CONTRIBUTI DI RICERCA CRENOS

SKILL BIASED TECHNICAL CHANGE AND MISALLOCATION: A UNIFIED FRAMEWORK

Michele Battisti
Massimo Del Gatto
Christopher F. Parmeter

WORKING PAPERS

2019/08

Centro Ricerche Economiche Nord Sud
(CRENoS)
Università di Cagliari
Università di Sassari

CRENOS was set up in 1993 with the purpose of organising the joint research effort of economists from the two Sardinian universities (Cagliari and Sassari) investigating dualism at the international and regional level. CRENoS' primary aim is to improve knowledge on the economic gap between areas and to provide useful information for policy intervention. Particular attention is paid to the role of institutions, technological progress and diffusion of innovation in the process of convergence or divergence between economic areas. To carry out its research, CRENoS collaborates with research centres and universities at both national and international level. The centre is also active in the field of scientific dissemination, organizing conferences and workshops along with other activities such as seminars and summer schools.
CRENoS creates and manages several databases of various socio-economic variables on Italy and Sardinia. At the local level, CRENoS promotes and participates to projects impacting on the most relevant issues in the Sardinian economy, such as tourism, environment, transports and macroeconomic forecasts.

www.crenos.unica.it
crenos@unica.it

CRENoS – Cagliari
Via San Giorgio 12, I-09124 Cagliari, Italia
tel. +39-070-6756397; fax +39-070- 6756402

CRENoS - Sassari
Via MURONI 25, I-07100 Sassari, Italia
tel. +39-079-213511

Title: SKILL BIASED TECHNICAL CHANGE AND MISALLOCATION: A UNIFIED FRAMEWORK

ISBN: 978 88 68512 279

Prima Edizione: Giugno 2019

Viale Bonaria 98 - 09125 Cagliari
Tel. 070/6848663 - info@arkadiaeditore.it
www.arkadiaeditore.it

Skill Biased Technical Change and Misallocation: A Unified Framework

Michele Battisti
University of Palermo and RCEA

Massimo Del Gatto[1]
"G.d'Annunzio" University, LUISS and CRENoS

Christopher F. Parmeter
University of Miami

Abstract

Due to strict reliance on competitive labor markets, standard approaches which measure skill biased technical change (SBTC) conflate labor market distortions which prevent firms from choosing the efficient ratio between skilled and unskilled labor and 'true' SBTC. This contrasts with recent evidence on decoupling between wages and productivity. To overcome this limitation, we present a unified framework to estimate SBTC which accounts for factor accumulation (FA) effects, and quantifies the discrepancy (i.e., relative misallocation) between the wage ratio (skilled to unskilled) and the marginal rate of technical substitution (MRTS). The suggested methodology takes advantage of recent developments in nonparametric estimation methods (i.e., discrete smoothing) that allow us to estimate the marginal productivity of inputs at the country-sector level directly from data. Over the 1995-2005 period, we find a 3% yearly growth rate for the MRTS between skilled and unskilled labor and show such change to be almost entirely driven by SBTC, rather than FA, on average. In most cases, SBTC and MRTS growth do not come with increasing skill premia; this fosters the decoupling and results in relative misallocation patterns (across countries and sectors) which are quite heterogeneous, for which we report a 6% overall increase. Finally, we show evidence that relative misallocation increased less in country-sectors in which it was larger at the beginning of the period and grew more in country-sectors characterized by: (a) higher skill-intensity; (b) lower bargaining power of skilled over unskilled workers; and (c) lower FA effects.

[1] Corresponding author: Massimo Del Gatto, `G.d'Annunzio' University, Department of Economics (DEc), Viale Pindaro 42, 65127 - Pescara (Italy). massimo.delgatto@unich.it

1 Introduction

In perfectly competitive markets, firms choose the amount of each input to deploy by equalizing marginal revenue product (MRP) to its corresponding price. In relative terms, this economic efficiency condition entails that the marginal rate of technical substitution (MRTS) between any two inputs equals the corresponding price ratio. This condition is widely used to investigate the direction of technical change. In fact, if technical change affects the marginal product of all inputs in the same proportion (i.e., 'Hicks-neutral' technological progress), the relative demand of inputs remains the same, thereby leaving the input price ratio unaffected. Differently, when technological progress affects the marginal product of inputs in different proportions (i.e., 'factor biased' technical change), the MRTS changes at given input levels. This induces changes in terms of relative demand of inputs and input price ratio.

The literature on skill biased technical change (SBTC) uses the condition of economic efficiency to study whether technological progress actually results in a relatively higher productivity of skilled labor, with respect to unskilled labor, or vice-versa. Indeed, under economic efficiency, skill bias is easily understood in terms of discrepancy between the observed wage ratio between skilled and unskilled labor in the economy and the labor ratio between skilled and unskilled workers actually chosen by firms. While this (standard) approach attributes the full discrepancy to technology, the literature on misallocation documents that deviations from the efficiency condition are likely to be driven by the action of market frictions preventing the flow of factors from less productive (where marginal products are lower) to more productive firms (where marginal products are higher). Thus, standard SBTC measures are likely to conflate 'true' SBTC and misallocation effects when labor market inefficiencies are such that firms are prevented from choosing the efficient ratio between skilled and unskilled labor.

This mis-measurement jeopardizes the capacity to draw correct policy conclusions on the allocative efficiency effects of technological progress. Indeed, following the analysis carried out by OECD (2018) in absolute terms, Figure 1 highlights how the recent evolution of the wage ratio of high to medium-low skilled labor is actually mixed: the skill premium increases in countries such as Canada and the US but decreases, sometimes substantially, in many other cases, most notably in Italy, Sweden and France. By contrasting these patterns with the (almost always negative) corresponding percentage changes in relative productivity, Figure 1 suggests the occurrence of a progressive 'decoupling' between wage and productivity gaps. While this circumstance is arguably related to the presence of labor market frictions affecting the skilled and unskilled labor markets asymmetrically, the direction of the decoupling points to a situation in which medium-low skilled workers do not reap the benefits of their technology-induced relative increase in productivity, compared to skilled labor (only five countries lie below the 45 degree line). As we will see in the analysis, this policy message is highly misleading (actually the opposite of the one suggested by our analysis).

Although sharing a common root, the misallocation and SBTC literatures mainly developed independently of one another. The main reason for this is empirical: estimating a country by sector by year specific production function is a daunting task with standard econometric techniques as the number of production function parameters to be estimated equals the number of observations when using country by sector by year data. This prevents one from estimating SBTC directly from the production function, thereby making the hypothesis of perfect markets unavoidable.

We overcome this limitation by taking advantage of recent developments in nonparametric estimation (see Li and Racine, 2007 and Henderson and Parmeter, 2015 for textbook treatments) to control for country-sector-year effects in our estimates of the marginal product (MP) of inputs from aggregate international data. This allows us to disentangle variation in SBTC and MRTS by estimating SBTC directly from the production function, net of factor accumulation (FA) effects. With this we can carry out an economic efficiency analysis by quantifying the misalignment between MRTS and relative wages (i.e., 'relative misallocation'), arguably driven by asymmetric frictions between skilled and unskilled labor markets (at the country-sector level).

We bring this approach to data using information drawn from the WIOD database covering 40 countries over the years 1995-2005 at the 2-digit sectoral level. We find that the MRTS between skilled and unskilled labor has been growing at a yearly rate of 3.23% on average, over the decade 1995-2005. Overall, most of this change is driven by SBTC, for which we report a yearly growth rate of 3.61%, and much less by FA, associated to a slightly negative MRTS yearly growth (-0.39%). However, these averages values hide substantial heterogeneity across countries and sectors, with the FA effects dominating the SBTC component in several cases.

We then ask to what extent SBTC can be thought of to bring about a less efficient use of labor. To this aim, we consider the change in the discrepancy between the MRTS and the wage ratio of high to medium-low skilled labor. For this measure, referred to as 'relative misallocation', we document an overall 6% increase.

Although with considerable cross-country and cross-sector variability, we also find the skill premium to grow less then the MRTS in the vast majority of countries (notably, the US and Germany are found to be among the few countries in which the skill premium has grown more than the productivity ratio). Thus, the direction of the 'decoupling' in our estimates is opposite to the simple analysis carried out in Figure 1 and suggests that it is unskilled labor that is not able to reap the benefits of the increase in productivity induced by technological progress.

Since we find the average wage ratio to be quite stable during the period under consideration, and since our numbers point to a dominant role played by SBTC over FA in determining the average change in the MRTS between skilled and unskilled workers, our analysis suggests that SBTC induces a less efficient use of labor as long as the relative increase of skilled workers' MRP (i.e., growth of the MRTS between skilled and unskilled workers) does not come with higher skill premia. Our econometric analysis suggests that this is more likely to happen in skill-intensive country-sectors (even more so when skill-intensity is coupled with higher FA effects associated with an increasing relative use of skilled labor) and in country-sectors characterized by lower bargaining power of skilled (over unskilled) workers, which arguably prevents skilled workers to be paid higher wages.

The remainder of the paper is organized as follows. Section 2 presents the related literature. Section 3 gives a simple presentation of the standard approach and of the motivation underlying our proposed approach, while Section 4 presents the empirical strategy. Section 5 contains our decomposition coupled with our baseline estimates. Section 6 reports some robustness checks. Section 7 deals with the evolution of relative misallocation and with its relationship with potential measures of labor market frictions. Section 8 concludes. Appendix 9 discusses the empirical methodology more in details. Appendix 10 reports the overall distributions featuring our estimated measures.

2 Related literature

While a large body of work has documented a balanced growth in wages and labor productivity from the 1960s to the 1980s, there is evidence pointing towards a divergent patterns beginning in the 1990s (see Katz and Murphy, 1992). OECD (2018) highlights how the growth in wages of low-medium skilled workers has been lagging behind average wage growth in several OECD economies between 1995 and 2013. This resulted in increasing (within-country) wage inequality. The 7% overall increase in measured decoupling (between labor productivity and real median wage) is equally attributed to increasing wage inequality and labor accumulation (versus capital). Among others, Faggio et al. (2010) find evidence of a positive correlation (for Swedish firms) between average wages and labor productivity, while Berlingieri et al. (2017) highlight how wage dispersion is significantly linked to increasing differences between high and low productivity firms, even controlling for the sectors' skill composition. Berlingieri et al. (2018) find a positive link between firm productivity, measured as per worker output, and wage premium. Card and Di Nardo (2002) show that, notwithstanding a rising skill premium (associated to eventual complementarity between computers and skilled work), relative wage inequality was stabilized from the 1990s.

The literature on SBTC mainly developed under the assumption of perfectly competitive labor markets (Acemoglu and Autor, 2011). Under such an assumption, firms choose the amount of skilled and unskilled labor by equalizing the MRTS between the two types of labor to their relative price, the ratio of skilled to unskilled workers' wage. With a Constant Elasticity of Substitution (CES) production function, SBTC can be retrieved by regressing relative wages of skilled to unskilled workers on the ratio of skilled to unskilled labor actually used, together with possible control variables (Acemoglu and Autor, 2011). This approach, carefully described in Caselli (2017), is used in several studies at the firm or industry level (Card and Lemieux, 2001; Katz and Murphy, 1992; Henderson, 2009; Caselli and Coleman, 2006; Krusell et al., 2000, Violante, 2016, Rossi, 2018).

As highlighted, this methodology attributes the whole deviation of the labor ratio from relative wages to SBTC, neglecting the presence of asymmetric imperfections (by skill) in the labor market. The growing body of literature concerned with misallocation studies the aggregate productivity effects of the inefficient allocation of inputs across firms and/or sectors (Alfaro et al., 2008; Banerjee and Duflo, 2005; Bartelsman, et al., 2013; Battisti et al., 2019; Hsieh and Klenow, 2009, 2010; Jones, 2011; Restuccia and Rogerson 2008, 2013; Olley and Pakes, 1996). In these studies, the extent of misallocation is easily understood in terms of deviation from the efficiency condition (i.e., in efficient markets, the MRP of an input equals its price). The general conclusion reached by these studies is that the aggregate productivity losses associated with misallocation are substantial and, as a consequence, eliminating or reducing the within-industry distortions is key to improving aggregate productivity and, definitively, the aggregate income of countries (Calligaris et al., 2018; Garcia-Santana et al., 2015; Gopinath et al., 2017; Dias et al., 2014; Bellone and Mallen-Pisano, 2013).

Moreover, Calligaris et al. (2018) show that the within-sector dimension of misallocation is more important than the between sector dimension, so that reducing aggregate productivity loss is more a matter of resource reallocation across productive units operating in the same sector, rather than a matter of redistributing resources across different sectors. From a policy perspective, this calls for more detailed analysis of labor and product market regulations (e.g., Blanchard and Giavazzi, 2003; Bassanini et al., 2009; Cette et al., 2016), on the one hand, and the identification of possible misallocation markers and relevant correction policies, on the other. Although some work has been done in this direction (e.g. Asker et al., 2014; Calligaris et al., 2018 for country level studies and Hopenhayn, 2014 for a review of the field), this type of analysis faces intrinsic difficulties.

Indeed, unless one can take advantage of specific variability associated to a policy change in a given country (as in the case of the banking reforms in Chile documented by Chen and Irarrazzabal, 2014) or to different regulations at a sub-national tier of government (as in the case of Boeri et al. (2019) for Italian provinces), the opportunity to relate the variability in terms of misallocation to the variability in terms of policy implementation (notably of labor market regulations) is hampered by the fact that, while policies are mainly country-sector specific, the quantification of misallocation requires firm-level data. With internationally comparable firm-level data, misallocation can be estimated for each firm so that, by aggregating, country-sector-year indicators can be obtained. However, comparable international data encompassing all the information needed to estimate the production function at the firm level (i.e., firms' capital, labor and output) is rarely available and, even in the fortunate cases in which it is, the chance to reach unequivocal conclusions in terms of misallocation drivers is limited by a poor country coverage. Our approach enables us to obtain a (relative) misallocation measure featuring country-sector-year variability directly on aggregate international data (firm-level information is not needed). This is key in order to carry out a comprehensive analysis of the drivers/markers of the cross-country and cross-sector evolution of the eventual misalignment between relative wages and relative productivity.

Disentangling the sources of technological progress is also related to the literature on technology embodied in physical capital goods (see Greenwood et al., 1997, Hercowitz, 1998, Sakellaris and Wilson, 2004) and then on 'directed technical change'. In these studies (Zeira, 1998; Acemoglu 1998, 2002, 2003; Autor et al., 2003), the emergence of a new machine, embodying technology, that may replace manual routines, make less profitable hiring workers when the adoption price is relatively lower than workers' wage. For example, Acemoglu and Autor (2011) consider how routine tasks may be replaced by capital/machines embodying technical progress and how the subsequent wage changes are transmitted to high or low skill workers depending on relative substitutability with routine tasks.

