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MANUFACTURING SKILL-BIASED WAGE INEQUALITY, NATURAL RESOURCES AND INSTITUTIONS

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Manufacturing skill-biased wage inequality, natural resources and institutions

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ABSTRACT

We use an extensive dataset on occupational wages to measure the manufacturing skill premium and evaluate the importance of the main drivers in literature plus the effects of natural resources and institutions. Results, regarding a panel of 21 countries between 1987 and 2003, suggest the manufacturing skill premium of technologically advanced countries: (i) increases with tertiary enrolment, net FDI and the quality of governing institutions; (ii) decreases with the centralization of wage negotiations and the use of unskilled workers by geographically-diffuse natural resource re-exportation activities. In less advanced countries, the skill premium: (iii) augments with net FDI, scale effects, the centralization of wage negotiations, and scarcity of skilled workers absorbed by concentrated resource activities; (iv) decreases with trade, the use of unskilled workers by diffuse resource exploration, and the emergence of national low-end technological industrial sectors paying less for skilled labor than more advanced and predominant foreign-led industrial sectors.

Keywords: Wage inequality; Economic growth; Natural resources; Institutions; Worldwide study; Panel data.

JEL classification: C23, J31, O13, O50.

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1. INTRODUCTION

There is wide evidence that intra-country skill wage inequality has increased in many developed countries since the 1980s despite an increase in the skilled labour proportion (e.g., Nickel and Bell, 1996; Machin and Van Reenan, 1998; Acemoglu, 2003a,b; Autor *et al*., 2008). The same trends occurred in several (newly industrialised) developing countries, such as Hong Kong, India, Thailand and Uruguay, as shown by Zhu and Trefler (2005). The rise in wage inequality is also confirmed in Latin America and East Asia by Avalos and Savvides (2006) and in Russia by Brainerd (1998). The two major explanations to date – the skilled bias technological change literature (SBTC) and international trade literature – contradict at least one of these observed trends (e.g., Wood, 1998; Afonso, 2012) as shown below.

The dominant explanation, provided by the Skill Biased Technical Change (SBTC) literature (e.g., Bound and Johnson, 1992; Katz and Murphy, 1992), considers that the technological-knowledge bias and the resulting path of the wage premium are driven by the rise in skilled-labour supply. This bias, resulting from both the market-size effect and the price effect (e.g., Acemoglu, 2003a,b; Afonso, 2006, 2008), leads to a faster productivity growth in skilled labour which, in turn, enlarges college enrolment and thus the market for skill-complementary technologies. This process ensures that the relative demand of skilled workers grows more rapidly than the relative supply, thus explaining the skill premium rise.

However, many empirical studies on SBTC consider the rise of the skill premium in developed countries as resulting solely from the market-size effect in closed economies (e.g., Katz and Murphy, 1992, Berman *et al*., 1994; Juhn *et al*., 1993; Autor *et al*., 1998; Berman *et al*., 1998; Machin and Van Reenen, 1998; Gera *et al*., 2001). Also in a closed-economy framework, more recent studies relate the rise in wage inequality to organisational and institutional change generated by a new General Purpose Technology (e.g., Caroli and Van Reenen, 2001; Aghion, 2002).

Since these results do not consider open-economy effects, they are challenged by authors that focus on trade, such as Leamer (1996) and Wood (1998). The international trade literature explanation to the rise of the wage skill premium in developed countries is based on the Stolper-Samuelson theorem: imports of goods produced by unskilled labour reduce unskilled wages in the skilled-abundant country. However, the same argument applied to the exporter country would predict a rise in unskilled wages, which contradicts the increase of the wage skill premium in (newly industrialised) developing countries.

Other studies highlight the importance of foreign direct investment in easing technology transfer and thus leading to a rise of the wage skill premium, not only in the case of foreign investment from advanced in less advanced countries, (e.g. Aitken *et al*., 1996, Te Velde and Morrissey, 2004), but also between advanced countries (e.g., Aitken *et al*., 1996; Doms and Jensen, 1998; Girma and Greenway, 2001).

More recent studies linking SBTC and endogenous-growth models (e.g., Afonso and Alves, 2008; Afonso, 2012), by shifting to the price channel (instead of the market size) and by accounting for technological-knowledge diffusion, generate predictions compatible with the above mentioned trend of wage inequality in developed and (newly industrialised) developing countries.

As mentioned above, in addition to the market-size channel, the direction of R&D is also influenced by the price of goods (price channel), since they command higher profits for the producers of the respective inputs. Thus, if scale effects are removed (following the dominant growth literature on scale effects since Jones, 1955a,b), the focus shifts to the price channel. In this case, technologies that use the scarcer labour type are favoured (e.g., Afonso, 2012). For example, the relative abundance of skilled labour increases the price of goods produced by unskilled labour and thus the demand for R&D directed towards advances in goods produced by unskilled labour. That is, when the skilled labour-abundant country A exports inputs incorporating its R&D results to an unskilled-abundant country B, it benefits from the higher prices of goods produced by skilled labour in B. The resulting profit opportunities redirect R&D towards inputs that boost the marginal productivity and wages of skilled labour.

By considering trade between two countries with different development levels, but both capable of conducting R&D (innovative in the North and imitative in the South), it is also feasible to link technological-knowledge diffusion with the technological-knowledge path.[1] Hence, we can relate technological-knowledge diffusion to the dynamics of intra-country wage inequality (e.g., Afonso and Alves, 2008; and Afonso, 2012). By removing scale effects, changes in the paths of intra-country wage inequality result similarly from the technological-knowledge bias, but are induced by the price channel under trade (e.g., Afonso, 2012). In contrast with the market-size channel and bearing in mind the results in Afonso (2012), the operation of the price-channel certainly results in an increase in the skilled technological-knowledge bias following openness. This perspective is more in line with the recent trends observed in developed and (newly industrialised) developing countries.

Despite these recent advances in SBTC literature in an open economy context, they address only the described general trends in the skill premium and relative skilled labour supply, which conceal several notable exceptions and do not consider less developed countries, thus justifying the search for additional complementary explanations that cover a wider diversity of situations, especially in the case of developing countries.

For example, Acemoglu (2003a) stresses the importance of wage institutions to justify the inexistent or much smaller increases of the skill premium in continental European countries over the last decades when compared to the US and the UK. The author dismisses the possibility that the relative supply of skills increased faster in Europe and sustains instead that labour market institutions creating wage compression in Europe encouraged the investment in technologies that increase the productivity of less skilled workers (and, consequently, reduce their demand), thus implying less skilled-biased technical change in Europe than in the US.

