Human Capital and the Adoption and Diffusion of Technology

Zainab Asif

Queensland University of Technology

zainab.asif@hdr.qut.edu.au

Radhika Lahiri

Queensland University of Technology

r.lahiri@qut.edu.au

Abstract: The empirical literature on the link between human capital and technological diffusion remains inconclusive, with controversies pertaining to both the measurement of human capital as well as that of technological adoption and diffusion. In this paper we revisit this issue, by examining this link using newly created measures for both of these concepts. Specifically, we examine the impact of *qualitative* measures of human capital (based on data on tests of cognitive skills), and direct measures of technology adoption using country level panel data for the period 1964-2003. Our measure of cognitive skills is drawn from Trends in Mathematics and Science Study (TIMSS). For measures of technology we use the Cross Country Historical Adoption of Technology (CHAT) data set due to Comin and Hobijn (2009), which presents measures of intensity and timing of adoption for a large number of technologies from various sectors of the economy. Our analysis suggests that the link between human capital and technological adoption and diffusion is a *conditional* one, which rests on various aspects of human capital and the nature of the technology in question. We find, for example, that technologies in transport, tourism and health exhibit a stronger evidence of correlation between our measures of technology adoption and human capital, than technologies from "traditional" sectors such as agriculture. Our interpretation for the lack of correlation in the latter sector is not that human capital does not matter in agriculture; rather, other unmeasured aspects of human capital such as "learning by doing" could matter more. Our analysis, which also controls for institutional variables and other factors that determine technological adoption, therefore suggests that future explorations of the link between human capital and technological adoption need to be more comprehensive, in that they take into account the appropriate dimensions of human capital associated with the nature of the technology in question.

I. 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 canbe related not only to technological change, but other unmeasured inputs in the process of production.[1] 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 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

[1] Other researches such as Thijs, R., & Victoria, S. (2011), provide a general framework which explains and interrelates different approaches to measurement and decomposition of TFP growth. This may be reviewed for information on concepts such as Solow residual.

through its impact on technology adoption and diffusion, the appropriate empirical exercise to address this issue should focus on *direct* measures of both human capital and technology diffusion.

A key objective of this study, therefore, is to empirically investigate and analyze the link between technology and educational quality in the light of direct measures of technology adoption and diffusion, as well as of educational quality. To that end, we examine the impact of educational quality, as measured using the data set on cognitive skills created by Hanushek and Woessman (2012), and on direct measures of technology adoption and diffusion based on the recently created Cross Country Historical Adoption of Technology (CHAT) data set due to Comin and Hobijn (2009).[2] To our knowledge, this is the first attempt to examine the link between human capital and technology adoption and diffusion by incorporating disaggregated qualitative aspects of education (in the form of cognitive skills measured as Trends in International Mathematics and Science Study (TIMSS) test scores and direct measures of technology.

The literature on cognitive skills and growth suggests that the quality of human capital has a close, consistent and stable relationship with economic growth (Hanushek and Kimko, 2000; Hanushek and Woessman, 2012).[3] However, in this paper we suggest 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 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

[2] 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.
[3] The literature that uses quantitative measures of human capital, such as years of schooling and enrolment rates in contrast exhibits mixed evidence on the link between human capital and economic growth.

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".[4]

Apart from the two dimensions of human capital mentioned above –i.e. 'generic' and 'specific' human capital, a third dimension pertains to what has often been referred to as "learning by doing" in several theoretical and empirical studies of technology adoption (Parente 1994; Jovanovic and Nyarko1996; Conley and Udry 2010). 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 and Acemoglu and Zilibotti 2001). However, while direct measures of such 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. Therefore, another objective of our study is to capture this aspect and examine its implications for technology adoption. In terms of our methodology, we do so by incorporating lags of the dependent variable in our regressions, along with the human capital measures based on the TIMSS data set.[5]

As our study analyzes two dimensions of technology; usage intensity and usage lags of technologies, we may also argue that a change in the *measure* or dimension of technology may bring a change in the association between a particular technology and skill under discussion. For instance, human capital embodying knowledge of numeracy skills may not be as relevant in

[4] 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.

[5] 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.

reducing adoption lags of a digital technology, since the invention of that technology took place elsewhere and other factors, such as trading relationships and property rights have a greater bearing on when the transfer of that technology takes place. However the usage intensity after adoption may depend more critically on such human capital.[6]

In order to explore these issues we create two panels based on science and mathematics scores from TIMSS and technology adoption measures from CHAT for the years 1964-2003 and 1973-2003 respectively. Given that we add a lagged measure of technology in our empirical specifications in addition to other human capital measures, dynamic-panel methodologies are required. For this purpose, we employ the dynamic GMM methodology due to Arellano and Bond (1991). In our specifications we also include certain control variables that may be of relevance to technology adoption and diffusion, such as health and foreign direct investment (FDI), but have received less attention in previous literature pertaining to these issues.[7] Further, in order to compare the impact of qualitative and quantitative measures of human capital, we also include the average years of schooling measure from Barro and Lee (2010).

Our results support our premise about 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 technologies we consider, 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; 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

[6] 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 services. It is in this sense that we suggest that the generic nature of mathematics skills is relevant.

[7] Barro (2013) uses life expectancy to measure the dimension intrinsic to human capital by introducing it in the literature on economic growth. Sinani and Myer (2004) and Branstetter (2005) highlight the role of foreign direct investment on technological spillovers which contribute to physical capital accumulation, increasing domestic employment and generating positive effects on domestic industries and firms. We introduce these measures in the literature on technology adoption and human capital to control for possible determinants of usage intensity and usage lags of technology.

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 measure, which we interpret as representative of the experiential, learning-by-doing aspect of adoption, is positive and significant across *all* regressions.

Nevertheless, it is interesting to note that the human capital measure yields a positive and significant impact on usage intensity in only 16 out of the 21 technologies we consider. In the case of adoption lags evidence regarding the hypothesis that human capital facilitates adoption by reducing adoption lags is substantially weaker; only 6 of the 21 regressions yield a negatively significant coefficient for the variable representing human capital. There is a consistency between the two sets of regressions, in the sense that if the coefficient of the human capital variable is positive and significant for the usage intensity of a particular technology, it is then likely to be negatively significant for the usage lags for that technology. Furthermore, the regressions also suggest that qualitative measures of generic human capital matter more relative to quantitative measures such as average years of schooling; there are very few regressions for which the coefficient of this variable is positive and significant.

Referring back to the literature suggesting a strong and stable positive impact of human capital as measured by cognitive skills on economic growth, as in Hanushek and Woessmann (2012), it is perhaps surprising that the impact of this measure is not persuasively positive in the context of technology adoption, which is regarded as a *mechanism* through which growth takes place. Even so, we believe analyses of this type, focusing on mechanisms of growth rather than growth *per se* are more informative from the point of view of policy. Here, the insight that emerges is that the notion of human capital relevant for different types of technologies is diverse, and not easily captured by either the qualitative measures (such as test scores) or quantitative measures (such as years of schooling). Further, there is robust and clear-cut evidence to suggest that the learning-by-doing aspect associated with technology adoption matters, given the significance of the lagged measure of technology in all specifications considered in our analysis. The appropriate design of policy, then, is better informed by examining the nature of technologies and the types of human capital more relevant for their adoption.

The analysis based on science scores reinforces this point. In this case, the human capital measure has the hypothesized impact on usage intensity in only 4 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 3 of these technologies. The lagged technology measure, however, remains positive and significant across all regressions. Lastly, we also consider the inclusion of institutional quality, in the form of political rights and civil liberties along with GDP per capita and R&D expenditures to carry out some simple robustness checks. Even when we control for these variables the signs of the coefficients of human capital as measured by cognitive skills and the lagged dependent variable remain similar to baseline regressions in both the mathematics and science panel estimations.

To summarize, our study considers the impact of qualitative (generic and specific) and quantitative measures of human capital on technology adoption. We also consider the experiential, learning associated aspect through the presence of past levels of technology in our specifications. We find that the most important determinant of technology adoption is the past level of technology, reflecting the importance of the learning-by-doing aspect of technology adoption. Qualitative measures also matter, but are conditional on the nature of technology, with generic skills being far more relevant compared with specific skills. Finally, quantitative measures such as average years of schooling matter even less in comparison with qualitative measures. Based on our analysis, we suggest a multi-dimensional approach to studying human-capital barriers to technology adoption may be more informative from a policy making point of view.

The remainder of this document is organized as follows: Section 2 outlines the main features of theoretical and empirical framework relevant to our study. In section 3 we summarize results analyzing the role of cognitive skills in the process of technology adoption. Section 4 provides examines this role from the perspective of diffusion of technologies within and across selected sectors. Section 5 provides the results for robustness checks. 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.

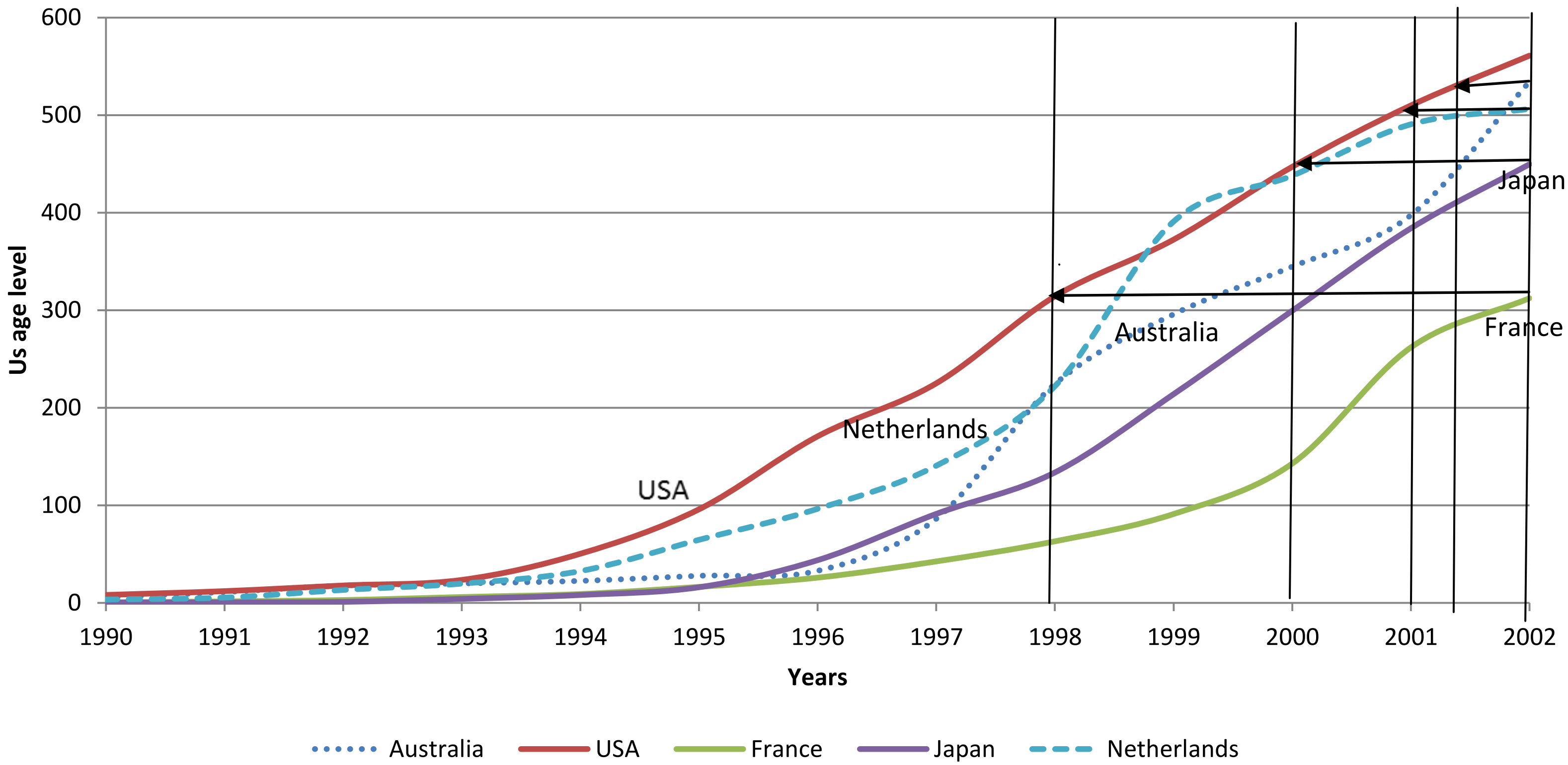
A. Measures of Technology Adoption and Diffusion

In this section we briefly explain our measures of technology adoption and diffusion, which we have borrowed from Comin, *et al* (2008).They consider two measures: usage intensity and usage lags. The former is relatively simple and captures the intensity with which each adopter uses the technology- i.e intensive margin *Comin et al* (2008).[8] In our study usage intensity or intensive margin is measured as the number of technology employed at a particular point in time scaled by the population in a country.[9] Therefore, the usage intensity of 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. Using this technique we estimate usage intensity of technology for 21 technologies in six sectors given in the CHAT data set.

The latter, however, is more complex and as such we choose to reiterate and explain it in this section for the benefit of the reader. 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 1, and perform an exercise similar to Comin *et al* (2008).[10] 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 the figure, 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 such as; in 2002 US led Australia by a few months, France by 4 years and Netherlands by a year. This illustration makes it somewhat easier to understand the theoretical definition provided in Comin et al (2008). Again, since our analysis heavily draws on this measure we reiterate its method of calculation here, rather than inconvenience the reader by omitting the explanation presented below.

[8] Comin and Mestieri (2013), use a different theoretical construct for intensive margin of technology in their theoretical framework.
[9] Comin and Mestieri (2013), suggest use of population or Gross Domestic Product as scaling factors.
[10] This graphical representation is based on author's own calculations for usage levels.

Figure 1: Graphical Representation of Technology Usage Lags.



