Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

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Ifo Working Paper No. 156

March 2013

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Abstract

International specialization is a strong driver of sectoral productivity. This specialization is not only characterized by the diversity of final goods, but also by the variety of intermediate inputs. Thereby the importance of inputs is not only demonstrated by its large shares in gross output, but also as intermediate inputs constitute important parts of higher value products on later stages of assembly. At that, intermediate inputs encapsulate innovation efforts of upstream sectors facilitating technology diffusion into the wider economy. Due to the usual assumption of technology being exclusively embodied in capital, this paper analyzes the importance of embodied technology in intermediate inputs as well as the validity of productivity effects stemming from embodied technology diffusion on sectoral level. Therefore, based on the idea of Romer's model of the variety of inputs, two hypotheses are formally tested. The first hypothesis postulates embodied technological change in high-tech inputs, while the second hypothesis assumes that embodied technology diffusion increases aggregate sectoral productivity via use of high-tech inputs. For a sample of 12 OECD countries over the 1995–2007 period, the empirical evidence of this paper shows that there is indeed a bias in technological change toward high-tech inputs and embodied technology diffusion is a source of sectoral productivity increases. However, the effect is more pronounced for goods-producing sectors than for services.

JEL Code: D57, E23,O33, O47.
Keywords: Technology diffusion, augmenting technological change, intermediate inputs, productivity.

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1. Introduction

Intermediate inputs play an increasingly important role in production processes and value chains of industrialized economies. Thereby intermediates are defined as products, which are not consumed as final output but are further used in the production of other goods and services. While value added made up around 51 percent of gross output on average in the EU-15 countries during the mid–1980s to the mid–1990s, its importance steadily declined from its peak in 1993 at almost 52 percent to around 47 percent in 2007. On the contrary, the share of intermediate inputs increased correspondingly.

However, the importance of intermediate inputs is not only demonstrated by their high shares in the generation of gross output, but also due to the fact that modern economies are more and more characterized by strong sectoral interconnection via the channel of intermediate inputs. Especially since intermediates are important parts of higher value products on later production stages, they encapsulate interrelations through which innovation and technology diffuse throughout the economy. Long and Plosser (1983) and Horvath (2000), for example, show that sectoral shocks can spread through an input-output structure and give rise to fluctuations in aggregate total factor productivity (TFP).

These models point out that the linkages among sectors, represented by intermediate inputs, contribute to aggregate TFP movements. Besides the sectoral dependence of intermediate inputs, intermediates become increasingly important in world trade. According to an OECD study by Miroudot et al. (2009) intermediate inputs in 2009 represented 56% of goods trade and 73% of services trade, and thus dominated international trade flows. Hence, sectoral output analyis that solely focuses on primariy inputs of capital and labor is missing an essential part regarding our understanding of output generation and technology diffusion.

The idea of this paper is to explicitly take into account intermediate inputs and their role in diffusing technology. It is assumed that R&D-intensive upstream sectors produce high-tech inputs, which can be used in the production process of downstream as well as upstream sectors. Since R&D-intensive upstream sectors are more heavily engaged in R&D activities than other upstream sectors, intermediate inputs of R&D-intensive upstream sectors embody more technology than inputs produced by those sectors which are not R&D-intensive. Thereby embodied technology refers to an increase in the variety of but also to improvements in the quality of inputs, similar as in case of capital goods (OECD, 2001b; Jorgenson, 1966). It is expected that spillover effects from utilization of high-tech inputs supplied by R&D-intensive upstream sectors to other sectors positively affect other sectors' productivity growth (embodied technology diffusion).

Recent studies that consider the incorporation of intermediate inputs into the production process are Jones (2011) and Moro (2011). While Moro only allows for capital- and labor-augmenting technological change, Jones sets up a model that additionally accounts for intermediate-augmenting technological change. In their analyses both authors consider a linkage between intermediate inputs and productivity growth, where the latter is measured either in terms of total factor or labor productivity. While Moro argues that increasing inputs generated a negative impact on Italy's total factor productivity (TFP), Jones shows that the share of intermediates can provide a multiplier on the productivity level that is able to explain cross-country differences in the level of TFP.

In another study Ciccone (2002) analyzes the effect of industrialization on aggregate output and TFP. In Ciccone's model, new technologies adopted with industrialization are more intensive in intermediate goods. When an increase in productivity occurs in sectors producing intermediate goods, final producers benefit from that increase and become more productive themselves. As new technologies are more intensive in intermediate goods, it follows that industrialization provides a TFP increase. Similar to Jones, Ciccone exploits the multiplier effect triggered by intermediate goods first, which was first described in Hulten (2002).

On contrary, in Moro's model the share of intermediate goods does not necessarily generate a multiplier on the productivity level, when neutral technological change is assumed to be solely embodied in capital and labor. In his model without intermediates-augmenting technological change, the share of intermediate goods provides only a level effect on TFP, inversely related to the level of the share. While all of the previously mentioned papers focus on aggregate intermediates, this paper provides an new view by analyzing the linkage between two different types of intermediate inputs and technological change, and their effect on the productivity performance of sectors. Moreover, the study explicitly allows for parameter heterogeneity among two types of broad industry groups, which are the goods-producing and the services sectors.

Although economic theory has accorded great importance to the role of capital in technological change and economic growth, and much new technology is in fact embodied in the capital goods (machinery and structures) that industries purchase to expand and improve production (Jorgenson, 1966), this study will allow for embodied technology in intermediates in the first place. The role of capital investment in the diffusion of technology among industries is straight forward as final products, i.e. machinery and equipment, embody research and development performed by the manufacturing sector and other sectors obtain access to most of that research through purchase of such capital equipment.

In order to satisfactorily evaluate the determinants of output and productivity, however, it is necessary to consider the diffusion of technology through intermediate goods as well. Empirical studies of the relative impact of capital and intermediate inputs on productivity have provided very diverse results. Terlecky (1974), for example, reported separate significant effects for research contained in capital and research contained in materials for manufacturing industries; however, the capital effect was much greater. In non-manufacturing sectors, research embodied in materials had an effect but, surprisingly, research contained in capital did not. Subsequently, Sveikauskas (1981) and Scherer (1982) report extremely high returns for purchased capital, but none for intermediate inputs (materials), while other results in Scherer's work find significant positive effects for purchase of research through materials. Moreover, Griliches and Lichtenberg (1984) conclude that the influence of R&D embodied in purchases from other sectors is "weak and unstable over time".

As the paper analyzes the importance of embodied technology in intermediate inputs as well as the validity of embodied technology diffusion on sectoral productivity, two main hypotheses based on the idea of Romer's model of the variety of inputs are formally tested. The first hypothesis, H_A, postulates that there is embodied technological change in intermediate inputs, especially in high-tech input. The validity of this hypothesis depends on the empirical evidence of technology bias toward high-tech inputs. The second hypothesis, H_B, postulates given that there is embodied technological change in high-tech inputs that there is embodied technology diffusion that increases aggregate productivity via use of such high-tech inputs in firms' production process. The validity of this hypothesis will be formally tested by focusing on aggregate productivity effects for subsamples of downstream sectors in goods-producing and services sectors. The results show that for a sample of 12 OECD countries there is indeed a bias in technological change toward high-tech inputs (hypothesis H_A), whereas the effect is more pronounced for goods-producing sectors. Also, there is confirming empirical evidence of productivity increases via embodied technology diffusion in goods-producing sectors (hypothesis H_B).

The paper is organized as follows. Section 2 provides the theoretical underpinning for the interaction of productivity and intermediate inputs derived from a steady state equation of intermediate inputs. Section 3 outlines the data employed for the estimation strategy, which is demonstrated in Section 4. Section 5 then provides the estimation results for Cobb-Douglas and translog production specifications, while robustness tests of the estimated specifications are conducted in Section 6. It is especially the robustness section that will speak to the validity of both hypotheses. Section 7 discusses potential drawbacks of the empirical strategy, while Section 8 concludes.

2. Theoretical Underpinning

The model assumes that the economy consists of a number sectors i, where each sector produces a final good, an investment good, and/or an intermediate good. The production output of sector i is Y_i measured as gross output, which is produced by employing capital K_i (measured as capital stock), labor L_i (measured as hours worked), and intermediate inputs purchased either within the same sector or from other sectors. Regrading intermediate inputs the model allows for a separation into high-tech inputs H_i (produced by R&D-intensive sectors) and non-high-tech or ordinary inputs M_i (produced by non-R&D-intensive sectors). Given these input factors the production function has the following form:

$$Y_i = \left[(A_K K_i)^{\alpha}(A_L L_i)^{\beta}\right]^{1-\theta_1-\theta_2} (A_H H_i)^{\theta_1} (A_M M_i)^{\theta_2} \tag{1}$$

where A_l for $l \in (K, L, H, M)$ represents input-specific technology parameters, while α and β are the input elasticities of capital and labor. Correspondingly, θ_1 and θ_2 are the input elasticities of high-tech and non-high-tech inputs, which also enter the production process in terms of substitution parameters. The modeling of input-specific technology parameters assumes that there is a bias in technological change toward capital, labor, and intermediate inputs.[1]

In allowing intermediate inputs to differ by high-tech inputs, equation (1) follows the idea of product variety introduced by Romer (1990), in which productivity is caused by innovation created from new, but not necessarily improved, variates of input products.

