and time spent acquiring formal knowledge of certain subjects or disciplines represents an opportunity cost.[21] However, the results certainly do not rule out the significance of specific knowledge; rather the qualitative measures in our regressions do not adequately address the specificity of knowledge required in agriculture.

Our empirical analysis also includes a quantitative dimension of human capital measured as average years of schooling, and the evidence for the human capital and technology diffusion link is the weakest in this case. For instance, in Table 2 for the mathematics scores panel the variable is positively and significantly associated with only 2 technologies. In Table 3 which presents

[20] While such technologies do not require mathematics skills per se, their prevalence requires human capital in the form of qualified technicians and engineers to provide maintenance and technical support service, who are typically endowed with such skills. It is in this sense that we suggest that the generic nature of mathematics skills is relevant. Following Hanushek and Kimko (2000) we interpret these measures as an *indirect* proxy of the quality of the labour-force of an economy.

[21] Other factors, such as property rights associated with technological transfer may be of relevance, as suggested by Spielman and Ma (2015).

science panel estimations, we find the association between average years of schooling positive and significant for only 3 technologies. Our results also show that another measure of human capital, i.e. life expectancy, is positively and significantly associated with usage intensity regressions involving the technologies labelled aviation pkm/ air, lung transplant, internet, cell phone and fertilizer in the mathematics panels. In the corresponding science panel estimations the coefficient for life expectancy is positive and significant for aviation pkm/ air, computer, internet user and cell phone.

Based on the above one may conclude that there is a hierarchy in the effectiveness of different types of human capital. In the above regressions human capital associated with learning-by-doing seems to be the most important contributor to technology adoption followed by other types of human capital reflected in qualitative and quantitative measures. Of the latter measures there is some evidence to suggest that human capital of the generic type as reflected in mathematics test scores is important in the context of technology adoption.

A caveat applies to this discussion; some of the cases presented in tables 2 and 3 are worthy of discussion especially in relation to alternate measures of human capital such as average years of schooling and life expectancy. In technologies such as cell phones it seems that average years of schooling and life expectancy are more relevant as they have a relatively larger impact than qualitative measures of human capital. We find that an increase in one year of schooling is associated with 11.36% increase in the usage intensity of cell phone technologies. In addition, a similar increase in life expectancy leads to 21.26% increase in adoption of cell phones. On the other hand, we find a negative and significant association between cognitive skills and these technologies.

We also control for other possible determinants of technology adoption and introduce foreign direct investment in both sets of analyses involving usage intensity of the technologies presented in tables 2 and 3. We find foreign direct investment shows a positive and significant association with the measure of technology indicated by the labels cell phones, mail and telephone. Overall, this control variable shows inconclusive evidence as indicated by the signs of the coefficients. This probably suggests that macroeconomic, aggregate variables such as FDI may have relatively lower explanatory power in the context of specific technologies and we would need sectoral, microeconomic counterparts of these variables to get a more accurate idea of their relevance.

Furthermore, some caveats apply to variables selected for the analysis. For example, generic skills may be less relevant for the adoption of medical technologies such as bone marrow transplant in comparison to measures such as per capita number of medical graduates or surgeons. In addition, number of pilots per capita may be a more relevant determinant of adoption of aviation technologies in comparison to specific human capital reflected in science scores. This implies that for a particular technology a specific knowledge variable and set of determinants is required for a technology-specific discussion. However, apart from issues relating to availability of data the aim here is to find *common* determinants of technology in addition to specific ones. With regard to the latter, it is difficult to find comparable and consistently measured variables for all of the countries in the sample. For example, finding per capita measures of the number of medical graduates or surgeons is difficult because such kind of data is mostly available from country specific sources rather than international databases.[22] In regard to the former – i.e. common determinants - the contribution of the current analysis is that learning-by-doing and generic skills matter relatively more compared to other dimensions of human capital.

[22] For example, World Development Indicators (WDI) do not have such indicators for health. However, some country specific studies do provide this information from their respective national databases (Ceppa et al, 2012).

IV. Empirical Evidence on Measures of Human Capital and Technology Usage Lags

We estimate equation (2) to examine the contribution of human capital to technology usage lags. We present results in tables 4-5.[23] Table 4 includes mathematics (generic) panel and Table 5 presents science (specific) panel results with selected technologies.