Moreover, some authors (Koeninger and Leonardi (2007), Alesina et al. (2018), among others) highlight how adopting a new technology can be relatively more or less convenient, depending on the pressure exerted by labor market institutions on wages. If this is the case, technology adoption is not independent of relative wages (see also Karabarbounis and Neiman, 2014), i.e. the SBTC is theoretically endogenous with respect to the wage ratio. This possibility, which is very high in the IT revolution (Beaudry et al., 2006), emphasizes the importance of trying to estimate SBTC directly from the production function, as suggested by our approach.

3 Theoretical motivation: shortcomings of 'standard' SBTC estimates

SBTC is usually thought of as any form of technical change directly affecting the marginal rate of technical substitution (MRTS) between skilled (S) and unskilled (U) labor, at given input levels - i.e., $\frac{MRPL_s}{MRPL_u}$, with $MRPL_s$ and $MRPL_u$ denoting the marginal revenue product of skilled and unskilled labor, respectively.

The standard approach to SBTC estimation (see, e.g., Violante, 2016; Krusell et al., 2000) assumes the following Cobb-Douglas production function, with a nested CES specification for S and U[2]

$$Y^c = Z^c (K^c)^\alpha [(A_s^c S^c)^\sigma + (A_u^c U^c)^\sigma]^{\frac{1-\alpha}{\sigma}}. \tag{1}$$

where index c refers to the country and everything is sector-specific.

This form proves useful in identifying SBTC. To see this, consider the partial derivatives:

$$\frac{\partial Y^c}{\partial S^c} = Z(K^c)^\alpha \frac{1-\alpha}{\sigma} A_s^\sigma S^{\sigma-1} \text{ and } \frac{\partial Y^c}{\partial U^c} = Z(K^c)^\alpha \frac{1-\alpha}{\sigma} A_u^\sigma U^{\sigma-1} \tag{2}$$

with the MRTS amounting to

$$MRTS_{s,u}^c = \left(\frac{A_s^c}{A_u^c}\right)^\sigma \left(\frac{S^c}{U^c}\right)^{\sigma-1}. \tag{3}$$

Standard profit maximization under the assumption of homogeneous (for skilled and unskilled) competitive labor markets yield the efficiency condition according to which the MRTS between skilled and unskilled labor has to be equal to the skilled to unskilled price (wage) ratio: $MRTS_{s,u}^c = \frac{W_s^{c,t}}{W_u^{c,t}}$, where W_s and W_u are used to refer to the wage of skilled and unskilled labor, respectively.

[2] See Duffy *et al.* (2004).

SBTC can be constructed through the residuals of the following equation, estimated for a number of countries:

$$\ln\left(\frac{W_s^{c,t}}{W_u^{c,t}}\right) = \underbrace{\sigma\ln\left(\frac{A_s^{c,t}}{A_u^{c,t}}\right)}_{\text{Estimatedresidual}(\hat{B}_{s,u}^{c,t})} + (\sigma-1)\ln\left(\frac{S^{c,t}}{U^{c,t}}\right) + \varepsilon_c \tag{4}$$

in which t denotes time and ε_c is the iid error term.

The SBTC index is given by the growth rate of the residual in (4), from time t to time T:

$$\Delta\hat{B}_{s,u}^{c,tT} = \hat{B}_{s,u}^{c,T} - \hat{B}_{s,u}^{c,t}. \tag{5}$$

"Biased" Biased Technical Change

By relying on the assumption that the whole deviation from the efficiency condition is due to technical change, the approach in (4) and (5) attributes to SBTC the effect of any type of eventual frictions affecting the market of skilled and unskilled labor differently (this point is highlighted in Caselli, 2017). To see this, assume, similarly to Hsieh and Klenow (2009), that firms in country c face distortion τ_u (for sake of simplicity assumed to be the same for all firms in the country-sector) in the market of unskilled labor, entailing that $(1+\tau_u)$ units of unskilled labor have to be hired in order to be able to use one unit of it. This induces hiring an inefficiently high share of skilled labor (more generally we may think that τ_u embodies asymmetric imperfections affecting skilled labor differently from unskilled labor). In the presence of such a type of market imperfection, the firm (assuming product markets are competitive and firms face the same profit maximization problem) maximizes profits:

$$\pi^c = P^cY^c - rK^c - W_s^cS^c - W_u^cU^c(1+\tau_u). \tag{6}$$

Profit maximization yields

$$MRTS_{s,u}^c = \left(\frac{A_s^c}{A_u^c}\right)^{\sigma}\left(\frac{S^c}{U^c}\right)^{\sigma-1} = \frac{W_s^c}{W_u^c(1+\tau_u)}. \tag{7}$$

This yields the following estimating equation for SBTC:

$$\ln\left(\frac{W_s^{c,t}}{W_u^{c,t}}\right) = \underbrace{\sigma\ln\left(\frac{A_s^{c,t}}{A_u^{c,t}}\right) + \ln(1+\tau_u)}_{\text{estimatedresidual}} + (\sigma-1)\ln\left(\frac{S^{c,t}}{U^{c,t}}\right) + \varepsilon_c \tag{8}$$

Equation (8), which nests (4) as a special case with $\tau_u = 0$, highlights how the standard approach conflates the 'true' SB and labor market distortions in the presence of asymmetric distortions between the skilled and unskilled labor markets. In particular, the estimated SB results to be overstated in the presence of distortions affecting unskilled labor relatively more (that is, increasing the 'effective' wage of unskilled labor relatively more than skilled labor, or limiting the use of unskilled labor relatively more than skilled labor). Thus, the necessary assumption is the presence of symmetric (by skill type) labor market distortions (hence, "Biased" Biased Technical Change).

A very specific theoretical specification

In the standard approach, SBTC is identified only under very specific assumptions on the way in which S and U enter the production function (i.e., the CES hypothesis). This has two order of consequences. First, As shown by Caselli (2017), the estimated SB varies considerably with the value of the elasticity of substitution (EoS). Second, with a different production function, it is not possible to isolate the SBTC component. To see this, consider the alternative specification

$$Y^c = Z^c (K^c)^\alpha [(A_s^c S^c)^\sigma (A_u^c U^c)^{1-\sigma}]^\beta. \tag{9}$$

This is a special case of (1), with unitary EoS between skilled and unskilled labor. The derivatives with respect to S and U are given by, respectively:

$$\frac{\partial Y^c}{\partial S^c} = \sigma \beta Y^c \frac{1}{S^c} \qquad \text{and} \qquad \frac{\partial Y^c}{\partial U^c} = (1-\sigma)\beta Y^c \frac{1}{U^c}. \tag{10}$$

Thus, the MRTS between skilled and unskilled labor amounts to

$$\frac{\partial Y^c / \partial S^c}{\partial Y^c / \partial U^c} = \frac{\sigma}{1-\sigma} \frac{U^c}{S^c}. \tag{11}$$

In this case, the SBTC component disappears from MRTS.

It is also worth noting how a time-varying measure of SBTC can be obtained only provided that the EoS does not vary across units (Diamond et al., 1978 and Caselli, 2017). However, the literature shows how the EoS can differ even substantially across industries (Krusell et al., 2000; Blankenau and Cassou, 2011), countries and time (Henderson, 2009).

4 Identification strategy: linking SBTC to 'relative misallocation'

Let us start with the production function (in logarithmic form) of country c, at time t (to condense our notation we omit the industry index with the understanding that everything is also specific to a given sector)

$$y^{c,t} = m^{c,t}(k^{c,t}, s^{c,t}, u^{c,t}) + z^{c,t}. \tag{12}$$

Here country c's output (in a given sector) at time t, $y^{c,t}$, depends on contemporaneous values of capital $k^{c,t}$, skilled labor $s^{c,t}$ and unskilled labor $u^{c,t}$, through the production technology $m^{c,t}(\cdot)$, as well as on $z^{c,t}$, which captures Total Factor Productivity and idiosyncratic productivity shocks.

According to (12), given the amount of inputs, country c's actual technology at time t can make the country more productive than a generic country f at time t (i.e., $m_t^c > m_t^f$) or more productive compared to itself at $t-1$ (i.e., $m_t^c > m_{t-1}^f$).[3]

For each input, we are able to estimate country-sector-time specific partial derivatives. For skilled and unskilled labor, these amount to $\widehat{m}_s^{c,t}(k^{c,t}, s^{c,t}, u^{c,t}) = \frac{\partial m_t^c}{\partial s^{c,t}}$ and $\widehat{m}_u^{c,t}(k^{c,t}, s^{c,t}, u^{c,t}) = \frac{\partial m_t^c}{\partial u^{c,t}}$, respectively. Thus, the MRTS between skilled and unskilled labor at time t can be written as:

$$\widehat{MRTS}_{s,u}^{c,t} = \frac{\widehat{m}_s^{c,t}(k^{c,t}, s^{c,t}, u^{c,t})}{\widehat{m}_u^{c,t}(k^{c,t}, s^{c,t}, u^{c,t})}. \tag{13}$$

The rate of change of MRTS can be defined as:

$$\Delta \ln \widehat{MRTS}_{s,u}^{c,tT} = \ln\left(\frac{\widehat{MRTS}_{s,u}^{c,T}}{\widehat{MRTS}_{s,u}^{c,t}}\right) =$$
$$= \ln\left(\frac{\widehat{m}_s^{c,T}(k^{c,T}, s^{c,T}, u^{c,T})}{\widehat{m}_u^{c,T}(k^{c,T}, s^{c,T}, u^{c,T})}\right) - \ln\left(\frac{\widehat{m}_s^{c,t}(k^{c,t}, s^{c,t}, u^{c,t})}{\widehat{m}_u^{c,t}(k^{c,t}, s^{c,t}, u^{c,t})}\right). \tag{14}$$

Our approach allows us to examine cross-country differences in technical change (by sector) in greater detail. To this aim, note that the changes in marginal product can depend on either changes in technology or changes in the amount of inputs used (as for instance in Battisti et al., 2018)[4].

To isolate the technical component, a counterfactual analysis is needed, as we are interested in the change in output (associated with technological progress) that the country would

[3] At the firm level, Battisti et al. (2019) use mixture models to deal with the presence of multiple technologies within the sector, following the intuition that a firm has a discrete number of potential available technologies within an industry. Here in a country-industry setting, our nonparametric approach allows us to identify country-sector-time specific technologies.

[4] This is a fundamental difference with respect to standard approach. There, the effect is measured as what remains after the changes in relative skilled supply. Here we consider the relative impact on the country-industry production, that imply not the potential labor supply, but the equilibrium employment for each skill type.

have experienced without changing the amount of inputs used. Note that, for each input (say skilled labor) we are able to compute counterfactual partial derivatives $\widetilde{m}_s^{c,T}(k^{c,t}, s^{c,t}, u^{c,t})$ measuring the additional output (associated to the marginal unit of input s) that country c would have produced at time t using time T's technology, given the quantity of inputs used. These counterfactual values can be used to decompose variation in MRTS in (14) into the following two components:

$$\Delta\ln\widehat{MRTS}_{s,u}^{c,tT} = \Delta\ln\widetilde{\mathbb{B}}_{s,u}^{c,tT} + \Delta\ln\widetilde{\mathbb{F}}_{s,u}^{c,tT}. \tag{15}$$

The first term, $\Delta\ln\widetilde{\mathbb{B}}_{s,u}^{c,tT}$, is a SBTC component encompassing the technical change not affecting the marginal revenue product of skilled and unskilled labor in the same proportion:

$$\Delta\ln\widetilde{\mathbb{B}}_{s,u}^{c,tT} = \ln\widehat{MRTS}_{s,u}^{c,T} - \ln\widehat{MRTS}_{s,u}^{c,t} = \ln\left(\frac{\widetilde{m}_s^{c,T}(k^{c,t},s^{c,t},u^{c,t})}{\widetilde{m}_u^{c,T}(k^{c,t},s^{c,t},u^{c,t})}\right) - \\ - \ln\left(\frac{\widehat{m}_s^{c,t}(k^{c,t},s^{c,t},u^{c,t})}{\widehat{m}_u^{c,t}(k^{c,t},s^{c,t},u^{c,t})}\right). \tag{16}$$

$\Delta\ln\widetilde{\mathbb{F}}_s^{c,tT}$ is a factor accumulation component measuring the MRTS variation related to the change in the quantity of inputs (factor accumulation):

$$\Delta\ln\widetilde{\mathbb{F}}_{s,u}^{c,tT} = \ln\left(\frac{\widehat{m}_s^{c,T}(k^{c,T},s^{c,T},u^{c,T})}{\widehat{m}_u^{c,T}(k^{c,T},s^{c,T},u^{c,T})}\right) - \ln\left(\frac{\widetilde{m}_s^{c,T}(k^{c,t},s^{c,t},u^{c,t})}{\widetilde{m}_u^{c,T}(k^{c,t},s^{c,t},u^{c,t})}\right). \tag{17}$$

The factor accumulation component can be further decomposed in order to isolate the contribution of each factor with respect to changes in relative productivity of labor inputs:

$$\Delta\ln\widetilde{\mathbb{F}}_{s,u}^{c,tT} = \underbrace{\ln\left(\frac{\widehat{m}_s^{c,T}(k^{c,T}, s^{c,T}, u^{c,T})}{\widehat{m}_u^{c,T}(k^{c,T}, s^{c,T}, u^{c,T})}\right) - \ln\left(\frac{\widetilde{m}_s^{c,T}(k^{c,T}, s^{c,t}, u^{c,T})}{\widetilde{m}_u^{c,T}(k^{c,T}, s^{c,t}, u^{c,T})}\right)}_{\text{accumulation(s)}}$$

$$+\underbrace{\ln\left(\frac{\widetilde{m}_s^{c,T}(k^{c,T}, s^{c,t}, u^{c,T})}{\widetilde{m}_u^{c,T}(k^{c,T}, s^{c,t}, u^{c,T})}\right) - \ln\left(\frac{\widetilde{m}_s^{c,T}(k^{c,T}, s^{c,t}, u^{c,t})}{\widetilde{m}_u^{c,T}(k^{c,T}, s^{c,t}, u^{c,t})}\right)}_{\text{accumulation(u)}}$$

$$+\underbrace{\ln\left(\frac{\widetilde{m}_s^{c,T}(k^{c,T},s^{c,t},u^{c,t})}{\widetilde{m}_u^{c,T}(k^{c,T},s^{c,t},u^{c,t})}\right) - \ln\left(\frac{\widetilde{m}_s^{c,T}(k^{c,t},s^{c,t},u^{c,t})}{\widetilde{m}_u^{c,T}(k^{c,t},s^{c,t},u^{c,t})}\right)}_{\text{accumulation(k)}}. \tag{18}$$

This approach nicely fits into a "relative" misallocation framework.[5]. In fact, under standard profit maximization, the MRTS equals the wage ratio: $\widehat{MRTS}_{s,u}^{c,t} = \mathbb{W}_{s,u}^{c,t} = \frac{W_s^{c,t}}{W_u^{c,t}}$. Any deviation from this condition can be attributed (see Equation (7)) to market imperfections affecting skilled and skilled labor asymmetrically. Thus, a relative measure of misallocation is given by the ratio

$$\ln\hat{\tau}_{s,u}^{c,t} = \ln\left(\frac{\widehat{MRTS}_{s,u}^{c,t}}{\mathbb{W}_{s,u}^{c,t}}\right). \quad (19)$$

Our efficiency condition, $\tau_{s,u}^{c,t} = 0$ suggests that positive values denote a marginal product of skilled labor which is too high, relative to unskilled labor, compared to the actual wage ratio. The opposite is true for $\tau_{s,u}^{c,t} < 0$.

