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A Meta-Regression Analysis**

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Abstract

In this paper, we apply meta-regression analysis to 58 studies that explore the impact of ICT on economic growth. We find evidence of econometric specification bias and publication selection bias in favor of positive growth effects. After correcting these biases, we show that ICT has contributed positively to economic growth, on average. We find that both developed and developing countries benefit equally from landline and cell technologies, with cell's contribution to growth being double that of landline. However, developed countries gain significantly more from computing than do developing countries. In contrast, the Internet has had little effect on growth.

Keywords: ICT, economic growth, meta-regression analysis

JEL codes: O3, O4

1. INTRODUCTION

The rate of technological progress has been and continues to be impressive. Kurzweil (1999) argues that it follows a pattern of exponential growth or what he terms a “Law of Accelerating Returns.” Then there is the famous Moore’s law that the microprocessor density doubles approximately every two years, a trend which has maintained itself for over four decades. Given this phenomenally explosive growth in information and communication technologies (ICT), it has stimulated much research into ICT’s contributions to economic growth. Identifying the sources of growth is important for all nations, especially for developing countries, and it is, in fact, one of the longest standing issues in development economics (Dougherty & Jorgenson, 1996; Hall & Jones, 1999).

Theoretically, most researchers argue that ICT should be a key stimulant of economic growth. According to neoclassical growth theory, growth is driven by exogenous technological change. In contrast, endogenous growth theory emphasizes how growth naturally unfolds from investments in human capital and technology development. Endogenous growth theory views ICT as contributing to economic growth through the development of new products, processes and business models (Czernich, Falck, Kretschmer & Woessmann, 2011). ICT is said to result in a permanent (rather than a one-time) increase in productivity growth and thereby raising a country’s economic growth rate and creating new employment opportunities. However, negative effects are also theoretically possible (e.g., Kenny, 2003).

The exponential growth in technology over recent decades and the cumulative force of Moore’s law should make the impact of ICT on economic growth not merely detectable, but obvious. However, the absence of a clear and large impact is exactly what some economists have long contended, perhaps best exemplified by Brynjolfsson’s (1993) classic article on the

“Productivity Paradox.” He notes that despite the exponential growth in computing power, economic growth remains comparative sluggish.

This paper contributes to the literature by providing the first comprehensive meta-regression analysis of the evidence base on ICT’s macroeconomic impact.¹ Meta-regression analysis is an effective means of synthesizing the results from diverse studies, detecting and correcting biases that arise from the research process (e.g., publication selection bias and econometric model misspecification), and statistically testing hypotheses about the underlying effects. Recent applications of meta-analysis in development economics include Iršová and Havránek (2013) on FDI spillovers and Benos and Zotou (2014) on human capital. Here we apply meta-analysis to test the impact of ICT on growth and explore issues such as the productivity paradox. Importantly, we apply meta-regression to address the problem of publication bias. As Gordon (2000) reviews, there is a widely held conventional view that ICT can have a positive effect on growth and this can create a preference by both researchers and reviewers to report results that match this view. If this preference is widespread, it can cause a selection bias (called ‘publication’ bias) among the published research results that inflates estimates of the relationship between ICT and economic growth. We are particularly interested in exploring whether the level of development influences the impact of ICT and whether the marginal contribution to growth differs according to the type of ICT, e.g. Internet versus landline communications.

¹ Conventional reviews of the literature include Dedrick, Gurbaxani and Kraemer (2003) and Indjikian and Siegel (2005). Kohli and Devaraj (2003) report a meta-analysis of some of the firm-level studies. Stiroh (2005) reports a partial meta-analysis of 20 studies, reporting wide differences in estimates of the effect of ICT. More recently Polák (2014) updated Stiroh’s meta-analysis to 68 studies, finding an extremely weak effect at the firm level. Also, Cardona, Kretschmer and Strobel (2013) survey and summarize the field at the firm, industry and country level, though notably the national level analyses is based on only a total of six studies.

We structure the paper as follows. We commence in section 2 with a discussion of some of the key issues related to the ICT-growth literature and state the research questions that meta-analysis will be employed to investigate. Then in section 3, we briefly review the meta-regression analysis methodology. This is followed in section 4 by a discussion of our data representing the results and key research characteristics of this ICT-growth literature. The results are presented and discussed in section 5. Conclusions are presented in section 6.

2. ICT INVESTMENT AND ECONOMIC GROWTH

As per the example of Moore's Law, the degree of technological progress has been phenomenal. It extends beyond processing power, with some estimating the increase to be nearly a billion fold to a ten million fold improvement in memory storage and a ten thousand fold improvement in communications speed (Kessler, 2015). The effect of ICT on economic growth is often studied under the rubric of total factor productivity, a measure of rising outputs holding constant capital and labor inputs. For example, the process of growth accounting usually quantifies this technological contribution through the Solow residual, which essentially is unaccounted growth after taking into account inputs. As reviewed by Biagi (2013), The Solow residual has several ICT mechanisms that could contribute to its rise, including: i) the more efficient dissemination of information (e.g., cell phones and texting), ii) reduced transaction costs and more efficient market transaction (e.g., online banking), iii) improved organizational efficiency and marginal productivity of skilled labor (e.g., enterprise software). Such organizational efficiency should be particular salient in the productivity of both ICT-producing firm, as well as ICT-using firms.

Still, Nobel laureate and developer of Solow residual accounting is skeptical, with his famous and almost universally cited quip "You can see the computer age everywhere but in the

productivity statistics” (Solow, 1987, p. 36). Such is Solow’s connection to this issue that originally, and often still, the productivity paradox is referred to as the Solow paradox or the Solow Computer Paradox. Others have followed up his investigation, with many agreeing with Solow’s finding, that there is a notable lack of connection (e.g., Brynjolfsson & Hitt, 1998; Gordon, 2000; Harris, 1994; Willcocks & Lester, 1996). In fact, some developments of ICT may be harmful to growth. For example, ICT advancements enable an impressive amount of procrastination (Steel, 2010), with several estimates finding it consumes up to three hours of work a day (e.g., cyberslacking or cyberloafing; Machado, Machado, & Sousa, 2014; Vitak, Crouse, & LaRose, 2011).

Nevertheless, some of the raw data show a link between technology and national output. For example, Figure 1 compares the stock of US patents to US real GDP per capita, for the period 1870 to 2010. Two salient features can be seen from the graph. First, while the two series do diverge, sometimes for long periods, over the long term, real incomes have grown in line with technological advances, at least for the world’s largest economy. Second, it is clear that incomes are also driven by factors other than technology. This complexity presents a major challenge to empirical studies to separate the macroeconomic impact of ICT from other factors.

[FIGURE 1 ABOUT HERE]

Our first goal is simply to estimate the force of the productivity paradox. We do this at a national level, which distinguishes from previous individual, firm or industry related examinations (Han, Hsie, Lai, & Li, 2011) Is there really no connection or is the connection unexpectedly weak or difficult to isolate? Also, we want to explore possible moderators of the ICT-growth relationship. First, does the type of ICT advancement make a difference? Is it more tangible in computing power rather than Internet advancements? Second, does the type of

country make a difference? Especially, does ICT make a bigger impact in more or less developed countries? Third, if ICT does affect economic indicators, are some better suited to detect this effect? For example, are we more likely to see ICT's effect in productivity or economic growth data? Finally, causality may be an issue where the connection between the two is reversed, that is productivity gains are invested into ICT. What does the empirical literature find with respect to these and other related issues?

(a) Type of ICT

ICT refers to a wide variety of technologies, including landlines, cellphones and other mobile communication, computing, and Internet connectivity. Are all these equivalently important to growth? Carlaw and Lipsey (2002) note that a General Purpose Technology can “expand the space of possible inventions and innovations, creating myriad new opportunities for profitable capital investment, which in turn create other new opportunities, and so on in a chain reaction that stretches over decades, even centuries” (p. 1306). ICT is considered a General Purpose Technology in that it can influence the economy through a myriad of “spillovers” and “technological complementaries.” However, not all aspects of ICT have the same potential for impact. We would expect computing power and Internet connectivity, which eventually can subsume other forms of telecommunication, to have greater marginal returns. Our meta-analysis will specifically investigate the differential growth impact for these separate types of ICT.