Similar to our evidence for usage intensity of technologies we find a strong association between the past with current usage lags of technologies. As can be seen from tables 4 and 5 lagged dependent variable is *positively* and *significantly* associated with usage lags of technologies in almost all regressions. A similar interpretation, pertaining to the learning-by-doing dimension of human capital is applicable here. Specifically the pace of technology adoption is small (representing quicker adoption) if past levels of the usage lag is small. If the gap in usage is small "learning by doing" has occurred to a greater degree.

[23] Supplementary appendix B contains descriptive evidence regarding data used for analysis. A complete sector-wise overview of these results including a larger set of technologies is available on request. The more succinct presentation of these results in the form of tables in the paper does not affect the overall findings and interpretation of the analysis.

Table 4 Mathematics Skills and Usage Lags of Technologies

Variables	Computers	Internet User	Telephone	Mail	Cable TV	Cellphones	Transplant Lung
Lagged dependent variable	0.88*** (0.470)	0.551*** (0.106)	0.736*** (0.037)	0.804*** (0.051)	0.581*** (0/075)	0.7633*** (0.057)	0.7715*** (0.075)
Cognitive Skills	-0.015*** (0.004)	-0.184* (0.0101)	-0.003 (0.005)	-0.0601 (0.013)	-0.0106 (0.006)	0.0075** (0.057)	-0.099*** (0.056)
Years of Schooling	-0.290 (0.226)	-0.042 (0.27)	0.0563 (0.367)	0.109 (1.08)	0.713 (0.439)	-0.709*** (0.202)	12.72*** (3.54)
Life Expectancy	0.183 (0.120)	-0.0012 (0.163)	0.070 (0.201)	0.098 (0.523)	0.347 (0.260)	-0.238* (0.134)	-0.0286 (1.11)
FDI	0.018 (0.028)	0.0016 (0.032)	-0.400*** (0.106)	-1.068** (0.043)	0.047 (0.051)	-0.044 (0.046)	0.009 (0.151)
GDP/income lag	-0.0073 (0.027)	0.003 (0.047)	-0.117* (-0.117)	0.135 (0.124)	0.0095 (0.051)	-0.0138 (0.028)	0.253 (0.033)
Observations	140	125	154	140	123	142	59
Sargan test: p val	0.057	0.505	0.000	0.405	0.184	0.040	0.636

Standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively. Sargan-Hansen test to check for over-identifying restrictions; p values in brackets. In the cases where the test identifies issues of endogeneity we perform system GMM technique to cater for this issue. The results for system GMM are presented in Supplementary Appendix B.

Table 4 (continued), Mathematics Skills and Usage Lags of Technologies

Variables	Transplant Heart	Transplant Kidney	Transplant Liver	Visitor rooms	Visitor beds	Tractor	Fertilizers
Lagged dependent variable	0.856*** (0.057)	0.6304*** (0.06)	0.121 (0.12)	0.835*** (0.046)	0.535*** (0.118)	0.961*** (0.018)	0.609*** (0.062)
Cognitive Skills	0.007 (0.004)	0.0011 (0.007)	-0.0103 (0.01)	-0.0063 (0.005)	0.0086 (0.008)	0.0017 (0.001)	0.020*** (0.006)
Years of Schooling	0.310 (0.32)	0.261 (0.565)	1.278 (0.997)	-0.655 (0.404)	1.073** (0.484)	0.024 (0.068)	1.407*** (0.505)
Life Expectancy	0.418** (0.203)	1.249*** (0.399)	2.613*** (0.555)	0.594 (0.209)	0.549* (0.319)	0.0415 (0.054)	0.387 (0.257)
FDI	0.016 (0.02)	0.183** (0.087)	-0.0101 (0.07)	0.051 (0.055)	0.004 (0.06)	0.015 (0.012)	0.012 (0.073)
GDP/income lag	-0.0072 (0.024)	-0.032 (0.071)	0.001 (0.067)	0.124** (0.053)	-0.0033 (0.094)	-0.0105 (0.013)	0.012 (0.06)
Observations	58	150	60	182	100	214	183
Sargan test: p val	0.756	0.856	0.446	0.094	0.092	0.571	0.889

Standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively. Sargan-Hansen test to check for over-identifying restrictions; p values in brackets. In the cases where the test identifies issues of endogeneity we perform system GMM technique to cater for this issue. The results for system GMM are presented in Supplementary Appendix B.