Data for developing countries reveals several exceptions to the general trends. Crinò (2005), for example, shows that Hungary and the Czech Republic experienced an increase in the skill premium between 1993 and 2004 accompanied by decline in the employment of skilled workers. Robertson

[1] Recent empirical studies by, e.g., Amiti and Konings (2007), Goldberg and Pavcnik (2007), and Goldberg *et al*. (2008) provide evidence showing that imports can improve Southern productivity, hence supporting the theoretical focus on the role of trade on Southern progress. Moreover, Acemoglu (2003b) suggests that increased international trade can cause endogenous skill-biased technological change.

(2004), among others, finds that the ratio between the 90th and the 10th wage percentiles decreased in Mexico between 1994 and 2002 even with the increase of high-education workers. A similar situation is reported by Zhu and Trefler (2005) regarding Bolivia, South Korea and the Philippines.

Despite the SBTC wider acceptance in the literature, the theoretical debate dominates empirical research. Empirical studies usually analyse the impact of just one explanation and ignore cross-country analysis. In order to close the gap between the theoretical debate and the empirical research, this study uses an extensive dataset on occupational wages to widen the empirical research on skill wage inequality in a panel analysis considering intra and inter country variation for 63 countries from 1983 to 2003, although the main results only cover 21 countries since 1987. The dataset on occupational wages is the standardized ILO October Inquiry 1983-2003 (September 2005 version), an updated and improved version of Freeman and Oostendrop (2000, 2001).

As most empirical studies on the subject, we focus on the wage skill premium of the industrial sector, where the traditional explanations apply. However, unlike the majority of previous studies, our empirical analysis tests several possible explanations at the same time for both technologically advanced and less advanced countries. In particular,

(i) we re-evaluate the importance of the traditional drivers for the industrial skill premium (as proxied by the ratio of a representative high-skill industrial occupation wage to that of an undifferentiated low-skill occupation), specifically SBTC, foreign direct investment and trade, while controlling for the relative skilled labour supply, labour market institutions and possible scale effects;

(ii) we assess the potential effect of natural resource abundance and institutions on the industrial wage premium in connection with its traditional drivers, taking into account recent explanations of the resource curse result – this is a novel approach that adds to the existent wage inequality literature.

The resource curse is a puzzling empirical result that associates countries' natural-resource abundance and dependence with lower economic growth after controlling for other relevant variables. The result was confirmed by a large number of cross-section studies initiated by Sachs and Warner (1995, 1999, 2001). According to the most consensual explanation of the curse result, based on institutions, the access to abundant natural resources appears to amplify the negative growth-effects of weaker institutions in developing countries, but only in those that depend on geographically-concentrated resources (resource points), such as oil and ores (e.g., Sala-i-Martin and Subramanian, 2003; Isham *et al*., 2005).[2]

By affecting growth, natural resources and institutions may also influence wage inequality and its determinants; therefore, they must be considered in our analysis. For example, natural resources may crowd-out entrepreneurial activity and innovation by encouraging potential innovators to work in the resource sector (through a wage premium), and it thus directs funds away from the R&D sector into the primary sector (Sachs and Warner 2001). In a similar fashion, a booming natural resource sector may absorb scarce skilled workers available to the industrial sector in developing countries (e.g., Sachs and Warner, 2001), following a Dutch Disease crowding-out logic. These effects are more likely to happen in the case of geographically-concentrated resources, usually requiring a higher technological intensity than diffuse resource exploration. In turn, diffuse resource exploration using unskilled labour should potentially decrease the wage skill premium.

Regarding trade, its impact on the industrial wage premium can only be properly evaluated if we control for the importance of resource exports, which can significantly affect trade patterns and the effect of openness on growth (Birdsall and Hamoudi, 2002). To measure the effect of foreign direct investment on the industrial wage skill premium it is also necessary to control for the presence of the natural resource sector, as it may attract a significant part of the foreign capital afflux (as is the case of many developing oil economies). In addition, the access to significant resource revenues may lower investment in education (e.g., Gylfason, 2001) in the absence of proper institutions, thus reducing the supply of skilled workers.

Since institutions influence all the above mentioned variables, they must also be considered in the analysis. For example, the wage skill premium is expected to decrease in response to rigidities introduced by certain labour market institutions (e.g., Acemoglu, 2003a). However, the development of other institutions may increase the skill premium by fostering productivity (see, e.g., Acemoglu *et al*., 2005, for the positive impact of institutions on economic growth), for example in the case of organizational change (e.g., Caroli and Van Reenen, 2001). Therefore, if natural resource abundance

[2] In turn, diffuse resources, such as agricultural and forest products, were not correlated with institutional quality.

amplifies the negative growth-effects of weaker institutions in developing countries (in the case of concentrated resources as pointed by, e.g., Isham *et al*., 2005), then the skill premium may also be affected. Moreover, since institutional quality is crucial for the R&D effort, especially in developing countries (Clarke, 2001), it must be controlled for to estimate the separate effect of R&D on the wage skill premium. In addition, countries with better institutions also tend to trade more (Dollar and Kraay, 2003), and attract more foreign direct investment (Busse and Hefeker, 2007), factors that also influence the skill premium in the literature as previously mentioned.

The paper proceeds as follows. Section 2 presents the data and estimation procedures, preceding the analysis and discussion of results in Section 3. Finally, Section 4 presents the main conclusions.

2. ESTIMATION PROCEDURES AND DATA

2.1. Panel estimation specification and proxies

Let us consider the relative supply-demand framework (in line with, e.g., Acemoglu, 2003a) to assess the impact of the wage skill premium determinants. The aggregate production function for a country at time *t* is given by the constant elasticity of substitution (CES) form:

$$Y(t) = \left\{ \left[F_l(t) L(t) \right]^{\rho} + \left[F_h(t) H(t) \right]^{\rho} \right\}^{1/\rho}, \text{ where:} \quad (1)$$

(i) Y is the real aggregate output; (ii) H (L) denotes high (low) skilled labour; (iii) F_h and F_l are factor augmenting technology terms; (iv) $\sigma = 1/(1-\rho) \geq 1$ is the elasticity of substitution between H and L, with $\rho \leq 1$.[3]

The marginal productivity expressions for H (MP_H) and L (MP_L) are as follows:

$$\begin{aligned} MP_H(t) &= (F_h(t))^{\rho} \left[(F_l(t))^{\rho} (H(t)/L(t))^{-\rho} + (F_h(t))^{\rho} \right]^{(1-\rho)/\rho} \\ MP_L(t) &= (F_l(t))^{\rho} \left[(F_h(t))^{\rho} (H(t)/L(t))^{\rho} + (F_l(t))^{\rho} \right]^{(1-\rho)/\rho} \end{aligned} \quad (2)$$

