The productivity paradox: A Meta-analysis

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Abstract

The impact of ICT (information and communication technology) on economic performance has been the subject of academic research for several decades, and despite the remarkable and significant innovation in computer technology, usage, and investments, only a small growth in productivity was observed. This observations has been coined the productivity paradox. Using meta-analysis, my paper answers the following two questions related to the productivity paradox: What is the true effect of the ICT investment on the productivity? and Is there a publication bias among the results in empirical literature? The paper starts with an overvivew of productivity related literature, continues with the description of meta-analytical methods used in economics for publication bias detection and estimation of genuine effects and then uses them in the empirical part. The empirical part is based on a collection of more then 800 estimates of IT payoff effects from almost 70 studies written in the last 20 years. The meta-analysis reveals the presence of publication bias and estimates the ICT elasticity to be only 0.3%.

JEL Classification	JEL C83, O12, O32, D24
Keywords	meta-analysis, meta-regression analysis, publication bias, productivity paradox, Solow paradox, productivity, firm, ICT elasticity, IT payoff, information technology

1 Introduction

Economic significance of productivity is well established and productivity as such is an indivisible part of economic theory. Even Adam Smith discussed the importance of productivity in his literary work *Wealth of nations*, published in 1776. Productivity determines wealth and economic growth and is also an indicator of competitiveness. The level of productivity creates foundations for management decisions not only at firm level, but also at the national level for policy makers. Productivity growth is a desirable outcome of development and technological progress. In the second half of the twentieth century Information and communication technology (ICT) gained in importance in production processes, especially with the emergence of the so-called "new economy" (service-based economy) in the last decades of the previous century.

Economics tries to find the most effective allocation of resources and ICT is more and more part of the production process. The obvious question is how large are the gains from this production factor? Are the gains worth the investments? In the 1980s, studies found no evidence of increased productivity due to ICT investments (Mahmood & Mann, 1993). Robert M. Solow, the Nobel laureate in economics, wrote in 1987 in a book review that: "You can see the computer age everywhere but in the productivity statistics". His famous quip may have been the starting point of two decades or research and discussions on the influence of the ICT on productivity. Economists such as Brynjolfsson (1993), Harris (1994), Willcocks and Lester (1996), Brynjolfsson and Hitt (1998) point to this phenomena as the "productivity paradox", which is discussed in section 2 of this paper. The size of the effect is important for businesses as well as for academia. In order to undertake the best investment decisions, businesses need to know how ICT investments will influence the productivity and if such estimate is biased in any direction then resources will be allocated inefficiently. Investment decisions are based on the returns and therefore precise and unbiased estimates are demanded. For academic purposes, it is important that research produces unbiased results in the same way that for economic theory it is important that data we have do correspond with what the theory expects. If this is wrong, we need a different theory or different assumptions. If we are able to explain why results differ among the literature, we can provide a very important information for researchers. As soon as key spots of differences are identified, we can take a closer look at them and enhance current knowledge about the topic.

Attempts to explain why empirical results are contradicting the economic theory followed. David (1990) put the productivity paradox into historical perspective by comparing computers to steam engines and electricity. These inventions needed decades until their contribution became visible and the same holds for computers, which are the backbone of ICT today. Such technology is called the General Purpose Technology (GPT). Brynjolfsson (1993) formulated and discussed four possible reasons why empirical literature failed to find positive returns of ICT investments. Later on Triplett (1999) discussed seven possible explanations for Solow's productivity paradox and empirical evidence dismissing the paradox such as Oliner and Sichel (2000) followed. Dedrick, Gurbaxani, and Kraemer (2003) provided a narrative review of published research and evidence from more than 50 articles refuting the productivity paradox. Rajiv Kohli and Sarv Devaraj (2003) were the first to summarize empirical results at the firm level in a meta-analysis and clearly stated that there is no productivity paradox. Later, Stiroh (2005) in his meta-analysis included studies based on more aggregated data and mentioned possible publication bias among the results, but didn't take any steps to check for such bias.

Sterne, Gavaghan, and Egger (2000) argue that published results are biased due to publication or selection bias. Such bias stems from researchers' motivation to get their work published. This means to provide results that are unlikely to be rejected by journals' reviewers. If the outcome of an empirical study is not in line with the underlying economic theory then something is wrong and reviewers would require proper explanation. It's easier to select such form of model or data that fits the expectations.

C. Doucouliagos and T. D. Stanley (2011) focused on publication bias, gathered and analysed several thousands of estimates from approximately three and half thousand separate empirical studies from 87 separate areas of empirical economic research (productivity paradox was not included). Large part of those fields has been found to be burdened by publication bias. Especially macroeconomic research contained evidence of severe selectivity that significantly distort empirical findings. This is a very serious problem which might also be present in the productivity paradox literature.

How large are the productivity effects of ICT capital? We need to draw aside the shadow of bias to answer such question properly. Stiroh (2005) said that: "evidence clearly points to a positive productivity effect from IT", but we could compare this to the area of European monetary union and trade benefits. So called Rose-effect also clearly pointed to a positive effect of European monetary union (EMU) (Rose, 2000), but Havranek (2010) found no significant return of EMU after he took publication bias into account. Theory of currency unions expects that after integration the common trade will increase and this argument is widely used in politics to promote such type of integration. Havranek's (2010) examination discovered skewed distribution of the estimates and subsequently no significant genuine effect[1]. For other monetary unions, the effect was found to be positive and significant. Possible explanation is that European Union creates such a close type of integration that there are no significant gains from the common currency. The same might be the case of ICT, with the studies in the 80s being right and the only positive effect we can see in the literature is caused by the publication bias.

Those two concepts, productivity paradox and the publication bias, create basis of this paper. My intention is to discover the true effect of ICT investments on productivity.

In order to analyse available empirical results empirically again, meta-analytic methods which I used in this paper have been developed. Meta-analysis also makes it possible to test for presence of publication bias, therefore we can test the hypothesis made by Stiroh (2005) that such bias exists among productivity paradox oriented literature. Furthermore meta-analysis allows us to estimate the true size of the underlying effect even if publication bias is present. This paper therefore follows Dedrick et al. (2003), Rajiv Kohli and Sarv Devaraj (2003), Stiroh (2005), T.D. Stanley (2008) and uses meta-analytical technique to test for publication bias in the literature about the productivity paradox, and also tries to explain how different study characteristics influence the size of the estimate of the effect size of ICT investments on productivity. The research goal is to find and quantify the true effect[2] and not to prove that there is no productivity paradox.

This paper aims to find the size of the effect of ICT investments on the productivity, and I am the first to research this topic at the firm level. So far, researchers have been actually circulating around the productivity paradox – they tried to explain which factors influence the results. If we take the literature published about the Information technology (IT) payoff, we can divide it into several groups by their approach. The most important ones are mentioned in the section 2, where the productivity paradox itself is discussed. However, I would like to point out that some general conclusions about the magnitude of the IT payoff or the determinants of it are missing. The first attempt to make a more general and precise summary of the IT payoff was done on the country level by Stiroh (2005). As mentioned already, I have not found any study examining this at the firm level. Research is also still only pointing at what is influencing the effect, but we should be having enough evidence to estimate the magnitude as well. Especially as economics should not only provide answers in form of "yes or no" but also "how much". That is exactly what has been done in the last empirical part.

Compared to the previous studies in the area of meta-analysis and IT productivity payoff, performed by Rajiv Kohli and Sarv Devaraj (2003) and Stiroh (2005), there are several aspects that make this paper unique. Firstly, publication bias treatment has not been done yet. Secondly, never have all the estimates

[1] Meta-analytic techniques connected to the publication bias and distribution of estimates are discussed in section 3 of this paper.

[2] In meta-analyses "true effect" and "genuine effect" are interchangeably and commonly used terms identifying the underlying effect of the examined phenomena.

from each study been collected, so modern econometric framework, taking between study heterogeneity into account, has not been used in this area of research until now. Thirdly, the only focus of Rajiv Kohli and Sarv Devaraj (2003) and Stiroh (2005) was to show differences between studies and thus determine what explains the heterogeneity of the results, but this paper also targets to find the effect size of the IT payoff.

This paper begins with the productivity paradox as such, the next part of this paper is devoted to meta-analysis, an econometric technique that is used in the empirical part. Having described theoretical framework and background of the research, data is introduced, regressions performed, and that is followed by a description of results from conducted analysis. Interpretation of the results together with final notes conclude.

