Technology adoption and employment in less developed countries:

A mixed-method systematic review*

Mehmet Ugur, University of Greenwich Business School; M.Ugur@gre.ac.uk
Arup Mitra, Institute of Economic Growth, Delhi; arup@iegindia.org

ABSTRACT

The implications of technology adoption for productivity, income and welfare have been studied widely in the context of less developed countries (LDCs). In contrast, the relationship between technology adoption and employment has attracted less interest. This systematic review evaluates the diverse yet sizeable evidence base that has remained below the radars of both reviewers and policy makers. We map the qualitative and empirical evidence and report that the effect of technology adoption on employment is skill-biased and more likely to be observed when technology adoption favour product innovation as opposed to process innovation. Technology adoption is also *less likely* to be associated with employment creation when: (i) the evidence is related to farm employment as opposed to firm/industry employment; (ii) the evidence is related to low-income countries as opposed lower-middle-income or mixed countries; and (iii) the evidence is based on post-2001 data as opposed to pre-2001 data. There is also qualitative evidence indicating that international trade, weak forward and backward linkages and weaknesses in governance and labour-market institutions tend to weaken the job-creating effects of technology adoption. We conclude by calling for compilation of better-quality survey data and further attention to sources of heterogeneity in modeling the relationship between technology adoption and employment in LDCs.

* Accepted (March 2017) for publication in *World Development*. Research for this paper benefits from funding by the UK's Department for International Development (DFID), with reference no. PO 40043268. We thank the funders for their support, subject to usual disclaimer: the views expressed here are those of the authors only, who are responsible for any errors or omissions.

Technology adoption and employment in less developed countries:

A mixed-method systematic review

1. Introduction

Since 2005, national, regional and international organisations have been emphasizing the importance of innovation and technology adoption for growth and employment in less developed countries (LDCs). The consensus is that promoting innovation and technology adoption is essential for growth and jobs in developing countries (UN, 2005; Commission for Africa, 2005; NEPAD, 2006).

Although technological change may be a driver of growth and employment in the long run, the adjustment process may be protracted and could lead to job losses in the short-to-medium run (Aghion and Howitt, 1992; Baumol and Wolff, 1998). There is also a wealth of evidence indicating that technological change may be skill-biased (Acemoglu, 1998 and 2003; Berman, Bound and Griliches, 1994; Berman and Machin, 2000; Berman et al., 2005; Cirillo, 2014; Machin and Van Reenen; 1998). Finally, the type of new technology matters: while product-oriented technology adoption is usually expected to have a positive effect on employment, process-oriented technology adoption is expected to have adverse employment effects (Katsoulakos, 1986; Harrison et al, 2014; Edquist et al., 2001).

These findings are usually reported in the literature investigating developed and upper-middle-income developing countries, of which several reviews exist (Pianta, 2004; Piva, 2003; Spiezia and Vivarelli, 2002; and Vivarelli, 2011, 2012, 2013 and 2014). Existing narrative reviews offer three general conclusions. First, the employment effect of technological change is contingent on a range of moderating factors, including labour market flexibility, product market competition, types of innovation, and international trade. Second, the balance of evidence does not point out a negative effect on employment, but process innovation is more likely to be associated with job destruction whereas product innovation is more likely to be associated with job creation. Finally, the effect is more likely to be negative when the data relates to unskilled labour.

Vivarelli (2011, 2013 and 2014) discusses at length the displacement and compensation mechanisms at work. Vivarelli (2013) reminds us that labour-saving and deskilling effects of capital-intensive technology has been a concern since the Luddite movement of the early 19th century. However, he also draws attention to the theoretical debate, which identifies a range of compensation mechanisms that may alleviate such concerns. Labour-saving effects of technology can be offset through: (i) additional employment in industries producing the new machines; (ii) higher demand for goods/services due to lower prices; (iii) new investments made using extra profits; (iv) decreases in wages resulting from price adjustment mechanisms; (v) higher income resulting from redistribution of innovation gains; and (6) new products created using new technologies. However, Vivarelli (2014) concludes that the compensation mechanisms require strict assumptions, overlook the secondary adverse demand effects that may result from falling wages, and may not all work in tandem. Therefore "…economic theory does not have a clear-cut answer regarding the employment effect of innovation." Hence, one should "…

focus on aggregate, sectoral, and microeconomic empirical analyses that take into account the different forms of technical change … the various compensation mechanisms and the possible hindrances they face."

A recent meta-analysis (Ugur et al., 2016) synthesizes the empirical evidence from a sub-set of the literature that estimates a derived labour demand model (DLDM) of technological change and employment. This study reports that the extent of between-study heterogeneity is high (over 75%). Moreover, the effect-size is positive but small; and indicates skill bias. Although the overall level of selection bias (i.e., the propensity to report evidence supporting the preferred hypotheses) is moderate, the risk of bias is higher when process or product innovation is investigated separately. Product- and labour-market flexibility matters but, contrary to theoretical predictions, its effect on the innovation-employment relationship is not monotonic. Finally, there is evidence that the effect is larger in primary studies published after 2000, but the effect is relatively smaller when primary-study authors use: (a) intellectual property assets as a proxy for innovation; (b) instrumental variable (IV) estimation methods; and (c) data related to high-innovation-intensity firms/industries.

This mixed-method review aims to complement the existing reviews by evaluating the findings from the diverse yet sizeable volume of work on LDCs[1], which has so far remained below the radars of policy makers and reviewers. We evaluate the qualitative and quantitative evidence reported in 55 primary studies published between 1970 and 2015; and offer three contributions to the existing literature.

[1]In this review, less developed countries (LDCs) correspond to low- and lower-middle-income countries as defined by the World Bank. http://data.worldbank.org/about/country-classifications/country-and-lending-groups#Low_income.

First, we combine narrative synthesis with meta-analysis to provide a tractable synthesis of qualitative and quantitative findings, which are heterogeneous in nature. Secondly, we provide a quantitative synthesis of the 'effect size' estimates reported in empirical studies and account for the sources of variation in the empirical evidence. Third, we demonstrate that policy statements about the relationship between technology adoption and employment in LDCs are too optimistic. We find that technological innovation does not have a significant effect on total employment; and the positive effects that can be identified are either skill-biased or limited to product innovation.

We identify two implications for future research and practice. Given the evidence on poverty-reducing effects of employment (Islam, 2004), there is a significant need to complement the work on productivity, income and consumption effects of technology adoption in LDCs with work on employment effects. However, this requires more and better-quality data on technology adoption and employment in LDCs. Such datasets can be built through community innovation surveys (CIS) similar to those implemented in developed and upper-middle-income countries and/or by extending the survey questions in the World Bank's Business Enterprise Surveys to include more detailed questions on innovation and technology adoption by LDC firms.

The review is organised in six sections. Section 2 introduces the analytical framework and the LDC context that informs the reviewed literature. Section 3 presents the systematic review methodology, including the definition and measurement of technology adoption and employment data, the search and screening strategy, and the inclusion/exclusion criteria. Section 4 discusses the mixed-method methodology and section 5 presents the findings from narrative synthesis and meta-analysis. Section 6 concludes and offers recommendations for future research and practice.

2. The analytical framework in the LDC context

The literature on technology adoption and employment is varied. One strand utilizes a derived labour demand model of technology adoption and employment, which can be estimated at the firm or industry levels (see reviews by Chennells and Van Reenen, 1999; Vivarelli, 2012). The second investigates the skill bias associated with technological change at the industry or country levels (Berman et al., 1994; Acemoglu, 1998; Machin and Van Reenen. 1998). Thirdly, a number of studies discuss the distinction between product and process innovation and emphasize the relative importance of the former for job creation (Freeman et al., 1982; Katsoulakos, 1986; Vivarelli et al., 1996; Antonucci and Pianta, 2002; Harrison et al., 2014). The fourth strand consists of work in labour economics, which models the demand for labour as an outcome of technology adoption in addition to labour-force characteristics, macroeconomic factors, wage costs, and labour market institutions (Pissarides and Vallanti, 2004).

The existing reviews suggest that the overall effect of technology adoption on employment is ambiguous (Enthorf et al, 1999; Simonetti and Tancioni, 2002; Pianta, 2004; Piva, 2003; Spiezia and Vivarelli, 2002; and Vivarelli, 1995 and 2012). This is due to a range of mediating factors that determine the balance between *displacement* and *compensation* mechanisms (**Table 1**). The mediating factors include capital intensity and/or skill bias inherent in adopted technology, international trade, labour-market and governance specific institutions, existing income inequalities, product-market competition, and the strength of forward/backward linkages between innovative firms/farms/industries and their upstream/downstream counterparts.

In the context of this study, the majority of the reviewed work is concerned with skill bias and capital intensity; and whether there is scope for choosing an optimal mix between *off-the-shelf technology* and *technology adaptation* suited to domestic skill and factor supply. The emphasis on skill bias quite often predates the work on developed countries. The reviewed work tends to argue that skill bias would reduce not only the employment of unskilled labour but also the level of overall employment. The adverse effect on overall employment is expected to result from a mixture of skill mismatch and weak absorption capacity that, in turn, lead to underutilization of the labour input, lower growth rates, and adverse effects on employment. Even if overall job destruction is avoided, the rate of job creation may be too small to absorb the increase in the supply of labour.

The range of moderating factors that affect the balance between the *compensation* and *displacement* effects of technology adoption on employment are summarised in **Table 1** below. Displacement reflects the labour-saving effects of technological change, which amounts to either an upward shift of the short-term production function or a downward shift of the cost function or both. However, economic theory has long tried has tried to point out the range of compensation mechanisms that may counterbalance the direct and harmful effects of technological change on employment (Vivarelli, 2014). The moderating factors that increase the likelihood of compensation effects include both market mechanisms and institutional quality.

One moderating factor that affects the balance between the compensation and displacement effects is international trade, which enables innovative firms and industries to create employment as they capture new markets overseas (James, 1993). However, international trade can also exacerbate the adverse employment effects of technology adoption as a result of high levels of capital intensity and skill bias inherent in the technology imported directly or via intermediate inputs (Jacobsson, 1980; Entorf and Pohlmeier, 1990; Mitra, 2009). Import penetration is seen to reduce employment particularly in large firms and more so in exporting units in spite of improvements in export competitiveness and export growth (Edwards, 2004). Trade openness, FDI inflows and technology spill-overs and their impacts on employment and wages are reported to exacerbate the segmentation of the LDC labour markets along skill types (Almeida, 2009; Cornia, 2004; Feenstra and Hanson, 1997; Gkypali, Rafailidis, and Tsekouras, 2015; Lee and Vivarelli, 2004; Lee and Vivarelli, 2006).

Table 1: Technology adoption and employment: Displacement, compensation and mediating factors

Level of analysis and technology type	Displacement mechanisms	Compensation mechanisms	Overall effect/Mediating factors
Firm/industry Level: Process-oriented technology adoption	Productivity, Skill-bias	Output growth, institutional quality, strong forward/ backward linkages	**Uncertain:** Depends on skill bias, technology mix affected by international trade and institutional quality, wage and price behaviour, and strength of forward/backward linkages.
Firm/industry Level: Product-oriented technology adoption	Product displacement	Output growth, market structure, strong forward/ backward linkages.	**Positive effect more likely:** But still contingent on price and wage behaviour, income inequalities that determine type of product innovation, and forward/backward linkages
Macro Level: both types of technology adoption	Factor substitution, skill substitution	Total factor productivity (TFP) growth, investment growth	**Uncertain:** Depends on skill bias, level of TFP growth, price and wage behaviour, income distribution, institutional quality, international trade

The balance between the effects of compensation and displacement mechanisms also depends on governance and labour-market institutions. When labour-market institutions are rigid and/or do not provide sufficient incentives for investment in skill upgrading, technology adoption is usually associated with job losses (Pissarides and Vallanti, 2004; Benavente et al, 2006). On the other hand, weak governance institutions may create perverse incentives that induce managers to prefer off-the-shelf technologies that may enhance productivity/profitability at the cost of lower demand for labour (Sen, 1974; Sigurdson, 1990).

Income distribution is also reported as a factor that mediates the effect of technology adoption on employment. Work in the Keynesian tradition (Pasinetti, 1981; Boyer 1988) demonstrates that reduced factor-income inequalities leads to increased aggregate demand that, in turn, leads to higher output and employment. Aryee (1984) draws attention to a different dynamic, which suggests that higher levels of income inequality induce firms to adopt skill- and capital-intensive technologies used in the production of goods and services that cater to a small segment of the consumers with higher incomes. Therefore, in countries with high income inequalities technology may increase the demand for skilled labour but this effect may be more than offset by reduced demand for unskilled labour.