[1] Besides the technology bias toward input factors, the substitution parameters θ_1 and θ_2 reflect an intermediate bias in high-tech and non-high-tech inputs, respectively.

Thus, the channel through which productivity increases occur is intermediate inputs used in the production process of final output, whereas inputs embody new and/or better technology (process innovation). Based on Romer's idea of product variety in inputs, equation (1) is an extension to the models of recent studies by Jones (2011) and Moro (2011). More precisely, while Moro (2011) assumes embodied technological change in capital and labor only, without allowing for technology changes in intermediate inputs, the model of Jones (2011) specifies Hicks-neutral technological change augmenting in *all* inputs equally. However, none of these studies differentiate intermediates inputs by different types or sectoral R&D intensity.

In allowing inputs to differ by type depending on the R&D effort of sectors, the assumption of a strictly exogenous technological change is dropped. As the Romer model – in its basics – follows the idea of innovation-based growth models, it does no longer assume that there is only capital (or other input) accumulation, but that it is the R&D effort of upstream sectors that leads to the production of more productive high-tech inputs. This generates directed technological change toward high-tech inputs, which contributes to productivity growth in upstream as well as in downstream sectors through the mechanism of process innovation.

Continuing with equation (1) intra-sectoral firms solve the following maximization problem with respect to intermediate inputs:

$$\begin{aligned} \max_{H_i, M_i} \{ \, p \left[(A_K K_i)^{\alpha} (A_L L_i)^{\beta} \right]^{1-\theta_1-\theta_2} (A_H H_i)^{\theta_1} (A_M M_i)^{\theta_2} \\ -rK_i - wL_i - p_H H_i - p_M M_i \, \} \end{aligned} \tag{2}$$

where p resembles the price of gross output products, p_H is the price of high-tech inputs, and p_M the price of non-high-tech inputs. The prices of capital and labor are given by r and w, respectively. For ease of calculation gross-output prices are set as the numeraire and intermediate input prices equal those of the numeraire. In the empirical part later on, intermediate input prices are employed for both types of inputs. Since the maximization problem of the firm is static time subscripts are avoided.

Given the Cobb-Douglas production function of equation (1), the first-order conditions of equation (2) with respect to the two intermediate inputs yields the following equilibrium conditions:

$$\theta_1 = \frac{H_i}{Y_i} \tag{3}$$

$$\theta_2 = \frac{M_i}{Y_i} \tag{4}$$

Equation (3) and (4) highlight the direct relationship between the intermediate bias reflected by the parameters θ_1 and θ_2, and the utilization of intermediate inputs per unit of gross output. These results are similar to those of Moro (2011).

Substituting equation (3) and (4) into equation (1) the following steady-state representation of the production function is derived:

$$Y_i = (A_K K_i)^{\alpha} (A_L L_i^{\beta}) (A_H \theta_1)^{\frac{\theta_1}{1-\theta_1-\theta_2}} (A_M \theta_2)^{\frac{\theta_2}{1-\theta_1-\theta_2}} \tag{5}$$

To theoretically investigate the relationship between different types of intermediate inputs and productivity, a measure of productivity called the Solow residual or total factor productivity (TFP) is calculated. This measure accounts for all those changes in output that are not derived from the inputs of capital, labor, and intermediates, and thus reflects changes in productivity induced by changes in technological change.

In standard growth-accounting exercises the measurement of TFP is derived from the value-added concept, i.e. under the consideration of capital and labor only. However, using value-added based concepts of TFP as a proxy of technological change is only valid, if the value-added production function is separable from gross output. By this assumption the role of technological change is restricted as it is assumed that technological change only affects the usage of capital and labor, so that intermediate inputs cannot be a source of improvements in productivity (Gollop, 1979). But empirical testing suggests that there is no separability between the value-added function and intermediate inputs. A study by Jorgenson et al. (1987) found that the conditions necessary and sufficient for the existence of a sectoral value-added function did not exist in 40 out of 42 industries analyzed.

Due to the evidence of non-separability in gross output and value added, TFP is derived according to the gross-output concept:

$$TFP_i = \frac{Y_i}{(K_i^{\alpha} L_i^{\beta})^{1-\theta_1-\theta_2} H_i^{\theta_1} M_i^{\theta_2}} \tag{6}$$

Substituting gross output by equation (5) and using the steady-state representation for the denominator of equation (6), sectoral TFP can be reformulated according to

$$\begin{aligned} TFP_i = \frac{(A_K K_i)^{\alpha} (A_L L_i^{\beta}) (A_H \theta_1)^{\frac{\theta_1}{1-\theta_1-\theta_2}} (A_M \theta_2)^{\frac{\theta_2}{1-\theta_1-\theta_2}}}{K_i^{\alpha} L_i^{\beta} \theta_1^{\frac{\theta_1}{1-\theta_1-\theta_2}} \theta_2^{\frac{\theta_2}{1-\theta_1-\theta_2}}} \\ = A_K^{\alpha} A_L^{\beta} A_H^{\gamma} A_M^{\delta} \\ = f(A_l) \end{aligned} \tag{7}$$

where $l \in (K, L, H, M)$, $\gamma = \theta_1/(1-\theta_1-\theta_2)$, and $\delta = \theta_2/(1-\theta_1-\theta_2)$. Equation (7) shows that TFP is determined by the different technological parameters A_l. Since all technological parameters, especially A_H and A_M, cannot be observed directly, the overall impact of a change in intermediate inputs on TFP is undetermined and needs to be estimated.

To estimate the impact of θ_1 and θ_2 on productivity, in the empirical strategy section the unobserved A_H and A_M will be approximated by a time trend interacted with both types of intermediate inputs, respectively. The same is performed for A_K and A_L and both inputs K and L. This approach helps to identify whether technological change is augmenting or saving in intermediate inputs. Given there is a positive and statistically significant interaction between input shares and technological change, then the bias in technological change is input augmenting, which can be attributed to embodied technology. In case of a statistically significant negative interaction, the bias in technological change is input saving. While an increase in input shares thus equals an increase in TFP given the bias is input augmenting, it decrease TFP in case of input-saving technological change. If there is no statistically significant interaction, technological change does not exhibit any kind of input bias and there is not effect on TFP from changing inputs.

Concerning the empirical part of the paper, the main focus will be to show that there is indeed input-augmenting technological change that increased sectoral productivity. It will be shown that this is most relevant for high-tech inputs in the goods-producing sectors (hypothesis H_A) and that embodied technology diffusion particularly affects goods-producing sectors (hypothesis H_B).

3. Data

Regrading the data, I start with employing gross output, capital stocks, hours worked by persons engaged, and aggregate intermediate inputs provided by the socio-economic accounts of the newly released WIOD database for 30 SIC-coded sectors and 12 OECD countries (Timmer, 2012). To separate intermediate inputs into high-tech and non-high-tech, I use the inter-country industry-by-industry table provided by the World Input-Output tables of the WIOD database (Timmer, 2012).

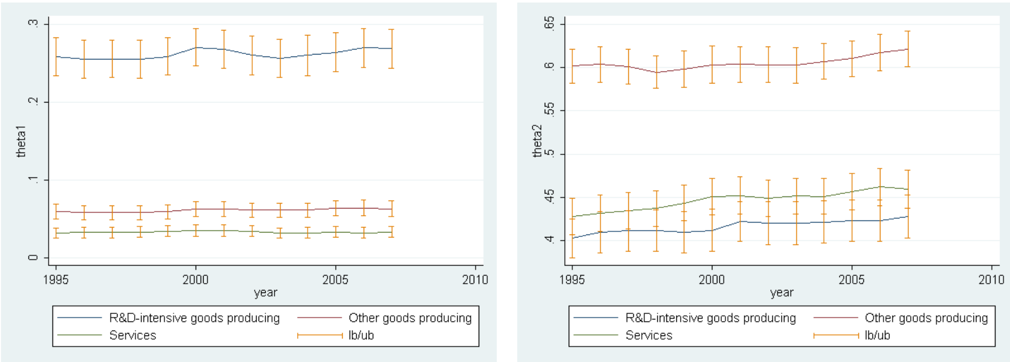
Separation of aggregate intermediate inputs into high-tech and non-high-tech is accomplished by applying the OECD technology intensity classification (OECD, 2011), where the two categories of high-technology industries and medium-high-technology industries are classified as R&D intensive accordingly. Due to its larger economy-wide R&D intensity, the classification focuses on manufacturing industries. The grouping of industries according to the OECD technology intensity classification is based on the OECD methodology to determine R&D intensities of sectors. This methodology is based on mainly two indicators: i) R&D expenditures divided by value added and ii) R&D expenditures divided by production. These indicators are provided by 12 OECD countries, which are nearly equal to the 12 countries used in this study.[2] A list of all used variables is provided in Table A.1 in the Appendix. For a list of country and sector coverage see Table A.2 and Table A.3.