From a theoretical perspective technology usage lag x for a country c at time t explains the time in terms of number years before a leader last have usage of technology. This shows difference in time period in the usage and adoption of a technology between a country c and that of leader. Following Comin et al (2008), we denote $X_{j,t}$ as the technology usage intensity lag of a specific technology for country j at a time period$t$. We evaluate this usage intensity lag in country j with the past time series of the leader. Then the time series of U.S is given as $\{X_{U.S,s}\}$where the observations over time are indexed as S. As the time series data for U.S has missing observations, let S denote the set of observations available in the past data. In this time series S for U.S they further select two observations each indicating a technology usage level. In the first case they select$\bar{s}$:

$$\bar{s} = \underset{s \in S}{\arg min} \left\{ s \middle| X_{U.S,s'} \geq X_{j,t} for all \acute{s} \in S and \acute{s} \geq s \right\} \tag{1}$$

In equation (1) $\bar{s}$ is the set of observation that denotes the first time U.S passed the level of technology usage $X_{j,t}$ for country$j$. On the other hand, the second observation$\underline{s}$ denotes the last time U.S recorded a level of technology usage which was either equal or lower than $X_{j,t}$ which is given as:

$$\underline{s} = \underset{s \in S}{\arg min} \left\{ s \middle| X_{U.S,s} \geq X_{j,t} \right\} \tag{2}$$

Given these two observations, we denote τ as the last time U.S had technology usage level $X_{j,t}$ which can be computed as follows:

$$\tau = \left(\frac{X_{j,t} - X_{U.S\underline{s}}}{X_{US,\bar{s}} - X_{US,\underline{s}}} \right) \left(\bar{s} - \underline{s} \right) \tag{3}$$

Equation (3) shows, it is known that $\bar{s}$ comes after observation $\underline{s}$ in the historical time series data for U.S, then technology usage lag between country j and U.S at time t can be given as$t - \tau$.

B. Measures of Cognitive Skills

Furthermore, following Hanushek and Woessmann (2012), we develop the measure of educational quality to incorporate the dimension of human capital in our model which facilitates technology adoption and diffusion. Educational quality reflects the 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] The common metric of educational quality assists in tracking the distribution of cognitive skills and developing comparisons across countries, time and tests. Hanushek and Woessmann (2012) develop this metric first 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 Tests (ISAT) relative to the known previous comparable performance of students from students which is expressed as:

$$U_{a,s,t}^{US} = \left(NAEP_{a,s,t}^{US} - NAEP_{a,s,1999}^{US}\right)\frac{SD_s^{US,PISA}}{SD_{a,s}^{US,NAEP}} \qquad (4)$$

In equation (4), U is the standardized performance difference of students from the benchmark country US, a is the age of student and s denotes subject at relative time t, which is in this case year 1999. $SD_s^{US,PISA}$is the subject specificstandard deviation of U.S students on Programme for International Student Assessment (PISA) test, while $SD_{a,s}^{US,NAEP}$ is the age and subject specific standard deviation of U.S students onNational Assessment of Educational Progress (NAEP) test.

Moreover in order to bring in variation in test scores over time comparable across countries they select a group of OECD countries as a benchmark to develop a comparable scale for the variation on different ISATs.[12] The framework transforms original test scores denoted as $O$of country i, for each age a and subject s at time t into a transformed test score X which is expressed as:

$$X_{a,s,t}^{i} = \left(O_{a,s,t}^{i} - \overline{O_{a,s,t}^{OSG}}\right)\frac{SD_{s,PISA}^{OSG}}{SD_{a,s,t}^{OSG}} \qquad (5)$$

[11] The measure developed here is an extension of Hanushek and Kimko (2000). Details for countries and tests are present in Hanushek and Woessmann (2012).
[12] This group of countries is called OECD standardized group (OSG) which include countries: Austria, Belgium, Canada, Denmark, France, Germany, Iceland, Japan, Norway, Sweden, Switzerland, United Kingdom and United States.

Given equation (5), the transformed test score X has mean zero among theOECD standardized group countries. Furthermore it shows that between country standard deviation among the OSG and group of countries on the PISA test is the same in a particular subject. The variation in the metric of rescaled test score termed as X in the above equation is comparable across tests. In order to generate the common metric for educational quality that is comparable across time, country and subject, they combine equation (4) and (5), where the standardized test score can be formally expressed as:

$$I_{a,s,t}^{i} = X_{a,s,t}^{i} - X_{a,s,t}^{US} + O_{s,PISA}^{US} + U_{a,s,t}^{US} \tag{6}$$

Equation (6) gives the standardized test score $I_{a,s,t}^{i}$. It determines the performance in ISAT for all participating countries on a common scale that can be compared across ISATs.After performing the standardization procedures this exercise provides cognitive skills measuredas a simple average of all standardized science and mathematics test scores of the ISAT's for a participating country.

C. Econometric Methodology

This section explains the empirical methodology used to examine the link between technology diffusion and educational quality. We develop our empirical methodology based on the earlier literature mentioned above suggestive of positive influence of previous period's technology on current period's technology and learning by doing dimension of technology. (Parente 1994; Jovanovic and Nyarko 1996; Skinner and Staiger 2007; Conley and Udry 2010). In addition, Comin et al (2008), suggest that current analysis of adoption and diffusion of technology requires incorporating the dynamics of technology in the form of technology lags incorporated in panel data estimations. For that reason, we suggest that the intensity of technology builds up from one period to another and examine the role of educational quality on technology adoption and diffusion measured as usage intensity and usage lags of technology by estimating dynamic panel regressions. The dynamic panel regression can be expressed as:

$$T_{c,t}^{i} = \alpha_c + \gamma T_{c,t-1}^{i} + \beta_1 CS_{c,t} + \beta_2 AS_{c,t} + \beta_3 X_{c,t} + \mu_{c,t} \tag{7}$$

$$Lag_{c,t}^{i} = \theta_c + \gamma Lag_{c,t-1}^{i} + \beta_4 CS_{c,t} + \beta_5 AS_{c,t} + \beta_6 X_{c,t} + \varepsilon_{c,t} \tag{8}$$

In equation (7), T is the usage intensity of technology, $CS$are the 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 (8) Lag is the usage lag of technology diffusion and the rest of the variables are the same as equation (7). The dynamics of technology and dimension of "learning by doing" are introduced as$T_{c,t-1}^{i}$ and $Lag_{c,t-1}^{i}$to denote the lag of the dependent variables in period 1 in equation (7) and (8) respectively. Here, we expect the sign of $\gamma > 0$. This implies a positive association between previous period's usage intensity and usage lag of technology with the current period's usage intensity and usage lag. 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 issue of correlation we employ the dynamic GMM estimators of Arellano and Bond (1991). These GMM estimators take into account the dynamic nature of the model and correlation generated due to introducing the lag of the dependent variable.[13]

In our analysis cognitive skills are a measure of human capital and educational quality. In equation (7), we expect the sign of $\beta_1 > 0$. This implies that human capital embodying skills increases usage intensity of a given technology. In equation (8), we expect the sign of $\beta_4 < 0$ which implies that better skills results in reducing timing of adoption of a given technology. Models of economic growth predict this association because human capital directly or indirectly facilitates the use of technology adoption and diffusion (Lucas 1988, Mankiw, Romer and Weil 1992, Aghion et al 2009, Galor 2011). Moreover, literature focusing on the role of human capital and technology diffusion from the perspective of specific technologies and countries also reveals the significance of human capital in technological adoption and diffusion (Caselli and Coleman 2001, Comin and Hobijn 2007 and Riddell and Song 2012). Therefore, based on earlier studies, we suggest that cognitive skills as a measure of educational quality and human capital lead to better adoption and diffusion of technology. In addition, we include quantitative measure of human capital as average years of schooling based Barro and Lee (2010). In equation (7), the expected sign of the coefficient of this variable$\beta_2 > 0$. This indicates that human capital with higher educational attainments enhances usage intensity of technology. In equation (8), we

[13] In this estimation procedure we instrument current variable at time t for their past lags, which eliminates correlation between explanatory variables and error term. For further details see Arellano and Bond (1991).

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 (Ainsworth and Over 1996, 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). Specifically, our hypothesis is that a country with higher life expectancy has better health and human capital which in turn facilitates the adoption of technologies. 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.[14] Moreover, the literature on technology suggests that FDI inflows may contribute to spillovers and affect domestic industries and firms (Sun 2011). However, the empirical evidence about FDI affecting technology diffusion and adoption remains mixed (Aitken and Harrison 1999, Li *et al* 2001, Sun 2011). The empirical analysis introduces FDI as a determinant of technology adoption and uses the WDI of the World Bank (2015) data for the years 1964-2003 where FDI is measured as net inflows percentage of Gross Domestic Product.[15]

[14] See www.worldbank.org
[15] See www.worldbank.org

III. Disaggregated measures of Cognitive Skills and Usage intensity of Technology as a measure of Technology Adoption: Empirical Evidence.

We begin by estimating equation (7) to examine the association between human capital embodied with mathematics and science knowledge on technology adoption. The current analysis includes a sample of 21 usage intensity of technologies that can be classified into six broad categories. We 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.[16] Specifically, we consider technologies in transportation, tourism, telecommunications and information, health, electricity production and agriculture sectors. Appendix 1 contains definitions and descriptive evidence regarding the data used for analysis. The results reported in appendix 2 consist of several tables organized as follows: each table presents a sector of economy. The left-hand side panel reports results for cognitive skills measured as mathematics test scores while the right-hand side report results for science based cognitive skills. In turn each of these panels consists of various sub-panels, which represent a particular technology in that sector.

In all the regressions reported in appendix 2, the coefficients of cognitive skills measured as mathematics and science test scores for majority of technologies are *positive* suggesting that human capital embodying mathematics and science skills is associated with *increase* in usage intensity of technology. Moreover, workforce equipped with knowledge of generic in contrast to specific skills serves as a more appropriate channel to enhance usage intensity of technologies in our sample. This implies that countries perhaps need a workforce with generic skills that are more analytical in nature and relevant across a broad range of sectors in order to be able to improve adoption of technologies. A sector-wise review of both sets of results show that embodiment of a certain skill is not positively associated with adoption of all technologies. This empirical evidence indicates that the link between human capital and technology adoption is conditional which rests on various aspects of human capital and the nature of technology in question. To illustrate this we provide sector-wise explanation of our empirical evidence on mathematics and science skills in the context of usage intensity of technologies.

[16] Comin *et al* (2008) include technologies such as; electricity production, internet, personal computers, telephones, cell phones, cars, trucks, passenger and cargo planes and tractors.

Table 1, presents the link between cognitive skills measured as mathematics and science test scores and technology adoption in the context of transportation sector. Sub-panel 1 considers usage intensity of air transportation represented in regressions as Aviationpkmp/air. The other two sub-panels represent car and ship transportation technologies, and are represented by vehicle car/land and shipton steammotor/sea respectively. The estimates obtained suggest a significant and positive association between cognitive skills as measured by mathematics scores and usage intensity of air and vehicle technologies in transportation. However, presence of human capital with such generic skills may not be a channel facilitating adoption of sea transportation technologies. This implies that human capital embodying mathematics skills is one of the possible mechanisms facilitating usage intensity of few but not all technologies within the transportation sector. This evidence reinforces our *a priori* hypothesis that technology response to skill is conditional on the type of technology under discussion. Moreover, technology responses to a particular skill vary within a sector. Hence, we may argue that countries that have human capital equipped with generic skills may well be better placed among other countries to adopt air and land in contrast to sea transportation technologies.

In addition, we also find that the association between type of skill and technology varies not only within but across sectors. A review of our results in table 2- 5, show that in some sectors work force possessing knowledge of mathematics is positively and significantly associated with usage intensity of majority of technologies in health, electricity production and tourism sectors. On the other hand, the sign of the coefficient for cognitive skills is negative and significant in case of usage intensity of radio, telephone and cellular phone technologies in telecommunications and information sector. This implies that technologies in the later sector are not biased towards human capital equipped with generic skills in contrast to former sectors.

We also find this notable feature of a mismatch between science skills termed as specific skills and usage intensity of technologies within and across sectors. Our empirical evidence shows that knowledge of science is positively associated with usage intensity of technologies in telecommunications and information, electricity production and tourism sectors. For example, the coefficient for science skills is positive and in some cases significant for per capita usage of vehicle and sea aviation, cable TV, cellular phone, radio, computer and internet, electricity production and, visitor beds and rooms technologies. However, the results for science skills may seem to be in contrast to our perceptions for technologies in health sector. In this sector usage intensity of all other technologies except for bone marrow transplant procedure indicate a lack of association with human capital embodied with such specific skills. We find technologies in health sector biased more in favour of human capital embodying mathematics rather than science skills. This may be supported by earlier evidence in the field of medical procedures related to organ transplants, which shows that knowledge of mathematics assists in designing advanced mathematical models required to design organ transplant procedures (Day, *et al* 2015; Rashidi, A.2016).[17]

Interestingly and somewhat counter-intuitively, results for mathematics and science based cognitive skills are significant in majority of technologies in agriculture but the association is *negative*. Table 5 presents results exploring the link between cognitive skills and per capita usage of technology in the context of agriculture sector. This inverse relationship indicates an absence of skill-technology link in agriculture. Our results lend support to earlier empirical evidence by Foster and Rosenzweig (1995) which suggest that agricultural technologies fail to respond to skills because such technologies are associated to a greater degree with “learning by doing” and may not require formal knowledge of certain subjects or disciplines. Furthermore, adoption of technologies in this sector is also affected by learning spillovers and experience of neighbouring farmers. These farmers perhaps are reluctant to take up new technological advancements on their own in agriculture and prefer learning from their own or fellow farmers’ experiences. Therefore, we may suggest that technologies in agriculture are perhaps more inclined towards learning by doing practices rather than skills that are embodied in individuals who perform better on test scores.

In our empirical analysis we include the quantitative dimension of human capital measured as average years of schooling. The coefficient of average years of schooling has the expected positive sign for a few technologies in mathematics panel. For instance, cable TV, mail, computer, radio, telephone, cellular phone and internet technologies respond positively to an increase in average years of schooling in telecommunications and information sector. On the other end, in the science panel average years of schooling facilitates adoption of sea aviation, kidney and lung transplant, cell phone, radio and computer based technologies. Based on these results we suggest that the quantitative dimension of human capital particularly generic skills

[17] We do understand that the mathematical capabilities of individuals may not be reflected in their mathematics scores, but there is a likely possibility of a correlation between mathematics scores and advanced mathematics skills.

matter more relative to quantitative measures of human capital. As we examine the possibility of technology building up from one period to another we find that intensity of usage of technology in the previous period has a positive and significant impact on current period's usage intensity of *all* technologies in our analysis. This clear-cut and robust evidence reinforces our argument that learning-by-doing aspect of technology is indeed one of the important determinants of adoption of technology.