2 Productivity paradox

Productivity growth arises from innovation and development of new production methods, procedures and technology. Therefore ICT as a new technology was expected to boost productivity. However, the initial results were inconclusive (Barua, Kriebel, & Mukhopadhyay, 1995; Teo, Wong, & Hui Chia, 2000) and hardly any positive effects of IT investments on productivity were found. This paradox is called the *productivity paradox*, more precisely and formally defined by Turban, McLean, and Wetherbe (2002, p. 592) as: "The discrepancy between measures of investment in information technology and measures of output at the national level." Methods and models used to analyse the quantitative data are mostly based on the neoclassical production theory that clearly predicts the sign and magnitude of capital's elasticity: in case of constant returns and competitive markets, elasticity should be equal to the share of the factor. Initially, however, this relationship was not found in the data.

The productivity paradox opened up a wide debate, the continuous examination of the topic, and also attempts to explain the theory contradicting results (Dedrick et al., 2003; Stiroh, 2005; Draca, Sadun, & Reenen, 2006). First pieces of economic literature trying to clarify the paradox were of a narrative and descriptive nature, then studies like Thatcher and Oliver (2001) employed microeconomic theory and models, and also theoretical estimations of the elasticity of IT investments using simulated data have been conducted by e.g. Yorukoglu (1998). Narrative explanations provided first by Baily, Gordon, Nordhaus, and Romer (1988), David (1990), Brynjolfsson (1993) and later by Triplett (1999), David (2000), Horzella (2005), can be divided into three general categories, or perspectives, depending on how they approach the productivity paradox: 1) measurement problems 2) context and mismanagement 3) ICT as GPT. The researchers tried to reason why non-significant empirical results were found. Narrative works were followed by empirical findings which create a base for our research.

Because of the huge research interest in IT payoff, researchers have done a few narrative studies summarizing IT productivity, but let us focus on the empirical ones. Rajiv Kohli and Sarv Devaraj (2003), unlike a standard meta-analysis, do not examine the effect size, but only the research factors that contribute to discovering a relation between IT and firm performance. Authors use a wide range of literature, and use data from various research approaches and models. Therefore, only the signs of explanatory variables having any effect can be interpreted, not the magnitude. Additionally to that, they mainly compare studies reporting positive and negative estimates regardless of the magnitude of the effect. Stiroh (2005) estimated also the underlying true effect – the elasticity of ICT investments – based on the previous results. He calculated the pure arithmetic mean value from 20 estimates in range between -0.06 and 0.24, and got a result equal to 0.054 and using fixed effects and Ordinary least squares (OLS) method he got significant estimate of 0.065. In this study, the researcher uses both firm level and more aggregated level studies (industry and national), which is not done by Rajiv Kohli and Sarv Devaraj (2003) nor by this paper. Since we discussed IT payoff and meta-analysis research, I woud like to mention also a related study done by Lim, Dehning, Richardson, and Smith (2011). The focus of the authors is the effect of IT on firms' financial performance. This study uses again only one estimate per paper and does not use regression techniques, only correlations and significance testing.

2.1 Production process modelling

To analyse contributions of factors of production to the output it is necessary to describe the production process mathematically and create an economic model. We can simply imagine the process as a functional relation between outputs and inputs. Therefore, the most used approach by economists to the model production process is using specific production functions which algebraically formulate the relation between inputs and outputs. A simple version of an aggregate production function that puts together similar inputs was described by Solow (1957) in form that is depicted in equation 1. Q represents output, K capital, L labour, A is multiplicative factor, which captures technological development that determines how efficiently inputs are used to produce output, and $f(\cdot)$ represents functional relation.

$$Q = Af(L, K) \tag{1}$$

Standard approach in the economics literature is to consider Cobb-Douglass production function (Brynjolfsson & Hitt, 2000; Stiroh, 2005; Venturini, 2009), expressed as:

$$Q = AK^{\alpha}L^{\beta} \quad \alpha, \beta > 0 \tag{2}$$

For econometric estimation the logarithmic form (eq. 3) of the Cobb-Douglas production relation is more useful. Coefficients of interest are α and β, which denote elasticity of capital and labour respectively.

$$\ln Q = \ln A + \alpha \ln K + \beta \ln L \quad \alpha, \beta > 0 \tag{3}$$

To estimate the effect of ICT, we need to separate capital into ICT (K_{ICT}) and non ICT (K_{ICT}). Next to it studies may vary in additional firm or industry specific inputs (M) that are part of the production. The simplest form of production function used for estimation that includes above mentioned 2 types of capital, labour and intermediate inputs is depicted in equation 4, where ε stands for disturbance term.

$$\ln Q = \alpha + \beta_{IT} \ln K_{IT} + \beta_{nonIT} \ln K_{nonIT} + \beta_L \ln L + \beta_M \ln M + \varepsilon \tag{4}$$

In general, using model 4 augmented by several inputs, we are able to determine how each factor influences the production. Effects that are measured by the presented framework are mostly direct, but since ICT costs are from its nature investments, indirect effects (spillovers) are also present. Evidence about indirect effects provided e.g. Mittal and Nault (2009) or Han, Chang, and Hahn (2011), but in our analysis we focus on direct effects which are important for decision making of individual firms.

3 Meta-analysis

In his pioneering work Glass (1976, p.1) defined "meta-analysis" as the statistical "analysis of analyses", a tool for integrating findings from collection of individual studies, which is exactly what we are going to do. Only models used in the empirical part are presented, see e. g. Nelson and Kennedy (2009) or T.D. Stanley, Doucouliagos, and Jarrell (2008) for a more complex overview of contemporary methods used in meta-analysis. The basic idea of meta-analysis is to examine factors that influence research results of some phenomena. The dependent variable is the effect size of each estimate, while the independent variables consist of various information about each study like data characteristics, method used for analysis, sample size, sometimes even the occupation of the researcher.

Studies provide estimates of different sizes, and in cases when the variance of the results is too large to be justified by the disturbance terms, we speak about between study heterogeneity. We try to explain this heterogeneity by specific differences between the studies. Thus, we code properties of the studies into variables, and later on we test for the presence of heterogeneity. As Christensen (2003) describes, there are two general types of heterogeneity present in the research: factual and methodological. Factual heterogeneity concerns real differences in the effect due to actual differences in the tested sample, for example when a study was conducted at a different time or in a different country. In our case of ICT capital, there could be a difference between developing countries, where the economy is based on manufacturing, and developed countries with a service oriented economy. Methodological heterogeneity is the result of different study approaches, it could be models used, data characteristics, or econometric methods. Christensen (2003), Nelson and Kennedy (2009) present two common ways of how to deal with the heterogeneity in the data. The first one uses moderating variables and meta-regression to detect the sources of the heterogeneity, the second approach uses Random effect size (RES) models. This paper uses both methods, but RES model is replaced with mixed effects model.

When we want to determine which study characteristics influence the results, we might overlook an important factor that might cause significant bias of the outcome – the researcher. T.D. Stanley (2005) has for publication bias two categories. If the main motivation of the researcher is to get published, findings contradicting previous studies or such that are in conflict with the theory may get concealed. In many cases different model specification produces completely different outcome and thus modifying of the model or data until results are acceptable can occur. Any modification (e.g. restraining dataset or model modification) to obtain results that are in line with the theory is labelled as publication bias of *type I*. Adjusting of models may also happen in case standard procedure has insignificant outcome and it is not the deserved outcome. *Type II* of publication bias can be therefore described as reaching the statistical significance no matter what the effect size would be.

Handling of results needs to be measured and taken into account when conducting empirical summaries. Saying that such practices are common in all areas of research would be too strong, but we can formulate a similar hypothesis, which can be tested and accepted or rejected. Hypothesis that a large part of economic studies is affected by publication or selection is tested and supported by H. Doucouliagos and T. D. Stanley (2008). In their work based on 65 distinct empirical economics literatures, involving approximately two thousand separate empirical studies. This only confirmed that publication bias has been a serious issue in the empirical economics research (Long & Lang, 1992; Card & Krueger, 1995; Ashenfelter & Greenstone, 2004; T.D. Stanley, 2005). Publication bias is usually detected using two methods – graphical and quantitative. The first one is an informal examination but in some cases (e.g. publication bias in effect of currency unions discovered by Rose and T. D. Stanley (2005) and confirmed by Havranek (2010)) provides sufficient evidence. Econometric methods can not only discover the presence of the publication bias but also estimate the true effect beyond (Hunter & Schmidt, 2004).

4 Model

In empirical part models 8 and 9 are used. The logic behind those models is explain step by step in the following part. The funnel plot, also called funnel diagram, is widely used in meta-analyses mainly as a tool for detecting possible publication bias (Egger, Smith, Schneider, & Minder, 1997; Sterne, Egger, & Smith, 2001). Individual observations (estimates of effect sizes) are plotted on the horizontal axis against a measure of the precision, mostly inverted standard error or the square root of sample size, on the vertical axis. Large studies will show lower variation then small studies that are less precise. This should generate a plot that looks like an inverted funnel with the most precise estimates (with the shortest confidence intervals) on the top and less precise estimates on the bottom. Theory of funnel symmetry originates in the idea that there is one underlying population value – it can even be zero –

and probability distribution that would converge to normal distribution with the mean value equal to the underlying true effect. In case of funnel asymmetry, especially when the plot is skewed or one side is missing, we should be suspicious of publication bias. On the other hand, the apparent symmetry might not foreclose the publication bias. Extensive description of funnel plots is provided by T.D. Stanley and H. Doucouliagos (2010).