An empirical representation of θ_1 and θ_2 is shown in Figure 1. It shows the timely development of θ_1 and θ_2 for industry averages by three groups of sectors. It becomes obvious that it is especially the R&D-intensive goods-producing sectors that exhibit the highest average share of high-tech inputs in gross output, followed by other goods-producing sectors and services. On contrary, non-high-tech average shares are highest in other goods-producing sectors. Services exhibit the second highest average share, while the lowest shares are given for R&D-intensive goods-producing sectors.

While Figure 1 shows a stable development of high-tech input shares in gross-output throughout, non-high-tech input shares exhibit a slight upward trend with a relatively stable increase. The empirical development is particularly important as it is assumed that in a steady state variables grow at some constant rate. In case of θ_1 and θ_2 the descriptive statistics suggest the steady-state assumption is fulfilled why the application of the model appears to be appropriate.

[2]The OECD countries resemble those 12 countries listed in Table A.2, except for Ireland and Spain, which are replaced by Australia and the Netherlands in this study.

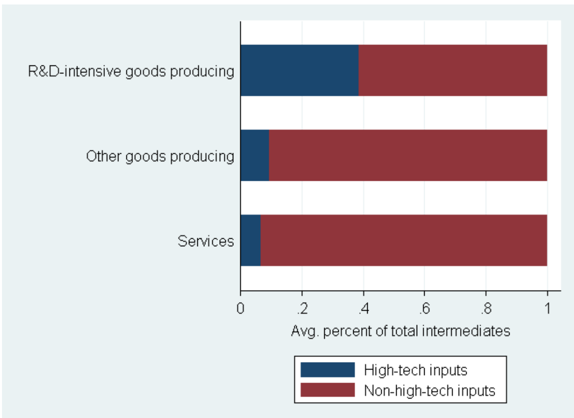
Figure 1: Intermediate Shares in Gross Output



Notes: Goods-producing sectors include only manufacturing sectors. Services are market services. Averages are across sectors within groups by year. Lb/ub denote lower/upper bound of the 95 percent confidence interval.

Separating intermediate inputs by high-tech and non-high-tech inputs, Figure 2 shows the importance of high-tech inputs by group of sectors. It becomes apparent that high-tech inputs are most important in the R&D-intensive sectors themselves. The average share in those sectors is at around 40 percent of total inputs. This may be explained by the fact that R&D-intensive sectors, which are the producers of high-tech inputs on the one hand, are their primary users on the other. However, non-high-tech inputs still play a strong role in R&D-intensive sectors. In contrast, non-R&D-intensive sectors mainly use non-high-tech inputs. Although the average share of high-tech inputs is below 10 percent in the latter, there is nevertheless a low diffusion of technology inputs among those sectors. A similar picture emerges for services also showing a very low share of high-tech inputs. Similar to non-R&D-intensive sectors, services are dominated by inputs of lower technology standard.

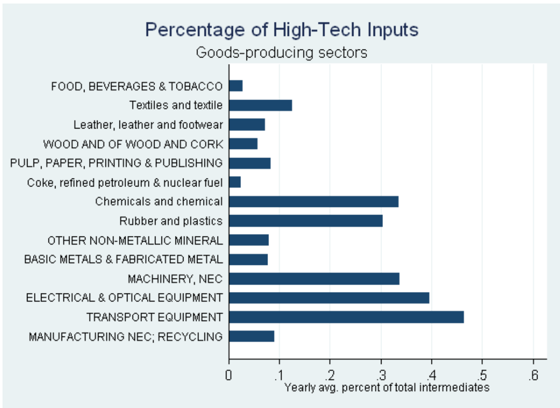
Figure 2: The Importance of Different Types of Intermediate Inputs, by Sectors



Notes: Goods-producing sectors include only manufacturing sectors. Services are market services.

A more detailed descriptive analysis of sectors that use high-tech inputs is displayed in Figure 3 and Figure 4. Figure 3 shows the share of high-tech inputs in total intermediates separated by goods-producing sectors. As has already been pointed out in the previous figure, it is especially the R&D-intensive sectors like chemicals, machinery, electrical & optical equipment, and the transport equipment industries, which are strong purchasers of high-tech inputs. It is those sectors that are by definition the producers of high-tech intermediate inputs. But as can been see, there are also other non-R&D-intensive goods-producing sectors purchasing high-tech inputs. Such industries are for example, rubber & plastics and textiles.

Figure 3: The Importance of High-Tech Intermediate Inputs, by Sectors

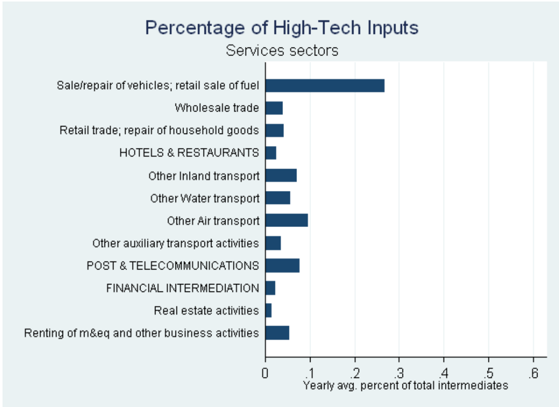


Notes: Goods-producing sectors include only manufacturing sectors.

With respect to the importance of high-tech intermediate inputs in services the previous picture of Figure 2 is confirmed across a wide range of services sectors. Most of services sectors have low shares of high-tech inputs in total intermediate inputs, except for the sales & repair of vehicles industry (see Figure 4. Here the high-tech input share is about 30 percent on average, which is due to the inputs and parts supplied by the manufacturing transportation industry. Since the business of this particular industry is mainly in replacing vehicle parts, the embodied technology hypothesis according to which productivity is fueled through the use of high-tech inputs (process innovation) is less convincing.

As has been shown in the descriptive statistics, there is a lot of sectoral idiosyncrasies that should be accounted for in the econometric analysis of high-tech inputs and technological change. More precisely, an empirical strategy that employs a broad sample of industry groups (like including all sectors of goods-producing or services) should account for differences in the results contingent on the exclusion of a) the R&D-intensive sectors (in case of goods-producing sectors) and b) the sales & repair of vehicles industry (in case of services). Such a sensitivity analysis serves as a robustness check of the bias of empirical estimates and will be employed in the paper later on.

Figure 4: The Importance of High-Tech Intermediate Inputs, by Sectors



Notes: Services are market services.

4. Empirical Strategy

4.1. Accounting for Technological Change in a Cobb-Douglas Specification

The empirical strategy starts with log-linearization of equation (1) obtaining the following estimable form

$$\ln Y_i = A_0 + \alpha \ln K_i + \beta \ln L_i + \frac{\theta_1}{1-\theta_1-\theta_2} \ln \theta_1 + \frac{\theta_2}{1-\theta_1-\theta_2} \ln \theta_2 \tag{8}$$

where $A_0 = \alpha \ln A_K + \beta \ln A_L + \theta_1/(1-\theta_1-\theta_2) \ln A_H + \theta_2/(1-\theta_1-\theta_2) \ln A_M$. Since the factors' marginal products need not necessarily correspond to the observable factor prices, the elasticities of intermediate input shares will be estimated as well. Since the estimation of different types of gross-output production functions enables the analysis of different aspects with respect to technological change and the technology bias toward intermediate inputs, the subsequent analysis starts with a Cobb-Douglas before proceeding with a translog production specification.

Assuming that technological change takes on the estimable form $A = ae^{\gamma_t t}$ approximating $A_0 = \ln A$ and that there is no explicitly modeled interaction between A and θ_1 and θ_2, equation (8) can be rewritten into

$$\ln Y_i = a_0 + \beta_K \ln K_{i,t} + \beta_L \ln L_{i,t} + \beta_{\theta_1} \ln \theta_1 + \beta_{\theta_2} \ln \theta_2 + \gamma_t t + \epsilon_{i,t} \tag{9}$$

where t is a time trend and γ_t is its unknown semi-elasticity to be estimated. The parameter $a_0 = \ln a$ resembles a constant, while $\epsilon_{i,t}$ is an error term assumed to be i.i.d. According to the idea of standard growth-accounting exercises, which is formulated in equation (7), sectoral TFP resembles the following identity:

$$TFP \equiv a_0 + \gamma_t t + \epsilon_{i,t} \tag{10}$$

which includes all those changes in Y_i not accounted for by the four factors, K_i, L_i, θ_1, and θ_2. While the estimated parameters of θ_1 and θ_2 reflect the bias in intermediate inputs for generating gross output, a more detailed analysis of the impact of changes in intermediate input shares on TFP is not feasible within this functional setting. Therefore a different type of production function that enables the interaction between technological change and intermediate inputs is needed, as is the case for a translog production function.