The level of analysis and innovation type should also be taken into account. Technology adoption increases the productivity and reduces the marginal costs of innovative firms/farms, enabling them to capture new markets or increase their market shares. Consequently, innovative firms/farms may create employment but their job creation may be at the expense of output and employment losses in non-innovative counterparts. Hence the effect of technology adoption on employment at the sector/industry level may be negative or smaller than the effect at the firm/farm level. With respect to innovation type, Cirilo (2014) builds on existing work and investigates the innovative patterns of Chilean firms, distinguishing between three innovation strategies: product innovation strategy; cost-minimising innovation strategy; and non-innovators. Analysing the relationship between innovation strategies and wages, the study reports a positive effect of product innovations on wages except those of unskilled manual workers.

Finally, most studies draw attention to the role of forward and backward linkages (Hirschman, 1969). Technology adoption is more likely to have a positive employment effect the stronger are the forward and backward linkages between innovative firms/industries and their upstream or downstream counterparts.

Given the contingent nature of the technology-employment relationship discussed above, the overall effect of technology adoption on employment is ambiguous and can be verified only empirically. The aim of this review is to synthesize the evidence on LDCs, with respect to which the evidence base is limited and highly heterogeneous. Given the heterogeneity of the existing work and the ambiguity of the effect, we adopt a mixed-method synthesis proposed by Harden and Thomas (2005). The method allows for combining the strengths of the qualitative analysis in terms of conceptual constructs and contextual information with those of meta-analysis. The latter allows for the synthesis of quantitative evidence, taking into account the effects of the observable sources of heterogeneity in the evidence base, which include selection (reporting) bias, publication type, level of analysis, estimation methods and technology and skill types.

3. Review methodology and data

In this review, technology adoption refers to *implementation* of new technologies and new methods of workplace organisation or marketing with a view to enhance the quality and variety of the goods and services supplied. This definition is in line with OECD's *Oslo Manual* on innovation, the origins of which dates back to mid-1960s (OECD, 2005). Hence, we included studies that investigate the employment effects of technology adoption that is 'new to the firm' or 'new to the industry' or 'new to the world'.

In terms of technology type, we included studies that investigate the employment effects of both process- and product-oriented technology adoption. Whilst the former refers to mechanization, new irrigation systems, fertiliser use, imported technology, etc.; the latter involves use of high-yield variety seeds and introduction of new products or services. The distinction between process- and product-oriented technology adoption is not clear-cut; and the two types are rarely mutually-exclusive. Nevertheless, we maintained this distinction as primary studies make explicit references to the types of technology adoption they investigate. In this review, 80% of the primary studies investigate the employment-effects of the process-oriented or undifferentiated technology adoption, whilst 20% examine the effects of product-oriented technology adoption. The latter are mainly on agriculture and relate to the employment effects of introducing high-yield varieties (HYVs) in the context of the Green Revolution.[2]

[2] The few that focus on manufacturing include Agbesor (1984) and Aryee (1984) as qualitative studies and Otsuka et al. (1994) and Crespi and Tacsir (2012) as quantitative studies.

The outcome variable in this review is *employment*. Primary studies with a focus on sector or macro levels utilise national employment statistics compiled in accordance with International Labour Organisation (ILO) guidelines. Studies that examine the employment effects at the firm or farm level utilise employment data based on national surveys or field-study surveys.

We included studies that examine the effect of technology adoption on total employment as well as employment of skilled or mixed-skill labour. We have coded the skill types with a view to verify whether technology adoption is skill-biased. However, we did not include studies that examine the effect of technology adoption on skill shares in the wage bill. This is because wage shares capture not only the difference in the demand for skilled and unskilled labour but also the difference in wage-income.

We synthesize the evidence at the firm/farm, industry/sector and macro levels; and within two broad sectors consisting of agriculture and manufacturing. This is in contrast to the 'manufacturing bias' that characterises the primary studies on developed and upper-middle-income countries (Piva, 2003; Vivarelli, 2012). While 52% of the primary studies examine the employment-effects of technology adoption in agriculture, 46% focus on manufacturing. Only one study (Moore and Craigwell, 2007) examines the effects of technology adoption on employment in services (banking in Barbados in the 1980s and 1990s).

We followed an inclusive search strategy to take account of the diverse nature of the research field.[3] We also implemented study screening, evaluation and inclusion/exclusion criteria informed by best-practice in systematic reviews of public policy and health literature [Joanna Briggs Institute (JBI), 2008; Centre for Reviews and Dissemination (CRD), 2009]. In stage one of the review process, we applied *population-intervention-outcome-study design (PIOS)* criteria to *title* and *abstract* of 4,055 results obtained from electronic searches. PIOS criteria ensure that the study is on low-income countries, the intervention variable is technology adoption, the outcome variable is the level of employment, and the study is either qualitative or quantitative or both. Of the total number of hits, we selected 379 studies as relevant - including 22 studies identified through hand search and snowballing. In stage two, we re-applied the PIOS criteria to full-text information about the selected studies; and decided to keep 80 studies for critical evaluation. In stage three, we evaluated the included studies using *validity-reliability-applicability (VRA)* criteria for critical evaluation; and excluded studies which did not meet at least one of the VRA criteria.

Data for the narrative synthesis is organised along thematic (vertical) and content (horizontal) identifiers that enabled us to capture the dimensions of the research field (Popay et al., 2006). The thematic identifiers capture two types of technology adoption: process-oriented and product-oriented. The content identifiers capture the level of analysis – i.e., whether primary studies investigate the employment effects at the

[3] We searched in 30 electronic databases for journal articles, book chapters, working papers, and reports; using 24 search terms for technology adoption as the *intervention variable*; 20 terms for employment as the *outcome variable;* and 20 terms for LDCs as *population*. In addition, we hand-searched journals and conference proceedings that tend to publish work on the technology adoption-employment relationship.

firm/farm, industry/sector or macro levels. Hence, we have a maximum of 2x3 evidence clusters for recording the main finding(s), the context of the findings, and the effect of the moderating factors on the relationship between technology adoption and employment. We repeated this exercise twice: once for agriculture and once for manufacturing.

Data for meta-analysis consists of 181 effect-size estimates reported in 12 primary studies.[4] We included all effect-size estimates instead of a 'representative' single estimate because selection criteria are rarely objective and there is no consensus within the literature on the 'best' estimation method from which the preferred estimate should be chosen. Besides, reliance on a single 'representative' estimate implies inefficient use of all available information (de Dominicis et al, 2008; Stanley, 2008; and Stanley and Doucouliagos, 2009). In addition, we extracted standard errors (or test statistics) associated with each effect-size estimate. Finally, we coded each effect-size estimate to identify the publication type, the model and estimator type, the level of analysis, the employee skill type, the type of technology adoption, and the country/region of the study.

4. The mixed-method

Mixed-method reviews (Harden and Thomas, 2005) map qualitative and empirical evidence from primary studies that differ with respect to method (qualitative *versus* quantitative), context, and analytical framework. The mixed method combines the strength of the *narrative synthesis* in synthesizing qualitative evidence with those of *meta-*

[4] Eligible empirical studies that do not report standard errors or t-values for the effect-size estimates (e.g., Edwards, 2004) are excluded. This is because standard errors or t-values are necessary for meta-regression analysis.

regression analysis that provides a quantitative synthesis of comparable effect-size estimates whilst taking into account the effects of selection (reporting) bias, variety of empirical models and estimation methods, and the metrics with which the intervention and outcome variables are measured.

In the narrative synthesis, we focus on the contextual and institutional factors that determine the balance between the displacement and compensation mechanisms, paying attention to contexts and levels of analysis. The narrative synthesis enabled us to: (i) account for how technology adoption affects employment, why and for whom; (ii) synthesize the overall findings; and (iii) capture the effects of the mediating factors on reported findings.

In the meta-analysis section, we provide three sets of evidence. First, we present median values of the effect-size estimates reported in 12 empirical studies. This is followed with funnel graphs that depict the extent of heterogeneity and the risk of selection (reporting) bias. Then, we present bivariate met-regression estimates of the 'average' effect size after controlling for selection (reporting) bias. Finally, we provide multivariate meta-regression results that quantify the effects of the moderating factors on the relationship between technology adoption and employment. All models and estimation methods are presented and discussed in the *Appendix*.

The meta-analysis results are based on partial correlation coefficients (PCCs), calculated in accordance with equations (1) and (2) in the *Appendix*. PCCs are necessary to ensure comparability between the effect-size estimates based on different metrics for the dependent and independent variables. However, the PCC is truncated between -1 and +1;

and its variance becomes smaller as its absolute value |PCC| gets closer to 1. In contrast, the variance of the Fisher's Z transformation is approximately constant for all values of the *PCC*. Although the Fisher's Z is not defined when $|PCC| = 1$, Corey et al. (1998) report that Fisher's Z is a less biased estimate of the population correlation even in small samples.

We group the primary-study estimates into nine clusters that correspond to unique pairs of technological innovation types (process, product and undifferentiated innovation types) and skill types (skilled, unskilled and mixed-skill labour). We conduct bivariate meta-regression analysis (BVMRA) of the effect-size estimates within such clusters provided that the cluster contains at least 10 effect-size estimates reported by more than one primary studies. The BVMRA allows: (a) a precision-effect test (PET) for verifying if 'genuine' effect exists after controlling for selection (reporting) bias; and (b) a funnel asymmetry test (FAT) for establishing whether selection (reporting) bias exists. Our PET-FAT model specification (model 3b in the *Appendix*) draws on earlier work by Stanley (2008), Stanley and Doucouliagos (2012), and Ugur et al. (2016) among others. The underlying theoretical model (Egger et al., 1997) and issues in its estimation are discussed in the *Appendix*.

If the precision-effect test indicates 'genuine' effect beyond selection bias, the consistent estimate is obtained after allowing for non-linear relationship between effect-size estimates and their standard errors (Moreno et al., 2009; Stanley and Doucouliagos, 2014). In this case, the model is estimated by supressing the constant term and the procedure is known as precision-effect test with standard errors (PEESE) (model 4b in The *Appendix*).

We estimate the BVMRA models with different estimators (OLS, fixed effects, and hierarchical model estimators) that correspond to different assumptions about data dependence. We report the results from the estimator that yields the lowest values for the Akaike and Bayesian information criteria (AIC and BIC).

PET-FAT-PEESE estimations allow for making inference about the existence or absence of 'genuine effect' for the typical study, but they assume that all moderating factors that may influence the reported estimates are all at their sample means and independent of the standard error. This is a restrictive assumption, given the heterogeneous nature of the evidence base. Therefore, we also estimate a multivariate meta-regression model (MVMRM), which allows for quantifying the effects of the observable sources of heterogeneity in the evidence base (Model 5 in the *Appendix*). Similarly to PET/FAT/PEESE estimations above, we estimate the MVMRM with different estimators and rely on results from the estimator that yields the lowest value for AIC and BIC.

5. Results from narrative synthesis and meta-analysis

The narrative synthesis findings are based on 43 qualitative studies, the overview of which is presented in **Table A1** in the *Appendix*. We synthesize the qualitative evidence on the innovation-employment relationship *in agriculture*, *in manufacturing* and *with respect to female employment*. As much as the data allows, we organise the narrative synthesis at the micro (firm/farm), meso (industry/sector) and macro (country/region) levels. We also differentiate between technology and skill types, including: *process* and *product* innovation; and *skilled*, *unskilled* or *mixed-skill* labour. In all cases, we pay special attention to the role moderating factors, which affect the balance between the *displacement* and *compensation* effects. The moderating factors include institutional quality, income distribution, the role of forward/backward linkages, and the role of international trade.

5.1 Narrative synthesis of the evidence in agriculture

With respect to *process-oriented technological change* in agriculture, a number of studies investigated the effects of mechanization on *farm-level employment*. The overall conclusion is that mechanization on its own tends to have a negative effect on farm employment. The effect is reported as positive when mechanisation is accompanied by extension of the farm size and hiring of outside labour. This conclusion is based on evidence reported by: Chopra (1974) on farmers in 13 Punjabi villages, India; Bhatia and Gangwar (1981) on 965 small farms in Karhal district of India; Agarwal (1981) on 240 farms in India; De Klerk (1984) on 61 maize farms in South Africa; Inukai (1970) on rice farmers in Thailand; and Lalwani (1992) on dairy farming in India.