Econometric testing for publication bias follows this logic, this if reported estimates are dependent on their standard errors (Card & Krueger, 1995):

$$b_i = \beta + \alpha_0 \cdot se_i + u_i, \quad u_i | se_i \sim N\left(0, \delta^2\right) \tag{5}$$

In the model 5 the estimate b_i depends on its standard error (se_i). The degree of dependence is measured by the coefficient α_0, which represents the degree of the publication bias and if it is significant, we have a formal proof for funnel asymmetry. However, model 5 suffers from heteroskedastic se_i. To solve this issue, we follow recommendations of T.D. Stanley et al. (2008), who suggests the use of Weighted least squares (WLS) in the form of where standard errors are used as weights which will result in dependent variable to be t-statistic:

$$\frac{b_i}{se_i} = t_i = \frac{\beta}{se_i} + \alpha_0 + \xi_i, \quad \xi_i | se_i \sim N\left(0, \sigma^2\right) \tag{6}$$

There is also an issue of within study heterogeneity. Studies usually present more than one estimate of the effect size. Estimates thus share the same dataset, methods and are likely to be highly correlated, and as a result, we cannot handle them as independent values. This issue has been known for a long time (T.D. Stanley & Jarrell, 1989). To solve possible dependence mostly used – examples and discussions are found in Johnston, Besedin, and Wardwell (2003), Bateman and Jones (2003), Bickel (2007), Gelman and Hill (2006), Hox (1995), Hox and Leeuw (2003), Peters et al. (2010) – is the remedy described by Nelson and Kennedy (2009), H. Doucouliagos and Laroche (2009) and called mixed-effects multilevel model. As Nelson and Kennedy (2009) further elaborate, the mixed-effects multilevel model is analogous to the random-effects model widely used in panel-data econometrics. Mixed-effect model is a combination of models with fixed effects (β) and random part $\left(\zeta_j\right)$ that gives the flexibility to the model and is therefore better for meta-analytic purposes. It considers diversity of the data and also allows multiple random effects. Extending model 6 we obtain model following Havranek and Irsova (2011):

$$t_{ij} = \frac{\beta}{se_{ij}} + \alpha_0 + \zeta_j + \varepsilon_{ij}, \quad \zeta_j | se_{ij} \sim N(0, \psi), \quad \varepsilon_{ij} | e_{ij} \sim N(0, \theta) \tag{7}$$

In the final specification of model (7) j and i denote index of the study and of the estimate within the study, t-statistics are therefore analogically labelled (t_{ij}). As we have j studies we have in total $J = \sum J_j$ estimates. The overall error term (ξ_{ij}) consists of study-level random effects (ζ_j) and estimate disturbances (ε_{ij}). We assume independence of both values thus we can simply sum their variance to get the composite error: $\mathrm{Var}\left(\xi_{ij}\right) = \psi + \theta$ with θ being within-study variance and ψ between study variance. The closer the value of ψ is to zero, the less advantageous is the usage of mixed-effects framework instead of OLS.

Since the aim of this paper is not only to determine effect of ICT investments, but also to explain the variation of reported values, we use characteristics of individual studies and following T.D. Stanley and Jarrell (1989), T.D. Stanley et al. (2008) add vector of explanatory variables Z_k to model 7:

$$t_{ij} = \frac{\beta}{se_{ij}} + \alpha_0 + \sum_{k=1}^{K} \gamma_k Z_{kij} + \zeta_j + \varepsilon_{ij}, \quad \zeta_i | se_{ij} \sim N(0, \psi), \quad \varepsilon_{ij} | e_{ij} \sim N(0, \theta) \tag{8}$$

Explained variable is the t-statistic and not the estimate of effect size, but it since we are interested in sign and significance of coefficients, it does not raise any concerns.

Since we aim at finding also the magnitude of the ICT payoff, we follow TD Stanley and C. Doucouliagos (2007), Havranek, Irsova, and Janda (2012), T. D. Stanley and H. Doucouliagos (2014) and augment model 7 by additional standard error variable (which stems from the possibility that standard errors effect can be quadratic), which results in so call Heckman meta-regression.

$$t_{ij} = \frac{\beta}{se_{ij}} + \alpha_0 \cdot se_{ij} + \zeta_j + \varepsilon_{ij}, \quad \zeta_j|se_{ij} \sim N(0, \psi), \quad \varepsilon_{ij}|e_{ij} \sim N(0, \theta) \tag{9}$$

where β reports the magnitude of the underlying effect corrected for the publication bias. This last specification completes framework needed for our analysis. In the next part, dataset used for that is described.

5 Dataset

For our purposes no dataset exists, and thus all data had to be retrieved manually. Base for the list of studies was provided by the two meta-analyses mentioned in the introduction, namely Rajiv Kohli and Sarv Devaraj (2003) and Stiroh (2005). Getting all studies used by Stiroh (2005) was without any problem[3], though not all of them were used due to level of data aggregation. On the other hand, retrieval and usage of studies included in the second meta-analysis by Rajiv Kohli and Sarv Devaraj (2003) was more problematic. First, I was not able to get the complete list of studies due to limited availability[4] and secondly some of the studies were not suitable for this meta-analysis – reasons are described in the following paragraphs. Since researches are still investigating effects of ICT on productivity, the literature sample was further extended by searching on RePEc website. This database not only covers all journals[5] used by the two previous studies but also extends the searching area.

Search criteria followed previous empirical studies who took included only papers written after 1990, and therefore search was focused on "productivity paradox", "ICT productivity" and "information technology"[6], and only items with empirical firm level research written in English since 1990 were taken into account.

For proper meta-analysis it is important to have a coherent research design so we can compare the results, especially when we focus on publication bias. I checked whether all studies use the production function framework as introduced in the second chapter, and work with ICT capital as a separate explanatory variable, thus I excluded papers testing probability of e.g. product innovation via probit or logit models. Next, I only included studies that somehow calculated the value of the ICT capital – therefore I did not take into account studies using only dummy variable for usage or non-usage of IT like e.g. Atrostic and Nguyen (2005). All these restrictions are needed for the studies to be comparable and suitable for an aggregated analysis, and that is also the reason why several studies Rajiv Kohli and Sarv Devaraj (2003) used were excluded due to an inconsistent framework.

[3] Additionally e.g. study Brynjolfsson and Hitt (2000) was replaced by Brynjolfsson and Hitt (2003) as it is a newer and in a journal published version.

[4] Availability issue relates mainly to dissertations, studies retrieved from books, and articles published in journals not accessible from Charles University.

[5] With the exception of *Information Systems Research*, *Information & Management* and *Journal of Management Information Systems*, which were searched using isr.journal.informs.org

[6] Exact search query used in RePEc was firm + ((information + technology + (productivity | payoff)) | (productivity + paradox) | (ICT + (productivity | payoff))) + estimate and also term ((information+technology)|ICT)+ investment + firm + productivity, searched in abstract since 1990.

We need a framework where we can observe ICT elasticity, therefore log-log or translog models, as we cannot compare coefficients' estimates to e.g. level-log models. Let us recall equation 4:

$$\ln Q = \alpha + \beta_{IT} \ln K_{IT} + \beta_{nonIT} \ln K_{nonIT} + \beta_L \ln L + \beta_M \ln M + \varepsilon$$

For us, the important coefficient is β_{IT} which is the elasticity of IT capital, in other words it tells us that increase in K_{IT} by 1 percent increases Q by β_{IT} percent. I focus on ICT investments related to productivity or profitability, therefore studies analysing e.g. effect of ICT on the technological progress represented by some index could not be used. Neither studies where the target is to lower something – e.g. mortality (S. Devaraj & R. Kohli, 2003) or measures on scale of e.g. process changes (Grover, Teng, Segars, & Fiedler, 1998) or production hours (Kelley, 1994) can be used. Additionally, studies using pure growth accounting approach or correlations only like (Kivijärvi & Saarinen, 1995; Lubbe, Parker, & Hoard, 1995) and therefore no regression were excluded, as we do not have the precisions indicators in such studies.

In total, I identified 49 published studies and 19 working papers. These 68 works written between 1992 and 2012 report more than 830 estimates of IT elasticity. To get an idea about the size of those numbers we can compare them to the numbers from Nelson and Kennedy (2009) who report mean and median of 191 and 92 observations and mean and median of number of studies equal to 42 and 33 respectively. All those values are based on the survey consisting of 125 meta-analyses. Our sample greatly exceeds both indicators. The list of the studies together with the number of estimates and indication if they were previously used in one of the mentioned meta-analysis is presented in table A3.