The translog production function, which was proposed by Christiansen et al. (1971, 1973), represents a more flexible functional form that constitutes a generalization of the Cobb-Douglas specification. Besides the possibility to account for input-biases in technological change, another main advantage of the translog function is that, unlike the Cobb-Douglas function, it does not assume such rigid premises as perfect substitution between input factors or perfect competition on the input factors markets. But especially the latter exerts a strong influence on the estimated TFP residual. The following section describes the accounting of technological change for this specific functional form.

4.2. Accounting for Technological Change in a Translog Specification

Assuming that the production function is now of translog type and technological change takes on a quadratic estimable form $A = ae^{\gamma_t t + 0.5\gamma_{tt} t^2}$ approximating $A_0 = \ln A$ as well as the possibility of biases in *all* input factors, equation (8) can be rewritten into

$$\begin{aligned}
\ln Y_i = a_0 &+ \beta_K \ln K_{i,t} + \beta_L \ln L_{i,t} + \beta_{\theta_1} \ln \theta_1 + \beta_{\theta_2} \ln \theta_2 + \gamma_t t + 0.5\gamma_{tt} t^2 \\
&+ 0.5\beta_{KK} \ln K_{i,t}^2 + 0.5\beta_{LL} \ln L_{i,t}^2 + 0.5\beta_{\theta_1\theta_1} \ln \theta_1^2 + 0.5\beta_{\theta_2\theta_2} \ln \theta_2^2 \\
&+ \beta_{LK} \ln L_{i,t} \ln K_{i,t} + \beta_{\theta_1 K} \ln \theta_1 \ln K_{i,t} + \beta_{\theta_2 K} \ln \theta_2 \ln K_{i,t} \\
&+ \beta_{\theta_1 L} \ln \theta_1 \ln L_{i,t} + \beta_{\theta_2 L} \ln \theta_2 \ln L_{i,t} \\
&+ \beta_{\theta_2\theta_1} \ln \theta_2 \ln \theta_1 \\
&+ \gamma_{tK} t \ln K_{i,t} + \gamma_{tL} t \ln L_{i,t} + \gamma_{t\theta_1} t \ln \theta_1 + \gamma_{t\theta_2} t \ln \theta_2 \\
&+ \epsilon_{i,t}
\end{aligned} \tag{11}$$

where t and t^2 reflect the quadratic time trend, while γ_t and γ_{tt} are the unknown semi-elasticities to be estimated. The parameter $a_0 = \ln a$ resembles a constant and $\epsilon_{i,t}$ is the error term that is assumed to be i.i.d. Analogously to the Cobb-Douglas case, sectoral TFP would be approximated by $a_0 + \gamma_t t + 0.5\gamma_{tt} t^2 + \epsilon_{i,t}$. These estimated technological parameters represent the neutral part of technological change. But since the translog specification also allows for biases in technological change, it expands the TFP measure displayed in equation (6) by different types of input-augmenting and/or -saving technological change; hence, sectoral TFP additionally includes a non-neutral part:

$$TFP \equiv a_0 + \gamma_t t + 0.5\gamma_{tt} t^2 \underbrace{+ \gamma_{tK} t \ln K_{i,t} + \gamma_{tL} t \ln L_{i,t} + \gamma_{t\theta_1} t \ln \theta_1 + \gamma_{t\theta_2} t \ln \theta_2}_{non-neutral\ part} + \epsilon_{i,t} \tag{12}$$

It is especially this extension in technology parameters that is of particular importance to answer the question whether technological change embodied in intermediate inputs affects TFP. While changes in TFP are derived from the partial derivative of equation (12) with respect to time

$$\frac{\partial TFP}{\partial t} = \gamma_t + \gamma_{tt}t + \gamma_{tK} \ln K_{i,t} + \gamma_{tL} \ln L_{i,t} + \gamma_{t\theta_1} \ln \theta_1 + \gamma_{t\theta_2} \ln \theta_2 \tag{13}$$

the effect of a change in a specific type of intermediate input is derived according to

$$\frac{\partial TFP}{\partial \ln \theta_m} = \gamma_{t\theta_m} t \tag{14}$$

where $m \in (1, 2)$.

All of the production functions are estimated by fixed-effects regression (within transformation) employing clustered standard errors. Besides being heteroskedasticity consistent, the standard error estimates are robust to general forms of intra-sectoral correlation.

5. Estimation Results

The results of estimating equation (9) separated by the two sectoral groups of goods-producing and services are provided in Table 1. Regarding the estimated elasticities of capital (β_K) and labor (β_L) in case of goods-producing sectors, the results are in the range of the expected magnitudes. While the elasticity of capital is slightly below 1/3, that of labor is around 2/3. Both are estimated as highly statistically significant. In contrast, high-tech intermediate inputs (β_{θ_1}) are estimated as statistically insignificant, while non-high-tech inputs (β_{θ_2}) exhibit a significant elasticity, which is slightly above the elasticity of capital. The time trend parameter (γ_t) that captures technological change is also estimated statistically significant. These results suggest that in the goods-producing sector and over the entire period of coverage Hicks-neutral technological change positively affected gross output.

In case of services, the results are qualitatively similar. However, while the estimated capital coefficient provides reasonable results, the gross-output elasticity with respect to labor suggests to be less important compared to the case of goods-producing sectors. On contrary, especially the elasticity of non-high-tech inputs, which is about twice the size as in the case of goods-producing sectors, plays an important role in generating gross output. High-tech inputs again are estimated statistically insignificant. Similar to goods-producing sectors the positively estimated time trend suggests a positive effect of Hicks-neutral technological change.

The results of Table 1, which are based on a Cobb-Douglas specification, suggest that there is a direct increase of gross output by utilizing more non-high-tech intermediate inputs in the first place. High-tech inputs and their embodied technological change show no effect in this specification. As technological change is assumed to be Hicks neutral and thus productivity increases originate from increases in technology that by definition affect all inputs equally, there is no possibility to test whether sectoral productivity is actually increased via a technology bias toward one of the specific inputs. But especially the existence of technology bias would provide the evidence whether the hypothesis of

Table 1: Growth Regressions by Sectoral Type, Cobb-Douglas Specification

	Goods Producing	Services
β_K	0.204***	0.272***
	[0.054]	[0.051]
β_L	0.692***	0.214***
	[0.057]	[0.067]
β_{θ_1}	-0.015	0.017
	[0.047]	[0.027]
β_{θ_2}	0.378**	0.622***
	[0.157]	[0.095]
γ_t	0.023***	0.017***
	[0.002]	[0.002]
Constant	0.665	2.990***
	[0.420]	[0.295]
Observations	2184	1859
Within R^2	0.57	0.73
# of clusters	168	144

Notes: Regressions are fixed-effects estimations controlling for time-invariant country and industry effects. Robust standard errors in brackets allow for heteroskedasticity and intra-sectoral correlated standard errors. Significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%. *Source*: Author's calculations.

embodied technology is a valid concept to explain increases in sectoral productivity (hypothesis H_A). It also lays the empirical foundation of embodied technology diffusion driving aggregate sector productivity (hypothesis H_B).

As the Cobb-Douglas specification provides a first estimate of neutral technological change, the main focus of the paper will be on the bias of technological change toward different types of intermediate inputs. Therefore a translog specification of the production function is employed, which allows for interactions between technological change and all inputs, especially high-tech and non-high-tech inputs. Depending on the estimated sign of the elasticity, the direction of the bias can be formally tested. Table 2 provides the estimation results of equation (11) separated by goods-producing and services sectors. Because of the technology focus of the paper, only the results for technology interactions are subsequently discussed in more detail.

The results of the estimated parameters of the translog specification show an interesting picture of the nature of technological change with respect to capital (γ_{tK}), labor (γ_{tL}), high-tech intermediate inputs ($\gamma_{t\theta_1}$), and non-high-tech intermediate inputs ($\gamma_{t\theta_2}$) by group of sectors. In case of goods-producing sectors, the empirical evidence suggests labor- as well as high-tech input-augmenting technological change. As the elasticities are estimated with differing magnitude and the other elasticities are insignificant, the assumption of technology change that equally affects inputs (Hicks neutrality) is no longer supported. The positively estimated interaction between high-tech inputs and technological change supports the hypothesis that there is embodied technological change in high-tech inputs (hypothesis H_A). Moreover, the findings indicate that the diffusion of embodied technology increased aggregate sectoral productivity of good-producing sectors (hypothesis H_B). These findings strengthen the interpretation of technology in high-tech inputs, as there is no empirical evidence of a bias in non-high-tech inputs.

