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Effects of innovation on employment in low-income countries: A mixed-method systematic review

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Abstract

We conduct a meta-analysis of the effect-size estimates from 9 empirical studies and a narrative synthesis of the qualitative evidence from 53 qualitative studies on the relationship between innovation and employment in low-income countries (LICs). The meta-analysis reveals a positive but small effect, with evident bias in favour of skilled-labour employment. Both meta-analysis and narrative synthesis findings indicate that innovation's effects on employment in LICs tend to be larger when: (i) the evidence is related to manufacturing as opposed to agriculture; (ii) the analysis is at the firm level as opposed to sector level; and (iii) the evidence relates to South Asian countries as opposed to other world regions. Further findings from the narrative synthesis of the qualitative evidence indicate that the positive effect of innovation on employment is likely to be augmented by strong forward and backward linkages; but the adverse effects are likely to be exacerbated by capital-intensity of imports and weaknesses in governance and labour-market institutions.

Key words: innovation, employment, low-income countries, systematic reviews, meta-analysis

1. Introduction

Since 2005, national, regional and international organisations have been emphasizing the importance of innovation for growth and employment in low-income countries (LICs). The consensus view is that promoting science, technology and an innovation is essential for inclusive growth in low-income countries (LICs) (UN, 2005; Commission for Africa, 2005; NEPAD, 2006).

Although innovation is necessary for growth and employment in the long run, the adjustment to innovation shocks may lead to job losses in the short-to-medium run (Aghion and Howitt, 1992; Baumol and Wolff, 1998). In addition, skill-biased innovation (unlike the skill-replacing innovation of the late-eighteenth and nineteenth centuries) is likely to increase the demand for skilled labour at the expense of unskilled labour

(Acemoglu, 1998 and 2003; Berman and Machin, 2000; Berman et al., 2005). Finally, product innovation is usually expected to have a positive effect on employment, but process innovation is expected to reduce demand for labour (Edquist et al., 2001).

These findings are usually reported in the literature on developed and developing countries. The aim of this systematic review is to uncover and synthesize the evidence on LICs, which have remained below the radar of most researchers, reviewers and research users. The review is based on evidence reported in 62 primary studies published between 1970 and 2011, with a focus mainly on LICs.[1] It contributes to existing knowledge on employment creation in LICs by:

1. Providing a *narrative synthesis* of the qualitative evidence from 53 qualitative studies, with detailed findings on the effects of mediating factors such as forward and backward linkages, institutions, skill levels, type of innovation, and international trade;
2. Providing a *meta-analysis* of the empirical evidence from 9 empirical studies, with a view to establish the extent to which the findings of the qualitative studies are congruent with quantitative estimates;
3. Mapping the findings in (1) and (2) to establish the extent of convergence or divergence between qualitative and quantitative evidence;
4. Relating the mapped findings to underlying theoretical perspectives and distilling some policy and future research implications.

The review is organised in six sections. Section 2 introduces the theoretical/analytical framework utilised in the studies of innovation-employment relationship in general. Section 3 presents the systematic review methodology, including the definition and measurement of the intervention (innovation) and outcome (employment) variables, the search and screening protocol, and the way in which we combine the narrative synthesis of the qualitative evidence with meta-analysis of the quantitative estimates. In section 4, we present the narrative synthesis and meta-analysis findings; followed by conclusions based on mapped evidence in section 5.

2. Innovation and employment: the analytical framework

The debate on economic consequences of innovation goes back to Schumpeter (1934), who analysed the relationship between innovation, growth and competition as a process of 'creative destruction'. The work gathered a new momentum with the advent of endogenous growth theory (Romer, 1986) and the incorporation of innovation as an

[1] World Bank's current income-based country classification is reported at http://data.worldbank.org/about/country-classifications/country-and-lending-groups#Low_income. Countries included in this review also include countries such as India and China, which are currently in the low-middle-income category but were considered as LICs until the end of the 1990s.

endogenous source of growth (Aghion and Howitt, 1992). A comprehensive review of the work until mid-1990s can be found in Bardhan (1995).

One strand in the literature focuses on firms' 'innovation effort', measured either in terms of inputs (e.g. research and development [R&D] investment or imported technology) or in terms of innovation outputs such as patents or trade-marks (see reviews by Chennells and van Reenen, 1999; and Vivarelli, 2012). The other strand is that of labour economists, who explain changes in employment (and other labour market outcomes such as wages) by labour force demography, macroeconomic factors, wage costs, labour market institutions, and innovation variables (see, reviews in Vivarelli, 1995; Enthorf et al, 1999; and Simonetti and Tancioni, 2002).

Pianta (2004), Spiezia and Vivarelli (2002) and Vivarelli (2012) provide good reviews of both types of work on developed and developing countries. Piva (2003), on the other hand, focuses mainly on developing countries. The existing reviews suggest that the overall effect of innovation on employment is uncertain. The uncertainty is due to conditionality of the findings on the range of displacement and compensation mechanisms and their job-creating and job-destroying effects, respectively.

The displacement and compensation mechanisms that determine the overall effects of innovation on employment are summarised in Table 1 below. The summary indicates that innovation's adverse effect on employment is due to three displacement mechanisms: (i) productivity increases that enable firms to produce the same level of output with less labour input; (ii) the degree of capital augmentation caused by new technologies; and (iii) the rate at which old products are replaced by new products.

One compensation mechanism that qualifies the adverse effects is labour-market institutions. In the context of developed countries, Pissarides and Vallanti (2004) demonstrate that the rate of job creation is higher than that of job destruction when labour market institutions are flexible or when the latter induce workers to upgrade their skills in the face of technological change. In the LIC context, the literature indicates that the job-destroying effects may dominate not because of labour-market rigidity but due to capital-intensity of the technologies.

Compensation effects may also fail to counterbalance the displacement effects as a result of international trade. James (1993) suggests that export can be considered as a kind of forward linkage that enables innovative firms and industries to create employment. However, the majority of the related literature draws attention to negative employment effects via imports channel. This literature demonstrates that innovation is more likely to be associated with job losses when imported technology is capital intensive and/or skill-biased (Jacobson, 1980; Mitra, 2009). However, such adverse effects should be considered in the light of positive effects on skilled labour employment (Conte and Vivarelli, 2007).

**Table 1: Effects of innovation on employment:
A summary of displacement and compensation mechanisms**

	Displacement mechanisms (Job-destroying effects)	Compensation mechanisms (Job-creation effects)	Overall effect
Firm-Level Process innovation	**Negative** effect through productivity: less labour for a given output. **Mixed** effect through skill-bias: higher demand for labour with matching skills; lower demand otherwise.	**Positive** effect through lower wages; output growth; competitive market structure; and strong forward/ backward linkages. **Negative** effect otherwise.	**Uncertain** effect – depending on skill bias of innovation, strategic firm behaviour and scope for forward/backward linkages.
Firm-Level Product innovation	Effect through product displacement: **Negative** effect if job destruction in old product lines is greater than job creation in new product lines; **positive** effect otherwise.	**Positive** effect if product prices fall and linkages are strong; **Negative** effect otherwise.	**Uncertain** effect: Depends on productivity differences, product prices, and forward/backward linkages.
Industry-Level Process innovation	**Negative** effect through productivity: less labour for a given output. **Mixed** effect through skill-bias: higher demand for labour with matching skills; lower demand otherwise.	**Positive** effect through lower wages; output growth; competitive market structure; and strong forward/ backward linkages. **Negative** effect otherwise.	**Uncertain** effect – depending on skill bias of innovation, strategic firm behaviour and scope for forward/backward linkages.
Industry-Level Product innovation	Effect through product displacement: **Negative** effect if job destruction in old industries is greater than job creation in innovative industries; **positive** effect otherwise.	**Positive** effect if product prices fall and linkages are strong; **Negative** effect otherwise.	**Uncertain** effect: Depends on productivity differences, product prices, and forward/backward linkages.
Macro-level (Process + Product) innovation	Substitution between capital and labour: **Negative** effect if innovative technologies are capital-augmenting. Substitution between skill-levels: **Higher demand** for skilled, **lower demand** for unskilled labour. Skewed income distribution: **Exacerbates** displacement.	Effect through total factor productivity (TFP): **Positive** effect due to higher TFP and higher output. Effect through investment: higher innovation > higher profits > higher investment > **Positive** effect on demand for labour. Less-skewed income distribution: **Enhances** compensation effects.	**Uncertain** effect: Depends on skill bias, TFP growth, demand-side and supply-side constraints, income distribution, and overall institutional quality.