After suitable studies were identified, gathering and coding of all variables was carried out. The most important variables were of course the estimate of ICT elasticity and respective t-statistic, standard error or significance level only when reported. If neither the significance level nor any other measure of precision was reported, the estimate was dropped (17 observations). Various measures of productivity can be used at firm-level, thus I created two groups of dependent variables and coded the measures according to it. The first group aggregates productivity measures such as output or sales and second group is related to profitability, thus mostly financial measures like Return on asset (ROA) or Return on equity (ROE). In most cases, the industry type was not reported or industries were mixed, thus the dummy for services and production types of industry was not used.

As the main target of this paper is to determine publication related effects, variables that are likely to have influence on the effect size were collected – econometric *method* used for estimation, *sample size*, *data source*, *time span* and *average year* of the data in the sample. Primary connected to the publication bias, we are not only interested when and if the work was published or not, but also how the study is further used. As a proxy I use the *number of citations* of the study provided by Google Scholar in early November 2012. Using absolute number of citations would handicap newly published works, thus we normalize the number of citations using the year of publication. Journals or other *place of publication* were also coded which will allow us use the multi-level mixed-effects model. Regional differences are captured in region dummies – I created 2 main regions based on the data source: US and the rest of the world. Table A2 provides list of variables used.

5.1 Data description

I collected a pretty much complete data matrix[7]: number of observations in the studies varies from 24 to 36305 (Tambe & Hitt, 2012) and an average study uses 2609 observations for estimates. I gathered most estimates (113) from Brynjolfsson and Hitt (2003), but half of the studies report less than 9 estimates of the effect size. Average and median of publication year is 2002 – this year the dataset for the last meta-analysis by Stiroh (2005) ends. In total, I identified 64 Journals and working paper sources and

[7]I was not able to determine only the sample size for Steindel (1992), but it should not affect the results much

21 sources of data. 39 studies – more than the half – have not been used before for meta-analysis of IT productivity. Further basic dataset description is provided in table 1.

Table 1: Basic dataset description

	Min	Max	Mean	Median
$\hat{\gamma}$ per study	1	113	12	9
observations in study	24	36305	2609	1074
time span	1	30	7	6

$\hat{\gamma}$ – estimate of IT elasticity
numbers are rounded to the nearest integer

A bit closer look on collected estimates is provided in table 2. I divided the estimates into groups depending on some of the characteristics related to publication bias. The minimum and maximum values are in all samples far away from the mean value. The highest estimates - close to one - are from Rai, Patnayakuni, and Patnayakuni (1996). This study uses the whole Information systems (IS) budget and the production function lacks several explanatory variables. The next highest results come from Zwick (2003), where the anomaly is caused by Maximum likelihood estimation (MLE) method and data selection procedure. Results on non-selected data are around 0,05 when estimated with OLS method. The other side of the interval, with largely negative values, is covered by Paton, Siegel, and Williams (2004) who conduct a case study of the gaming industry.

Table 2: Descriptive statistics of the dataset – elasticity estimates

	Mean	Std. Dev.	Min	Max	Average*	Obs
Full sample	0.0653	0.1390	−1.124	0.994	0.0035	835
Kohli	0.0740	0.1985	−0.516	0.994	0.0110	133
Stiroh	0.0334	0.0432	−0.086	0.222	0.0033	253
new studies	0.0782	0.1438	−1.124	0.98	0.0210	495
Working paper	0.0504	0.1635	−1.124	0.98	0.0373	216
Published	0.0705	0.1291	−0.516	0.994	0.0032	619

* average = weighted average calculated using formula 10
Kohli – studies also included in Rajiv Kohli and Sarv Devaraj (2003)
Stiroh – studies also included in Stiroh (2005)
new studies – not used by Kohli or Stiroh

One of the basic meta-analytic techniques is a calculation of weighted averages of all available estimates. Such approach to IT productivity literature was done by Lim, Richardson, and Roberts (2004) but the aim of this work was to determine differences between specific groups of firms, not to find out the underlying true effect of ICT investments. Calculated weighted average for each group is also included in table 2 using formula 10. As weights the inverted variance of the estimate is used.

$$r_w = \frac{\sum_{i=1}^{n} w_i \gamma_i}{\sum_{i=1}^{n} w_i}, \quad w_i = \frac{1}{Var(\gamma_i)} \tag{10}$$

Weighted averages are much smaller than simple averages and there is no common ration for all groups, thus smaller mean in one group does not necessarily results also in smaller weighted average, like for working papers. On average working papers report smaller effect size than published papers, but weighted average of published estimates is less than half of weighted average of working paper estimates. The more precise values count more and the more the estimate is close the zero, the more precise it has to be, to be significant at generally respected 5% significance level. There is also difference between studies selected by Stiroh (2005) and Rajiv Kohli and Sarv Devaraj (2003). The latter one uses studies with higher and more diversified estimates (larger variance). Also studies that were not used in any of those two papers contain on average higher effect sizes. This may be the time effect or e.g. due to selection process. The main conclusion of the basic stratification of the data is that mean value of effect size is around 0.06 but weighted average is close to zero with values around 0.01. If we use inverted standard errors as weights, the values are around 0.03.

As for the groups, weighted average was calculated for each of 68 studies with the weights equal to inverse of variance. The result depicted the forest graph on figure 1, where the dashed line close to zero represents the weighted average of all studies estimated with Fixed effect size (FES) method (model 5) equal to 0.004 with z-stat. $= 50.43$. This results is influenced by studies like Lehr and Lichtenberg (1999) and Hitt and Brynjolfsson (1996) who report significant estimates very close to zero (0.00061 and -0.0008 respectively). If we remove these two studies, we immediately end up with a weighted average equal to 0.029 and z-statistic equal to 134.6. Without any data modification, the basic RES analysis provides $\hat{\gamma} = 0.036$ and $CI = (0.034; 0.037)$, z-stat. $= 49.54$. For the final analysis we use multilevel mixed effects model – estimates from each study are mutually correlated because they are based on the same data set and methodology and have to be treated that way. We combine the fixed effect within the study with random component among the studies.