Table 2: Growth Regressions by Sectoral Type, Translog Specification

	Goods Producing	Services
β_K	2.068**	2.214**
	[0.899]	[0.973]
β_L	0.922	0.227
	[0.908]	[0.660]
β_{θ_1}	-0.372	0.318
	[0.394]	[0.324]
β_{θ_2}	4.426**	3.465***
	[1.876]	[1.096]
γ_t	0.007	-0.058
	[0.046]	[0.062]
γ_{tt}	0.000	-0.001*
	[0.001]	[0.001]
β_{KK}	-0.215	-0.185
	[0.135]	[0.128]
β_{LL}	0.132	0.168
	[0.205]	[0.344]
$\beta_{\theta_1\theta_1}$	0.007	0.039
	[0.056]	[0.026]
$\beta_{\theta_2\theta_2}$	1.124	0.849***
	[0.845]	[0.273]
β_{LK}	-0.224***	-0.226
	[0.069]	[0.267]
$\beta_{\theta_1 K}$	-0.002	-0.017
	[0.083]	[0.033]
$\beta_{\theta_2 K}$	-0.356	0.088
	[0.323]	[0.142]
$\beta_{\theta_1 L}$	0.083	0.003
	[0.078]	[0.070]
$\beta_{\theta_2 L}$	-0.342	-0.420*
	[0.360]	[0.245]
$\beta_{\theta_2\theta_1}$	0.096	0.102*
	[0.122]	[0.058]
γ_{tK}	-0.009	0.011
	[0.008]	[0.008]
γ_{tL}	0.020**	0.005
	[0.010]	[0.012]
$\gamma_{t\theta_1}$	0.010***	0.001
	[0.003]	[0.001]
$\gamma_{t\theta_2}$	0.017	-0.014***
	[0.013]	[0.004]
Constant	-3.216*	-0.004
	[1.807]	[2.700]
Observations	2184	1859
Within R^2	0.63	0.76
# of clusters	168	144

Notes: Regressions are fixed-effects estimations controlling for time-invariant country and industry effects. Robust standard errors in brackets allow for heteroskedasticity and intra-sectoral correlated standard errors. Significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%. *Source*: Author's calculations.

Regarding the translog results of technology parameters for services, there is only an indication of input-saving technological change in case of non-high-tech inputs. This finding is opposed to the results of goods-producing sectors and rejects the previously determined assumption of Hicks neutrality in the Cobb-Douglas specification. As non-high-tech inputs are supplied by less R&D-intensive sectors, those inputs embody lower technology and are thus expected to be productivity reducing. This may serve as an explanation for why services are technology saving in this type of input. Taking stock, the econometric analysis suggests that embodied technology is a less important ingredient in services than it is in goods-producing sectors. Moreover, the large extent of insignificantly estimated technology biases in both groups of sectors, strongly questions the assumption of Hicks neutrality.

6. Robustness Analysis

6.1. Exclusion of Sectors

For robustness analysis the embodied technology hypothesis of intermediate inputs (hypothesis H_A) and the assumption of spillover effects generated from high-tech inputs among sectors affecting aggregate sectoral productivities (hypothesis H_B) are further tested. In particular, to test hypothesis H_B specific industries are excluded from the sample to validate whether the estimated coefficients of the technology biases still show the same sign and statistical significance. In another robustness test the entire sample from 1995 to 2007 is separated into two time periods and the coefficients are estimated for these two periods using the entire and the reduced subsample.

I begin the robustness analysis with the goods-producing sample, in which the R&D-intensive sectors are excluded (reduced subsample). The R&D-intensive sectors are by definition the high-tech inputs producing sectors. Since the previously estimated technology biases included these sectors, this test aims at corroborating the spillover thesis of embodied technology from high-tech inputs into other sectors' productivity, whereas only those sectors are considered that are exclusively *using* these inputs. There is a good reason to test the overall validity of hypothesis H_B by exclusion of the R&D-intensive sectors, since the descriptive statistics in Figure 3 suggest R&D-intensive sectors to be the main users of high-tech inputs. Their inclusion could cause a bias in the estimated technology coefficient ($\gamma_{t\theta_1}$) and thus induces a misinterpretation of the economy-wide spillover effect of embodied technological change from high-tech inputs.

Table 3 shows two columns for each of the two main industry types, goods-producing and services sectors, whereas column I always includes the previous results of the entire sample, while column II shows the new results excluding specific sectors. It is shown that the exclusion of R&D-intensive sectors does not alter most of the estimated coefficients in case of goods-producing sectors as most of the estimates remain similar in magnitude and statistical significance. However, an interesting finding is the support of high-tech input-augmenting technological change. Despite of reduced magnitude of the estimated technology coefficient ($\gamma_{t\theta_1}$), it is still significant and positive suggesting productivity spillovers in goods-producing sectors from high-tech inputs. In contrast, non-high-tech inputs still show no significant spillover effects ($\gamma_{t\theta_2}$).

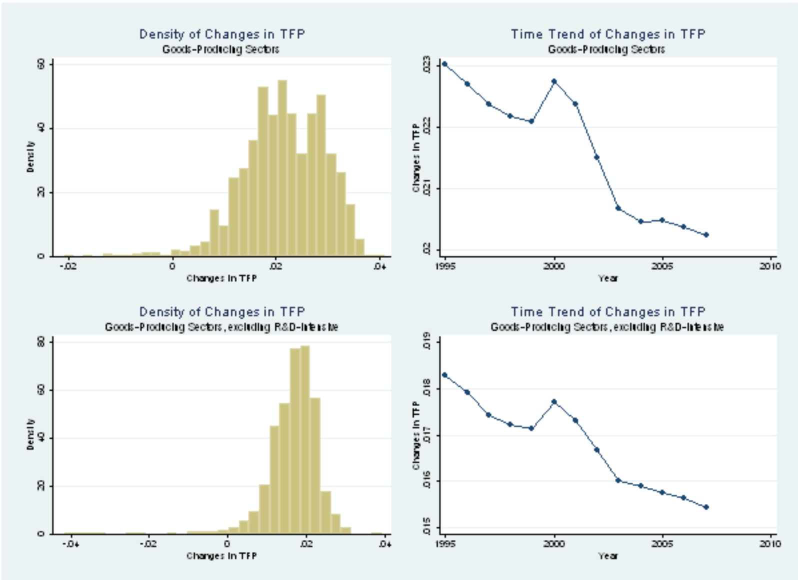
Table 3: Translog Growth Regressions by Sectoral Type and Excluded Sectors

	Goods Producing		Services	
	I	II	I	II
β_K	2.068**	2.341***	2.214**	2.160**
	[0.899]	[0.885]	[0.973]	[0.957]
β_L	0.922	0.919	0.227	0.419
	[0.908]	[0.853]	[0.660]	[0.676]
β_{θ_1}	-0.372	0.320	0.318	0.363
	[0.394]	[0.340]	[0.324]	[0.375]
β_{θ_2}	4.426**	5.896***	3.465***	3.549***
	[1.876]	[1.794]	[1.096]	[1.263]
γ_t	0.007	0.028	-0.058	-0.059
	[0.046]	[0.045]	[0.062]	[0.063]
γ_{tt}	0.000	0.000	-0.001*	-0.002**
	[0.001]	[0.001]	[0.001]	[0.001]
β_{KK}	-0.215	-0.311**	-0.185	-0.205
	[0.135]	[0.131]	[0.128]	[0.131]
β_{LL}	0.132	0.242	0.168	0.071
	[0.205]	[0.210]	[0.344]	[0.342]
$\beta_{\theta_1\theta_1}$	0.007	0.082	0.039	0.037
	[0.056]	[0.054]	[0.026]	[0.032]
$\beta_{\theta_2\theta_2}$	1.124	0.089	0.849***	0.736**
	[0.845]	[1.184]	[0.273]	[0.313]
β_{LK}	-0.224***	-0.299***	-0.226	-0.186
	[0.069]	[0.068]	[0.267]	[0.264]
$\beta_{\theta_1 K}$	-0.002	-0.159*	-0.017	-0.008
	[0.083]	[0.091]	[0.033]	[0.051]
$\beta_{\theta_2 K}$	-0.356	-0.561*	0.088	0.102
	[0.323]	[0.295]	[0.142]	[0.184]
$\beta_{\theta_1 L}$	0.083	0.156	0.003	-0.011
	[0.078]	[0.097]	[0.070]	[0.082]
$\beta_{\theta_2 L}$	-0.342	-0.510	-0.420*	-0.441
	[0.360]	[0.328]	[0.245]	[0.282]
$\beta_{\theta_2\theta_1}$	0.096	0.138	0.102*	0.136*
	[0.122]	[0.150]	[0.058]	[0.077]
γ_{tK}	-0.009	-0.018**	0.011	0.013*
	[0.008]	[0.008]	[0.008]	[0.008]
γ_{tL}	0.020**	0.022**	0.005	0.003
	[0.010]	[0.010]	[0.012]	[0.013]
$\gamma_{t\theta_1}$	0.010***	0.007*	0.001	0.000
	[0.003]	[0.004]	[0.001]	[0.003]
$\gamma_{t\theta_2}$	0.017	0.015	-0.014***	-0.011
	[0.013]	[0.016]	[0.004]	[0.007]
Constant	-3.216*	-2.534*	-0.004	-0.196
	[1.807]	[1.497]	[2.700]	[2.706]
Observations	2184	1560	1859	1703
Within R^2	0.63	0.64	0.76	0.76
# of clusters	168	120	144	132