Lastly, we also control for other possible determinants of technology adoption and introduce life expectancy and foreign direct investment in both set of analyses. These control variables show inconclusive evidence as indicated by the sign of the coefficient. This probably suggests that macro aggregate level variables may have threshold effects in the context of micro level aggregates such as usage intensity of technologies in different sectors. As hypothesized and argued earlier, we find mathematics skills more relevant for a larger set of technologies in contrast to science skills. Hence, we may suggest that generic skills being analytical in nature are more relevant in the process of technology adoption.

IV. Disaggregated Measures of Cognitive Skills and Technology Usage Lags as Measures of Technology Diffusion: Empirical Evidence

We estimate equation (8) to examine the contribution of disaggregated mathematics and science skills in the process of technology diffusion. This analysis includes a sample of 18 technologies that can be classified into five broad categories.[18] Specifically, we consider usage lags for technologies in tourism, telecommunications and information, health, electricity production and agriculture. Appendix 3 includes the descriptive evidence regarding data for technology usage lags. The results reported in appendix 4 consist of several tables arranged in the same manner as mentioned before for analysis of technology adoption.

In all the regressions, the coefficients of mathematics and science test scores as measures of cognitive skills are negative for majority of technologies. It suggests that improvement in human capital equipped with these skills is associated with *decrease* in usage lags of these technologies. In other words, this decrease in usage lags means an implied increase in diffusion

[18] In some cases U.S was not the technology leader therefore, we were not able to calculate the lags. In other cases there were not enough observations for lags to perform regressions.

of technologies. An overview of both sets of results indicates that mathematics or generic skills are more significant in increasing diffusion of technologies in contrast to science or specific skills. This empirical evidence reinforces our *a priori* hypothesis indicating the presence of a conditional technology-skill association which rests on various aspects of human capital and technology under discussion. This association between type of technology and skill changes within and across sectors. A comparison of empirical evidence on usage intensity and usage lag of technology shows that a change in the measure or dimension of technology may also bring a change in the association between a particular technology and skill under question. To further illustrate these propositions we provide a sector-wise explanation on mathematics and science skills in the context of technology usage lags.

Table 1a and 1b, presents the link between cognitive skills and technology usage lags measuring the extent of technology diffusion in the context of telecommunications and information sector. This sector consists of seven technologies, i.e., internet, telephone, computer, mail, cable TV, cell phones and radio.[19] The estimates obtained for mathematics skills suggest a significant and negative association between usage lags for internet and computer technologies, and a negative association between diffusion of telephone, mail and cable TV technologies. This implies that workforce equipped with generic skills measured as mathematics test scores act as a channel reducing time lags associated with diffusion of these technologies. On the other hand, we find knowledge of mathematics as not among the factors reducing the delays associated with diffusion of cell phones and radio technologies. The first set of technologies indicate a bias in favour of human capital possessing generic skills, while the later exhibit an absence of skill-technology link. This evidence supports our earlier stated hypothesis revealing that skill-technology link is conditional on the type of technology under discussion and technology responses to a particular skill vary within a sector.

Furthermore, we also observe that the degree of bias for a particular skill varies not only within but across sectors. An examination of other sectors in contrast to telecommunications and information shows that usage lags of a few technologies in health and tourism sectors do not respond to improvement in mathematics skills. We also review our results from the perspective

[19] Due to greater number of technologies the results for mathematics skills are presented in table 1a and for science skills in table 1b.

of Comin and Mestieri (2013), who suggest that the date of invention of a particular technology has an impact on its international rate of diffusion. According to them technologies with a recent date of invention and where US is the technology leader tend to have faster rate of international technology diffusion. Given this argument we may interpret our results for some of the recently invented technologies in our sample such as internet with caution and suggest that perhaps human capital with mathematics based cognitive skills contribute more in reducing diffusion lags for technologies that have a recent date of invention.[20]

A review of our empirical evidence examining the role of human capital embodying science skills and technology usage lags further indicates the presence of a mismatch of skill-technology link within and across sectors. For example, we find the coefficient of science skills negative and in some cases significant for usage lags of mail, cable TV, computer, visitor beds and electricity production technologies. In contrast, these specific skills do not facilitate diffusion of technologies such as liver, kidney and heart transplant procedures in the health sector. These results imply that countries may require a workforce with generic skills in order to reduce the timing lags associated with diffusion of specific set of technologies in telecommunication and information, tourism and electricity production sectors in contrast to heath sector.

Furthermore, table 4 presents results exploring the link between cognitive skills measured as science test scores and technology usage lags in the context of agriculture sector. Counter intuitively and somewhat interestingly the coefficient of mathematics and science skills is positive in majority of estimations. This sector is the only sector which exhibits a complete absence of skill-technology link. Hence, we may say that diffusion of technologies in agriculture sector does not require human capital as measured in terms of qualitative measures of achievement such as mathematics and science test scores. As mentioned above these technologies do not respond to these skills because they are associated to a greater degree with informal channels of diffusion such as learning by doing or learning from social networks and may not require a proper understanding of subjects under discussion (Conley and Udry 2001). Moreover, following Comin and Mestieri (2013) argument about the date of invention of

[20] See Comin and Mestieri (2013). In their sample of technologies internet has the most recent date of invention. We employ this argument with caution as in case of some technologies the invention dates are very close but in those technologies US is not the technology leader therefore, their results for usage lags tend to be different from each other.

technologies and its impact on international rate of diffusion, we may suggest with caution that cognitive skills do not seem to facilitate diffusion of agriculture technologies as they are a comparatively older set of technologies in our sample.

Our analysis for usage lags of technology also incorporates quantitative measure of human capital. The coefficient of average years of schooling has the expected negative and significant association with usage lags of a few set of technologies such as cellular phones, radio and heart transplant in mathematics and science based estimations. Based on this evidence we again find generic skills measured as mathematics test scores relatively more appropriate for diffusion of a larger set of technologies in our sample. In addition, our empirical evidence indicates a strong impact of lagged effects across all regressions implying the presence of learning-by-doing dimension associated with diffusion of *all* technologies.

Lastly, we control for other possible determinants of technology diffusion and introduce life expectancy and foreign direct investment in both set of analyses. A few set of technologies in mathematics and science estimations such as radio, cellular phone, mail and internet show that life expectancy measured as better health of individuals assists in technological diffusion. Empirical evidence for FDI indicates that increased flow of financial resources not only leads to faster diffusion of technologies in telecommunications and information, but also provides mechanism conducive for diffusion of health based technologies such as liver, lung and heart transplant procedures. To summarize, in the context of usage lags of technologies we again find human capital embodying generic skills as a better channel in contrast to specific skills in reducing adoption delays associated with technologies in our analysis.

V. Robustness Checks

In what follows we carry out three robustness checks for separate panels of mathematics and science cognitive skills for adoption and diffusion of technology respectively. Firstly, we control for the quality of institutions using measures of political rights and civil liberties. Secondly, we use GDP per capita to examine the influence of economic growth on both adoption and diffusion of technology. Lastly, we use expenditure on research and development (R&D) as percentage of GDP and evaluate its impact on technology adoption and diffusion. The robustness results for disaggregated measures of cognitive skills are reported in Appendix 5. Table 1and 2 summarize results for adoption of technologies for mathematics and science skills respectively. In addition, results for diffusion of technologies for mathematics and science are reported in table 3 and 4 respectively.[21] Each panel in table represents a specific technology. The first column in each panel reports results about the impact of institutional quality on adoption and diffusion of selected technologies, while second and third columns describe how GDP per capita and R & D expenditures affect adoption and diffusion of technology.

There has been recent emphasis on the role of institutions in the process of economic growth as poor quality institutions adversely affect economic performance of a country (Acemoglu *et al* 2005). On the other hand, good quality institutions ensure efficient allocation of resources, protect and safeguard political rights and civil liberties, reduce uncertainties, enable investment in high return projects and facilitate coordination among economic agents (See Aghion *et al,* 2008; Rodrik *et al,* 2004; Glaeser *et al,* 2004; and Flachaire *et al,* 2014). Moreover, another strand of literature argues that sound institutional framework creates an environment providing incentives which encourage competition and knowledge acquisition. This type of environment is conducive to technological innovations and up gradations and fosters flow of technologies across economies (North, 1990; Meyer and Sinani, 2009; Jude and Levieuge, 2015). Based on these findings we are interested in exploring the role of institutions from the perspective of technology adoption and diffusion thereby examining whether institutions intensify process of technology adoption and diffusion.

Adoption and diffusion responses of majority of technologies are similar as in baseline regressions with the inclusion of institutional quality in both mathematics and science panel estimations. These findings reinforce the outcomes of baseline regressions that human capital equipped with cognitive skills facilitates adoption of technologies. Moreover, there exists skill-technology mismatch implying that specific technologies respond to specific skills. In relation to the role of institutions, we obtain variable coefficients for the proxies of institutional quality.[22] More specifically, mathematics results show that first measure of institutional quality; political

[21] We include robustness checks for a few set of technologies representing all sectors that are also a part of base line regressions.

[22] A possible reason might be that the measures of institutional quality used in this study are perhaps unable to capture the soundness of institutions appropriately as there is lack availability of authentic data on institutions beginning from early 60's, as the data on institutional quality from World Bank starts from mid-1990s. The current study employs Freedom House data set on political rights and civil liberties as a proxy for institutional quality which begins in the early 1970s. See for details; Freedom House official website for access to data and Freedom in the World Report 2016.

rights have a positive association with usage intensity of vehicle and tractor technologies. In case of science panel political rights are positively associated per capita intensity of usage of tractors and fertilizers agriculture. In addition, civil liberties used as a second proxy for institutions positively and significantly influence adoption of; cable television, vehicle car and agriculture technologies in both mathematics and science results. These results show that our measure of civil liberty capturing several dimensions of equality, freedom, legality and fairness in society facilitates adoption of majority of technologies in the sample. On the other hand results for technology diffusion in mathematics panel indicate that access to political rights and civil liberties reduce usage lags associated with bone marrow transplant procedures, cable television, visitor beds, and tractor and fertilizer technologies. In the background of these results we may suggest that sound institutions providing access to political rights and safeguarding civil liberties facilitate adoption and diffusion of certain technologies in health, telecommunications and information, agriculture and tourism sectors.

Furthermore, improvements in technology through investment in human capital lead to economic growth. Developed economies experience higher growth because they are technologically more advanced than developing economies (See Romer, 1990; Aghion and Howitt, 1992). Given these findings we examine whether economic performance of an economy influences the process of technology adoption. We introduce GDP per capita as a measure of economic performance in our empirical analysis as another determinant of adoption and diffusion of technology. The results for robustness checks for both generic and specific human capital reinforce earlier findings of baseline regressions. Our results for adoption of technologies in health sector indicate that liver and lung transplant procedures respond positively to GDP per capita in both mathematics and science panels. In addition we see diffusion process of technologies such as bone marrow transplant, computer and tractor responding positively towards increases in GDP per capita. This perhaps implies that adoption and diffusion mechanism in health sector respond to indicators of economic performance.

Lastly, literature on technology suggests that expenditure on research and development is linked with technological innovations (Acemoglu and Zillibotti, 2001). Moreover, new entrants invest in R&D to innovate and develop a best practice in technology which adds to the product line and provides them a lead in the market (Acemoglu *et al* 2013). We therefore, examine whether expenditure on R&D impacts upon technology adoption. We introduce expenditure on

R&D as the third determinant for robustness checks. Our results show that coefficient for skills and lagged dependent variables remain similar to baseline regressions. Moreover, expenditures on R&D are significant in case of usage intensity of health and transportation sector technologies such as liver and lung transplant and vehicle usage in mathematics based cognitive skills panel. On the other hand evidence for diffusion of technology shows that increase in R&D is associated with reduced usage lags for cable television, visitor beds and fertilizer technologies.

Based on the above empirical evidence, we see that the basic result suggesting that adoption and diffusion of technologies respond positively to disaggregate measures of skills remains robust even after controlling for other determinants of technological adoption and diffusion.

VI. Concluding Remarks:

This study analyzes the link between human capital and technology in the light of direct measures of educational quality and technology adoption and diffusion. Earlier literature in the field of human capital and economic growth use 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 outcomes and ignores the channels through which human capital affects economic growth of an economy. We believe that one of the channels through which human capital may impact economic growth is its role in improving adoption and diffusion of technologies. This study bridges this gap by investigating the missing link between human capital and technology adoption and diffusion using direct measures of educational quality and technology. We contribute in the literature by examining this relationship of how disaggregated measures of educational quality facilitate technology adoption and diffusion through improvement in human capital.

In testing the hypothesis whether educational quality enhances technology adoption and diffusion, we use cognitive skills data for international mathematics and science test scores along with data on direct measures of technology adoption. We use Hanushek and Woessman (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. Moreover, we use CHAT data set developed by Comin and Hobijn (2009) to borrow direct measures of technology. In order to empirically analyze our hypothesis of learning-by-doing dimension of technology, we follow the econometric approach by Comin *et al* (2008) based on dynamic panel specification and incorporate the lagged effect of technology.

Based on empirical analysis our main finding reveals that the link between human capital and technological adoption and diffusion is a conditional one, which rests on various aspects of human capital and technology under consideration. Moreover, this skill-technology association indicates that appropriateness of skills required for adoption and diffusion of technologies changes within and across sectors. In summary for technology adoption, technologies from transportation, tourism and health sectors positively respond to both disaggregated measures of cognitive skills. However, telecommunication and information based technologies are more influenced by generic in contrast to specific skills. On the other end, for usage lags as a measure of technology diffusion, mathematics based generic skills assist diffusion of certain technologies in telecommunications and information, electricity production and health sectors. Empirical evidence for science indicates that specific skills reduce lags associated with technologies in telecommunications and information, electricity production and health sectors. However, to our surprise skill implications for both adoption and diffusion of technologies in agriculture are weak as compared to other technologies in our sample.