(b) Developing versus developed

ICT's impact may depend on where it occurs, especially whether the contribution of ICT to growth is a function of a country's stage of economic development. For example, Gordon (2000, 2012) argues that ICT may show diminishing returns, having a greater impact on first

adoption, and Watanabe, Naveed and Zhao (2015) suggest that nations with advanced ICT infrastructure actually experience decreases in marginal productivity. Specifically, they write about “the two-faced nature of ICT in which advancement of ICT contributes to increase its marginal productivity and subsequent price increases due to new functionality development while dramatic advancement of the Internet has resulted in price decreases due to freebies, easy copying and mass standardization” (p. 2). Consequently, the development of ICT infrastructure can be plausibly counseled as part of a foreign aid package for developing nations, such as the Clinton Bush Haiti Fund efforts to create wireless broadband in that country.

On the other hand, it might be too optimistic to hope that ICT will offer higher returns to developing countries than developed nations. Coming under the heading of the Complementary Hypothesis (Bresnahan, Brynjolfsson, & Hitt, 2001; Milgrom & Roberts, 1990), developing countries suffer serious constraints that hinder capital accumulation and obstruct the efficient use of existing resources. ICT might require the availability of skilled labor, a solid economic infrastructure and a business environment that can take advantage of the opportunities that ICT offers. For example, Mack and Faggian (2013) conclude that “broadband only produces positive productivity impacts when used by more educated and/or highly skilled occupations” (p. 411). If this and other prerequisites are lacking, then the potential returns from ICT might not be fully realized. ICT also involves learning-by-doing, and it might take some time for developing countries to capitalize on these new opportunities. Moreover, even if ICT’s marginal productivity is higher, it does not operate in a vacuum. Private and public infrastructure investment is required to compliment ICT, and the ability of governments to contribute to infrastructure is a function of their country’s level of economic development.

It is even possible for ICT to have adverse effects on growth. For example, a negative growth effect might arise if ICT contributes to widening inequality within a country, which can

subsequently have a detrimental impact on growth (Piketty & Saez, 2014). This can occur, for example, if ICT accelerates the automation processes that substitute capital for labor, especially unskilled labor. Such considerations would then suggest that developing countries should be cautious about investing in ICT.

(c) Types of economic indicator

In general, the empirical literature explores the impact of ICT either on economic growth or on productivity, with most studies focused on growth. Productivity is a key driver of growth and hence studies that explore the effect of ICT on productivity are estimating a transmission channel from productivity to growth. Studies that explore the effect of ICT on growth provide estimates from reduced form models, but they in general do not address the issue of the transmission channel.² Which of these is best to study the Solow Paradox is unclear, with Brynjolfsson and Yang (1996) writing that, “it is possible that the benefits of IT investment are quite large, but that a proper index of its true impact has yet to be identified.” Consequently, in the meta-analysis we explore whether it makes a difference whether the focus is on productivity or economic growth.

(d) Causality

The issue of causality has been a matter of concern throughout the economic growth and development literatures. Sometimes it can be addressed meta-analytically. For example, in a meta-analysis of slack and innovation, Bowen, Rostami and Steel (2009) correct for confused temporal sequence to establish that innovation does lead to improved future performance while the reverse is less clear. Here, we want to find out the causal relationship between ICT and growth as there is a possibility that growth causes higher investment in ICT rather than ICT

² For example, some studies exclude capital from the econometric specification, often because of lack of data but sometimes because capital is seen as a transmission channel. This presents a challenge for empirical research. Ignoring capital from a growth regression can result in econometric misspecification bias. On the other hand, including capital in the growth regression effectively excludes capital as a transmission channel.

causing growth. Many drivers of growth might in turn be driven by prior growth, as per General Purpose Technology (Carlaw & Lipsey, 2002). For example, if the income elasticity of ICT is greater than zero, which is almost certainly the case, then growth and increases in income will cause greater purchases and investments in ICT. Of course, causation might run in both directions, simultaneously. Primary researchers attempt to deal with this issue in several ways and in our meta-analysis we explore whether controlling for endogeneity produces different results.

3. META-REGRESSION ANALYSIS

Meta-analysis systematically reviews all comparable research literature on a specific topic of interest and employs statistical methods to aggregate the information from independent studies. Systematic reviews differ from conventional narrative reviews of the literature by making serious effort to identify *all* research results through the use of a comprehensive search strategy and by employing rigorous statistical methods. As one form of meta-analysis, meta-regression analysis (MRA) examines the results of previously published studies that are based upon the use of multiple regression models on empirical data and, in turn, use multiple regression methods themselves. As Stanley defines: “(M)eta-regression analysis is a form of meta-analysis especially designed to investigate empirical research in economics” (Stanley, 2001, p. 131). By now, hundreds of MRAs have been published in economics, and many have succeeded in providing a comprehensive summary and understanding of the topic under scrutiny (Roberts & Stanley, 2005; Stanley & Doucouliagos, 2012; Valickova, Havranek & Horvath, 2015).

A major advantage of meta-regression analysis is that it enables researchers to systematically review and compare the effects of relevant econometric models. Through these

comparisons, it is able to identify the variation that can be explained by the main variables above and beyond the biases that exist in single studies in the literature. In this study, we use meta-regression analysis to identify the differential effect that ICT investments may have on economic growth, especially after accommodating the possible effects from publication bias.

Publication selection has been found to be widespread across several fields, including economics. It occurs when: 1) reviewers and editors tend to accept papers that are consistent with the conventional view, 2) researchers may select models based on the presence of conventionally expected results, and 3) there is a general inclination among scholars to treat statistically significant results and the results that match the conventional view more favorably (Card and Krueger, 1995). Publication selection can result in an over-representation of larger, more significant, effects in the research record. “(E)ven a careful review of the existing published literature will not provide an accurate overview of the body of research in an area if the literature itself reflects selection bias” (De Long & Lang, 1992, p. 1258).

Since publication selection can significantly distort and thereby bias the research record, some allowance for its presence must be made when conducting meta-analyses (Stanley & Doucouliagos, 2012). Here, our primary focus is on the overall contribution of ICT to economic growth. As mentioned above, the general view among economics researchers is that ICT has a positive effect on economic growth. Thus, there is a possibility that some researchers or reviewers will use the presence of a positive and statistically significant effect between ICT and economic growth as a model specification test or as a requirement for the plausibility of a given finding. The current meta-analytic study enables us to examine the existence of publication bias in the ICT literature and, more importantly, to peer through this potential distortion to identify the likely genuine effects of ICT and how these effects are affected by specific technologies and by the level of development.

4. SEARCHING, CODING AND COMPILING THE RESEARCH RECORD

(a) Data collection and literature search

Our search for studies, data selection, coding and reporting all meet the MAER-NET guidelines (Stanley et al., 2013). The starting point of our systematic review was to track down every academic paper (both published and unpublished available before our cutoff date of February 2014) that studies the relationship between information and communication technologies (ICT) and economic growth. We include papers from a variety of fields, including economics, public policy, computer science, political science, engineering, and public administration. The fundamental criteria for inclusion in the initial systematic review is that the study mentions either ICT or a related keywords and either economic growth or a related keyword (see Table 1 for the lists of related keywords). We independently searched Google Scholar, Proquest, and SSRN for keyword matches, and then searched the works cited in each paper that fulfilled the keyword requirement for further papers. After independently running these searches, we combined and deduplicated our dataset. Ultimately, there were 1,253 papers that fulfilled the keyword requirement.

Next, we analyzed the relevance of the papers to the academic study of the relationship between ICT and economic growth. Because of the breadth of our initial keyword search, a variety of obviously unrelated papers appeared in the initial literature review. In the second stage of our systematic review, we excluded papers that were obviously unrelated to the topic of our research and, as a result, would not contain empirical estimates of ICT's effect on growth. At this stage, we also excluded non-academic articles (summaries of academic articles in popular

media, opinion and editorial pieces, etc.) from our sample. We excluded 908 papers this way, leaving a set 348 papers that might potentially report relevant estimates.