Notes: Regressions are fixed-effects estimations controlling for time-invariant country and industry effects. Robust standard errors in brackets allow for heteroskedasticity and intra-sectoral correlated standard errors. Significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%. *Source*: Author's calculations.

A graphical illustration of the change in TFP over time for goods-producing sectors is provided in Figure 5. It shows the partial derivative of the estimated TFP residual according to equation (13) based on the results of Table 3, averaged over all sectors and countries. The figures depict histograms of the average changes in TFP for goods-producing sectors with and without R&D-intensive sectors. It becomes apparent that the inclusion of R&D-intensive sectors introduces a stronger variability in the TFP estimates. However, for both samples, there is a declining trend of changes in TFP over the period of coverage.

Figure 5: Changes in TFP, by Goods-Producing Sectors

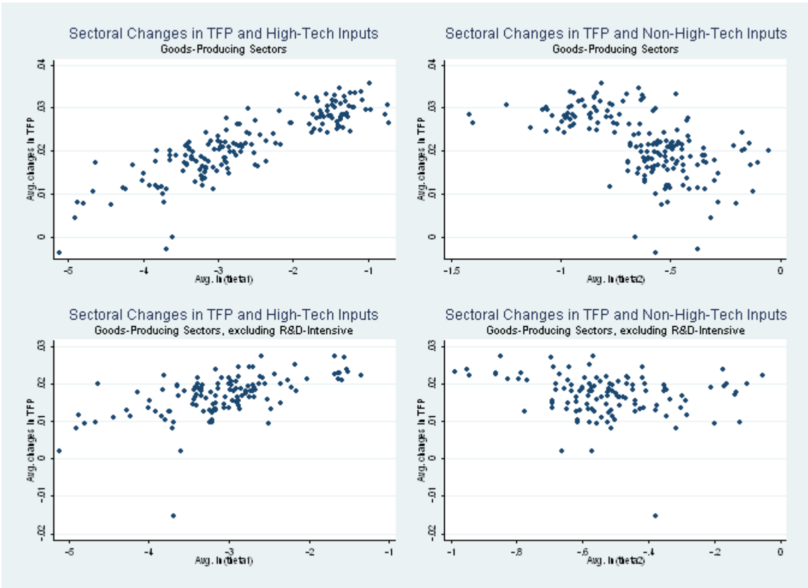


Notes: Goods-producing sectors include only manufacturing sectors. Changes in TFP reflect the partial derivative of the estimated TFP residual with respect to time. Averages are across sectors by year. *Source:* Author's calculations.

Although Figure 5 indicates a decline in TFP, this decline is not induced by the utilization of high-tech inputs. To illustrate the relationship between changes in TFP and the types of intermediate inputs, Figure 6 shows scatter plots of changes in TFP by the share of high-tech and non-high-tech inputs for goods-producing sectors with and without R&D-intensive sectors. This time, averages in changes of TFP and input shares (θ_1, θ_2) reflect averages across years by each countries' sectors. As shown, high-tech inputs are positively correlated with changes in TFP of goods-producing sectors. Such a relationship is not found for non-high-tech inputs. These findings also hold for the reduced sample, where R&D-intensive sectors are excluded.

In case of services, Table 3 also shows two columns. Column I again includes the previous results for the entire sample of services sectors, while column II represents the services sample with the sales & repair of vehicles industry excluded. According to Figure 4, it is especially this specific industry that exhibits strong shares in high-tech inputs and which may induce a bias in the estimated technology coefficients. Regarding column II, most of

Figure 6: Changes in TFP and Intermediate Inputs, by Goods-Producing Sectors



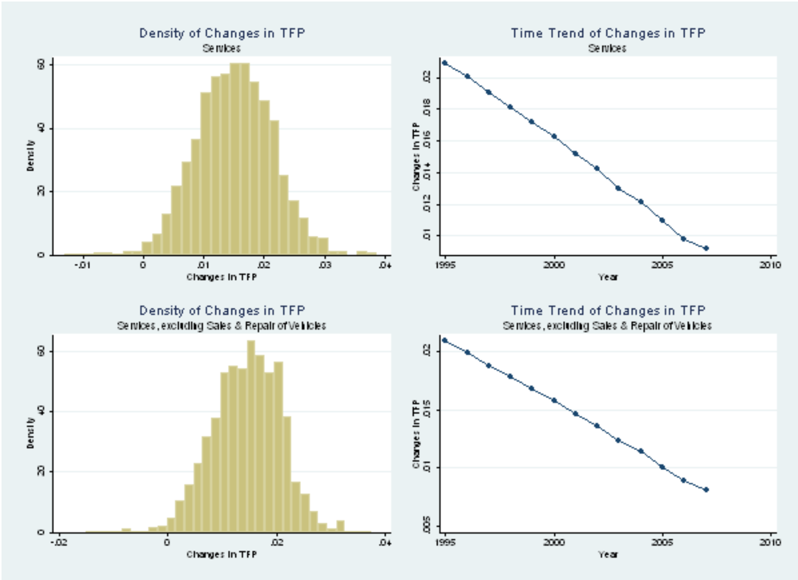
Notes: Goods-producing sectors include only manufacturing sectors. Changes in TFP reflect the partial derivative of the estimated TFP residual with respect to time. Theta1 and theta2 reflect the shares of high-tech and non-high-tech inputs in gross output, respectively. Averages are across years by sectors. *Source:* Author's calculations.

the coefficients remain of similar magnitude and statistical significance. However, with respect to the interaction of technological change and high-tech inputs, the results no longer provide empirical evidence for embodied technological change ($\gamma_{t\theta_1}$). This finding rejects the hypothesis of technology spillovers into aggregate TFP of services. Moreover, the exclusion of the sales & repair of vehicles industry also turns non-high-tech input-saving technological change to be insignificant ($\gamma_{t\theta_2}$).

A graphical representation of the change in TFP for services is shown in Figure 7, which provides the averaged partial derivative of the estimated TFP residual according to the results of Table 3. The histograms for services with and without the sales & repair of vehicles industry show a similar shape, whereas the sales & repair of vehicles industry introduces no significant variability in the TFP estimates. Regrading the trend of changes in TFP, it is declining as in case of goods-producing sectors. However, a comparison of time trends by goods-producing and services sectors for common scales in axes shows that the decline in TFP changes is much more pronounced in the latter (see Figure B.1 in the Appendix).

Although services account for an increasing share of economic activity, it is well known that their productivity performance is less positive compared to goods-producing sectors in most advanced economies, especially outside the US. Besides the European productivity slowdown, which is attributable to a slower emergence of the knowledge economy and a lower growth contributions from investment in information and communication

Figure 7: Changes in TFP, by Services



Notes: Services are market services. Changes in TFP reflect the partial derivative of the estimated TFP residual with respect to time. Averages are across sectors by year. *Source:* Author's calculations.

technology in Europe compared to the US (Van Ark et al., 2008), services' productivity potential is also hampered by government policies that were largely designed for manufacturing industries (OECD, 2001a).