Income distribution is also reported as a factor that influences the relationship between innovation and employment. Work in the Keynesian tradition (Pasinetti, 1981; Boyer 1988) demonstrates that part of the gains from innovation may be appropriated by labour. As wage increases, aggregate demand increases and this eventually leads to higher output and employment. On the other hand, Aryee (1984) demonstrates that higher levels of income inequality induce firms to adopt skill- and capital-intensive technologies used in the production of goods and services for high-income consumers – with negative effects on employment due to conflicts with existing skill endowments.

Innovation's effects on employment would also depend on the level of analysis. At the firm level, innovation increases the productivity of innovative firms and enables them to increase their market shares. However, the output and employment growth in innovative firms may be at the expense of output and employment losses in their non-innovative counterparts – with the implication that effect of innovation on employment may be different between firms and between the latter and industries in which they operate.

Finally, Innovation's employment effects are also mediated through backward and forward linkages (Hirschman, 1969). Innovation is more likely to have a positive employment effect the stronger are the forward and backward of linkages between innovative firms/industries and the rest of the economy.

Given the range of displacement and compensation effects at work and the opposing effects they have on the innovation's employment effects, Vivarelli (2012) indicates that the overall effect of innovation on employment can be ascertained only empirically. This systematic review sets out to accomplish this task in the context of LICs, with respect to which the evidence base is limited and highly heterogeneous. Given the heterogeneity of the existing work and the ambiguity implied by opposing effects of the displacement and compensation mechanisms summarised above, the review adopts a mixed-method synthesis proposed by Harden and Thomas (2005). The method involves mapping the qualitative and quantitative evidence in a systematic manner. While qualitative synthesis compensates for the limited extent to which contextual factors can be incorporated into quantitative meta-analysis, the latter allows for synthesizing evidence form diverse studies, after controlling for the effects of publication selection bias and observable sources of heterogeneity in the evidence base.

3. Review methodology

In this section, we present the systematic review methodology we have adopted, including: (i) the definition of the intervention (innovation) and outcome (employment) variables; (ii) the search and screening protocol for identifying the primary studies; and (iii) the narrative synthesis and meta-analysis methods used to synthesize the evidence and account for the heterogeneity that characterise the research field.

3.1 Defining innovation and employment

The intervention (innovation) variable in this review is informed by OECD's *Oslo Manual* (OECD, 2005), according to which innovation is 'the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations.' Two features of innovation stand out in this definition: (i) innovation must be *implemented* rather than an indication of potential innovative capacity; and (ii) the range of innovation activities includes both activities that are 'new to the firm' and those that are 'new to the world or industry'.

In line with the *Oslo Manual*, we adopt an inclusive definition of innovation and we include primary studies that focus on both agriculture and manufacturing. Innovative activities include mechanization, new irrigation systems, fertiliser use, introduction of high-yield variety seeds (HYVs) in agriculture; and technology import, technology adaptation, and introduction of new products or processes in manufacturing.

We pool the different innovation activities into two innovation clusters: *product* and *process* innovation. As indicated in Table 1 above, product innovation affects employment through product/service quality and variety. On the other hand, process innovation affects employment primarily through change in productivity. Although the distinction between product and process innovation analytically convenient, we are aware that the distinction between the two is not clear cut. Firms/enterprises may engage in both types of innovation at the same time. The primary studies we review, however, maintain a distinction between the two innovation types by focusing on the primary innovation type and treating the other type as necessary adjustment. In this review, 85% of the included primary studies investigate the employment-effects of process innovation and 15% examine the effects of product innovation. The latter are mainly related to product innovation in agriculture, with the exception of two qualitative studies (Agbesor, 1984 and Aryee, 1984) and one empirical study (Otsuka et al, 1994) on product innovation in manufacturing.

The outcome variable is *employment*, which is defined as economically-active persons (usually, aged 15-64) who were in paid or self-employment for a specified period at the time when data is compiled (ILO, 2000). Primary studies with a focus on sector or macro levels use national employment statistics compiled in accordance with ILO guidelines. Nevertheless, adherence to these guidelines is known to be uneven – depending on capacity and traditions of the national statistical offices (Inter-Secretariat, 1993). On the other hand, studies that examine the effect of employment at the firm or farm level utilise employment data based on national surveys or field-study surveys.

The primary studies examine the effects of innovation on total employment as well as employment of skilled and unskilled labour. We have coded the skill types and investigated whether innovation in LICs is skill-biased. However, we do not include studies that examine the effect of innovation on the composition of the wage bill only. This is because the wage-share is an indicator of wage-income distribution rather than the levels of employment per se.

We synthesize the evidence at three levels of aggregation: firm, industry/sector and macro levels. With respect to sector coverage, we review primary studies that focus on manufacturing and agriculture. As such, this review represents a deliberate attempt to ameliorate the 'manufacturing bias' (Piva, 2003; Vivarelli, 2012) of the innovation studies and their existing reviews. Hence, 53% of the primary studies included in this review examine the innovation-employment relationship in agriculture, and 46% are devoted to manufacturing. Only one study (Moore and Craigwell, 2007) examines the effects of innovation on employment in services (banking in Barbados).

3.2. Searching, screening and critical evaluation of the literature base[2]

We followed an inclusive search strategy to take account of the heterogeneity in the literature base.[3] Our screening and evaluation procedures are informed by best-practice recommendations for systematic reviews in health care and public policy [Joanna Briggs Institute (JBI), 2008; Centre for Reviews and Dissemination (CRD), 2009]. In stage 1 of the study selection process, we applied *population-intervention-outcome-study design (PIOS)* criteria to *title* and *abstract* information of 4,055 results obtained from electronic sources listed in the pre-published systematic review protocol. In stage 2, we applied a new set of PIOS criteria to full-text information of the studies screened in the previous stage. Finally, in stage 3, we apply *validity-reliability-applicability (VRA)* criteria for critical evaluation of the selected studies, which also include studies identified through hand search and snowballing. The numbers of included and excluded studies at each stage are indicated in Figure A1 in the Appendix.

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[2] This section is based on a peer-reviewed and pre-published Protocol that sets out the systematic review methodology in detail. Full bibliographic reference and link to the protocol will be provided here after the anonymous review process.

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

At stage 3, we evaluated the included studies on the basis of *validity, reliability and applicability (VRA)* criteria; where validity refers to methodological rigour that would minimise the risk of bias, reliability refers to the extent to which the findings of the study are re-producible, and applicability refers to the extent to which the findings can be generalised/applied to low-income countries. At the end of the critical evaluation, we included 62 studies for the review, of which 53 are qualitative/analytical and 9 are empirical.

3.3. The mixed-method approach

We draw on the mixed-method proposed by Harden and Thomas (2005) for mapping qualitative and empirical evidence in systematic reviews. We derive a *narrative synthesis* (Popay et al, 2006; CRD, 2009) of the qualitative evidence from studies that are dissimilar in terms of methods used and/or questions types of innovation investigated. The synthesis consists of main findings in primary studies, including the overall effect of innovation on employment and mediating effects of the compensation and displacement mechanisms summarised in Table 1 above.

