Imported Skill Biased Technological Change in Developing Countries

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Abstract

This paper discusses the occurrence of skill-enhancing technology import, namely the relationship between imports of embodied technology and widening skill-based employment differentials in low and middle-income countries.

GMM techniques are applied to an original panel dataset comprising 28 manufacturing sectors for 23 countries over a decade.

Econometric results provide robust evidence of the determinants of widening employment differentials in low and middle-income countries. In particular, the proposed empirical evidence indicates capital-skill complementarity as a possible source of skill-bias, while imported skill-enhancing technology emerges as an additional driver of increasing demand for the skilled workers in these countries.

Keywords: Skill Biased Technological Change, Capital Skill Complementarity, GMM estimation, General Industrial Statistics, World Trade Analyzer.

JEL classification: F16, J23, J24, O33

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1 Introduction

Since the beginning of the 1980s, a growing wage and employment divide between skilled and unskilled workers has been documented in the US (Juhn *et al.,* 1993), in the UK (Machin, 1996), in Japan (Katz and Revenga, 1990) and in other OECD countries (Nickell and Bell, 1996).

Many scholars have applied the insights of the classical Stolper-Samuelson (S-S) theorem and related the rising trend of inequality in high-income countries to trade with low and middle-income (LMICs) economies (Wood, 1995)[1]. On the contrary, technology-based explanations have emphasised the role of Skill-Biased Technological Change in shifting relative employment levels between skilled and unskilled labour (Bound and Johnson, 1992). While much economic literature has dealt with the determinants of within-country inequality in OECD economies (Katz and Autor, 1999), recent contributions have started to assess the inequality-enhancing effect of the contemporaneous occurrence of economic integration and technology diffusion in LMICs (Vivarelli, 2004). Indeed, both trade-based and technology-based explanations suggest an increase in within-country inequality in high-income countries while they imply an opposite theoretical prediction in low and middle income countries since trade integration should favour an increase in the relative demand of unskilled labour and, therefore, reducing within-country inequality (while technology diffusion working in the opposite direction).

This paper discusses the occurrence of Skill-Enhancing Technology Import (SETI), namely the relationship between imports of embodied technology and the employment of skilled and unskilled labour in LMICs. The aim is to empirically test the skill bias effect of international technology transfer in countries which rely mainly on this channel for their technological upgrading.

[1] Stolper-Samuelson (S-S) theorem suggests that - under some economic assumptions (i.e. perfect competition, constant returns) - a rise (fall) in the relative price of a good will lead to a rise (fall) in the return to that factor which is used most intensively in the production of the good, and conversely, to a fall (rise) in the return to the other factor. If skilled and unskilled labour represents these two factors, trade specialisation and FDI inflows will increase the international demand for unskilled labour in low and middle-income countries (where this is the abundant factor) and, thus, decrease wage dispersion and inequality in these countries. The opposite will occur in high income countries, namely an increase in the demand of the relative abundant factor (skilled labour) and, thus, an increase in the level of within-country inequality (Wood, 1994, p. 59).

Three aspects make this paper different from other empirical studies in this field. First, it provides an original detailed measure of SETI, while previous research has focused only on indirect proxies of technology transfer across countries. As described in Section 3.2, the advantage of this indicator refers to its accountability which, in turn, allows a detailed analysis of technological trade flows across countries. Second, this study offers a unified multi-country analysis by using an original time-series cross-sectional dataset of 4934 observations at the sector level for 23 LMICs. In turn, this allows to overcome the limitations which characterise country-specific research, namely the possible occurrence of institutional or other country-specific factors which may affect the results obtained. Finally, the empirical analysis verifies the hypotheses of "skill-enhancing technology import" and "capital-skill complementarity", where the latter investigates the relationship between capital investment and the employment of skilled labour, by looking at two separate employment equations for skilled and unskilled workers rather than using a single-equation framework. In turn, this allows to identify the separate effect of capital and SETI on the two categories of labour (skilled and unskilled) and, thus, verify the occurrence of absolute or relative skill-bias[2].

The remainder of the paper is organised as follows: the discussion about the theoretical framework (Section 2) is followed by the description of the data (Section 3) and the adopted econometric methodology (Section 4). Subsequently, the empirical results obtained from the descriptive analysis (Section 5) and the econometric estimates (Section 6) are discussed. Section 7 concludes this paper by summarising the main findings.

[2] Absolute skill bias indicates an opposite effect of capital and/or SETI on the two labour categories (i.e. negative on unskilled labour and positive on skilled labour). On the contrary, relative skill bias indicates a similar effect - but different magnitude - on skilled and unskilled labour (i.e. positive and greater for the former).

2 Interpretative Background

Two main streams of literature have provided competing theoretical frameworks for assessing the employment evolution of skills over time (Moore and Ranjan, 2005). On the one hand, some scholars have focused on the employment effect of trade and foreign direct investment (FDI) by stressing the role of recipient economies in the international division of labour. On the other hand, technology-based explanations have pointed to the intrinsic factor bias of technological change while neglecting the effect of international trade and/or a country's relative factor endowments. The core of the disagreement between these two approaches refers to the degree of endogeneity between technological change and trade, namely which factor has to be declared ultimately responsible for the increase in within-country inequality worldwide. Although starting from different perspectives, these two lines of research have sometimes converged over time in the assessment of the employment effect of international technology transfer.

2.1 The Employment Effect of Economic Integration

The classical Heckscher-Ohlin (H-O) and Stolper-Samuelson (S-S) trade theorems provide an analytical framework consistent with the expansion of international trade and widening skill-based inequality in high-income countries (Burtless, 1995). However, its predicted egalitarian effect in low and middle-income countries appears at odds with available empirical evidence of increased within-country inequality (Revenga, 1997).

The basic dichotomic framework depicted by the H-O/S-S theorem has been extended in three main directions (Slaughter, 1998). These research lines have related the degree of within-country inequality to the distributive outcome of a country' specific trade flows. For instance, the skill-based tripartite distinction of the workforce proposed by Wood (1994, p. 213) allows for the possibility that international trade may lead to different within-country inequality trends in low and middle-income countries (Meschi and Vivarelli, 2009). In a similar way, the representation of countries along a skill supply continuum, rather than in a standard North-South framework, suggests that the direction of a country´s trade flows will determine the final distributional outcome (Davis, 1996). A final departure from the standard H-O/S-S theorem is represented by the classification of traded goods according to their embodied (skill-related) technological content (Dornbusch *et al.*, 1980).

Indeed, this setting allows for the possible counter-effects of economic integration on within-country inequality while promoting technological upgrading in low and middle-income countries. Trade economists have advocated the H-O/S-S theorem as a suitable analytical framework for explaining long-run distributional dynamics whereas competing trade-based factors, such as the occurrence of defensive endogenous innovation (Leamer, 1996), "market stealing" effects and/or "crowding out" of domestic production (Beyer *et al.*, 1999), explain the upward short-run inequality trend in low and middle-income countries.

2.2 The Employment Effect of Technological Change

Economic research on the employment effect of technological change has focused mainly on the occurrence of both a mismatch technology-based explanation of unemployment and the effectiveness of compensation mechanisms in the labour markets (Vivarelli and Pianta, 2000). Research has since moved into the employment impact of technological change on different skills by providing a significant amount of evidence of the occurrence of skill-biased technological change (SBTC) among OECD countries (Machin and Van Reenen, 1998). The SBTC hypothesis implies that the exogenous adoption of a new technology will result in a *relative* employment shift from unskilled to skilled workers which raises both *relative* wage and employment levels[3]. Several findings support the SBTC hypothesis against competing explanations of within-country inequality. First, the predominance of the within-industry component of the overall employment shift of different skills is more consistent with SBTC than with changes in product demand, trade patterns or Hicks-neutral sector-biased technological change. The latter, on the contrary, favour between-industry reallocations towards skill-intensive sectors (Katz and Murphy, 1992). Second, such within-industry employment shifts, coupled with available evidence of higher relative wages, are consistent with the occurrence of a pervasive phenomenon across industries and countries such as the diffusion of SBTC (Bresnahan and Tratjenberg, 1995)[4]. Finally, some authors support the occurrence of SBTC by providing evidence

[3]Indeed, this definition does not require an *absolute* decline in the demand for unskilled workers or an *absolute* increase in the demand for skilled workers (Berman *et al.*, 1998).

[4]At the same time, such pervasive effects weaken competing explanations of within-country inequality based on country-specific shifts in domestic labour demand/supply (Wood, 1994 p. 171) or institutional variables, such as the decline in trade union membership and the extent of pay-setting norms (DiNardo *et al.,* 1996).

of within-industry correlations between measures of technological change and skilled employment (Autor *et al.*, 1998).

While the bulk of economic research on the employment effect of technological change has focused on high-income countries, there has been a growing recognition of the role of skill-biased technological change in raising within-country inequality in low and middle-income countries (Pavcnik, 2003). Trade- and technology-based explanations of within-country inequality have found common analytical patterns in the assessment of the effects of technology transfers to low and middle-income countries.

2.3 The Employment Effect of Technology Transfer

International technology transfer represents a crucial determinant of technological upgrading and economic growth in low and middle-income countries, given the negligible level of aggregate R&D investment in these economies (Coe *et al.*, 1997). Economic literature has discussed several channels of international technology diffusion, such as trade and FDI, licensing, scientific journals, internet, and other sources of cross-border communication (Schiff *et al.,* 2002). From a theoretical perspective, the relaxation of the H-O hypothesis of technological homogeneity among countries opens the way to the assessment of the within-country inequality effect of technology transfer in low and middle-income countries (Acemoglu, 1998).