Next, we examined each paper in-depth in order to quantify the results of the paper. We discarded papers from the remaining that did not: include data (quantitative analysis), use a statistical analysis (no econometrics), or provide results. Note that this means that we exclude growth accounting studies.³ We also excluded papers that did not use an independent variable related to telecommunications investment and a dependent variable related to economic growth. Without both, there could be no ICT-growth estimate. The final dataset consisted of 425 estimates from 59 studies that were directly related to ICT and economic growth, featured econometrics with results and data, and examined one measure of economic growth. The studies are listed in Appendix A.⁴

[TABLE 1 ABOUT HERE]

(b) Coding methodology

In order to employ meta-regression analysis (Stanley, 2005; Stanley & Doucouliagos, 2012; Stanley & Jarrell, 1989), we needed to quantify the relevant information in each study. For each relevant study, we recorded: the study's title, author, year, publication status and method of data collection (cross-sectional, time-series, and panel data), the effect size of interest (i.e., an estimated regression coefficient of some measure of telecommunications or ICT on the measure

³ The main reasons for excluding growth accounting studies is that they are not directly comparable to the econometric studies and also they do not provide a measure of the precision of the estimated effect of ICT. This is essential for detecting and correcting publication bias. Moreover, standard errors are necessary to construct inverse variance weights that are used for weighted least squares MRA and all conventional meta-analysis calculations.

⁴ The vast majority the estimates are published in internationally recognized journals (71%) or working paper series (9%). A further 7% are published by internationally renowned private sector organizations (e.g. Vodafone, Deloitte and Capco). The remaining 13% of estimates are published in less recognized journals or they are as yet unpublished. Removing these estimates from the meta-analysis does not alter the findings presented in the text.

of economic growth) and either the standard error or the t-statistic, depending on which value the authors reported. Furthermore, we recorded the number of observations, the time period the study covered, the number of degrees of freedom, and the names of the independent variables in the regression. Finally, we recorded the type of country studied (e.g., a developing country, OECD), and whether the authors used any method for correcting endogeneity problems. See Table 7 for a list of the substantive research dimensions coded.

(c) Conversion to a common effect-size

Our search and coding process revealed the existence of four different measures of telecommunication (i.e., landline, cell phone, IT, and Internet) with three measures of economic performance (i.e., GDP growth, GDP per capita growth, and productivity). By converting each estimated coefficient to the partial correlation coefficient as a common metric (Stanley & Doucouliagos, 2012), we were able to compare the relationship between telecommunication and economic growth across different specifications and alternate measures. To include and combine as many estimates as possible, telecommunication-growth effects were measured in two ways: partial correlation and Fisher's z-transformed correlation effect size. Partial correlation coefficients are commonly used to measure the strength and the association between two variables. They isolate the effect of ICT on growth by holding other variables included in the model constant.

However, since partial correlations are never reported directly in the econometric studies, we had to calculate them from the conventional regression statistics reported in the papers. Partial correlation coefficients can be calculated using the following formula:

$$r = \frac{t}{\sqrt{t^2 + df}} \quad (1)$$

where t denotes the t -statistic of the related multiple regression model and df is the degrees of freedom of this t -statistic.⁵ The standard error of the partial correlation, SE , can be calculated using the following formula:

$$SE = \sqrt{(1 - r^2)/df} \quad (2)$$

The use of partial correlation coefficients in meta-analysis has several advantages. The most important advantage is that it is a unit less measure. This allows the use of partial correlations for comparing the results of studies using different measures of economic growth. Compared to other potential effect size measures, partial correlations allow the compilation of a larger, more comprehensive, set of research findings on a particular economic subject. Finally, most researchers are familiar with the meaning and interpretation of correlations.

While the use of partial correlations has several advantages, it has drawbacks. In particular, its distribution is not normal when its value gets close to +1 and -1. This is not a serious problem in most economic applications because partial correlations of economic relations tend to be small. However, in some cases, the truncation at +1 and -1 might cause an asymmetry. Fisher's z -transform is the most common method that is used to solve this problem.

$$z = \frac{1}{2} \ln \left(\frac{1 + r}{1 - r} \right) \quad (3)$$

Fisher's z -transformation can also address the problem of interdependence between r and the standard error of r . Thus, in order to increase the robustness of our results and to ensure that an asymmetry was not inadvertently introduced, we reported the results of our meta-analysis using both partial correlation and Fisher's z -transform.

⁵ A common mistake in the literature is when there is a negative effect size reported. At this time, some researchers report the t -statistics imprecisely without mentioning its minus sign. Therefore, careful reading of the full paper was required in order to understand and correctly code the direction of the relationship.

Another limitation with the partial correlation is that it is a statistical measure rather than an economic measure, such as an elasticity. Nevertheless, by calculating partial correlations, we are able to use the largest possible evidence base from which to assess the growth effects of ICT. While we refer to the partial correlation as an effect size statistic, it is necessary to interpret it as a measure of correlation rather than causation. We return to this issue below when we assess endogeneity.

(d) Exclusion of overly influential estimates

Before we report the meta-analysis of our coded research data, we removed a few implausibly influential estimates from the collected set of papers and estimates. Although we believe that meta-analysts should error on the side of inclusion (Stanley & Doucouliagos, 2012), balance demands that no single estimate, especially one among hundreds, drive how an entire research literature is viewed or understood. We follow Bollen and Jackman (1990) in identifying any observation to be influential if $|DFBETA| > 1$. The DFBETA statistic calculates the difference in some target regression coefficient (the ‘beta’) caused by the inclusion of a given observation, relative to the standard error that is calculated from the data which does not include the observation in question. For our target regression, we use the FAT-PET-MRA model, (Equation 4 outlined below), that accommodates publication selection bias and the simple fixed-effects weighted average, which does not correct for publication bias. Eight of the ten estimates reported by Sridhar and Sridhar (2009) cause both of these summary estimates to increase by more than fourteen standard errors and would be identified as implausible by any reference meta-regression model or statistic. The t -values reported by Sridhar and Sridhar (2009) are many times larger and as much as 100 times larger than what any other study reports. Despite being a substantial part of Cardona et al.’s (2013) ICT review paper, we omit this study from further consideration.

Influence statistics identifies two further estimates. One of the thirty-four telecommunication-growth estimates reported in Dewan and Kraemer (2000, Table 7, p. 557) has a DFBETA that exceeds 1 for both reference meta-regressions {1.25; 3.64}. The estimate in question is one that Dewan and Kraemer (2000) use as a robustness check and to correct for potential autocorrelation and heteroskedasticity. Lastly, we identify an estimate from Andrianaivo and Kpodar (2012) as overly influential; DFBETA = {1.05; 2.97}. After removing Sridhar and Sridhar (2009) and one estimate each from Dewan and Kraemer (2000) and from Andrianaivo and Kpodar (2012), 415 estimates from 58 studies remain. Of the 415 estimates, 120 relate specifically to landline communications, 55 to cell, 48 to computing, and 112 to Internet. The remaining 80 estimates come from studies that look at the growth impact across more than one type of ICT.⁶

5. META-ANALYSIS RESULTS

We analyzed this area of research in three steps. First, we report basic meta-analysis in the form of weighted averages of the estimated effects, but not controlling for bias or heterogeneity likely contained in the research record. Second, potential publication selection bias is accommodated and explored. Here, we also go a little further and investigate potential differences among the type of ICT technologies (*Landlines, Cell, Computing, and Internet*) and in the level of a country's level of development. Third, multiple meta-regression is employed to analyze more complicated heterogeneity, identify moderator variables, and to ensure the robustness of our main findings.

⁶ As ICT development expands, there is no particular reason to believe its benefits will be consistently linear, that every doubling of speed or memory capacity will have the same effect on productivity. Unfortunately, there are far too few estimates from which to conduct a meta-analysis on non-linear effects. Hence, our meta-analysis explores only whether there is a linear effect.