Another noteworthy finding of this analysis is that the most important determinant for technology adoption and diffusion is the past level of technology. This highlights the presence of learning-by-doing aspect of technology across all sectors in our analysis. Our evidence shows that qualitative measures of education are one of the channels facilitating adoption and diffusion of technology. More specifically, generic human capital measured as mathematics test scores are more relevant in comparison to specific science based skills. We also find that quantitative measures of human capital such as average years of schooling to be of lesser relevance in comparison with qualitative measure. Finally, the impact of cognitive skills remains robust even after controlling for other determinants of technology adoption and diffusion which include; institutional quality, GDP per capita and R&D expenditures. Against this background, we suggest that in order to develop more relevant policy insights we need an approach based on analyzing the various aspect of human capital as barriers to technology adoption and diffusion.

Appendix 1: Definitions and Descriptive Statistics:

Variable Name	Definition	Source
Mathematics Cognitive skills	Mathematics test scores for grade 8	National Center for Education Statistics (1992). Report on TIMSS and PIRLS byInternational Study Center, Lynch School of Education, Boston College & International Association for the Evaluation of the Educational Achievement. 2011.
Science Cognitive Skills	Science test scores for grade 8	National Center for Education Statistics (1992). Report on TIMSS and PIRLS byInternational Study Center, Lynch School of Education, Boston College & International Association for the Evaluation of the Educational Achievement. 2011.
Years of Schooling	Average years of total schooling	Barro and Lee 2010
Life Expectancy	Life expectancy at birth, total (years)	World Bank, World Development Indicators.(2015)
Foreign Direct Investment	Foreign direct investment, net inflows (% of GDP)	World Bank, World Development Indicators.(2015)
Unemployment Rate	Unemployment, total (% of total labor force) (national estimate)	World Bank, World Development Indicators.(2015)
Harvester	Number of self-propelled machines that reap and thresh in one operation	Comin and Hobijn (2009)
Milking machine	Number of installations consisting of several complete milking units	Comin and Hobijn (2009)

Tractor	Number of wheel and crawler tractors (excluding garden tractors) used in agriculture	Comin and Hobijn (2009)
Fertilizer	Metric tons of fertilizer consumed. Aggregate of 25 individual types listed in source	Comin and Hobijn (2009)
Bone marrow Transplant	Number of bone marrow transplants performed	Comin and Hobijn (2009)
Heart Transplant	Number of heart transplants performed	Comin and Hobijn (2009)
Kidney Transplant	Number of kidney transplants performed	Comin and Hobijn (2009)
Liver Transplant	Number of liver transplants performed	Comin and Hobijn (2009)
Lung Transplant	Number of lung transplants performed.	Comin and Hobijn (2009)
Cable TV	Number of households that subscribe to a multi-channel television service delivered by a fixed line connection	Comin and Hobijn (2009)
Cell phone	Number of users of portable cell phones	Comin and Hobijn (2009)
Mail	Number of items mailed/received, with internal items counted one and cross-border items counted once for each country. May or may not include newspapers sent by mail, registered mail, or parcel post	Comin and Hobijn (2009)

Newspaper	Number of newspaper copies circulated daily. Note that there is a tendency for news circulation to be under-reported, since data for weekly and biweekly publications are not included	Comin and Hobijn (2009)
Radio	Number of radios	Comin and Hobijn (2009)
Telephones	Number of mainline telephone lines connecting a customer's equipment to the public switched telephone network as of year end	Comin and Hobijn (2009)
Internet	Number of people with access to the worldwide network	Comin and Hobijn (2009)
Computer	Number of self-contained computers designed for use by one person	Comin and Hobijn (2009)
Visitor beds	Number of visitor beds available in hotels and elsewhere visitor rooms	Comin and Hobijn (2009)
Visitor rooms	Number of visitor rooms available in hotels and elsewhere. years)	Comin and Hobijn (2009)
Aviationp kmp/air	Civil aviation passenger-KM traveled on scheduled services by companies registered in the country concerned. Not a measure of travel through a country’s airports	Comin and Hobijn (2009)
Shipton Steammotor/sea	Tonnage of steam and motor ships (above a minimum weight) in use at midyear	Comin and Hobijn (2009)

Vehicle car/land	Number of passenger cars (excluding tractors and similar vehicles) in use. Numbers typically derived from registration and licensing records, meaning that vehicles out of use may occasionally be included.	Comin and Hobijn (2009)
Electricity production	Gross output of electric energy (inclusive of electricity consumed in power stations) in KwHr	Comin and Hobijn (2009)
Population	Population	Comin and Hobijn (2009)
Political Rights	Countries are ranked on the scale of 1-7 with countries and territories with a rating of 1 enjoy a wide range of political rights. These include free and fair elections. Candidates who are elected actually rule, political parties are competitive, the opposition plays an important role and enjoys real power, and the interests of minority groups are well represented in politics and government.	Freedom in the World Report (2016)
Civil Liberties	Countries are ranked on the scale of 1-7 with countries and territories with a rating of 1 enjoy a wide range of civil liberties. These include freedoms of expression, assembly, association, education, and religion. They have an established and generally fair legal system that ensures the rule of law (including an independent judiciary), allow free economic activity, and tend to strive for equality of opportunity for everyone, including women and minority groups.	Freedom in the World Report (2016)
GDP per capita	GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making	World Bank, World Development Indicators (2015)

	deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars.	
Expenditure on R& D	Expenditures for research and development are current and capital expenditures (both public and private) on creative work undertaken systematically to increase knowledge, including knowledge of humanity, culture, and society, and the use of knowledge for new applications. R&D covers basic research, applied research, and experimental development.	World Bank, World Development Indicators (2015)

Appendix 1 (continued): Descriptive Statistics for Mathematics Cognitive Skills Panel for Usage Intensity as measure of Technology Adoption (1964-2003).

Variable	Observations	Mean	Std Dev	Min	Max
Mathematics Cognitive skills	480	424.064	111.452	122.4	609
Years of Schooling	1000	8.001	2.582	0.92	12.64
Life Expectancy	1038	71.68183	6.006965	44.92385	81.76
Foreign Direct Investment	672	2.015817	2.899249	-0.6519227	22.38404
Unemployment Rate	495	7.360606	4.875179	0.9	36.7
Harvester	856	2.217481	2.440021	0.0000996	10.21824
Milking machine	494	4.761195	5.033899	0.0067787	21.15954
Tractor	894	13.80816	12.18866	0.001072	58.20502
Fertilizer	893	46.68103	40.69915	0.599535	229.3602
Bone marrow Transplant	176	0.0214691	0.0183561	0.0001206	0.0746298
Heart Transplant	165	0.0049186	0.0033667	0	0.0147882
Kidney Transplant	398	0. 0210578	0.0128271	0.0000962	0.0507885
Liver Transplant	176	0.0064384	0.0046055	0	0.0184819
Lung Transplant	120	0.0017186	0.0012383	0	0.0046925
Cable TV	457	94.04078	109.0733	0	401.346
Cell phone	671	97.31201	205.5867	0	1026.304

Mail	554	0.1775561	0.1306173	0.0023467	0.6652465
Radio	845	0.5986825	0.4161835	0.0517568	2.147192
Telephone	678	284.8042	234.0749	2.089562	1013.462
Internet	310	105.475	150.6394	0	573.1446
Computer	368	159.2686	153.634	.8779043	696.3917
Visitor beds	491	13.39978	9.011875	0.2283789	40.57656
Visitor rooms	577	6.565598	4.312404	0.2860303	17.09582
Aviationpkmp/air	600	0.9307605	1.56559	0.001707	13.57749
Shipton Steammotor/sea	389	0.2673012	0.5718443	0.0018271	3.300755
Vehicle car/land	798	216.9602	177.0675	0. 5360206	791.4692
Electricity production	909	5465321	5501502	35040.34	3.12e+07
Population	962	39562.11	63868.29	1017	291200
Political Rights	742	2.448787	1.926992	1	7
Civil Liberties	742	2.568733	1.797432	1	7
GDP per capita	903	9823.426	9927.19	105.1262	50111.66
Expenditure R&D	168	1.611943	0.9913625	0.10166	4.22244

Appendix 1 (continued): Descriptive Statistics for Science Cognitive Skills Panel Usage Intensity as measure of Technology Adoption (1973-2003).

Variable	Observations	Mean	Std Dev	Min	Max
Science Cognitive skills	418	131.2	367.3213	151.1557	580
Years of Schooling	713	8.317363	2.450953	1.79	12.64
Life Expectancy	744	72.27863	5.067044	53.47881	81.76
Foreign Direct Investment	578	2.219367	2.994509	-0.6519227	22.38404
Unemployment Rate	432	7.180787	5.252941	0.9	36.7
Harvester	552	2.557819	2.6157	0.0007337	10.21824
Milking machine	271	4.700926	5.172172	0.0067787	21.15954
Tractor	610	14.06253	13.14737	0.0085992	58.20502
Fertilizer	609	47.60572	42.00031	0.599535	229.3602
Bone marrow Transplant	136	0.0179578	0.0167072	0.0001206	0.067665
Heart Transplant	117	0.0041423	0.0025224	0	0.0089563
Kidney Transplant	272	0.0227518	0.0129084	0.0006714	0.0507885
Liver Transplant	121	0.0063818	0.0046032	0	0.0184819
Lung Transplant	95	0.0018226	0.0013436	0	0.0046925
Cable TV	396	65.82861	82.7646	0	278.7279
Cell phone	615	89.85775	192.0515	0	939.4391

Mail	329	0.1697851	0.1492096	0.0036425	0.6652465
Radio	567	0.6420931	0.4513853	0.0857526	2.147192
Telephones	431	292.6813	251.6995	6.327229	1013.462
Internet	276	102.5083	149.4308	0	573.1446
Computer	332	147.8118	158.4431	0.8779043	696.3917
Visitor beds	410	12.78704	9.883768	0.2283789	40.57656
Visitor rooms	536	6.199816	4.514737	0.2860303	17.09582
Aviationkmp/air	357	1.196812	1.939648	0.0357245	13.57749
Shipton Steammotor/sea	253	0.3441496	0.6950479	0.0042609	3.300755
Vehicle car/land	519	225.8919	189.7235	2.190707	791.4692
Electricity production	612	6120185	6228404	181876.8	3.12e+07
Population	669	42246.37	67901.2	1674	291200
Political Rights	640	2.720312	1.965642	1	7
Civil Liberties	640	2.829687	1.853152	1	7
GDP per capita	633	10574.13	10243.84	269.8519	50111.66
Expenditure R&D	149	1.372285	0.9553502	0.10166	3.91382

Appendix 2: Results for Cognitive Skills and Technology Adoption.

Table 1: Cognitive Skills and Usage Intensity of Technology in Transportation

	Mathematics Skills Panel			Science Skills Panel		
Variables	**(1) Aviation pkm air**	**(2) Vehicle car/land**	**(3) Shipton Steam motor/ sea**	**(1) Aviation pkm air**	**(2) Vehicle car/land**	**(3) Shipton Steam motor/ sea**
Cognitive Skills	0.00087*** (0.0003)	0.016 (0.03)	-0.00005 (0.0004)	-0.000028 (0.0001)	0.01673 (0.01)	0.00003*** (0.000005)
Years of Schooling	-0.138*** (0.02)	-1.0545 (2.55)	0.0056 (0.003)	-0.0681** (0.03)	-0.75244 (2.45)	0.0037*** (0.001)
Life Expectancy	0.0413*** (0.013)	1.016 (1.66)	0.00011 (0.001)	0.28313* (0.016)	1.0993 (1.45)	-0.00154*** (0.0005)
FDI	0.0136 (0.011)	0.088 (0.48)	0.00111 (0.001)	0.00299 (0.109)	0.13722 (0.41)	-0.00074*** (0.0002)
Lagged dependent variable	0.889*** (0.032)	0.9483*** (0.026)	0.955*** (0.027)	1.0220*** (0.03)	0.93327*** (0.025)	0.81053*** (0.06)
Observations	170	241	111	162	250	88

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 2: Cognitive Skills and Usage Intensity of Technology in Health

	Mathematics Skills Panel					Science Skills Panel				
Variables	**(1) Transplant Liver**	**(2) Transplant Lung**	**(3) Transplant Heart**	**(4) Transplant Bone marrow**	**(5) Transplant Kidney**	**(1) Transplant Liver**	**(2) Transplant Lung**	**(3) Transplant Heart**	**(4) Transplant Bone marrow**	**(5) Transplant Kidney**
Cognitive Skills	0.000012** (0.000006)	0.000026*** (0.000006)	0.0000011 (0.000006)	0.0000052 (0.00001)	0.000012 (0.000008)	-0.000006*** (0.000002)	-0.000005*** (0.000001)	-0.0000011 (0.000001)	0.000017** (0.000007)	-0.0000015 (0.000003)
Years of Schooling	0.00069 (0.0005)	-0.00089** (0.0003)	-0.00064 (0.0004)	-0.00056 (0.001)	0.000031 (0.0006)	0.00031 (0.0004)	-0.00124*** (0.0003)	-0.00064 (0.0004)	-0.0021 (0.001)	0.00059 (0.0007)
Life Expectancy	-0.000303 (0.0002)	0.0004*** (0.0001)	0.000064 (0.0001)	0.0014 (0.0009)	-0.000072 (0.0003)	0.000401 (0.0002)	0.00023 (0.0001)	0.00016 (0.0001)	0.00115 (0.0007)	0.000521 (0.0003)
FDI	-0.000012 (0.00004)	0.000002 (0.00002)	-0.000021 (0.00004)	-0.00003 (0.0001)	-0.00019* (0.0001)	0.000032 (0.00003)	-0.0000024 (0.00002)	-0.000015 (0.00004)	-0.00007 (0.0001)	-0.00014 (0.0001)
Lagged dependent variable	0.7933*** (0.077)	0.2136 (0.1171)	0.761*** (0.075)	0.817*** (0.06)	0.757*** (0.046)	0.6794*** (0.08)	0.40465*** (0.104)	0.70625*** (0.083)	0.7417*** (0.062)	0.730*** (0.05)
Observations	83	68	93	106	196	90	72	92	109	209

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 3a: Mathematics based Cognitive Skills and Usage of Intensity of Technology in Telecommunications & Information