The extent and the timing of the employment effect of technology transfer in these countries depend on the interaction between their degree of economic integration, the characteristics of the imported technologies and some specific “absorptive capacities" of recipient economies (Cohen and Levinthal, 1989; Lee and Vivarelli, 2004 and 2006)[5]. In turn, the extent of the inequality-enhancing effects of technology transfer depends on the intrinsic labour-saving and skill-bias features of imported technologies, and it may be reinforced by trade-based adverse competitive effects over time. Indeed, integration among markets increases international competitive pressures and the need for firms in low and middle-income countries to modernise. On the one hand, this may stimulate investments in human capital and, therefore, the occurrence of *defensive skill-bias* (Thoenig and

[5] These capacities are strongly related to a country´s labour market institutions (Acemoglu, 2003), skill supply (Schiff and Wang, 2004) and the extent of skill-biased organisational changes (Caroli *et al.,* 2001).

Verdier, 2003). On the other hand, firms in these countries may invest more in the imports of capital goods from high-income countries. Trade liberalisation, therefore, shows a skill-enhancing effect in low and middle-income countries (Robbins, 2003) since it induces both capital deepening, which increases relatively skilled employment because of capital-skill complementarities, and skill-biased technological change diffusion (Berman and Machin, 2000 and 2004). The economic literature does not provide clear-cut evidence of the relative importance of these two factors in explaining skill upgrading in low and middle-income countries. The methodology and the econometric analysis adopted in this paper aim at providing an answer to this question.

3 Dataset and Indicators

The empirical analysis in this paper is based on an original panel dataset characterised by an unbalanced structure comprising 4934 observations representative of 28 three-digit ISIC Rev. 2 manufacturing sectors (Major Division 3) of 23 low and middle-income countries over the period 1980 - 1991. The main original data source is the United Nations General Industrial Statistics Vol. 1 (GIS), which provides annual sector data on employment and wage by production categories, value added and capital formation. These variables are merged with the Skill-Enhancing Technology Import (SETI) indicator (Section 3.2), which is computed on data obtained from Statistics Canada´s World Trade Analyzer. This dataset allows us to track the economic value of bilateral trade flows worldwide since 1980 at the four-digit level of SITC Rev. 2 classification. Finally, purchasing power parity and the GDP deflator are taken from Penn World Tables 6.1 and The World Bank Development Indicators 2004 respectively.

Table 1 provides a list of the variables employed in the empirical analysis and their definitions. Appendix A describes these indicators in more detail.

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3.1 Methodological Issues

The absence of exhaustive sources of innovation and employment data in low and middle-income countries represents a common problem faced by applied research in this field. This issue becomes critical in the context of a multi-country study, since the lack of comparability between different national data sources restricts the choice of data providers to international agencies only. In particular, the only available dataset which offers data for "operative" and "non-operative" workers at the sector level is the UN-GIS Vol. 1[6]. Therefore, the UN-GIS Vol. 1 represents a unique and valuable source of information regarding the labour market of many low and middle-income countries in a very informative decade - the 1980s - which has witnessed the appearance of the globalisation process in terms of an exponential increase in total real trade between high-income countries and low and middle-income countries (Wood, 1998). This data source allows us therefore to gain useful insights into the occurrence of some structural relationships between economic variables such as the impact of technology transfer on within-country inequality, as described in this paper. Indeed, precisely this approach justifies recent use of this dataset among scholars (Berman and Machin, 2000 and 2004; Zhu, 2005).

The lack of primary data does not represent the only problem the empirical researcher has to deal with. The procedure for merging different available datasets does allow us to overcome the absence of a specific data source on innovation and employment in low and middle-income countries. However, the absence of a direct one-to-one conversion table between trade and sector classifications represents a serious challenge for the empirical definition of a measure of technology transfer. In the next section we discuss a suitable solution to this problem by offering an original procedure for creating a meaningful one-to-one conversion table of SITC - ISIC values.

3.2 Skill-Enhancing Technology Import (SETI)

The methodological problems discussed in the previous section have affected economic research in two ways. First, many studies dealing with technological change and employment in low and middle-income countries have adopted a country-specific approach[7]. This may represent a limi-

[6] After 1993, the collection of industrial statistics passed from UN to UNIDO. However, the new dataset, whose name became UNIDO Industrial Statistics, did not comprise data for "operative" workers, providing, instead, an aggregate variable "employees" only. Such a methodological shift has resulted in the disturbing lack of updated cross-country statistics on relative employment and wage by production categories.

[7] Some examples are Robbins and Gindling (1999) for Costa Rica; Feliciano (2001) for Mexico; Kang and Hong (2002) for Southern Korea; Attanasio *et al.* (2004) for Colombia; Berman *et al.* (2005) for India.

tation if country-specific factors, such as the institutions in the labour market, may affect results on the relationship between technology and skill adoption. Second, empirical research adopting a multi-country perspective has been based mainly upon indirect tests[8]. Although this line of research has advocated the occurrence (and pervasiveness) of skill-biased technology transfer in low and middle-income countries, it does in fact lack a direct measure of technology transfer, and thus, the technologies transferred, the transmission channels adopted and, finally, the actual direct employment impact of technology transfer on different skills in low and middle-income countries. To summarise, the key issue is that "... about lowincome countries we know very little. Our data are not particularly info*rmative about technology transfer*" (Berman and Machin, 2004, p. 66). The absence of a direct measure of technology transfer inevitably weakens empirical analysis. Such an ideal indicator would allow a more reliable and straightforward assessment of the casual relationship between technological change and employment of different skills in low and middle-income countries.

This paper provides an original measure of skill-enhancing technology import (SETI), which aims precisely at overcoming the use of indirect proxies of technology transfer. This indicator is direct and accountable since it comprises the annual sum of the economic value of trade flows from high-income countries to each low and middle-income country of those capital goods which reasonably incorporate technological upgrading. In particular, SETI will include the import of industrial machinery and equipment, power generating machinery, electrical machinery and apparatus and ICT capital goods such as office machines, automatic data processing equipment and TLC apparatus (for a detailed list of the four-digit goods used to construct the SETI variable, see Appendix B). The indicator of SETI therefore permits a detailed analysis of such trade flows, since traded goods are selected at the highest available level of detail, namely the four-digit level of SITC Rev. 2 taxonomy.

Three motivations sustain the strategy adopted in the construction of this variable. First, capital goods are selected in line with previous economic literature which underlines the importance of "general purpose technologies" (Bresnahan and Trajtenberg, 1995) for technological upgrading in many economic sectors. Since they embody newer technologies and are widely used across different

[8] In particular, technology transfer has been proxied by the occurrence of pairwise correlations of within-industry skill upgrading in different countries and by cross-country correlations between skill upgrading in low and middle-income countries and current and lagged technological variables in OECD countries (Berman and Machin, 2004).

economic sectors, these capital goods are very likely to affect labour market dynamics (Piva, 2003) - as, for instance, in the case of ICT (Keller, 2002). Second, high-income countries are also those economies which produce and employ the most advanced technologies[9]. Finally, low and middle-income countries have a negligible level of R&D and innovative investment and their (almost) unique channel of technological upgrading is represented by the import of technological change from high-income countries (see Section 2.3).

However, the choice of this measure raises the above-mentioned problem of value conversion between different taxonomies. This consists of a meaningful distribution of the aggregate SETI value - for instance US$445.6M in Peru in 1986 - across recipient ISIC manufacturing sectors in this country. Three competing strategies have been evaluated. The first requires the definition of a vector of (theoretical) sector weights for each (SITC) imported good - say electronic microcircuits - which would describe its final distribution across ISIC sectors[10]. This hypothesis has been rejected because of the computational effort required in providing/assuming reasonable weights over time, across sectors and countries. A second option suggests the aggregation of the total annual value of SETI for each low and middle-income country and then its distribution through annual sector input-output tables. Unfortunately, such tables are not available at the necessary level of detail, neither for the low and middle-income countries discussed in this paper, nor for the years of interest.

The adopted choice consists, therefore, in an original procedure which aims at exploiting the different sources of variability available in the dataset without introducing heroic assumptions and possible distortions in its empirical verification. This is based upon the following hypothesis:

[9] The following countries are classified as high-income countries: USA, UK, Italy, Japan, Israel, Switzerland, Sweden, Norway, Germany, France, Netherlands, Australia, Austria, Belgium, Canada, Denmark, Finland, Iceland, New Zealand.

[10] Conversion tables between ISIC and SITC taxonomies are only available in the one-to-many format (that is, a SITC product is distributed to many ISIC sectors) with no weights attached (i.e. World Bank's conversion tables available online). In turn, this means that no exact sector allocation of SITC products is possible on the basis of these tables.

Hypothesis: *An annual SETI value is distributed across the recipient country's sectors each year assuming the following relationship:*

$$\frac{(SETI)_{cit}}{Tot(SETI)_{ct}} = Sh(SETI)_{cit} = Sh(MEI)_{cit} = \frac{(MEI)_{cit}}{Tot(MEI)_{ct}} \tag{1}$$

where $Sh(SETI)_{cit}$ and $Sh(MEI)_{cit}$ represent the annual share (over total manufacturing) of SETI and total machinery and equipment investment (MEI) respectively, for each sector i of country c in year t. Therefore, the sector distribution of MEI is used to distribute the annual value of SETI across the different manufacturing sectors within the recipient country. This assumption implies that cross-sectoral differences in SETI, in each country and each year, may be reasonably proxied by the inter-sectoral shares of total machinery and equipment investment. In turn, this means that sectors with a relatively high share of total machinery and equipment investment are also those sectors with a higher proportion of SETI in each country[11]*.*

4 Econometric Issues

This section provides a framework for the theoretical specification of an employment equation and its econometric analysis. The skill-enhancing technology import (SETI) hypothesis, namely the relative increase in skilled employment in low and middle-income countries due to imports of embodied technology from richer countries is verified through GMM techniques applied to two distinct equations for skilled and unskilled labour.