Since the MRTS in Equation (13) can be obtained at different points in time, we are able to relate the variation in $\hat{\tau}_{s,u}^{c}$ to SBTC as follows:

$$\Delta\ln\hat{\tau}_{s,u}^{c,tT} = \ln\left(\frac{\widehat{MRTS}_{s,u}^{c,T}}{\mathbb{W}_{s,u}^{c,T}}\right) - \ln\left(\frac{\widehat{MRTS}_{s,u}^{c,t}}{\mathbb{W}_{s,u}^{c,t}}\right) =$$

$$= \underbrace{\Delta\ln\widetilde{\mathbb{B}}_{s,u}^{c,tT} + \Delta\ln\widetilde{\mathbb{F}}_{s,u}^{c,tT}}_{\ln\left(\frac{\widehat{MRTS}_{s,u}^{c,T}}{\widehat{MRTS}_{s,u}^{c,t}}\right) = \Delta\ln\widehat{MRTS}_{s,u}^{c,tT}} - \ln\mathbb{W}_{s,u}^{c,tT} \qquad (20)$$

where $\ln\mathbb{W}_{s,u}^{c,tT} = \ln\left(\frac{\mathbb{W}_{s,u}^{c,T}}{\mathbb{W}_{s,u}^{c,t}}\right)$. Equation (20) is our nonparametric equivalent of Equation (5) and provides information concerning the dynamics of the eventual (relative) decoupling between relative wages and relative productivities. Positive values imply that the MP of skilled labor has grown relatively more than wages, compared to unskilled labor.

To operationalize (20) in terms of increasing or decreasing relative misallocation, it is convenient to express the variation of $\hat{\tau}_{s,u}^{c}$ using absolute values:

$$\widehat{\Theta}_{s,u}^{c,tT} = \left|\ln\hat{\tau}_{s,u}^{c,T}\right| - \left|\ln\hat{\tau}_{s,u}^{c,t}\right| = \left|\ln\left(\frac{\widehat{MRTS}_{s,u}^{c,T}}{\mathbb{W}_{s,u}^{c,T}}\right)\right| - \left|\ln\left(\frac{\widehat{MRTS}_{s,u}^{c,t}}{\mathbb{W}_{s,u}^{c,t}}\right)\right|. \quad (21)$$

Positive values of $\widehat{\Theta}_{s,u}^{c,tT}$ point to increasing relative misallocation, that is to a widening discrepancy between relative wages and MRTS. This circumstance can be driven by a change in relative wages, the adoption of skill biased technologies (i.e., SBTC), a change in the skilled to

[5] In a similar vein, Caselli (1999) studies the relation between skill acquisition (cost) and relative wages.

unskilled labor actually used (i.e., factor accumulation).[6] The absence of changes in relative misallocation (i.e., $\widehat{\Theta}_{s,u}^{c,tT} = 0$) does not rule out SBTC.

Two comments are in order concerning the issues highlighted in Section 3.

First, it is worth noting that our nonparametric approach enables us to estimate SBTC using output - and not wages as in Equation (8) - as the dependent variable, so that the estimated SBTC is no longer affected by the presence of market imperfections on relative factors' prices, whose effect can be studied *ex-post* through (20). The ability to address the evolution of the discrepancy between relative wage and relative productivity stems from the fact that, differently from the standard approach described in Section 3, our MRTS, SBTC and FA components are estimated directly from the production function and not retrieved as residuals with respect to the wage gap itself.

Second, our approach does not require any estimate of σ.

5 Analysis

In this section we bring the decompositions in Equations (15) and (18) to data, basing the analysis on WIOD (Timmer et al., 2015; Erumbam et al., 2012) Socio-Economics Accounts. Specifically, we use Value Added (in current value) as the output measure and real fixed capital stock at 1995 prices for capital. To differentiate between high, medium and low skill labor, we multiply total employment by the share of hours worked in each category. To build wage ratios, we divide shares in labor compensation by shares in hours worked (i.e., hourly wage ratios).

To ease the counterfactual analysis, and thus the identification of SBTC, we group medium and low skilled workers together and work with two skill categories only: medium-low and high. In the robustness section we check how the results differ when medium skills are considered together with high skills.

Current price variables are first converted in real terms using the price level of gross value added and then transformed in PPP using absolute 1995 PPPs - i.e., exchange rate from PWT 9.1 (Feenstra et al., 2015) times relative PPP at 1995. Benchmark analysis is carried out over two periods, centered in 1995 and 2005. We draw information on years 1995-1996, on the one hand, and 2005-2006, on the other. We then work with the three-year averages in the two periods. After cleaning for missing, zeros and negative value added values, we are left with a final sample of 975 observations in each period. The sample covers 38 countries and 25 sectors.

Tables 1 and 2 report the (by country and by sector, respectively) descriptive statistics at the beginning and the end of the period, highlighting a 3.7% increase in value added, associated with a 4.5% increase in capital. The stock of skilled labor displays a huge increase 11.5%, while unskilled labor slightly decreases -0.6%.

[6] The use of absolute values, as we see in convergence exercise on section 7 avoid biased information on relative misallocation driven by positive values becoming negative ones. This problem is, to some extent, similar to the β-convergence problem in the presence of criss-crossing and leap frogging effects.

5.1 Marginal productivity estimation

The first step in the analysis is the estimation of marginal productivity of inputs. To this aim, we estimate the (unknown) smooth function $m(\cdot)$ in Equation (12) using a local-linear least-squares (LLLS) estimator, which performs weighted least-squares estimation around a point x with weights determined by a kernel function and bandwidth vector. More weight is given to observations in the neighborhood of x.

Specifically, taking a first-order Taylor expansion of (12) around x, yields

$$g_i \approx m(x) + (x_i - x)\beta(x) + \varepsilon_i, \qquad (22)$$

where $\beta(x)$ is defined as the partial derivative vector of $m(x)$ with respect to x and is an estimate of the marginal products $\widehat{m}_s^{c,t}(\cdot)$ and $\widehat{m}_u^{c,t}(\cdot)$. The amount of local information used to construct the average is controlled by the bandwidth. We utilize AIC_c bandwidth selection (Hurvich et al., 1998) to chose the appropriate bandwidth, which has been shown to have superior finite sample performance (Li and Racine, 2004). More details are presented in Appendix 9.

The distribution of the estimated marginal products (MP) are reported in Appendix 10. Figure 2 shows that the estimates are quite consistent over time. MPS and MPU both increase by slightly more than 25% on average. However, unskilled labor features a lower median and a higher (much higher than skilled labor) dispersion. Interestingly, we report an average reduction in MPK (-5.6%), associated with a slight increase in dispersion (around 10%).

These trends complement with the evidence on marginal productivities reported in Figures 3 and 4. Differently from capital, increasing labor, either skilled or unskilled, is not associated with lower marginal productivity, neither in levels (Figure 3) nor in growth rates (Figure 4). This is a key point, which motivates our counterfactual analysis aimed at separating out the variation in MP into a technology-driven and a factor-driven component. For instance, we find the high-skill share of hours worked to increase from 23.1% to 28.5%, with the low-medium skill share shrinking from 31.3% to 24.2% (mostly driven by low skills). Under the conventional view of decreasing MPs and Hicks-neutral technical change, this would imply a relative reduction in the MRTS between skilled and unskilled labor, which is not the case in our estimates. This points to a prevalent role played by SBTC.

5.2 Decomposition analysis

With the MPs in our hands, we are able to compute Equations (15) and (18) through the relevant counterfactual analysis. Results are detailed in Table 3, by country, and 4, by sector. To ease the interpretation, we report in the same table the computed values of our relative misallocation measure (Θ_(s,u)^(c,tT)), together with the changes in relative wages used to compute it.

The results on Equation (15) are visualized in Figure 6 (whole distributions are reported in Appendix 10).

Overall, we report a positive change in MRTS (about 30%), which maps into a roughly

3% yearly increase in the MP of skilled labor, relative to unskilled workers. Within this average figure, we observe extreme positive values in countries like Romania and Indonesia and sectors like 'Air transport', 'Retail trade', 'Hotels & restaurants' and 'Leather & footwear'. In only a few cases do we observe decreasing MRTS. This is the case for Korea and USA, on the one hand, and the 'Business Services' sector, on the other hand. In all these cases the FA effect is negative and very strong, able to overcome the positive SBTC effect.

As shown in the second column of Tables 3 and 4, the driving force of the MRTS variation is SBTC: 36.1% on average. Given our ten-year time span, this number maps into a yearly change of around 3.6%. Although with a certain degree of heterogeneity across sectors and countries, the average role of FA is negative and relatively small.

In only one sector do we detect a negative SBTC: 'Business Services'; coincidentally, this also corresponds to the most negative FA effect. By contrast, the analysis reveals that the FA contribution is negative in several industries and countries. According to our framework, this suggests that keeping the technology in use constant, the evolution of the input mix is such that the overall contribution to the MRTS growth rate is negative.

To further investigate this issue, we turn to the columns reporting the decomposition in Equation (18). These results point to a negative contribution of the change in the skilled labor component on the overall FA effect, with changes in capital stock mostly playing a positive (and often minor) role and the effect of unskilled labor displaying an equivocal sign. This is not surprising and suggests that, although the hypothesis of decreasing returns to scale is not verified for any skill category, increasing the relative use of skilled workers actually reduces the productivity of skilled labor. The positive effect associated with capital might be associated with skill complementarity effects, as suggested by Griliches (1969) and Krusell et al. (2000) among others.

One way to relate the above results to those that can be obtained following the standard approach, as described in Section 3, consists of using Equation (3) to retrieve the ratio (A_s/A_U) from actual values of the skilled to unskilled labor and wage ratios, under the assumption of perfectly competitive labor markets (i.e., $W_s/W_u=MRTS_{(s,u)}$). This strategy directly follows Caselli (2017) with two key differences: first, while the standard approach requires estimating the potential relative supply of labor, we use the relative stock of hours worked (i.e., equilibrium employment); second, the exercise reported in Caselli (2017) uses wages computed on schooling returns and is carried out on a different dataset than that used here. With these differences in mind, Table 5 reports the estimated SBTC under different scenarios concerning EoS. In the first scenario, we set the EoS to 1.5 (i.e., the preferred specification in Caselli, 2017). In the second scenario we use a value of 2. In the third scenario, we estimate σ as suggested by Equation (4) (with sector controls) and obtain the EoS as $1/(\sigma-1)$; this yields an estimated EoS of 4.16 (regressions report R^2 of 0.30 and 0.33, respectively). As is evident, the results are quite sensitive to the choice concerning the EoS, which is one of the shortcomings highlighted in Section 3. However, our annual estimated SBTC (see the first row of Table 6) of 3.61 lies within the range identified by the standard procedure.

5.3 Relative misallocation

Section 5.2 points to a prominent role played by SBTC, on average, as a determinant of the MRTS patterns. However, substantial heterogeneity is detected across sectors and countries, with FA taking the lead in several cases as a driver of MRTS changes.

In this Section we go back to the decoupling issue pointed out in Section 1 and highlight how things change when, instead of relying on a wide notion of productivity, the change in the wage ratio is contrasted with the change in MRTS between skilled and unskilled labor provided by our estimation. Indeed, Figure 5 (panel C) uses country averages to show how direction of the decoupling is reversed in almost all countries, compared with Figure 1, with the skill premium growing less then the MRTS in most cases. Notably, US and Germany are among the few countries in which the skill premium keeps growing more than the productivity ratio (as in Figure 1). Panels A and B highlight that the driver of this process is SBTC, as the FA component is negative in many countries.

To go into the details of this analysis, we can compute the relative misallocation measure Θ ˆ_(s,u)^(c,tT) presented in Equation (21). As previously mentioned, positive (negative) values refer to increasing (decreasing) discrepancy between relative wages and MRTS.

Under the hypothesis of perfectly competitive labor markets, or in the presence of distortions affecting the skilled and unskilled labor markets symmetrically, MRTS and wage ratio coincide both in levels and growth rates. Figure 6 shows that this is not the case, according to our estimates: MRTS and wage ratio growth rates are basically uncorrelated.

Estimates reported in Tables 3 and 4 point to an average 6% increase in relative misallocation with substantial cross-country and cross-industry heterogeneity (see Appendix 10 for the overall distribution in the two periods). Figures range from a rough 50% reduction in countries such as Cyprus, Korea and Italy to an more than 50% increase in Poland, Sweden and Lithuania. At the sectoral level, the biggest increases are reported in non-manufacturing industries such as Retail (around +70%) and Wholesale (+35%) trade, Hotels and Restaurants (+36%); among the manufacturing industries, the biggest increases are detected in Leather and Footwear and Motor Vehicles. The most evident decreasing patterns are those characterizing the Business Services and Financial Services industries, as well as Rubber and Plastic, among the manufacturing activities. It is worth noting how the average increase is substantially higher in Non-manufacturing sectors (1.5% in Manufacturing against 12% in Non-manufacturing) and in OECD countries (about 8% in OECD countries and 5% in Non-OECD countries).

According to our decomposition, the increase in relative misallocation can be driven by a change in relative wages, the adoption of skill biased technologies (i.e., SBTC), or a change in the skilled to unskilled labor actually used (i.e., factor accumulation). It is noteworthy how the situation was quite balanced in 1995, with the median of both MRTS and wage ratio standing around 2 (results available upon request), and how the increasing pattern reported is mainly associated with sustained growth in MRTS, in the face of an almost unchanged wage ratio.

To gain intuition on this dimension, Θ ˆ_(s,u)^(c,tT) is plotted against its various components (see Equation 20) in Figure 7. The figure clearly shows that the main responsible for the increasing pattern of relative misallocation is the change in the MRTS. A regression of $\hat{\Theta}_{(s,u)}^{(c,tT)}$ on the SBTC and FA components (together with country and sector fixed effects) reveals a positive and statistically significant impact of both SBTC and FA with, however, a larger role played by the former (the estimated coefficients are 0.729 and 0.460).

Thus, SBTC can be viewed as being mainly responsible for the increasing relative misallocation at the country-sector level. Coupled with the evidence reported on the role played by the different factors of accumulation (columns 4-6 in Tables 3 and 4), these results suggest that SBTC is likely to increase misallocation if it is not accompanied with a sufficiently higher skill premia, that is when the growth in MRTS exceeds the decrease in the MRTS associated with using a higher share of skilled labor (which is usually lower in magnitude with respect to SBTC, according to Tables 3 and 4) and not compensated by higher relative wages.

6 Robustness checks

In this section we report a number of checks aimed at evaluating the robustness of our results with respect to using alternative skill groupings than the "High vs Medium-Low" referred to as benchmark, as well as alternative time spans.