Variables	(1) Cable TV	(2) Mail	(3) Computers	(4) Internet user	(5) Radio	(6) Telephone	(7) Cell phones
Cognitive Skills	0.1072*** (0.03)	0.000122** (0.00004)	0.1891*** (0.057)	0.449* (0.25)	-0.000004 (0.00006)	-0.0666 (0.04)	-0.158* (0.08)
Years of Schooling	1.529 (2.61)	0.00048 (0.003)	7.331** (3.57)	7.018 (10.009)	0.0258*** (0.04)	0.514 (2.63)	11.365*** (6.35)
Life Expectancy	0.0402 (1.5)	-0.0022 (0.001)	3.0355 (2.20)	24.95*** (6.44)	0.0021 (0.002)	1.926 (1.23)	21.265*** (4.27)
FDI	-1.113*** (0.31)	0.0033** (0.001)	0.2325 (0.4)	0.591 (1.02)	-0.0013 (0.0008)	2.753 (0.70)	2.473*** (0.93)
Lagged dependent variable	0.8615*** (0.03)	0.9075*** (0.028)	1.0137*** (0.015)	0.945*** (0.03)	0.844*** (0.021)	1.0002*** (0.025)	1.001*** (0.018)
Observations	212	163	178	150	257	190	258

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 3b: Science based Cognitive Skills and Usage of Intensity of technology in Telecommunications & Information

Variables	(1) Cable TV	(2) Cell phones	(3) Radio	(4) Computers	(5) Internet user	(6) Mail	(7) Telephone
Cognitive Skills	0.0184* (0.01)	0.00006 (0.027)	0.00003 (0.00002)	0.01487 (0.01)	0.07052 (0.061)	-0.000046** (0.00001)	-0.00452 (0.01)
Years of Schooling	-0.6624 (2.23)	19.439*** (5.77)	0.01096** (0.005)	6.4531** (3.14)	2.3008 (8.45)	-0.00052 (0.004)	-1.026 (2.63)
Life Expectancy	0.39457 (1.38)	17.655*** (3.67)	0.00466* (0.002)	5.0570** (1.97)	33.118*** (6.36)	0.00581*** (0.001)	2.414 (1.634)
FDI	-0.9187*** (0.26)	1.9098** (0.81)	0.00099 (0.0008)	0.35111 (0.37)	0.3104 (0.94)	0.00237 (0.001)	2.3892*** (0.58)
Lagged dependent variable	0.89391*** (0.02)	1.0266*** (0.015)	0.9672*** (0.02)	1.0159*** (0.13)	0.92361*** (0.028)	0.9496*** (0.31)	0.9379*** (0.02)
Observations	253	304	265	215	177	153	162

Robust standard errors in parenthesis; *, **,*** imply 10%, 5%, and 1% significance levels respectively.

Table 4: Cognitive Skills and Usage Intensity of Technology in Electricity Production and Tourism.

	Mathematics Skills Panel			Science Skills Panel		
Variables	**(1) Electricity production**	**(2) Visitor beds**	**(3) Visitor rooms**	**(1) Electricity production**	**(2) Visitor beds**	**(3) Visitor rooms**
Cognitive Skills	4451.838*** (1461.9)	0.011*** (0.003)	0.004** (0.002)	256.248 (560.69)	0.00115 (0.001)	0.00185** (0.007)
Years of Schooling	12885 (92761.2)	-0.584 (0.211)	0.305** (0.15)	50849.27 (100069.4)	-0.10322 (0.18)	0.11308 (0.13)
Life Expectancy	39326.89 (53344.6)	-0.794 (0.13)	-0.0761 (0.08)	169130.4*** (55758.08)	0.19507* (0.11)	-0.082805 (0.077)
FDI	4499.4 (18550.1)	-0.687 (0.03)	-0.0387 (0.02)	6740.894 (19316.95)	-0.04587 (0.03)	-0.01549 (0.02)
Lagged dependent variable	0.7402*** (0.04)	0.7342*** (0.054)	0.8539*** (0.036)	0.73240*** (0.041)	0.81504*** (0.042)	0.85242*** (0.033)
Observations	279	157	244	289	190	269

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 5: Cognitive Skills and Usage Intensity of Technology in Agriculture

	Mathematics Skills Panel				Science Skills Panel			
Variables	**(1) Harvester**	**(2) Fertilizers**	**(3) Milking machine**	**(4) Tractor**	**(1) Harvester**	**(2) Fertilizers**	**(3) Milking machine**	**(4) Tractor**
Cognitive Skills	-0.0009** (0.0004)	-0.040*** (0.01)	0.000029 (0.001)	-0.0027* (0.001)	-0.00049** (0.0001)	-0.00746 (0.005)	0.00095*** (0.0003)	-0.0013** (0.0006)
Years of Schooling	0.032 (0.037)	-3.24*** (1.12)	-0.1537** (0.06)	0.0672 (0.12)	0.0342 (0.366)	-2.5538*** (0.98)	-0.06548 (0.05)	0.03154 (0.13)
Life Expectancy	-0.0084 (0.019)	3.099*** (0.64)	0.0126 (0.044)	-0.0049 (0.64)	-0.00816 (0.016)	2.2730 (0.46)	-0.0581** (0.02)	-0.00188 (0.57)
FDI	-0.011 (0.007)	-0.133 (0.21)	0.0207 (0.02)	-0.0053 (0.23)	-0.000841 (0.007)	-0.219 (0.18)	0.0395** (0.18)	-0.00566 (0.024)
Lagged dependent variable	0.8828*** (0.02)	0.834*** (0.03)	0.998*** (0.015)	0.8823*** (0.016)	0.83778*** (0.02)	0.08068*** (0.027)	0.98338*** (0.012)	0.9099*** (0.018)
Observations	287	293	170	293	288	305	174	305

Robust standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively.

Appendix 3. Descriptive Statistics for Mathematics Cognitive Skills Panel for Technology Usage Lags as measures of Technology Diffusion (19673-2003)

Variable	Observations	Mean	Std Dev	Min	Max
Mathematics Cognitive skills	440	428.1243	110.2615	122.4	609
Years of Schooling	960	7.866635	2.518101	0.92	11.76
Life Expectancy	998	71.5944	6.093759	44.92385	81.76
Foreign Direct Investment	638	2.082505	2.956014	-0.6519227	22.38404
Unemployment Rate	471	7.415711	4.980973	0.9	36.7
Harvester	706	22.52295	11.17289	1.803589	40.99407
Tractor	744	21.43499	11.06449	-2.269452	40.99862
Fertilizer	701	20.55985	11.52588	-2.603976	43.00351
Bone marrow Transplant	116	1.486409	3.937542	-6.049613	12.04657
Heart Transplant	102	7.153791	4.400163	2.974864	14.98844
Kidney Transplant	329	5.504315	7.862458	16.97348	27.2596
Liver Transplant	148	5.309744	4.722574	2.164151	21.02741
Lung Transplant	76	3.244937	4.922544	7.649384	14.53378
Cable TV	235	13.71066	8.345276	-18.62067	27.51526
Cell phone	333	2.391144	4.276329	-7.869115	12.14841
Mail	526	60.61741	25.1219	7.968489	107.4928
Radio	787	32.74951	10.11304	13.13484	60.64052

Telephone	613	42.08814	26.05534	-0.1616383	87.49915
Internet	277	2.755459	2.542218	-1.744918	9.251847
Computer	344	7.733123	4.754848	-0.7463593	19.51483
Visitor beds	365	9.568224	7.048247	-3.591774	23.91281
Visitor rooms	498	10.2466	8.419268	-24.9582	25.92233
Aviation pkmp/air	535	16.37194	10.78567	-17.4344	45.87047
Electricity production	753	31.76108	17.77717	-18	67.01201
Political Rights	710	2.514085	1.944708	1	7
Civil Liberties	710	2.639437	1.805686	1	7
GDP per capita	863	9446.723	9693.34	105.1262	50111.66
Expenditure on R& D	160	1.565586	0.9932934	0.10166	4.22244

Appendix 3 continued: Descriptive Statistics for Science Cognitive Skills Panel for Technology Usage Lags as measures of Technology Diffusion (1964-2003)

Variable	Observations	Mean	Std Dev	Min	Max
Mathematics Cognitive skills	387	372.5238	149.0293	131.2	580
Years of Schooling	682	8.147155	2.366785	1.79	11.76
Life Expectancy	713	72.16753	5.138295	53.47881	81.76
Foreign Direct Investment	547	2.298172	3.054491	-0.6519227	22.38404
Unemployment Rate	408	7.233824	5.389327	0.9	36.7
Harvester	438	27.26247	8.415413	11.3886	40.99407
Tractor	498	26.09841	8.535559	6.340208	40.99862
Fertilizer	494	24.48208	9.807492	-1.955834	40.96936
Bone marrow Transplant	89	1.729173	4.164594	-7.323859	12.04657
Heart Transplant	93	23.71823	47.77922	-6.02362	216.5907
Kidney Transplant	224	6.097456	9.264138	-27.43828	34.35971
Liver Transplant	102	5.430726	4.998367	-2.164151	21.02741
Lung Transplant	69	2.885949	5.33661	-7.649384	14.53378
Cable TV	201	15.65594	7.227921	-12.21838	43.27872
Cell phone	317	2.550117	4.362253	-7.869115	12.14841
Mail	307	67.58051	27.22576	7.968489	107.4928
Radio	518	36.40362	9.782321	13.13484	60.64052
Telephone	386	49.21271	27.22868	-0.1616383	87.66544

Internet	244	3.099174	2.666004	-1.744918	9.251847
Computer	309	8.416949	5.145492	-0.7463593	19.51483
Visitor beds	282	9.689905	7.206189	-2.562439	23.91281
Visitor rooms	445	25.69847	66.30322	-24.9582	327.4338
Aviation pkmp/air	309	19.55163	11.03387	-17.4344	45.87047
Electricity production	483	35.49276	17.83551	-18	67.01201
Political Rights	609	2.807882	1.975392	1	7
Civil Liberties	609	2.922824	1.851996	1	7
GDP per capita	602	9996.65	9918.367	269.8519	50111.66
Expenditure on R& D	141	1.306084	0.939365	0.10166	3.91382

Appendix 4: Results for Cognitive Skills and Technology Diffusion.

Table 1a: Mathematics based Cognitive Skills and Technology Usage lags in Telecommunications & Information.

Variables	(1) Internet user	(2) Telephone	(3) Computers	(4) Mail	(5) Cable TV	(6) Cell phones	(7) Radio
Cognitive Skills	-0.0178**	-0.00345	-0.015***	-0.0108	-0.0103	0.00728	0.003
	(0.009)	(0.005)	(0.004)	(0.012)	(0.006)	(0.0034)	(0.02)
Years of Schooling	-0.0405	-0.0384	-0.296	0.151	0.7291*	-0.7148***	-0.335
	(0.269)	(0.036)	(0.223)	(1.081)	(0.429)	(0.2023)	(0.151)
Life Expectancy	0.004	0.0859	0.181	-0.054	0.336	-0.23703*	0.1957
	(0.156)	(0.2)	(0.119)	(0..504)	(0..259)	(0.1346)	(0.87)
FDI	0.0016	-0.378***	0..018	-1.049	0.046	-0.04795	0.176
	(0.034)	(0.105)	(0.027)	(0.438)	(0.051)	(0.0456)	(0.028)
Lagged dependent variable	0.559***	0.752	0.879***	0.0818***	0.5823***	0.77059***	0.888***
	(0.103)	(0.036)	(0.046)	(0.050)	(0.073)	(0.0558)	(0.03)
Observations	125	154	157	140	123	142	222

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 1b: Science based Cognitive Skills and Technology Usage lags in Telecommunications & Information.

Variables	**(1) Mail**	**(2) Cable TV**	**(3) Computers**	**(4) Internet user**	**(5) Telephone**	**(6) Cell phones**	**(7) Radio**
Cognitive Skills	-0.001172*	-0.00199	-0.00259**	0.0015	0.01364	0.0014	0.0034***
	(0.006)	(0.0017)	(0.0012)	(0.0024)	(0.0077)	(0.001)	(0.0009)
Years of Schooling	-0.15316	0.81142**	0.0566	-0.42386	1.2338	-0.8317***	-0.5489***
	(1.416)	(0.362)	(0.204)	(0.2815)	(1.397)	(0.179)	(0.168)
Life Expectancy	-0.1228	0.3272	0.0251	-0.06973	-1.0989	-0.15883	0.5258***
	(0.649)	(0.213)	(0.1101)	(0.1625)	(0.7063)	(0.1098)	(0.1028)
FDI	0.0909	0.05177	-0.00667	0.0202	-0.2837	-0.0197	-0.01470
	(0.416)	(0.0405)	(0.0277)	(0.0343)	(0.3488)	(0.033)	(0.0300)
Lagged dependent variable	0.5672***	0.6093***	0.87239***	0.38503***	-0.0114462	0.84609***	0.7427***
	(0.0667)	(0.057)	(0.0447)	(0.1092)	(0.0934)	(0.0425)	(0.0382)
Observations	133	134	194	157	125	200	234

Robust standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively.