The adverse effect or mechanisation is more evident when farm size is large to begin with or mechanization is used for ploughing and harvesting operations instead of sowing (De Clerk, 1984; Agarwal, 1981). With respect to labour type, mechanization is reported to reduce the employment of family labour and that of young farmers (Agarwal, 1981; Chopra, 1974); but it tends to increase the employment of seasonal labour and child labour (De Clerk, 1984). In contrast, mechanization tends to have a positive effect on employment when it is accompanied with product differentiation and strong forward/backward linkages between agriculture and manufacturing industries (Lalwani, 1992; Bhatia and Gangwar, 1981; Chopra, 1974; Inukai, 1974). Type of process-oriented technology adoption also matters: the effect on farm employment is more likely to be positive when it consists of introducing new feeds/fertilizers and irrigation techniques (Lalwani, 1992; Bhatia and Gangwar, 1981; Chopra, 1974). The employment effect is also more likely to be positive when the evidence is on India compared to other countries.

Another cluster of studies examine the effects of process-oriented technology adoption on on-farm/off-farm employment in the context of the *Green Revolution (GR)*. Of these, 7 studies focus on South Asia, 2 on East Asia, 2 on the Middle-East and Africa, and 1 on LDCs in general. A number of these studies distinguish between short- and long-run employment effects of the GR technologies. In the short run, GR technologies are associated with uncertain employment effects – even though the long-run effect is reported as positive but only with respect to *off-farm* employment. The *on-farm* employment effect is negative even in the long run (Cepede, 1972; Sharma, 1974 and 1990; Singh and Day, 1975; Wills, 1972; Ahmed, 1988; and Baker and Jewitt, 2007). Two factors amplify the positive effect of the GR on *off-farm* employment: increased demand for new products/services due to increased farmer income; and strong forward and backward linkages between farm and non-farm activities (Ahammed and Herdt, 1983 and 1984; Sharma, 1974 and 1990; Ahmed, 1988).

Although GR technologies tend to reduce the seasonality of employment, they do reduce income or wealth inequalities (Sharma, 1974 and 1990; Cepede, 1972; Barker and Jewitt, 2007). As a specific GR technology, mechanization tends to have a negative effect on *on*-

farm employment in general; and the adverse effect is more pronounced when mechanization is combined with rain-fed instead of man-made irrigation systems (Ahammed and Herdt, 1983 and 1984; Clayton, 1972; Richards and Ramezani, 1990; and Nair, 1980).

Only a few studies examine the effect of *product-oriented technology adoption* (introduction of HYVs) on employment. These *sector-level* studies report that the use of HYVs had a positive effect on *on-farm* and *off-farm* employment. However, the effect is mediated through wage behaviour and forward/backward linkages. The evidence from the Philippines (Barker et al., 1972) and from Punjab (Chand, 1999) indicates that the effect is smaller and may even be negative if wages increase after introduction of HYVs. However, the effect is more likely to be positive when forward and backward linkages are strong.

5.2 Narrative synthesis of the evidence in manufacturing

Early studies on technology adoption and employment in manufacturing were informed by the *appropriate technology* debate, which focused on the scope for adapting off-the-shelf (usually, imported) technology to local skill and factor endowments. The findings of the early debate are summarised in Baer (1976), with the following conclusions: (i) factor-price distortions in LDCs encourage the selection of capital-intensive technology; (ii) existing technologies do not match factor supplies in LDCs; (iii) the scope for technology adaptation in LDCs is limited because of low levels of research and development by local firms and/or governments; and (iv) skewed income distribution results in a consumer demand profile that favours the establishment of industries with capital-intensive technologies. The overall conclusion in Baer (1976) is that technology adoption in LDCs is likely to have adverse effects on employment; or the employment effect is likely to be too small to absorb the excess supply of labour.

Appropriate technology is a useful concept that draws attention to issues of technology choice and whether the chosen technology can be adapted to local conditions. However, its policy uptake proved limited because of the conflict between the employment and productivity objectives of the policy makers. Sen (1974) proposed a model in which the policy-maker's objective includes a set of employment targets (such as informal sector employment, female employment, family employment, seasonal/casual employment and regular wage employment) in addition to productivity targets. Sen's overall conclusion is that the solution to the maximization problem depends on institutional factors rather than constraints implied by the production process. Therefore, institutional reforms can enhance the scope for *adaptation* of the off-the-shelf technology to local needs.

Although its influence on policy and practice has remained limited, Sen's work had informed a large number of studies on the scope for technology adaptation in the LDC context. Two features of the post-Sen literature are worth emphasizing. First, particular attention is paid to how moderating factors (such as institutions, income distribution, and international trade) affect the balance between displacement and compensation mechanisms associated with technology adoption. Secondly, a clear distinction is drawn between the effects of technology adoption on skilled and unskilled labour employment – well before the issue has occupied the scholarly and policy debate of the 1990s in the context of developed countries.

In manufacturing, only two studies analyse the employment effects of *product-oriented technology adoption* at firm level: Agbesor (1984) on two companies in Nigeria and Aryee (1984) on footwear industry in Ghana. Both studies report that the effect is positive, but mediated through three moderating factors: (i) income distribution; (ii) skills; and (iii) forward/backward linkages. The effect is more likely to be positive and larger if adopted technology is utilized in the production of goods/services catering for the demand of the lower income groups; the adopted technology matches the existing skill distribution; and the adopted technology is utilized in the segment(s) of the production process that generate strong forward and backward linkages either through production or through marketing/distribution channels.

Three studies investigate the effects of *process-oriented technology adoption* on *firm-level employment*. Ekwere (1983) studies the scope for job creation in small textiles industries in Nigeria, using field survey evidence. Usha (1985) examines the effects of technology adoption on employment in the Indian footwear industry after the Export Trade Control Order of 1973. Finally, Braun (2008) analyses the interaction between economic integration, technology adoption, and relative skill demand in a model of international oligopoly. One conclusion supported by the evidence from these studies is that firm-level technology adoption tends to be skill-biased and capital-intensive (Ekwere, 1983; Braun, 2008). Secondly, international trade tends to exacerbate the skill bias (Braun, 2008). Finally, weak institutions inhibit the choice of labour-absorbing technologies (Ekwere, 1983; Braun, 2008); and exacerbate segmentation in the labour market (Usha, 1985).

As indicated in section 1, above the distinction between product and process innovation has been discussed widely in the context of developed and upper-middle-income countries (Antonucci and Pianta, 2002; Harrison et al. (2014); Katsoulacos (1986); and Vivarelli, Evangelista, and Pianta, 1996). Our review includes 12 studies that examine the effects of process-oriented technology adoption at the industry/sector level in the LDC context. One conclusion from this literature is that the employment effect depends on capital intensity of the production process (Kelley et al, 1972; Mureithi, 1974; and Stewart, 1974). A second conclusion relates to the role of institutions. Sigurdson (1990) distinguishes between *technology adoption* in large-scale sectors and *technology adaptation* within local and small-scale enterprises in China. The study demonstrates that the dual approach in China was conducive to job creation, largely thanks to institutional and management norms that required planners and state officials to ensure that local needs are incorporated into technology designs and product development. The third conclusion relates to international trade as a mediating factor. Berman and Machin (2000) and Berman et al (2005) report that developing countries are importing capital-intensive technologies that increase the demand for skilled-labour at the expense of unskilled labour.

The adverse effect of process innovation is more likely if: (i) production is characterized by increasing returns to scale (Choi et al., 2002); the mismatch between imported technology and local absorption capacity is large (Mitra, 2009); and (iii) imported technology requires higher skill levels (Conte and Vivarelli, 2011).

Jacobbson (1980) also report that the adverse effect of international trade is evident in the case of booth North-South and South-South trade. Indeed, the latter is found to consist of imports and exports of intermediate inputs with high levels of capital intensity. A number of other studies report similar findings on the skill bias associated with imported technology (Araújo, Bogliacino and Vivarelli, 2011; Meschi and Vivarelli, 2009; Meschi, Taymaz and Vivarelli, 2011; Robbins, 2003; Robbins and Gindling, 1999).

Mitra and Jha (2015) argue that the R&D expenditure of several Indian firms does not mean actual technological innovation. Though the findings are not supportive of a positive relationship between R&D and productivity, the elasticity of employment with respect to R&D is seen to be positive in a number of industries. Even when R&D does not mean actual innovation, it involves processing of by-products and efforts pursued to bring in an improvement in product quality and efficiency, all of which may be resulting in employment gains. This finding has important policy implications, reinforcing the importance of incentives for pursuing R&D on a larger scale.

Some studies examine the employment effects of technology adoption at the macro level. One conclusion from this work is that institutional characteristics of the country and those of the labour markets determine the technology choice and hence the scope for employment creation (Annable, 1971; Fagerberg, 2010; Garmany, 1978; and Caballero and Hammour, 1996). Another conclusion is that employment creation in LDCs requires an optimal balance between capital-deepening in the main manufacturing sectors and use of labour-intensive technologies in other sectors (Annable, 1971; Garmany, 1978). A third conclusion is that imported technology is costly and may not be absorbed efficiently due to skill shortage (Abramovitz, 1986; Lall, 2004; and Perez, 1983; Mitra, 2009).

Finally, we have reviewed four studies on the relationship between innovation and *female employment* (Ahmed, 1987); Bhalla, 1989; Billings and Singh, 1981; and Tuyen, 1999). Their findings indicate that: (i) process innovation in agriculture is associated with lower female participation in farm employment, but higher female contribution to housework and child care; (ii) process innovation in manufacturing tends to increase employment of relatively better educated and younger women at the expense of less educated and older women; and (iii) process innovation in manufacturing is associated with gender-based job segmentation and this effect is more pronounced in textiles and electronics plants compared to others.

The synthesis above allows us to conclude that the effect of technology adoption on employment is uncertain at best. Job-creating effects are likely to dominate when: (i) skilled-labour employment is investigated; (ii) forward and backward linkages are strong; (iii) the evidence relates to India and China as opposed to other world countries; and (iv) institutional quality is conducive to optimal technology choice, investment in skills and wage flexibility. On the other hand, job-destroying effects are more likely when: (i) new technologies are adopted to cater for the demand of high-income consumers; (ii) international trade is capital-intensive; and (iii) mechanization in agriculture is not combined with new irrigation systems and fertiliser use.

5.3 Meta-regression analysis findings

Table 2 below presents an overview of the empirical studies. It summarises the innovation and skill types examined, the data period, and the number of reported estimates; followed by the median values for two standardised measures of the 'effect size' (PCC and Fisher's Z), together with associated median t-values. The close similarity between the PCCs and their Fisher's Z equivalents suggest that the truncated nature of the PCC is not likely to pose a serious problem in effect-size estimations below. The median effect-size is positive, but it is associated with median t-values that fall below the significance threshold. Moreover, between-study variation of the effect-size estimates is high, ranging from -0.129 (Sison et al, 1985) to 0.229 (Mitra and Jha, 2015). In five studies, the median effect size is associated with median t-values of 2 or greater. In the remaining seven studies it is associated with median t-values smaller than 2.