4.1 Model Specification

The starting framework for the empirical estimation of an employment equation is given by the consideration of a perfectly-competitive industry operating under the following general constant

[11] Unfortunately, data on MEI - obtained from UN-GIS dataset - are available only in 2500 cases out of the overall 4934 observations. Where missing, a country's sector distribution of SETI has been obtained from total capital investment shares rather than from total machinery and equipment investment shares. This appears as a safe alternative option due to the strong significant correlation between total capital and machinery investments (0.88).

elasticity of substitution (CES) production function:

$$Y = H[(AL)^{\frac{\sigma-1}{\sigma}} + (BK)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where Y is the output, L and K represent conventional inputs such as labour and capital; H, A and B distinguish a Hicks-neutral, a labour-augmenting and a capital-augmenting technology respectively. The first-order profit-maximisation condition for labour - when a distinction is made between "blue-collar" (BC) and "white-collar" (WC) workers - allows us to express the previous equation as follows:

$$\ln(BC) = \ln(Y) - \sigma \ln(WBC) + (\sigma_{BC} - 1)\ln(A_{BC}) \tag{3}$$

$$\ln(WC) = \ln(Y) - \sigma \ln(WWC) + (\sigma_{WC} - 1)\ln(A_{WC}) \tag{4}$$

where WBC and WWC indicate real wages for the two categories (equated with the marginal product of labour) and $\sigma = \frac{1}{(1-\rho)}$ measures the elasticity of substitution between capital and labour (Van Reenen, 1997)[12]. This setting may be extended by including some proxies of the unobserved labour-augmenting technology component. Two hypotheses are tested directly as extensions of this specification. The first, capital deepening (KD), verifies the importance of capital-skill complementarities (Griliches, 1969; Krusell et al., 2000). As in Berman et al. (1994) and Zhu (2005), capital deepening is defined as the ratio between gross fixed capital formation and value added (KA_{cit}/VA_{cit}). The second hypothesis refers to "technological import deepening" which is obtained by the ratio between the indicator on skill-enhancing technology import (SETI: see Section 3.2) and value added ($SETI_{cit}/VA_{cit}$).

The empirical analysis focuses, therefore, on the following dynamic specification of the two employment equations:

$$BC_{cit} = \alpha + \beta BC_{cit-1} + \gamma VA_{cit} + \delta WBC_{cit} + KD_{cit} + TID_{cit} + (\varepsilon_i + v_{cit}) \tag{5}$$

$$WC_{cit} = \alpha + \beta WC_{cit-1} + \gamma VA_{cit} + \delta WWC_{cit} + KD_{cit} + TID_{cit} + (\varepsilon_i + v_{cit}) \tag{6}$$

[12] The extent of labour-augmenting technology (A) and capital-labour elasticity (σ) varies between "blue collar" and "white collar" workers.

where all variables are expressed in logs. BC_{cit} and WC_{cit} are, respectively, the number of "blue-collar" workers (or operatives) and "white-collars" (or non-operatives) in sector i of country c at time t. VA represents Value Added, WBC and WWC the wage of each skill category. KD indicates capital deepening whereas TID represents the sector share of "technological import deepening" (Table 1 and Appendix A provides a description of the variables adopted in this study). Finally, the error term includes the idiosyncratic individual and time-invariant sector fixed effect ε_i and the standard white-noise error term v_{cit}.

4.2 Econometric Analysis

This paper adopts a dynamic specification for studying the relationship between technological change and skills. This choice is based on the occurrence of significant adjustment costs which determine serial correlation in the employment series (Van Reenen, 1997). Both the presence of sector-specific effects and the dynamic specification of the econometric model lead the pooled ordinary least squares (POLS) estimator to provide inconsistent and upward biased estimates (Sevestre and Trognon, 1985)[13]. While the presence of sector-specific effects does not affect the within-group (WG) estimator, the violation of the assumption of strict exogeneity makes this estimator inconsistent and downwards biased (Nickell, 1981)[14]. A more effective solution to obtain consistent estimates in a dynamic panel framework is, therefore, to consider a first-difference transformation (Anderson and Hsiao, 1981) which wipes out time-invariant sector effects and provides consistent estimators with an instrumental variable (IV) procedure[15]. The availability of additional moment conditions when the time dimension increases can be used to increase the efficiency of the estimator

[13] In particular, the former determine the correlation between the lagged dependent variable y_{cit-1} and the individual fixed effect ε_i. The latter implies the violation of the assumption of strict exogeneity of the regressors due to the presence of an endogenous first-order lagged dependent variable.

[14] Kiviet (1995) provides a correction of the WG estimator bias which declines as the time dimension approaches infinity. Nevertheless, the limited time dimension of the panel adopted in this analysis does not allow a satisfactory use of a WG estimator.

[15] IV techniques are necessary since the lagged difference of the dependent variable Δy_{cit-1} is correlated by construction with the differenced error term Δv_{cit}. Generally, further lags from the lagged level (y_{cit-2}) or difference (Δy_{cit-2}) can be used as instruments if there is no serial correlation in the v_{cit} process.

by means of a Generalized Method of Moments (GMM) procedure (Ahn and Schmidt, 1995). Based on Arellano (1989), who compares the use of instruments in difference and level, Arellano and Bond (1991) define the First-Differenced GMM (GMM-DIF) where standard deviations and t-statistics are based on a heteroscedasticity-robust covariance matrix (White, 1980) and each instrument depends on the specific assumption made about endogeneity, predetermination and exogeneity of the corresponding instrumented variable. However, two conditions weaken the efficiency of the GMM-DIF estimator, namely a short time dimension of the panel and/or a strong persistence in the time series. If one of these circumstances applies, the available instruments are only weakly correlated with the variables in first differences and the GMM-DIF estimate is close to its WG estimate (Bond *et al.*, 2001). In this case, an efficiency improvement may be obtained through the addition of the original equations in level, instrumented by their own first differences, to the equations in first differences which are instrumented as in the GMM-DIF case (Arellano and Bover, 1995)[16]. Indeed, this new estimator, called System GMM (GMM-SYS), exploits all available information through these additional moment conditions and is based on the assumption that $E(\Delta v_{cit}\varepsilon_i) = 0$ (Bond, 2002). The (robust) Hansen J statistic, which is the minimised value of the two-step GMM criterion function, replaces the Sargan statistic in both a one-step GMM robust estimation and a two-step GMM estimation, since the latter is not robust to either heteroskedasticity or autocorrelation. A two-step GMM estimation results in asymptotically more efficient standard errors than a one-step GMM estimation. Although these may be strongly biased downwards in the presence of a small sample size and/or heteroschedasticity (Blundell and Bond, 1998), a small-sample variance correction suggested by Windmeijer (2000) eliminates such bias and suggests, therefore, the adoption of this two-step estimator in the following econometric estimates.

[16] Blundell and Bond (1999) and Blundell *et al.* (2000) verify the efficiency improvement of GMM-SYS estimator for the AR(1) model by using Monte Carlo analyses. GMM-DIF and GMM-SYS are connected by the common presence of the equations in differences and by a general rule which applies to the instruments of both estimators: in particular, Δx_{cit-s} represents a good instrument for the equations in levels if it is not correlated with ε_i and $x_{cit-(s+1)}$ is a valid instrument for the first-difference equations.

5 Descriptive Analysis

A first assessment of the sources of variability in the dataset comes from the results of Table 2. In particular, an ANOVA analysis indicates that all the three dimensions which characterise the data sample, that is countries, sectors and year, are relevant for explaining the observed variability in the relevant variables.

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A detailed summary of the main features of the data is provided in Tables 3 and 4, which provide the growth rates of the variables adopted in the econometric analysis at the sector and country levels respectively[17].

——— INSERT TABLES 3 AND 4 ———

At the sector level, there has been *relative* skill bias in 25 industries out of 28, except for Tobacco (3140), Wood Products (3310) and Petroleum, Coal Products (3540). Such a widespread increase in the ratio of skilled to unskilled employment has not been followed by a similar marked trend in the ratio of skilled to unskilled wages which, instead, has appeared quite constant over time (Berman and Machin, 2000). This pattern is also consistent across countries. Indeed, there has been *relative* skill bias in all countries with the exception of Malaysia and Bangladesh where the growth rate of BC has been faster than the growth rate of WC. Eight countries out of 23 (three LICs) have witnessed absolute diverging employment paths between WC and BC whereas four countries - all MICs - have experienced a decrease in the employment of both "operative" and "non operative" workers. Such preliminary evidence allows us to introduce the econometric assessment of the determinants of WC and BC employment described in the next section.

[17] Growth rates at the country level are computed for the available period on data for the total Manufacturing sector ("Major Division 3"). Other industrial sectors, such as Mining and Quarrying ("Major Division 2") and Electricity, Gas and Water ("Major Division 4"), do not form part of the dataset. In contrast, the unbalanced structure of the panel makes the analysis of annual growth rates more meaningful at the sector level. These growth rates are weighted by the sector's share of total manufacturing employment.