Suppose that wages are related linearly to marginal productivity: $w_H(t) = \alpha MP_H(t)$ and $w_L(t) = \alpha MP_L(t)$. Then, regardless of the value of α (in the case $\alpha = 1$, workers are paid their

[3] As Acemoglu (2003a) points out, the case where σ <1 is not of great empirical relevance, since almost all existing estimates suggest that σ >1.

productivity) and assuming that firms will be along their labour demand curves, the wage skill premium, *WSP*, is:

$$WSP(t)=\frac{w_H(t)}{w_L(t)}=\frac{MP_H(t)}{MP_L(t)} \quad (3)$$

Replacing (2) in (3), it becomes:

$$WSP(t)=\left(\frac{F_h(t)}{F_l(t)}\right)^{\rho}\left(\frac{H(t)}{L(t)}\right)^{-(1-\rho)}=\left(\frac{F_h(t)}{F_l(t)}\right)^{(\sigma-1)/\sigma}\left(\frac{H(t)}{L(t)}\right)^{-1/\sigma)} \quad (4)$$

Assuming that σ >1, expression (4) shows that the skill premium is decreasing in the relative supply of skilled workers *H*/*L* (except in the case where the constant elasticity of substitution σ tends to infinite, where *H* and *L* are perfect substitutes) and increasing in the skill biased technological change term F_h/F_l (provided that $F_h>F_l$ as expected).

Let us suppose that the (unobserved) factor augmenting terms take the following forms:

$$F_h(t)=\prod_{j=1}^{B}e^{\theta_0}X_j(t)^{\theta_j}$$

$$F_l(t)=\prod_{j=1}^{B}e^{\gamma_0}X_j(t)^{\gamma_j}\text{ , where:} \quad (5)$$

B is the number of common technology determinants X_j, which differ between F_h and F_l only in the associated coefficients (θ_m and γ_m , *m*=0, 1, …, *B*+1; θ_0 and γ_0 are constant terms).

If (5) is replaced in (4), it becomes:

$$WSP(t)==\left(\frac{\prod_{j=1}^{B}e^{\theta_0}X_j(t)^{\theta_j}}{\prod_{j=1}^{B}e^{\gamma_0}X_j(t)^{\gamma_j}}\right)^{(\sigma-1)/\sigma}\left(\frac{H(t)}{L(t)}\right)^{-1/\sigma)}=\left(\prod_{j=1}^{B}e^{\theta_0-\gamma_0}X_j(t)^{\theta_j-\gamma_j}\right)^{(\sigma-1)/\sigma}\left(\frac{H(t)}{L(t)}\right)^{-1/\sigma)} \quad (6)$$

Taking logs in (6), the expression is written as:

$$\ln WSP(t)=\frac{\sigma-1}{\sigma}\ln\left(\prod_{j=1}^{B}e^{\theta_0-\gamma_0}X_j(t)^{\theta_j-\gamma_j}\right)-\frac{1}{\sigma}\ln\left(\frac{H(t)}{L(t)}\right)=$$
$$=\frac{\sigma-1}{\sigma}\left[(\theta_0-\gamma_0)+\sum_{j=1}^{B}(\theta_j-\gamma_j)\ln X_j(t)\right]-\frac{1}{\sigma}\ln\left(\frac{H(t)}{L(t)}\right) \quad (7)$$

If we consider that the above determinants for the whole economy apply to each sector, then the industrial wage skill premium, represented as *IWSP*, can also be written as:

$$\ln IWSP(t) = \frac{\sigma - 1}{\sigma}\left[(\theta_0 - \gamma_0) + \sum_{j=1}^{B}(\theta_j - \gamma_j)\ln X_j(t)\right] - \frac{1}{\sigma}\ln\left(\frac{H(t)}{L(t)}\right) \quad (8)$$

Since proxies for some technology determinants X_j assume negative or null values, as shown later on (such is the case of net foreign direct investment, Polity, and one of the tested measures for labour market institutions), our chosen panel estimation form does not apply logarithms in X_j (except in GDP, the scale effects proxy, in order to downsize the range of values closer to the other determinants' proxies, which are expressed in ratios or are discrete variables with small numbers). Therefore, the final specification presented below does not apply logs to *IWSP* and *H*/*L* variables as well, and thus does not estimate the coefficients as shown in (7), but the interpretations regarding variables' impacts provided in (4) (where variables are expressed in levels) still apply for SBTC.

To estimate the impact of the chosen determinants for the *IWSP* (which is measured as explained in subsection 2.2.), we use the following panel estimation specification for country *i* in each time *t*, where vector *Z* includes vector *X* above and *H*/*L*, from now on represented as *HL*:

$$IWSP_{it} = \rho_{it} + \sum_{j=1}^{7}\delta_j (Z_j)_{it} + \varphi_{it} \quad (9)$$

Panel estimation improves the estimation efficiency through variability across time and countries, and also allows the control of unobserved individual heterogeneity (Wooldridge, 2002)[4] through the use of models with different assumptions regarding the unobserved individual element, which, in our case, can be a country (c_i) and/or a time (d_t) effect in (1):

(i) $\rho_{it} = \delta_0$ and $\varphi_{it} = c_i + d_t + \omega_{it}$, in the case of the Pooled OLS and the random effects model (REM) with time and country effects, being ω_{it} white noise;

(ii) $\rho_{it} = \delta_0 + c_i + d_t$ and $\varphi_{it} = \omega_{it}$ in the case of the fixed effects model (FEM) with time and country effects.[5]

[4] Otherwise, the estimates may be inconsistent.

[5] The FEM asks how group and/or time affect the intercept, while the REM analyses error variance structures affected by group and/or time. In both, slopes are assumed unchanged. The pooled OLS assumes that countries would react in the same way to changes in explanatory variables and that intercepts are the same for all countries. The choice of the adequate estimation model is made in view of proper test statistics.