The WIOD database provides detailed information on three classes of labor skills (high, medium and low). In principle, this would allow us analyzing SBTC along three dimensions (i.e., high versus medium, high versus low, medium versus low), as well as studying, for the three categories, whether technical change is relatively biased towards capital or not. While the bias towards capital is beyond the scope of the analysis, reducing the skill categories from three to two helps the interpretation of the results, notably from a policy perspective. However, our results might differ depending on the classification adopted. While in our benchmark analysis we use a "High vs Medium-Low" classification, Table 6 reports, as well as the benchmark results in the first row for comparison, the results obtained under a scenario featuring "High-Medium vs Low" skilled labor. Figures on the MRTS are quite consistent. To ease comparison of the results, the last column reports the change in our measure of relative misallocation as in Equation 20 (that is, not in absolute values as in Equation 21). Also these estimates are quite consistent. On the contrary, less pronounced variation in both MRTS and relative misallocation arises. More substantial differences emerge in terms of SBTC and FA however, with expected and consistent signs: SBTC increases up to (slightly more than) 50%, while FA effect drops to around -26%.

Then we use different time splits. While our benchmark choice is a comparison among 1995-1996 and 2005-2006 averages, in the third row we use data centered in 1997 and 2007 (that is, average 1996-1998 versus average 2006-2008), in order to remain somehow removed with the effect of the economic crisis, and in the fourth row we use single year data (that is, 1995 versus 2005). Although the number of observations slightly changes across the different specifications (in particular, it shrinks by about 6-7% in the "Not averaged 1995-2005" case), as not all the country-sector combinations are covered in all the years, the results are quite robust.

To summarize the robustness checks in Table 6, we see how the average annual change of MRTS ranges from a minimum of 2.7% (in the "High-Medium vs Low" case) to 3.9% (in the "Not averaged 1995-2005" case) and the average of estimation is 3.37%. Similarly, for the change in $\hat{\tau}_{s,u}$, the "High-Medium vs Low" sets the lower bound, while the average across the various specification is very similar to our benchmark (3.41% compared to 3.39%).

7 Relative misallocation: convergence and drivers

Previous sections highlighted a positive trend in relative misallocation, that is a progressive decoupling between MRTS (between skilled to unskilled labor) and (skilled to unskilled) wage ratio in many countries and industries. In this section we carry out a very simple econometric analysis whose aim is twofold.

First, we ask whether relative misallocation at the country-sector level is actually converging (diverging), with the most misallocated country-sectors reporting decreasing (increasing) misallocation over time. Intuition on this issue can be gained from Figure 8, which visualizes the canonical convergence relationship (growth rate versus initial levels) for our relative misallocation measure, as expressed in Equation (21) (that is: $\hat{\Theta}_{s,u}^{c,tT}$ against $|\ln\hat{\tau}_{s,u}^{c,1995}|$). Visual inspection reveals a quite clear negative relationship, pointing to convergence in relative misallocation.

Second, we study whether and how the country-sector relative misallocation patterns tend to be affected by bargaining power differences between skilled and unskilled workers, arguably associated to the presence of frictions in labor markets and the action of labor market institutions. In fact, Di Nardo et al. (1996), Acemoglu et al., (2001) and Autor et al. (2016), among others, find wage ratio compression effects associated with the actions of trade unions and labor market institutions. Card et al. (2018) estimate that trade unions reduce wage inequality by 10%. This is one of the candidate explanations for the fact that wage inequality does not follow anymore productivity change as inferred from skill premium and higher use of capital complementary to skilled as personal computers, in the 1990s, according to, for instance, Card and Di Nardo (2002). As Caselli (2017) remarks, the wage ratio gap between developed and developing countries is likely to be affected by the presence of "more generous" labor market institutions in the former. While works in this field usually regard labor markets effects in the aggregate, we disentangle skilled and unskilled labor. To deal with labor market frictions in relative terms, we use mark-up ratios (MUR) computed, for each country-industry as $MUR_{s,u}=\frac{(W_s-W_s^r)N_s}{(W_u-W_u^r)N_u}$, where N and W^r are the reservation wage (i.e., minimum wage in the industry) and the number of hours worked by worker type. We think of $MUR_{s,u}$ as subsuming the difference in terms of bargaining between skilled and unskilled workers.

Table 7 summarizes the regressions results. A first result is the strong evidence of convergence in relative misallocation. This results resists in all the specifications adopted. A second issue is the negative effect that MUR seems to exert on relative misallocation: relative misallocation tends to be lower in country-sectors in which skilled workers have a relatively higher reservation wage (in other words: the higher the relative bargaining power of skilled workers, the lower the difference between their productivity and wage, relative to unskilled workers). As further controls, we include in column (5) Employment Protection legislation (EPL) and Union density (TrUnion). A large literature dealt with the influence exerted by these variables in influencing wage inequality (Machin, 1997, Koeninger et al., 2007, Checchi and Garcia-Penalosa, 2008). This does not help and also reduces the sample size substantially.

In column (6) we include the average (skilled to unskilled) labor ratio in US and UK (i.e., SecSkInt). Under the assumptions of US and UK featuring fairly frictionless labor markets, this a sectoral measure of skill intensity which is reported to be positively related to relative misallocation. Hence, the decoupling between relative MP and relative wages seems to be more an issue in more skill-intensive sectors.

Finally, in the last column, we add the relative misallocation components: SBTC and FA (which sum up to MRTS) and the wage ratio. Although this regression has to be taken with more than a grain of salt (SBTC, FA and the wage ratio growth rate form the basis of the relative misallocation measure), it highlights that the variation in relative misallocation is mainly driven by SBTC and FA, with the growth rate of the wage ratio playing no significant role. Moreover, when the FA component is interacted with the skill-intensity measure, it emerges that the (skill biased) effect of factor accumulation on MRTS grows with the (sectoral) degree of skill intensity. This effect results into higher relative misallocation.

8 Conclusions

The standard approach to SBTC estimation attributes the full deviation from the efficiency condition to technology. Alternatively, the literature on misallocation documents that such deviations are likely to be driven by the action of market frictions preventing the flow of factors from less productive (where marginal products are lower) to more productive units (where marginal products are higher). As a result, standard SBTC estimates are likely to be biased: they actually conflate 'true' SBTC and labor market inefficiencies when labor market frictions do exist in the labor market, such that firms are prevented from choosing the efficient ratio of skilled to unskilled labor.

In this paper, we presented a decomposition framework that allows us to: i) quantify the discrepancy between the wage ratio of skilled to unskilled workers and MRTS (i.e., relative misallocation); ii) obtain country-sector SBTC estimates which are net of the effect of FA, thereby disentangling the SBTC and FA contribution to the estimated change in MRTS.

The suggested approach allows for a unified analysis of SBTC and misallocation, connecting these two separate literatures.

Estimation relies on nonparametric methods allowing for country-sector-year specific estimates of the MP of inputs directly from country-sector-year data, which would be a daunting task with standard parametric techniques. This methodology enables us to depart from extant literature by inoculating our analysis from the two most critical assumptions typical of the SBTC literature: perfect competition in the labor market and perfect substitutability among inputs. The ability to

retrieve the MP of inputs directly from the production function enables us to avoid conflating 'true' SBTC and labor market distortions.
Based on WIOD data, our empirical analysis reveals that the MRTS between skilled and unskilled labor has been growing by 32.3% on average over the decade 1995-2005. Whether the change in MRTS is technology-driven (and thus associated to our SBTC component) or factor-driven (and thus associated to our FA component) can have relevant implications in terms of reasons behind the eventual decoupling between the wage ratio and relative productivity. By decomposing the MRTS variation into a SBTC component and a FA component through counterfactual analysis, we discover that most of the MRTS change is associated with SBTC, whose average effect on MRTS we quantify to be 36.1%. This value compares with the -3.9% that we find for FA.
We then show that SBTC and increasing MRTS often do not come with increasing skill premia (relative wages are quite stable over time), thus fostering relative misallocation, for which we report a 6% overall increase (although with substantial heterogeneity across sectors and countries). Interestingly, the average increase is higher in Non-manufacturing sectors (1.5% in Manufacturing against 12% in Non-manufacturing) and in OECD countries (about 8% in OECD countries and 5% in Non-OECD countries). The US and Germany are among the few countries in which the skill premium grows more than the productivity ratio.
Our analysis suggests that SBTC can induce a less efficient use of labor as long as the growth of the MRTS between skilled and unskilled workers does not come with sufficiently higher skill premia. Consistently, we report econometric evidence suggesting that this is more likely to happen in skill-intensive country-sectors (even more when skill-intensity is coupled with higher FA effects associated to an increasing relative use of skilled labor) and in country-sectors characterized by a lower bargaining power of skilled (over unskilled) workers, which arguably prevents skilled workers to be payed higher wages.

References

Acemoglu, D. (1998). Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality, *Quarterly Journal of Economics*, 113, 1055-1089.

Acemoglu, D. (2002). Directed technical change. *Review of Economic Studies*, 69, 781-810.
Acemoglu, D. (2003). Labor- and Capital-Augmenting Technical Change, *Journal of European Economic Association*, 1, 1-37.

Acemoglu, D. & Aghion. P. & Violante, G.L. (2001). Deunionization, technical change and inequality, *Carnegie-Rochester Conference Series on Public Policy*, 55, 229-264.

Acemoglu, D. & Autor, D.H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. *Handbook of Labor Economics*, Volume 4b, 1043-1171.

Acemoglu, D. & Restrepo, P. (2018a) The Race between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment, *American Economic Review* 108, 1488-1542.

Acemoglu, D. & Restrepo, P. (2018b) Robots and Jobs: Evidence from US Labor Markets, mimeo.

Alfaro, L. & Kalemli-Ozcan, S. & Volosovych, V. (2008). Why doesn't Capital Flow from Rich to Poor Countries? An Empirical Investigation, *Review of Economics and Statistics*, 90(2), 347-368.

Alesina, A. & Battisti, M. & Zeira, J. (2018). Technology and labor regulations: theory and evidence, *Journal of Economic Growth*, 23(1), 41-78.

Asker, J. & Collard-Wexler, A. & Jan De Loecker (2014). Dynamic Inputs and (Mis)Allocation, *Journal of Political Economy*, 122(5), 1013-1063.

Autor, D.H.& Manning, A. & Smith, L.C. (2016). The Contribution of the Minimum Wage to US Wage Inequality over Three Decades: A Reassessment, *American Economic Journal: Applied Economics*, 8 (1), 58-99.

Autor, D.H. & Levy, H. F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4), 1279-1333

Banerjee, A. & Duflo, E. (2005). Growth Theory through the Lens of Development Economics, *Handbook of Development Economics*, Vol. 1a. Amsterdam: Elsevier, 473-552.

Bartelsman, E. & Haltiwanger, J. & Scarpetta, S. (2013), Cross-Country Differences in Productivity: The Role of Allocation and Selection, *American Economic Review*, 103(1), 305-334.

Bassanini, A. & Nunziata, L. & Venn, D. (2009). Job protection legislation and productivity growth in OECD countries, *Economic Policy*, 24(04), 349-402.

Battisti, M. & Del Gatto, M. & Parmeter, C.F. (2018a). Labor productivity growth:

disentangling technology and capital accumulation, *Journal of Economic Growth*, 23(1), 111-143.

Battisti, M. & Belloc, F. & Del Gatto, M. (2019). Technology Specific Production Functions, *Review of Economic Dynamics*, forthcoming.

Battisti, M. & Di Vaio, G. & Zeira, J. (2013). Global divergence in growth regressions, *CEPR Discussion Paper* No. DP9687.

Beaudry, P. & Doms, M. & Lewis, E. (2006). Endogenous Skill Bias in Technology Adoption: City-Level Evidence from the IT Revolution, *NBER Working Papers 12521*.

Bellone, F. & Mallen-Pisano, J. (2013). Is Misallocation Higher in France than in the United States? GREDEG Working Papers 2013-38.

Berlingieri, G. & P. Blanchenay & Criscuolo, C. (2017). The Great Divergence(s), OECD Science, Technology and Industry Policy Papers, No. 39.

Berlingieri, G. & Calligaris, S. & Criscuolo, C. (2018). The Productivity-Wage Premium: Does Size still Matter in a Service Economy? OECD Science, Technology and Industry Working Papers 2018/13

Blanchard O.J. & Giavazzi, F. (2003). Macroeconomic Effects of Regulation and Deregulation in Goods and Labor Markets, *Quarterly Journal of Economics*, 118(3), 879-907.

Blankenau, W.F. & Cassou, S.P. (2011). Industry estimates of the elasticity of substitution and the rate of biased technological change between skilled and unskilled labour, *Applied Economics*, 43(23), 3129-3142.

Boeri, T. & Ichino, A. & Moretti, E. & Posch, J. (2019). Wage Equalization and Regional Misallocation: Evidence from Italian and German Provinces, *CEPR discussion paper* No. DP13545.

Booth, A. & Burda, M. & Calmfors, L. & Checchi, D.   Naylor, R. & Visser, J. (2000). What Unions Do in Europe? Prospects and challenges for union presence and union influence, Report for Fondazione Rodolfo De Benedetti.

Calligaris, S. & Del Gatto M. & Hassan, F. & Ottaviano, G. & Schivardi, F. (2018). The productivity puzzle and misallocation: an Italian perspective, *Economic Policy*, 33(96), 635?684.

Card, D. & Di Nardo, J. (2002). Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles, *Journal of Labor Economics*, 20(4), 733-783.

Card, D. & Lemieux, T. (2001). Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis, *Quarterly Journal of Economics*, 116(2), 705-746.

Card, D. & Lemieux, T. & Riddel, W.C. (2018). Unions and Wage Inequality: The Roles of Gender, Skill and Public Sector Employment, *NBER Working Paper* No. 25313

Caselli, F. (1999). Technological Revolutions, *American Economic Review*, 89(1), 78-102.

Caselli, F. (2017). *Technology Differences among Space and Time*, Princeton University Press.

Caselli, F., & Coleman, W. J. (2006). The world technology frontier, *American Economic Review*, 96(3), 499-522.

Cette, G. & Lopez, J. & Mairesse, J. (2016). Market Regulations, Prices, and Productivity, *American Economic Review, Papers and Proceedings*, 106(5), 104-108.

Cette, G. & Lopez, J. & Mairesse, J. (2018). Rent Creation and Sharing: new Measures and Impacts on TFP, NBER WP no. 24426.

Chen, K. & Irarrazabal A. (2014). The role of allocative efficiency in a decade of recovery, *Review of Economic Dynamics*, 18, 523-550.

Checchi, D. & Garcia-Penalosa, C. (2008). Labour market institutions and income inequality, *Economic Policy*, 23(56), 602-649.

Crespo, A. & Segura-Cayuela, R. (2014). Understanding Competitiveness, Economics Working Papers MWP2014/20, European University Institute.