6 Empirical Results

In Section 4.2 we have already indicated that the short time dimension of the panel and a strong persistence in the time series recommend the adoption of a GMM-SYS estimator. Indeed, these two conditions occur in the context of the empirical analysis here since the time span covers only a decade whereas Table 5 shows the high persistence of the employment series of both BC and WC.

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Previous economic research has investigated the relative upskilling of the workforce mainly through shifts in the payroll share of skilled labour in a cost-function setting (Bartel and Lichtenberg, 1987; Zhu, 2005). A single-equation setting cannot however distinguish the determinants of either relative and absolute skill bias or the employment dynamics of BC and WC separately. The econometric strategy adopted in this paper allows us to overcome these two problems through the estimation of two independent employment equations for BC and WC. This section thus presents the results from the two employment equations, together with some sensitivity checks. Each specification also includes country and sector dummies to check for the robustness of the results obtained. Time dummies are always included, to take possible macroeconomic shocks common to all the considered variables into account. As far as the instrumentation of the included regressors is concerned, we assumed the conservative hypothesis of considering all the variables as endogeneous. Indeed, it may well be the case that in most low and middle-income countries – highly dependent on the global economic climate and on the occurrence of external unobserved shocks – employment, wages, investments and sales may be jointly determined. Accordingly, all the regressors have been instrumented starting from the two-lags instrumental variables, which is the GMM procedure for dealing with endogeneous variables. This methodological choice not only puts us on the safe side in terms of the possible endogeneity of the included variables, but is also supported by a battery of Hansen tests. In fact, all the six joint Hansen tests – reported in Tables 6 and 7 – indicate that the null of adequate instruments is never rejected. Moreover, in Appendix D each instrument for each specification is tested separately (five regressors times six specifications, equal to thirty Hansen tests). As can be seen, the null of correct instrumentation is never rejected, with only two partial exceptions[18].

——— INSERT TABLE 6 ———

Table 6 provides the GMM-SYS estimator for the BC equation. All the three estimates give similar and significant results. The high persistence of the employment series and the predictable behaviour of the coefficients of BC wages and value added are confirmed. In particular, wages depict the usual negative relationship consistent with a demand for labour specification. On the contrary – and not surprisingly - the expansion of a sector's value added affects the demand for blue collars positively. An interesting pattern emerges from the comparison of the coefficients of capital deepening and skill-enhancing technology import (SETI) deepening since they show different impacts on the employment of BC workers. This result appears to be at odds with the homogeneous treatment of capital stock and technology commonly adopted in empirical literature. In particular, "generic" capital displays a positive and significant coefficient: sectoral gross investments are positively correlated with the demand for blue collars. However, the coefficient of SETI deepening, namely of those capital goods which embody the technological level of the most advanced countries, exhibits a non-significant (even negative in one case out of three) impact on the employment of the unskilled workers.

All these results appear robust to the introduction of country and sector dummies which, in turn, are jointly significant (see Table 6)[19]. As already discussed, the Hansen tests advocate the validity of the GMM instruments, while the AR tests support the overall validity of the model by providing evidence of a significant negative AR(1) and the absence of AR(2)[20].

——— INSERT TABLE 7 ———

[18] These concern the wages of the white collars in the specifications with the additional dummies; however, even in these cases, the Hansen test is never significant at the 99% level of confidence.

[19] A Wald test, asymptotically distributed as χ^2 where the degrees of freedom (dof) equate the number of restricted coefficients, allows us to test the overall significance of the independent variables and both time and individual effects.

[20] Since the consistency of the GMM estimates requires non serial-correlated errors v_{cit}, Arellano-Bond (1991) provide a Lagrange multiplier (LM)-based test of autocorrelation which is applied to the residuals of the first-difference equation in order to drop the time-invariant fixed effect ε_i. This test, distributed as $N(0,1)$ under the H_0 of no autocorrelation, provides strong evidence of AR(1) in first differences because of the correlation between the first differences of the (uncorrelated) errors Δv_{cit} and Δv_{cit-1} due to the common term v_{cit-1}. Finally, the absence of

Table 7 provides the GMM-SYS estimator for the WC equation. In this case too, the three estimates give consistent results, while the Hansen tests and the AR tests validate the Table 7 models. As expected, the coefficient of the lagged dependent variable indicates a high persistence of the employment series of WC. The coefficients of WC wages and value added are similar to those in the BC equation, showing a negative and a positive sign respectively. The coefficient of capital deepening is positive and larger than that in the BC equation (in two out of three estimations[21]). This evidence suggests that capital deepening may affect the relative skill bias of the employment series, since it increases the labour demand for both BC and WC, the latter more intensively. This result is consistent with a line of economic research which has related the employment of skills in low and middle-income countries to the capital-skill complementarity hypothesis (Goldin and Katz, 1998; Flug and Hercowitz, 2000)[22]. Differently, skill-enhancing technology import (SETI) deepening determines absolute skill bias since it affects the employment of the white collars positively and significantly, while at the same time its coefficient in the BC equation was never significant, even being negative in one case.

The skill biased role of the SETI variable is reinforced by the findings presented in Appendix C. In line with the findings discussed in Tables 6 and 7, this variable turns out to be one of the crucial factors affecting the upskilling of the labour force in the relative employment equation (see Table C2) while no similar effect appears in the case of capital deepening. Indeed, the coefficient of SETI deepening in a a single-equation setting points out to the effect of technology import on the relative demand of skills and, thus, confirms the evidence of the two-equation framework where the two coefficients of this variable - on white collars and blue collars - indicate the occurrence of skill

AR(2) supports the consistency of the GMM estimator.

[21] Indeed, in column 2 of Table 7 the capital deepening coefficient turns out to be barely significant and this impedes a common ground comparison with the correspondent column in Table 6.

[22] For instance, Berman and Machin (2000 and 2004) verify the occurrence of SBTC in low and middle-income countries through changes in capital-labour ratios (based on the capital-skills complementarity hypothesis) whereas Wood (1994, p. 224) controls for the average ratio of investment to GDP.

bias[23].

To sum up, the econometric results highlight the fact that technology transfer from high-income countries seems to drive the tendency towards a greater employment divide in low and middle-income countries. Indeed, given the importance of technology transfer as a major determinant of economic growth and technological catching-up in low and middle-income countries, policies favouring international technology diffusion have to be complemented in recipient economies by the design of more comprehensive labour market policies - including issues such as skill mismatch and continuos training - which have been generally neglected so far.

7 Concluding Remarks

This paper has discussed the employment impact of Skill-Enhancing Technology Import (SETI) in a sample of low and middle-income countries. We have provided a detailed measure of direct technology transfer across countries, which in turn is obtained by an original procedure for the conversion of trade data into sector values, which may be valuable for future research in this field.

Our econometric analysis has tested the SETI and capital-skill complementarity hypotheses through an unbalanced panel dataset comprising 4934 observations for 28 manufacturing sectors of 23 low and middle-income countries in the period 1980-1991.

GMM-SYS techniques have been applied to the estimation of two similar employment equations for both BC and WC. This has allowed us to distinguish the determinants of the relative and the absolute skill bias of employment over time. Econometric results indicate that capital deepening is responsible for relative shifts towards skilled labour. In contrast, SETI appears to be the crucial determinant of an absolute diverging path between skilled and unskilled employment in low and middle-income countries. Indeed, the transferred technology embodied in imports of industrial machinery, equipment and ICT capital goods involve a significant increase in the demand for skilled workers, while it has no significant impact on the demand for the unskilled.

[23] An additional robustness check has been made by re-running all the regressions presented in this section on a smaller dataset - that is, by excluding those countries and sectors with the highest value of TID. The outcome of this test confirms the evidence presented in this Section (results available on request).

References

Acemoglu, Daron. 1998. Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality. *Quarterly Journal of Economics*, **Vol. 113**(4), pp. 1055–1089.

Acemoglu, Daron. 2003. Patterns of Skill Premia. *Review of Economic Studies*, **Vol. 70**(2), pp. 199–230.

Ahn, Seung C., & Schmidt, Peter. 1995. Efficient Estimation of Models for Dynamic Panel Data. *Journal of Econometrics*, **Vol. 68**(1), pp. 5–27.

Anderson, T. W., & Hsiao, Cheng. 1981. Estimation of Dynamic Models with Error Components. *Journal of the American Statistical Association*, **Vol. 76**(375), pp. 598–606.

Arellano, Manuel. 1989. A Note on the Anderson-Hsiao Estimator for Panel Data. *Economics Letters*, **Vol. 31**(4), pp. 337–341.

Arellano, Manuel, & Bond, Stephen. 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies*, **Vol. 58**(2), pp. 277–297.

Arellano, Manuel, & Bover, Olympia. 1995. Another Look at the Instrumental Variables Estimation of Error-components Models. *Journal of Econometrics*, **Vol. 68**(1), pp. 29–51.

Attanasio, Orazio, Goldberg, Pinelopi K., & Pavcnik, Nina. 2004. Trade Reforms and Wage Inequality in Colombia. *Journal of Development Economics*, **Vol. 74**(2), pp. 331–366.

Autor, David, Katz, Lawrence F., & Krueger, Alan. 1998. Computing Inequality: Have Computers Changed the Labor Market? *Quarterly Journal of Economics*, **Vol. 113**(4), pp. 1169–1213.