The generic estimation form (9), which derives from a production function as explained above, includes the several determinants of the skill premium discussed in the Introduction (see also Table 1 below). The vector of chosen *IWSP* regressors is:[6]

$$Z_j = \begin{Bmatrix} A*SE, A*SBTC, A*FDI, A*T, A*HL, A*LMI, A*IQ, A*NresD, A*NresP, \\ LA*\ln GDP, LA*SBTC, LA*FDI, LA*T, LA*HL, LA*LMI, LA*IQ, LA*NresD, LA*NresP \end{Bmatrix}, \text{where:}^{7}$$

(i) *A*=1(0) and *LA*=0(1) if country *i* belongs (does not belong) to the advanced technological convergence club of Castellacci and Archibugi (2008) in the year 2000, thus representing the group of advanced (less advanced)[8] countries;[9] (ii) *SE* represents scale effects, measured by the natural logarithm of current US dollars GDP (in power purchase parity terms); (iii) *SBTC* stands for skill biased technological change, assessed by high-technology industrial exports (divided by other industrial exports; available beginning in 1987);[10] this proxy captures both the price channel (high- to low-technology export prices) and the market channel in industrial SBTC, but only applied to exports, thus the domestic R&D market is not considered – it is partly assessed by the *HL* proxy presented

[6] Data sources and details for the main proxies and tested alternatives are provided in Appendix Table A1.

[7] As mentioned above, the natural logarithm is applied to GDP in order to reduce the range of values more in line with the other variables' proxies, which are ratios or discrete variables with small numbers.

[8] Less advanced countries include follower and marginalized countries in terms of convergence clubs, and countries in our sample not classified by Castellacci and Archibugi (2008) but recognisably not advanced.

[9] By using a multiplicative dummy for each category (advanced and less advanced countries), we are able to directly assess in one single estimation the separate impacts of the skill wage determinants for advanced and less advanced countries (instead of getting a differential effect with respect to a reference country group category if only one dummy for both categories is used). This is necessary because period aggregation reduces the number of observations and impedes separate estimations for subsamples of advanced and less advanced countries.

[10] This proxy produced better results (see Section 3) than alternative measures also available for a wide range of countries and years but not specific to the industrial sector. In addition to the usual indicator of technological progress given by national R&D expenses in percentage of GDP, which is only available beginning in 1996, we tested alternative indicators included in the ArCo technological indicator (Archibugi and Coco, 2004) that are available since 1983 in most cases: patents, scientific and technical articles, internet use, electric power consumption, mobile phone subscriptions and telephone lines (data details are provided in Appendix Table A1).

below, regarding tertiary enrolment (in proportion of non-enrolled); (iv) *FDI* is net foreign direct investment (measured in percentage of GDP); (v) *T* is international trade, gauged by trade openness; (vi) *HL* is the total relative supply of skilled workers, measured by tertiary enrolment (in proportion of non-enrolled),[11] which determines the relative demand of skilled workers in the presence of the SBTC market channel; (vii) *LMI* represents labour market institutions, gauged by the centralization of wage bargaining coordination;[12] (viii) *IQ* is institutional quality, assessed by the Polity indicator;[13] (ix) *NresD*(*P*) represent geographically-diffuse (concentrated) natural resources, measured by the shares of agricultural raw materials and food products (fuels, ores and metals) in merchandise exports (in line with, e.g., Leite and Weidmann, 2002).[14] We note that the *HL* coefficient is estimated keeping constant the natural resource variables, which capture the impact of natural resource booms on the industrial skill premium by affecting the relative supply of workers available to the industrial sector.

Table 1 – Summary of explanatory variables and main references

Explanatory variables	References
SE, HL	Machin and Van Reenen (1998); Gera *et al*. (2001).
SBTC	Bound and Johnson (1992); Katz and Murphy (1992).
FDI	Aitken *et al*. (1996); Doms and Jensen (1998).
T	Leamer (1996); Wood (1998).
LMI	DiNardo *et al*. (1995); Acemoglu (2003a).
IQ	Acemoglu (2005); Caroli and Van Reenen (2001).
NresD, NresP	Sachs and Warner (1995, 2001), Isham *et al*. (2005).

[11] Tertiary enrolment requires secondary education (as noted by Archibugi and Coco, 2004, which use this indicator in their technological ArCo index), thus providing information for the skilled labour supply in a large number of countries and years. Data regarding labour force by education level (more precise than tertiary enrolment) was also tested but proved insufficient to produce good results.

[12] The minimum wage setting variable (which also shows enough variability for estimation) from the same database was also tested but did not prove significant as reported in Section 3.

[13] This indicator analyzes political dynamics and their effect on the essential qualities of governing institutions. We note that measures of institutional quality are highly correlated (e.g., Gradstein, 2008). The Freedom House indicator rating political rights and civil liberties was also tested, but small variability impeded good results .

[14] We also test resource net-export shares (in line with the net-export dependence proxy by Owens and Wood, 1997) to adjust for the re-exportation as reported in Section 3.

2.2. Measuring the industrial wage skill premium

To measure the industrial wage skill premium (variable *IWSP*) in a high number of countries and years, we use data on occupational wages from the standardized ILO October Inquiry 1983-2003 (September 2005 version), the updated and improved version of Freeman and Oostendrop (2000, 2001), covering 150 countries and 161 occupations. Firstly, the industrial occupation codes of the database were matched to the corresponding major groups of the International Standard Classification of Occupations (ISCO-88) to find the associated skill levels. Following the International Standard Classification of Education (ISCED), the occupations classified with the third and fourth ISCO skill levels denote competences corresponding to tertiary education (conversely, the first two ISCO skill levels correspond to primary and secondary education).

Among the six available industrial occupations corresponding to tertiary education,[15] we chose the electronics engineering technician to represent the industrial high-skill wage, since this occupation is potentially present in a higher number of industrial sectors, and also because it shows a high correlation with the other available high-skill occupations (between 85% and 97% with no calibration and between 93% and 98% with the highest calibration) and allows a higher number of observations. In a similar fashion, the textile labourer was selected to represent the industrial low-skill wage (among 50 industrial occupations corresponding to primary and secondary education) due to the high correlation with the other industrial low-skill occupations (between 83% and 99% with no calibration and between 90% and 99% with the highest calibration). More important, the labourer occupation is described as requiring a minimum of training and little or no previous experience (the textile labourer was preferred to labourers in other industrial sectors to maximize the data), which ensures that the associated wage is not subject to possible oscillations that could occur in a low-skill but specialized occupation, with a more limited number of available workers.

Therefore, our measure for the industrial wage skill premium *IWSP* is calculated as the ratio of the electronics engineering technician average wage to the textile labourer average wage for each

[15] Journalist, chemical engineer, chemistry technician, occupational health nurse, electronics draughtsman and electronics engineering technician.

country and year.[16] This is done to maximize information and precision regarding the evolution of the *IWSP* with the available industrial occupations for best estimation results, an approach we deem preferable to finding an average *IWSP* level, which depends on the available industrial occupations in each year and country, and thus introduces a composition bias in the *IWSP* evolution. Our approach allows *IWSP* information for 63 countries before considering the regressors' data limitations.