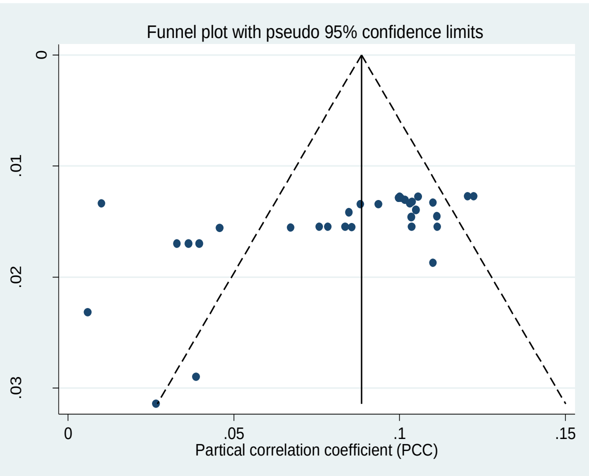
Table 2: Overview of the empirical studies

Study	Data period	Reported estimates	Country, Data and Estimation method	Type of technological innovation	Skill type	Sector	Median PCC	Median t-value (PCC)	Median Fisher's Z	Median t-value (Fisher's Z)
Almeida (2010)	2003-2005	25	East Asia; Survey data; OLS	Process	Skilled	Manufacturing	**0.102**	**7.519**	**0.102**	**7.506**
Benavente and Lauterbach (2008)	1998-2001	3	Chile; Survey data; OLS, IV	Product		Manufacturing	0.024	0.548	0.024	0.548
Conte & Vivarelli (2011)	1980-1991	12	Multi-country; UN data; GMM	Process	Skilled, Unskilled	Manufacturing	0.028	1.659	0.028	1.659
Crespi and Tacsir (2013)	1995-2009	20	Argentina, Chile, etc. Survey data; OLS	Product	Mixed	Manufacturing Non-manufac.	**0.184**	**4.784**	**0.187**	**4.836**
Lundin et al (2007)	1998-2004	18	China; Survey Data; Heckman selection	Process	Mixed	Manufacturing	-0.006	-0.865	-0.006	-0.868

Mitra and Jha (2015)	1998-2010	11	India; FE, RE, OLS	Mixed	Mixed,	Manufacturing	**0.229**	**2.190**	**0.233**	**2.178**
Moore and Craigwell (2007)	1979-2001	6	Bank data; IV	Process	Mixed	Services	0.034	0.401	0.034	0.419
Oberai and Ahmed (1981)	1977	8	ILO H/hold survey; OLS	Process, Product	Mixed	Agriculture	0.022	0.645	0.022	0.648
Otsuka et al (1994)	1966-1990	34	Farm survey; 2SLS	Process, Product	Mixed	Agriculture	-0.003	-0.070	-0.003	-0.071
Pandit & Siddhartan (2008)	1991-2001	1	Survey data; GLS	Process	Mixed	Manufacturing	-0.039	-0.630	-0.039	-0.676
Raju (1976)	1968-1971	38	Farm survey; OLS	Process, Product	Mixed	Agriculture	**0.574**	**2.230**	**0.653**	**2.355**
Sison et al (1985)	1979-1980	5	Rice survey data; Covariance analysis	Process	Mixed	Agriculture	**-0.129**	**-2.620**	**-0.130**	**-2.654**
All		*181*					*0.074*	*1.330*	*0.074*	*1.334*

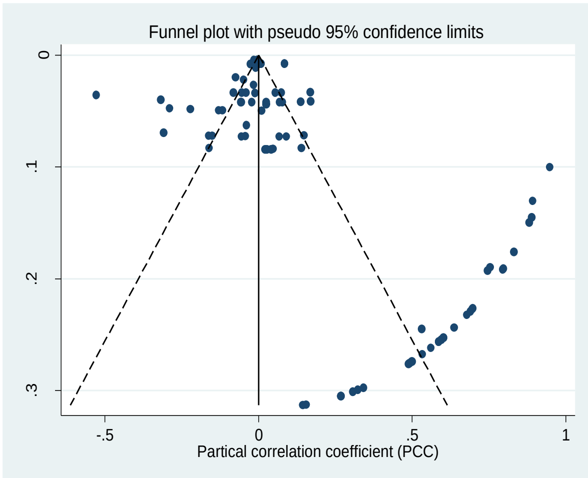
Although Table 2 provides useful information about the evidence base, it does not allow for conclusions concerning the effect of technology adoption on employment. For that purpose, we first break down the evidence into pools that correspond to specific pairs of innovation and skill types, followed by the full sample. Separate estimates for each pool are provided if the pool contains evidence from at least two studies reporting 10 estimates or more. The funnel plots that correspond to qualifying pools are presented in **Figure 1**.

Figure 1: Funnel plots of tecnology adoption and employment evidence pools



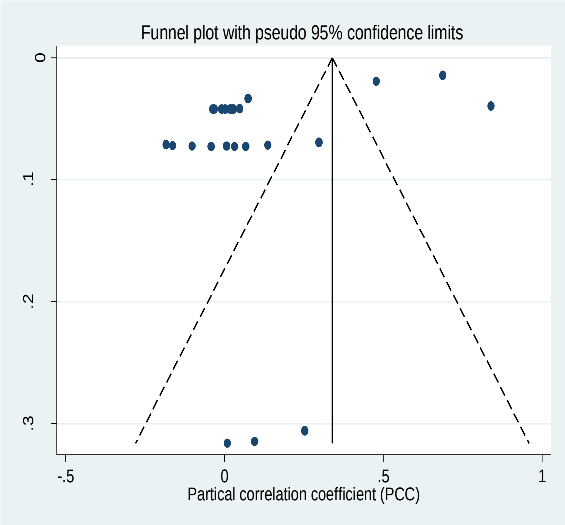
A. Process innovation and skilled-labour demand

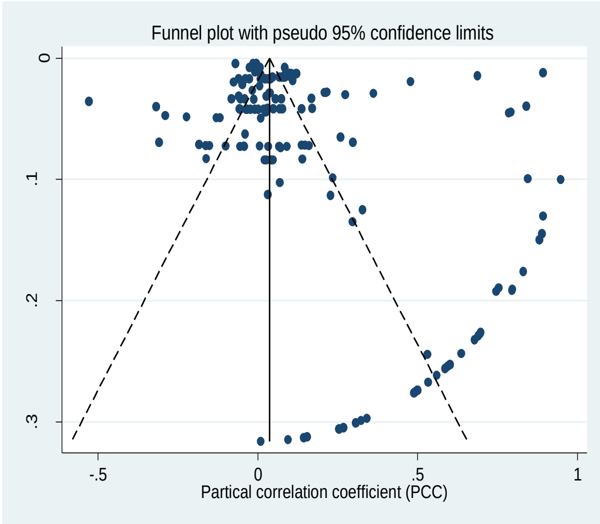
Residual variation due to heterogeneity: 66.21%



B. Process innovation and mixed-skill labour demand

Residual variation due to heterogeneity: 91.77%





C. Product innovation and mixed-skill labour demand

Residual variation due to heterogeneity: 97.62%

D. Full sample (all innovation and skill types)

Residual variation due to heterogeneity: 98.41%

Note: Residual variation due to heterogeneity is obtained from random-effect meta-regression proposed by Harbord and Higgins (2008), who suggest that residual variation above 75% reflects high levels of heterogeneity. The fixed-effect mean and 95% pseudo confidence intervals are based on Sterne and Harbord (2004).

The plots provide visual indicators about heterogeneity (number of observations outside the 95% pseudo confidence intervals); the fixed-effect mean of the effect size (the vertical lines); and the risk of selection bias (uneven distribution of the observations around the fixed-effect mean) (Sterne and Harbord, 2004). These funnel graphs suggest that technology adoption is associated with employment creation (positive effect) only in the case of skilled-labour employment (pool A) and product innovation and mixed-skill labour employment (pool C). Furthermore, the level of heterogeneity is moderate in pool A but high in pools B, C and D. This is confirmed by estimates of residual variation, which is 66.21% in pool A; and ranges from 91.77% to 98.41% in pools C to D. Finally, the funnel plots indicate risk of selection bias in all pools.

Two issues arise from these empirical patterns: (ii) summary statistics (means or medians) based on estimates reported in primary studies are unreliable as they are contaminated with selection (reporting) bias; and (ii) high levels of heterogeneity limit the extent to which summary measures can be generalised – even if they take account of selection bias.

We address the first issue by estimating the bivariate PET/FAT/PEESE models, which take account of selection bias and non-linear relationship between the effect-size estimates (PCCs) and their standard errors. The second issue is addressed by estimating a multivariate meta-regression model in which various dimensions of the research field (e.g., publication type, estimation method, data period, country type, etc.) are controlled for via dummy variables interacted with precision (the invers of the standard error) (Stanley and Doucouliagos, 2012).

Table 3: Testing for genuine effect beyond selection bias: Using partial correlation coefficients (PCCs)

	PET/FAT(1)	PET/FAT(2)	PET/FAT(3)	PET/FAT(4)	PET/FAT(5)	PEESE(6)	PEESE(7)
	Process/Skilled	Process/Unskilled	Product/Mixed	Full sample	Full sample	Process/Skilled	Product/Mixed
	Unweighted	Unweighted	Unweighted	Unweighted	Weighted	Unweighted	Unweighted
Dependent variable: t-values	FE, B/strap	FE, B/strap	FE, B/strap	FE	FE	OLS, BS	OLS, BS
Precision of PCC	0.189***	-0.025	0.397*	0.072	0.063	0.118***	0.363**
(Effect)	(0.042)	(0.027)	(0.224)	(0.109)	(0.138)	(0.014)	(0.149)
Constant (Bias)	-6.908**	1.661*	-4.031	-0.022	-0.483		
	(2.888)	(0.892)	(3.654)	(3.752)	(5.143)		
Std. Error of PCC						-137.941**	-13.938
						(63.263)	(13.664)
Observations	33	93	25	180	180	33	25

Studies	3	9	4	12	12	3	4
F					0.208		
p>F					0.657		
Chi^2	19.912	0.879	3.160	0.442		406.944	7.009
p>Chi^2	0.000	0.349	0.075	0.506		0.000	0.030
Log likelihood	-61.125	-231.789	-63.215	-598.264	-574.069	-64.691	-86.686
AIC	126.249	467.578	130.429	1200.527	1150.137	133.382	177.373
BIC	129.242	472.643	132.867	1206.913	1153.330	136.375	179.810

Note: PET/FAT/PEESE models are as specified in the *Appendix*. Estimator choice is based on minimum AIC and BIC values, comparing OLS, fixed-effect and hierarchical model estimations. Estimator comparison applies within PET/FAT and PEESE estimations separately. Fixed-effect estimations in (1) to (5); OLS estimations in (6) and (7). Standard errors are bootstrapped (BS) with 2000 replications, with the exception of (5). Model (5) is based on the full sample as model (4) is, but it is estimated by weighting the primary-study estimates with *1/N*, where *N* is the number of effect-size estimates per study. Hence, the weight of each study in the full sample adds up to 1. Observations with undue influence (outliers) are excluded using the DFBETA influence statistics. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

Results in Table 3 column 1 indicate that the effect of *process innovation* on *skilled-labour employment* is positive and significant (0.189). The effects is also positive in the case of *product innovation* and *mixed-skill labour employment* (0.397) in column 3. Although both effect-size estimates are associated with negative selection bias, the latter is significant only in the case of process innovation and skilled-labour employment (-6.908). The consistent (PEESE) estimates for these effect sizes are reported in columns 6 and 7. According to Doucouliagos (2011), the effect on skilled-labour employment (0.118) is medium and that for product innovation (0.363) is large. However, the effect is non-significant in remaining pools, including the full sample. We have also checked if the results differ when Fisher's Z transformation of the PCC is used. The results are presented in Table A2 in the *Appendix* and confirm the findings reported here.

The significant effects we identify here are in line with the narrative synthesis findings, which suggest that the employment effect of technology adoption is more likely to be positive when skilled-labour demand is estimated and when technology adoption involves product innovation. However, it must be noted that our findings are based on a narrow evidence base, which consists of 58 estimates from 7 primary studies. With this caveat in mind, it is possible to add that the absence of significant effects in the full sample is also compatible with the narrative synthesis. As indicated above, the latter indicates that the overall employment effect of technology adoption is uncertain due to multiplicity of the mediating factors that affect the balance between the displacement and compensation effects of the technology adoption.

To identify the sources of heterogeneity in the evidence base, we estimate a MVMRM (model 5 in the *Appendix*) with a range of moderating variables and control for within-study dependence. Summary statistics for and definitions of the moderating variables are presented in Table A3 in the *Appendix*.

The preferred estimates with minimum AIC and BIC values are in column (5) of Table 4, followed by those in column (4). The first point to make is that multicollinearity is not a serious issue as the variance inflation factor of 4.09 is much lower than the maximum threshold of 10 usually adopted in applied econometric work. However, the maximum number of moderating factors that we could model without incurring the cost of multicollinearity reduces the residual heterogeneity only by about 2.5% - from 98.41 in the bivariate model to 95.93% in the MVMRM. Nevertheless, it is in line with Ugur et al. (2016) on innovation and employment in the context of developed and upper-middle-income countries. This latter study reports that observable sources of variation reduce residual heterogeneity form 85% to 80% only. The findings from the two reviews suggest that the empirical evidence on technological change and employment is highly heterogeneous, albeit the level of heterogeneity is higher in the LDC context.