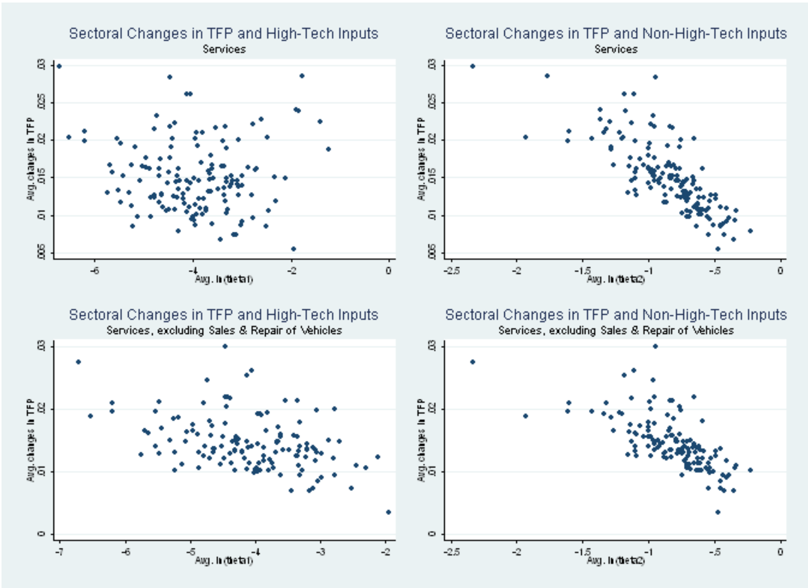
Regarding the declining trend in services' TFP as illustrated in Figure 7, scatter plots of the relationship between changes in TFP and the type of intermediate inputs suggest that there is no clear relationship between high-tech inputs for services with and without the sales & repair of vehicles industry (see Figure 8). In contrast, the scatter plots for non-high-tech inputs suggest a negative correlation with changes in TFP of services. While this holds for both samples, the negative correlation appears to be more pronounced for the entire sample, including the sales & repair of vehicles industry.

6.2. Different Time Periods

Continuing the robustness analysis, I proceed with regressing the translog specifications for different time periods. Therefore the sample is split into three periods from 1995 to 1998, from 1999 to 2003, from 2004 to 2007. In Table 4, column I always shows the period split for the entire goods-producing sample, while column II provides the results for the reduced goods-producing sample, excluding the R&D-intensive sectors.

According to column I in Table 4, the previously determined technology bias toward high-tech inputs ($\gamma_{t\theta_1}$) for goods-producing sectors is supported for the 1999–2003 period, while there is no technology bias toward non-high-tech inputs ($\gamma_{t\theta_2}$) in either of the three periods. These findings suggest that the statistical significance of high-tech input-

Figure 8: Changes in TFP and Intermediate Inputs, by Services



Notes: Services are market services. Changes in TFP reflect the partial derivative of the estimated TFP residual with respect to time. Theta1 and theta2 reflect the shares of high-tech and non-high-tech inputs in gross output, respectively. Averages are across years by sectors. *Source:* Author's calculations.

augmenting technological change as previously estimated in Table 3 (column I) mainly originates from this second period.

Regarding the reduced sample of goods-producing sectors, there is an interesting finding with respect to high-tech input-augmenting technological change ($\gamma_{t\theta_1}$). Despite a low statistical significance of technology diffusion into goods-producing sectors when estimated across the entire period (Table 3, column I), the period split supports the TFP effect from diffusion of high-tech inputs for the 1993–2003 period. In contrast, splitting the sample by time periods leaves the technology bias toward non-high-tech inputs statistically insignificant throughout all periods.

Taking stock, while the positively estimated coefficient for high-tech inputs supports the hypothesis of embodied technological change in high-tech inputs (hypothesis H_A), the significant technology bias for the reduced sample strengthens the assumption of productivity effects stemming from high-tech inputs outside the R&D-intensive sectors and therefore the hypothesis of productivity effects from embodied technology diffusion into aggregate goods-producing sectors (hypothesis H_B).

For services, the estimation results of the period split as shown in Table 5 show the most interesting results, as they weakly support the technology bias toward high-tech inputs for the 1999–2003 period (column I). However, the previous findings of input-saving technological change in case of non-high-tech inputs (Table 3, column I) are supported for the same period as well. Since there is no technology bias during both periods 1995–1998

Table 4: Translog Growth Regressions by Different Time Periods and Excluded Sectors

	Goods Producing					
	1995–1998		1999–2003		2004–2007	
	I	II	I	II	I	II
β_K	-1.362	0.212	1.849*	2.458**	1.848**	2.357***
	[2.118]	[1.995]	[1.047]	[1.112]	[0.786]	[0.807]
β_L	10.233**	9.615**	1.403	0.573	-0.876	-0.417
	[4.923]	[4.384]	[1.009]	[0.954]	[0.766]	[0.763]
β_{θ_1}	-0.651	-0.235	0.022	0.270	0.711**	0.568*
	[0.516]	[0.399]	[0.475]	[0.522]	[0.316]	[0.343]
β_{θ_2}	3.105*	5.263***	5.311**	9.285***	3.663***	2.283
	[1.786]	[1.948]	[2.369]	[3.193]	[1.129]	[1.381]
γ_t	-0.393	-0.269	0.018	0.042	-0.132	-0.029
	[0.240]	[0.247]	[0.104]	[0.114]	[0.096]	[0.108]
γ_{tt}	0.011***	0.008**	-0.005**	-0.003	0.005*	0.006*
	[0.003]	[0.003]	[0.002]	[0.003]	[0.003]	[0.004]
β_{KK}	-0.005	-0.140	-0.215	-0.309	-0.254**	-0.148
	[0.232]	[0.221]	[0.229]	[0.257]	[0.102]	[0.092]
β_{LL}	-2.861**	-2.686**	0.191	0.365**	0.327*	0.286*
	[1.372]	[1.275]	[0.195]	[0.184]	[0.195]	[0.164]
$\beta_{\theta_1\theta_1}$	0.058	0.094**	0.039	0.024	0.148***	0.104**
	[0.038]	[0.037]	[0.034]	[0.034]	[0.050]	[0.050]
$\beta_{\theta_2\theta_2}$	0.027	0.035	0.642	-0.287	1.067	-0.185
	[0.549]	[0.638]	[0.559]	[0.945]	[0.672]	[0.938]
β_{LK}	0.516	0.365	-0.325***	-0.386***	-0.133	-0.224**
	[0.353]	[0.352]	[0.071]	[0.062]	[0.102]	[0.094]
$\beta_{\theta_1 K}$	0.190*	0.244**	-0.159*	-0.200*	-0.103	-0.034
	[0.112]	[0.098]	[0.095]	[0.120]	[0.077]	[0.087]
$\beta_{\theta_2 K}$	0.581	0.826*	-1.202**	-1.765**	0.004	0.039
	[0.372]	[0.472]	[0.517]	[0.794]	[0.247]	[0.308]
$\beta_{\theta_1 L}$	-0.011	-0.120	0.179*	0.169	0.057	-0.002
	[0.120]	[0.107]	[0.091]	[0.104]	[0.064]	[0.068]
$\beta_{\theta_2 L}$	-1.113**	-1.805***	0.218	-0.094	-0.456	-0.313
	[0.431]	[0.417]	[0.396]	[0.436]	[0.297]	[0.296]
$\beta_{\theta_2\theta_1}$	0.028	0.051	0.038	0.139	0.193*	0.253**
	[0.129]	[0.122]	[0.111]	[0.115]	[0.110]	[0.119]
γ_{tK}	-0.016	-0.002	-0.032	-0.058**	-0.014	-0.040**
	[0.037]	[0.037]	[0.022]	[0.022]	[0.018]	[0.020]
γ_{tL}	0.105**	0.059	0.051***	0.067***	0.039***	0.039***
	[0.040]	[0.038]	[0.017]	[0.015]	[0.012]	[0.014]
$\gamma_{t\theta_1}$	0.004	-0.002	0.010**	0.009*	0.007	0.003
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.006]
$\gamma_{t\theta_2}$	0.006	-0.006	0.035	0.042	-0.019	-0.004
	[0.019]	[0.021]	[0.023]	[0.027]	[0.017]	[0.021]
Constant	-16.209**	-17.562***	-2.918*	-1.374	3.542	0.052
	[7.844]	[6.171]	[1.534]	[1.620]	[2.938]	[3.243]
Observations	672	480	840	600	672	480
Within R^2	0.62	0.62	0.56	0.64	0.51	0.44
# of clusters	168	120	168	120	168	120

Notes: Regressions are fixed-effects estimations controlling for time-invariant country and industry effects. Robust standard errors in brackets allow for heteroskedasticity and intra-sectoral correlated standard errors. Column I and II show the results for goods-producing sectors with and without R&D-intensive sectors, respectively. Significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%. *Source*: Author's calculations.

and 2004–2007, these findings suggest that most of the previously determined technology biases in services originate during the second period. The entire sample of services also shows non-high-tech input-augmenting technological change for the last period.