(a) *Basic meta-analysis*

As this first step in our meta-analysis, Table 2 provides overall weighted averages of ICT's effect on growth for both partial correlations (columns 1 to 3) and their associated Fisher's z-transformations (columns 4 to 6). The fixed effect estimate (FEE) weights each ICT-growth estimate by the inverse of its squared standard error, $1/SE_i^2$. The random effects estimate (REE) uses more complex weights that allow for excess between-study heterogeneity, τ^2 , as well as individual estimation error, $1/(SE_i^2 + \tau^2)$. Lastly, the unrestricted WLS estimate has the same individual weights as FEE and, as a result, has the same point estimate. However, like REE, this unrestricted WLS allows for excess between-study heterogeneity. Stanley and Doucouliagos (2015) have recently shown that the unrestricted WLS estimator often provides superior estimates to both conventional fixed effect and random effects.⁷

Table 2 combines all estimates regardless of the type of ICT and stage of development. As can be seen from that table, the estimated fixed-effect average is the same as the WLS average. However, the confidence interval is wider for the WLS estimate. Hence, taking all estimates into account, it appears that the partial correlation between ICT and growth is approximately 0.2. Following Cohen's (1988) guidelines for assessing the strength of a correlation coefficient, ICT has a small effect on growth.⁸ However, any simple overall meta-analysis needs to be interpreted with caution if there is publication selection bias and/or heterogeneity in the reported estimates. The Cochrane's Q-test indicates clear evidence of excess heterogeneity beyond what is measured by random sampling alone ($p < 0.001$). To account for

⁷ Specifically, Stanley and Doucouliagos (2015) show that WLS is superior to REE when there is publication selection bias and it is superior to FEE when there is heterogeneity. Both publication selection bias and heterogeneity are present in our data.

⁸ According to Cohen (1988), the absolute value of a correlation is small if it is 0.10, while 0.30 is a medium effect. Doucouliagos (2011) finds a partial correlation of 0.23 for the 50th centile of nearly 10,000 partial correlations of the determinants of economic growth. ICT's effect on growth is thus on par with the median effect size in the empirical growth literature.

this heterogeneity, we identify ten moderator variables in the relationship between ICT and economic growth—see Table 8. Before we turn to this multiple meta-regression, we need to explore whether there is publication selection bias and how it might affect the reported ICT estimates in this literature.

[TABLE 2 ABOUT HERE]

(b) Publication Selection Bias

Publication selection is potentially a serious issue. By selectively reporting empirical estimates that are statistically significant or that conform to the expectations of economic researchers, an empirical research literature can greatly exaggerate ‘true’ effects (Doucouliagos et al., 2013; Stanley & Doucouliagos, 2012, 2014). Because the presumption of a positive economic effect from technology is so strong, it would not be surprising if a few negative or statistically insignificant estimates were seen as evidence of model misspecification and not reported. If so, the reported research base may exaggerate the growth effect of these technologies.

Figures 2 and 3 are funnel graphs of the effects of telecommunication technologies on economic growth (Sutton, Abrams, Jones, Sheldon, & Song, 2000). A funnel plot is a scatter diagram of precision (as measured by the inverse of the standard error) versus estimated effect (i.e., partial correlation coefficients or Fisher’s z-transform). Large variation among reported estimates is expected and observed at the bottom of the funnel graphs, Figures 2 and 3, because the associated standard errors are quite large. On the other hand, a wide spread of estimates in the upper portions of the funnel graphs, where there is higher levels of precision, cannot be attributed to sampling error alone. Consistent with the results of Cochrane’s Q test for heterogeneity reported above, this wide scattering at the top of the funnels indicate that ICT’s effect on

economic growth will likely depend on moderating factors, and it is important to control for such effects through multiple meta-regression or separate subgroup MRAs, as per below.

In addition, a literature free of publication bias has a symmetric funnel plot, randomly distributed around the ‘true’ effect. But, when one side of the funnel is missing and the results are skewed in the opposite direction, publication, reporting or small-sample bias may exist. Note that both Figures 2 and 3 are skewed to the right. Because asymmetry might be the result of publication selection bias (Egger, Smith, Schnieder & Minder, 1997; Stanley, 2008; Stanley & Doucouliagos, 2012), it is important to accommodate potential selection bias in all subsequent meta-regression analyses. While the inspection of funnel graphs is useful for the initial detection of publication bias, more statistically rigorous methods are required. Visual inspection is always susceptible to subjective interpretation.

[FIGURES 2 AND 3 ABOUT HERE]

A simple MRA between a study's reported effect and its standard error provides a more objective method to investigate and accommodate publication bias (Egger et al. 1997; Stanley, 2005, 2008). In the presence of publication selection bias, the reported effect sizes are positively correlated with their standard errors. Conversely, in the absence of publication selection, the estimates are independent of their standard errors and vary randomly around the true effect size value. The independence of a given empirical effect from its standard error is a necessary assumption made by all researchers of the effect telecommunications on economic growth. Otherwise, the conventional *t*-test that they all report would not be valid (Stanley & Doucouliagos, 2012). In the presence of publication selection bias, researchers who have small samples and large standard errors need to use those model specifications, data, and econometric

techniques that give correspondingly larger estimates in order to obtain statistical significance. On the other hand, researchers who have larger studies and smaller standard errors do not need to put much effort into model specification searching because small estimated empirical effects are likely to be statistical significant.

With selection for statistical significance, reported estimates will depend on their standard errors (Egger et al., 1997; Stanley, 2008; Stanley & Doucouliagos, 2012):

$$r_i = \alpha_0 + \alpha_1 SE_i + \varepsilon_i \quad (4)$$

where r_i is the estimated partial correlation, SE_i is its standard error, and ε_i is the conventional random sampling (or estimation) error. The term, $\alpha_1 SE_i$, allows for publication selection bias, and estimates of α_1 can be used to test for publication, reporting or small-sample bias. In medicine, MRA model (4) is known as the Egger regression, and the hypothesis test of α_1 ($H_0: \alpha_1 = 0$), is sometimes called the ‘funnel asymmetry test’ (or FAT) (Egger et al., 1997; Stanley, 2008). Note that as $SE_i \rightarrow 0$, $E(effect_i) \rightarrow \alpha_0$. As a result, investigating whether $\alpha_0 = 0$ provides a test for a genuine empirical effect beyond publication selection bias. Therefore, testing $H_0: \alpha_0 = 0$, referred to as precision-effect test (PET), identifies whether there is any genuine underlying empirical effect remaining after potential publication, reporting or small-sample bias is accommodated (Stanley, 2008; Stanley & Doucouliagos, 2012).

However, simulations have shown that the use of the variance, SE_i^2 , in MRA model (4) will often give a better estimate of the size of the genuine effect, corrected for publication bias:

$$r_i = \gamma_0 + \gamma_1 SE_i^2 + v_i \quad (5)$$

MRA model (5) provides the best Taylor polynomial approximation to the expected value of a truncated distribution, called precision-effect estimate with standard error (PEESE) (Stanley & Doucouliagos, 2012, 2014).

The FAT-PET model (4) results are reported in Table 3 for all 415 estimates combined. Column 1 reports uses weighted least square (WLS). WLS is preferred because both meta-regression models (4) and (5) have obvious heteroskedasticity due to the reported effects' widely different standard errors (and thereby different variances). The WLS version of models (4) and (5) can be obtained by weighing the squared errors by the inverse of each estimates' variance (*i.e.*, $1/SE_i^2$). MRA regression coefficients from the simple WLS MRA models can be used to test for the presence of publication selection ($H_0:\alpha_i=0$), and a genuine effect beyond publication selection bias ($H_0:\alpha_o=0$), Table 3. Because several estimates are reported by most studies, we also correct for potential within-study dependence by calculating cluster-robust standard errors and by explicitly recognizing the panel structure of our meta-data— columns 2, 3, 5 and 6 of Table 3.

First, note that columns 1-6 of Table 3 provide evidence of publication or small-sample bias (reject $H_0:\alpha_i=0$ $p<.01$) in all cases except panel estimates using partial correlations.⁹ However, there is a possibility that publication (or small-sample) bias is more complex or that the funnel asymmetry is due to other moderating factors. In the following section, we will investigate other sources of heterogeneity and differential publication bias, as well. There, we show that clear evidence of publication selection bias remains even after controlling for the effect of all the relevant moderators. Regardless of publication bias or whether this correlation with the standard error is due some other bias, there is also clear evidence of a genuinely positive ICT effect on economics development (reject $H_0:\alpha_o=0$; $p<.05$) in all cases. This means that even after

⁹ This result is not surprising nor does it conflict with the other evidence of publication selection bias. When WLS is used in the context FAT-PET-MRA panel models, the study effects allow a different amount of publication selection for each study. The fact that there is clear evidence of study-level effects is evidence that there is significant differential publication bias— $F_{(57, 356)} = 7.27$; $p<.001$.

accommodating publication selection bias, there is still clear evidence of an overall positive effect from standard on economic growth.