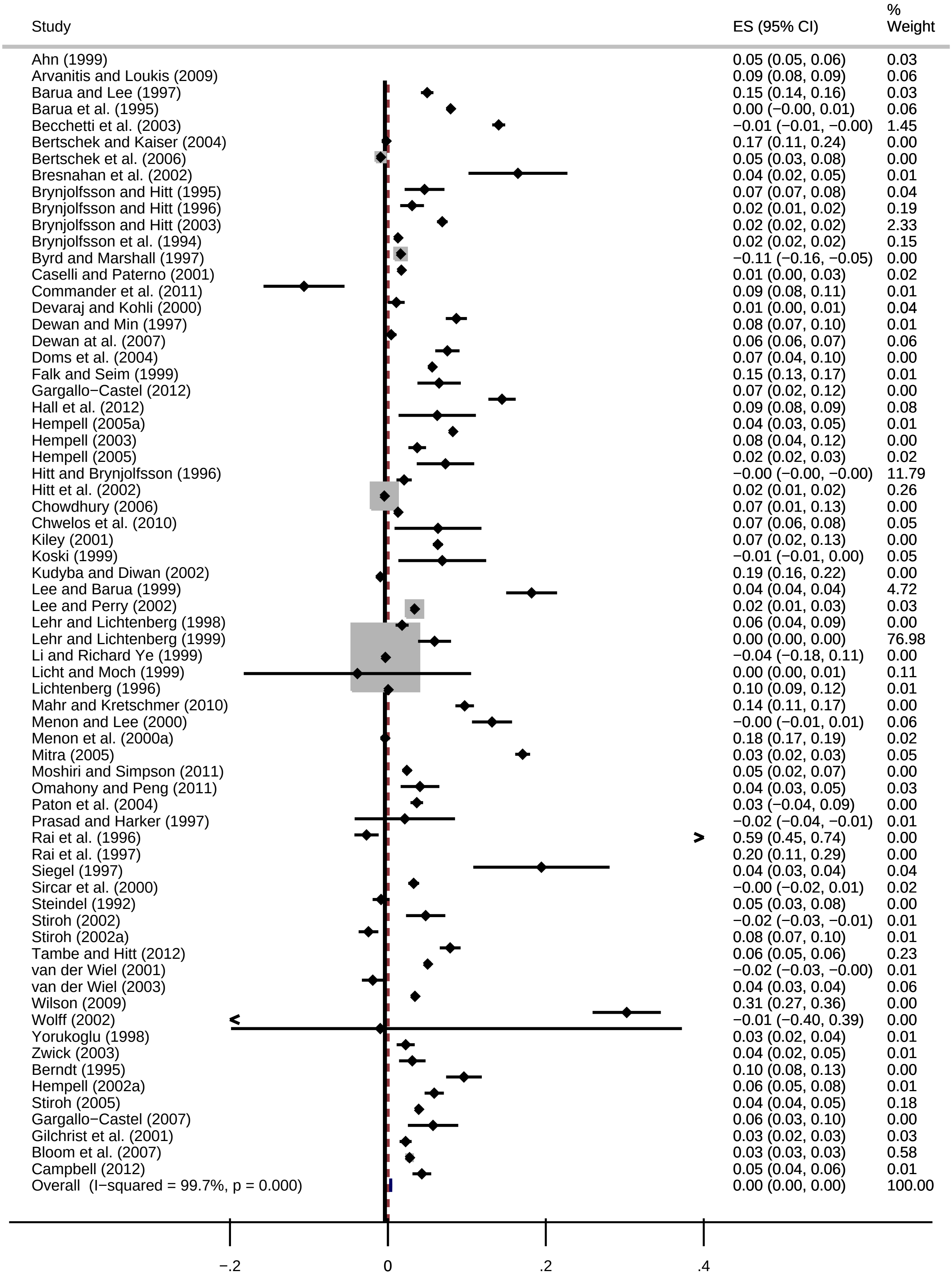

Figure 1: Forrest plot – weighted averages γ by study

6 Results

In case some of the estimates are more likely to be published, the simple arithmetic averages will be deviated from the "true" value (Havranek et al., 2012). Figure 2 depicts the Epanechnikov kernel density of the estimates. The distribution of estimates deviates form the normal distribution represented by the dashed line. Normal distribution is a standard assumption in the meta-analysis framework for the absence of publication bias. This assumption results from an econometric approach to the estimates determination by researchers. With respect to the several sources of publication bias, its presence should be one of the assumption for every meta-analysis (T.D. Stanley, 2005, 2008).

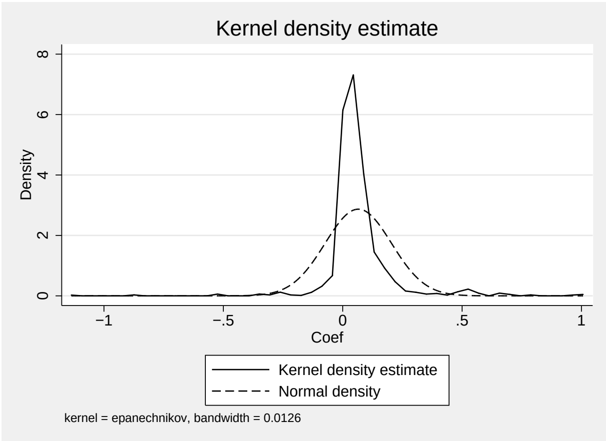

Figure 2: Kernel density of estimates

Graphical tests provide the easiest and fastest way for publication bias detection. First, funnel plots are depicted on Figure 3 for all studies and the detail on Figure 4. The size of estimates (on the x-axis) is plotted against its precision (inverted standard error) on the y-axis. The vertical dashed line depicts the value of 0.03, which represents the weighted average when using inverse of standard error for weighting the effect sizes. The detail view allows us to observe that the estimates are clouded more on the positive part of the x-axis. A funnel plot usually identifies publication bias of type I – only estimates that fit the theory are accepted, as described in section 3.

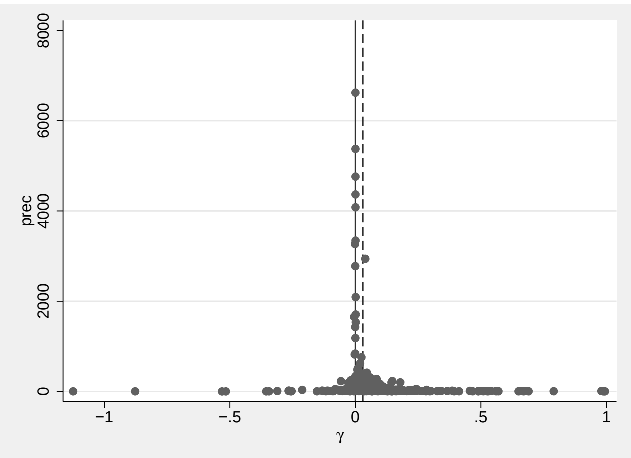

Figure 3: Funnel graph – full sample

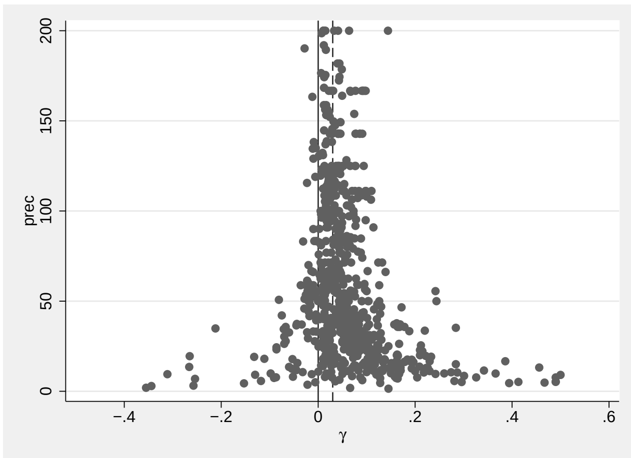

Figure 4: Funnel graph – detail

When I split the sample by year 2002 – into two groups of the same size – the difference is clearly observable. On one hand, the funnel graph on Figure 5, depicting estimates from studies written before 2002, is more or less symmetric, but on the other hand Figure 6 depicts an obviously skewed funnel graph. Mostly, the deviation from the symmetry is caused by "missing" negative values of effect sizes, which is consistent with the type I of publication bias.

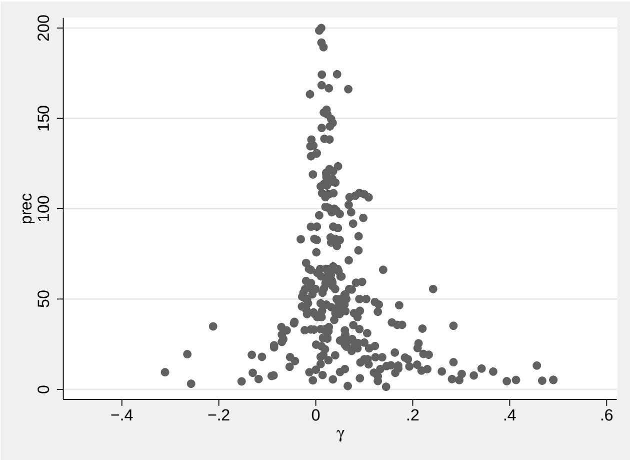

Figure 5: Funnel graph – before 2002

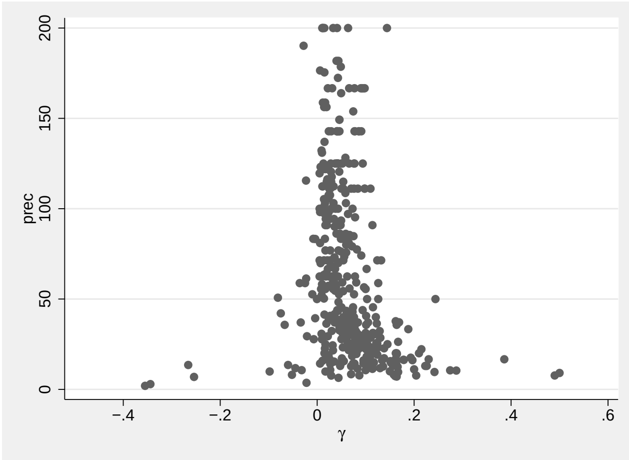

Figure 6: Funnel graph – after 2002

Graphical testing of publication bias is vivid and possible selection can be easily revealed, but it is necessary to verify the visual results with precise econometric testing. Formal testing for publication bias use the same logic as graphical tests of funnel plots, as described in the previous section. We estimated model 7 and for robustness check, Clustered OLS method was used. Table 3 summarizes the results. In all cases, publication bias is positive and significant at 1% significance level in all specifications. Magnitude of the publication bias is around 3, which according to H. Doucouliagos and T. D. Stanley (2008) means that publication bias is so strong, that it can produce significant results even if there is there is no true underlying effect. Positive and significant effect of ICT capital is found only for productivity using mixed-effects method and reaching only 0.003, while effect on profitability is not significantly different from zero. To estimate the true effect more precisely, we use model 9 proposed by TD Stanley and C. Doucouliagos (2007), results are reported in table 4. We again use mixed-effect method for estimation and clustered OLS method for robustness check.