The estimations shown in Section 3 use the highest wage calibration (with sector and country specific data, and uniform weighting, which is most efficient if measurement errors affect the reported wage data) to maximize the number of observations. Data was aggregated in six panels (1983-86, 1987-89, 1990-92, 1993-96, 1997-99, 2000-03) to proceed estimations, since results with annual data are too volatile and noisy to be considered. The first panel could only be estimated using alternative proxies for technological progress as reported in Section 3.

3. RESULTS AND DISCUSSION

Table 2 shows descriptive statistics of the main variables (taking into account the most significant regressors in Section 3 results) between 1983 and 2003 in the panel of 63 countries for which we have data regarding the chosen industrial wage skill premium measure. The statistics (based on non-missing observations for annual data) are also presented for the subsamples of technologically advanced and less advanced countries.[17]

As expected, the average value for the industrial wage-skill premium measure is superior in less advanced counties, where the skilled labour supply is scarcer as reflected by smaller tertiary enrolment. The mean values for high-technology industry exports (as percentage of other industry exports), total R&D (as percentage of GDP), trade openness, Polity and wage bargaining centralization are also higher in the subsample of advanced countries. However, less advanced countries present superior values of net foreign direct investment (confirming that technology transfer is relatively more

[16] For robustness, other combinations of similar high- and low-skill occupations were tested. The resulting premia produced similar or worse (due to loss of observations) results compared to the chosen combination, which we deem the most appropriate for the exposed theoretical and empirical reasons.

[17] According to the technology clubs classification by Castellacci and Archibugi (2008).

Table 2 – Descriptive statistics of main variables (1983-2003) for the panel of 63 countries with annual data regarding the chosen industrial wage skill premium measure

	All countries (*n*=63)[18]		*A* (*n*=12)		*LA* (*n*=51)	
	Mean	S.D.	Mean	SD	Mean	SD
IWSP	2.034	0.970	1.834	0.430	2.209	1.235
SE: lnGDP (USD, PPP)	24.786	1.929	26.243	1.503	24.409	1.871
SBTC: high-tech. industry exports (% other ind.exp.)	17.241	33.847	28.559	32.355	13.146	34.221
SBTC: R&D (%GDP)	0.944	0.851	2.258	0.671	0.532	0.329
FDI: net FDI (%GDP)	4.901	29.657	2.898	4.108	5.423	33.289
T: total trade (%GDP)	77.066	60.381	86.049	91.487	71.928	46.227
HL: tertiary enrolment/ (1-tert.enrol)	0.595	1.863	1.884	4.037	0.280	0.340
LMI: wage coordination [a)]	2.428	1.020	2.629	1.101	2.249	0.917
IQ: Polity [b)]	3.953	6.756	8.748	3.677	2.863	6.850
NresD: export shares (%)	23.237	23.629	13.914	14.193	27.214	25.118
NresP: export shares (%)	7.009	12.515	4.823	4.821	8.012	14.195
NresD: net exp.shares+100 [c)]	112.307	23.457	106.702	13.914	114.995	25.640
NresP: net exp.shares+100 [c)]	104.207	12.940	101.808	5.362	105.364	14.611

Results based on non-missing observations for *n*= 63 countries between 1983 and 2003. [a)] Discrete variable with values ranging from 1 (fragmented bargaining, mostly at company level) to 5 (economy-wide bargaining); [b)] discrete variable ranging from -10 (strongly autocratic) to +10 (strongly democratic); [c)] values convey indices of abundance. SD: standard deviations. Source: authors own calculations.

important there) and natural resource abundance, but the standard deviations are bigger as well, thus indicating more diversity of situations. Interestingly, the standard deviation for high-technology industry exports (as percentage of other industry exports) is also higher in less advanced countries and the same happens for the wage skill premium, which main explain the significance of the previously mentioned regressors in those countries as shown below in the main results.

[18] Full sample (*A* subsample) composition: Algeria, Angola, Argentina, Antigua and Barbuda, Australia (*A*), Austria (*A*), Bangladesh, Belarus, Bolivia, Brazil, Canada (*A*), Chile, China, Colombia, Congo Dem. Rep., Costa Rica, Croatia, Cyprus, Denmark (*A*), Estonia, Finland (*A*), Germany (*A*), Ghana, Honduras, Hong Kong (*A*), Hungary, India, Iran, Isle of Man, Italy, Ivory Coast, Kazakhstan, Korea Rep. (*A*), Latvia, Lithuania, Luxembourg, Madagascar, Malawi, Mauritius, Mexico, Mozambique, New Zealand (*A*), Nigeria, Papua New Guinea, Peru, Philippines, Poland, Portugal, Puerto Rico, Romania, Samoa, Singapore (*A*), Slovakia, Slovenia, Sudan, Sweden (*A*), Thailand, Trinidad and Tobago, Turkey, Uganda, USA (*A*), Venezuela, Virgin Islands US.

Table 3 presents the main estimation results with panel specification (9). The REM is the apt model in most regressions (except in regression 1, where the FEM is the chosen model), according to the test statistics.[19] As previously mentioned, the estimations are based on data aggregation in six panels (1983-86, 1987-89, 1990-92, 1993-96, 1997-99, 2000-03), since results with annual data are too volatile and noisy to be considered. However, the first panel is only estimated in regression 5, where scientific and technical journal articles (*per* million people) are included as a measure of *SBTC* in alternative to the preferred proxy regarding industrial high-technology exports (in percentage of other industrial exports), for which data is only available beginning in 1987.

Data requirements are particularly high regarding the centralization of wage bargaining, the chosen proxy for labour market institutions, but the inclusion of this control variable is crucial to the significance of results,[20] thus stressing the relevance of these institutions in the study of the industrial wage skill premium. Indeed, the inclusion of *LMI* reduces the number of observations from close to 100 to nearly half or even less (57 in regressions 1 to 3, 62 in regression 5, and 37 in regression 4) depending on the *SBTC* measures. Although the number of observations is small, the use of period aggregation increases the significance of results and we find enough diversity of situations to carry estimations. The most significant results with all variables, shown in regression 2, include data regarding 21 countries from 1987 to 2003 – these countries and panels are presented in Appendix Table A2, which is analyzed below when regression 2 is presented.

In regression 1, we include more traditional determinants of the wage skill premium (*SE*, *SBTC* – gauged by industrial high-technology exports in percentage of other industrial exports –, *FDI*, *T* and *HL* – assessed by tertiary enrolment divided by non-enrolled),[21] and add the above-mentioned *LMI* proxy as a control variable (without which there are no significant coefficients in the estimation). In the technology club of advanced countries, the scale effects variable (*A*SE*) is significant at 10%, with

[19] The possibility of endogeneity regarding our regressors is dismissed by the Durbin-Wu-Hausman test.