Table 4: Sources of variation in reported evidence:

Multivariate meta-regression results

	(1)	(2)	(3)	(4)	(5)
Precision of PCC	0.014	0.014	0.225***	0.225	0.010
	(0.029)	(0.088)	(0.083)	(0.170)	(0.080)
Journal article	0.175	0.175	-0.033	-0.033	0.166*
	(0.156)	(0.241)	(0.099)	(0.281)	(0.082)
Farm-level data	-0.288	-0.288	-0.191	-0.191	-0.270**
	(0.335)	(0.328)	(0.149)	(0.473)	(0.097)
Product innovation	0.455***	0.455***	0.314***	0.314***	0.467**
	(0.056)	(0.140)	(0.051)	(0.111)	(0.195)
Unskilled labour	-0.071	-0.071**	-0.061	-0.061**	-0.082***
	(0.050)	(0.031)	(0.041)	(0.030)	(0.010)
Low-income country	-0.063	-0.063	-0.120	-0.120	-0.071**
	(0.161)	(0.040)	(0.107)	(0.118)	(0.023)
IV estimator	-0.366***	-0.366*	-0.276***	-0.276*	-0.258*
	(0.084)	(0.219)	(0.059)	(0.161)	(0.127)
Data midpoint	-0.052	-0.052	-0.105*	-0.105	-0.051***
after 2001	(0.077)	(0.238)	(0.057)	(0.259)	(0.015)
Constant	2.352	2.352	0.810	0.810	2.127
	(2.454)	(2.153)	(1.089)	(2.148)	(1.609)

Observations (N)	180	180	180	180	180
Studies	12	12	12	12	12
F	12.294				27.08
p>F	0.000				0.000
Chi^2		353.225	78.708	19.109	
p>Chi^2		0.000	0.000	0.014	
Log likelihood	-557.550	-557.550	-551.693	-551.693	-535.561
AIC	1133.099	1133.099	1127.386	1127.386	1081.122
BIC	1161.836	1161.836	1165.702	1165.702	1097.087
VIF	4.09	4.09	4.09	4.09	4.09
Residual heterogeneity	95.93%	95.93%	95.93%	95.93%	95.93%

Note: Dependent variable is t-value of PCC. (1) is fixed effect estimates; (2) is fixed effect estimates with bootstrapped standard errors; (3) is Hierarchical method estimation with random slopes and intercepts; (4) is Hierarchical method estimation with random slopes/intercepts and bootstrapped standard errors; (5) is weighted fixed effect estimates using *1/N* as weights. Bootstrapping is with 2000 replications. Observations with undue influence (outliers) are excluded using the DFBETA influence statistics. VIF is variance inflation factor. ***, **, * indicate significance at 1%, 5% and 10% respectively. Estimates of random effect components in hierarchical models (standard deviations of between- and within-study variation) are not reported to save space.

Another set of conclusions that can be derived from findings in Table 4 relate to the role of moderating factors. We conclude that there is:

- Strong evidence if the estimate is significant in the preferred model (5) and consistent with estimates in at least two other models;
- Moderate evidence if the estimate is significant in the preferred model (5) and consistent with estimates in one other model; and

- Weak evidence if the estimate is significant in the preferred model (5) only.

Applying these criteria, we derive the following conclusions.

A. There is strong evidence that:

- Primary-study estimates on the relationship between *product innovation* and employment are larger than those on the relationship between employment and process innovation or undifferentiated innovation. This finding reinforces the BVMRA finding that product innovation is associated with a positive effect on employment. It is also with the narrative synthesis finding on the role of product innovation.
- Primary-study estimates on the relationship between technological change and *unskilled-labour employment* are smaller than those related to skilled- or mixed-skill-labour employment. This finding lends support to both meta-regression and narrative synthesis findings that technology adoption in LDCs is skill-biased.
- Technology adoption may not be strictly exogenous due to simultaneity in the innovation-employment relationship, mismeasurement or model misspecification. This is reflected in relatively smaller effect-size estimates obtained from IV estimators that take account of endogeneity. This is in line with Ugur et al., (2016), who report relatively smaller estimates from IV estimators in the context of both developed and developing countries.

B. There is moderate evidence that more recent data (specifically, datasets with mid-year after 2001) is associated with smaller effect-size estimates compared to pre-2001 data. A quick inspection of Table 2 indicates that this findings is *not* due to the preponderance of IV-based estimators in the post-2001 period. Indeed a slight majority of the IV estimates come from studies with data mid-points before 2001. Therefore, we conclude that increased globalisation and rapid technological change in the latter period is likely to be associated with smaller (or negative) job-creating effects. Although the evidence base is limited and heterogeneous, this finding suggests that policy statements that establish a positive relationship between technological innovation and employment in LDCs may be over optimistic.

C. There is weak evidence that:

- Journal articles tend to report larger effect-size estimates compared working papers and reports.
- Effect-size estimates based on farm data are relatively smaller than those related to employment in firms and industries.
- Effect-size estimates related to low-income countries are relatively smaller than those related to employment effects in lower-middle-income or mixed countries.
- Although they are based on weak evidential support, the latter two findings lend some support to the narrative synthesis that the employment effects of technology adoption in LICs may be too small to absorb the increasing labour supply due to higher population growth rates or higher rates of rural-urban migration.

8. Overall conclusions

This systematic review demonstrates that the mixed-method evidence synthesis is effective in integrating research findings from primary studies that differ with respect to method (qualitative versus quantitative), country and period coverage, and the type of technology adoption and skill types investigated. The mixed-method approach has enabled us to add to existing knowledge by: (i) bringing into attention of the research and policy community a sizeable literature that has remained outside the mainstream debate on employment effects of technological change; and (ii) demonstrating that this below-the-radars literature often predates the wider literature in its emphases on the role of institutions, market structure, income distribution, skill bias, and international trade in the innovation-employment relationship.

Both narrative synthesis and meta-analysis findings indicate that the effect of technology adoption on employment is more likely to be positive when the evidence is related to skilled-labour employment and product innovation. In contrast, the effect is smaller or negative when the data relates to: (i) unskilled labour employment; (ii) on-farm employment as opposed to off-farm employment; and (iii) low-income countries as opposed to lower-middle-income countries.

Review findings supported by narrative synthesis only indicate that the employment-effects of technology adoption are more likely to be positive when: (i) there are strong forward/backward linkages between innovative firms/farms/industries and their upstream or downstream counterparts; and (ii) governance institutions encourage and facilitate technology adaptation instead reliance on off-the-shelf technology only. In contrast, the employment effects are more likely to be small or negative when technology adoption is dependent on imported technology

These findings indicate that policy statements that establish or suggest a short-cut relationship between technology adoption on the one hand and employment creation on the other should be qualified. Our findings indicate that the effect of technology adoption on employment in LDCs is skill-biased; and the overall effect is uncertain. To ensure that the employment-creation effect dominates the job-destruction effect, technology adoption should be combined with policies aimed at enhancing institutional quality and encouraging investment in skill upgrading.

Our findings also indicate that the evidence base is highly heterogeneous. Heterogeneity does not invalidate the findings we report as the latter are robust to method variation and informed by best practice in evidence synthesis. However, excessive heterogeneity limits the extent to which the findings can be generalised. Stated differently, the findings provide useful insights about what has worked and what has not worked with respect to innovation-driven job creation in a range of LDCs, but further and less heterogeneous evidence is needed to discover what works and does not work in the future.

One avenue for strengthening the future research effort is investment in compilation of new and better-quality data on technology adoption and employment in LDCs. Such datasets can be built through community innovation surveys (CIS) similar to those implemented in developed and middle-income countries; and/or by extending the survey questions in the World Bank's Business Enterprise Surveys to include innovation and technology adoption questions. Another avenue would be to support and make effective use of the emerging regional initiatives on the compilation of R&D and technology adoption indicators. One example consists of indicators compiled by the New Partnership for Africa's Development (NEPAD), of which the first batch on 19 African countries has been finalised recently.

References

Abramovitz, M., (1986). Catching-up, Forging Ahead and Falling Behind. Journal of Economic History, 46, 385-406.

Abreu, M., H.L.F. de Groot and R.J.G.M. Florax (2005). A meta-analysis of beta convergence: The legendary two-percent. *Tinbergen Institute Discussion Papers*, no. TI 2005-001/3.

Acemoglu, D. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. *Quarterly Journal of Economics,* 113(4): 1055–1089.

Acemoglu, D. (2003). Patterns of skill premia. *The Review of Economic Studies, 70*(2): 199.230.

Aghion, P. and P. Howitt (1992), A model of growth through creative destruction, *Econometrica*, 60: 323 - 351.

Almeida, R. (2009). Openness and technological innovation in East Asia: have they increased the demand for skills?. IZA Discussion Papers N.4474, Institute for the Study of Labour (IZA), Bonn.

Antonucci, T., Pianta, M., 2002. Employment effects of product and process innovation in Europe. International Review of Applied Economics, 16, 295-307.

Araújo B.C., Bogliacino F., & Vivarelli M. (2011). Technology, trade and skills in Brazil: some evidence from microdata. CEPAL Review, 105, 157-171.

Bardhan, P. (1995), The contributions of endogenous growth theory to the analysis of development problems: An assessment, in Behrman, J. and T. N. Srinivasan (eds.), *Handbook of Development Economics*, Amsterdam: Elsevier Science.

Benavente, J.M, R. Lauterbach and C. Neilson (2006), Technological innovation and employment: Complements or substitutes? University of Chile, Department of Economics, Working Papers wp221.

Berman, E., J. Bound and Z. Griliches (1994). Changes in the demand for skilled labour within U.S. manufacturing: evidence from the annual survey of manufactures. *Quarterly Journal of Economics*, 109(2): 367–397.

Berman E and Machin S. (2000) Skill-biased technology transfer around the world, *Oxford Review of Economic Policy*, 16(3): 12-22.

Berman, E. and Machin, S. (2002). Globalization, skill-biased technology adoption and labour demand, paper presented at the Workshop on Globalization, Employment and Poverty Reduction, ILO, Divonne (October).

Berman, E. and Machin, S. (2004). Globalization, Skill-Biased Technological Change and Labour Demand. In Lee, E. and Vivarelli, M. (Eds) Understanding Globalization, Employment and Poverty Reduction (pp. 39-66). New York: Palgrave Macmillan.

Berman, Eli, Rohini Somanathan and Hong W. Tan (2005).*Is Skill Biased Technology adoption Here Yet? Evidence from India Manufacturing in the 1990s*, World Bank Policy Research Working Paper 3761, November 2005.

Berman, E., Bound, J., Griliches, Z., 1994. Changes in the demand for skilled labour within US manufacturing industries: Evidence from the annual survey of manufacturing. Quarterly Journal of Economics, 109, 367-397.

Bogliacino, F., Pianta, M., 2010. Innovation and employment. A reinvestigation using revised Pavitt classes. *Research Policy*, 39, 799-809.

Bogliacino, F., Vivarelli, M., 2012. The job creation effect of R&D expenditures. *Australian Economic Papers*, 51, 96-113.

Bogliacino, F., Piva, M., Vivarelli, M., 2012. R&D and employment: An application of the LSDVC estimator using European data. *Economics Letters*, 116, 56-59.

Boyer, R. (1988). New technologies and employment in the 1980s: From science and technology to macroeconomic modelling, in J. A. Kregel, E. Matznerand A. Roncaglia (eds), *Barriers to Full Employment*, London: Macmillan, 233-68

Cameron, A. C. and D. L. Miller (2011). Robust inference with clustered data, in A. Ullah and D. E. Giles (eds.), *Handbook of Empirical Economics and Finance*, CRC Press, pp.1-28.

Card, D. and Krueger, A.B. (1995). Time-series minimum-wage studies: A meta-analysis. *American Economic Review* 85: 238–243.

Chennells, L., & Van Reenen, J. (1999). Has technology hurt less skilled workers? *The Institute for Fiscal Studies, Working Paper Series*, (W99/27).

Chennells, L.; Van Reenen, J. (2002). Technology adoption and the Structure of Employment and Wages: A Survey of the Microeconometric Evidence, in N. Greenan, Y. L'Horty and J. Mairesse (eds.), *Productivity, Inequality and the Digital Economy – A Transatlantic Perspective*, Cambridge MA: MIT Press, 175-223.

Ciriaci, D., Moncada-Paternò-Castello, P., Voigt, P., 2016. Innovation and job creation: A sustainable relation? *Eurasian Business Review*, 6, 189-213.