Bartel, Ann P., & Lichtenberg, Frank R. 1987. The Comparative Advantage of Educated Workers in Implementing New Technology. *Review of Economics and Statistics*, **Vol. 69**(1), pp. 1–11.

Berman, Eli, & Machin, Stephen. 2000. Skill-Biased Technology Transfer around the World. *Oxford Review of Economic Policy*, **Vol. 16**(3), pp. 12–22.

BERMAN, ELI, & MACHIN, STEPHEN. 2004. *Globalization, Skill-Biased Technological Change and Labour Demand.* In Lee E. and Vivarelli M. (eds.), "Understanding Globalization, Employment and Poverty Reduction", London: Palgrave MacMillan, pp. 39-66.

BERMAN, ELI, BOUND, JOHN, & GRILICHES, ZVI. 1994. Changes in the Demand for Skilled Labor within US Manufacturing: Evidence from the Annual Survey of Manufactures. *Quarterly Journal of Economics*, **Vol. 109**(2), pp. 367–397.

BERMAN, ELI, BOUND, JOHN, & MACHIN, STEPHEN. 1998. Implications of Skill - Biased Technological Change: International Evidence. *Quarterly Journal of Economics*, **Vol. 113**(4), pp. 1245–1279.

BERMAN, ELI, SOMANATHAN, ROHINI, & TAN, HONG W. 2005. *Is Skill-Biased Technological Change Here Yet? Evidence From Indian Manufacturing in the 1990.* The World Bank, Policy Research Working Paper Series, Working Paper No. 3761.

BEYER, HARALD, ROJAS, PATRICIO, & VERGARA, RODRIGO. 1999. Trade Liberalization and Wage Inequality. *Journal of Development Economics*, **Vol. 59**, pp. 103–123.

BLUNDELL, RICHARD, & BOND, STEPHEN. 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics*, **Vol. 87**(1), pp. 115–143.

BLUNDELL, RICHARD, & BOND, STEVE. 1999. *GMM Estimation with Persistent Panel Data: an Application to Production Functions.* Institute for Fiscal Studies, UCL, Working Paper No. 99/04.

BLUNDELL, RICHARD, BOND, STEVE, & WINDMEIJER, FRANK. 2000. *Estimation in Dynamic Panel Data Models: Improving on the Performance of the Standard GMM Estimators.* Institute for Fiscal Studies, UCL, Working Paper No. 00/12.

BOND, STEPHEN. 2002. *Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice.* CEMMAP, UCL, Working Paper No. 09/02.

BOND, STEPHEN ROY, HOEFFLER, ANKE, & TEMPLE, JONATHAN. 2001. *GMM Estimation of Empirical Growth Models.* Centre for Economic Policy Research, Working Paper No. 3048.

BOUND, JOHN, & JOHNSON, GEORGE. 1992. Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations. *American Economic Review*, **Vol. 82**(3), pp. 371–392.

BRESNAHAN, TIMOTHY F., & TRAJTENBERG, M. 1995. General Purpose Technologies "Engines of Growth"? *Journal of Econometrics*, **Vol. 65**(1), pp. 83–108.

BURTLESS, GARY. 1995. International Trade and the Rise in Earnings Inequality. *Journal of Economic Literature*, **Vol. 33**(2), pp. 800–816.

CAROLI, EVE, GREENAN, NATHALIE, & GUELLEC, DOMINIQUE. 2001. Organizational Change and Skill Accumulation. *Industrial and Corporate Change*, **Vol. 10**, pp. 481–506.

COE, DAVID T., HELPMAN, ELHANAN, & HOFFMAISTER, ALEXANDER W. 1997. North - South R&D Spillovers. *Economic Journal*, **Vol. 107**(440), pp. 134–149.

COHEN, WESLEY M., & LEVINTHAL, DANIEL A. 1989. Innovation and Learning: the two Faces of R&D. *Economic Journal*, **Vol. 99**(397), pp. 569–596.

DAVIS, DONALD R. 1996. *Trade Liberalization and Income Distribution*. National Bureau of Economic Research, Working Paper No. 5693.

DINARDO, JOHN, FORTIN, NICOLE M., & LEMIEUX, THOMAS. 1996. Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, **Vol. 64**(5), pp. 1001–1044.

DORNBUSCH, RUDIGER, FISCHER, STANLEY, & SAMUELSON, PAUL A. 1980. Heckscher-Ohlin Trade Theory with a Continuum of Goods. *Quarterly Journal of Economics*, **Vol. 95**(2), pp. 203–224.

FELICIANO, ZADIA. 2001. Workers and Trade Liberalization: The Impact of Trade Reforms in Mexico on Wages and Employment. *Industrial and Labor Relations Review*, **Vol. 55**(1), pp. 95–115.

FLUG, KARNIT, & HERCOWITZ, ZVI. 2000. Equipment Investment and the Relative Demand for Skilled Labor: International Evidence. *Review of Economic Dynamics*, **Vol. 3**(3), pp. 461–485.

Goldin, Claudia, & Katz, Lawrence F. 1998. The Origins of Technology Skill Complementarity. *Quarterly Journal of Economics*, **Vol. 113**(3), pp. 693–732.

Griliches, Zvi. 1969. Capital-Skill Complementarity. *Review of Economics and Statistics*, **Vol. 51**(4), pp. 465–468.

Juhn, Chinhui, Murphy, Kevin M., & Pierce, Brooks. 1993. Wage Inequality and the Rise in Returns to Skill. *Journal of Political Economy*, **Vol. 101**(3), pp. 410–442.

Kang, Seoghoon, & Hong, Dong-Pyo. 2002. Technological Change and Demand for Skills in Developing Countries: An Empirical Investigation of the Republic of Korea's Case. *Developing Economies*, **Vol. 40**(2), pp. 188–207.

Katz, Lawrence F., & Autor, David H. 1999. *Changes in the Wage Structure and Earnings Inequality*. In O. Ashenfelter and D. Card (eds.), "Handbook of Labor Economics", Vol. 3. Amsterdam: Elsevier-North Holland, pp. 1463-1555.

Katz, Lawrence F., & Murphy, Kevin M. 1992. Changes in Relative Wages, 1963 - 1987: Supply and Demand Factors. *Quarterly Journal of Economics*, **Vol. 107**(1), pp. 35–78.

Katz, Lawrence F., & Revenga, Ana L. 1990. *Changes in the Structure of Wages: The U.S. versus Japan*. National Bureau of Economic Research, Working Paper No. 3021.

Keller, Wolfgang. 2002. Geographic Localization of International Technology Diffusion. *American Economic Review*, **Vol. 92**(1), pp. 120–142.

Kiviet, Jan F. 1995. On Bias, Inconsistency, and Efficiency of Various Estimators in Dynamic Panel Data Models. *Journal of Econometrics*, **Vol. 68**(1), pp. 53–78.

Krusell, Per, Ohanian, Lee E., Rios-Rull, Jose-Victor, & Violante, Giovanni L. 2000. Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica*, **Vol. 68**(5), pp. 1029–1053.

Leamer, Edward E. 1996. Wage Inequality from International Competition and Technological Change: Theory and Country Experience. *American Economic Review*, **Vol. 86**(2), pp. 309–314.

Lee, Eddy, & Vivarelli, Marco (eds). 2004. *Understanding Globalization, Employment and Poverty Reduction*. London: Palgrave MacMillan.

Lee, Eddy, & Vivarelli, Marco. 2006. The Social Impact of Globalization in the Developing Countries. *International Labour Review*, **Vol. 145**(3), pp. 167–184.

Machin, Stephen. 1996. Wage Inequality in the UK. *Oxford Review of Economic Policy*, **Vol. 12**(1), pp. 47–64.

Machin, Stephen, & Reenen, John Van. 1998. Technology and Changes in Skill Structure: Evidence from Seven OECD Countries. *Quarterly Journal of Economics*, **Vol. 113**(4), pp. 1215–1244.

Meschi, Elena, & Vivarelli, Marco. 2009. Trade and income Inequality in Developing Countries. *World Development*, **Vol. 37**(2), pp. 287–302.

Moore, Mark P., & Ranjan, Priya. 2005. Globalisation vs Skill-Biased Technological Change: Implications for Unemployment and Wage Inequality. *Economic Journal*, **Vol. 115**(503), pp. 391–422.

Nickell, Stephen. 1981. Biases in Dynamic Models with Fixed Effects. *Econometrica*, **Vol. 49**(6), pp. 1417–1426.

Nickell, Stephen, & Bell, Brian. 1996. Changes in the Distribution of Wages and Unemployment in OECD Countries. *American Economic Review*, **Vol. 86**(2), pp. 302–308.

Pavcnik, Nina. 2003. What Explains Skill Upgrading in Less Developed Countries? *Journal of Development Economics*, **Vol. 71**(2), pp. 311–327.

Piva, Mariacristina. 2003. *The Impact of Technology Transfer on Employment and Income Distribution in Developing Countries: a Survey of Theoretical Models and Empirical Studies*. International Labour Organisation - International Policy Group, Working Paper No. 15.

Revenga, Ana. 1997. Employment and Wage Effects of Trade Liberalization: The Case of Mexican Manufacturing. *Journal of Labor Economics*, **Vol. 15**(3), pp. S20–S43.

Robbins, Donald, & Gindling, T. H. 1999. Trade Liberalization and the Relative Wages for More-Skilled Workers in Costa Rica. *Review of Development Economics*, **Vol. 3**(2), pp. 140–54.