Diamond, P. & McFadden, D. & Rodriguez, M. (1978). Measurement of the elasticity of factor substitution and bias of technical change, in *Production Economics: A Dual Approach to Theory and Applications*, Vol. 2, ed. by Fuss M. and McFadden D., North-Holland, Amsterdam, 125-147.

Dias, D.A. & C.R. Marques & C. Richmond (2016). Misallocation and Productivity in the Lead Up to the Eurozone Crisis, *Journal of Macroeconomics*, 49, 46-70.

Di Nardo, J. & Fortin, N.& Lemieux, T., (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, 64, 1001- 1044.

Duffy, J. & Papageorgiou, C. & Perez-Sebastian, F. (2004). Capital-skill complementarity? Evidence from a panel of countries, *Review of Economics and Statistics*, 86, 327-344.

Erumbam, A.A. & Gouma, R. & De Vries, G. &De Vries, K. & Timmer, M. (2012). WIOD Socio-Economic Accounts (SEA): Sources and Methods.

Faggio, G. & Salvanes, K. & Van Reenen, J. (2010). The Evolution of Inequality in Productivity and Wages: Panel Data Evidence, *Industrial and Corporate Change*, 19(6), 1919-1951.

Feenstra, R.C. & Inklaar, R.C., & Timmer, M. P. (2015). The next generation of the Penn World Table, *American Economic Review*, 105(10), 3150-3182.

Galiani, S. & Cruces, G. & Acosta, P. & Gasparini L.C. (2017). Educational Upgrading and Returns to Skills in Latin America: Evidence from a Supply-Demand Framework, *NBER Working Paper* No. 24015.

Garcia-Santana, M. & Ramos, R. (2015). Distortions and the size distribution of plants:

evidence from cross-country data, *SERIEs*, 6, 279-312.

Gopinath, G. & Kalemli-Ozcan, S. & Karabarbounis, L. & Villegas-Sanchez, C. (2017). Capital Allocation and Productivity in South Europe, *Quarterly Journal of Economics*, 132(4), 1915-1967

Greenwood, J. & Z. Hercowitz & Krusell, P. (1997). Long-Run Implications of Investment-Specific Technological Change. *American Economic Review*, 87, 342-362.

Griliches, Z. (1969). Capital-Skill Complementarity, *Review of Economics and Statistics*, 51, 465-468.

Henderson, D.J. (2009). A Non-parametric Examination of Capital-Skill Complementarity, *Oxford Bulletin of Economics and Statistics*, 71(4), 519-538.

Henderson, D. J., & Parmeter, C.F. (2015). *Applied Nonparametric Econometrics*. Cambridge University Press.

Hercowitz, Z. (1998). The 'embodiment' controversy. A review essay, *Journal of Monetary Economics*, 41, 217-224. Hideki, N. & Zeira, J. (2018). Automation and Unemployment: Help is on the Way, CEPR Working paper no. DP12974.

Hopenahyn, H.A. (2014). Firms, Misallocation, and Aggregate Productivity: A Review, *Annual Review of Economics*, 6, 735-770.

Hsieh, C.T. & Klenow, P.J. (2009). Misallocation and Manufacturing TFP in China and India, *Quarterly Journal of Economics*, 124(4), 1403-1448. Hsieh, C.T. & Klenow, P.J. (2010). Development Accounting, *American Economic Journal: Macroeconomics*, 2(1), 207-223.

Hurvich, C. M. & Simonoff, J. S. & Tsai, C.-L. (1998). Smoothing parameter selection in nonparametric regression using an improved Akaike information criterion, *Journal of the Royal Statistical Society, Series B*, 60(2), 271-293.

Jones, C.I. (2011). Misallocation, Economic Growth, and Input-Output Economics, *NBER Working Papers* 16742,

Karabarbounis, L., & Neiman, B. (2014). The global decline of the labor share, *Quarterly Journal of Economics*, 129(1), 61-103.

Katz, L. F. & Murphy, K. M. (1992). Changes in relative wages, 19631987: Supply and demand factors, *Quarterly Journal of Economics*, 107, 35-78.

Koeniger, W. & Leonardi, M. (2007). Capital deepening and wage differentials: Germany versus US, *Economic Policy*, 22(49), 72-116.

Koeniger, W. & Leonardi, M. & Nunziata, L. (2007). Labor Market Institutions and Wage Inequality *Industrial Labor Relations Review*, 60(3), 340-356.

Krugman, P. (2000). Technology, trade and factor prices, *Journal of International Economics*, 50, 51-71.

Krusell, P. & L. Ohanian & J.V. Ros-Rull & Violante, G.L. (2000). Capital Skill Complementarity and Inequality: A Macroeconomic Analysis, *Econometrica*, 68, 1029-1054.

Lawrence, S. & Ishikawa, J. (2005). Trade union membership and collective bargaining coverage: Statistical concepts, methods and findings, ILO Working Papers no. 59.

Lemieux, T. (2008). The changing nature of wage inequality, *Journal of Population Economics*, 21, 21-48.

Li, Q. & Racine, J.S. (2004). Cross-validated local linear nonparametric regression, *Statistica Sinica*, 14, 485-512.

Li, Q., & Racine, J.S. (2007). *Nonparametric Econometrics*. Princeton University Press.

Machin, S. (1997). The decline of labour market institutions and the rise in wage inequality in Britain, *European Economic Review*, 41(3-5), 647-657.

Naticchioni, P. & Ricci, A. & Rustichelli, E. (2010). Far away from a skill-biased change: falling educational wage premia in Italy, *Applied Economics*, 42(26), 3383-3400.

OECD (2018a). OECD Employment Protection Indicators Database.

OECD (2018b). Decoupling of Wages from Productivity: what Implications for Public Policies? in OECD Economic Outlook, Volume 2018 Issue 1, Chapter 2, OECD Publishing, Paris.

Olley, G.S. & Pakes A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry, *Econometrica*, 64(6),1263-1297. Parteka, A. (2012). Skilled-Unskilled Wage Gap Versus Evolving Trade and Labour Market Structures in the EU, Institute for Development Working Papers No. 4/2012.

Restuccia, D. & R. Rogerson (2008). Policy distortions and aggregate productivity with heterogeneous establishments, *Review of Economic Dynamics*, 11(4), 707-720.

Restuccia, D. & Rogerson, R. (2013). Misallocation and Productivity, *Review of Economic Dynamics*, 16, 1-10.

Rossi F. (2018). The Relative Efficiency of Skilled Labor Across Countries: Measurement and Interpretation, unpublished, Johns Hopkins University.

Sakellaris, P. & Wilson, D.J. (2004). Quantifying Embodied Technological Change, *Review of Economic Dynamics*, 7(1), 1-26.

Timmer, M.P. & Dietzenbacher, E. & Los, B. & Stehrer, R. & de Vries, G.J. (2015). An Illustrated User Guide to the World Input-Output Database: the Case of Global Automotive

Production, *Review of International Economics*, 23, 575-605.

Violante, G.L. (2016). Skilled-biased Technical Change, in *The New Palgrave Dictionary of Economics*, ed. by Durlauf, S.N. and Blume, L.E. New York: Palgrave Mac-Millan.

Visser, J. (2016). ICTWSS Data base. version 5.1. Amsterdam: Amsterdam Institute for Advanced Labour Studies AIAS.

Zeira, J. (1998). Workers, Machines, and Economic Growth, *Quarterly Journal of Economics*, 113(4), 1091-1117.

Figures, Tables and Appendix

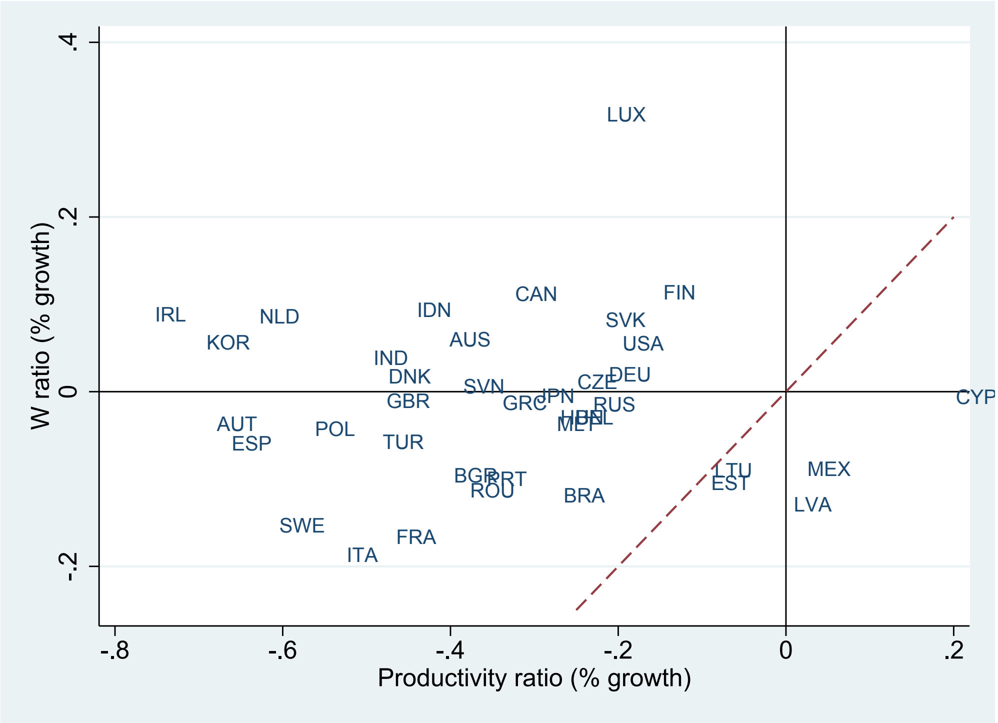

Figure 1: Relationship between (skilled to unskilled) wage gaps and productivity (output/hours worked) gaps (% growth, 1995-2005).

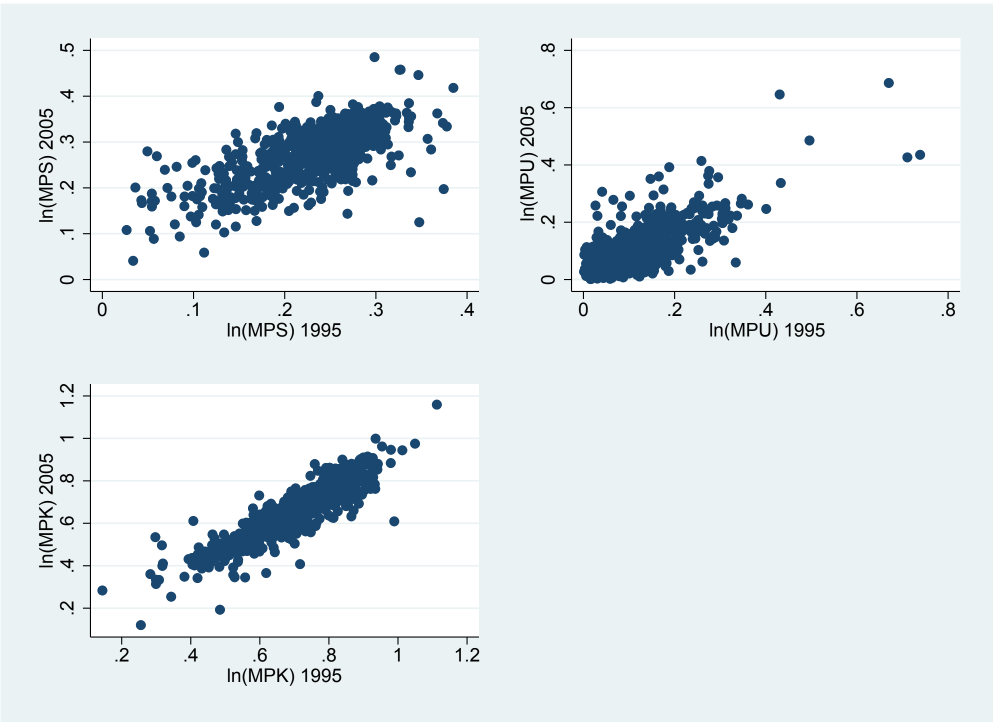

Figure 2: Marginal Productivity (MP): over time estimation consistency.

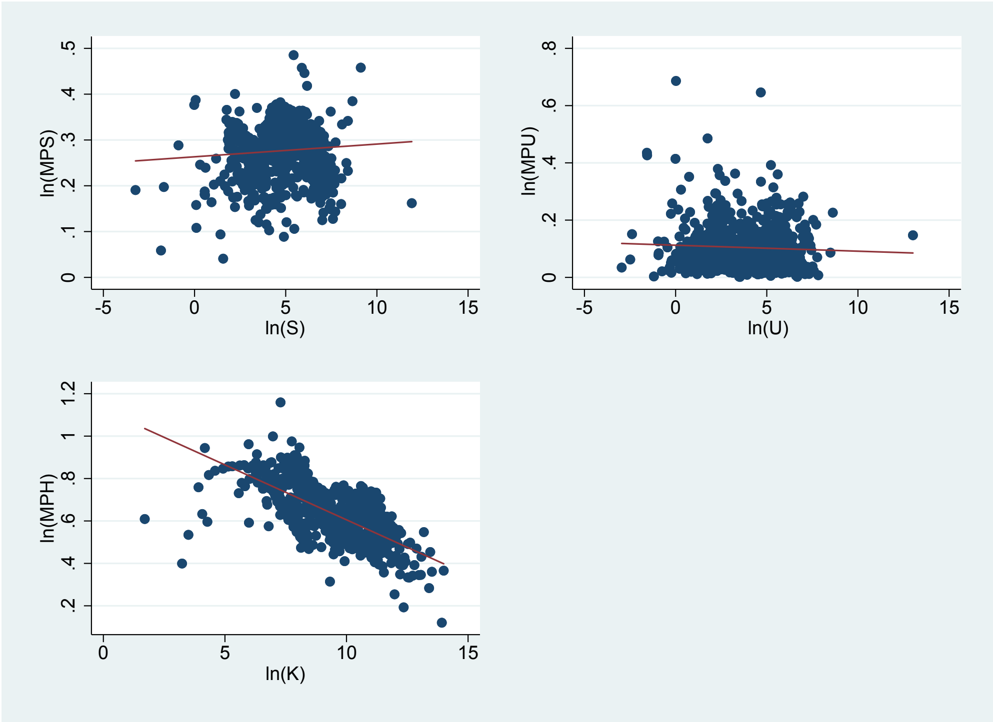

Figure 3: Returns to scale: Marginal Productivity (MP) versus input quantity (2005).