Cirillo V., 2014. Patterns of innovation and wage distribution. Do innovative firms pay higher wages? Evidence from Chile. *Eurasian Business Review*, 4, 181-206.

Cohen, J. (1988). *Statistical Power Analysis in the Behavioural Sciences*, 2nd ed., Hillsdale, NJ and London: Lawrence Erlbaum Associates.

Cornia, G.A. (2004). Trade Liberalization, Foreign Direct Investment and Income Inequality. In Lee, E. and Vivarelli, M. (2004) (Eds), *Understanding Globalization, Employment and Poverty Reduction*, (pp. 169-208). New York: Palgrave Macmillan.

Corey, D. M., W. P. Dunlap and M. J. Burke (1998). Averaging correlations: Expected values and bias in combined Pearson r's and Fisher's z transformations, *Journal of General Psychology*, 125(3), 245-261.

CRD – Centre for Reviews and Dissemination (2009), *Systematic Reviews: CRD's Guide for Undertaking Reviews in Health Care*, York: York Publishing Services.

De Dominicis, L., Raymond J. G. M. Florax and Henri L. F. de Groot (2008), A meta-analysis on the relationship between income inequality and economic growth', *Scottish Journal of Political Economy*, 55(5): 654-682.

Doucouliagos, H. (2011). How large is large? Preliminary and relative guidelines for interpreting partial correlations in economics. Deakin Faculty of Business and Law, *Working Papers*, no. SWP 2011/5.
https://www.deakin.edu.au/__data/assets/pdf_file/0003/408576/2011_5.pdf

Eaton, J.; Kortum, S.S. (1999). International patenting and technology diffusion: Theory and measurement. *International Economic Review*, 40(August), 537-570.

Edquist, C., L. Hommenand M. McKelvey (2001) *Innovation and Employment: Process Versus Product Innovation*, Cheltenham: Edward-Elgar.

Egger, M., G. D Smith, M. Scheider, and C. Minder (1997). Bias in meta-analysis detected by a simple, graphical test, *British Medical Journal*, **316**: 629-34.

Entorf, H. and W. Pohlmeier (1990). Employment, innovation and export activity: evidence from firm-level data, in J. P. Florens, M. Ivaldi, J.J. Laffont and F. Laisney (eds.), *Microeconometrics: Surveys and Applications*, Oxford, 394-415.

Everitt, B.S., S. Landauand M. Leese (2001) *Cluster Analysis* (4th edition) London: Arnold.

Feenstra, R. and Hanson, G. (1997). Foreign Direct Investment and Relative Wages: Evidence from Mexico's Maquiladoras. *Journal of International Economics*, 42, 371-93.

Freeman, C., Clark, J., Soete, L., 1982. *Unemployment and Technical Innovation*. London: Pinter.

Gkypali, A., Rafailidis, A. & Tsekouras, K. (2015). Innovation and export performance: do young and mature innovative firms differ? *Eurasian Business Review*, 5, 397-415.

Harbord, R. M and J. P. Higgins (2008). Meta-regression in Stata. *Stata Journal*, 8(4), 493-519.

Harden. A & J. Thomas (2005), Methodological issues in combining diverse study types in systematic reviews, *International Journal of Social Research Methodology*, 8(3): 257-271.

Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B., 2014. Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization*, 35, 29-43.

Hedges, L. V. and I. Olkin (2014). *Statistical Methods for Meta-analysis*. New York and London: Academic Press.

Hirschman, Albert O (1969). The strategy of economic development, in Agarwal, A.N. and S. P. Singh (eds), *Accelerating Investment in Developing Economies,* Oxford: Oxford University Press.

Hox, Joop J. (2002). *Multilevel Analysis: Techniques and Application*, Mahwah, NJ: Lawrence Erlbaum Associates.

Islam, R. (2004). The nexus of economic growth, employment and poverty reduction: An empirical analysis. *Discussion Papers* no. 14, Recovery and Reconstruction Department, International Labour Office.

Jaumandreu, J. (2003), Does innovation spur employment? A firm-level analysis using Spanish CIS data, mimeo, Madrid, http://www.eco.uc3m.es/temp/jaumandreu.pdf.

JBI - Joanna Briggs Institute (2008), *Reviewers' Manual*, The Joanna Briggs Institute, Adelaide: Australia.

Katsoulacos, Y. S. (1986). *The Employment Effect of Technical Change: A Theoretical Study of New Nechnology and the Labour Market*. University of Nebraska: Wheatsheaf

Konishi, S. (1981). Normalizing transformations of some statistics in multivariate analysis. *Biometrika*, 68(3), 647-651.

Krolzig, H. M. and D. F. Hendry (2001). Computer automation of general-to-specific model selection procedures. *Journal of Economic Dynamics and Control*, 25(6): 831-866.

Lachenmaier, S., Rottmann, H., 2011. Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization*, 29, 210-220.

Lall, S. (2004). The Employment Impact of Globalization in Developing Countries. In Lee, E. and Vivarelli, M. (2004) (Eds), *Understanding Globalization, Employment and Poverty Reduction*, (pp. 73-101). New York: Palgrave Macmillan.

Lee, E. & Vivarelli, M. (2004) (eds). *Understanding Globalization, Employment and Poverty Reduction*. New York: Palgrave Macmillan.

Lee, E. and Vivarelli, M. (2006). The Social Impact of Globalization in Developing Countries. *International Labour Review*, 145 (3), 167-184.

Machin, S. J. van Reenen (1998). Technology and changes in skill structure: evidence from seven OECD countries. *Quarterly journal of economics*, 113(4): 1215-1244.

Meschi, E. & Vivarelli, M. (2009). Trade and income inequality in developing countries. *World Development*, 37, 287-302.

Meschi E., Taymaz E., & Vivarelli, M. (2011). Trade, technology and skills: evidence from Turkish microdata, *Labour Economics*, 18, S60-S70.

Moreno, S.G., A. J. Sutton, A. Ades, T. D. Stanley, K. R. Abrams, J. L. Peters, and N. J. Cooper (2009). Assessment of regression-based methods to adjust for publication bias through a comprehensive simulation study, *BMC Medical Research Methodology*, 9(2), 1–17.

OECD (2005), *Oslo Manual: Guidelines for Collecting and Interpreting Technology adoption Data*, 3rd edition, Paris: OECD.

Pasinetti, Luigi L. (1981). *Structural Change and Economic Growth*. Cambridge: Cambridge University Press.

Perez, C. (1983), Structural change and the assimilation of new technologies in the economic and social system, *Futures*, 15, 357-375

Pianta, M. (2001). Innovation, demand and employment, in Petit, P. and Soete, L. (eds) (2001a). *Technology and the Future of European Employment*. Cheltenham, Elgar. 142-165

Pianta, M. (2004). Innovation and employment, in Jan Fagerberg, David C. Mowery, and Richard R. Nelson (eds), *The Oxford Handbook of Technology adoption*, Oxford: Oxford University Press, ch. 21

Pissarides, C., and G. Vallanti (2004). Productivity growth and employment: Theory and panel estimates, LSE Centre for Economic Performance, Discussion Paper.

Piva, M. (2003). The impact of technology transfer on employment and income distribution in developing countries: a survey of theoretical models and empirical studies. ILO Policy Integration Department Working Papers, no. 15 (September).

Popay, Jennie, Helen Roberts, Amanda Sowden, Mark Petticrew, Lisa Arai, Mark Rodgers, and Nicky Britten (with Katrina Roen and Steven Duffy) (2006), Guidance on the conduct of narrative synthesis in systematic reviews: A product from the ESRC methods programme, http://www.lancs.ac.uk/shm/research/nssr/research/dissemination/publications/NS_Synthesis_Guidance_v1.pdf

Raveh, O. and Reshef, A. (2016). Capital Imports Composition, Complementarities, and the Skill Premium in Developing Countries. *Journal of Development Economics*, 118, 183-206.

Robbins, D. (2003). The impact of trade liberalization upon inequality in developing countries - A review of theory and evidence. ILO Working Paper, n.13, International Labour Organization, Geneva.

Robbins, D. and Gindling, T.H. (1999). Trade Liberalization and the Relative Wages for More-Skilled Workers in Costa Rica. *Review of Development Economics*, 3(2), 140-154.

Romer, P. M. (1986). Increasing returns and long-run growth, *Journal of Political Economy*, 94(5), 1002-1037.

Rosenthal, R. (1979). The “file drawer problem” and tolerance for null results, *Psychological Bulletin*, 86(3), 638-641.

Simonetti, R. and Tancioni, M (2002), A Macroeconometric model for the analysis of the impact of technology adoption and trade on employment, *Journal of Interdisciplinary Economics*, 13: 185–221.

Singh, K. (1972). The impact of new agricultural technology on agricultural wage rates and employment in the IADP Districts, *Indian Journal of Agricultural Economics*, 1972

Stanley, T. D. (2006). Wheat from chaff: Meta-Analysis as quantitative literature review, *Journal of Economic Perspectives,* 15(3):131–150.

Stanley, T.D. (2008). Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection, *Oxford Bulletin of Economics and Statistics*, 70(2): 103-127.

Stanley, T. D. and H. Doucouliagos (2007). Identifying and correcting publication selection bias in the efficiency-wage literature: Heckman meta-regression, *Economics Series 2007_11*, Deakin University, Faculty of Business and Law, School of Accounting, Economics and Finance.

Stanley, T.D. and H. Doucouliagos (2012), *Meta-Regression Analysis in Economics and Business*. London and New York: Routledge.

Stanley, T. D., and Doucouliagos, H. (2014). Meta-regression approximations to reduce publication selection bias. *Research Synthesis Methods*, 5(1), 60-78.

Stanley, T. D. & S. B. Jarrell (2005). Meta-regression analysis: A quantitative method of literature surveys, *Journal of Economic Surveys*, 19(3), 299-308.

Stanley, T. D., S. B. Jarrell and H. Doucouliagos (2009). Could it be better to discard 90% of the data? A statistical paradox. Deakin University, Economics Working Papers No. SWP 2009/13.

Sterne, J.A. and R.M. Harbord (2004). Funnel plots in meta-analysis. *The Stata Journal*, 4(2), 127–141.

Ugur, M., E. Trushin and E. Solomon (2016), Technological innovation and employment in derived labour demand models: A hierarchical meta-regression analysis, *Journal of Economic Surveys*, forthcoming.

Van Reenen, J., 1997. Employment and technological innovation: Evidence from U.K. manufacturing firms. *Journal of Labour Economics*, 15, 255-284.

Vivarelli, Marco (1995). *The Economics of Technology and Employment: Theory and Empirical Evidence*. Cheltenham, UK: Edward Elgar Publishing.

Vivarelli, M., Evangelista, R., Pianta, M. (1996), Innovation and employment in Italian manufacturing industry. *Research Policy*, 25, 1013-1026.

Vivarelli, M. (2011). Innovation, employment and skills in advanced and developing countries: a survey of the literature, IDB Publications 61058, Inter-American Development Bank

Vivarelli, Marco (2012).Innovation, employment and skills in advanced and developing countries: A survey of the literature, Discussion Paper series, Forschungsinstitut zur Zukunft der Arbeit, No. 6291.

Vivarelli, M. (2013). Technology, employment and skills: an interpretative framework. Eurasian Business Review, 3, 66–89.

Xu, B.; Wang, J., 2000. Trade, FDI, and international technology diffusion, *Journal of Economic Integration*, 15(4), 585-601.

Primary studies included in the systematic review

Agarwal, B. (1981). Agricultural mechanisation and labour use: A disaggregated approach. *International Labour Review*. 120: 115.

Agbesor, N. (1984).*Employment Creation and Economic Growth through Technology Adaptation and/or Appropriate Choice of Technology: Case Studies of Manufacturing Companies in Nigeria (Criteria, Adjustment Policies)*. PhD Thesis: University of Miami.

Ahammed, C. and R. Herdt (1983). Farm Mechanization in a semiclosed input-output model: The Philippines. *American Journal of Agricultural Economics*. 65: 516-525.

Ahammed C. S. and R. W. Herdt (1984).Measuring the impact of consumption linkages on the employment effects of mechanization in Philippine rice production. *Journal of Development Studies*. 20: 242-255.

Ahmed, I. (1987). Technology, production linkages and women's employment in South Asia. *International Labour Review*. 126: 21.

Ahmed, I. (1988). The bio-revolution in agriculture: Key to poverty alleviation in the Third World? *International Labour Review*. 127: 53.