We also draw on *meta-analysis* methods, which allow for a quantitative synthesis of heterogeneous effect-size estimates reported in primary studies. (Stanley, 2006; Stanley and Jarrell, 2005; Stanley and Doucouliagos, 2012). The meta-analysis results are based on partial correlation coefficients (PCCs) that are comparable across studies. The PCCs measure the association between innovation and employment after controlling for other explanatory variables; and they are independent of the metrics with which the innovation and employment variables are measured in the primary studies. Against these advantages, PCCs have the drawback of reflecting association rather than causal effects such as elasticities. (Stanley and Doucouliagos, 2012).

The PCCs and associated standard errors are calculated in accordance with equations (1) and (2) below, where pcc_i is the PCC; t_i is the t-statistic associated with the original effect-size estimate; df_i is the corresponding degrees of freedom; and se_{pcci} is the standard error of the PCC.

$$pcc_i = t_i / \sqrt{t_i^2 + df_i} \qquad (1)$$

$$se_{pcci} = \sqrt{(1 - pcc_i^2)/df_i} \qquad (2)$$

In the meta-analysis, we included all effect-size estimates reported by primary studies instead of choosing a 'representative' single estimate per study. The latter is not preferable because selection criteria are rarely objective and there is no consensus within the literature on the 'best' estimation method on which the preferred estimate should be based. In addition, 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).

The meta-analysis results begin with summary measures calculated as fixed-effect weighted means (FEWMs) of the PCCs. The FEWMs are calculated in accordance with equation (3) below, for each study and for a specific combination of innovation and labour skill type that the study estimates.

$$\bar{X}_{fee} = \sum pcc_i(1/se^2_{pcci})/\sum(1/\,se^2_{pcci}) \qquad (3)$$

Here, $\bar{X}_{fee}$ is the fixed-effect weighted mean. The weight ($1/se^2_{pcci}$) is precision-squared and as such it assigns lower weights to less precise estimates. FEWMs are more reliable than simple means; but they cannot be considered as reliable measures of *genuine effect size* (or partial correlation) if the original-study estimates are subject to publication selection bias and/or affected by within-study dependence due to data overlap. They are based on the assumption that that each study estimates a fixed effect size, subject to sampling error captured by the associated standard error (de Dominicis et al, 2008: 663).

Therefore, we also conduct precision-effect and funnel-asymmetry tests (PETs/FATs) that allow for establishing the existence or absence of 'average genuine effect' after controlling for reporting (publication selection) bias. The PET/FAT procedure involves estimating a weighted least square (WLS) model that minimizes the risk of heteroskedastacity (see, Stanley, 2008; Stanley and Doucouliagos; 2007; Abreu et al, 2005; and Stanley, 2005).

$$t_i = \alpha_0 + \beta_0(1/se_{pcci}) + \varepsilon_i \qquad (4)$$

Here t_i is the t-value associated with each PCC. The funnel asymmetry test (FAT) involves testing for publication selection bias, which is confirmed if $\alpha_0 \neq 0$. The precision-effect test (PET) tests genuine effect, which is confirmed if $\beta_0 \neq 0$. As such, model (4) allows for establishing whether genuine effect exists after controlling for publication selection bias. Card and Krueger (1995) and Stanley (2008: 108) indicate that the bias is severe if $\alpha_0 > 2$ in absolute value.

According to Stanley and Doucouliagos (2007; 2012, chapter 4), reported effect-size estimates and their standard errors have a nonlinear relationship if the PET indicates the existence of genuine effect. In such cases, they propose a precision-effect estimation with standard errors (PEESE) to obtain a corrected estimate of the effect size (β_0). The PEESE model can be stated as follows:

$$pcc_i = \beta_0 + \alpha_0\left(se^2_{pcci}\right) + u_i \qquad (5a)$$

Dividing both sides by (se_{pcci}) to address the problem of heteroskedasticity, we obtain model (5b) - which must be estimated *without* the constant term.

$$t_i = \alpha_0(se_{pcci}) + \beta_0(1/se_{pcci}) + v_i \qquad (5b)$$

We conduct PET/FAT estimations for different combinations of innovation and skill types, provided that the number of observation is greater than 10. The PEESE test is conducted only when the PET/FAT results indicate existence of genuine effect.

PET-FAT estimations allow for making inference about the existence or absence genuine effect for the typical study, but they assume that moderating variables that may be structurally related to study characteristics or other moderating variables are all equal to their sample means and independent of the standard error. This is a restrictive assumption. Therefore, we also conduct multivariate meta-regression analysis (MRA) model, which follows Stanley and Jarrell (2005) and Stanley (2008). The model can be stated as follows:

$$t_i = \ \alpha_0 + \beta_0\, 1/se_{pcci} + \sum \beta_k\, Z_{ki}/se_{pcci} + \epsilon_i \qquad (6)$$

Here ($1/se_{pcci}$) is precision, Z_{ki} is a vector of ($K \times 1$) study characteristics (or moderating variables) that may explain the variation in the evidence base, and ϵ_i is the disturbance term due to sampling error. Ordinary least-squares (OLS) estimation of model (6) allows for estimating genuine effect, conditional on moderating variables that characterise the research field. These are constructed as dummy variables and include: (i) general method of moments (GMM) estimation method as opposed to other methods, (ii) sector-level as opposed to firm-level evidence; (iii) process innovation as opposed to product innovation; (iv) skilled-labour employment as opposed to unskilled or mix-skill labour employment; (v) manufacturing sector data as opposed to agriculture or services; (vi) South Asian data as opposed to other world regions; and (vii) journal articles as opposed other publication types such as working papers, book chapters or reports.

The MRA model is first estimated with all moderating variables for which data exists. Then, we follow a general-to-specific modelling approach to minimise the risk of multicollinearity and over determination. The approach involves omitting the most statistically-insignificant variables (i.e., the variables with the largest p-value) one at a time, until all remaining variables are significant. The validity of the reduction is confirmed by examining the goodness of fit and stability of the significant coefficients (Krolzig and Hendry, 2001).

To take account of any residual heteroskedastacity, we estimate model (6) with robust standard errors. To control for within-study dependence, we use one-way and two-way cluster robust estimation. In both methods, standard errors would be adjusted upward and hence the risk of incorrect inference will be reduced if there is within-study dependence between reported estimates and the correlation between such estimates is positive (Everitt et al, 2001; Hox 2002).

4. Narrative synthesis of the qualitative evidence

The narrative synthesis below is based on qualitative evidence from 53 studies, of which 27 investigate the employment effects of innovation in agriculture and 26 investigate the effect in manufacturing. For each sector, we present the findings with respect to innovation type (process *versus* product innovation) and different levels of aggregation (farm/firm, industry/sector and macro levels). This is followed by meta-analysis of 147 effect-size estimates extracted from 9 empirical studies. Finally, we establish the extent of congruence between the narrative synthesis and meta-analysis findings with respect to overall effects as well as effects of the moderating factors that reflect the displacement/compensation mechanisms at work.

4.1 Narrative synthesis1 - agriculture

One cluster of studies investigates the effects of *process innovation* on *farm-level employment* in India, South Africa and Thailand. In these studies, process innovation includes mechanization, new irrigation methods, and use of fertilizers in crop farming or new feeds in dairy farming. The findings can be summarized as follows:

1. Mechanization on its own tends to have a negative or uncertain effect on farm employment, unless it is accompanied with extension of farm land and hiring of outside labour. This conclusion is supported by evidence in Chopra (1974) on farmers in 13 Punjabi villages, Bhatia and Gangwar (1981) on 965 small farms in Karhal district of Inidia, Agarwall (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.
2. The negative employment effect of mechanization is exacerbated as the farm size increases and when mechanization is used for ploughing and harvesting operations instead of sowing (De Clerk, 1984; Agarwall, 1981).
3. Mechanization tends to reduce the employment of family labour as opposed to hired labour; and that of young farmers as opposed to older farmers (Agarwall, 1981; Chopra, 1974). However, it may increase the employment of child labour (De Clerk, 1984).