Table 3: Publication bias testing

	Mixed-effects multilevel			Clustered OLS		
	Profitability	Productivity	All	Profitability	Productivity	All
prec	−0.0000653	0.00267**	0.00215**	−0.00119†	0.00236	0.00191
(effect size)	(−0.08)	(5.07)	(5.08)	(−1.89)	(1.12)	(1.04)
Constant	3.073**	3.171**	3.136**	3.323**	2.781**	2.912**
(publication bias)	(6.17)	(4.20)	(5.57)	(12.47)	(10.10)	(12.51)
Observations	290	528	818	290	528	818
rmse				3.164	6.394	5.495

t statistics in parentheses

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Dependent variable: tstat

Results in table 4 which are corrected for publication bias in line with findings reported in table 3. Effect on profitability is found to be insignificantly different from zero and corrected effect on productivity is 0.003 and significant at 1% level. These results are in strong contrast to weighted average of all estimates, but is close to weighted average of published studies.

We found publication bias in the IT productivity literature, the highest reliable estimate of IT elasticity being 0.003 and some estimates not being significant even at 10% level. Our next question is

Table 4: True ICT payoff

	Mixed-effects multilevel			Clustered OLS		
	Profitability	Productivity	All	Profitability	Productivity	All
prec	0.000793	0.00277^{**}	0.00224^{**}	0.00241	$0.00371^{\dagger}$	$0.00355^{\dagger}$
(true effect)	(0.85)	(5.26)	(5.28)	(1.25)	(1.70)	(1.86)
se	-8.065^{*}	-3.039	-3.986	15.47^{**}	8.933^{**}	10.37^{**}
	(-1.97)	(-0.77)	(-1.28)	(3.50)	(2.83)	(3.56)
Observations	290	528	818	290	528	818
rmse				4.351	6.887	6.111

t statistics in parentheses
† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$
Dependent variable: tstat

how study characteristics influence the results. Variables collected in the data gathering process will be used in a simple explanatory Meta-regression analysis (MRA), which aims at heterogeneity of the estimates. Disparateness between estimates from studies is given not only by some random error, but also by other factors including data source or used methodology. Explaining differences between studies was the main target of previous meta-analyses Rajiv Kohli and Sarv Devaraj (2003), Stiroh (2005), but neither of them considered publication bias. We also use all estimates from every study and even those estimates vary. One of the limitation of meta-analysis is that we have only a limited number of possible explanatory variables for this kind of differences and we cannot capture all of it mainly because of limited degrees of freedom. Variables used in MRA are selected with respect to the previous studies and summarized in Table A2. For heterogeneity modelling we used multilevel mixed effects model, specified in model 8 which is best suits for explaining diversity of studies.

Results of multilevel Random intercept model (RIM) observing effects on productivity, profitability are reported in Table 5. Explanatory meta-regression analysis is sensitive to its specification and the interpretation of results is not straightforward. The dependent variable is the t-statistic, thus coefficients of explanatory variables do not provide the magnitude of the effect, we can only interpret the sign and significance. In case the coefficient is negative, corresponding variable underestimates the effect and if the coefficient is positive than it results in a overestimation.

The findings are not revealing much evidence about factors influencing results: only a few of gathered explanatory variables turned out to be significant and thus influencing research outcomes. Number of observations used in regression for estimation is found to be meaningful. The higher the number of observations (*nobs*), the higher also the effect. ICT effect on profitability is higher in the US than in the rest of the world, but there is not difference in productivity. We found no difference between working papers and published works. On 10% significance level specification for profitability finds lower effects of IT when the dependent variable is normalized with labour. Interestingly, the length of the period used for estimating the IT effects as well as average year (more recent studies) diminish the reported effect on productivity.The number of citation references are also not related to the size of the effect estimate as well as the methodology used.

6.1 Discussion of results

Previous meta-analyses aimed at explaining heterogeneity between studies, and for this reason the results of performed MRA are comparable to the previous findings in the literature. Table 6 captures main findings of two previous meta-analyses and compares them to this paper. As mentioned, focus of the previous studies was a bit different and thus I did not included all of their propositions. I also wanted

Table 5: Explanatory meta-regression analysis

	Mixed-effects multilevel			Clustered OLS		
	Profitability	Productivity	All	Profitability	Productivity	All
prec	−0.0000132	0.00348**	0.00258**	0.000883	0.00233	0.00178
	(−0.01)	(6.28)	(5.96)	(0.70)	(1.11)	(0.96)
nobs	0.000236**	0.000270**	0.000300**	0.000239**	0.000138	0.000222**
	(6.68)	(2.61)	(5.57)	(7.86)	(1.29)	(4.68)
Years	0.0709	−0.322*	−0.0903	0.0474	−0.251	−0.0999
	(1.15)	(−2.32)	(−1.10)	(0.87)	(−1.29)	(−1.07)
Labour	−4.973†	−1.088	−2.116*	−6.998**	−0.101	−0.826
	(−1.73)	(−0.74)	(−1.99)	(−3.99)	(−0.16)	(−1.46)
year	−0.0660	0.679*	0.210	−0.0953*	0.558†	0.217†
	(−0.61)	(2.54)	(1.41)	(−2.00)	(1.81)	(1.67)
Citations	−0.00602	−0.00483	−0.0119	−0.00245	0.00222	0.000864
	(−0.54)	(−0.15)	(−0.65)	(−0.64)	(0.21)	(0.13)
isWP	−0.201	0.795	0.302	−0.250	2.144†	1.063†
	(−0.19)	(0.39)	(0.22)	(−0.57)	(1.75)	(1.92)
ols	0.350	0.0376	0.155	0.904*	0.216	0.796*
	(0.84)	(0.05)	(0.31)	(2.60)	(0.41)	(2.44)
countryUS	2.588*	0.239	0.665	2.008**	1.098†	1.024†
	(2.15)	(0.11)	(0.45)	(3.76)	(1.96)	(1.74)
avgYear	0.0920	−0.717**	−0.279*	0.0798	−0.446	−0.162
	(1.08)	(−3.63)	(−2.45)	(1.23)	(−1.32)	(−0.91)
depvar			−0.680			−0.617
			(−1.04)			(−1.64)
Constant	−50.89	74.63	139.7	32.23	−225.3*	−110.4
	(−0.20)	(0.19)	(0.52)	(0.34)	(−1.97)	(−0.91)
Observations	290	520	810	290	520	810
rmse				2.525	6.304	5.350

t statistics in parentheses

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Dependent variable: tstat

to test for difference of IT payoff between sectors, but data I managed to gather were not suitable for such analysis as the vast majority of estimates is not industry sector specific.

Table 6: Summary and comparison of findings

Proposition	Kohli (2003)	Stiroh (2005)	This paper (2014)
IT payoff differ among industry sector	Supported	Mixed results	–
Larger sample size leads to greater IT payoff	Supported	–	Supported
Estimates of profitability-base dependent variable differ from productivity based	Supported	Not supported	Supported
Labour productivity differ form not-per-labour normalized dependent variable	–	Not supported	Mixed results
Longitudinal estimates are higher than short term	Not supported	–	Mixed results*
Estimates base on more recent data show higher estimates	–	Supported	Mixed results*
There is publication bias in IT payoff literature	–	–	Supported
Genuine effect size	–	0.06	0.002 – 0.003

* proposition not supported by all specifications

My main focus was on publication bias and its presence was found in all specifications. Next to publication bias detection also estimation of the underlying effect was performed, which was found to be positive for the productivity. However, I was unable to clearly identify the sources of the publication bias.

First, no difference was found between OLS and other methods of estimation. Furthermore, most of the study characteristics related to publication bias were found insignificant. Nor relation to number of citations or year of publication and the effect size has been identified neither there is a difference between estimates from working papers and published studies. This signs that effect size is not related to the "popularity" of the estimate.

The hypothesis that the data from US will lead to higher effect size is partially supported in the results. Positive effect is found only for profitability estimates.

Similarly to Rajiv Kohli and Sarv Devaraj (2003) we can say that larger sample size leads to higher IT payoff, and I also agree with the conclusion that: "studies with profitability based dependent variable have different IT payoff than those that measure productivity" (Rajiv Kohli & Sarv Devaraj, 2003, p. 130). With Stiroh (2005) we disagree that no significant difference is between estimates of productivity and profitability. He also finds a positive relation between average year in the dataset and effect size of IT investment, but our analysis finds negative relationship when data were analyses by a multilevel model. The rest of the results is mixed – we do not have clearly contradicting or conformable results.

What implications can be drawn from this paper? First, effects of ICT investment on productivity are lower than commonly expected. Second, productivity paradox literature carries a burden called publication bias that causes the overestimation of the ICT elasticity. Some of the results also show the possibility that productivity paradox is "reborn". It seems that method of estimation do not affect the results, and therefore either the general Cobb-Douglas production function framework is not proper for investigating ICT effects, or the model should incorporate possible explanations of the productivity paradox as a control variable. If ICT does not increase productivity per se, then any company should make a proper case study before investing into ICT, because otherwise it will probably result in misinvesting.