Robbins, Donald J. 2003. *The Impact of Trade Liberalization upon Inequality in Developing Countries: A Review of Theory and Evidence.* International Labour Organisation - International Policy Group, Working Paper No. 13.

Schiff, Maurice, & Wang, Yanling. 2004. *Education, Governance and Trade-related Technology Diffusion in Latin America.* IZA - Institute for the Study of Labor, Working Paper No. 1028.

Schiff, Maurice, Wang, Yanling, & Olarreaga, Marcelo. 2002. *Trade - Related Technology Diffusion and the Dynamics of North-South and South-South Integration.* The World Bank Development Research Group, Working Paper No. 2861.

Sevestre, P., & Trognon, A. 1985. A Note on Autoregressive Error Components Models. *Journal of Econometrics*, **Vol. 28**(2), pp. 231–245.

Slaughter, Matthew J. 1998. International Trade and Labour Market Outcomes: Results, Questions and Policy Options. *Economic Journal*, **Vol. 108**(450), pp. 1452–1462.

Thoenig, Mathias, & Verdier, Thierry. 2003. A Theory of Defensive Skill-Biased Innovation and Globalisation. *American Economic Review*, **Vol. 93**(3), pp. 709–728.

Van Reenen, John. 1997. Employment and Technological Innovation: Evidence From UK Manufacturing Firms. *Journal of Labor Economics*, **Vol. 15**(2), pp. 255–284.

Vivarelli, Marco. 2004. *Globalization, Skills and Within-Country Income Inequality in Developing Countries.* In Lee E. and Vivarelli M. (eds.), "Understanding Globalization, Employment and Poverty Reduction", London: Palgrave MacMillan, pp. 211-243.

Vivarelli, Marco, & Pianta, Mario (eds). 2000. *The Employment Impact of Innovation: Evidence and Policy.* London: Routledge.

White, Halbert. 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica*, **Vol. 48**(4), pp. 817–838.

WINDMEIJER, FRANK. 2000. *A Finite Sample Correction for the Variance of Linear Two-step GMM Estimators.* Institute for Fiscal Studies, UCL, Working Paper No. 00/19.

WOOD, ADRIAN. 1994. *North - South Trade, Employment and Inequality.* Oxford University Press.

WOOD, ADRIAN. 1995. How Trade Hurt Unskilled Workers. *Journal of Economic Perspectives*, **Vol. 9**(3), pp. 57–80.

WOOD, ADRIAN. 1998. Globalisation and the Rise in Labour Market Inequalities. *Economic Journal*, **Vol. 108**(450), pp. 1463–1482.

ZHU, SUSAN CHUN. 2005. Can Product Cycles Explain Skill Upgrading? *Journal of International Economics*, **Vol. 66**(1), pp. 131–155.

Tables and Appendices

Table 1. List of Variables and Definitions

BC	Number of employees engaged in production activities (or "blue collar")
WC	Number of employees engaged in non-production activities (or "white collar")
WBC	Per-capita wage/payment made to BC workers
WWC	Per-capita wage/payment made to WC workers
VA	Value Added - value of census output less the value of census input
KA	Gross Fixed Capital Formation
SETI	Trade Value of Technology Import
KD	Capital Deepening, namely KA_{cit}/VA_{cit}
TID	SETI Deepening, namely $SETI_{cit}/VA_{cit}$
SECTORS	International Standard Industrial Classification Rev. 2 - 28 Man. Sectors
COUNTRIES	23 LMICs - The World Bank Development Indicators - Classification at 1980
YEARS	Annual Observations - Time Period: 1980 - 1991

Table 2. Factorial Analysis of Variance (ANOVA) of Key Variables.

	BC	WC	WBC	WWC	VA	KD	TID
Country	974.90**	1091**	18664**	24507**	3717**	312.10**	3451**
Industry	498.93**	536.44**	250.31**	194.49**	429.27**	146.33**	118.23**
Year	3.44**	12.66**	55.85**	55.69**	39.91**	8.59**	19.84**

Notes:
1) * significant at 5%; ** significant at 1%
2) Data are weighted by the annual sector number of employees.

Table 3. Sector Annual Growth Rates of Key Variables

ISIC Rev. 2 - Sectors	Tech. Intensity[1]	BC	WC	Rel. Wage	VA	KD	TID
3110 - Food Products	Low	-.0069	-.0002	.0055	.0947	.0265	.0188
3130 - Beverages	Low	.0084	.0176	.0303	.0823	.0594	.0230
3140 - Tobacco	Low	.0167	-.0110	.0709	.0198	.3144	.0789
3210 - Textiles	Low	-.0155	-.0050	.0013	.0121	.0519	.0045
3220 - Wearing Apparel	Low	.0463	.0783	.0023	.0960	.1360	.0081
3230 - Leather Products	Low	.0320	.0638	-.0001	.0943	.1306	.0406
3240 - Footwear	Low	.0068	.0460	.0104	.0311	.2711	.0194
3310 - Wood Products	Low	.0084	-.0014	.0223	.0496	.1694	.0466
3320 - Furniture, Fixtures	Medium-Low	.0245	.0534	.0239	.0651	.1327	.0404
3410 - Paper Products	Low	.0078	.0149	.0111	.0563	.2125	.0551
3420 - Printing, Publishing	Low	.0067	.0332	.0153	.0670	.1810	.0667
3510 - Industrial Chemicals	Medium-High	.0165	.0208	.0064	.1171	.0867	.0057
3520 - Other Chemicals	High	.0119	.0230	-.0041	.0651	.1062	.0481
3530 - Petrol. Refineries	Medium-Low	.0242	.0729	-.0415	.2425	.3978	.0097
3540 - Petrol. Coal Prod.	Medium-Low	.0302	.0171	.0281	.2437	.6071	.1282
3550 - Rubber Products	Medium-Low	.0434	.0637	-.0174	.1072	.1504	.0353
3560 - Plastic Products	Medium-Low	.0513	.0841	-.0044	.1053	.0878	.0406
3610 - Pottery, China etc.	Medium-Low	.0259	.0532	.0225	.0806	.2893	.0997
3620 - Glass and Products	Medium-Low	.0007	.0231	.0227	.0693	.3864	.0727
3690 - Non-metal Products	Medium-Low	.0160	.0331	.0337	.0797	.1826	.0222
3710 - Iron and Steel	Medium-Low	.0019	.0031	.0133	.0650	.1665	.0873
3720 - Non-ferrous Metals	Medium-Low	.0158	.0476	.0090	.1528	.3035	.0394
3810 - Metal Products	Medium-Low	.0097	.0254	.0061	.0705	.0689	.0551
3820 - Machinery	Medium-High	.0230	.0430	.0019	.0824	.0605	-.0132
3830 - Electrical Machinery	Medium-High	.0459	.0519	.0110	.1214	.0804	.0349
3840 - Transport Equipm.	Medium-High	.0147	.0169	.0062	.0818	.0851	.0498
3850 - Professional Goods	High	.0416	.0686	.0042	.1166	.2508	.0378
3900 - Other Industries	Low	.0300	.0510	-.0064	.0898	.1852	.0219

[1] Technological intensity is defined by OECD Science, Technology and Industry Scoreboard which classifies ISIC sectors according to the three-digit Rev. 3 taxonomy (at four-digit for some specific sub-sectors). Sector conversion from ISIC Rev. 3 to ISIC Rev. 2 is provided by the author (see note 14). Another source of equivalent information on technological intensity is provided by Keller (2002) which finds that about 80% of all manufacturing expenditure in R&D is conducted in the following industries: Chemical Products (3510/3520), Electrical and Non-Electrical Machinery (3820/3830) and Transportation Equipment (3840).

Table 4. Growth Rates of Key Variables by Country

	BC	WC	Rel. Wage	VA	KD	TID	Period
Middle-Income Countries							
Chile	.4399	.4530	.0099	.6412	.0256	.1334	1980-1990
Cyprus	.2475	.3128	.0280	.4755	-.2804	.0838	1980-1991
Greece	-.2089	.2698	-.0911	-.0572°	-.3007	.4768	1980-1990
Ireland	-.1971	-.0045	.0601	.7372°	-.4396	-.0396	1980-1989
Malaysia	.7560	.1387	.3295	.9955°	.8149	.0064	1983-1990
Malta	-.0926	.1536	.0080	.2150	.7339	.0888	1980-1988
Mexico	-.1640	.2617	.4151	-.0418	.3319	1.4537	1986-1991
Panama	-.1080	-.0216	-.1908	-.1951	-.7022	-.2147	1981-1989
Portugal	-.0966	-.0164	.1415	.1059	-.2573	.1250	1980-1987
South Korea	.4213	.6420	-.0984	2.1222	.0382	-.0804	1980-1990
Spain	-.2256	-.0861	.1671	-.0308°	.4927	2.0223	1980-1990
Turkey	.1408	.8146	-.1139	1.0770	.7104	.3889	1980-1990
Venezuela	.1223	.4846	-.0161	.2558	.1093	-.3429	1981-1991
TOT - MICs♣	.1118	.3179	.0757	.7953	.2526	.6547	1980-1991
Low-Income Countries							
Bangladesh	.1443	.0226	.0036	.2634	.1095	-.5299	1981-1988
Colombia	-.1168	.1775	-.0189	.2931	.9445	-.2517	1980-1990
Egypt	.1453	.3548	-.0509	.8656	-.5262	-.1951	1980-1988
Ethiopia	.1889	.6340	-.1211	.1646	.1559	.6800	1980-1988
Guatemala	-.3149	.1082	-.1966	-.2287	-.4480	.3916	1980-1988
India	-.0207	.0302	-.0763	.5922°	.1043	.0624	1980-1988
Pakistan	.1347	.1593	.2015	.6704	-.2188	.3641	1981-1988
Peru	.0663	.2056	.1552	.4197	-.4205	-.6732	1980-1988
Philippines	-.2386	1.1727	-.4131	.3189	-.3832	-.5733	1980-1988
Tanzania	-.1123	.0894	.1049	-.2910°	.1432	-.0751	1980-1985
TOT - LICs♣	-.0145	.1850	-.0787	.5452	.0118	-.0586	1980-1990
TOT♣	.0438	.2463	-.0074	.6606	.1229	.2705	

Notes:
1) Chile: 1987-1988; Cyprus: 1987; Malaysia: 1984 not available.
2) Malta. Purchasing Power Parity from The World Bank Development Indicators 2004.
3) Mexico. Econometric analysis for the period 1980-1991 (1986 not available).
Estimates of total manufacturing investment for missing years are computed in order to calculate sector shares through a three-years backward moving average.
VA and KA from UNIDO Industrial Statistics Database 2002.
4) Pakistan: 1985; Panama: 1986-1987-1988 not available.
5) Perú. Employment from UNIDO Industrial Statistics Database 2002.