4. Other types of process innovation such as new feeds, fertilizers and irrigation systems are more likely to have positive effect on farm employment (Lalwani, 1992; Bhatia and Gangwar, 1981; Chopra, 1974).
5. Process innovation in general and mechanization in particular 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)
6. The employment effect of process innovation is more likely to be reported as positive when the evidence is on India compared to other countries.

The second cluster investigates the employment-effects of *product innovation* in agriculture (Barker et al., 1972; Ahmed, 1987; and Chand, 1999). Product innovation in agriculture usually involves use of high-yield-variety seeds (HYVs) as the primary innovation type. The overall conclusion is that introduction of HYVs has a positive effect on on-farm and off-farm employment. With respect to compensation mechanisms, the evidence from the Philippines (Barker et al., 1972) and from The Punjab (Chand, 1999) indicates that the effect is smaller or even negative if wages increase after introduction of HYVs. With respect to forward and backward linkages, all three studies report that strong linkages amplify the positive effect of product innovation on on-farm and off-farm employment.

The third cluster consists of studies that examine the effects of *process and product innovation* on *sector-level employment* in agriculture in South Asia (7 studies), East Asia (2), the Middle-East and Africa (2), and low-income developing countries in general (1). Most of these studies examine the innovation-employment relationship in the context of the Green Revolution (GR). Their findings can be summarized as follows:

1. Green Revolution (GR) technologies tend to have uncertain employment effects in the short-run. In the long run (over 30 years), GR technologies are associated with higher levels of off-farm employment; but the effect on on-farm employment remains uncertain (Cepede, 1972; Sharma, 1974 and 1990; Singh and Day, 1975; Wills, 1981; Ahmed, 1988; and Barker and Jewitt, 2007).
2. 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).
3. GR technologies tend to reduce the seasonality of employment; but without reducing income or wealth inequalities (Sharma, 1974 and 1990; Cepede, 1972; Barker and Jewitt, 2007).
4. 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).

4.2 Narrative synthesis2 - manufacturing

Early studies on the innovation-employment relationship in LICs were informed by the *appropriate technology* debate. Baer (1976) provide a comprehensive review of the early debate and points out the following conclusions: (i) factor-price distortions in LICs encourage the selection of capital-intensive technology; (ii) existing technologies do not match factor supplies in LICs; (iii) technology adaptation in LICs is limited due to low level 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 is that innovation in LICs is likely to have adverse effects on employment.

Appropriate technology is a useful concept that draws attention to issues of technology choice and adaptation to local conditions. However, its practice- and policy-relevance proved limited for two reasons. First, there was no commonly-agreed method that could inform policy-makers or managers to choose the technology that reflects the optimal trade-off between productivity and employment gains. Secondly, the proponents of the concept did not analyse the complex set of displacement and compensation mechanisms that eventually determine the employment-effects of the chosen technology.

Amartya Sen (1974) attempts at addressing these shortcomings by proposing that the policy-maker's objective should include a set of employment targets (such as informal sector employment, female employment, family employment, seasonal/casual employment and regular wage employment) in addition to the productivity targets. He also proposes that the employment effects of technology are mediated through institutions that shape and inform the decision-making of policy makers and entrepreneurs. Sen's (1974) overall conclusion is that firms in developing countries should make use of available technologies (i.e., they should choose from the 'technology shelf') but improve the institutional set up that will facilitate the right technology choice and enhance the scope for employment creation.

The narrative synthesis below summarises the evidence on the innovation-employment relationship in LICs that have become available after Sen's (1974) seminal contribution to the *appropriate technology* debate. Two features of the post-Sen literature worth emphasizing. First, particular attention is paid to how moderating factors (such as institutions, forward and backward linkages, and international trade) affect the balance between displacement and compensation mechanisms. Secondly, a distinction is made between product and process innovation and between skilled and unskilled labour employment.

In manufacturing, only two studies analyze the effect of *product innovation* on employment at the *firm level*: Agbesor (1984) on two companies in Nigeria and Aryee (1984) on footwear industry in Ghana. Both studies report that product innovation is associated with employment creation and the positive effect is more likely if:

1. Product innovation creates new markets by catering for local needs;
2. It generates forward linkages through new distribution/dealership networks;
3. It leads to second-round innovation in marketing and product development;
4. Product innovation responds to increased incomes of low-income groups as opposed to high-income groups; and
5. The new technology is skill-matching - i.e., it is standard, semi-automatic and labour-intensive.

Three studies investigate the effects of *process innovation* on *firm-level* employment. Ekwere (1983) analyses the scope for job creation in small textiles industries in Nigeria, using field survey evidence. Usha (1985) examines the effects of technological change on employment in the Indian footwear industry after the Export Trade Control Order of 1973. Finally, Braun (2008) analyses the interaction between economic integration, product and process innovation, and relative skill demand in a model of international oligopoly.

The findings can be summarized as follows:

1. Firm-level process innovation in LICs is characterized by skill-bias and capital-intensity (Ekwere, 1983; Braun, 2008).
2. International trade tends to exacerbate the substitution of employment away from unskilled towards skilled-labour (Braun, 2008).
3. Weak institutions inhibit the choice of labour-absorbing technologies (Ekwere, 1983; Braun, 2008); and exacerbate segmentation in the labour market (Usha, 1985).

We reviewed 12 qualitative studies that examine the effects of *process innovation* on employment at the *industry/sector level*. One conclusion from this literature is that the effect of process innovation on employment at the industry/sector level 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. Drawing on the Chinese experience, Sigurdson (1990) distinguishes between *technological innovation* in large-scale sectors and *technology adaptation* within local and small-scale enterprises. The author demonstrates that this dual approach was effective in job creation because of the 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. Berman and Machin (2000) and Berman et al (2005) report that developing countries are importing capital-intensive technologies, with the consequence of skill-biased technological change (SBTC) and increased demand for skilled-labour at the expense of unskilled labour. Similar findings are reported in Choi et al (2002) and Mitra (2009), who demonstrate that: (i) technological change may lead to primary growth without employment growth if firms are operating with variable returns to scale (Choi et al., 2002); and (ii) the effects of imported technology on labour absorption in the manufacturing sector is negative, after controlling for real wage rate and per-capita GDP in a number of developing and low-income countries (Mitra, 2009). Further evidence is provided by Conte and Vivarelli (2011), who report that skill-enhancing imported technology (SETI) has a negative effect on the employment of unskilled workers' but positive effect on skilled-labour employment.

Finally, Jacobbson (1980) addresses the question as to whether technology embodied in trade among developing countries may have a different effect on employment compared to trade between developed and developing countries. The author reports that technology transfers implicit in *South-South trade* are likely to create *fewer* jobs than technology transfers implicit in *North-South trade* – mainly because the capital intensity of the goods in South-South trade is *higher* than the North-South trade.

4.3 narrative synthesis3 - the macro level

We have reviewed 5 studies that examine the innovation-employment relationship at the macro level. These studies do not distinguish between process and product innovation; but their overall conclusions can be summarised as follows:

1. Institutional characteristics of the country and those of the labour markets determine technology choice and hence employment creation (Annable, 1971; Fagerberg, 2010; Garmany, 1978; and Caballero and Hammour, 1996).
2. Preferred technologies do not generate sufficient employment to absorb the excess labour supply caused by rural-urban migration (Annable, 1971).
3. Innovation may have an employment-creating effect if LICs strike an optimum balance between capital-deepening in the main manufacturing sectors and use of labour-intensive technologies in other sectors (or if they can have such duality across different stages of the production process) (Garmany, 1978; Annable, 1971).