Table 5 Science Skills and Usage Lags of Technologies

Variables	Computers	Internet User	Mail	Cable TV	Cell phones	Electricity Production	Transplant Heart
Lagged dependent variable	0.866*** (0.044)	0.385*** (0.11)	0.568*** (0.067)	0.603*** (0.058)	0.849*** (0.042)	0.792*** (0.043)	0.856*** (0.057)
Cognitive Skills	-0.002** (0.001)	0.0016 (0.002)	-0.011* (0.006)	-0.002 (0.001)	0.0013 (0.001)	-0.0015 (0.001)	0.007 (0.004)
Years of Schooling	0.047 (0.204)	-0.434 (0.002)	-0.144 (1.42)	0.792** (0.365)	-0.830 (0.180)	0.175 (0.278)	0.310 (0.32)
Life Expectancy	0.029 (0.109)	-0.063 (0.165)	-0.128 (0.653)	0.347 (0.212)	-0.154 (0.109)	0.275* (0.163)	0.418** (0.203)
FDI	-0.006 (0.027)	0.020 (0.034)	0.083 (0.421)	0.051 (0.04)	-0.192 (0.033)	0.039 (0.072)	0.016 (0.02)
GDP/income lag	-0.0108 (0.021)	-0.003 (0.33)	0.022 (0.87)	0.005 (0.03)	0.0132 (0.018)	0.105* (0.045)	-0.0072 (0.024)
Observations	194	157	133	134	200	203	58
Sargan test: p val	0.251	0.537	0.113	0.081	0.012	0.592	0.016

Standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively. Sargan-Hansen test to check for over-identifying restrictions; p values in brackets. In the cases where the test identifies issues of endogeneity we perform system GMM technique to cater for this issue. The results for system GMM are presented in Supplementary Appendix B.

Table 5 (continued) Science Skills and Usage Lags of Technologies

Variables	Transplant Bone marrow	Transplant Kidney	Transplant Lung	Visitor rooms	Visitor beds	Tractor	Fertilizers
Lagged dependent variable	0.693*** (0.087)	0.296*** (0.079)	0.208 (0.163)	0.790*** (0.047)	0.624*** (0.093)	0.979*** (0.018)	0.790*** (0.039)
Cognitive Skills	-0.004* (0.002)	0.012*** (0.004)	-0.0019 (0.008)	-0.003* (0.002)	0.002 (0.003)	0.00058 (0.0005)	0.0013 (0.001)
Years of Schooling	0.217 (0.509)	-1.408* (0.835)	5.668 (2.106)	-0.505 (0.395)	0.588 (0.430)	0.124 (0.080)	0.747*** (0.266)
Life Expectancy	0.847*** (0.26)	1.951*** (0.423)	0.117 (0.991)	0.800*** (0.243)	0.635** (0.279)	-0.0388 (0.064)	0.426*** (0.134)
FDI	0.0417 (0.041)	0.270** (0.138)	0.071 (0.130)	0.071 (0.061)	0.015 (0.058)	-0.008 (0.014)	0.028 (0.036)
GDP/income lag	-0.0286 (0.034)	0.020 (0.104)	-0.032 (0.109)	0.050 (0.046)	-0.031 (0.085)	-0.001 (0.012)	0.026 (0.02)
Observations	67	166	48	198	101	210	215
Sargan test: p val	0.348	0.515	0.610	0.505	0.356	0.738	0.231

Standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively. Sargan-Hansen test to check for over-identifying restrictions; p values in brackets. In the cases where the test identifies issues of endogeneity we perform system GMM technique to cater for this issue. The results for system GMM are presented in Supplementary Appendix B.

Our empirical evidence indicates a weaker link for both generic and specific skills with usage lags of technologies when compared to learning-by-doing aspect of human capital. In terms of generic skills based on mathematics test scores the results presented in Table 4 show the hypothesized negative and significant association in only 3 technologies, labelled computers, internet, and transplant lung. In Table 5 the estimations for specific skills measured as science test scores also provide a similar picture with a significant and negative association in the case of only 4 technologies such as computers, mail, transplant bone marrow and visitor rooms. This inverse association, when present, indicates that the presence of a workforce with generic and specific skills tends to reduce usage lags, thereby improving diffusion of technologies.