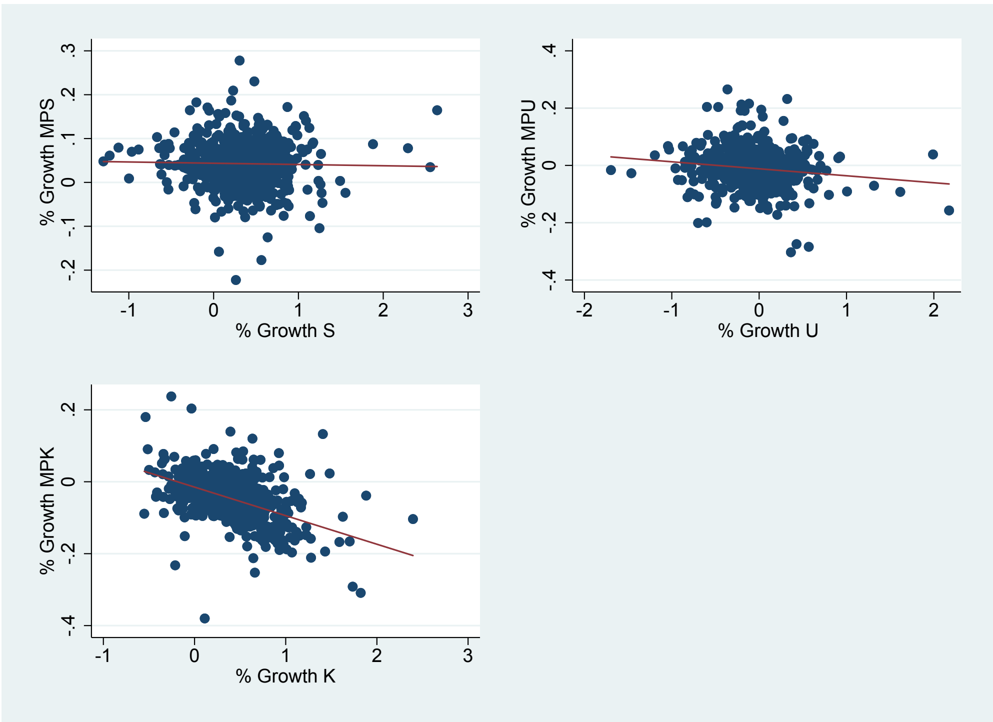

Figure 4: Returns to scale: change in Marginal Productivity (MP) versus change in input quantity (1995-2005).

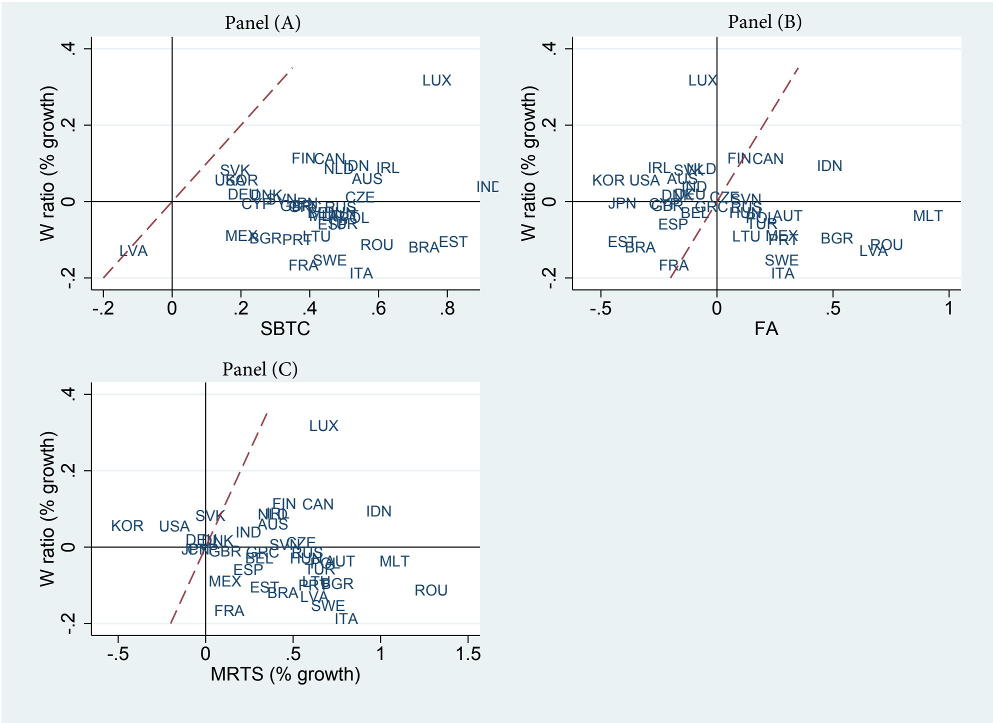

Figure 5: Growth rate of the wage ratio versus growth rate of MRTS, SBTC and FA (growth rates: 1995-2005; levels: 2005).

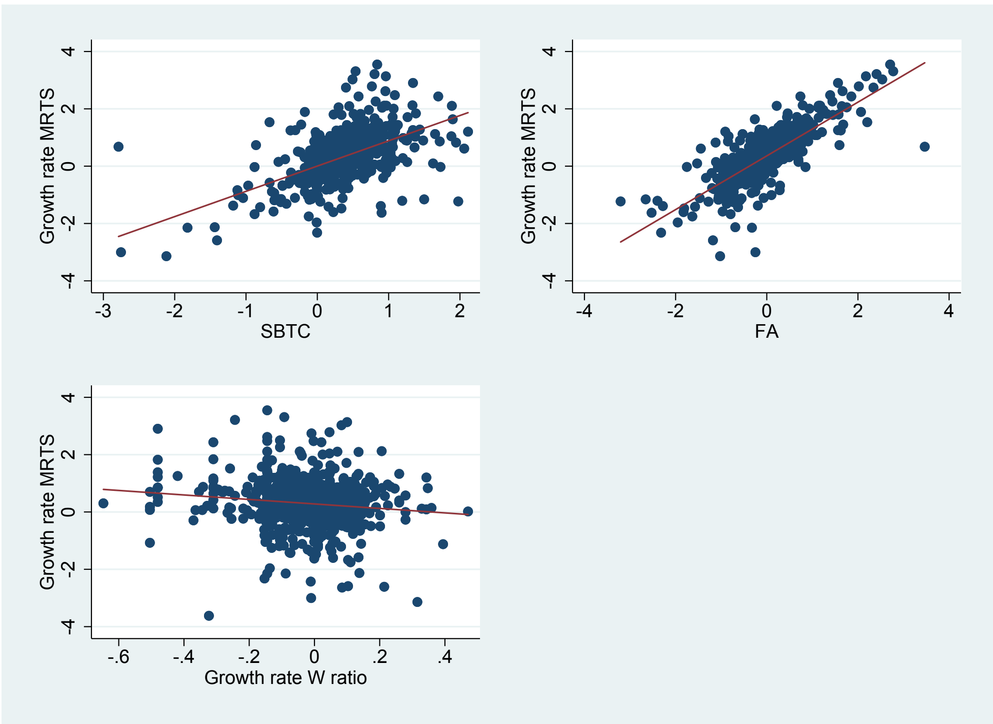

Figure 6: Growth rate of MRTS versus SBTC, FA and growth rate of the wage ratio (growth rates: 1995-2005; levels: 2005).

Figure 7: Relative misallocation and its components (growth rates: 1995-2005; levels: 2005).

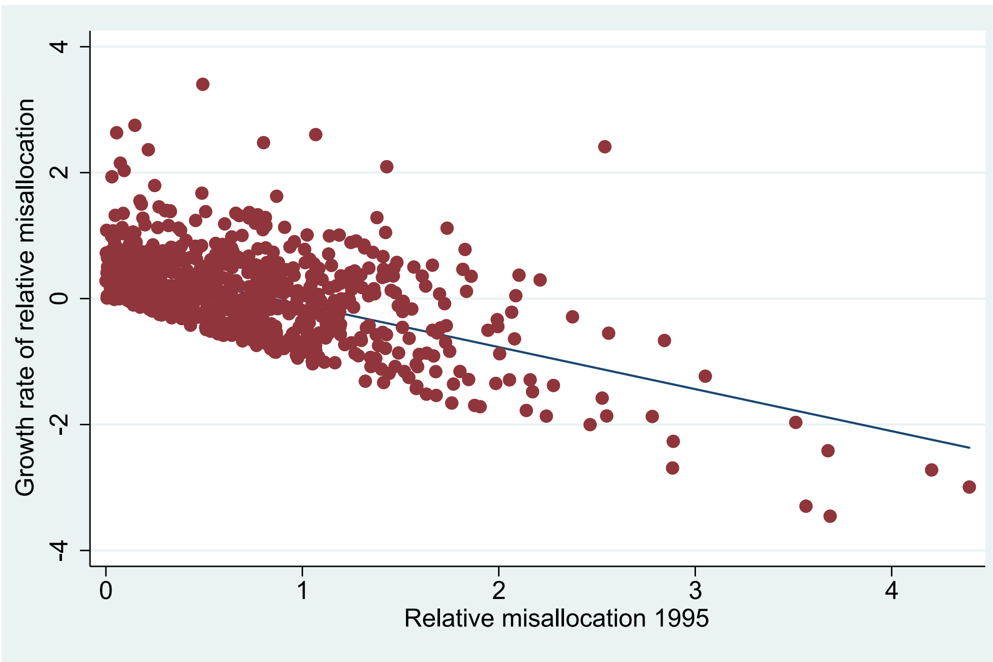

Figure 8: Relative misallocation: 1995-2005 growth rates versus 1995 levels (absolute values).

Table 1: Descriptive statistics by country (logarithmic values)

	Y		K		S		U		
COUNTRY	1995	2005	1995	2005	1995	2005	1995	2005	#obs
AUS	8.74	8.98	9.41	10.01	2.90	3.30	5.38	5.38	27
AUT	8.38	8.60	9.11	9.27	2.07	2.70	4.60	4.54	25
BEL	8.46	8.59	9.22	9.46	2.11	2.25	4.41	4.32	23
BGR	5.84	6.08	6.59	6.99	1.17	1.42	4.45	4.31	29
BRA	9.61	9.85	10.35	10.85	4.70	5.13	7.31	7.49	28
CAN	8.98	9.27	9.51	9.73	3.43	3.81	5.58	5.62	26
CYP	4.86	5.06	5.50	5.60	0.62	0.47	1.90	1.92	24
CZE	7.31	7.40	8.34	8.67	2.40	2.46	5.10	4.90	29
DEU	10.49	10.55	11.09	11.19	4.90	4.92	6.54	6.3	27
DNK	7.81	7.90	8.39	8.66	2.17	2.47	4.02	3.84	26
ESP	9.28	9.55	9.96	10.41	3.99	4.72	5.74	5.82	26
EST	4.55	5.34	5.28	6.29	1.68	1.60	2.79	2.67	28
FIN	7.53	7.83	8.22	8.38	2.50	2.67	3.76	3.77	25
FRA	9.83	10.09	10.37	10.55	4.24	4.52	6.03	5.84	27
GBR	9.71	9.86	10.02	10.26	4.44	4.61	6.24	5.93	24
GRC	7.48	7.80	7.98	8.35	2.28	2.62	4.54	4.54	23
HUN	6.76	7.01	8.02	8.25	2.37	2.60	4.72	4.66	29
IDN	9.17	9.44	9.94	10.37	3.45	4.45	6.87	7.37	20
IND	9.43	10.06	10.33	11.07	5.83	6.57	8.37	8.58	27
IRL	6.81	7.20	7.29	7.86	1.63	2.43	3.49	3.56	21
ITA	10.04	10.10	10.87	11.14	3.47	3.98	6.66	6.65	24
JPN	11.15	11.07	11.83	12.08	5.67	5.71	7.55	7.25	22
KOR	9.45	9.80	10.26	10.60	5.23	5.68	6.50	6.25	28
LTU	6.24	6.95	6.94	7.79	1.92	2.00	3.26	3.27	29
LUX	5.45	5.91	6.09	6.65	-0.45	0.02	1.49	1.77	20
LVA	4.10	4.89	4.90	5.62	1.03	1.14	2.55	2.77	30
MEX	8.91	9.24	9.57	9.73	4.74	5.00	6.71	6.97	28
MLT	4.35	4.50	5.04	5.35	-1.65	-1.29	1.46	1.46	24
NLD	8.66	8.85	9.17	9.35	2.72	3.21	4.83	4.67	24
POL	8.09	8.57	8.78	9.28	3.47	3.91	5.95	5.78	29
PRT	7.62	7.87	8.36	8.81	1.47	1.85	4.68	4.69	23
ROU	7.01	7.19	7.67	8.06	2.19	2.54	5.50	5.45	28
RUS	9.47	9.75	10.30	10.42	4.65	4.72	7.44	7.28	25
SVK	6.35	6.72	7.04	7.62	1.59	1.65	4.15	4.00	28
SVN	6.06	6.30	6.85	7.45	0.96	1.15	3.24	3.03	29
SWE	8.13	8.39	8.65	8.99	2.18	2.63	4.56	4.40	24
TUR	8.87	9.48	9.55	10.08	3.07	3.78	6.15	6.33	25
USA	11.48	11.72	11.93	12.14	6.15	6.21	7.75	7.62	21
AVG	7.95	8.25	8.71	9.10	2.88	3.20	5.04	5.01	975

Table 2: Descriptive statistics by sector (logarithmic values)

	Y		K		S		U		
SECTOR	1995	2005	1995	2005	1995	2005	1995	2005	#obs
Food, beverage & tobacco	8.67	8.80	9.46	9.71	3.32	3.57	5.69	5.57	37
Textile products	8.23	8.17	8.76	8.79	3.05	3.06	5.56	5.15	37
Leather & footwear	6.41	6.12	6.95	6.89	1.35	1.15	3.81	3.21	33
Wood products	7.02	7.34	7.55	7.98	2.07	2.41	4.48	4.44	38
Paper, printing & publishing	7.90	8.18	8.53	8.91	2.71	3.01	4.94	4.88	37
Coke & refined petroleum	6.30	6.22	7.48	7.85	1.02	1.11	3.12	2.90	22
Chemical products	7.97	8.33	8.69	9.02	2.67	2.81	4.75	4.59	29
Rubber & plastics	7.15	7.68	7.75	8.25	2.06	2.47	4.34	4.41	38
Non-metallic mineral products	7.83	8.20	8.70	8.96	2.43	2.63	4.72	4.56	36
Basic & fabricated metal	8.37	8.71	9.16	9.40	3.11	3.49	5.41	5.43	38
Machinery	7.87	8.29	8.24	8.56	2.82	3.02	5.07	4.88	37
Electrical & optical equipment	7.80	8.42	8.21	8.72	2.65	2.98	4.90	4.88	33
Transport Equipment	7.64	8.12	8.17	8.64	2.45	2.82	4.69	4.68	37
Other manufacturing	7.29	7.64	7.59	8.03	2.39	2.77	4.67	4.68	35
Motor vehicle & fuel trade	7.78	8.16	8.23	8.63	2.89	3.37	5.09	5.27	34
Wholesale trade	9.08	9.50	9.34	9.77	3.94	4.34	6.12	6.20	33
Retail trade	9.02	9.40	9.34	9.79	4.42	4.88	6.66	6.80	37
Land transport	8.62	8.87	9.94	10.32	3.72	4.05	5.93	5.95	38
Water transport	5.99	6.13	7.33	7.62	0.92	1.04	3.06	2.88	32
Air transport	5.97	6.31	7.30	7.63	1.02	1.39	3.19	3.24	33
Transport services	7.91	8.31	9.18	9.72	2.50	3.05	4.66	4.92	37
Post & telecommunications	8.10	8.84	8.92	9.69	2.79	3.35	5.08	5.18	32
Real estate	9.55	10.10	11.83	12.19	4.96	5.51	5.59	5.99	4
Business services	8.94	9.47	9.07	10.10	4.97	5.61	5.61	6.03	33
Agriculture, forestry & fishing	9.52	9.64	10.45	10.73	4.12	4.34	7.39	7.07	32
Mining & quarrying	7.10	7.18	8.40	8.55	1.81	1.84	4.18	3.92	31
Utilities	8.03	8.20	9.80	10.21	2.90	3.26	5.02	4.81	20
Construction	8.92	9.18	8.98	9.44	3.80	4.11	6.35	6.50	30
Hotels & restaurants	8.36	8.63	8.69	9.27	3.27	3.79	6.00	6.22	38
Financial services	9.07	9.38	9.26	9.66	4.21	4.64	5.22	5.16	24
AVG	7.95	8.25	8.71	9.10	2.88	3.20	5.04	5.01	975

Table 3: Decomposition by country.