6.2 Limitations and Future Research

Results presented in this paper do have some limitations that stems from used methods. Some of them can be challenged in future research. First and foremost, as every meta-analysis, the main limitation is data availability and quality. If the underlying studies are properly done, then also conclusions of meta-analysis are more reliable. As my sample contains almost 70 studies and more that two thirds of the used studies were published, a sufficient quality of the estimates should be reached. It is enough for publication bias testing, but for explanatory MRA characteristic of the studies and estimates are needed to capture the differences in quality.

The second main source of limitation is the method I have chosen. Given the current state of art of meta-analysis in economics, I used the most recent methodology, but there are still missing tests for determination of the most optimal one for each specific case. Models are so far used according to the setting and again, economic theory. If one thinks that the genuine effect is constant and same everywhere, fixed-effect is more suitable. Also, the fact that I decided to use all estimates from each study can change the results in some way. However, this should only increase the reliability of the results due to the law of large numbers. Nevertheless, there are still probably studies and working papers that were not found due to search definitions and thus the used dataset could be extended.

Strong publication bias was found, but most of the variables used to explain it were found insignificant. Further research should therefore try identify key drivers of such bias. MRA overall was able to explain only a small proportion of all the variability of the results. Thus, finding additional explanatory variables that would help to increase proportion of explained variability is needed. This could also remove mixed results we obtained. I employed several models to check for robustness of estimated numbers. Wide range of methods used usually help to check for robustness of the results and diminish doubts about the reliability of estimates, but in the case of this research I got mixed results about the signs which leads to ambiguous conclusions.

It is also questionable, whether we can draw some really general and broad recommendations for every company. Most of the studies are based on US data (63% US, 29% Europe, 8% other), therefore implications in Europe might be different. This study also investigated only firm level and direct effect of ICT. Aggregated levels should also be investigated to determine significance of public spending and test for spillover effects.

We also should not forget that ICT capital requires skilled workers. Proposition for future research is to make a meta-analysis on relation between investments into workers working with ICT and firm performance. Positive results would not only be intuitive, but also consistent with theory and having relevance for business decisions.

7 Conclusion

The central topic of this paper was to access productivity paradox from meta-analytical perspective with focus on publication bias and with aim to reveal the genuine effect of ICT investments on the productivity on a firm level, which makes this paper unique. Meta-analysis is a quite powerful and widely used tool for synthesis of empirical research findings, but specific methods differ, and this paper is set out accordingly. The first part reviews the IT productivity paradox itself together with main literature findings, the second part is devoted to meta-analysis and techniques used for publication bias investigation, followed by the third - empirical - part, where data gathered across available literature are analysed.

Emphasis is put on multilevel analysis as we used all estimates from the studies and estimation of the genuine effect filtered from publication bias. Last part of the paper concludes.

Productivity paradox was investigated for decades and from the large amount of published literature one can only hardly expect to make a general conclusion without proper summarizing techniques. I employed meta-analysis to find the true effect of IT investments on productivity. For that purpose more than 830 estimates from almost 70 studies were collected together with some other descriptive indicators. Previous literature firstly focused on finding a positive effect to refute the paradox, later the diversity of results was approached by Rajiv Kohli and Sarv Devaraj's 2003 meta-analysis and Stiroh (2005) found IT payoff to be around 0.06 when using a mixture of firm and aggregated level literature and one estimate per study.

This paper found clear and substantial evidence of publication bias present in the IT productivity paradox literature. Filtered from this bias, the underlying effect was identified to be 0.003 when data were analysed using RIM. If we combine the last finding with evidence from MRA showing that IT elasticity is decreasing with increasing average year in the dataset, it seems like the productivity paradox might be reborn after it was refuted. A possible explanation could be the fact that in today's PC driven world, technology is a must, and thus IT technology is so incorporated into any capital and production technology that we cannot clearly separate it and find positive effects of IT related investments. Another explanation could be the investment into ICT, which lowers the resulting effect. Main drivers of inadequate investment are mostly wrong management, but it can also be the impact of fashions in IT[8] which was investigated by Wang (2010). Managers are better evaluated when chasing newest IT and thus they have high incentive to invest in such technology even if the payoff is insignificant.

Publication bias was identified, but explanatory variables related to publication bias were found mostly insignificant when heterogeneity was explained by MRA. We found small evidence of different results between working papers and published studies, concluding that higher estimates are present in the first mentioned group. Also, no support for the economics research cycle hypothesis has been found. The limitations of this paper are based on the ability to explain the diversity of results from only a few and quite general descriptive variables about each study whose estimates can be retrieved from the studies and coded.

The size of the effect is not only to prove the validity of neoclassic theory, which predicts the effect to around $0.02 - 0.04$ as argued by Stiroh (2005), but also to meet the right decision in business related investments. From this perspective, our result of IT elasticity very close to zero supports the argument that there are better forms of investment to be made.

[8] "An IT fashion is a transitory collective belief that an information technology is new, efficient, and at the forefront of practice." (Wang, 2010, p. 63)

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A Appendix

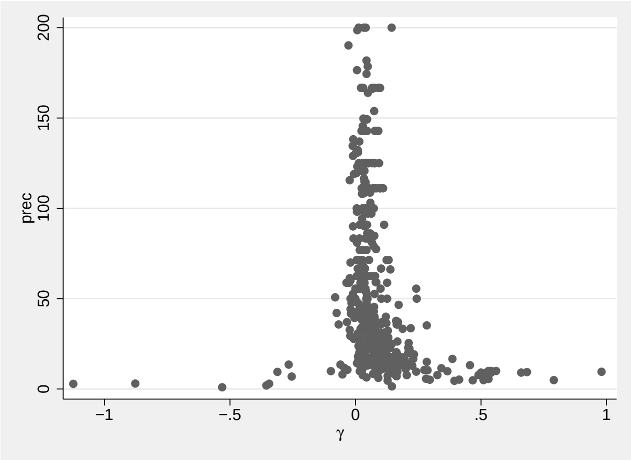

Figure A1: Funnel graph – new studies

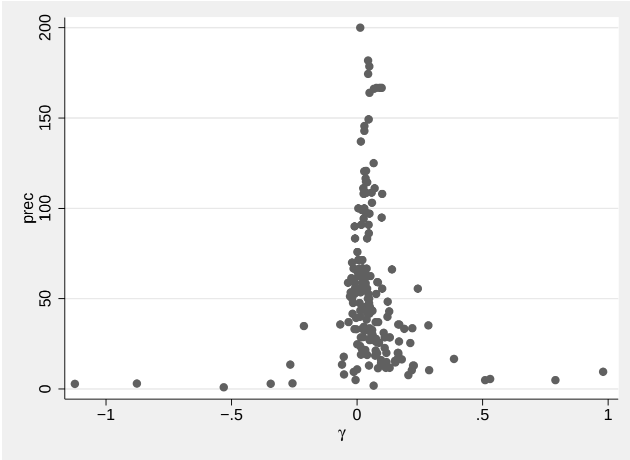

Figure A2: Funnel graph – working papers

Table A1: List of data sources used in papers

Data source	Studies
ACES, Compustat	1
ARD	1
BLS	2
CII, Compustat	16
CITDB	1
CPB	2
EU KLEMS	1
FDIC	1
IAB	1
IDG, Compustat, BEA	17
Informationweek	1
Mediocredito	1
MIP-S	5
MPIT	3
own	7
SBS	2
Washington state department of Health	2
WES	1
ZEW	2
ABI	1

Table A2: Explanatory variables used in regressions

Variable	Description
gamma	point estimate of effect of IT on productivity
se	standard error of the estimate γ
nobs	number of observations the estimate is calculated from
tstat	t-statistic for γ with $H_0 : \gamma = 0$
prec	inverse of *se*
	explanatory variables influencing publication bias
year	year of publication, reference year 1990
year_sq	square of *year*
isWP	dummy=1 if study is a working paper, 0 otherwise
citations	number of citations per year since publication found in Google Scholar
ols	dummy=1 if model used was OLS, 0 otherwise
	explanatory variables directly influencing effect size
countryUS	dummy=1 if dataset is from US, 0 otherwise
years	number of years in the dataset
depvar	dummy=1 if dependent variable was productivity 0 for profitability
labour	dummy=1 if dependent variable was normalized by labour, 0 otherwise
	dummy variables used for grouping
datasourceid	ID of data source
journalid	ID of Journal
authorid	ID of group of authors
kohli	dummy=1 if study was used by Rajiv Kohli and Sarv Devaraj (2003), 0 otherwise
stiroh	dummy=1 if study was used by Stiroh (2005), 0 otherwise

B Studies Included in the Meta-Analysis

Table A3: Studies used for meta-analysis

Cite	**Year**	**Estimates**	**Kohli**	**Stiroh**
Ahn (1999)	1999	2	No	No
Arvanitis and Loukis (2009)	2009	21	No	No
Barua, Kriebel, and Mukhopadhyay (1995)	1995	5	Yes	No
Barua and B. Lee (1997)	1997	2	No	No
Becchetti, Bedoya, and Paganetto (2003)	2003	11	No	No
Berndt and Morrison (1995)	1995	20	No	No
Bertschek and Kaiser (2004)	2004	4	No	No
Bertschek, Kaiser, and Fryges (2006)	2006	3	No	No
Bloom, Sadun, and Van Reenen (2007)	2007	31	No	No
Bresnahan, Brynjolfsson, and Hitt (2002)	2002	5	No	Yes
Brynjolfsson and Hitt (1994)	1994	17	No	No
Brynjolfsson and Hitt (1995)	1995	10	Yes	Yes
Brynjolfsson and Hitt (1996)	1996	17	Yes	Yes
Brynjolfsson and Hitt (2003)	2003	113	No	Yes
Byrd and Marshall (1997)	1997	4	Yes	No

Continued on Next Page...