In contrast to previous results on usage intensity of technologies the hierarchy in the degree of importance of various types of human capital is not seen in these regressions. Both generic and specific skills seem to be of equal and limited importance compared to learning-by-doing which is positively and significantly associated with almost all usage lags of technologies. However, in terms of other dimensions of human capital such as average years of schooling and life expectancy our results are similar to the evidence presented for usage intensity of technologies. Overall, we again find learning-by-doing to be the most appropriate determinant of technology adoption followed by both qualitative measures of human capital, average years of schooling and life expectancy respectively.

The association between skills and usage lags is weaker when compared to results for usage intensity of technologies in the previous section. One plausible argument here is that in the case of usage lags of technologies it is not just the presence of skills among the potential adopters that matters for an economy. There may be other factors which inhibit diffusion of a technology such as governmental and political motives, industrial policy dynamics and demographic or cultural factors. These factors are better explored in single country and single technology studies aimed at unearthing country-specific issues pertaining to technology adoption.

One of the most important points to be made here is that even though our empirical evidence for human capital is weaker for usage lags of technologies, it still lends support to our hypothesis that the human capital and technology is *conditional* one which rests on various aspects of human capital and the nature of technology under question. In common with results for usage intensity of technology our evidence for usage lags of technology also reinforces that the association between human capital and technology diffusion varies within and across sectors. A glance at the first 5 technologies in Table 4 highlights this variation of association between generic skills and technologies in the telecommunications and information sector. In the first and second columns we find a negative and significant association between generic skills and computer and internet usage lags. However, in the third and fourth column the impact is insignificant for telephone and mail, while in the fifth column (cell phone) the impact is positive and significant. This shows that usage lags of technologies within a sector can have a different link with the same measure of human capital, as was the case with usage intensity regressions. In the case of the agricultural sector our results indicate an absence of skill-technology link for generic and specific skills, similar to what we found in the case of usage intensity regressions. A similar interpretation may be applicable, i.e these technologies have greater degree of association with informal channels of diffusion such as learning from social networks (Conley and Udry, 2001).

In contrast to our usage intensity analysis we also include income or GDP lags in the usage lag estimations. We follow Comin et al (2008) who employ these lags to capture the dynamics of technology. They argue that if a country is progressing well in terms of reducing its income lags then it should have shorter technology lags as well. Hence, higher economic growth should improve the diffusion prospects of technology in an economy. Our results indicate that GDP lags are positive and significant in only 3 estimations across these two panels. This weak significance presented in our results reinforces the findings of Comin et al (2008) and indicates that technology lags measuring the past level of technology are relatively more important that the income lag of a country. Therefore, the dynamics of technology itself play a more vital role in the process of technological diffusion rather than the dynamics of an economy as reflected in income usage lags.

V. Pooled Panel and Developed and Developing Country Analysis

In order to further investigate our skill-technology association we pool all technologies in a single regression and develop panels for our data set to generate a bigger sample size, as discussed in Section II. Hence, the corresponding panel has cross-sectional dimensions including country-technology pairs and the usual time dimension, increasing the number of observations available to study the impact of human capital on the usage intensity and usage lags of technologies. We are also able to study additional issues of interest by splitting the whole sample of countries into developed and developing countries. These regressions enable us to study whether there are any differences in the human capital and technology diffusion link that pertains to the level of development.

Table 6 presents the results for panel-pooled estimations for usage intensity and usage lags of technologies respectively.[24] Columns 1 and 2 correspond to the response of the usage intensity of technology to mathematics and science test scores respectively, in addition to other human capital variables that are common to both regressions. Columns 3 and 4 present analogous estimations for usage lags of technology.

[24] We use a system GMM approach given the persistent nature of the lagged variable; the Sargan test in the difference-GMM approach also suggested inappropriate identifying restrictions.