[TABLE 3 ABOUT HERE]

Table 4 reports the estimates of γ_0 from MRA model (5) to be about 0.20 and is roughly consistent with the weighted averages reported previously. These estimates provide the least biased correction for publication selection (Stanley & Doucouliagos, 2014). As discussed above, a correlation of 0.20 is regarded as small by conventional standards. It implies that telecommunications can explain about four per cent of the variation in economic growth not already accounted for by other explanatory factors, such as capital, labor, human capital, level of development, and trade. Together, these analyses indicate that Solow's Paradox is rejected in its hard form, that ICT has no effect on economic growth, but it is supported in its soft form, that ICT has an unexpectedly weak effect.

[TABLE 4 ABOUT HERE]

Thus far, we have reported ICT effects using both partial correlation coefficients and Fisher's z-transforms. Although Fisher's z-transforms are important to investigate to ensure the robustness of our results, we see no substantive difference between these two measures of effect. Thus, the below analyses will focus on partial correlation coefficients.

As we explore potential moderator variables, we first focus on the type of ICT technology. As already noted, there are four types of ICT investment reported in the literature: telephone landlines, cell phones, computer or information technology (IT) and Internet or broadband access. Because these different technologies could have a differential effect on economic growth (i.e., as

General Purpose Technologies), we examine the effects of ICT technologies separately. As Table 5 indicates, there is evidence of notable selection for positive effects among those studies investigating the effect of the Internet or broadband access (i.e., column 4). Substantial publication bias for a positive effect in this one area alone, the Internet, could be responsible for the significant FAT results that we report in Table 4 for ICT in general. Even after accommodating potential publication selection or reporting bias, a notable growth effect ($\hat{\alpha}_0$) remains for landlines, cell phones and conventional IT computing technologies and it is especially large for IT.¹⁰ The PEESE MRA model (5), indicates a rather large effect for IT, a medium effect for cell phones and a small effect for landlines on economic growth (see Table 5). However, the full story of ICT on the economy is likely to be more complex and nuanced than this.

[TABLE 5 ABOUT HERE]

Next, we consider the level of development. Table 6 extends the analysis of Table 5 by allowing a differential impact of ICT on growth in the developed versus developing countries. Again, we report the WLS FAT-PET models for each technology separately, but now allowing for the stage of development. The variable *Developing*, which is 1 if a country is less developed, is added to the previous MRA model to compare the effect of each technology type on developed (or OECD) countries versus developing nations. The results presented in Table 6 use OECD as the base.

[TABLE 6 ABOUT HERE]

¹⁰ Note, however, that the sample size is relatively small for IT, with 48 estimates from six studies.

The results for landline and cell technologies presented in columns (1) and (2) are essentially the same as those reported in Table 5. Landline and cell technologies have a positive effect on growth, show no signs of selection for statistical significance and are not notably moderated by the level of development. Both developed and developing countries gain from these telephony technologies, though the growth effect from cell technologies is approximately double that of landlines.

In contrast, computing/IT exhibits a clear differential effect on economic development ($t = -3.88$; $p < 0.01$) with a large positive effect on economic growth among developed nations ($\hat{\alpha}_0 = 0.562$; $p < 0.001$; column (3) in Table 6). However, no noticeable net effect on developing countries remains when the coefficient on *Developing* is added to the intercept ($\hat{\alpha}_0 + \textit{Developing} = 0.085$; $t=0.59$; $p \gg .05$). This suggests that developed countries have gained more out of computers, supporting Mack and Faggian's (2013) conclusion that the advantages of computer technology mostly accrue to regions populated with the highly skilled; less so to developing countries that rely more on agriculture and extractive industries.

Regarding the Internet, its effect is statistically insignificant for OECD countries ($t = -0.73$; $p \gg 0.05$) but significantly positive, 0.265, for developing nations ($t = 2.99$; $p < 0.01$). Though supportive of the position that ICT may show diminishing returns (e.g., Gordon, 2012, Watanabe et al., 2015), this result should be interpreted cautiously. It is not robust when other forms of heterogeneity are considered. The next section reports the effects from multiple sources of heterogeneity simultaneously.

(c) *Multiple meta-regression analysis*

The meta-regression models presented so far have only considered a couple of potential sources of variation in the reported research results. However, both publication bias and the authentic empirical effects are likely to be more complex than what the above simple meta-regression models can depict. To accommodate potential complexities related to the effect of ICT investments on economic growth, the simple MRA model (4) can be expanded:

$$effect_i = \beta_0 + \sum \beta_k Z_{ki} + \beta_1 SE_i + \sum \delta_j SE_i K_{ji} + \varepsilon_i. \quad (6)$$

In this model, α_0 from equation (4) is replaced by $\beta_0 + \sum \beta_k Z_{ki}$, where the Z -variables represent heterogeneity and/or misspecification biases. The $SE_i K_{ji}$ terms represent any factor related to publication bias or the researchers' inclination to report a statistically significant positive ICT effect. For example, if the effect of ICT on economic growth were ancillary to the paper's main message, researchers would have little incentive to report significantly positive ICT effects, selectively (Dalton, Aguinis, Dalton, Bosco, & Pierce, 2012). On the other hand, if ICT is mentioned in a paper's title or abstract, then selective reporting may become more likely. Below, we used the variable, *TitleAb_SE*, to account for this differential publication bias and find that it is statistically significant (Table 8). We also investigate whether the reporting of robust standard errors, *Robust_SE*, is associated with differential selection, but find no evidence of such an effect. For a more detailed explanation of the Z/K MRA model (Equation 6), see Stanley and Doucouliagos (2012).

Table 7 list all the Z and K moderator variables that are coded and investigated by this study. Specifically, we examined differences in the type of technology by means of dummy variables coded with the landline technology as the omitted or reference category in our multiple

regression model, Table 8. The second type of moderator variable concerns the type of data used to estimate ICT's effect: cross-sectional, time series or panel. Panel data is used as the reference category. These variables pick up differences between partial and general equilibrium effects. We also consider various regional (i.e., country and continent) dummies and important model specification differences. Note that we deliberately choose to code only a limited number of specification dimensions, those driven by economic theory. Studies can adopt wide ranging differences in specification and it is not possible to model all these differences in an MRA. Instead of pursuing a statistically driven choice of moderator variables, our choice was theory driven.

[TABLE 7 ABOUT HERE]

In order to simplify the multiple WLS-MRA model, we employed the general-to-specific approach.¹¹ “The strength of general to specific modeling is that model construction proceeds from a very general model in a more structured, ordered (and statistically valid) fashion, and in this way avoids the worst of data mining” (Charemza & Deadman, 1997, p.78). Note that this multiple MRA model is applied to all 415 observations combined, including estimates from individual technologies and estimates from data on several technologies combined. At the first step, we include all the moderators listed in Table 7 to the WLS model. Next, we remove the variable that had the largest p-value and repeat this step until all p-values were less than 0.05. Table 8 presents the set of moderator variables that were included in the final WLS-MRA model, all but one of which was statistically significant on the first step. In order to ensure the robustness of our main results, we also calculate cluster-robust standard errors, a random-effects panel, and

¹¹ An alternative approach is to use Bayesian model averaging (BMA). See, for example, Iršová and Havránek (2013).

a robust regression.¹² The last column shows which moderator variables remained consistently significant across all four estimation approaches and identifies which factors are most likely to be genuinely associated with the observed heterogeneity in this area of research.

[TABLE 8 ABOUT HERE]

The analysis of the multiple MRA model revealed several interesting results. First, the *TitleAbs-SE* variable is robustly significant and positive ($p < 0.05$), consistent with selection for positive results among those studies that focus on the growth effect of telecommunication. If there were publication selection bias, this is where we would expect to see it most clearly.

Second, the combined research results (Table 8) find much the same overall effects for specific technologies as seen in the separate meta-regressions (Table 6). In particular, there is robust evidence of: a small positive growth effect from the installation landlines (see the intercept in Table 8), a larger but still small positive effect from cell phones, and a much larger, positive effect of computer technology (*IT*) in developed countries that is washed away in the developing nations (*Developing_IT*). Lastly, the effect of the Internet remains ambiguous and unclear. Although the separate meta-regression of Internet and broadband connections (column 4 of Table 6), provided some evidence that its effect might be positive among developing nations, no statistical trace of this positive effect remains when all types of ICT are combined.