° Value added based on factor prices - otherwise measured on producer´s prices.
♣ Weighted by a country' share of total employment averaged over the initial and final period. Values are obtained from data on aggregate manufacturing.

Table 5. Time Persistence in the Employment Series

	BC	WC
AR(1)	.9851***	.9928***
	(.0011)	(.0014)

Notes:
1) *** significant at 1%
2) Standard errors in brackets.
3) AR(1) computed on OLS in levels.

Table 6. Employment Equation of "Blue Collar" Workers

Dependent Var.	Employment "Blue Collar" Workers		
Variable	GMM - SYS		
	(1)	(2)	(3)
Lag_Employment	0.775***	0.829***	0.861***
	(0.062)	(0.050)	(0.035)
BC Wages	-0.194***	-0.277***	-0.112***
	(0.052)	(0.086)	(0.026)
Value Added	0.195***	0.142***	0.124***
	(0.056)	(0.045)	(0.033)
Capital Deepening	0.082***	0.120***	0.058***
	(0.020)	(0.045)	(0.012)
SETI Deepening	0.010	-0.085*	0.016
	(0.010)	(0.045)	(0.010)
Constant	-1.418***	-1.054***	-0.884***
	(0.447)	(0.352)	(0.268)
Country Dummies		2.54***	
Sector Dummies			1.52**
Time Dummies	7.49***	5.24***	5.78***
Wald Test		6.16***	4.78***
Hansen Test	16.93	14.30	11.24
AR(1)	-6.61***	-6.68***	-7.02***
AR(2)	-0.82	-1.91*	-0.84
Observations	3468	3468	3468

Table 7. Employment Equation of "White Collar" Workers

Dependent Var.	Employment "White Collar" Workers		
Variable	GMM - SYS		
	(1)	(2)	(3)
Lag_Employment	0.824***	0.769***	0.820***
	(0.036)	(0.047)	(0.038)
WC Wages	-0.075***	-0.146***	-0.071***
	(0.027)	(0.051)	(0.026)
Value Added	0.132***	0.194***	0.132***
	(0.031)	(0.043)	(0.031)
Capital Deepening	0.095***	0.058*	0.105***
	(0.021)	(0.035)	(0.024)
SETI Deepening	0.049***	0.065**	0.050***
	(0.015)	(0.027)	(0.015)
Constant	-0.930***	-1.474***	-0.851***
	(0.253)	(0.375)	(0.251)
Country Dummies		2.88**	
Sector Dummies			1.68**
Time Dummies	4.57***	2.95***	3.45***
Wald Test		3.40***	2.67***
Hansen Test	55.81	63.17	59.11
AR(1)	-7.92***	-9.47***	-9.01***
AR(2)	-0.06	-0.56	-0.21
Observations	3468	3468	3468

Notes:
1) * significant at 10%; ** significant at 5%; *** significant at 1%
2) White-robust standard errors in brackets.
3) Wald Test applied to the joint significance of the dummies.

Appendix A: Variables Definition and Data Source

Number of Operatives / Blue Collars (BC): All employees engaged in production or the related activities of the establishment, including any clerical or working supervisory personnel whose function is to record or expedite any step in the production process. **Source: United Nations General Industrial Statistics, Vol. 1 (GIS)[2].**

Number of Non Operatives / White Collars (WC): All persons engaged other than working proprietors, active business partners, unpaid family workers and operatives. **Source: GIS.**

Wage: All payments in cash or in kind made to "*operatives*" or "*non operatives*" during the reference year. The payments include: (a) direct wages and salaries; (b) remuneration for time not worked; (c) bonuses and gratuities; (d) housing allowances and family allowances paid directly by the employer; and (e) payments in kind. Excluded are the employers' contributions in respect of their employees paid to social security, pension and insurance schemes, as well as the benefits received by employees under these schemes and severance and termination pay. **Source: GIS.**

Value Added: The value of census output less the value of census input, which covers: (a) value of materials and supplies for production (including cost of all fuel and purchased electricity); and (b) cost of industrial services received (mainly payments for contract and commission work and repair and maintenance work). The valuation may be in factor values or in producers' prices, depending on the treatment of indirect taxes and subsidies. **Source: GIS.**

Gross fixed capital formation: The value of purchases and own-account construction of fixed assets during the reference year less the value of corresponding sales. The fixed assets covered are those, whether new or used, with a productive life of one year or more which are intended for the use of the establishment, including fixed assets made by the establishment's own labour force for its own use. Major additions, alterations and improvements to existing assets which extend with normal economic life or raise their productivity are also included. **Source: GIS.**

Skill-Enhancing Technology Import (SETI): The annual value of the import from high income countries (HICs) of a detailed list of capital goods which embody a technological component (Appendix C). **Source: World Trade Analyzer (WTA).**

Purchasing Power Parity: The number of currency units required to buy goods equivalent to what can be bought with one unit of the base country (US). **Source: Penn World Tables 6.1.**

US GDP Deflator: Rate of price change in the economy as a whole. The GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency. Base year = 1986. **Source: World Bank Development Indicators 2004.**

[2] Economic literature adopts two competing definitions of skills based on either the wage level of the workers or the amounts of education, training and experience they possess. The two indicators are often correlated, but they can also diverge (Wood, 1994, p. 47). The concept of skills throughout this paper refers to the latter concept - namely human capital accumulated through education which is assumed to be reflected by the dycothomic distinction between occupational categories in this empirical analysis. A craftsman with low education is therefore classified among blue collars and he will be loosely considered as an "unskilled" worker.

Appendix B: Skill-Enhancing Technology Import (SETI)

SETI is created through the sum of the following SITC Revision 2 codes[3]:

SITC	DESCRIPTION
7111	Steam & Other Vapour Generating Boilers
7112	Auxiliary Plant For Use With Boilers, Condensors
7119	Parts Of Boilers & Aux. Plant Of 711.1- / 711.2-
711A	Steam & Other Vapour Generating Boilers & Parts
7126	Steam & Other Vapour Power Units, Steam Engines
7129	Parts Of The Power Units Of 712.6-
712A	Steam & Other Vapour Power Units, Steam Engines
7131	Internal Combustion Piston Engines For Aircraft
7132	Int. Combustion Piston Engines For Propelling Veh.
7133	Int. Combustion Piston Engines For Marine Propuls.
7138	Int. Comb.Piston Engines, N.E.S.
7139	Parts Of Int. Comb. Piston Engines Of 713.2- / 713.8-
713A	Internal Combustion Piston Engines & Parts
7144	Reaction Engines
7148	Gas Turbines, N.E.S.
7149	Parts Of The Engines & Motors Of 714- And 718.8-
714A	Engines & Motors, Non-Electric
7161	Motors & Generators, Direct Current
7162	Elect.Motors & Generators, Generating Sets
7163	Rotary Converters
7169	Parts Of Rotating Electric Plant
716A	Rotating Electric Plant And Parts
7187	Nuclear Reactors And Parts
7188	Engines & Motors, N.E.S. Such As Water Turbines Etc.
718A	Other Power Generating Machinery And Parts
71AA	POWER GENERATING MACHINERY AND EQUIPMENT
7243	Sewing Machines, Furniture For Sewing Mach.& Parts
7244	Mach. For Extruding Man-Made Textiles And Parts
7245	Weaving, Knitting Mach. For Preparing Yarns, Parts
7246	Auxil. Machinery For Headings 724.51 / 52 / 53
7247	Mach. For Washing, Cleaning, Drying, Bleaching Text.
7248	Mach. For Preparing, Tanning Or Working Hides
724A	Textile & Leather Machinery And Parts
7251	Mach. For Mak. / Finis. Cellul. Pulp, Paper, Paperbo.
7252	Paper & Paperboard Cutting Mach. Of All Kinds
7259	Parts Of The Mach. Of 725–
725A	Paper & Pulp Mill Mach., Mach For Manuf. Of Paper
7263	Mach., Appar., Access. For Type Founding Or Setting
7264	Printing Presses
7267	Other Printing Mach. For Uses Ancillary To Printing
7268	Bookbinding Machinery And Parts
7269	Parts Of The Machines Of 726.31, 726.4-, 726.7-
726A	Printing & Bookbinding Mach. And Parts

[3] Letter A indicates the sum of the related sub-SITC codes. SETI represents the total annual economic value of the following goods classified at the four-digit level of SITC Rev. 2.