The narrative synthesis of the qualitative evidence from 53 studies indicates that innovation's overall effect on employment is uncertain at best and it is more likely to be negative when innovation is *process* rather than *product* innovation. The 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 countries in East Asia, Africa and the Middle East; and (iii) governance and labour market institutions are conducive to optimal technology choice and wage flexibility. On the other hand, the 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. Meta-analysis findings from empirical studies

In this section, we first present the fixed-effect weighted means (FEWMs) of the partial correlation coefficients (PCCs) from 9 empirical studies. This is followed by precision-effect and funnel-asymmetry tests (PETS/FATs). Finally, we present evidence from a multi-variate meta-regression model to establish how moderating factors such as innovation type, employment type, level of analysis, sectors, and publication type affect the PCCs, which are derived from regression results in primary studies.

Table 2 below presents FEWMs, which assign lower weights to less precise estimates. They indicate a high degree of heterogeneity among primary-study estimates, ranging from -0.1529 to 0.6998. They also indicate that only four studies report effect-size estimates that yield statistically-significant weighted means. Almeida (2010) and Conte and Vivarelli (2011) yield small but positive FEWMs (0.0947 and 0.0698 respectively) for the effects of process innovation on skilled labour in manufacturing. In agriculture, Raju (1976) yields a large and positive FEWM (0.6998) for the effects of process innovation on the employment of all-skills labour. However, Sison et al (1985) yields a medium and negative effect (-0.1529) for the same combination.

Table 4: Fixed-Effects weighted means (FEWMs) – using partial correlation coefficients

Study	Data Period	No. of Estimates	Type of Innovation (Product, process)	Type of Employment (Skilled, Unskilled, All-skills)	Sector (Agriculture, Manufacturing, Services)	Fixed-Effects Weighted Mean	Confidence Interval
Study 1 Almeida (2010)	2003 - 2005	25	Process	Skilled	Manufacturing	**0.0947***	(0.0837, 0.1056)
Study 2 Conte & Vivarelli (2011)	1980 - 1991	6	Process	Skilled	Manufacturing	**0.0598***	(0.0349, 0.0846)
Study 2 Conte & Vivarelli (2011)	1980 - 1991	6	Process	Unskilled	Manufacturing	-0.01138	(-0.0475, 0.0249)
Study 3 Lundin et al (2007)	1998 - 2004	18	Process	All-skills	Manufacturing	0.0100	(-0.0128, 0.0328)
Study 4 Moore & Craigwell (2007)	1979 - 2001	6	Process	All-skills	Services	0.0186	(-0.0851, 0 .1223)
Study 5 Oberai and Ahmed (1981)	1977	7	Process	All-skills	Agriculture	0.0161	(-0.0658, 0.0980)
Study 5 Oberai and Ahmed (1981)	1977	1	Product	All-skills	Agriculture	0.0740	N.A.
Study 6 Otsuka et al (1994)	1966 - 1990	17	Process	All-skills	Agriculture	-0.0706	(-0.1813, 0.0402)
Study 6 Otsuka et al (1994)	1966 - 1990	17	Product	All-skills	Agriculture	0.0066	(-0.0360, 0.0492)
Study 7 Pandit & Siddhartan (2008)	1991 - 2001	1	Process	All-skills	Manufacturing	0.0316	N.A.+
Study 8 Raju (1976)	1968 - 1971	34	Process	All-skills	Agriculture	**0.6998***	(0.6246, 0.7749)
Study 8 Raju (1976)	1968 - 1971	4	Product	All-skills	Agriculture	0.1562	(-0.0369, 0.3492)
Study 9 Sison et al (1985)	1979 - 1980	5	Process	All-skills	Agriculture	**-0.1529***	(-0.2945, -0.0114)

Note: According to Cohen (1988), the weighted mean of the PCCs should be regarded as small if its absolute value is less than 0.10, medium if it is 0.25, and large if it is greater than 0.4.

FEWMs are more reliable than simple means. However, they may be biased if the underlying effect-size estimates suffer from reporting (publication selection) bias and/or within-study dependence. In addition, FEWMs take account of within-study variations, but it does not reveal any information about the sources of such variations. Therefore, in what follows, we conduct PET and FAT estimations to address the first issue and meta-regression analysis to account for sources of heterogeneity. Table 2 below presents the PET/FAT results for different clusters of innovation and skill types if the number of observations in each cluster is greater than 10.

Table 3: PET/FAT and PEESE results
Dependent variable: t-statistics

	PET/FAT results				**PEESE results**	
	1. Process innovation and skilled labour	**2. Process innovation and all-skill labour**	**3. Product innovation and all-skill labour**	**4. Full sample**	**5. Process innovation and skilled labour**	**6. Full sample**
Precision	**0.214*** (0.036)**	0.004 (0.008)	0.009 (0.041)	**0.015** (0.007)**	**0.102*** (0.006)**	**0.026*** (0.005)**
Constant	-8.751*** (2.524)	0.728 (0.598)	0.135 (0.735)	1.177** (0.472)		
St. Error					-19.118*** (5.425)	-0.077* (0.044)
R^2	0.546	0.004	0.003	0.032	0.936	0.156
Prob > F	0.000	0.571	0.827	0.031	0.000	0.000
N	31	88	22	147	31	147

PET/FAT estimations are for different combinations of innovation and skill types, provided that the number of observation is greater than 10.

The sign of precision's coefficient in Table 3 indicates the direction of innovation's effect on employment; whereas the magnitude indicates the average effect size - i.e., the effect size based on the assumption that all moderating variables that influence the variation within and between studies are at their sample mean. On the other hand, the constant term indicates the direction and the level of publication selection bias. The results indicate that the effect of *process innovation* on *skilled-labour* employment (0.214 in column 1) is positive, significant and greater than the effect of *process* or *product* innovation on *unskilled labour* employment (in columns 2 and 3), which are not significantly different than zero. The effect on skilled labour is also larger than the effect of *both types of innovation* on the sum of *skilled* and *unskilled* labour employment (0.015 in column 4). The significant effect-size estimates are associated with severe negative publication bias (-8.751) in column 1 and a substantial positive bias (1.177) in column 4.[4]

Nevertheless, publication bias does not invalidate the effect-size estimate. Hence, we carry out PEESE estimation for two clusters of innovation and skill types that yield significant effects. After the correction for the non-linear relationship between effect-size estimates and their standard errors, the average effect of process innovation on skilled-labour employment is 0.102 (column 5) and that of undifferentiated innovation on all-skill labour employment is 0.026 (column 6). These average effects are small in the case of process innovation and skilled labour employment, and too small to be practically significant in the case of all types of innovation and all-skill labour employment.[5] The PEESE results lend support to the narrative synthesis findings that indicate skill bias in the effect of innovation on employment in LICs. Overall, innovation is more likely to increase the demand for skilled-labour, with the effect on unskilled labour employment being either negative or too small to be practically significant.

The PET/FAT and PEESE results are valid if all moderating variables apart from the standard errors are equal to their sample means. This is a restrictive assumption as it overlooks other sources of heterogeneity in the evidence base. To account for heterogeneity, we estimate a multivariate meta-regression model (model 6 above) with three different specifications to control for heteroskedastacity, within-study dependence, and two-way dependence. Summary statistics for and definitions of the moderating variables are presented in the Appendix in Table A2 and BoxA1, respectively.

Table 4 below presents three sets of results with heteroskedasticity-robust, one-way cluster-robust and two-way cluster-robust standard errors. In all estimations, the coefficients from the specific model are significant and joint significance is confirmed by the very small (practically zero) p-values from the F-test. Assuming that all moderating variables in the model are equal to 1, the marginal effect of *all types of innovation* on *all-skill labour employment* is equal to 0.151 (= -0.133 – 0.042 + 0.070 + 0.133 + 0.123).