Table 2: Cognitive Skills and Technology Usage lags in Health

	Mathematics Skills Panel					Science Skills Panel				
Variables	**(1) Transplant Bonemarrow**	**(2) Transplant Lung**	**(3) Transplant Liver**	**(4) Transplant Kidney**	**(5) Transplant Heart**	**(1) Transplant Bone marrow**	**(2) Transplant Lung**	**(3) Transplant Liver**	**(4) Transplant Kidney**	**(5) Transplant Heart**
Cognitive Skills	-0.0106*	-0.0726*	-0.0103	0.00174	0.0063	-0.00439**	-0.00268	0.000809	0.01226***	0.0636**
	(0.005)	(0.043)	(0.010)	(0.0069)	(0.004)	(0.002)	(0.007)	(0.002)	(0.004)	(0.0272)
Years of Schooling	-0.1432	12.145***	1.283	0.3413	0..3103	0.16846	5.6606***	-0.11991	-1.3248	-13.104**
	(0.367)	(3.449)	(0.971)	(0.568)	(0.331)	(0.501)	(2.075)	(0.431)	(0.8300)	(6.345)
Life Expectancy	0.689***	-0.1803	2.611***	1.139***	0.412**	0.87889***	0.127909	1.5232***	1.9597***	0.777
	(0.187)	(1.087)	(0.544)	(0.409)	(0.204)	(0.255)	(0.975)	(0.382)	(0.4309)	(2.641)
FDI	0.028	-0.0249	-0.0104	0.1841**	0.0169	0.04682	0.07635	0.0150	0.2679*	-0.215409
	(0.028)	(00249)	(0069)	(0.086)	(0.020)	(0.040)	(0.1273)	(0.0384)	(0.138)	(0.534)
Lagged dependent variable	0.7580***	0.0111	0.121	0.637***	0.8602***	0.68134***	0.2139	0.52290***	0.30162***	0.89726
	(0.0717)	(0.205)	(0.125)	(0.065)	(0.056)	(0.0859)	(0.1600)	(0.102)	(0.0795)	(0.045)
Observations	59	33	60	150	58	67	48	76	166	71

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 3: Cognitive Skills and Technology Usage lags in Tourism and Electricity Production.

	Mathematics Skills Panel			Science Skills Panel		
Variables	**(1) Visitor beds**	**(2) Visitor rooms**	**(3) Electricity production**	**(1) Visitor beds**	**(2) Visitor rooms**	**(3) Electricity production**
Cognitive Skills	-0.0043	0.0077	-0.0024	-0.0032	0.00354	-0.00249
	(0.005)	(0.007)	(0.006)	(0.001)	(0.003)	(0.0018)
Years of Schooling	-0.5191	1.041**	-0.0355	-0.4609	0.561	0.02506
	(0.394)	(0.472)	(0.376)	(0.3915)	(0.4012)	(0.274)
Life Expectancy	0.6029**	0.573*	0.1862	0.79315***	0.6225**	0.33661**
	(0.207)	(0.315)	(0.268)	(0.242)	(0.276)	(0.1645)
FDI	0.057	0.0069	0.0713	0.0809	0.0170	0.06272
	(0.054)	(0.0609)	(0.110)	(0.0606)	(0.0581)	(0.0733)
Lagged dependent variable	0.8028***	0.533***	0.8285***	0.7796***	0.61821***	0.8351***
	(0.043)	(0.117)	(0.048)	(0.046)	(0.094)	(0.0396)
Observations	182	100	197	198	101	203

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 4: Cognitive Skills and Usage lags of Technology in Agriculture

	Mathematics Skills Panel			Science Skills Panel		
Variables	**(1) Fertilizers**	**(2) Harvester**	**(3) Tractor**	**(1) Fertilizers**	**(2) Harvester**	**(3) Tractor**
Cognitive Skills	0.0204***	0.0002*	0.014	0.00106	-0.00037	0.00061
	(0.005)	(0.0001)	(0.001)	(0.0013)	(0.0002)	(0.0004)
Years of Schooling	1.413***	-0.0018	0.0158	0.69462***	-0.00797	0.1267
	(0.503)	(0.006)	(0.0671)	(0.263)	(0.0356)	(0.0793)
Life Expectancy	0.382	0.003	0.0406	0.4039***	-0.04956**	-0.02906
	(0.255)	(0.0057)	(0.054)	(0.133)	(0.025)	(0.06574)
FDI	0.0131	0.0015	0.0152	0.02846	-0.00823	-0.00948
	(0.073)	(0.001)	(0.012)	(0.037)	(0.006)	(0.014)
Lagged dependent variable	0.6091***	0.995***	0.963***	0.805***	1.01967***	0.976***
	(0.062)	(0.001)	(0.018)	(0.0363)	(0.007)	(0.017)
Observations	183	179	214	215	192	210

Robust standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively.

Appendix 5: Table1: Robustness Checks for Mathematics Skills Usage Intensity of Technology.

	(1) **Transplant Liver**			**(2)** **Transplant Lung**			**(3)** **Visitor beds**		
Variables	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive Skills	0.000013	0.0000065	0.000073	0.00002***	0.000020***	-.0000179	0.01187***	0.007998*	-0.023136
	(0.000006)	(0.000006)	(0.000068)	(0.000006)	(0.000007)	(0.0000633)	(0.0034)	(0.00438)	(0.02688)
Years of Schooling	0.0007603	0.00007416	0.0015205	-0.000898 **	-0.001069***	-0.000356	-0.019472	-0.079915	0.10662
	(0.00052)	(0.000522)	(0.00132)	(0.00036)	(0.000369)	(0.00118)	(0.21529)	(0.21935)	(0.56180)
Life Expectancy	-0.000268	-0.000217	-0.0014993	0.000416**	0.0004319***	-0.0000532	0.05572	0.075843	-0.060272
	(0.00027)	(0.000275)	(0.00077)*	(0.000163)	(0.00016)	(0.00075)	(0.14597)	(0.14708)	(0.21628)
FDI	-0.000012	-0.000008	-0.0000985	-0.000001	-0.0000015	(0.00010)	-0.07433**	-0.07094**	-0.10202
	(0.00004)	(0.00004)	(0.00011)	(0.00002)	(0.000025)	(0.00010)	(0.03480)	(0.03503)	(0.10031)
Political Rights	-0.00067	-0.00022					-0.29977	-0.248431	-0.06508
	(0.00077)	(0.00081)					(0.26496)	(0.26874)	(0.47271)
Civil Liberties	0.000173	-0.000006		-0.000222	-0.00043		-0.03345	-0.027362	-0.327765
	(0.00074)	(0.00074)		(0.00058)	(0.00058)		(0.33508)	(0.336527)	(0.56605)
GDP Per capita		0.00000006*	0.00000007		0.00000005**	0.00000004		0 .000043	-0.0000686
		(0.0000003)	(0.00000007)		(0.00000002)	0.00000007		(0.00003)	(0.000142)
Research & Development			0.0094451**			0.0028803			0.0026051
			(0.00438)			(0.00413)			(1.2998)
Lagged dependent variable	0.7909***	0.751695***	0.2716344	0.2529***	0.268187**	-0.10466	0.7162***	0.7228***	0.6902***
	(0.07891)	(0.08180)	(0.22203)	(0.11872)	(0.117072)	(0.81608)	(0.05667)	(0.0565)	(0.1841)
Observations	83	83	16	68	68	16	157	157	32

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 1 continued: Mathematics Panel

	(4) Vehicle car/land			**(5) Cable TV**			**(6) Computer**		
Variables	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive Skills	0.018992 (0.03530)	-0.040395 (0.03768)	0.543810 (0.95384)	0.1142*** (0.0353)	0.06643* (0.03926)	-0.239419 (0.82716)	0.20109*** (0.05913)	0.21552*** (0.07104)	0.873177 (0.67931)
Years of Schooling	-1.4853 (2.7145)	-1.436219 (2.6172)	-3.651587 (10.026)	1.550353 (2.6539)	1.315192 (2.6218)	1.799311 (9.2926)	7.683769** (3.59070)	7.852866** (3.62043)	15.3934 (10.954)
Life Expectancy	1.240549 (1.8851)	1.710958 (1.8221)	4.333874 (5.7518)	-.608835 (1.50703)	-.9733144 (1.49295)	4.953014 (4.70411)	2.635373 (2.2624)	2.581063 (2.2829)	4.982002 (5.9151)
FDI	0.09599 (0.50518)	0.072433 (0.48711)	-2.778173 (2.4257)	-1.045*** (0.31227)	-0.92542*** (0.31161)	-0.168778 (0.88461)	0.20785 (0.40405)	0.18115 (0.40856)	-1.86743* (1.1231)
Political Rights	-0.72536 (2.6632)	0.358174 (2.5846)	6.11402 (7.3948)	-8.769*** (2.7068)	-8.513206*** (2.6737)	-6.928899 (8.1358)	-0.0467878 (2.5885)	-0.09809 (2.6046)	13.3344 (10.406)
Civil Liberties	4.943798* (2.9863)	1.892107 (2.9968)	1.896459 (7.81754)	5.316003** (2.4019)	3.424606 (2.4759)	-0.9417895 (7.71469)	-2.68915 (3.3899)	-2.64764 (3.4598)	-9.09771 (9.5067)
GDP Per capita		0.0011*** (0.00030)	-0.0000721 (0.00124)		0.000583*** (0.00021)	-0.0011603 (0.00110)		-0.000115 (0.000353)	.0011837 (0.001381)
Research & Development			67.29925* (35.716)			9.355411 (16.2555)			-41.75186 (26.099)
Lagged dependent variable	0.9425*** (0.02786)	0.8667*** (0.03387)	0.5731*** (0.1569)	0.8569*** (0.03136)	0.8442*** (0.03133)	0.5337*** (0.1466)	1.0147*** (0.0154)	1.015*** (0.0157)	1.011*** (0.0548)
Observations	227	227	26	212	212	54	178	178	63

Robust standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively.

Table 1 continued: Mathematics Panel

	(7) Tractor			(8) Fertilizer		
Variables	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive Skills	-0.00303* (0.00162)	-0.000582 (0.00198)	0.029655 (0.06046)	-0.0442351*** (0.01492)	-0.00104908 (0.01703)	-0.1352981 (0.12974)
Years of Schooling	0.029415 (0.13385)	0.034499 (0.13383)	0.464117 (0.72843)	-3.601329*** (1.1844)	-3.52864** (1.171003)	0.4274924 (1.58566)
Life Expectancy	0.0058313 (0.06975)	0.018735 (0.07005)	0.033375 (0.35982)	3.437704*** (0.70235)	3.9067*** (0.70433)	-1.824247** (0.80098)
FDI	0.0048781 (0.02503)	0.0027866 (0.02487)	-0.0097704 (0.0986123)	-0.1256564 (0.221213)	-0.1922653 (0.2193273)	-0.1750385 (0.2115905)
Political Rights	0.1729604 (0.14262)	0.1287412 (0.14399)	-0.0546575 (0.67600)	0.2797649 (1.24716)	-0.61966 (1.2536)	-1.11979 (1.4850)
Civil Liberties	0.2545829* (0.15025)	0.364131** (0.15872)	0.073563 (0.844675)	2.09251 (1.36454)	4.102527*** (1.44108)	0.591595 (1.8202)
GDP Per capita		-0.0000308** (0.000014)	-0.0000616 (0.000101)		-0.0005*** (0.00012)	-0.0005043** (0.00023)
Research & Development			-0.5875405 (1.47783)			-4.359462 (3.1697)
Lagged dependent variable	0.8800*** (0.0198)	0.88801*** (0.0201)	0.7385*** (0.0895)	0.8244*** (0.0346)	0.7930*** (0.03514)	0.134858 (0.14849)
Observations	279	279	50	279	279	50

Table 2:Robustness Checks for Science Skills and Usage Intensity of Technology.

	(1) **Transplant Liver**			**(2)** **Transplant Lung**			**(3)** **Visitor beds**		
Variables	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive Skills	0.000006** (0.000002)	0.000005** (0.000002)	(0.00002)** (0.000009)	0.000004*** (0.000001)	0.000004** (0.000001)	-0.00001 0.0000007	0.00157 (0.00129)	-0.00013 (0.0014)	0.00712 (0.006)
Years of Schooling	0.000312 (0.00043)	0.00028 (0.00043)	-0.000350 (0.00127)	-0.0012427*** (0.00037)	-0.0013*** (0.0003)	-0.00026 (0.0009)	-0.07229 (0.1886)	-0.16391 (0.1895)	0.371475 (0.4379)
Life Expectancy	-0.00041 (0.00026)	-0.000381 (0.00026)	0.000532 (0.0006)	0.00023 (0.00017)	0.00028* (0.0001)	0.00008 (0.0004)	0.16711 (0.1131)	0.15817 (0.1123)	-0.067138 (0.1762)
FDI	0.000035 (0.00004)	0.000036 (0.00004)	0.00025*** (0.00008)	-0.0000016 (0.00002)	-0.000003 (0.00002)	0.000013 (0.00006)	-0.05184* (0.0312)	-0.04324 (0.0312)	-0.002219 (0.0506)
Political Rights	-0.00073 (0.00058)	-0.000373 (0.00062)					-0.23799 (0.2235)	-0.195155 (0.2222)	-0.19829 (0.4002)
Civil Liberties	.0001867 (0.00038)	0.000162 (0.00038)		-0.000446 (0.0006)	-0.000594 (0.0005)		-0.09759 (0.216)	-0.053984 (0.2155)	0.03184 (0.4145)
GDP Per capita		0.000000005 (0.00000003)	0.0000001* (0.00000008)		0.00000005** (0.00000002)	0.000000056 (0.00000005)		0.0000651* ** (0.00002)	-0.000005 (0.0001)
Research & Development			-0.0053*** (0.00173)			0.00036 (0.00167)			-0.52165 (0.9345)
Lagged dependent variable	0.6807*** (0.0867)	0.65282*** (0.08798)	0.498817 (0.20351)	0.4123*** (0.10644)	0.4101*** (0.1038)	0.14207 (0.5139)	0.79578*** (0.0445)	0.7813*** (0.0445)	0.7563*** (0.1548)
Observations	90	90	22	72	72	21	190	190	44

Robust standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively.