To try to clarify this ambiguity, we add those additional moderators found to be significant from Table 8 into the simpler MRA that we ran on only Internet estimates (Table 6 column 4); that is, we add those variables that have any variation in the Internet subsample and can thereby be estimated by this subsample. When we do so, the WLS and panel specifications

¹²Note that fixed effects panel estimator cannot be used for our data because the differential publication bias terms do not vary within studies.

gives clear evidence that Internet access increases GDP growth; however, these findings are not robust when robust regression methods are employed. Although it would be preferable to have clear evidence that Internet access has had a positive effect on developing nations and that this effect is large enough to help close the development gap, more research is needed before such a conclusion could be defended confidently.

In general, the magnitude of the effects reported in Table 8 are smaller than the corresponding ones in Table 6. But this is to be expected, because 80 of the estimates used in Table 8 were calculated across more than one ICT technology. Thus, sharp contrasts are likely to be moderated by mixing these distinct technologies together. Also, the publication selection effect identified in the combined data (recall the *TitleAbs-SE* variable) will reduce the estimated growth effect for those ICT technologies that do not exhibit clear signs of selection for positive growth effects in their separate meta-regressions (Table 6).

Third, this overall meta-regression identifies two other moderator variables that are associated with stronger or weaker ICT growth effects. The largest such effect concerns the failure to control for growth convergence (*Converge*). Half of the estimates in this literature come from regression models that did not control for growth convergence, and these tend to report more positive correlations by approximately 0.12. Because the separate meta-regressions reported in Table 6 do not allow for the effect of ignoring convergence, they are likely to overestimate ICTs growth effects. Table 8 provides robust evidence that ICT effects are smaller when the dependent variable is measured by productivity (*Prod*).

Other moderator effects are not robust. For example, the inclusion of capital stock and openness (trade) in the econometric model do not appear to be important determinants of heterogeneity. Neither is the year of data, indicating that the extant data does not support the notion of diminishing returns to ICT. This result is actually rather encouraging for policy makers.

The variable *Endog* was also not statistically significant in the MRA. Studies that specifically accommodate endogeneity do not report results that are different to studies that do not address this issue. This suggests that ICT causes economic growth and productivity, rather than the reverse.

6. SUMMARY AND CONCLUSIONS

Vast amounts of resources are invested in new technologies, transforming all aspects of our human experience. But does ICT affect economic growth? We apply meta-regression analysis to the estimates from 58 empirical studies. Our central finding is that, on average, these technologies have contributed positively to growth. For developed countries, all types of ICT contribute to growth, except for the Internet. For developing countries, there is robust evidence that landlines and cell technologies contribute to growth. When investigated on its own, there is evidence that Internet access contributes to growth in developing countries and that this effect might even be larger for productivity. However, these positive findings about Internet technology in the developing world are not robust across plausible MRA specifications. More research is needed to understand the effect of Internet technology on developing nations.

For developed countries, we find that the greatest effect arises from computing (partial correlation, $r = 0.36$), followed by cell ($r = 0.19$), landlines ($r = 0.07$), and no notable effect from the Internet. The growth effect of computing here is moderate, whereas the other effects are small.¹³ For developing countries using evidence from all ICT technologies combined, the greatest effect arises from cell ($r = 0.19$), followed by landlines ($r = 0.07$), and both of these effects are small. However, when each technology is viewed separately, there is some, although not robust, indication that the Internet might also have a small positive effect for developing

¹³ These effects can be cumulative, i.e. the positive effect of cell technologies adds to the growth effect from IT.

countries. Still, these mixed results do not support making broadband access a centerpiece of foreign aid programs for developing nations, notably counter to *The World Bank* adopting in Africa “the assumption that the use of broadband will have a positive developmental impact, as has been shown to be the case for mobile networks” (William, 2010, p. 2).

Also, the strength of these relationships is similarly to Polák’s (2014) firm level ICT meta-analysis, that is “lower than commonly expected” (p. 6) though consistent with Gordon’s (2000) pessimistic expectations. Our meta-analytic findings do not suggest that technological investment will provide economic growth rates that will exceed rate of return to capital, which is of concern (Piketty & Saez, 2014). Similarly, with an aging world population, many nations and public policies are depending on technology to generate substantive increases in productivity to offset a shrinking labor pool (Manyika et al., 2015), while our results suggest more modest impacts. For example, U.S.’s yearly economic growth was on average approximately 2.85% from 1970 to 2014, transforming \$4.7 trillion GNP to \$16.2 trillion GNP. A four percent reduction in growth rate, a modest estimate that might be attributable to ICT, would reduce annual growth to approximately 2.74%, which would translate over the same period of time into a \$15.5 trillion economy. Though \$700 billion additional dollars is substantial, the time span of 44 years to achieve this does not make ICT a plausible mechanism to “grow” our way out of public policy problems.

This research can be extended in several directions. To properly contextualize ICT’s impact, we need to compare it to those of other alternate infrastructures, such as investment in basic infrastructure and human capital. Even if ICT’s impact is modest, is it relatively better than these alternatives? Advocates suggest that ICT has higher rates of return because of positive externalities, mainly in the form of knowledge spillovers and network externalities. For example, Röller and Waverman (2001) argue that in contrast to ICT, basic infrastructure might suffer from

negative externalities such as congestion. This is especially important from a developing country's perspective, where generating growth is particularly pressing. To provide effective advice, each of these alternatives should be properly meta-analyzed, explicitly considering publication bias and developmental status.

Also, our finding that ICT affects growth in reduced-form equations raises the issue of the transmission channel: how does ICT increase growth? For example, we found that ICT's effects are smaller when measured in terms of productivity. There are several potential reasons for this. Perhaps ICT investments add to capital stock or induce longer hours of work, thereby increasing output independently of productivity. Or, it may be the case that the contribution of ICT is confined to the development of new products, expanding the size of an economy without necessarily increasing productivity. Aside from continued focus on aggregate economic performance, a useful extension will be to apply meta-analysis to the literature that has explored the impact of ICT at the microeconomic level. In particular, it will be informative to explore the relative contribution of product, process and business model innovation. Finally, the results suggest that policies that encourage landline and cell ICT will promote growth in developing countries. Evaluation of which policies will best promote these investments should be considered.

In conclusion, the Solow or Computer Paradox is understandable. While ICT is associated with economic growth, the relationship is so slight that it can be easily missed. Furthermore, ICT's effect appears largely contingent on both level of development, type of ICT (e.g., landlines versus computers), and the interaction between the two. Still, this meta-analytic review of ICT doesn't preclude future discontinuities in this trend, which suggests the need to revisit the topic periodically. Presently, for example, there is considerable concern regarding what Kurzweil (1999) called the singularity, where computer advances eventually create artificial intelligence sufficiently advanced to pose an existential threat to humanity (Barrat, 2013; Gent,

2015). This is of sufficient possibility that it is promoted by technical and scientific luminaries such as Bill Gates, Stephen Hawking and Elon Musk (Holley, 2015). However, we would suggest that a likely precursor to the realization of this threat is that ICT first demonstrates a substantive increase in economic growth. Some skepticism is warranted regarding outsized outcomes given that we have an extended history of exaggerating ICT's expected impact.

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Table 1. *List of keywords for inclusion in first stage systematic review*

Keyword 1		Keyword 2
ICT		Determinants of Growth
Telephone		Economic Growth
Mobile Phone		Growth
Cell Phone		GDP
Communication Technology		GDP per capita
Broadband	and one of	Productivity
Internet		Total Factor Productivity
Telephony		Investment
Information Technology		Policy
Telecommunication		
IT		
General Purpose Technology		

Table 2. *Basic meta-analysis, weighted averages*

Statistics	Partial correlations			Fisher's z-transformed		
	(1) FEE	(2) REE	(3) WLS	(4) FEE	(5) REE	(6) WLS
Weighted Average	0.195	0.245	0.195	0.191	0.264	0.191
95% CI	0.190 to 0.200	0.227 to 0.264	0.177 to 0.212	0.185 to 0.196	0.244 to 0.284	0.172 to 0.209
<i>n</i>	415	415	415	415	415	415
<i>k</i>	58	58	58	58	58	58

Notes: Columns (1) to (3) report the overall weighted average for partial correlations coefficients, and columns (4) to (6) display the averages for Fisher's z-transformed correlations. FEE, REE and WLS denote fixed effects, random effects and weighted least squares, respectively. *n* is the number of estimates. *k* is the number of studies.