	Eq. (15)			Eq. (18)					
COUNTRY	$\Delta \ln \widehat{MRTS}^{c,tT}_{s,u}$	$\Delta \ln \widetilde{\mathbb{B}}^{c,tT}_{s,u}$	$\Delta \ln \widetilde{\mathbb{F}}^{c,tT}_{s,u}$	accum (k)	accum (s)	accum (u)	$ln\mathbb{W}^{c,tT}_{s,u}$	$\widehat{\Theta}^{c,tT}_{s,u}$	# obs
AUS	0.251	0.500	-0.249	0.163	-0.331	-0.081	0.060	0.123	26
AUT	0.637	0.432	0.205	0.263	-0.106	0.048	-0.037	0.465	25
BEL	0.181	0.371	-0.190	0.062	-0.157	-0.096	-0.029	0.179	21
BGR	0.614	0.202	0.412	0.295	0.043	0.075	-0.096	0.012	18
BRA	0.233	0.664	-0.431	0.248	-0.554	-0.125	-0.127	0.064	15
CAN	0.507	0.389	0.118	0.270	-0.157	0.005	0.112	0.280	23
CYP	-0.149	0.179	-0.327	0.222	-0.595	0.046	-0.006	-0.526	8
CZE	0.414	0.480	-0.066	0.118	-0.173	-0.010	0.011	0.234	24
DEU	-0.080	0.139	-0.219	0.030	0.003	-0.251	0.024	-0.130	25
DNK	-0.068	0.206	-0.273	-0.008	-0.182	-0.084	0.017	-0.077	25
ESP	0.113	0.401	-0.287	0.119	-0.359	-0.047	-0.060	0.152	22
EST	0.247	0.752	-0.505	0.197	-0.218	-0.484	-0.098	0.158	7
FIN	0.335	0.325	0.010	-0.026	-0.030	0.067	0.114	0.224	23
FRA	0.031	0.316	-0.284	0.083	-0.132	-0.235	-0.170	0.118	24
GBR	-0.027	0.291	-0.318	0.078	0.001	-0.397	-0.011	-0.067	22
GRC	0.185	0.315	-0.130	0.053	-0.122	-0.061	-0.013	0.114	19
HUN	0.436	0.418	0.018	0.022	-0.021	0.053	-0.029	0.295	22
IDN	0.870	0.475	0.395	0.670	-0.116	-0.159	0.094	-0.301	16
IND	0.673	0.860	-0.188	0.310	-0.405	-0.093	0.004	-0.108	5
IRL	0.238	0.570	-0.332	0.073	-0.237	-0.168	0.088	0.177	14
ITA	0.691	0.493	0.198	0.301	-0.114	0.011	-0.187	-0.508	22
JPN	-0.184	0.319	-0.502	-0.045	-0.241	-0.216	-0.005	-0.098	16
KOR	-0.438	0.133	-0.571	-0.130	-0.308	-0.133	0.054	-0.369	14
LTU	0.388	0.357	0.031	0.167	-0.194	0.059	-0.086	0.365	15
LUX	0.547	0.704	-0.157	0.150	-0.053	-0.255	0.317	-0.093	8
LVA	0.403	-0.175	0.578	0.127	0.324	0.128	-0.125	-0.218	6
MEX	0.306	0.132	0.174	0.114	0.044	0.016	-0.080	0.239	18
MLT	1.184	0.375	0.809	0.725	0.076	0.008	-0.033	-0.339	8
NLD	0.252	0.418	-0.166	-0.004	-0.136	-0.025	0.086	0.209	21
POL	0.552	0.463	0.090	0.420	-0.352	0.021	-0.042	0.608	19
PRT	0.484	0.297	0.187	0.317	-0.143	0.012	-0.100	-0.214	21
ROU	1.148	0.524	0.624	0.532	0.061	0.031	-0.113	0.063	25
RUS	0.446	0.421	0.025	0.143	-0.169	0.051	-0.015	0.085	17
SVK	-0.104	0.117	-0.221	0.067	-0.349	-0.032	0.082	-0.272	23
SVN	0.275	0.251	0.025	0.040	-0.139	0.123	0.010	-0.019	23
SWE	0.557	0.386	0.171	0.256	-0.110	0.025	-0.153	0.532	23
TUR	0.520	0.427	0.093	0.430	-0.263	-0.074	-0.058	0.102	24
USA	-0.311	0.101	-0.412	0.019	-0.256	-0.175	0.055	-0.262	11
Non OECD	0.423	0.360	0.063	0.225	-0.161	-0.005	-0.028	0.047	283
OECD	0.254	0.362	-0.108	0.137	-0.155	-0.090	-0.011	0.078	415
Avg/Tot	0.323	0.361	-0.039	0.172	-0.157	-0.055	-0.018	0.066	698

Table 4: Decomposition by sector.

	Eq. (15)			Eq. (18)					
SECTOR	$\Delta \ln \widehat{MRTS}_{s,u}^{c,tT}$	$\Delta \ln \widetilde{\mathbb{B}}_{s,u}^{c,tT}$	$\Delta \ln \widetilde{\mathbb{F}}_{s,u}^{c,tT}$	accum (k)	accum (s)	accum (u)	$ln\mathbb{W}_{s,u}^{c,tT}$	$\widehat{\Theta}_{s,u}^{c,tT}$	# obs
Food, beverage & tobacco	0.462	0.530	-0.068	0.169	-0.178	-0.059	-0.056	0.180	32
Textile products	0.333	0.408	-0.075	0.096	0.143	-0.315	-0.084	-0.023	27
Leather & footwear	0.621	0.542	0.079	0.316	-0.001	-0.236	-0.082	-0.089	18
Wood products	0.455	0.426	0.029	0.122	-0.056	-0.037	-0.057	0.002	25
Paper, printing & publishing	0.018	0.217	-0.199	0.154	-0.274	-0.080	-0.057	-0.059	28
Coke & refined petroleum	0.530	0.571	-0.041	-0.177	-0.077	0.213	-0.004	0.117	15
Chemical products	0.020	0.278	-0.257	0.136	-0.300	-0.093	-0.049	-0.104	27
Rubber & plastics	0.040	0.191	-0.151	0.244	-0.338	-0.057	-0.040	-0.135	27
Non-metallic mineral products	0.128	0.295	-0.167	0.073	-0.165	-0.075	-0.026	-0.079	30
Basic & fabricated metal	0.429	0.376	0.053	0.152	-0.084	-0.015	-0.049	0.161	30
Machinery	0.296	0.451	-0.155	0.138	-0.207	-0.085	-0.036	0.179	25
Electrical & optical equipment	0.266	0.372	-0.106	0.234	-0.225	-0.114	-0.027	0.099	24
Transport Equipment	0.208	0.334	-0.126	0.222	-0.303	-0.044	-0.032	0.002	25
Other manufacturing	0.295	0.259	0.035	0.292	-0.044	-0.213	-0.023	-0.063	21
Motor vehicle & fuel trade	0.468	0.465	0.002	0.164	-0.166	0.004	0.023	0.222	25
Wholesale trade	0.327	0.305	0.022	0.214	-0.212	0.020	-0.040	0.236	26
Retail trade	0.701	0.400	0.301	0.593	-0.192	-0.100	-0.050	0.698	18
Land transport	0.392	0.387	0.005	0.166	-0.198	0.038	0.024	0.110	30
Water transport	0.491	0.480	0.010	0.120	-0.095	-0.070	0.061	0.053	25
Air transport	0.611	0.402	0.209	0.301	-0.037	-0.056	0.070	0.183	24
Transport services	0.296	0.384	-0.088	0.203	-0.293	0.002	0.044	-0.132	33
Post & telecommunications	0.184	0.350	-0.167	0.164	-0.285	-0.046	0.095	0.091	26
Real estate	-0.392	0.015	-0.407	-0.093	-0.298	-0.017	-0.003	0.350	1
Business services	-0.758	-0.002	-0.756	-0.172	-0.784	0.199	0.012	-0.851	8
Agriculture, forestry & fishing	0.475	0.253	0.222	0.138	0.027	0.058	-0.059	-0.153	24
Mining & quarrying	0.407	0.456	-0.049	-0.044	0.045	-0.050	-0.013	0.188	26
Utilities	-0.010	0.313	-0.323	0.088	-0.301	-0.110	-0.010	0.235	18
Construction	0.642	0.280	0.362	0.302	0.018	0.042	-0.002	0.315	17
Hotels & restaurants	0.757	0.494	0.263	0.426	-0.073	-0.090	-0.040	0.364	26
Financial services	-0.301	-0.036	-0.265	-0.061	-0.159	-0.046	-0.002	-0.264	17
Manufacturing	0.278	0.367	-0.089	0.159	-0.158	-0.090	-0.046	0.015	354
Non-Manufacturing	0.369	0.356	0.013	0.186	-0.157	-0.020	0.010	0.118	344
Avg/Tot	0.323	0.361	-0.039	0.172	-0.157	-0.055	-0.018	0.066	698

Table 5: Standard approach: SBTC computation

	EoS ($\frac{1}{\sigma-1}$)	($\frac{W_s}{W_u}$)	($\frac{S}{U}$)	($\frac{A_s}{A_u}$)	SBTC (yearly avg)
1995	1.5	1.96	0.13	0.13	-
2005	1.5	1.92	0.19	0.25	9.35%
1995	2	1.96	0.13	0.51	-
2005	2	1.92	0.19	0.70	3.75%
1995	4.44	1.96	0.13	1.32	-
2005	4.16	1.92	0.19	1.39	0.57%

Table 6: Robustness checks: alternative specifications (annual changes)

	$\Delta \ln \widehat{MRTS}_{s,u}^{c,tT}$	$\Delta \ln \widetilde{\mathbb{B}}_{s,u}^{c,tT}$	$\Delta \ln \widetilde{\mathbb{F}}_{s,u}^{c,tT}$	$ln \mathbb{W}_{s,u}^{c,tT}$	$\Delta \ln \widehat{\tau}_{s,u}^{c,tT}$
High vs Medium-Low (benchmark)	3.22%	3.61%	-0.39%	0.18%	3.39%
High-Medium vs Low	2.70%	5.32%	-2.62%	-0.29%	2.41%
1997-2007	3.64%	3.95%	-0.31%	0.14%	3.78%
Not averaged	3.90%	3.77%	0.13%	0.16%	4.06%
Average	3.37%	4.16%	-0.80%	0.05%	3.41%

Table 7: Relative misallocation analysis: markers and convergence.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\left\lvert \widehat{\tau}_{s,u}^{c,1995} \right\rvert$	-0.667***	-0.703***	-0.657***	-0.705***	-0.476***	-0.711***	-0.497***
	(0.05)	(0.06)	(0.05)	(0.05)	(0.08)	(0.06)	(0.06)
$MUR_{s,u}$			-0.269***	-0.381**	-0.482**	-0.507**	-0.029
			(0.10)	(0.17)	(0.20)	(0.21)	(0.16)
TrUnion					0.001		
					(0.00)		
EPL					-0.037		
					(0.04)		
SecSkInt						11.255***	1.155***
						(2.57)	(0.28)
$\mathbb{W}_{s,u}^{c,tT}$							0.299
							(0.26)
SBTC							0.603***
							(0.06)
FA							-1.047***
							(0.30)
SecSkInt*FA							1.916***
							(0.41)
Const	0.564***	0.611***	0.623***	0.655***	0.781***	-8.096***	-0.633***
	(0.04)	(0.13)	(0.04)	(0.13)	(0.22)	(2.00)	(0.23)
Country FE	N	Y	N	Y	N	Y	Y
Sector FE	N	Y	N	Y	Y	N	N
# obs	716	716	716	716	431	642	628
Adj. R^2	0.311	0.417	0.317	0.422	0.240	0.421	0.601

Dependent Variable: Relative misallocation (i.e., $\widehat{\Theta}_{s,u}^{c,tT}$)
Bootstrapped standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX – FOR ONLINE PUBLICATION

A Empirical methodology

Nonparametric kernel regression is becoming an increasingly popular method of estimation in applied economic milieus. The main perceived benefit is that it allows for consistent estimation when the underlying functional form of the regression function is unknown. While this is true, there are many other benefits which may prove to be just as useful in our context. In this section we will discuss nonparametric regression, and address the issue of bandwidth selection which can expose irrelevant covariates and detect linearity of others. Finally, we will introduce nonparametric methods which can handle instrumental variables.

Estimation. Arguably the most popular regression model in the growth empirics literature is the linear parametric model

$$y_i = \alpha + \beta x_i + \varepsilon_i, \qquad\qquad i = 1, 2, \ldots, n, \tag{23}$$

where y_i is our response (in this case output growth), x_i is a vector of q regressors, α and β are unknown parameters to be estimated and ε_i is the additive (mean zero) random disturbance. Consistent estimation of this model requires that all relevant regressors are included in x_i (and that they are uncorrelated with ε_i) and the functional form is correctly specified. However, when either of these two assumptions do not hold, the estimates the model produces will most likely be inconsistent. While non-linear functional forms are possible in a parametric framework, the data generating process still must be assumed *a priori*.

Nonparametric kernel methods have the ability to alleviate many of the restrictive assumptions made in the parametric framework. Consider the nonparametric regression model

$$y_i = m(x_i) + u_i, \quad i = 1, 2, \ldots, n, \tag{24}$$

where $m(\cdot)$ is an unknown smooth function and the remaining variables are the same as before. Here, $m(\cdot)$ is interpreted as the conditional mean of y given x. Note that in the (linear) parametric setting above, it is implicitly assumed that $E(y_i|x_i) = \alpha + \beta x_i$. Further note that the linear model is a special case of our nonparametric estimator and thus, if the true data generating process is indeed linear, then the nonparametric estimator will give results consistent with that model.