Table A3 – Continued

Cite	Year	Estimates	Kohli	Stiroh
Campbell (2012)	2012	10	No	No
Caselli and Paterno (2001)	2001	15	No	Yes
Commander, Harrison, and Menezes-Filho (2011)	2011	40	No	No
Devaraj and Kohli (2000)	2000	2	Yes	No
Dewan and Min (1997)	1997	8	Yes	Yes
Dewan, Shi, and Gurbaxani (2007)	2007	12	No	No
Doms, Jarmin, and Klimek (2004)	2004	6	No	No
Falk and Seim (1999)	1999	6	No	No
Gargallo-Castel and Galve-Górriz (2007)	2007	3	No	No
Gargallo-Castel and Galve-Górriz (2012)	2012	1	No	No
Gilchrist, Gurbaxani, and Town (2001)	2001	18	No	No
Hall, Lotti, and Mairesse (2012)	2012	7	No	No
T. Hempell (2002)	2002	21	No	No
Thomas Hempell (2003)	2003	8	No	No
Thomas Hempell (2005a)	2005	14	No	Yes
Thomas Hempell (2005b)	2005	32	No	No
Hitt and Brynjolfsson (1996)	1996	10	Yes	No
Hitt, Wu, and Zhou (2002)	2002	6	No	No
Chowdhury (2006)	2006	4	No	No
Chwelos, Ramirez, Kraemer, and Melville (2010)	2010	10	No	No
Kiley (2001)	2001	3	No	Yes
Koski (1999)	1999	9	No	No
Kudyba and Diwan (2002)	2002	15	No	No
B. Lee and Barua (1999)	1999	5	Yes	Yes
G. Lee and Perry (2002)	2002	6	Yes	No
W. Lehr and Lichtenberg (1998)	1998	3	Yes	No
B. Lehr and Lichtenberg (1999)	1999	27	No	Yes
Li and Richard Ye (1999)	1999	2	Yes	No
Licht and Moch (1999)	1999	4	No	No
Lichtenberg (1996)	1996	6	Yes	Yes
Mahr and Kretschmer (2010)	2010	17	No	No
Menon and B. Lee (2000)	2000	1	Yes	No
Menon, Lee, and Eldenburg (2000)	2000	1	Yes	No
Mitra (2005)	2005	10	No	No
Moshiri and Simpson (2011)	2011	6	No	No
O'Mahony and Peng (2011)	2011	24	No	No

Continued on Next Page...

Table A3 – Continued

Cite	Year	Estimates	Kohli	Stiroh
Paton, Siegel, and Williams (2004)	2004	10	No	No
Prasad and Harker (1997)	1997	8	Yes	No
Rai, Patnayakuni, and Patnayakuni (1996)	1996	10	Yes	No
Rai, Patnayakuni, and Patnayakuni (1997)	1997	4	Yes	No
Siegel (1997)	1997	18	Yes	No
Sircar, Turnbow, and Bordoloi (2000)	2000	13	Yes	No
Steindel (1992)	1992	8	No	Yes
Stiroh (2002a)	2002	12	No	Yes
Stiroh (2002b)	2002	9	No	Yes
Stiroh (2005)	2005	30	No	No
Tambe and Hitt (2012)	2012	38	No	No
van der Wiel (2001)	2001	4	No	No
van der Wiel and van Leeuwen (2003)	2003	10	No	No
Wilson (2009)	2009	14	No	No
Wolff (2002)	2002	1	No	Yes
Yorukoglu (1998)	1998	1	No	No
Zwick (2003)	2003	8	No	No

Table A4: List of journals present in papers

Journal	Studies
Annales d'Economie et de Statistique	1
Bank of Italy, Economic Research and International Relations Area	1
Canadian Journal of Economics	1
Carnegie-Rochester Conference Series on Public Policy	1
Communications of the ACM	1
CPB[9] Netherlands Bureau for Economic Policy Analysis	2
Decision Support Systems	1
Discussion Papers in Business Administration	1
Economics of Innovation and New Technology	3
Empirical Economics	1
FRBNY[10] Quarterly Review	1
Industrial and Corporate Change	1
Information & Management	1
Information Economics and Policy	1
Information Systems Research	4
Innovation and Information Technology in Services	1

Continued on Next Page…

[9]Centraal Planbureau
[10]Federal Reserve Bank of New York

Table A4 – Continued

Journal	**Studies**
International Journal of Flexible Manufacturing Systems	1
International Journal of the Economics of Business	1
Journal of International Development	1
Japan and the World Economy	1
Journal of Business & Economic Statistics	1
Journal of Econometrics	1
Journal of Information Technology Impact	1
Journal of Management Information Systems	4
Journal of Productivity Analysis	2
Journal of Public Administration Research and Theory	1
Management Science	4
MIS[11] Quarterly	1
MPRA[12] Paper	1
National Institute Economic Review	1
NBER[13] Working Papers	4
Omega	2
Procedia - Social and Behavioral Sciences	1
Rensselaer Working Papers in Economics	1
Research Policy	1
Review of Economic Dynamics	1
Review of Economics and Statistics	1
Review of Income and Wealth	1
The American Economic Review	1
The Journal of Industrial Economics	1
The Quarterly Journal of Economics	1
The Review of Economics and Statistics	2
The Wharton Financial Institutions Center Working Papers	1
University of California	1
WP MIT[14]	1
WP OECD[15]	1
ZEWZentrum für Europäische Wirtschaftsforschung Discussion Papers	3
Journal of Organizational Computing and Electronic Commerce	1

[11]Management Information Systems
[12]Munich Personal RePEc Archive
[13]National Bureau of Economic Research
[14]Massachusetts Institute of Technology
[15]Organisation for Economic Co-operation and Development

Table A5: List of group of authors of papers

Authors	Studies
Ahn	1
Arvanitis, Loukis	1
Barua, Lee, Perry, Menon	6
Becchetti, Bedoya, Paganetto	1
Berndt	1
Bertschek, Kaiser, Fryges	2
Bharadwaj, Konsynski	1
Brynjolfsson, Hitt, Bresnahan	8
Byrd, Marshall	1
Caselli, Paterno	1
Commander, harrison, Menezes-Filho	1
Devaraj, Kohli	1
Dewan, Min, Shi, Gurbaxani	2
Doms, Jarmin, Klimek	1
Falk, Seim	1
Gargallo-Castel	2
Hall, Lotti, Mairesse	1
Hempell	4
Chowdhury	1
Chwelos, Kraemer, Melville, Ramirez	1
Kiley	1
Koski	1
Kudyba, Diwan	1
Lehr, Lichtenberg	3
Li, Richard Ye	1
Licht, Moch	1
Mahr, Kretschmer	1
Mitra	1
Moshiri, Simpson	1
Omahony, Peng	1
Paton, Siegel, Williams	1
Prasad, Harker	1
Rai, Patnayakuni, Patnayakuni	2
Siegel	1
Sircar, Turnbow, Bordoloi	1
Steindel	1
Stiroh	3
van der Wiel	2

Continued on Next Page…

Table A5 – Continued

Authors	Studies
Wilson	1
Wolff	1
Yorukoglu	1
Zwick	1
Gilchrist, Gurbaxani, Town	1
Bloom, Sadun, Reenen	1
Campbell	1

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EMU European monetary union

FES Fixed effect size

GPT General Purpose Technology

ICT Information and communication technology

IS Information systems

IT Information technology

MLE Maximum likelihood estimation

MRA Meta-regression analysis

OLS Ordinary least squares

RES	Random effect size
RIM	Random intercept model
ROA	Return on asset
ROE	Return on equity
WLS	Weighted least squares