Table 6: Panel Systems GMM for Usage Intensity and Lags of Technologies; Mathematics and Science Test scores

	Usage Intensity of Technologies		Usage lags of Technologies	
	1	2	3	4
Variables	**Maths Panel**	**Science Panel**	**Maths Panel**	**Science Panel**
Lagged dependent variable	1.0676***	1.0802***	0.9861***	0.9289***
	(0.0126)	(0.0144)	(0.0066)	(0.0282)
Cognitive Skills	0.1173**	0.0178	-0.0028	0.0084
	(0.0558)	(0.0234)	(0.0025)	(0.0053)
Years of Schooling	-1.8608	-1.6067	0.0553	-0.4382*
	(1.2666)	(1.4531)	(0.0813)	(0.2509)
Life Expectancy	0.9293	1.3685**	-0.0316	0.0040
	(0.6655)	(0.6243)	(0.0405)	(0.0832)
FDI	1.3369*	0.8210	-0.0483**	-0.1353*
	(0.6897)	(0.5879)	(0.0200)	(0.0748)
Observations	2642	2889	2130	2403
AB test AR (1) (p-val)	-2.13 (0.033)	-1.98(0.048)	-4.49 (0.000)	-2.47(0.013)
AB test AR (2)(p-val)	-1.08 (0.281)	-1.13(0.259)	2.53 (0.012)	1.56(0.12)
Hansen test (p-val)	249.33 (1.000)	223.20(1.000)	196.40 (1.000)	185.81(1.000)

Robust Standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively. For systems GMM regression, we use lag 2 of the dependant variables lags of independent variables as instrumented variables to prevent potential endogeneity of our dependent and independent variables with the residuals. Two standard diagnostic tests for system GMM dynamic model estimations are reported. The first is the Arellano–Bond tests for auto-covariance in residuals of order 1 as shown in the AB test AR(1) and of order 2 as shown in the AB test AR(2) with H_0: no auto-correlation. The second is the Hansen test to check for over-identifying restrictions; p-values are mentioned.in brackets.

Our results across all regressions reinforce our hypothesis that past levels of usage intensity and lags of technologies impact significantly on the current usage intensity and lags of technologies in our pooled panel regressions. Furthermore, in common our assessment of regressions relating to individual technologies, we find that the more generic mathematics skills are significant in improving the usage intensity of technologies across countries. Results in relation to other human capital variables are mixed, as was the case with results in the previous section.

We present the results of developed and developing country regressions in Table 7 below.

Table 7: Systems GMM for Developed and Developing Country Panel (Usage Intensity; Mathematics Panel)

	Systems GMM	
	1	**2**
Variables	**Developed Countries**	**Developing Countries**
Lagged dependent variable	1.0650***	1.1278***
	(0.0130)	(0.0491)
Cognitive Skills	0.0057	-0.0120
	(0.0652)	(0.1132)
Years of Schooling	-3.8004**	2.7749
	(1.6650)	(2.6662)
Life Expectancy	1.4230**	3.2779*
	(0.6605)	(1.6989)
FDI	1.5173**	0.6097
	(0.646)	(1.3475)
Observations	2360	349
AB test AR (1) (p-val)	-2.11 (0.035)	-0.17 (0.862)
AB test AR (2)(p-val)	-0.80 (0.424)	-1.46 (0.144)
Hansen test (p-val)	197.82(1.000)	31.21(1.000)

Robust Standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively. For systems GMM regression, we use lag 2 of the dependant variables lags of independent variables as instrumented variables to prevent potential endogeneity of our dependent and independent variables with the residuals. Two standard diagnostic tests for system GMM dynamic model estimations are reported. The first is the Arellano–Bond tests for auto-covariance in residuals of order 1 as shown in the AB test AR(1) and of order 2 as shown in the AB test AR(2) with H_0: no auto-correlation. The second is the Hansen test to check for over-identifying restrictions; p-values are mentioned.in brackets.

In Table 7, columns 1 and 2 present the results for developed and developing country cases employing a system-GMM approach which is more appropriate given the persistent nature of the lagged variable, as well the fact that the Sargan test for the difference-GMM approach suggested invalidity of identifying restrictions in both cases. Similar to our earlier estimations, we again find that learning-by-doing, which we measure as past levels of technology usage intensity, plays a significant role in improving the current level of technology usage intensity. A closer review suggests that magnitude of the learning-by-doing effect seems stronger in developing countries; intuitively this is plausible given that many of these countries are followers rather than leaders in technological development and innovation, making the learning by-doing dimension more important. Furthermore, life expectancy plays a significant role in improving diffusion of technology and this impact is greater in developing countries. Again, this is plausible as gains from small improvements in health are likely to be higher in developing economies.

An interesting aspect, however, is that cognitive skills (as represented by mathematics scores) are no longer significant. Perhaps this was to be expected, given that the evidence in the case of individual technologies was weak. In the pooled sample, which represents, in some sense, an average effect, the result is that overall there is no evidence of a link between cognitive skills and technological diffusion.