One popular method for estimation of the unknown function is by local-constant least-squares (LCLS) regression. The LCLS estimator of the conditional mean function is given as

$$\widehat{m}(x) = \frac{\sum\limits_{i=1}^{n} y_i \prod\limits_{s=1}^{q} K\left(\frac{x_{si}-x_s}{h_s}\right)}{\sum\limits_{i=1}^{n} \prod\limits_{s=1}^{q} K\left(\frac{x_{si}-x_s}{h_s}\right)}, \tag{25}$$

where $\prod\limits_{s=1}^{q} K\left(\left(x_{si}-x_s\right)/h_s\right)$ is the product kernel and h_s is the smoothing parameter (bandwidth) for a particular regressor x_s (see Pagan and Ullah, 1999). The intuition behind this estimator is that it is simply a weighted average of y_i. It is also known as a local average, given that the weights change depending upon the location of the regressors. We estimate the conditional mean function by locally averaging those values of the left-hand-side variable which are 'close' in terms of the values taken on by the regressors. The amount of local information used to construct the average is controlled by the bandwidth.

While LCLS is undoubtedly the most popular, and widely available, nonparametric regression estimator, recently there has been an enthusiastic use of the local-linear least-squares (LLLS) regression estimator as an alternative to LCLS. The LLLS regression estimator possesses several theoretical and empirical advantages. Theoretically, the LLLS estimator has a simple finite sample bias that the LCLS estimator, being unbiased in the setting where the conditional mean is indeed linear. Moreover, the LLLS estimator possesses greater flexibility near the boundaries of the data. Empirically, the LLLS estimator automatically produces estimates of the conditional mean **and** the associated derivatives. This is beneficial as numerical derivatives can be noisy and behave poorly depending upon the localness of the surrounding data, something that the LCLS estimator can suffer from.

In short, LLLS performs weighted least-squares regressions around a point x with weights determined by a kernel function and bandwidth vector. Again, more weight is given to observations in the neighborhood of x. This is performed over the range of x and then the unknown function is estimated by connecting the point estimates. An added benefit is that if indeed the true functional form is linear, the LLLS estimator nests the OLS estimator when the bandwidth is very large.

Specifically, taking a first-order Taylor expansion of (24) around x, yields

$$g_i \approx m(x) + (x_i - x)\beta(x) + \varepsilon_i, \tag{26}$$

where $\beta(x)$ is defined as the partial derivative of $m(x)$ with respect to x. The LLLS estimator of $\delta(x) \equiv \binom{m(x)}{\beta(x)}$ is given by

$$\widehat{\delta}(x) = \left(X'K\left(x\right)X\right)^{-1} X'K\left(x\right)g, \tag{27}$$

where X is a $n \times (q_c + 1)$ matrix with ith row being $(1, (x_i^c - x^c))$ and $K\left(x\right)$ is a $n \times n$ diagonal matrix with kernel weights along the diagonal. Note that here we obtain a fitted value and derivative estimate (for each regressor) for each x. This allows us to observe (potential) heterogeneity in the partial effects.

Bandwidth selection. It is believed that the choice of the continuous kernel function matters little in the estimation of the conditional mean (see Härdle, 1990) and that selection of the bandwidths is the most salient factor when performing nonparametric estimation. As indicated above, the bandwidths control the amount by which the data are smoothed. For continuous variables, large bandwidths will lead to large amounts of smoothing, resulting in low variance, but high bias. Small bandwidths, on the other hand, will lead to less smoothing, resulting in high variance, but low bias. This trade-off is well known in applied nonparametric econometrics, and the 'solution' is most often to resort to automated determination procedures to estimate the bandwidths. Although there exist many selection methods, we utilize the popular least-squares cross-validation (LSCV) criteria. Specifically, the bandwidths are chosen to minimize

$$CV(h) = \frac{1}{n}\sum_{j=1}^{n} \left[y_j - \widehat{m}_{-j}(x_j)\right]^2, \tag{28}$$

where $\widehat{m}_{-j}(x_j)$ is the leave-one-out estimator of $m(\cdot)$. As the sample size grows and/or the number of regressors increases, computation time increases dramatically. However, it is highly recommended that a bandwidth selection procedure is used as opposed to a rule-of-thumb selection, especially in the presence of discrete data as no rule-of-thumb selection criteria exists.

An alternative selection mechanism is AIC_c bandwidth selection (Hurvich et al., 1998). The AIC_c criterion is

$$AIC_c(h) = \ln(\widehat{\sigma}^2) + \frac{1 + tr(\mathbf{H})/n}{1 - (tr(\mathbf{H}) + 2)/n}, \tag{29}$$

where

$$\widehat{\sigma}^2 = \frac{1}{n}\sum_{i=1}^{n} \left[y_i - \widehat{m}(x_i)\right]^2 \quad \text{and} \quad \mathbf{H} = \left(\mathbf{X}'K(x)\mathbf{X}\right)^{-1}\mathbf{X}'K(x).$$

Notice that a leave-one-out estimator for $m(\cdot)$ is not used. This is because the AIC_c criterion penalizes overfitting based on the number of effective parameters used, which is captured by the trace of $\mathbf{H}$. As the bandwidths decrease (fit improves) this trace increases and leads to larger penalties. The empirical results in the paper are derived from bandwidths selected using the criterion in (29).

As an aside, we note that an even simpler bandwidth selection procedure, the 'ocular' method, is not appropriate once the number of covariates is larger than two. As the number of regressors exceeds two, visual methods to investigate the fit of the model are cumbersome and uninstructive. With a large dimension for the number of regressors, it is suggested that cross-validation techniques be used as opposed to either ocular or rule-of-thumb methods.

B For Online Publication – Overall Distributions

In this Appendix we show the distributions of our estimated MPs, MRTS, SBTC, FA and relative misallocation measures.

Figure 9 reports the distribution of the estimated marginal product (MP) of (in order, from left to right) unskilled labor (MPU), skilled labor (MPS) and capital (MPK) at the start and finish of the period. Estimates are quite consistent over time.

Figure 10 reports the MRTS distribution at the beginning and the end of the period, together with the underlying SBCT and FA distributions.

In Figure 11, the initial and final distributions of $\tau^c_{s,u}$ are compared. In 2005, the distribution is more right-centered, compared to the beginning of the period, with no pronounced differences in terms of dispersion.

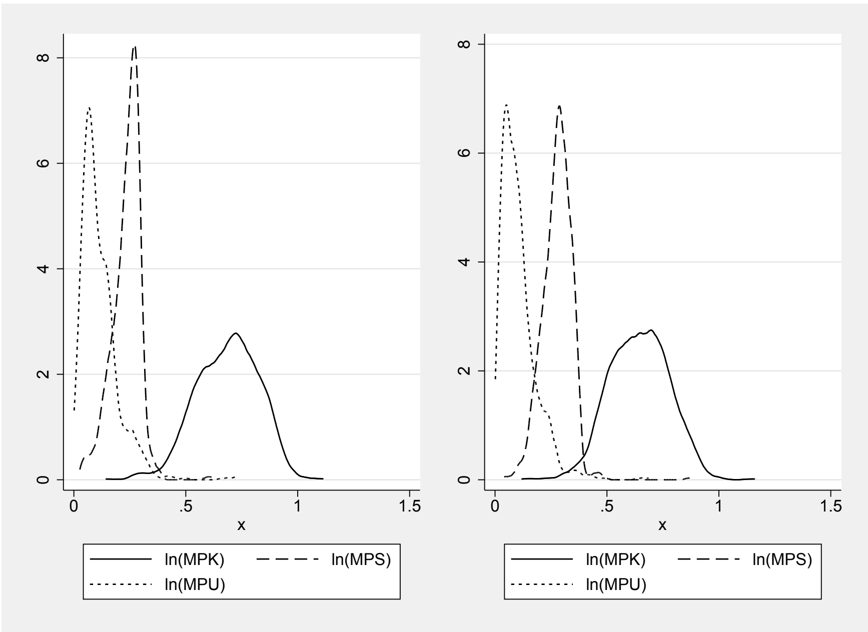

Figure 9: Estimated Marginal Products in 1995 (left) and 2005 (right).

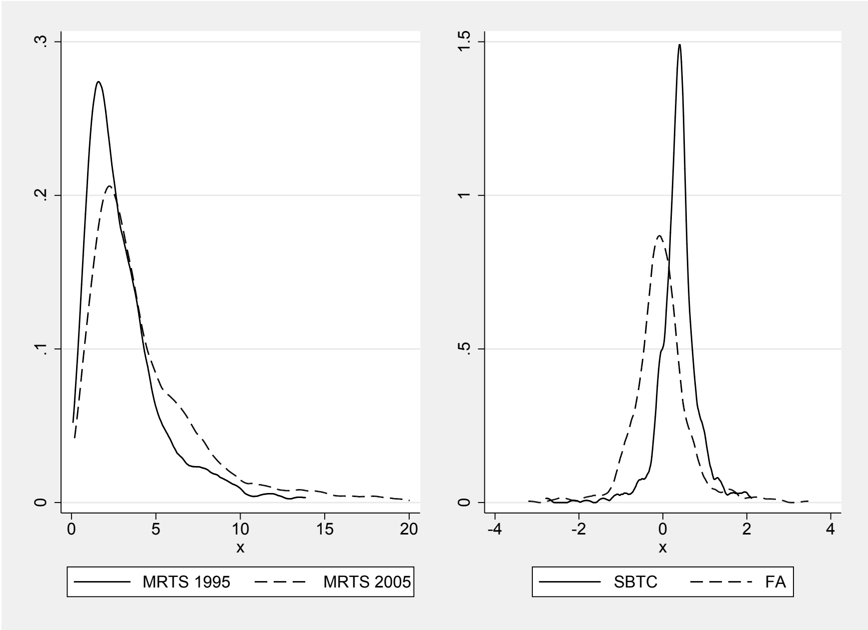

Figure 10: MRTS (1995-2005), SBTC (2005) and FA (2005)

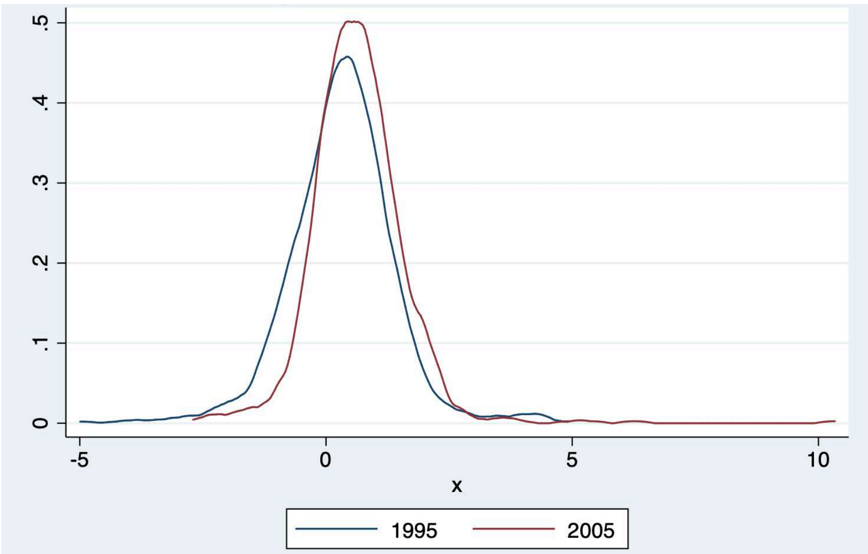

Figure 11: Relative misallocation in 1995 (i.e., $\widehat{\tau}^{c,t}_{s,u}$) and in 2005 (i.e., $\widehat{\tau}^{c,T}_{s,u}$).

Ultimi Contributi di Ricerca CRENoS

I Paper sono disponibili in: http://www.crenos.unica.it

19/07 *Fabrizio Fusillo, Francesco Quatraro, Stefano Usai,* "Going Green: Environmental Regulation, eco-innovation and technological alliances"
19/06 *Oliviero A. Carboni, Giuseppe Medda,* "External R&D Acquisition and Product Innovation"
19/05 *José J. Cao-Alvira, Luca G. Deidda,* "Development of Bank Microcredit"
19/04 *Vania Licio,* "When history leaves a mark: a new measure of Roman roads"
19/03 *Simone Franceschini, Gerardo Marletto,* "Reorganization of supply chains as a key for the envision of socio- technical transitions. The case of tourism"
19/02 *Elias Carroni, Dimitri Paolini,* "The business model of a streaming platform"
19/01 *Stefania Capecchi, Marta Meleddu, Manuela Pulina, Giuliana Solinas,* "Mixture models for consumers' preferences in healthcare"
18/13 *Adelaide Baronchelli, Teodora Erika Uberti,* "Exports and FDI: Comparing Networks in the New Millennium"
18/12 *Gabriele Cardullo, Maurizio Conti, Giovanni Sulis,* "Unions, Two-Tier Bargaining and Physical Capital Investment: Theory and Firm-Level Evidence from Italy"
18/11 *Jing Guan, J.D. Tena,* "Estimating the Effect of Physical Exercise on Juveniles' Health Status and Subjective Well-Being in China"
18/10 *Silvia Balia, Rinaldo Brau, Daniela Moro,* "Hospital choice with high long-distance mobility"
18/09 *Luca Deidda, Ettore Panetti,* "Banks' Liquidity Management and Financial Fragility"
18/08 *Gerardo Marletto, Cécile Sillig,* "Lost in mainstreaming? Agrifood and urban mobility grassroots innovations with multiple pathways and outcomes"
18/07 *Jing Guan, J.D. Tena,* "Do Social Medical Insurance Schemes Improve Children's Health in China?"
18/06 *Carmenr Aina, Daniela Sonedda,* "Investment in education and household consumption"
18/05 *Maria Gabriella Campolo, Antonino Di Pino, Edoardo Otranto*, "Reducing Bias in a Matching Estimation of Endogenous Treatment Effect"
18/04 *William Addessi, Bianca Biagi, Maria Giovanna Brandano,* "How tourist flows are affected by the introduction of the euro?"
18/03 *Luc Bauwens, Edoardo Otranto*, "Nonlinearities and Regimes in Conditional Correlations with Different Dynamics"
18/02 *Massimiliano Bratti, Maurizio Conti, Giovanni Sulis,* "Employment Protection, Temporary Contracts and Firm-provided Training: Evidence from Italy"
18/01 *Luca De Benedictis, Vania Licio, Anna Maria Pinna,* "The long-term effects of the historical Roman road network: Trade costs of Italian provinces"
17/11 *Massimo Del Gatto, Carlo S. Mastinu,* "A Huff model with heterogeneous retailers fits well in Southern Italy"
17/10 *Sara Calligaris, Massimo Del Gatto, Fadi Hassan, Gianmarco I.P. Ottaviano, Fabiano Schivardi,* "The Productivity Puzzle and Misallocation: an Italian Perspective"
17/09 *Michele Battisti, Filippo Belloc. Massimo Del Gatto,* "Technology-specific Production Functions"

www.crenos.unica.it

ISBN 9788868512279