[20] The minimum wage setting (the other variable form ICTWSS database showing enough variability to allow estimations) was tested as an alternative *LMI* proxy in all estimations, but produces less significant results.

[21] Data regarding labour force by education level (more precise than tertiary enrolment) was also tested but proved insufficient to produce good results, as the number of observations decreases.

Table 3 – Main estimation results (1983-2003)

Regression	1	2	3	4	5
Resource proxies		Unadjusted	Adjusted	Unadj.	Unadj.
Model	FEM G&T [(a)]	REM G&T	REM G&T	REM G&T	REM G&T
F [(b)]	13.91	42.24	29.87	25.23	15.84
LM [(b)]	19.58	16.31	6.75	9.98	9.34
Hausman [(b)]	31.92	22.01	11.23	4.81	16.58
Dep. variable			*IWSP*		
Constant	-24.480 (-1.319)	-5.644 (-0.526)	-3.107 (-0.322)	-5.413 (-0.982)	6.235 (1.051)
*A*SE*	1.115*** (1.711)	-0.259 (-1.485)	0.129 (0.595)	0.424** (1.959)	0.138 (0.581)
*A*SBTC*: ind. high-tech. exp	-0.004 (-0.173)	-0.008 (-0.626)	-0.009 (-0.530)		
*A*SBTC*: R&D				-0.908 (-1.142)	
*A*SBTC*: sci./tech. pub.					-0.001 (-0.738)
*A*FDI*	0.118 (1.153)	0.089*** (1.742)	0.025 (0.440)	-0.092 (-0.494)	-0.012 (-0.149)
*A*T*	-0.005 (-0.404)	-0.000 (-0.058)	-0.001 (-0.133)	0.012 (0.919)	0.004 (0.467)
*A*HL*	0.211 (1.329)	0.159** (2.138)	0.065 (0.682)	-0.198 (-1.243)	-0.040 (0.311)
*A*LMI*	-0.059 (-0.461)	-0.240** (-2.375)	-0.155 (-1.218)		-0.024 (-0.329)
*A*IQ*		1.473** (2.116)	0.257 (0.260)		-0.750 (-0.784)
*A*NresD*		-0.054* (-2.580)	-0.030 (-0.886)	0.047 (0.664)	-0.006 (-0.202)
*A*NresP*		0.060 (0.868)	0.022 (0.282)	-0.222 (-1.422)	-0.052 (-0.875)
LMI				0.300 (1.165)	
IQ				-0.202 (-1.409)	
*LA*SE*	0.775 (0.861)	0.418* (4.138)	0.606* (2.977)	0.415* (3.700)	-0.086 (-0.638)
*LA*SBTC*: ind. high-tech. exp	-0.023 (-0.482)	-0.105* (-6.880)	-0.103* (-5.267)		
*LA*SBTC*: R&D				-3.143* (-3.403)	
*LA*SBTC*: sci./tech. pub.					-0.002** (-2.044)
*LA*FDI*	0.113** (2.205)	0.079* (3.922)	0.135* (4.759)	-0.013 (-0.213)	0.106* (3.470)
*LA*T*	-0.015 (-1.280)	-0.028* (-4.312)	-0.030* (-4.778)	-0.023*** (-1.896)	-0.026* (-2.787)
*LA*HL*	-0.101 (-0.692)	-0.215 (-1.548)	0.117 (0.588)	0.314** (2.082)	0.244 (1.049)
*LA*LMI*	0.442* (3.086)	0.267* (4.510)	0.396* (6.036)		0.329* (3.737)
*LA*IQ*		0.045 (1.217)	0.056 (0.893)		0.058 (1.262)
*LA*NresD*		-0.162* (-7.227)	-0.194* (-5.606)	0.041 (0.877)	-0.076* (-2.743)
*LA*NresP*		0.176** (2.445)	0.104*** (1.862)	0.094 (0.777)	-0.005 (-0.058)
Observations	57	57	57	37	62
R^2 [(c)]	0.972	0.995	0.993	0.984	0.986
Adjusted R^2 [(c)]	0.922	0.980	0.973	0.971	0.951

Notes: T-ratios in parentheses. Significance levels of 1% (*), 5% (**) and 10% (***). [(a)] G&T is a joint Group (country) and Time effect. [(b)] The F/LM/Hausman tests choose between *Pooled* OLS and FEM/Pooled OLS and REM/FEM and REM; Significant G&T effects are chosen over single effects. [(c)] From the FEM G&T. Estimations run with Limdep 8.0 software.

a positive impact, but no other estimates are significant, which is rather surprising.

Regarding less advanced countries, the coefficient of net foreign direct investment (*LA*FDI*) has a significant (at 5%) positive impact on the wage skill premium as expected. *LMI* is also significant (at 1%), but the positive impact is rather unexpected at a first glance. In principle, a more decentralized wage negotiation benefits the skill premium by allowing remuneration more close to productivity (regression 2, analyzed below, shows evidence for a negative impact of wage bargaining centralization in advanced countries). However, if the wage bargaining is much decentralized in less advanced countries (Table 2 shows a smaller degree of centralization compared to advanced countries), for example at a company level, and is dominated by informal remuneration schemes (favours, corruption), we conjecture that some degree of centralization may actually raise the skill premium by reducing informality.

Regression 2 adds the natural resource variables, measured by export shares, and the institutional quality variable (*IQ*) proxied by Polity.[22] These are the most significant results in our estimations. The estimates for advanced countries show significant positive impacts (at 10% and 5%, respectively) of net foreign direct investment (significant at 10%), tertiary enrolment in proportion of non-enrolled (5%), and Polity (5%), represented by *A*FDI*, *A*HL* and *A*IQ*. The positive impact of *FDI* highlights that technology transfer is also important between advanced countries (e.g., Te Velde and Morrissey, 2004). As for the effect of tertiary enrolment, it is consistent with the SBTC market channel, even if the measure for *SBTC* is not significant, as it only captures technology exports and not the domestic R&D market (still, it is the only available measure for technical progress specific to the industrial sector and the result is confirmed below with alternative measures that capture domestic R&D). In the case of *IQ*, the development of institutions may increase the skill premium by fostering productivity (for example in the case of organizational change at firm level).

The estimates for *LMI* and *NresD* (geographically diffuse natural resources proxied with export shares) are also significant for advanced countries, but in this case with negative impacts on the

[22] The Freedom indicator was also tested but produces less significant results, as it show less variability (scale from 1 to 7, compared to -10 to 10 in the Polity indicator).

industrial wage skill premium as expected. As previously mentioned, less centralized wage negotiations should favour remuneration more in line with productivity and thus increase the industrial skill premium, while diffuse resource exploration using unskilled labour should decrease wage skill inequality.