Almeida, R. (2010). Openness and technological technology adoption in East Asia: Have they increased the demand for skills? *Asia-Pacific Development Journal*. 17(1): 63-95.

Annable, J. E. Jr (1971).*The Transfer of Technology, Industrialization and The Urban Employment Problem in Low-Income Countries*. PhD Thesis: Princeton University.

Aryee, G. A. (1984). Income distribution, technology and employment in the footwear industry in Ghana. In: C. Baron and W. Van Ginneken (eds), *Appropriate Products, Employment and Technology: Case-Studies On Consumer Choice and Basic Needs in Developing Countries.* New York: St. Martin's Press; London: Macmillan Press, Pages 120-147.

Baer, W. (1976) Technology, Employment and Development: Empirical Findings. *World Development*. 4: 121-130.

Baker, K. and S. Jewitt; (2007) Evaluating 35 Years of Green Revolution Technology in Villages of Bulandshahr District, Western Up, North India. *Journal of Development Studies*. 43: 312-339.

Barker, R., W. H. Meyers, C. M. Crisostomo, and B. Duff. (1972). Employment and Technology adoption in Philippine Agriculture. *International Labour Review*, 106 (2-3): 111-139.

Benavente, J.M., Lauterbach, R., 2008. Technological innovation and employment: Complements or substitutes? European Journal of Development Research, 20, 318-329.

Berman, E. and S. Machin (2000). Skill-biased technology transfer around the world, *Oxford Review of Economic Policy*, 16(3): 12-22.

Berman, E., S. Rohini and H. W. Tan (2005).*Is Skill Biased Technology adoption Here Yet? Evidence from India Manufacturing in the 1990s*, World Bank Policy Research Working Paper 3761, November 2005.

Bhatia, H. C. and A. C. Gangwar (1981). Impact of improved technology on farm employment. *Indian Journal of Industrial Relations*. 16(4): 623-629.

Braun, S. (2008). Economic integration, process and product technology adoption, and relative skill demand. *Review of International Economics*. 16: 864-873.

Caballero, R. J. and M. Hammour (1996). On the timing and efficiency of creative destruction. *The Quarterly Journal of Economics*. 111: 805-852.

Cepede, M. (1972). The Green Revolution and employment. *International Labour Review*. 105: 1.

Chand, R. (1999) Emerging crisis in Punjab agriculture: Severity and options for future. *Economic and Political Weekly*. 34: A2-A10.

Choi, J-Y, , E. S. H. Yuand J. C. Jin (2002).Technical progress, urban unemployment, outputs, and welfare under variable returns to scale. *International Review of Economics & Finance*. 11: 411.

Chopra Kusum (1974) Tractorisation and changes in factor inputs: A case study of Punjab. *Economic and Political Weekly*. 9: A119-A127.

Clayton, E. (1972). Mechanisation and employment in East African agriculture. *International Labour Review*. 105: 309.

Conte, A. and M. Vivarelli (2011). Imported skill-biased technology adoption in developing countries. *Developing Economies*. 49: 36-65.

Crespi, G., Tacsir, E., 2012. Effects of innovation on employment in Latin America. Inter-American Development Bank Institutions for Development (IFD) Technical Note No.IDB-TN-496. Inter-American Development Bank, Washington, DC.

De Klerk, M. (1984) Seasons that will never return: The impact of farm mechanization on employment, incomes and population distribution in The Western Transvaal. *Journal of Southern African Studies*. 11: 84-84-105.

Edwards, L. (2004). A firm level analysis of trade, technology and employment in South Africa, *Journal of International Development*, 16, 45-61.

Esfahani, H. S. (1987).technical change, employment, and supply response of agriculture in the Nile Delta - A system-wide approach. *Journal of Development Economics*. 25: 167-167.

Fagerberg, J., M. Srholec and B. Verspagen (2010) The role of technology adoption in development. *Review of Economics and Institutions*. 1: 1-29.

Garmany, J. W. (1978). Technology and employment in developing countries. *The Journal of Modern African Studies*. 16: 549-564.

Inukai, I. (1970). Farm mechanisation, output and labour input: A case study in Thailand. *International Labour Review*. 101: 453-473.

Jacobsson, S. (1980). Technical change employment and distribution in LDCs. *Science and Public Policy*. 7(2): 124-135.

James, J. (1993). New technologies, employment and labour markets in developing countries. *Development and Change*. 24: 405-405.

Kelley, A. C., J. G. Williamson and R. J. Cheetham (1972). Biased technological progress and labour force growth in a dualistic economy. *Quarterly Journal of Economics*. 86(3): 426-447.

Lalwani, M. (1992). Employment gains of technology adoption- A study of Haryana's dairy farmers. *Indian Journal of Agricultural Economics*. XlVII: 236-236.

Lundin, N. and S. Fredrik (2007) *Technology, Development and Job Creation in China*. Lund University: Research Institute of Industrial Economics.

Mitra, A. (2009). Technology import and industrial employment: Evidence from developing countries', *Labour*, 23 (4), 697–718.

Mitra, A., Jha, A. 2015. Innovation and employment: A firm level study of Indian industries. Eurasian Business Review, 5, 45-71.

Moore, W. and R. Craigwell (2007).Technology adoption and its impact on output, employment and wages. *Journal of Eastern Caribbean Studies*. 23(2): 73-81.

Mureithi. L. (1974). Demographic and technological variables in Kenya's employment scene. *Eastern Africa Economic Review*. 6: 27-43.

Nair, K. N. (1980).*Technology Adoptions in Agriculture: Impact on Productivity and Employment*. New Delhi: Vision Books.

Oberai, A. S. and Ahmed, I. (1981). Labour Use in Dynamic Agriculture: Evidence from Punjab. *Economic and Political Weekly*. 16: A2-A4.

Otsuka, K., Gascon, F., & Asano, S. (1994). Green revolution and labour demand in rice farming: The case of central Luzon, 1966–90. *Journal of Development Studies*, 31(1), 82-109.

Pandit, B and N. Siddhartan (2008). MNEs, product differentiation, skills and employment: Lessons from the Indian experience. In: B. Pandit and N. Siddhartan (eds) *High Tech Industries Employment and Global Competitiveness.* New Delhi: Routledge, pp. 165-179.

Raju, V. T. (1976). The impact of new farm technology on human labour employment. *Indian Journal of Industrial Relations*. 11: 493-510.

Richards, A and A. Ramezani (1990). Mechanization, off-Farm employment and agriculture. In: D. Tully (ed.), *Rain-fed Agriculture in West Asia and North Africa.* Dordrecht: Kluwer, pp. 49 - 65.

Sen, A. (2001).*Employment, Technology and Development - Some Policy Issues (3rdEd.)*. New Delhi and Oxford: Oxford University Press.

Sharma, R. K. (1974). Green Revolution & farm employment: An analysis of experience in the Punjab. *Indian Journal of Industrial Relations*. 9(3): 417-426.

Sharma, R. (1990).*The New Economics of The Green Revolution: A Study of Income and Employment Diffusion in Rural Uttar Pradesh, India*. PHD Thesis, Cornell University, May, 1990.

Sigurdson, J. (1974) Technology and employment in China. *World Development*. 2: 75-85.

Sison, J. F., R. W. Herdt and B. Duff (1985). The effects of small farm mechanization on production, income and employment in selected rice-growing areas in The Philippines. *Philippine Journal of Development*. 12(1): 29-82.

Stewart, F. (1974). Technology and employment in LDCs. *World Development*. 2: 17-46.

Usha, P. (1985). Mechanisation and labour utilisation: leather industry in Tamil Nadu. *Economic and Political Weekly*. 20: 167-172.

Wills, I. (1972). Projections of effects of modern inputs on agricultural income and employment in a community development block, Uttar Pradesh, India. *American Journal of Agricultural Economics*. 54: 452-460.

Appendix

Meta-analysis tools and models

Partial correlation coefficients (PCCs) are often used to standardise the regression estimates from different primary studies based on different metrics for the dependent and independent variables (Stanley and Doucouliagos, 2012). The *PCC* measures the strength of the association between technological innovation and employment – after controlling for other determinants of the demand for labour in the primary-study models. The *PCC*s and their standard errors (*SE_PCC*) are calculated in accordance with equations (1a) and (2a) below

$$PCC_i = t_i / \sqrt{t_i^2 + df_i} \qquad \text{(1a)} \quad \text{and} \quad SE\_PCC_i = \sqrt{(1 - PCC_i^2)/df_i}$$

(2a)

Here *i* is the effect-size estimate reported in primary studies; t_i is the associated t-statistic and df_i is the corresponding degrees of freedom, as reported in primary studies. The standard error (SE_PCC_i) represents the variance due to sampling error. Doucouliagos (2011) suggests that *PCC*s less than ± 0.07 can be regarded as small, even if they are statistically significant. The *PCC* indicates strong association (large effect) if it is greater than ± 0.33, while a *PCC* in between indicates moderate effect.

However, the *PCC* is constrained between -1 and +1; and its variance becomes smaller as its absolute value |*PCC*| gets closer to 1. In contrast, the variance of the Fisher's Z transformation is approximately constant for all values of the PCC. Therefore, the distribution of the Fisher's Z transformation is more likely to be normal provided that the sample size is large. Hence, we conduct sensitivity checks by deriving the Fisher's Z transformations of the PCCs - as suggested in Stanley and Doucouliagos (2012) and in accordance with (1b) and (2b) below.

$$FZ_i = \frac{1}{2} ln \frac{1+PCC_i}{1-PCC_i} \quad (1b) \quad \text{and} \quad SE\_FZ_i = \frac{1}{\sqrt{N-3}} \quad (2b)$$

Here FZ is Fisher's Z transformation of the PCC and N is the number of observations that underpin the regression estimate in the primary study (Hedges and Olkin, 2014; Konishi, 1981). Although the Fisher's Z is not defined when $|PCC| = 1$, Corey et al. (1998) report that FZ is a less biased estimate of the population correlation even when a small number of correlations are averaged (i.e., when the sample size is small).

We obtain the 'average' effect-size by estimating the meta-regression model proposed by Egger et al. (1997). The underlying postulate is that researchers search across model specifications, econometric techniques and data measures to find sufficiently large (hence statistically-significant) effect-size estimates. This postulate implies that reported estimates are correlated with their standard errors. Denoting the effect size with PCC_i and the standard error with SE_PCC_i, the selection process can be stated as follows:

$$PCC_i = \beta + \alpha SE\_PCC_i + u_i \quad (3a)$$

However, model (3a) is heteroskedastic because effect-size estimates have widely-different standard errors. Therefore, we estimate a weighted least squares (WLS) version, where precision-squared ($1/SE\_PCC_i^2$) is used as weights. This is equivalent to dividing both sides of (3a) with the standard error of the PCC (Stanley and Doucouliagos, 2014 and 2012) and yields:

$$t_i = \alpha + \beta \left({}^{1}/_{SE\_PCC_i} \right) + v_i \qquad (3b)$$

The dependent variable ($t_i = \ PCC_i/SE\_PCC_i$) is the t-value of the PCC; and this follows from the fact that the t-value of a regression estimate is equal to the ratio of the estimate to its standard error. Noting that the expected value of the idiosyncratic sampling error (v_i) is zero, the effect-size in the research field diverges from the estimate of the population effect size ($\hat{\beta}$) by α. As such, α reflects the asymmetry of the funnel plot that depicts the distribution of the primary-study estimates around the true effect size ($\hat{\beta}$) in the population. This is the so-called "file drawer problem" pointed out by Rosentahl (1979), which reflects the researchers' tendency to *under-report statistically non-significant* effect-size estimates. Hence, testing for $\alpha = 0$ is a test for publication selection bias or funnel asymmetry test (FAT); whereas testing for $\beta = 0$ is a precision-effect test (PET) (or genuine effect test) after controlling for selection bias (Stanley and Doucouliagos, 2014 and 2012).

The second issue is that the relationship between primary-study estimates and their standard errors may be non-linear. Indeed, Stanley and Doucouliagos (2014) provide evidence that a quadratic specification is superior if the PET rejects the null hypothesis of zero effect. Then, the specifications of the non-linear Egger model (4a) and its WLS equivalent (4b) are:

$$PCC_i = \gamma + \delta SE\_PCC_i^2 + \omega_i \qquad (4a)$$

$$t_i = \gamma \left({}^{1}/_{SE\_PCC_i} \right) + \delta SE\_PCC_i + \theta_i \qquad (4b)$$

Model (4b) is estimated without a constant term and only if the PET rejects the null hypothesis of zero effect. It is referred to as precision-effect test corrected for standard errors (PEESE).