This is a positive but still small effect, which is dampened (by -0.042) when the primary-study estimates are based on sector-level data as opposed to firm/farm data. The marginal effect is amplified when the underlying evidence relates to: (i) employment of skilled labour as opposed to all-skill labour; (ii) employment in manufacturing sector as opposed to agriculture or services; and (iii) employment effects in South Asian countries as opposed to other world regions. When all moderating variables are

[4] The bias classification is based on guidelines recommended by Card and Krueger (1995) and Stanley (2008), which indicate that the bias is severe if the absolute value of the constant term is greater than 2 and severe if it is greater than 1.

[5] This is based on Cohen's (1988) guidelines, which indicate that the effect is: (i) small if the absolute value of the PCC is less 0.25; (ii) medium if it is 0.25 and over; and (iii) large if it is greater than 0.4.

assumed equal to zero, the marginal effect of innovation on employment is negative (-0.133).

Table 4: Meta-regression results#
Dependent variable: t-values

	1. Robust Std. Errors	**2. Cluster-robust Std. Errors**	**3. Two-way cluster-robust Std. Errors**
Precision	-0.133**	-0.133**	-0.133**
	(0.053)	(0.046)	(0.048)
Sector-level employment	-0.042***	-0.042***	-0.042***
	(0.010)	(0.006)	(0.007)
Skilled labour employment	0.070***	0.070***	0.070***
	(0.013)	(0.006)	(0.008)
Manufacturing employment	0.133***	0.133**	0.133**
	(0.043)	(0.041)	(0.043)
South Asia data	0.123***	0.123**	0.123***
	(0.042)	(0.044)	(0.022)
Constant	1.787**	1.787*	1.787*
	(0.765)	(0.832)	(0.886)
Observations	147	147	147
Model degree of freedom	5	5	5
R-squared	0.339	0.339	0.339
P>F	0.000	0.000	0.000

Standard errors are in brackets. *, ** and *** denotes significance at 10%, 5% and 1%.

These estimates are based on the specific model, which is obtained through a general-to-specific modeling routine whereby most insignificant variables (i.e., variables with the largest p-value) are dropped one at a time until all remaining variables are statistically significant. General-to-specific modelling is recommended to reduce the risk of multicollinearity and over determination (Stanley and Doucouliagos, 2012).

Combining the results from PET-FAT-PEESE and multivariate meta-regression estimations, we can state that the effect of innovation on employment is very much context-dependent. Rather than an overall effect, we can identify a range of conditional effect estimates that depend on the set of moderating variables (and the compensation/displacement mechanisms they represent). The moderating variables we could include explain 33.9% of the variation in the evidence base and enable us to conclude that innovation's employment effect is more likely to be positive (albeit small) when the evidence relates to employment of skilled labour, employment in manufacturing, and employment in South Asian countries. The effect is dampened slightly when the evidence relates to sector-level employment as opposed to firm/farm or macro levels.

One conclusion that can be derived from multivariate meta-regression is that innovation in LICs is skill-biased. This finding is in line with the evidence reported in the wider literature on developed and middle-income countries. It is also in line with the narrative synthesis reported above for LICs.

The second conclusion is that the effect of innovation on employment at the sector-level is smaller than the average conditional effect. This is line with the theoretical literature that suggests that employment gains in innovative firms/farms are associated with job losses in their non-innovative counterparts within the same sector.

The positive effect associated with manufacturing employment is congruent with the findings of the qualitative studies that highlight the importance of forward and backward linkages as a compensation mechanism. This is because forward and backward linkages in manufacturing are reported to be stronger. Finally, the positive effect associated with data for South Asian countries is also congruent with the narrative synthesis, which indicates that the effect of the Green Revolution technologies on employment is positive particularly in India.

6. Mapping the key findings and conclusions

The review findings supported *both* by narrative synthesis and meta-analysis can be summarized as follows:

1. The effect of innovation on employment is mediated through a range of moderating factors such as type of innovation (product versus process innovation), skill types (skilled, unskilled and all-skill labour employment), level of analysis (effects at firm/farm, sector and macro levels), forward/backward linkages, income levels and distribution, international trade, and institutional quality.
2. Innovation's effect on employment is more likely to be positive when the evidence is related to skilled-labour employment, employment in the manufacturing sector, and employment in South Asian countries.
3. Innovation's effect on employment is more likely to be negative when the effect is measured at sector rather than firm/farm level, and the skill category is unskilled labour.

Review findings supported by narrative synthesis *only* can be summarized as follows:

1. The employment-effects of innovation are more likely to be positive when there are strong forward/backward linkages between innovative firms/farms/industries and upstream or downstream firms/industries;

and when governance institutions encourage and facilitate technology adaptation.
2. International trade between LICs or between the latter and developed countries is capital- and/or skill-intensive and hence it is more likely to increase the skill-bias of innovation.
3. There is qualitative evidence indicating that technology adaptation is more likely to create employment compared to off-the-shelf technology imported from developed countries. However, there is no consensus on how to strike an optimal balance between efficiency and employment gains when technology choices are made.

These findings have policy and practice relevance for international development agencies and policy makers. Also, they point out some implications for future research.

One policy implication concerns the positive relationship that policy statements tend to establish between innovation and desirable objectives such as growth, employment and achievement of the Millennium Development Goals. This systematic review does confirm that innovation has a small but positive effect on employment in LICs when some of the relevant moderating factors are controlled for. This finding constitutes the best evaluation of what we currently know about the innovation-employment relationship in LICs, given the evidence base. As such, it lends cautious support for policy choices that support innovation with a view to create employment. However, it must also be noted that the effect has a skill bias, it is too small to be practically significant with respect to overall employment, and the evidence base on which the findings are based is characterised by high degree of heterogeneity.

Another policy implication is related to skill bias established in the review. Skill bias is likely to exacerbate income and wage disparity in LICs. Furthermore, the narrative synthesis indicates that international trade is likely to exacerbate the skill bias and reinforce wage/income disparities. Therefore, policies aimed at fostering innovation must be combined with support for education and skill upgrading; as well as technology adaptation that takes account of existing skill and factor endowment in LICs. There are local/national/international policy fora and frameworks for addressing the issue of investment in education and skill upgrading; however such fora and frameworks are less developed with respect to technology adaptation. Hence, this review indicates that the national and international policy emphasis on innovation as a driver for growth should be accompanied with similar emphasis on the role of national/regional institutions that would facilitate technology adaptation with a view to maximize the employment-creating (or minimise the employment-destroying) effects of innovation.

Finally, we should also indicate two potential sources of weakness in the evidence base. First, the empirical evidence is limited and the qualitative studies tend to be dated, going back to the 1970s and 1980s. Secondly, and with the exception of few studies (e.g., Berman and Machine, 2000; Berman et al, 2005; and Conte and Vivarelli, 2011), there is little or no cross-fertilisation between recent studies on LICs and the large volume of work on innovation-employment relationship in developed and middle-income countries, which is usually based on comprehensive survey data. These constraints do not invalidate the proposed policy implications, but they indicate an evident need for further research on the innovation-employment relationship in LICs.

One avenue for future research is to make better use of existing firm-level survey evidence in *Enterprise Surveys* compiled by the World Bank and the International Finance Corporation (IFC). These surveys provide evidence on a wide range of firm-specific indicators including innovation and employment, export orientation, and financial and governance factors in a number of LICs. This evidence can be analysed and, if necessary, compared with evidence on middle-income countries to enrich the existing evidence base. Another avenue would be to make use of the emerging R&D and Innovation survey evidence compiled by the New Partnership for Africa's Development (NEPAD).