Table 2 continued: Science Panel

	(4) Vehicle car/land			**(5) Cable TV**			**(6) Computer**		
Variables	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive Skills	0.01653 (0.01064)	0.002474 (0.01166)	-0.06959 (0.11351)	0.0189* (0.01065)	-0.0086 (0.0124)	0.03256 (0.158)	0.023054* (0.0133)	0.01626 (0.0168)	0.041007 (0.1515)
Years of Schooling	-1.035602 (2.4878)	-2.363515 (2.4916)	-1.92958 (9.6117)	-0.8155 (2.242)	-0.477803 (2.202)	2.9533 (8.248)	6.446825** (3.125)	6.466533** (3.1075)	12.5284 (9.481)
Life Expectancy	1.319532 (1.5129)	0.88258 (1.4846)	0.17474 (4.794)	0.344787 (1.387)	-0.03924 (1.367)	4.67587 (3.999)	4.7476** (1.966)	5.060857** (2.020)	3.783758 (5.208)
FDI	0.1464266 (0.41812)	0.23612 (0.41285)	0.5974 (0.97135)	-0.8591*** (0.2698)	-0.68453** (0.2689)	-0.1067703 (0.7349)	0.3075012 (0.370)	0.32611 (0.3704)	-1.244442 (0.9531)
Political Rights	-0.553753 (2.2263)	-0.7617381 (2.1790)	0.16289 (6.5259)	-7.934*** (2.439)	-8.12762*** (2.398)	-6.833525 (7.417)	-0.354014 (2.625)	-0.3511 (2.6207)	11.24717 (9.7400)
Civil Liberties	1.579393 (2.2949)	0.4503156 (2.2914)	(-0.42590) (7.7340)	4.426275** (2.029)	2.908508 (2.029)	-0.84805 (7.086)	-5.355732** (2.723)	-5.523123** (2.731)	-10.03891 (8.862)
GDP Per capita		0.0007*** (0.0002)	0.000908 (0.00093)		0.0008*** (0.0002)	-0.00131 (0.0009)		0.0002313 (0.0003)	0.00134 (0.0012)
Research & Development			24.47498 (20.646)			8.946207 (13.985)			-50.38995** (21.225)
Lagged dependent variable	0.930445*** (0.0257)	0.8994*** (0.02788)	0.8647*** (0.11925)	0.8854*** (0.0262)	0.8680*** (0.0261)	0.5317*** (0.136)	1.013*** (0.0133)	1.011*** (0.013)	1.033*** (0.047)
Observations	250	250	36	253	253	62	215	215	75

Robust standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively.

Table 2 continued: Science Panel

	(7) Tractor			(8) Fertilizer		
Variables	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive Skills	-.0016292** (0.00068)	-0.000848 (0.00077)	0.003432 (0.00950)	-0.0096503* (0.00525)	0.00383 (0.00579)	0.03638 (0.02373)
Years of Schooling	.032197 (0.14000)	0.062953 (0.140382)	0.2297 (0.57673)	-3.077685*** (0.98504)	-2.402649** (0.97232)	-0.224506 (1.4558)
Life Expectancy	0.027081 (0.05957)	0.06487 (0.06216)	0.10401) (0.29298)	2.628*** (0.47795)	3.3597*** (0.48842)	-0.9713 (0.7097)
FDI	0.000843 (0.02464)	-0.00264 (0.02465)	-0.003406 (0.07303)	-.1793301 (0.1886)	-0.30106 (0.18593)	-0.16421 (0.1819)
Political Rights	0.164230 (0.13841)	0.145708 (0.13867)	-0.00545 (0.60253)	0.89101 (1.058)	0.49752 (1.0384)	-0.2900002 (1.520)
Civil Liberties	0.203979 (0.138376)	0.248134* (0.14002)		2.365319** (1.1027)	3.359013 (1.0956)	1.61003 (1.8532)
GDP Per capita		-0.000029** (0.00001)			-0.0005*** (0.0001)	-0.000307 (0.00021)
Research & Development			-0.51270 (1.1698)			-3.010473 (2.9443)
Lagged dependent variable	0.9100*** (0.01899)	0.91481*** (0.01912)	0.7356*** (0.07871)	0.7905*** (0.02794)	0.7590*** (0.0280)	0.4419*** (0.11920)
Observations	305	305	61	305	305	61

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Appendix 5 Continued: Robustness Checks for Mathematics and Science Skills and Technology Diffusion.

Table 3: Mathematics Panel and Technology Diffusion.

	(1) Cable TV			**(2) Computers**			**(3) Transplant Bone marrow**		
Variables	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive Skills	-0.00974	-0.01075	-0.11467	-0.0165***	-0.015***	-0.03509	-0.0102*	-0.0102	0.1609
	(0.0068)	(0.0089)	(0.128)	-0.005	-0.0053	(0.0307)	(0.0057)	(0.006)	(0.1805)
Years of Schooling	0.76188*	0.79133*	0.3984	-0.31083	-0.313	-0.66413	-0.2872	-0.339	2.743**
	-0.4347	-0.437	-1.199	-0.228	-0.2288	(0.502)	(0.406)	-0.414	(1.284)
Life Expectancy	0.35935	0.35145	0.3081	0.18962	0.1999	0.00311	0.7041***	0.7122***	0.4383
	(0.2618)	-0.264	-0.5417	-0.1228	-0.124	(0.2202)	(0.1908)	(0.195)	(0.979)
FDI	0.04336	0.04535	-0.05996	0.0233	0.0211	-0.05067	0.0321	0.0366	-0.0591
	(0.0521)	(0.0531)	(0.1214)	-0.028	-0.028	(0.0634)	-0.029	-0.029	(0.1615)
Political Rights	0.5064	0.59981	1.99704	0.05093	0.05189	0.27052	-0.6496	-0.686	
	(0.437)	-0.444	-1.117	-0.1644	-0.1644	(0.463)	(0.724)	-0.747	
Civil Liberties	-0.22001	-0.2534	-0.19641	0.1131	0.15041	-0.6508			
	(0.3834)	-0.415	(0.9463)	-0.217	-0.225	-0.5312			
GDP Per capita		0.000008	0.000068		-0.00002	-0.0000303		-0.0000009	-0.00008
		-0.00004	(0.0001)		(0.00002)	(0.00007)		(0.00003)	(0.0001)
Research & Development			-1.66798			3.17408**			3.235
			(2.476)			-1.07			(7.586)
Lagged dependent variable	0.572***	0.567***	0.433***	0.880***	0.889***	0.889***	0.747***	0.7466	0.5862429
	-0.0747	-0.079	-0.164	-0.046	-0.046	-0.068	(0.073)	(0.074)	(0.510)
Observations	123	122	43	157	157	56	59	59	12

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 3 continued: Mathematics Panel and Technology Diffusion.

	(4) Lung Transplant			(5) Fertilizers			(6) Tractor		
Variables	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive Skills	-0.07266 (0.0449)	-0.0752* (0.0454)		0.02034*** (0.006)	0.0185*** (0.006)	-0.00722 (0.0713)	0.00143* (0.0008)	0.00116 (0.0008)	-0.00489** (0.002)
Years of Schooling	12.145*** (3.579)	11.444*** (3.742)		1.3571*** (0.516)	1.3415*** (0.517)	0.836009 (0.908)	-0.0155 (0.0512)	-0.020002 (0.0515)	-0.01745 (0.029)
Life Expectancy	-0.1803 (1.128)	0.29431 (1.318)		0.4288 (0.268)	0.39953 (0.271)	0.51928 (0.478)	0.07571* (0.0447)	0.07677* (0.0447)	0.03677* (0.019)
FDI	-0.02495 (0.1499)	-0.041807 (0.1531)		0.0192 (0.075)	0.02507 (0.076)	-0.24803** (0.118)	0.00274 (0.009)	0.003307 (0.0096)	-0.000095 (0.0036)
Political Rights				-0.0044 (0.408)	0.04013 (0.414)	0.8273 (0.807)	-0.02102 (0.053)	-0.01483 (0.0539)	0.0258 (0.0302)
Civil Liberties				0.29271 (0.452)	0.1416 (0.502)	-0.46166 (0.942)	0.04024 (0.062)	0.01939 (0.067)	0.00091 (0.0309)
GDP Per capita		0.00023 (0.0003)			0.000033 (0.00004)	-0.000268* (0.0001)		0.0000058 (0.000006)	0.00000087 (0.000004)
Research & Development						-0.8623 (1.751)			0.00129 (0.058)
Lagged dependent variable	0.0111 (0.213)	-0.0425 (0.228)		0.601*** (0.0638)	0.5976*** (0.064)	0.622*** (0.165)	0.968*** (0.0152)	0.967*** (0.0152)	0.983 (0.008)
Observations	33	33		177	177	40	204	204	38

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 3 continued: Mathematics Panel and Technology Diffusion.

	(7) Visitor Beds		
Variables	**(1)**	**(2)**	**(3)**
Cognitive Skills	0.00870	-0.0044	0.2222**
	(0.0081)	(0.0115)	(0.053)
Years of Schooling	1.0828**	0.90871*	1.50019
	(0.4991)	(0.5023)	(1.154)
Life Expectancy	0.60671*	0.76900**	-0.3834
	(0.362)	(0.3706)	(0.6154)
FDI	0.01168	0.01634	0.0504
	(0.0625)	(0.0616)	(0.201)
Political Rights	0.32961	0.46067	0.11505
	(0.408)	(0.4104)	(1.125)
Civil Liberties	-0.25474	-0.10711	-0.13357
	(0.5779)	(0.5759)	(1.227)
GDP Per capita		0.0001205	0.000070
		(0.00007)	(0.00059)
Research &			-0.58387
Development			(2.880)
Lagged dependent	0.514***	0.4973	0.9658***
variable	(0.121)	(0.119)	(0.232)
Observations	100	100	28

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

Table 4: Science Panel and Technology Diffusion.

	(1) Cable TV			**(2) Computer**			**(3) Transplant Bone marrow**		
Variables	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive Skills	-0.00159	-0.00126	-0.00030	-0.00298**	-0.00216	-0.01042	-0.004**	-0.003	0.0007
	(0.0017)	(0.0023)	(0.0237)	(0.001)	(0.0014)	(0.006)	(0.002)	(0.002)	(0.0065)
Years of	0.83365**	0.8628**	0.5023	0.00215	0.01743	-0.57538	0.0746	0.2126	2.337**
Schooling	(0.3660)	(0.3678)	(1.057)	(0.205)	(0.204)	(0.426)	(0.535)	(0.534)	(1.024)
Life Expectancy	0.32017	0.30668	0.20431	0.0684	0.05239	0.01567	0.8817***	0.861***	0.9658*
	(0.2155)	(0.217)	(0.4522)	(0.112)	(0.113)	(0.187)	(0.259)	(0.2556)	(0.5012)
FDI	0.04677	0.04542	-0.0447	0.00406	0.00196	-0.04234	0.05008	0.05209	-0.0335
	(0.0413)	(0.042)	(0.098)	(0.0282)	(0.028)	(0.049)	(0.0416)	(0.0409)	(0.0628)
Political Rights	0.43229	0.47371	2.27096**	0.08507	0.09016	0.31481	-0.5854	-0.2937	
	(0.3684)	(0.3704)	(0.975)	(0.177)	(0.176)	(0.423)	(1.039)	(1.041)	
Civil Liberties	-0.23271	-0.22833	-0.11042	0.36952*	0.4033**	-0.6151			
	(0.3156)	(0.325)	(0.854)	(0.196)	(0.197)	(0.470)			
GDP Per capita		-0.0000075	0.00009		-0.00003	-0.000035		-0.00007	-0.00005
		(0.00003)	(0.0001)		(0.00002)	(0.00006)		(0.00004)	(0.00006)
Research &			-0.71047			3.1468***			3.793***
Development			(1.996)			(0.856)			(1.346)
Lagged	0.606***	0.605***	0.402***	0.853***	0.856***	0.897***	0.6753***	0.6444***	0.2237
dependent	(0.0585)	(0.059)	(0.116)	(0.045)	(0.044)	(0.059)	(0.087)	(0.088)	(0.125)
variable									
Observations	134	134	50	194	194	68	67	67	17

Robust standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively.

Table 4 continued: Science Panel and Technology Diffusion.

	(4) Transplant Lung			(5) Fertilizer			(6) Tractor		
Variables	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive Skills	-0.0024	-0.00287	0.03053	0.00094	-0.00029	-0.0144***	0.000577	0.00069	-0.01632
	(0.0079)	(0.0082)	(0.0294)	(0.001)	(0.001)	(0.004)	(0.0005)	(0.0005)	(0.0173)
Years of	5.7680***	5.5562**	2.553708	0.6763	0.59322**	-0.15482	0.12016	0.1264	0.19683
Schooling	(2.131)	(2.3304)	(4.011)	(0.2659)	(0.263)	(0.277)	(0 .0802)	(0.081)	(0.3984)
Life Expectancy	0.2029	0.33962	0.7405	0.4347**	0.3877***	0.23815	-0.01830	-0.01701	0.07600
	(1.003)	(1.166)	(1.453)	(0.140)	(0.139)	(0.2042)	(0 .06841)	(0.0678)	(0.2412)
FDI	0.0707	0.06916	0.12729	0.0335	0.0538	-0.00941	-0.00773	-0.00907	-0.1018**
	(0.1306)	(0.1321)	(0.1922)	(0.0377)	(0.037)	(0.033)	(0 .0144)	(0.014)	(0.0511)
Political Rights				-0.05465	-0.02404	0.14775	-0.02484	-0.03008	0.22837
				(0.2068)	(0.204)	(0.315)		(0.0792)	(0.425)
							(0 .079)		
Civil Liberties	2.8685	2.8214		0.20107	0.05176	-0.05082	0.0582	0.07131	-0.3397
	(2.923)	(2.958)		(0.214)	(0.217)	(0.329)	(0.084)	(0.0874)	(0.4615)
GDP Per capita		0.0000509	-0.000022		0.000079**	0.000046		-0.0000061	-0.000017
		(0.0002)	(0.0005)		(0.00002)	(0.00004)		(0.00001)	(0.00006)
Research &			6.568605			0.295008			0.32026
Development			(4.412)			(0.586)			(0.873)
Lagged	0.2159	0.20351	-0.36745	0.8005***	0.772***	0.988**	0.974***	0.976***	0.923***
dependent	(0.1641)	(0.1738)	(0.501)	(0.036)	(0.0375)	(0.0803)	(0.017)	(0.0177)	(0.105)
variable									
Observations	48	48	11	215	215	51	210	210	42

Robust standard errors in parenthesis; *,**,*** imply 10%, 5%, and 1% significance levels respectively.

Table 4 continued: Science Panel and Technology Diffusion.