Table 3. *FAT-PET meta-regression model of publication selection—MRA equation (4)*

Variables	Partial Correlations			Fisher's z-transformed		
	(1) WLS	(2) Cluster- robust	(3) Panel	(4) WLS	(5) Cluster- robust	(6) Panel
$SE_i: \hat{\alpha}_1$	1.92***	1.92***	0.21	2.46***	2.46***	1.07***
{FAT}	(5.97)	(2.89)	(0.45)	(7.60)	(3.84)	(2.20)
Intercept: $\hat{\alpha}_0$	0.109***	0.109**	0.195***	0.080***	0.080	0.148***
{PET}	(6.54)	(2.04)	(9.47)	(4.66)	(1.65)	(6.76)
n	415	415	415	415	415	415
k	58	58	58	58	58	58

Notes: The dependent variable is partial correlations in columns (1) to (3) and Fisher's z-transformed correlations in columns (4) to (6). Figures in brackets are t-statistics. n is the number of estimates. k is the number of studies. Estimates are based on MRA model (4) using weighted least squares, cluster-robust standard errors or random-effects panel estimators, all weighted by the inverse of variance. FAT tests the presence of publication selection bias. PET estimates and tests the effect of ICT on growth corrected for publication selection bias.

* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 4. *PEESE corrections for publication selection—MRA equation (5)*

Variable	Partial Correlations			Fisher's z-transformed		
	(1) WLS	(2) Cluster-robust	(3) Panel	(4) WLS	(5) Cluster-robust	(6) Panel
$\hat{\gamma}_0$	0.175	0.175	0.206	0.163	0.163	0.182
95% C.I.	0.155 to 0.195	0.098 to 0.251	0.175 to 0.236	0.142 to 0.184	0.089 to 0.238	0.151 to 0.214
n	415	415	415	415	415	415
k	58	58	58	58	58	58

Notes: The dependent variable is partial correlations in columns (1) to (3) and Fisher's z-transformed correlations in columns (4) to (6). Figures in brackets are t-statistics. n is the number of estimates; k is the number of studies. Estimates are based on MRA model (5) using weighted least squares, cluster-robust standard errors or random-effects panel estimators. $\hat{\gamma}_0$ is the estimated effect of ICT on growth corrected for publication selection bias.

Table 5. *FAT-PET meta-regression model by type of technology*

	(1)	(2)	(3)	(4)
Variables	Landline	Cell	IT	Internet
$SE_i: \hat{\alpha}_1$	0.86	1.42	-1.56	3.27***
{FAT}	(1.79)	(1.37)	(-1.91)	(10.14)
Intercept: $\hat{\alpha}_0$	0.117***	0.277***	0.596***	-0.011
{PET}	(4.87)	(4.40)	(8.29)	(-0.77)
$\hat{\gamma}_0$ from MRA (5)	0.145	0.328	0.510	0.069
95% C.I.	0.116 to 0.173	0.251 to 0.405	0.411 to 0.608	0.048 to 0.091
n	120	55	48	112
k	33	14	6	15

Notes: The dependent variable is partial correlations. Figures in brackets are t-statistics. n is the number of estimates; k is the number of studies. The top two rows report estimates based on MRA model (4). The third row reports estimates of MRA model (5). All estimates use the weighted least squares estimator. FAT tests for the presence of publication selection bias. $\hat{\alpha}_0$ and $\hat{\gamma}_0$ estimate the effect of ICT on growth after accommodation of potential publication selection bias is made using FAT-PET and PEESE, MRA model (4) and MRA model (5) respectively.

* $p < 0.05$; ** $p < .001$, *** $p < .001$.

Table 6. *WLS-MRA of partial correlations by technology and level of development*

Variable	(1) Landline	(2) Cell	(3) IT	(4) Internet
$SE_i: \hat{\alpha}_1$	0.851	1.320	-0.287	3.185***
{FAT}	(1.76)	(1.27)	(-0.37)	(10.17)
Intercept: $\hat{\alpha}_0$	0.117***	0.266***	0.562***	-0.010
{PET}	(4.80)	(4.15)	(8.85)	(-0.73)
Developing	0.005	0.075	-0.477***	0.274***
	(0.15)	(1.02)	(-3.88)	(3.16)
n	120	55	48	112
k	33	14	6	15

Notes: The dependent variable is partial correlations. Figures in brackets are t -statistics. n is the number of estimates; k is the number of studies. Estimates based on MRA model (4). All estimates use the weighted least squares estimator. *Developing* is a dummy variable for developing countries. FAT, $\hat{\alpha}_1$, estimates the presence of publication selection bias. The PET, $\hat{\alpha}_0$, estimates the effect of ICT on growth after accommodation of potential publication selection bias is made.

* $p < 0.05$; ** $p < .001$, *** $p < .001$.

Table 7. *Variables used in the MRA*

Variable	Definition	<i>M (SD)</i>
<i>r</i>	is the partial correlation of ICT and economic growth.	0.25 (0.21)
<i>SE</i>	is the standard error of the estimated partial correlation.	0.09 (0.06)
<i>Yr</i>	is the average year the data used.	1995 (8.0)
Types of Data		
<i>CS</i>	=1, if estimate comes from cross-sectional data.	0.31 (0.46)
<i>TS</i>	=1, if estimate comes from time series data.	0.02 (0.14)
<i>Panel</i>	=1, if estimate comes from panel data—omitted category.	--
Measures of Telecommunication Technology		
<i>LL</i>	=1, if all data concerns telephone land lines; 0, if none.	0.35 (0.43)
<i>Internet</i>	=1, if all data concerns broadband or the internet; 0, if none.	0.32 (0.43)
<i>IT</i>	=1, if all data concerns computer technology; 0, if none.	0.15 (0.32)
<i>Cell</i>	=1, if all data concerns cell phones; 0, if none.	0.18 (0.35)
Measures of Economic Growth		
<i>GDP</i>	=1, if GDP is the dependent variable.	0.24 (0.43)
<i>Prod</i>	=1, if productivity is the dependent variable.	0.15 (0.35)
<i>PerCap</i>	=1, if GDP per capita is used—omitted category.	--
Regional Variables		
<i>China</i>	=1, if the model uses data from China.	0.01 (0.11)
<i>Asia</i>	=1, if the model uses data from Asia.	0.06 (0.23)
<i>Africa</i>	=1, if the model uses data from Africa.	0.09 (0.29)
<i>OECD</i>	=1, if the model uses data from OECD countries.	0.28 (0.45)
<i>Developing</i>	=1, if the model uses data from developing countries	0.18 (0.39)
<i>CEE</i>	=1, if the model uses data from central or eastern Europe.	0.04 (0.19)
Differential Development Effects		
<i>Developing_Cell</i>	=1, if estimate concern cell phones in a developing country.	0.06 (0.21)
<i>Developing_IT</i>	=1, if estimate concern IT in a developing country.	0.04 (0.19)
<i>Developing_Inter</i>	=1, if estimate concern the internet in a developing country.	0.07 (0.24)
Model Specification		
<i>Endog</i>	=1, if the model controlled for reverse causation.	0.36 (0.48)
<i>Human</i>	=1, if a model omits a measure of human capital.	0.54 (0.50)
<i>Labor</i>	=1, if a model omits a measure of labor.	0.42 (0.50)
<i>Capital</i>	=1, if a model omits a measure of capital.	0.29 (0.46)
<i>Converge</i>	=1, if a model does not account for convergence.	0.50 (0.50)
<i>PoliEcon</i>	=1, if a model omits a measure of the political economy.	0.89 (0.32)
<i>Trade</i>	=1, if a model omits a measure of trade or openness.	0.70 (0.46)
Differential Publication Bias Variables		
<i>TitleAb_SE</i>	SE times whether telecom appears in the title or abstract.	0.08 (0.06)
<i>Robust_SE</i>	SE times whether robust standard errors are used.	0.02 (0.03)