With respect to less advanced countries, we find positive impacts arising from *FDI*, *LMI* (as in regression 1), *SE* and *NresP* (significant at 5% in the latter case and at 1% in the other cases). The positive impact of geographically concentrated resources is expected, since the exploration of these resources may absorb scarce skilled workers available to the industrial sector. As for negative effects, they arise from *T* (significant at 1%), as predicted by the Stolper-Samuelson theorem, from *NresD* (significant at 1% and also with the expected sign), and *SBTC* as measured by industrial high-tech exports (in percentage of other industrial exports). The negative impact of the *SBTC* proxy is unexpected, but the result – which is estimated considering FDI is constant – may be explained by the emergence of national low-end export-led technological industrial segments paying less for skilled labour than more advanced and predominant foreign-led industrial sectors, usually dedicated to exportation. Although industrial high-tech exports do not account for the domestic R&D market, which is a limitation of this *SBTC* proxy, the negative impact found in less advanced countries is confirmed below with nearly all alternative measures (not specific to the industrial sector).

Considering R^2 (from the comparable FEM) as a measure of fit, the explanatory variables in regression 2 capture (at least) 99.5% of the variation in *IWSP*; the adjusted R^2 is 98%. As above mentioned, the estimated countries and periods are presented in Appendix Table A2, in addition to the corresponding values for the *A* dummy and the *IWSP* measure. Among the 21 countries accounted for in the estimation, it can be observed an increase of the skill premium in several advanced (Australia, South Korea, Sweden and USA) and less advanced countries (China, Poland, Romania and Slovenia). However, several countries show declining (Austria and Finland, in the case of advanced countries, and Hungary, Portugal and Slovakia in the case of less advanced countries) or stable skill premia (Germany, Denmark and New Zealand, in the case of advanced countries, and Italy for less advanced countries).

In regression 3, we use resource net export shares to adjust for re-exportation in order to achieve a better measure of resource abundance. However, the results are less significant than in the previous regression, especially for advanced countries (where all coefficients become insignificant), which suggests that natural resource re-exportation activities also influence the wage skill premium and must be taken into account. In the case of advanced countries, less endowed in diffuse resources (see Table 2), the importance of related re-exportation activities appears relevant (for example, industrial food production, which uses significant amounts of unskilled labour). In the case of less advanced countries, the results are basically unaltered (despite slight changes in the magnitude of estimates) in comparison with regression 2, but *NresP* is now only significant at 10%, which suggests that re-exportation related activities (such as oil refining) may influence the wage skill premium in these countries.

Finally, regressions 4 and 5 show less significant results with available alternative measures of *SBTC* that are not specific to the industrial sector. Regression 4 presents results using the traditional *SBTC* measure regarding R&D expenses in percentage of GDP. Since this proxy only begins in 1996, the number of observations declines to 37 and there is not enough variability to allow a separate estimation of the discrete *LMI* and *IQ* proxies between advanced and less advanced countries, which is why we include these variables without multiplicative dummies. Despite the severe data constraints, we still find significant estimates. *SE* increases the skill premium in advanced (as in regression 1) and less advanced countries (as in regressions 2 and 3), where we now find a positive impact of *HL* and confirm the negative effects of *SBTC* (now measured by R&D intensity, significant at 1%) and *T* (now only significant at 10%). The resource measures are insignificant in both sets of countries.

Finally, in regression 5 we present results with scientific and technical journals articles (*per* million people), which constitute the only *SBTC* alternative proxy that allows the estimation with the discrete *LMI* and *IQ* proxies disaggregated between advanced and less advanced countries. The number of observations is raised to 62, since this variable is available beginning in 1983 (compared to 1987 in the case of industrial high-technology exports). We confirm the negative impact of *SBTC* in less advanced countries with the new proxy, but few other estimates are significant, all for less advanced countries (*T* and *NresD*). Results with patent applications and subscriptions of mobile phones and telephone lines (used in the ArCo technology index), also available since 1983, confirm the negative impact of *SBTC* in less advanced countries, but these estimations require the inclusion of *LMI* and *IQ* proxies without multiplicative dummies for advanced and less advanced countries. The same approach did not produce significant results with internet use (only available since 1990) and electric power consumption in less advanced countries. In all cases, the SBTC proxies are not significant for advanced countries, but again we remind that only the high-technology exports measure is specific to the industrial sector, due to data restraints.

4. CONCLUSIONS

This study re-evaluates the relative importance of the traditional determinants of industrial wage skill premium found in literature, and adds natural resources and institutional quality as important factors to take into account. The industrial wage skill premium is measured by using an extensive dataset on occupational wages, which provide intra- and inter-country variation for 63 countries between 1983 and 2003, although the main estimation results (using six panels) are narrowed down to 21 countries since 1987 as resulting from regressors' data constraints. The chosen skill premium measure is the ratio of a representative high-skill industrial occupation (electronics engineering technician) wage to that of an undifferentiated low-skill occupation (textile labourer). The estimation results are obtained following a generic panel specification in levels that takes into account the interpretations derived from a relative supply-demand framework.

Among the more traditional determinants of the industrial skill premium in advanced countries, trade is not significant and the only sign of skill biased technological change is provided by the positive impact of tertiary enrolment (in proportion of non-enrolled), as the technological progress measures are all insignificant. However, among the available measures (all insignificant for advanced countries) only the high-technology exports proxy is specific to the industrial sector but it does not account for the importance of the domestic R&D market. Also important is the positive impact of net foreign direct investment, which highlights the importance of technology transfer between advanced countries in increasing productivity. In turn, the centralization of wage bargaining (the most significant measure for labour market institutions in our results) has a negative impact in the skill premium of advanced countries as expected, since less centralized negotiations allow remuneration more in line with productivity.

With respect to the new determinants introduced in this study, they prove to be important control variables that take into account the diversity of situations between countries and allow new conclusions. Diffuse resource related activities, where significant amounts of unskilled labour are used, significantly decrease the industrial wage skill premium in advanced countries when the resource proxy is unadjusted for re-exportation. This suggests that the effect is mainly related to re-exportation activities associated with diffuse resources, such as (industrial) food production. The found positive impact of institutional quality (as measured by Polity) in advanced countries appears to be correlated with organizational changes that increase productivity and thus the skill premium.