The third issue is about potential data dependence, which arises when a primary study that draws on a particular dataset reports multiple estimates; or when different studies use overlapping datasets (Doucouliagos and Laroche, 2009; Ugur et al., 2016). We address this issue by estimating (3b) and (4b) with different estimators: (i) pooled OLS that overlooks the study-specific fixed effects; (ii) fixed effect estimator in which we model the within-study data dependence as part of the study-specific fixed effects; and (iii) hierarchical model estimators that take into account between- and within-study dependence. We report results from the estimators yielding the lowest AIC and BIC values.

When the issues discussed above are addressed, the meta-regression models in (3b) and (4b) allow for quantifying the average effect of technology adoption on employment beyond any selection bias that may exist in the research field. However, the average effect may conceal a high degree of heterogeneity in the evidence base. The latter issue, however, can be addressed by augmenting the meta-regression model of (3b) with covariates that capture the sources of heterogeneity. This is accomplished by estimating a multivariate meta-regression model (MVMRM) discussed in Stanley (2008), Stanley and Doucouliagos (2012), and Ugur et al. (2016) among others. The MVMRM can be stated as follows:

$$t_i = \delta_0 + \delta_1(1/SE\_PCC_i) + \sum_2^K \delta_k \, (Z_{ki}/SE\_PCC_i) + \epsilon_i \tag{5}$$

Here ($1/SE\_PCC_i$) is precision, Z_{ki} is a vector of ($K \, x \, 1$) study characteristics (or moderating factors) that may explain the variation in the evidence base, and ϵ_i is the disturbance term due to sampling error. The moderating factors are measured as dichotomous (dummy) variables that represent the dimensions of the research field, including the type of innovation, skill levels, levels of analysis, estimation methods, and publication type. Our choice of the moderating variables is informed by the theoretical debate on displacement and compensation mechanisms, skill-biased technical change literature, and best practice in meta-analysis. We estimate (5) with different estimators as indicated above; and report the results from estimators yielding the lowest AIC and BIC values.

Table A1: Overview of the qualitative studies

Study	Country / data period	Level of analysis	Technology / innovation type	Data and method
Agarwal, B.. (1981)	India: 1982-83	Farm	Mechanisation and HYV seeds Process + product innovation	Survey evidence: Decomposition
Agbesor, K. N. (1984)	Nigeria: 1982-83	Firm	Technology adoption Process + product innovation	Interviews, company records: Descriptive analysis
Ahammed and Herdt (1983)	Philippines: 1975	Sector	New irrigation techs., mechanisation Process innovation	Official statistics: Decomposition.
Ahammed and Herdt (1984)	Philippines: 1975	Sector	New irrigation techs., mechanisation Process innovation	Official statistics: Decomposition.
Ahmed (1987)	LDCs in South Asia: 1970s and early 1980s	Female labour	Green revolution tech., mechanisation Process innovation	Qualitative: Theoretical/analytical Study
Ahmed (1988)	Multiple LDCs: 1970s and early 1980s	Sector	Bio-technology/Bio-revolution Process and product innovation	Qualitative: Theoretical/analytical study

Annable, J. E. Jnr . (1971)	LDCs: 1970 and before	Macro	Technology transfer Process + product innovation	Qualitative: Theoretical/analytical study.
Aryee (1984)	Ghana: early 1980s	Firm	Mechanisation Process innovation	Survey evidence: descriptive analysis.
Baer, W. (1976)	LDCs: Pre-1970	Firm	Technology adoption Process + product innovation	Pre-1970 reported evidence: analytical
Baker and Jewitt (2007)	India: 1970-2001	Farm	Mechanisation and HYVs Process and product innovation	Field study survey evidence: descriptive analysis
Barker et al (1972)	Philippines: 1970	Farm	Mechanisation and HYVs Process and product innovation	Periodical farm surveys: descriptive analysis
Berman and Machin (2000)	37 LDCs and DCs: 1980s	Industry	Technological change Process innovation	Industry-level evidence from UNIDO Database: Decomposition

Table A1: Overview of the qualitative studies - continued

Study	Country / data period	Level of analysis	Technology / innovation type	Data and method
Berman et al (2005)	India: 1990s	Industry	Technological change Process innovation	Annual Survey of Industry: Decomposition
Bhalla (1989)	India: 1972-73.	Female labour	Mechanisation and HYVs Process and product innovation	Survey evidence: Descriptive analysis
Bhatia and Gangwar (1981)	India: 1970s	Farm	New technology; New farm plans Process innovation	Field survey of small farms: Descriptive analysis
Billings and Singh (1981)	India: 1970s	Female labour	New technology Process innovation	Government statistics on female employment and agriculture: Descriptive analysis
Braun (2008)	Multi-country: 1990s	Firm	R&D Product and process innovation	Official statistics: Theoretical/analytical study
Caballero and Hammour (1996)	General	Macro	Technological change Process and product innovation	Qualitative: Theoretical/analytical study

Cepede (1972)	LDCs: 1960s	Sector	Green revolution technologies Process innovation	Qualitative: Theoretical/analytical study
Chand (1999)	India: 1990s	Sector	Product diversification Product innovation	Mix of survey evidence and national statistics: Descriptive analysis
Choi et al (2002)	General	Sector	Technological change Process innovation	Qualitative: Theoretical/analytical study
Chopra (1974)	India: 1970-71	Farm	New Technology Process and product innovation	Farm survey/interview evidence: Descriptive analysis
Clayton (1972)	Nigeria, Uganda, Kenya, Tanzania: Late-1960s early 1970s	Sector	Mechanisation Process innovation	National statistics and review evidence: Descriptive analysis

Table A1: Overview of the qualitative studies - continued

Study	Country /data period	Level of analysis	Technology / innovation type	Data and method
De Klerk (1984)	South Africa: 1970s	Farm	Technology Process innovation	Farm survey data: Descriptive analysis
Edwards (2004)	South Africa	Firm	Import penetration	Estimation of demand function for unskilled labour and change in labour demand
Edquist et al (2001)	General	Firm / Industry	Technological change in general Process + product innovation	Qualitative: Analytical study
Ekwere (1983)	Nigeria: 1970s	Firm	Technology adoption Process innovation	Field survey of small textiles firms: Descriptive analysis
Esfahani (1987)	Egypt: 1970s	Sector	Mechanization Process innovation	Government statistics on agriculture: Descriptive analysis
Fagerberg (2010)	LMICs	Macro	Multiple technology measures Process and product innovation	Innovation surveys: Descriptive analysis

Garmany (1978)	LDCs:	Macro	Technology adoption Process innovation	Qualitative: Theoretical/analytical study
Inukai (1970)	Thailand: 1960s	Farm	New technology, mechanisation Process innovation	Survey data, field interviews: Descriptive analysis
Jacobsson (1980)	LDCs: 1973-80	Industry	Technology implicit in manufacturing trade Process and product innovation	Industry trade data: Descriptive analysis
James (1993)	LDCs: General	Industry	Technology adoption Process innovation	Qualitative: Theoretical/analytical study
Kelley et al (1972)	LDC: General	Sector	Technological change Process innovation	Qualitative: Theoretical/analytical study
Lalwani (1992)	India: 1980s	Farm	New feeding techniques Process innovation	Field survey of farms: Descriptive analysis
Mehta (1993)	Multi-country	Industry	Technology adoption Process innovation	UNIDO data: Decomposition

Table A1: Overview of the qualitative studies - continued

Study	Country / data period	Level of analysis	Technology / innovation type	Data and method
Mitra (2009)	Multi-country	Industry	Imported technology Process innovation	UNIDO data: estimation of labour-to-value added ratio
Mureithi (1974)	Kenya: General	Industry	Technological change Process innovation	Qualitative: Analytical study
Nair (1980)	India and other LDCs: 1970s	Sector	Mechanisation Process innovation	Survey evidence: Descriptive analysis
Richards and Ramezani (1990)	Middle-East and North Africa: 1960-85	Sector	Mechanisation Process innovation	National statistics: Descriptive analysis
Saviotti and Pyka (2004)	LDCs: General	Sector	Technology adoption Product innovation	Qualitative: Analytical study
Sen, A. (2001, 3rd ed.)	India: 1970s	Firm Sector	Technology adoption Process and product innovation	Qualitative: Theoretical/analytical study
Sharma (1990)	India: mid-1960s to mid-1980s	Farm	Green Revolution Process and product innovation	Field survey evidence: Descriptive analysis

Singh and Day (1975)	India: 1960s	Sector	Green Revolution	Official statistics: Simulation
			Process innovation	
Sigurdson (1990)	China: 1960s and 1970s	Industry	Technology adoption / adaptation	Qualitative: Analytical study
			Process and product innovation	
Stewart (1974)	LDCs: 1970s	Industry	Technology transfer	Qualitative: Analytical study
			Process + product innovation	
Tuyen (1999)	Vietnam: 1994-96	Female labour	New technology	Survey evidence and workplace
			Process	interviews: Descriptive analysis
Usha (1985)	India: 1970s	Firm	Mechanisation	Field survey and official
			Process innovation	statistics: Descriptive analysis
Wills (1972)	India: 1960s	Farm	Mechanisation, fertilisers and HYVs	Field survey data: Descriptive
			Process and product innovation	analysis

Table A2: Sensitivity check - PET/FAT/PEESE estimates using Fisher's Z

	PET/FAT(1) Process/Skilled Unweighted FE, B/strap	PET/FAT(2) Process/Mixed Unweighted FE, B/strap	PET/FAT(3) Product/Mixed Unweighted FE, B/strap	PET/FAT(4) Full sample Unweighted FE	PET/FAT(5) Full sample Weighted FE	PEESE(6) Process/Skilled Unweighted OLS	PEESE(7) Product/Mixed Unweighted OLS
Precision of FZ	0.188***	-0.026	0.335*	-0.022	-0.024	0.119***	0.319**
(Effect)	(0.044)	(0.026)	(0.193)	(0.046)	(0.036)	(0.014)	(0.145)
Constant (Bias)	-6.784**	1.653*	-2.745	3.512**	2.574*		
	(2.950)	(0.914)	(2.877)	(1.627)	(1.322)		
Std. Error of FZ						-139.528**	-12.262

						(63.473)	(15.347)
Observations	33	93	25	180	180	33	25
Studies	3	9	4	12	12	3	4
F					0.447		
p>F					0.518		
Chi2	18.452	1.039	3.011	0.228		397.747	5.383
p>Chi2	0.000	0.308	0.083	0.633		0.000	0.068
Log likelihood	-61.467	-226.962	-64.110	-565.582	-541.650	-64.891	-87.557
AIC	126.933	457.925	132.221	1135.163	1085.300	133.782	179.114
BIC	129.926	462.990	134.659	1141.549	1088.493	136.775	181.552

Table A3: Summary statistics for moderating variables in the MMRA

Variable	Observation	Mean	Std. Dev.	Min.	Max.
Precision	180	40.11	44.52	3.16	227.55
Journal article	180	0.74	0.44	0	1
Farm-level data	180	0.47	0.50	0	1
Product innovation	180	0.18	0.38	0	1
Unskilled labour	180	0.07	0.25	0	1
LIC	180	0.48	0.50	0	1
IV estimator	180	0.14	0.35	0	1
Data midpoint after 2001	180	0.27	0.44	0	1

Definition of the moderating variables

Journal article: Dummy variable that takes the value of 1 if the effect-size estimate is reported in a journal article; and 0 if it is reported in working papers or reports.

Farm-level data: Dummy variable that takes the value of 1 if the effect-size estimate is based on farm-level data; and 0 if it is based on firm- or industry-level data.

Product innovation: Dummy variable that takes the value of 1 if the effect-size estimate is based on product innovation data; and 0 if it is based on process innovation or mixed (undifferentiated) innovation.

Unskilled labour: Dummy variable that takes the value of 1 if the effect-size estimate is based on data for unskilled-labour employment data; and 0 if it is based on skilled- or mixed-skill-labour employment data.

LIC: Dummy variable that takes the value of 1 if the effect-size estimate is based on low-income-country (LIC) data; and 0 if it is based on data from lower-middle-income-country or undifferentiated LDC data.

IV estimator: Dummy variable that takes the value of 1 if the effect-size estimate is derived from instrumental variable estimators (2SLS, GMM, etc.); and 0 otherwise.