REFERENCES

Studies included in the systematic review

Agarwal, Bina (1981). Agricultural Mechanisation and Labour Use: A Disaggregated Approach. *International Labour Review*. 120: 115.

Agbesor, Nelson (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, Chowdhury and Robert 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, Iftikhar (1987). Technology, Production Linkages and Women's Employment in South Asia. *International Labour Review*. 126: 21.

Ahmed, Iftikhar (1988). The Bio-Revolution in Agriculture: Key to Poverty Alleviation in the Third World?. *International Labour Review*. 127: 53.

Almeida, Rita (2010). Openness and Technological Innovation in East Asia: Have They Increased The Demand For Skills?. *Asia-Pacific Development Journal*. 17(1): 63-95.

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

Aryee, George A (1984). Income Distribution, Technology and Employment in the Footwear Industry in Ghana. In: *Appropriate Products, Employment and Technology: Case-Studies On Consumer Choice and Basic Needs in Developing Countries.* : A World Employment Program Study. New York: St. Martin's Press; London: Macmillan Press, Pages 120-147.

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

Baker, Kathleen and Sara 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, Randolph, William H. Meyers, C. M. Crisostomo, and B. Duff. (1972). Employment and Technological Change in Philippine Agriculture. *International Labour Review*, 106 (2-3): 111-139.

Berman, Eli and Stephen Machin (2000). Skill-biased Technology Transfer around the World, *Oxford Review of Economic Policy*, 16(3): 12-22.

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

Bhalla, Sheila (1989). Technological Change and Women Workers: Evidence from the Expansionary Phase in Haryana Agriculture. *Economic and Political Weekly*. 24: Ws67-Ws78.

Bhatia H C and A C Gangwar (1981). Impact of Improved Technology on Farm Employment. *Indian Journal of Industrial Relations*. 16: 623-629.

Braun, Sebastian (2008). Economic Integration, Process and Product Innovation, and Relative Skill Demand. *Review of International Economics*. 16: 864-873.

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

Caballero, Ricardo J and Mohamad Hammour (1996). On the Timing and Efficiency of Creative Destruction. *The Quarterly Journal of Economics*. 111: 805-852.

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

Chand, Ramesh (1999). Emerging Crisis in Punjab Agriculture: Severity and Options for Future. *Economic and Political Weekly*. 34: A2-A10.

Choi, J-Y, E.S.H Yu and 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, Eric (1972). Mechanisation and Employment in East African Agriculture. *International Labour Review*. 105: 309.

Conte, Andrea and Marco Vivarelli (2011). Imported Skill-Biased Technological Change in Developing Countries. *Developing Economies*. 49: 36-65.

De Klerk, Michael (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.

Esfahani, Hadi Salehi; (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, Jan, Martin Srholec and Bart Verspagen (2010). The Role of Innovation 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, Staffan (1980). Technical Change Employment and Distribution in LDCs. *Science and Public Policy*. 7(2): 124-135.

James, Jeffrey (1993). New Technologies, Employment and Labour Markets in Developing Countries. *Development and Change*. 24: 405-405.

Kelley, Allen C, Jeffrey G. Williamson and Russel J. Cheetham (1972). Biased Technological Progress and Labour Force Growth in a Dualistic Economy. *Quarterly Journal of Economics*. 86: 426-447.

Lalwani, Mahesh (1992). Employment Gains of Technological Change - A Study of Haryana's Dairy Farmers. *Indian Journal of Agricultural Economics*. XlVII: 236-236.

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

Mehta R, Mohanty S K; (1993). Demand for Labour in Manufacturing Sector: A Decomposition Analysis for Developing Countries. *Indian Journal of Industrial Relations*. 29(2).: 171-190.

Mitra, Arup (2009). Technology Import and Industrial Employment: Evidence from Developing Countries', *Labour*, 23 (4), 697–718.

Moore, Winston and Roland Craigwell (2007). Technology Adoption and Its Impact on Output, Employment and Wages. *Journal of Eastern Caribbean Studies*. 23(2): 73-81.

Mureithi Leopold (1974). Demographic and Technological Variables in Kenya's Employment Scene. *Eastern Africa Economic Review*. 6: 27-43.

Nair K N; (1980). *Technological Changes in Agriculture: Impact on Productivity and Employment*. New Delhi: Vision Books.

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

Otsuka Et Al; (1994). Green Revolution and Labour Demand in Rice Farming: The Case of Central Luzon, 1966-90. *Journal of Development Studies*. 31: 82-82.

Pandit B, Siddhartan N (2008). MNEs, Product Differentiation, Skills and Employment: Lessons from the Indian Experience. In: Pandit B, Siddhartan N *High Tech Industries Employment and Global Competitiveness.* : , Pages 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, A Ramezani (1990). Mechanization, off-Farm Employment and Agriculture. In: Tully D Ed; *Rain-fed Agriculture in West Asia and North Africa.* Dordrecht: Kluwer, Pages 49 - 65.

Sabolo, Yves (1983). Trade Between Developing Countries, Technology Transfers and Employment. *International Labour Review*. 122: 593.

Saviotti, Pier Paolo and Andreas Pyka (2004). Economic Development, Variety and Employment. *Revue Économique*. 55: 1023-1049.

Sen A (2001). *Employment, Technology and Development - Some Policy Issues (3rd Ed.)*. 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, Rita (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, Jon (1974). Technology and Employment in China. *World Development*. 2: 75-85.

Sison, Jerome F., Robert W. Herdt and Bart 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, Frances (1974). Technology and Employment in LDCs. *World Development*. 2: 17-46.

Tuyen, Nguyen Nhat (1999). Transitional Economy, Technological Change and Women's Employment: The Case of Vietnam. *Gender, Technology and Development*. 3: 43-43.

Usha, P (1985). Mechanisation and Labour Utilisation: Leather Industry in Tamil Nadu. *Economic and Political Weekly*. 20: 167-172.

Wills, Ian (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.

Zarkovic Milica (1987). The Effects of Economic Growth and Technological Innovation on the Agricultural Labour Force in India. *Studies in Comparative International Development*. 22: 103.

Other references used in the review

Abreu, Maria, Henri L.F. de Groot and Raymond 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.

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.

Boyer, R. (1988). New Technologies and Employment in the 1980s: From Science and Technology to Macroeconomic Modelling, in J. A. Kregel, E. Matzner and A. Roncaglia (eds), *Barriers to Full Employment*, London: Macmillan, 233-68

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

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

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

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

De Dominicis, Laura, 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.

Enthorf, H. and W. Pohlmeier (1990). Employment, Innovation and Export Activity: Evidence from Firm-Level Data, in Florens, J.P., M. Ivaldi, J.J. Laffont and F. Laisney (eds.), *Microeconometrics: Surveys and Applications*, Oxford, 394-415.

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

Harden. A and J. Thomas (2005). Methodological Issues in Combining Diverse Study Types in Systematic Reviews, *International Journal of Social Research Methodology*, 8(3): 257-271.

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.

ILO (2000). *Current International Recommendations on Labour Statistics*, Geneva: ILO.

Inter-Secretariat Working Group on National Accounts (1993). *System of National Accounts 1993*. Brussels/Luxembourg, New York, Paris, Washington, D.C., 1993.

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

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.

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

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

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 Innovation*, 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, Mariacristina (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

Romer, P. M. (1986). Increasing Returns and Long-run Growth", *Journal of Political Economy*, 94(5): 1002-1037.

Schumpeter, J.A. (1934). *Theory of Economic Development*, Cambridge (Mass.), Harvard University Press (1st ed. 1911).

Simonetti, R. and Tancioni, M (2002). A Macroeconometric model for the analysis of the impact of technological change 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. (2010). Meta-Regression Models of Economics and Medical Research, in I. Shemilt, M. Mugford, Luke Vale, Kevin Marsh and Cam Donaldson (eds), *Evidence-Based Decisions and Economics: Health Care, Social Welfare, Education and Criminal Justice* (2nd ed.), Oxford: Wiley: 134 – 145.