In less advanced countries, the skill premium is led by foreign direct investment (confirming the importance of technology transfer in these countries), scale effects and geographically-concentrated natural resource activities, which appear to absorb scarce skilled workers available to the industrial sector and thus increase wage skill inequality. In this case, the wage centralization measure has a positive impact on the industrial skill premium, which is rather surprising but may be explained by a reduction of informality in remuneration schemes departing from very decentralized negotiations (at company level, for example).

In turn, the skill premium of less advanced countries is reduced by trade (as predicted by the Stolper-Samuleson theorem), the importance of diffuse resources, and by technology progress (confirmed with several proxies, although only one specific to the industrial sector), which is apparently surprising. We conjecture that the negative impact of the technology progress measures – estimated considering that foreign investment is constant – is explained by the emergence of national low-end technological industrial sectors paying less for skilled labour than more advanced and predominant foreign-led industrial sectors.

Despite data constraints, this study presents significant results that point to new evidence regarding traditional and novel determinants of industrial wage skill inequality.

APPENDIX: Appendix Tables A1 And A2

Table A1: Data Sources and Details

Variable	Name	Measure	Source	Comments
IWSP	Industrial wage skill premium	(electronics engineering wage)/(textile labourer wage)	OWW	
A(LA)	Tech. Advanced (Less Advanced) country *i*	*A*=1(0) and *LA*=(0(1) if *i* belongs to the advanced technology club	Castellacci and Archibugi (2008)	Data reported to the year 2000.
SE	Scale effects	lnGDP at current dollars (power purchasing parity)	WB	
SBTC	Skill biased technological change	high-technology industrial exports (% of other industrial exports)	WB	Data only begins in 1987.
		R&D expenses (% GDP)	WB	Data only begins in 1996.
		Patent applications (*per* million persons), total and residents	WB	
		Scientific and technical journal articles (*per* million people)	WB	
		Internet use (per 100 people)	WB	Data only begins in 1990.
		Mobile phone subscriptions and telephone lines (*per* 100 people)	WB	
		Electric power consumption (kWh *per* capita)	WB	
FDI	Net foreign direct investment	Net foreign direct investment (% GDP)	UN (NAD)	More data than WB.
T	Trade	(Exports + Imports) (% GDP)	UN (NAD)	More data than WB.
HL	Relative supply of skilled labour	Tertiary enrolment /(1-tert. enrolment)	WB	
		Labour force with tertiary (L_T) and secondary education (L_S) in proportion of labour force with primary education (L_P)	WB	Data available after 1990 for most of the panel.
		L_T /(L_S + L_P)	WB	Data available after 1990 for most of the panel.
LMI	Labour market indicators	centralization of wage bargaining coordination	ICTWSS	Discrete variable (D.V.) ranging from 1 (fragmented bargaining, mostly at company level) to 5 (economy-wide bargaining).
		minimum wage setting	ICTWSS	D.V. ranging from 0 (no statutory min.wage) to 8 (min.wage set by government without fixed rule)
IQ	Institutional Quality	Revised combined Polity score	Polity IV Project	D.V. ranging from -10 (strongly autocratic) to +10 (strongly democratic).
		Freedom indicator	FH	Rating for Political Rights and Civil Liberties ranging between 1 and 7.
NresP	Geographically-concentrated resources	Share of fuels, ores and metals in merchandise exports and net share (of the proportion in imports), %	WB	
NresD	Geographically-diffuse resources	Share of agricultural raw materials and food products in merchandise exports and net share, %	WB	

Sources:
FH, the Freedom House, Freedom in the World Country Ratings;
ICTWSS, Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts 1960-2010 (version 3.0, by Jelle Visser, University of Amsterdam);
OWW, Occupational Wages around the World Database – standardized ILO October Inquiry 1983-003 (September 2005 update of Freeman and Oostendrop 2000, 2001);
Polity IV Project (by Monty G. Marshall and Keith Jaggers), Polity IV Data Series version 2010;
UN (NAD), United Nations, National Accounts database online;
WB, World Bank, World Development Indicators 2011.

Table A2: estimated countries and periods (from regression 2 in Table 3) and key variables

	Country	Period	*A*	*IWSP*		Country	Period	A	IWSP
1	Australia	1987-89	1	1.2	16	Portugal	1997-99	0	2.6
1	Australia	1990-92	1	1.2	16	Portugal	2000-03	0	2.2
1	Australia	1993-96	1	1.5	17	Romania	1993-96	0	2.1
1	Australia	1997-99	1	1.5	17	Romania	1997-99	0	2.4
1	Australia	2000-03	1	1.7	17	Romania	2000-03	0	2.8
2	Austria	1987-89	1	2.7	18	Slovakia	1997-99	0	2.3
2	Austria	1990-92	1	2.7	18	Slovakia	2000-03	0	2.2
2	Austria	1993-96	1	2.6	19	Slovenia	1993-96	0	2.6
2	Austria	1997-99	1	2.8	19	Slovenia	1997-99	0	2.7
2	Austria	2000-03	1	2.6	20	Sweden	1987-89	1	1.1
3	Brazil	2000-03	0	3.2	20	Sweden	1990-92	1	1.1
4	Canada	1997-99	1	1.9	20	Sweden	1993-96	1	1.2
4	Canada	2000-03	1	1.8	21	USA	1987-89	1	1.7
5	China	1990-92	0	1.2	21	USA	1990-92	1	1.8
5	China	1993-96	0	1.8	21	USA	1993-96	1	1.8
5	China	1997-99	0	1.6	21	USA	1997-99	1	1.9
6	Germany	1990-92	1	1.9	21	USA	2000-03	1	1.9
6	Germany	1993-96	1	1.9					
6	Germany	1997-99	1	1.9					
7	Denmark	1987-89	1	1.2					
7	Denmark	1990-92	1	1.2					
8	Estonia	1993-96	0	1.4					
9	Finland	1987-89	1	1.8					
9	Finland	1990-92	1	1.7					
9	Finland	1993-96	1	1.7					
10	Hungary	1997-99	0	3.8					
10	Hungary	2000-03	0	2.7					
11	Italy	1987-89	0	1.2					
11	Italy	1990-92	0	1.2					
11	Italy	1993-96	0	1.2					
11	Italy	1997-99	0	1.2					
11	Italy	2000-03	0	1.2					
12	Korea, Rep.	1997-99	1	1.5					
12	Korea, Rep.	2000-03	1	1.6					
13	Latvia	2000-03	0	1.2					
14	New Zealand	1987-89	1	1.6					
14	New Zealand	1990-92	1	1.6					
15	Poland	1997-99	0	1.5					
15	Poland	2000-03	0	1.6					
16	Portugal	1993-96	0	2.9					

Data based on authors own estimations.

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