VI. Concluding Remarks

This paper analyzes the link between human capital and technology in the light of direct measures of technology adoption and diffusion and a comprehensive set of measures of human capital. Earlier literature in the field of human capital and economic growth uses average measures of educational quality and quantity (Barro, 1997; Hanushek and Woessmann, 2012). However, it focuses more on the link between human capital and economic growth and ignores the channels through which human capital affects growth of an economy. We hypothesize that one of the channels through which human capital may impact economic growth is its role in improving adoption and diffusion of technologies. We examine this relationship by taking a more holistic perspective of human capital as well as technology adoption. Specifically we use direct measures of technology, where technology is defined in a very broad sense, and also differentiate between different forms of human capital and examine their relative impact on the adoption and diffusion of technologies.

In testing the hypothesis whether educational quality enhances technology adoption and diffusion, we use data on cognitive skills based on international mathematics and science test scores, along with data on direct measures of technology adoption. We use Hanushek and Woessman's (2012) measure of educational quality and further decompose average cognitive skills into mathematics and science skills and construct separate panels for both the set of skills from 1964-2003 and 1973-2003 respectively. We also consider other measures of human capital, such as life expectancy and years of schooling. To measure the technological aspects, we use the CHAT data set developed by Comin and Hobijn (2009) and obtain direct, broadly defined measures of technology represented by *usage intensity* of a technology, or *usage lag* in the timing of adoption relative to the leading country. In order to empirically analyze the learning-by-doing dimension of technology we use a dynamic panel specification that incorporates past levels of technology.

Our main finding is that the link between human capital and technological adoption and diffusion is a conditional one, which rests on various aspects of human capital as well as the technology under consideration. In particular, we find that the appropriateness of skills required for adoption and diffusion of technologies changes within and across sectors. For example, technologies from transportation, tourism and health sectors positively respond to both measures of cognitive skills. However, telecommunication and information based technologies are more influenced by generic (i.e mathematics score based) in contrast to specific (i.e. science score based) skills. On the other hand, in the case of usage lags as a measure of technological diffusion, mathematics-based generic skills assist diffusion of certain technologies in telecommunications and information, electricity production and health sectors.

Overall, the broad theme that emerges from the analysis is that the most important determinant of technology adoption is its past use, reflecting the learning-by-doing element of human capital. In terms of the hierarchy of relevance, this is followed by generic measures of cognitive skills reflected in mathematics test scores, which is, in turn, followed by specific measures such as science based test scores. Measures such as years of schooling and life expectancy are also relatively less important as they are significant only for a few of the technologies in question. However, in these cases their magnitude of impact is greater relative to other measures of human capital.

A caveat that applies to our analysis is that we measure the learning-by-doing aspect *indirectly* through past levels of technological use. However, to our knowledge, comprehensive multi-technology and multi-country measures that examine this aspect directly do not exist in the extant literature. Any approach to understanding this further would entail collection of primary data for various technologies in a systematic way over time for many countries. In context of cognitive skills presence of a time series data could have been useful in terms of examining a perhaps a nonlinear relationship between human capital and technology adoption. Pending the availability of such data we leave this issue as a future direction of research.

Our results also highlight that conclusions about the human capital and technology adoption link based on a single technology (as is the case with micro-economic studies) or aggregate measures of technology (such as total factor productivity) can be misleading. Studies looking at aggregate measures, for example, may find a positive impact of human capital leading to a "one-size-fits-all" policy recommendations for investment in a certain type of human capital. Likewise evidence based on a single technology yields information of relevance to only that particular technology. By following a comprehensive approach that looks at different measures of human capital and a large set of technologies, we have taken a more cautious approach, leading to the insights that policies focused on learning-by-doing or technology-specific education may be a better facilitator of technology adoption and diffusion. Also, given that qualitative measures reflective of generic skills are of greater relevance relative to specific skills suggests greater gains from policies focused on targeting such skills.

In the light of these results, studies using qualitative measures of human capital in growth regressions may also be interpreted differently. The evidence in favour of such measures positively impacting on growth is relatively robust. Given the relatively weak results here, it may be the case that mechanisms other than technology adoption are more relevant when considering the impact of human capital on economic growth.

Compliance with Ethical Standards

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Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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