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

Stanley, T. D. & Stephen B. Jarrell (2005). Meta-Regression Analysis: A Quantitative Method of Literature Surveys, *Journal of Economic Surveys*, 19(3), 299-308.

Stanley, T. D. & 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., Stephen B. Jarrell and Hristos Doucouliagos (2009). Could it be Better to Discard 90% of the Data? A Statistical Paradox. Deakin University, Economics Working Papers No. SWP 2009/13.

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

Vivarelli, Marco (2012). Innovation, employment and skills in advanced and developing countries: A survey of the literature, Forschungsinstitut zur Zukunft der Arbeit

Discussion Paper series, No. 6291, http://nbn-resolving.de/urn:nbn:de:101:1-201203145587

Xu, B. and J. Wang (2000). Trade, FDI, and International Technology Diffusion, *Journal of Economic Integration*, 15(4), 585-601.

Appendix

Figure A1: Innovation and employment in LICs: Search and screening results

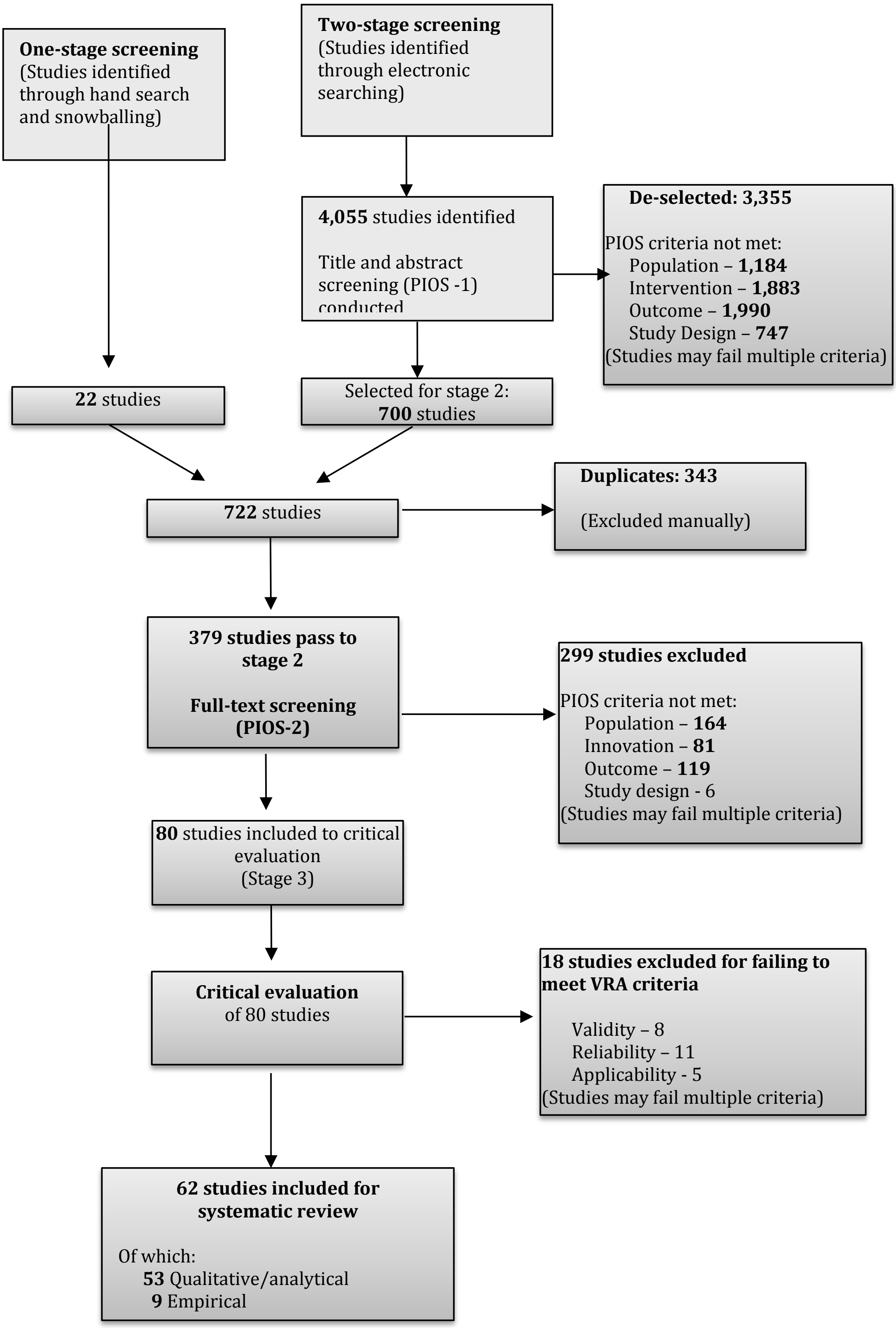

Table A1: Summary statistics for meta-regression analysis

	Obs.	Mean	Std. Dev.	Minimum	Maximum
Full sample: Un-weighted moderating variables					
t-Statistic	147	1.834	4.440	-16.000	24.000
Precision	147	45.084	54.084	3.162	342.450
Sector-level analysis	147	0.088	0.285	0.000	1.000
Skilled-labour employment	147	0.211	0.409	0.000	1.000
Manufacturing employment	147	0.381	0.487	0.000	1.000
South Asian countries	147	0.320	0.468	0.000	1.000
Full sample: Precision-weighted moderating variables					
t-Statistic	147	1.834	4.440	-16.000	24.000
Precision	147	45.084	54.084	3.162	342.450
Sector-level analysis	147	5.035	16.616	0.000	64.639
Skilled-labour employment	147	14.559	28.527	0.000	78.475
Manufacturing employment	147	36.696	58.724	0.000	342.450
South Asian countries	147	2.847	6.891	0.000	30.077

Box A1: Definitions of the MRA variables

t-Statistic is the dependent variable and it is equal to the *t-value* associated with each effect-size estimate reported in primary studies.

Precision is in the inverse of the standard error of the PCC.

Sector-level analysis is a dummy variable that takes the value of 1 if the original estimate measures the effect of innovation on employment at the sector or industry level as opposed to firm/farm level. Otherwise, it is equal to zero. Controlling for sector-level allows for establishing whether innovation's effects on employment are different at the sector level compared firm/farm level. The difference indicates whether job creation within innovative firms occurs at the expense job losses within non-innovative firms. The sector-level dummy has a sample average of 0.088, indicating that estimates of the sector-level effects constitute 8.8 per cent of the evidence base.

Skilled-labour employment is equal to 1 if the primary-study estimates measure the effect of innovation on skilled-labour employment; and it is zero if the effect is on unskilled or mixed-skill labour employment. Controlling for skilled-labour employment allows for testing if innovation is associated with skill bias in LICs. The skilled-labour dummy has a sample average of 0.211, indicating that estimates of skilled-labour employment constitute 21.1 per cent of the evidence base

Manufacturing is equal to 1 if the original estimates measure the effect of innovation in the manufacturing sector as opposed to services or agriculture. Controlling for manufacturing allows for establishing if innovation is more or less conducive to job creation in manufacturing. The manufacturing dummy has a sample average of 0.381, indicating that the estimates reporting effects on manufacturing employment constitute 38.1 per cent of the evidence base.

South Asia takes the value of 1 if reported estimates are based on data for South Asian countries; and it is 0 if they are based on data for other regions, which include East Asia, South-East Asia and Middle East and North Africa. We control for South Asia because the evidence from that region tends to be related to agriculture and Green revolution technologies. The South Asia dummy has a sample average of 0.32, indicating that estimates of employment effects in South Asian countries constitute 32 per cent of the evidence base