Table 8. *Multiple WLS-MRA of telecommunication-growth partial correlations*

Variables	(1) WLS	(2) Cluster-Robust	(3) Random-Effects Panel	(4) Robust Regression	(5) Consistently Significant (Robust)
TitleAb_SE	1.430*** (5.51)	1.430*** (3.69)	0.878* (2.15)	1.332*** (3.22)	Yes
Cell	0.124*** (5.26)	0.124* (2.13)	0.126*** (4.33)	0.124** (2.13)	Yes
IT	0.294*** (7.96)	0.294*** (3.42)	0.320*** (8.11)	0.294*** (3.42)	Yes
Internet	-0.054*** (-3.27)	-0.054 (-1.95)	-0.029 (-1.05)	-0.037** (-2.75)	No
Prod	-0.082*** (-3.65)	-0.082* (-2.18)	-0.104*** (-3.19)	-0.042* (-2.35)	Yes
Converge	0.123*** (8.11)	0.123*** (5.15)	0.120*** (6.55)	0.088*** (7.42)	Yes
Developing_IT	-0.555*** (-5.67)	-0.555*** (-9.72)	-0.421*** (-4.51)	-0.642*** (-8.31)	Yes
CS	0.063** (3.07)	0.063 (1.45)	0.038 (1.16)	0.022 (1.28)	No
Capital	0.047* (2.50)	0.047 (1.58)	0.014 (0.53)	0.057*** (3.67)	No
Trade	-0.033* (-2.01)	-0.033 (-0.97)	-0.011 (-0.44)	-0.004 (-0.34)	No
Intercept	0.065*** (4.07)	0.065* (2.65)	0.086*** (3.41)	0.054*** (3.74)	Yes
<i>n</i>	415	415	415	415	
<i>k</i>	58	58	58	58	
R ²	0.49	0.49	–	–	

Notes: The dependent variable is partial correlations. t-values are reported in parenthesis. n is the number of observations. k is the number of studies. See Table 7 for variable definitions. See also notes to Table 5. * $p < .05$; ** $p < .01$; *** $p < .001$.

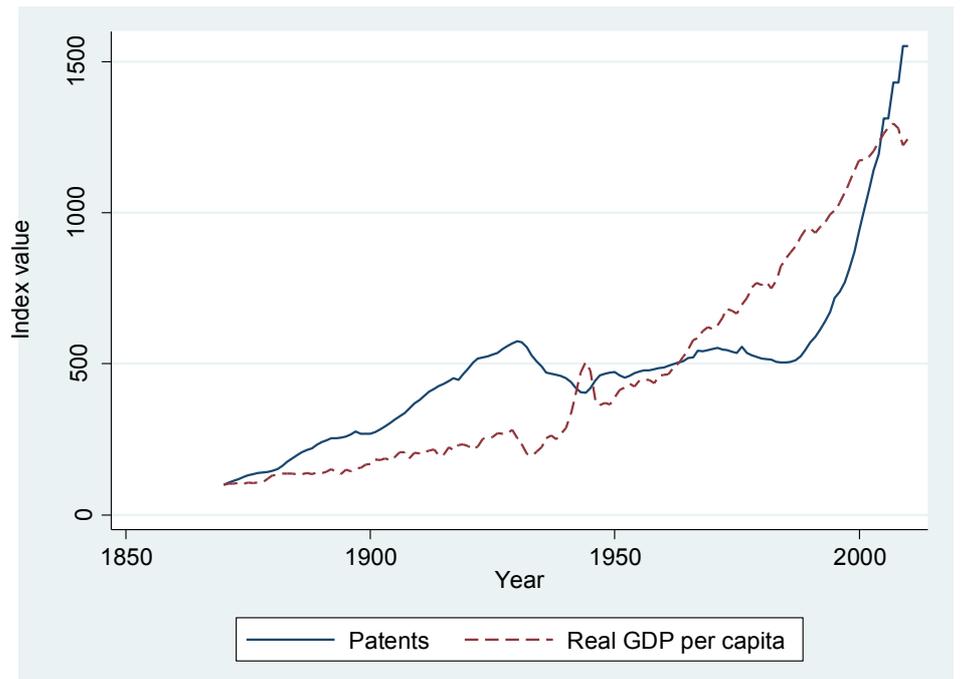


Figure 1: *US patent stock and real GDP per capita*

Source: Constructed from data sourced from Madsen (2008).

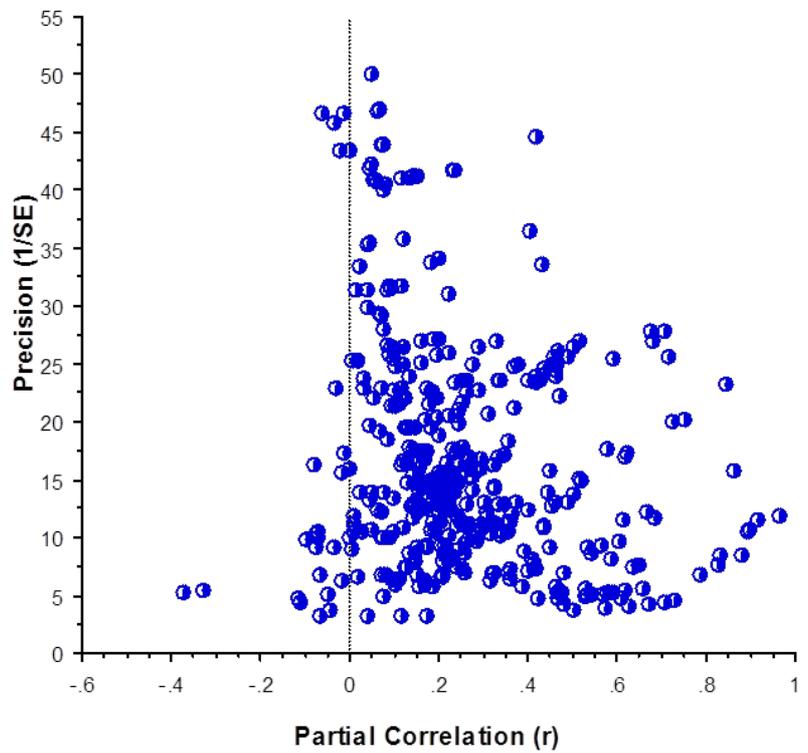


Figure 2: *Funnel plot, partial correlations of telecommunication and growth*

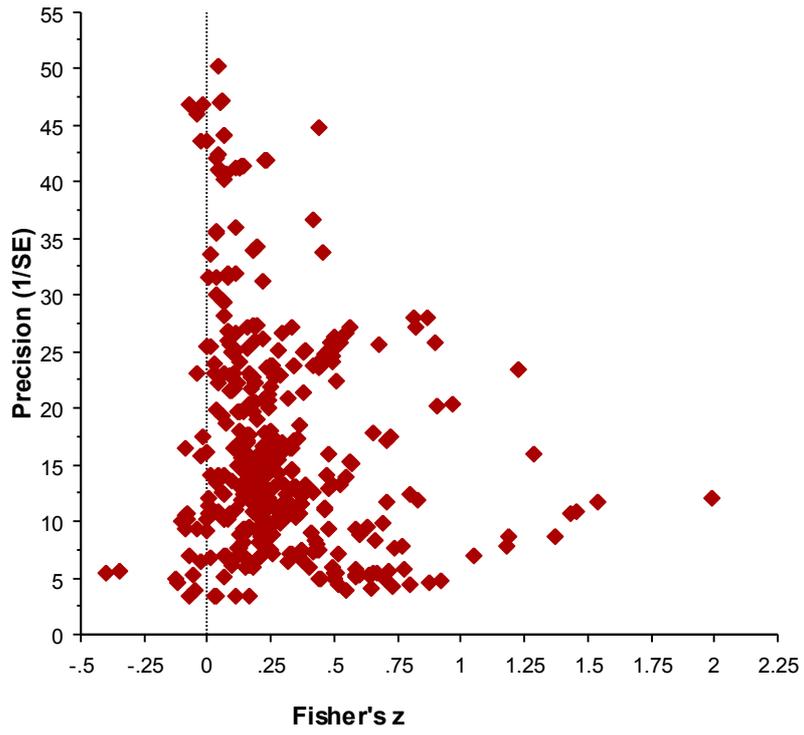


Figure 3: *Funnel plot, Fisher's z-transformed correlations of telecommunication and growth*

Appendix A: studies included in the meta-analysis

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