	(7) Visitor Beds		
Variables	(1)	(2)	(3)
Cognitive Skills	0.00469	-0.00135	0.06501**
	(0.0038)	(0.0050)	(0.03006)
Years of Schooling	0.49962	0.7647*	0.26665
	(0.4213)	(0.4342)	(1.0472)
Life Expectancy	0.71993**	0.81549***	0.03563
	(0.3109)	(0.305)	(0.5241)
FDI	0.02502	0.03678	-0.07857
	(0.0593)	(0.0578)	(0.1355)
Political Rights	0.33357	0.39917	0.789106
	(0.3816)	(0.3704)	(1.036)
Civil Liberties	0.02702	0.04315	-0.46337
	(0.5175)	(0.5008)	(0.981)
GDP Per capita		0.00011*	0.00002
		(0.00006)	(0.00049)
Research & Development			-1.407323
			(2.6306)
Lagged dependent variable	0.5964***	0.5202***	0.820***
	(0.0973)	(0.1034)	(0.216)
Observations	101	101	34

Robust standard errors in parenthesis; *, **, *** imply 10%, 5%, and 1% significance levels respectively.

References:

Acemoglu D. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. Quarterly Journal of Economics, CXIII (1998), 1055-1090.

Acemoglu, D., & Zilibotti, F. (2001). Productivity differences. Quarterly Journal of Economics, 116(2), 563–606.

Acemoglu D. (2002).Directed technical change. Review of Economic Studies, October 2002, 69(4), 781-810.

Acemoglu, D., Johnson, S. & Robinson, J. (2005), Institutions as the fundamental cause of long-run economic growth, in P. Aghion & S. Durlauf, eds, Handbook of Economic Growth, Vol. 1, North Holland, 385-472.

Acemoglu, Daron, Ufuk, A., Nicholas, B., &William. R.K. (2013).Innovation, Reallocation and Growth.Harvard Business School Working Paper, No. 13-088. (NBER Working Paper Series, No. 18993, April 2013.)

Aghion, P., & Howitt, P. (1992).A model of growth through creative destruction. Econometrica, 60, no. 2. 323-351

Aghion, P., & Howitt, P. (1998).Endogenous growth theory. Cambridge, MA: MIT Press.

Aghion, P., Boustan, L., Hoxby, C., & Vandenbussche, J. (2005). Exploiting states' mistakes to identify the causal impact of higher education on growth. Mimeo Harvard University.

Aghion, P., Meghir, C., & Vandenbussche, J. (2005). Growth, distance to frontier and composition of human capital. CEPR Discussion Papers No 4860.

Aghion, P., Alesina, A. &Trebbi, F. (2008), Democracy, technology, and growth, in E. Helpman, ed., Institutions and Economic Performance, Harvard University Press.

Aghion, P., & Howitt, P. (2009).The economics of growth. Cambridge, MA, MIT Press

Ainsworth, M., and M. Over (1994), Aids and African Development, World Bank Research Observer, 9(2), 203-240.

Aitken, B.J., & Harrison, A.E. (1999). Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. American Economic Review 89, no. 3: 605–18.

Archer, S., (2016). Late Afternoon Concurrent Sessions: Training and Education: Presentation: Pilot Study: Secondary Aviation/Aerospace Education Organization Design Survey. Aviation, Aeronautics, Aerospace International Research Conference. *Paper27.*

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies. 58(2), 277-297.

Arrow, K. J. (1962). The economic implications of learning by doing. The Review of Economic Studies, 29 (3), 155-173.

Atkinson. A., Anthony. B. & Stiglitz, J.E. (1969). A new view of technological change. Economic Journal, 79(315), 573–78.

Barro, R., & Sala-i-Martin, X. (1995).Economic growth. New York: Mac Graw-Hill.

Barro, R. (1998). Human capital and growth in cross-country regressions. Mimeo Harvard University.

Barro, R., & Lee, J. (2010).A new data set of educational attainment in the world, 1950–2010.

Barro, R. (2013). Health and economic growth. Annals of Economics and Finance. 14-2, 329-366.

Basu, S., & David N. Weil, (1998).Appropriate technology and growth. The Quarterly Journal of Economics, 113(4), 1025-1054.

Benhabib, J., & Spiegel, M. (1994). The role of human capital in economic development: Evidence from aggregate cross-country data. Journal of Monetary Economics, 34(2), 143–174.

Branstetter, L. (2005). Is foreign direct Investment a channel of knowledge spillovers? Evidence from Japan's FDI in the United States. Journal of International Economics, 68, no. 2: 325–44.

Caselli, F,. (2005). Accounting for Cross-Country Income Differences. In: Aghion, P & Durlauf,S (eds), Handbook of economic growth, Amsterdam: North-Holland.

Caselli, F & Coleman, W. J. (2001). Cross country technology diffusion: The case of computers. NBER Working Paper No. 8130.

Caselli, F & Coleman, W. J. II. (2006).The World Technology Frontier.American Economic Review 96, 499–522.

Caswell, M., Fuglie, K., Ingram, C., Jans S. & Kascak C. (2001). Adoption of agricultural production practices: Lessons learned from the US. Department of Agriculture Area Studies Project. US Department of Agriculture, Resource Economics Division, Economic Research Service, Agriculture Economic Report No. 792. Washington DC.

Conley, T. and Udry, C., (2001). Social learning through networks: The adoption of new agricultural technologies in Ghana. American Journal of Agricultural Economics, 83(3), pp.668-673.

Comin, D., & Hobijn, B. (2004).Cross-country technology adoption: Making the theories face the facts. Journal of Monetary Economics, 51, 39-83.

Comin, D., &Hobijn, B. (2007).Implementing technology. NBER Working Paper 12886.

Comin, D.,Hobijn, B., & Rovito, E. (2008). Technology usage lags. Journal of Economic Growth.,13, 237–256.

Comin, D., & Hobijn, B. (2009). The CHAT data set. NBER Working Paper. 15319

Comin, D., &Hobijn, B. (2009). Lobbies and technology diffusion. Review of Economics and Statistics, 91, 229-244.

Comin, D., & Mestieri, M. (2013). Technology diffusion: Measurement, causes and consequences. NBER Working Paper. 19052.

Chakraborty, S., & Das, M. (2005). Mortality, human capital and persistent inequality. Journal of Economic Growth 10:159–92.

Champernowne; A (1963). Dynamic growth model involving a production function. In: F. A. Lutz and D. C. Hague (eds), The theory of capital, New York: Macmillan

Day, J. D., Metes, D. M., & Vodovotz, Y. (2015).Mathematical Modeling of Early Cellular Innate and Adaptive Immune Responses to Ischemia/Reperfusion Injury and Solid Organ All transplantation. Frontiers in Immunology.6, 484.

Elo. Irma T. and Samuel H. Preston, (1996). Educational differentials in mortality: United States, 1979-85. Social Science and Medicine 42(1), 44-57.

Feder, G. & Slade R. (1984).The acquisition of information and the adoption of new technology. American Journal of Agricultural Economics, 66, 312-320.

Feldman J. D. Makuc, J. Kleinman & J. Cornoni-Huntley. (1989). National trends in educational differences in mortality.American Journal of Epidemiology.919-933.

Flachaire, E., Garcia-Penalosa, C. & Konte, M. (2014). Political versus economic institutions in the growth process. Journal of Comparative Economics 42(1), 212-229.

Fogel, R.W. (1994). Economic growth, population theory, and philosophy: The bearing of long-term processes on the making of economic policy. American Economic Review, 84(3), 369-395.

Foster, A. D., & Rosenzweig, M. R. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. The Journal of Political Economy, 103(6), 1176.

Galor, O., &, Weil, D. (1999). From Malthusian stagnation to modern growth. American Economic Review, 89:2,150–154.

Galor, Oded, &Weil, D. (2000). Population, technology, and growth: From Malthusian Stagnation to the demographic transition and beyond. American Economic Review, 90:4, 806–828.

Gerschenkron; A. (1962).Economic backwardness in historical perspective: A book of essays. Cambridge, MA: Belknap Press of Harvard University Press, 456 pp.

Glaeser, E., La Porta, R., Lopez-de-Silanes, F. & Shleifer, A. (2004).Do institutions cause growth?, Journal of Economic Growth 9(3), 271-303.

Glomm, G., & B. Ravikumar. (1992). Public versus private investment in human capital: Endogenous growth and income inequality. Journal of Political Economy 100:818–34.

Gregory,P., Susan ,Q.,Wolber, H., & Grail, F. (1993).The increasing disparity in mortality between socioeconomic groups in the United States, 1960 and 1986. The New England Journal of Medicine,.103-109.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. Econometrica 50, 1029–1054.

Hanushek .E.,&Kimko, D .(2000). Schooling labour force quality, and the growth of nations. American Economic Review, 90, 1184-1208.

Hanushek, E., &Woessmann, L. (2008). The role of cognitive skills in economic development. Journal of Economic Literature, 46, 607-668.

Hanushek, E., &Woessmann, L. (2012). Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation. Journal of Economic Growth, 17, 267–321.

Hulten,C,R; (2000). Measuring innovation in the new economy. University of Maryland and National Bureau of Economic Research.

Jamison, D.T., Lau, L.J., & J. Wang (1998). Health's contribution to economic growth, 1965-1990, in Health, Health Policy and Health Outcomes: Final Report, Health and Development Satellite WHO Director-General Transition Team(Geneva: World Health Organization): 61-80.

Jovanovic, B., & Nyarko, Y. (1996). Learning by doing and the choice of technology. Econometrica, 64(6), 1299.

Jude, C & Levieuge., G. (2015). Growth effect of FDI in developing economies: The role of institutional quality. Working papers 559, Banque de France.

Krueger, A. & Lindahl, M.(2001). Education and growth: Why and for whom? Journal of Economic Literature, 39, 1101-1136.

Lipsey, R., &Carlaw, K. (2004).Total factor productivity and the measurement of technological change. Canadian Journal of Economics, Canadian Economics Association, 37(4), 1118-1150.

Li, X., X. Liu.,& Parker, D.(2001). Foreign direct investment and productivity spillovers in the Chinese manufacturing sector. Economic System, 25: 305–21.

Lucas, R. E., Jr. (1988). On the mechanics of economic development. Journal of Monetary Economics, 22(1), 3-42.

Madsen, J, B., (2014). Human capital and the world technology frontier. The Review of Economics and Statistics, MIT Press, 96(3), 676-692.

Mankiw, N. G., Romer, D., & Weil, D. (1992).A contribution to the empirics of economic Growth Quarterly Journal of Economics, 107(2), 407–438.

Messinis, G., & Abdullahi, D,A. (2010). Cognitive skills, innovation and technology diffusion.Working paper No 48, Centre for Strategic Economic Studies, Victoria University.

Meyer, K. & Sinani, E. (2009). Where and when does foreign direct investment generate positive spillovers? A meta-analysis. Journal of International Business Studies 40, 1075-1094.

Muney, A .L.,& Lichtenberg, F.R. (2002). The effect of education on medical technology adoption: Are the more educated more likely to use new drugs. NBER Working Paper No. 9185

Nelson, R. & Phelps, E. (1966).Investment in humans, technology diffusion, and economic growth. American Economic Review, Papers and Proceedings, 56 (2), 69-75.

North, D. (1990), Institutions, Institutional Change and Economic Performance, Cambridge University Press.

Parente, S. L. (1994). Technology adoption, learning-by-doing, and economic growth. Journal of economic theory, 63(2), 346-369.

Parente, S., and E. Prescott. (1994). Barriers to technology adoption and development. Journal of Political Economy, 102:298–301.

Parente, S., and E. Prescott. (2004). A unified theory of the evolution of international income levels. Federal Reserve Bank of Minneapolis, Research Department Staff Report 333.

Pritcheet, L. (1997). Divergence, big time. Journal of Economic Perspective, 11, 3-17.

Rahman, A., Kamarulzaman, N.H & Murali, S. (2013). A study on organizational culture, performance, and technological adoption behaviours of Malaysian food-processing SMEs. Journal of social sciences and Humanities, 21, 231 – 256.

Rashidi, A. *(*2016*).* A mathematical model provides new insights into solid organ transplant-associated acute graft-versus-host disease*.* Clinical Transplantation*,* 00*:* 1–5.

Riddell, W. C., & Song, X. (2012). The role of education in technology use and adoption: evidence from the Canadian workplace and employee survey. IZA Discussion Papers 6377, Institute for the Study of Labor (IZA).

Rodrik, D., Subramanian, A. & Trebbi, F. (2004), `Institutions rule: The primacy of institutions over geography and integration in economic development', Journal of Economic Growth 9(2), 131-165.

Rodrik, D. (2011). Unconditional convergence. NBER Working Papers No. 17546.

Rodrik, D. (2013). Unconditional convergence in manufacturing. The Quarterly Journal of Economics, 128(1), 165-204.

Romer, P.M., (1990).Endogenous technological change. Journal of Political Economy, 98, 71–102.

Schumacher. (1973). Small is beautiful: A study of economics as if people mattered. Blond & Briggs (1973-2010), HarperCollins (2010-present) 288 pages.

Sinani, E., & K.E. Meyer. (2004). Spillovers of technology transfer from FDI: The case of Estonia. Journal of Comparative Economics, 32: 445–66.

Sun,S., (2011).Foreign direct investment and technology spillovers in China's manufacturing sector. The Chinese Economy, 44:2, 25-42.

Susana, I;& Giovanni, P. (2009). Schooling externalities, technology, and productivity: Theory and evidence from U.S. States. Review of Economics and Statistics 91, 420-431.

Thijs, R;& Victoria, S. (2011). The Solow residual, Domar aggregation, and inefficiency: a synthesis of TFP measures. Journal of Productivity Analysis, 36(1), 71-77.

Vandenbussche ,J., Aghion, P., & Meghir, C. (2006). Growth, distance to frontier and composition of human capital. Journal of Economic Growth 11:2, 97–127.

Wozniak, G. (1993). Joint information acquisition and new technology adoption: Late versus early adoption. The Review of Economics and Statistics, 75(3), 438-445.

Waller, B.E., Hoy. C.W., Henderson., J.L, Stinner B., & Welty C. (1998). Matching innovations with potential users: A case study of potato IPM practices. Agriculture, Ecosystems and Environment, 70,203-215.

Yeaple S., (2005). A simple model of firm heterogeneity, international trade and wages. Journal of International Economics, 65, 1-20.

Yusuff, R. M., Chek, L. W., & Hashmi, M. S. J. (2005a). Advanced manufacturing in Malaysia. CACCI Journal, 1, 23-29.

Zeira, J., (2009). Why and how education affects economic growth. Review of International Economics 17:10,3, 602-614.