7271	Mach. For Working Of Cereals Or Dried Vegetables
7272	Other Food Processing Machinery And Parts
727A	Food Processing Machines And Parts
7281	Mach. Tools For Specialized Particular Industries
7283	Mach. For Sorting, Screening, Separating, Washing Ore
7284	Mach. & Appliances For Spezialized Particular Ind.
728A	Mach. & Equipment Specialized For Particular Ind.
72AA	MACHINERY SPECIALIZED FOR PARTICULAR INDUSTRIES
7361	Metal Cutting Machine-Tools
7362	Metal Forming Machine Tools
7367	Other Mach. - Tools For Working Metal Or Met. Carbide
7368	Work Holders, Self-Opening Dieheads & Tool Holders
7369	Parts Of The Machine-Tools Of 736-
736A	Mach. Tools For Working Metal Or Met. Carb., Parts
7371	Converters, Ladles, Ingot Moulds And Casting Mach.
7372	Rolling Mills, Rolls Therefor And Parts
7373	Welding, Brazing, Cutting, Soldering Machines & Parts
737A	Metal Working Machinery And Parts
73AA	METALWORKING MACHINERY
7411	Producer Gas And Water Gas Generators And Parts
7412	Furnace Burners For Liquid Fuel And Parts
7413	Ind. & Lab. Furnaces And Ovens And Parts
7414	Refrigerators & Refr. Equipment, Ex. Household, Parts
7415	Air Conditioning Mach. Self-Contained And Parts
7416	Mach. Plant & Sim. Lab. Equip. Involv. A Temp. Change
741A	Heating & Cooling Equipment And Parts
7421	Reciprocating Pumps, Other Than 742.81
7422	Centrifugal Pumps, Other Than 742.81
7423	Rotary Pumps, Other Than 742.81
7428	Other Pumps For Liquids & Liquid Elevators
7429	Parts Of The Pumps & Liq. Elevators Of 742-
742A	Pumps For Liquids, Liq.Elevators And Parts
7431	Air Pumps, Vacuum Pumps & Compressors
7432	Parts Of The Pumps & Compressors Of 743.1-
7433	Free-Piston Generators For Gas Turbines, Parts
7434	Fans, Blowers And The Like, And Parts
7435	Centrifuges
7436	Filtering & Purifying Mach. For Liquids & Gases
7439	Parts Of The Machines Of 743.5-, 743.6-
743A	Pumps & Compressors, Fans & Blowers, Centrifuges
7441	Work Trucks, Mechanically Propelled, For Short Dist.
7442	Lifting, Handling, Loading Mach.Conveyors
7449	Parts Of The Machinery Of 744.2-
744A	Mechanical Handling Equip. And Parts
7451	Tools For Working In The Hand, Pneumatic, Parts
7452	Other Non-Electrical Mach. And Parts
745A	Other Non-Electrical Mach.Tools, Apparatus & Parts

7491	Ball, Roller Or Needle Roller Bearings
7492	Taps, Cocks, Valves Etc. For Pipes, Tanks, Vats Etc
7493	Transmission Shafts, Cranks, Bearing Housings Etc.
7499	Other Non-Electric Parts & Accessories Of Mach
749A	Non-Electric Parts And Accessories Of Machines
74AA	GENERAL INDUSTRIAL MACHINERY & EQUIPMENT, AND PARTS
7511	Typewritters; Cheque-Writting Machines
7512	Calculating Machines, Cash Registers. Ticket & Sim.
7518	Office Machines, N.E.S.
751A	Office Machines
7521	Analogue & Hybrid Data Processing Machines
7522	Complete Digital Data Processing Machines
7523	Complete Digital Central Processing Units
7524	Digital Central Storage Units, Separately Consigned
7525	Peripheral Units, Incl.Control & Adapting Units
7528	Off-Line Data Processing Equipment. N.E.S.
752A	Automatic Data Processing Machines & Units Thereof
7591	Parts Of And Accessories Suitable For 751.1-, 751.8
7599	Parts Of And Accessories Suitable For 751.2-, 752-
759A	Parts Of And Accessories Suitable For 751- Or 752-
75AA	OFFICE MACHINES & AUTOMATIC DATA PROCESSING EQUIP.
7641	Elect. Line Telephonic & Telegraphic Apparatus
7642	Microphones, Loudspeakers, Amplifiers
7643	Radiotelegraphic & Radiotelephonic Transmitters
7648	Telecommunications Equipment
7649	Parts Of Apparatus Of Division 76-
764A	Telecommunications Equipment And Parts
76AA	TELECOMMUNICATIONS & SOUND RECORDING APPARATUS
7711	Transformers, Electrical
7712	Other Electric Power Machinery, Parts Of 771-
771A	Electric Power Machinery And Parts Thereof
7721	Elect. App.Such As Switches, Relays, Fuses, Pwgs Etc.
7722	Printed Circuits And Parts Thereof
7723	Resistors, Fixed Or Variable And Parts
772A	Elect. App. Such As Switches, Relays, Fuses, Plugs Etc.
7731	Insulated, Elect. Wire, Cable, Bars, Strip And The Like
7732	Electric Insulating Equipment
773A	Equipment For Distributing Electricity
7764	Electronic Microcircuits
7781	Batteries And Accumulators And Parts
7782	Elect. Filament Lamps And Discharge Lamps
7783	Electr. Equip. For Internal Combustion Engines, Parts
7784	Tools For Working In The Hand With Elect. Motor
7788	Other Elect. Machinery And Equipment
778A	Electrical Machinery And Apparatus, N.E.S.
77AA	ELECTRICAL MACHINERY, APPARATUS & APPLIANCES N.E.S.

Appendix C: Relative Employment Equation

Table C1. Time Persistence in the Relative Employment Series

	Relative Employment
AR(1)	.9759***
	(.0011)

Notes:
1) *** significant at 1%
2) Standard errors in brackets.
3) AR(1) computed on OLS in levels.

Table C2. Relative Employment Equation

Dependent Var. Relative Employment			
Variable	GMM - SYS		
	(1)	(2)	(3)
Lag_Rel. Employment	0.693***	0.391***	0.691***
	(0.062)	(0.081)	(0.059)
Relative Wages	-0.101***	-0.407***	-0.095***
	(0.019)	(0.043)	(0.019)
Value Added	0.133***	0.071	0.158***
	(0.045)	(0.073)	(0.056)
Capital Deepening	-0.133***	-0.075	-0.201
	(0.047)	(0.071)	(0.069)
SETI Deepening	0.126***	0.116**	0.154***
	(0.047)	(0.055)	(0.058)
Constant	-2.059***	-1.151**	-2.688***
	(0.556)	(0.859)	(0.801)
Country Dummies		5.56***	
Sector Dummies			0.91
Time Dummies	2.24**	0.98	2.16**
Wald Test		4.95***	1.66**
Hansen Test	7.68	12.95	8.37
AR(1)	-9.64***	-7.35***	-9.49***
AR(2)	-0.97	-1.24	-1.37
Observations	4154	4154	4154

Notes:
1) * significant at 10%; ** significant at 5%; *** significant at 1%
2) White-robust standard errors in brackets.
3) Wald Test applied to the joint significance of the dummies.

Appendix D: Difference-in-Hansen tests

Difference-in-Hansen tests of exogeneity of instruments[4]

Dependent Var. Employment "Blue Collar" Workers
(Null H = Correct Instrument Specification)

	(1)	(2)	(3)
Lag_Employment	$\chi^2_{(9)} = 3.09$	$\chi^2_{(9)} = 7.51$	$\chi^2_{(9)} = 3.41$
BC Wages	$\chi^2_{(1)} = 0.05$	$\chi^2_{(1)} = 0.22$	$\chi^2_{(1)} = 0.08$
Value Added	$\chi^2_{(1)} = 0.02$	$\chi^2_{(1)} = 0.39$	$\chi^2_{(1)} = 0.18$
Capital Deepening	$\chi^2_{(2)} = 1.86$	$\chi^2_{(2)} = 3.52$	$\chi^2_{(2)} = 1.92$
SETI Deepening	$\chi^2_{(1)} = 0.26$	$\chi^2_{(1)} = 2.39$	$\chi^2_{(1)} = 0.84$

Dependent Var. Employment "White Collar" Workers
(Null H = Correct Instrument Specification)

	(1)	(2)	(3)
Lag_Employment	$\chi^2_{(44)} = 44.14$	$\chi^2_{(44)} = 47.63$	$\chi^2_{(44)} = 47.54$
WC Wages	$\chi^2_{(20)} = 25.06$	$\chi^2_{(20)} = 34.83^{**}$	$\chi^2_{(20)} = 29.89^{*}$
Value Added	$\chi^2_{(1)} = 0.18$	$\chi^2_{(1)} = 1.66$	$\chi^2_{(1)} = 0.50$
Capital Deepening	$\chi^2_{(1)} = 0.66$	$\chi^2_{(1)} = 1.00$	$\chi^2_{(1)} = 3.43^{*}$
SETI Deepening	$\chi^2_{(1)} = 0.27$	$\chi^2_{(1)} = 0.27$	$\chi^2_{(1)} = 0.41$

[4] Columns (1), (2) and (3) refer to the same econometric specifications described in the text, namely (1) estimates with yearly dummies, (2) years + countries, (3) years + industries.