Due to the fact that the sales & repair of vehicles industry constitutes a particularity in the utilization of high-tech inputs, Table 5 also provides estimation results for the reduced sample by period split (column II). The results are in line with the estimation results for the entire sample of services, in which there is a significant effect of non-high-tech input-saving technological change during the 1999–2003 period. However, in contrast to the previous estimates of the reduced sample in (Table 3, column II), the estimates provide weak empirical evidence of TFP effects from high-tech inputs on aggregate services during the first two periods. These findings suggest that after exclusion of the sales & repair of vehicles industry there is embodied technology in high-tech inputs (hypothesis H_A) and thus aggregate productivity increases of services due to embodied technology diffusion (hypothesis H_B). Noteworthy is also the positive TFP effect of non-high-tech inputs during the last period for the entire services sample, which turns statistically insignificant as soon as the sales & repair of vehicles industry is excluded from the sample.

7. Discussion

The setup of the model describes a mechanism that triggers productivity increases on the sectoral level. According to the idea of Romer (1990) it is the capability of R&D-intensive sectors to produce high-tech intermediate inputs that embody technologies that are utilized in the production process of other sectors (process innovations). Productivity in this setup is thus driven by research spillovers whereby each user of high-tech inputs benefits from the whole existing stock of high-tech innovations. In a standard Romer model productivity additionally originates from the increased specialization of labor that works along an increasing number of intermediate inputs. This is not explicitly modeled in this setup, but implicitly assumed. Furthermore, the model implicitly assumes that high-tech inputs are non-rival in nature, so that they can be used freely by other sectors in their own research activities. However, to some extend high-tech inputs are excludable to reward monopoly rents. In particular, it is these rents that motivate research activities aimed at discovering new varieties of high-tech inputs. A limitation of this model is that it does not capture any effects of creative destruction referred to by Schumpeter, which were developed in Aghion and Howitt (1992). More precisely, there is no role of entry or exit in the generation of output and productivity.

In a recent paper by Broda et al. (2006) the authors estimate the trade-induced effect of input variety on productivity. Therefore the authors analyze bilateral trade flows between 73 countries over the period from 1994 to 2003. From a production function setup they derive a model of TFP growth, in which a a higher share of intermediate goods results in a higher impact of increased input variety on TFP. According to their findings growth in new input varieties over the period from 1994 to 2003 increased a country's productivity only by 0.13 percent. The relationship between input variety and productivity is even lower for developed countries. Hence, the authors argue that most of the productivity growth in many of the largest countries cannot be accounted for by new imported inputs. A main argument against Broda et al. (2006) is that choosing only

Table 5: Translog Growth Regressions by Different Time Periods and Excluded Sectors

	Services					
	1995–1998		1999–2003		2004–2007	
	I	II	I	II	I	II
β_K	4.874**	5.234**	3.471***	3.471***	-0.457	-0.467
	[2.321]	[2.430]	[0.900]	[0.901]	[0.500]	[0.541]
β_L	-9.040**	-6.718*	-0.406	-0.285	0.059	0.354
	[3.862]	[3.921]	[1.505]	[1.527]	[0.881]	[0.927]
β_{θ_1}	0.292	0.103	0.116	0.233	0.603	0.781
	[0.330]	[0.377]	[0.315]	[0.353]	[0.425]	[0.487]
β_{θ_2}	0.524	0.987	-0.587	-1.008	1.748	1.249
	[1.031]	[1.191]	[1.415]	[1.485]	[1.081]	[1.275]
γ_t	0.004	0.056	-0.070	-0.048	-0.033	-0.052
	[0.236]	[0.248]	[0.131]	[0.131]	[0.092]	[0.093]
γ_{tt}	0.001	0.001	-0.006**	-0.006**	0.002	0.003
	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]
β_{KK}	-0.342	-0.352	-0.130	-0.112	-0.270**	-0.293***
	[0.263]	[0.277]	[0.104]	[0.113]	[0.105]	[0.110]
β_{LL}	2.640***	2.235**	0.726*	0.736**	-0.563**	-0.660**
	[0.950]	[0.973]	[0.370]	[0.365]	[0.281]	[0.301]
$\beta_{\theta_1\theta_1}$	0.053***	0.045**	0.012	0.016	0.010	0.029
	[0.019]	[0.020]	[0.014]	[0.014]	[0.025]	[0.032]
$\beta_{\theta_2\theta_2}$	0.630***	0.613***	0.699***	0.670***	0.924***	1.135***
	[0.192]	[0.217]	[0.183]	[0.199]	[0.284]	[0.358]
β_{LK}	-0.634	-0.699	-0.534***	-0.563***	0.399**	0.418**
	[0.451]	[0.461]	[0.170]	[0.163]	[0.161]	[0.167]
$\beta_{\theta_1 K}$	-0.008	-0.018	-0.051	-0.088**	0.000	-0.008
	[0.048]	[0.053]	[0.035]	[0.044]	[0.042]	[0.069]
$\beta_{\theta_2 K}$	0.120	0.172	0.525***	0.661***	-0.228	-0.240
	[0.160]	[0.167]	[0.171]	[0.194]	[0.141]	[0.203]
$\beta_{\theta_1 L}$	-0.007	0.039	0.035	0.047	-0.136*	-0.159
	[0.061]	[0.078]	[0.061]	[0.064]	[0.075]	[0.097]
$\beta_{\theta_2 L}$	-0.040	-0.169	-0.134	-0.177	-0.065	0.038
	[0.213]	[0.259]	[0.202]	[0.211]	[0.219]	[0.274]
$\beta_{\theta_2\theta_1}$	-0.025	-0.002	0.014	0.014	-0.122**	-0.186**
	[0.035]	[0.043]	[0.042]	[0.046]	[0.057]	[0.086]
γ_{tK}	0.028	0.030	0.029*	0.028*	-0.004	-0.004
	[0.038]	[0.040]	[0.016]	[0.016]	[0.011]	[0.011]
γ_{tL}	-0.023	-0.035	-0.007	-0.009	0.014	0.015
	[0.044]	[0.045]	[0.023]	[0.024]	[0.016]	[0.017]
$\gamma_{t\theta_1}$	0.003	0.006*	0.004*	0.007*	-0.001	-0.001
	[0.002]	[0.003]	[0.002]	[0.004]	[0.002]	[0.004]
$\gamma_{t\theta_2}$	-0.008	-0.015	-0.036***	-0.045***	0.020***	0.018
	[0.009]	[0.011]	[0.006]	[0.010]	[0.008]	[0.012]
Constant	13.893	7.334	-3.773	-4.066	7.163***	6.839***
	[10.041]	[10.360]	[4.048]	[4.092]	[1.986]	[2.131]
Observations	573	525	718	658	568	520
Within R^2	0.78	0.79	0.58	0.58	0.58	0.58
# of clusters	144	132	144	132	143	131

Notes: Regressions are fixed-effects estimations controlling for time-invariant country and industry effects. Robust standard errors in brackets allow for heteroskedasticity and intra-sectoral correlated standard errors. Column I and II show the results for services with and without the sales & repair of vehicles industry, respectively. Significance levels: * significant at 10%; ** significant at 5%; *** significant at 1%. *Source*: Author's calculations.

imported inputs underestimates the effects of input variety in more developed countries, which are likely to play a more important role in developed countries.

8. Conclusion

Intermediate inputs constitute an important part of industrialized economies' value chains. Their importance is not only demonstrated by its large shares in gross output, but also due to the fact that modern economies are more and more characterized by strong sectoral interconnection. As intermediate inputs are important parts of higher value products on later stages of assembly, they encapsulate innovation efforts of upstream sectors and thus facilitate technology diffusion throughout the economy. As usually technology is assumed to be exclusively embodied in capital, the purpose of the paper is in analyzing the importance of embodied technology in intermediate inputs as well as the validity of embodied technology diffusion on sectoral productivity. Therefore two hypotheses are formally tested, in which the first hypothesis postulates that there is embodied technological change in intermediate inputs, especially in high-tech input. The second hypothesis postulates given that there is embodied technological change in high-tech inputs that there is embodied technology diffusion that increases aggregate productivity via use of such high-tech inputs in firms' production process. The empirical evidence of this paper for a sample of 12 OECD countries shows that there is indeed a bias in technological change toward high-tech inputs and embodied technology diffusion is a source of sectoral productivity increases. However, the effect is more pronounced for goods-producing sectors.

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AppendixA. Tables

Table A.1: Variable List

Variable	Description
GO	Gross output by industry at current basic prices (national currency)
GO_real	Real gross output by industry, volume indices (1995 = 100)
K_real	Real fixed capital stock, volume indices (1995 = 100)
H	Total hours worked by persons engaged, volume indices (1995 = 100)
II	Intermediate inputs at current purchasers' prices (national currency)
II_HT	High-tech intermediate inputs at current purchasers' prices
II_NHT	Non-high-tech intermediate inputs at current purchasers' prices

Table A.2: Country Coverage

Country
Germany
France
Italy
Sweden
Finland
Netherlands
Denmark
United Kingdom
United States
Canada
Australia
Japan

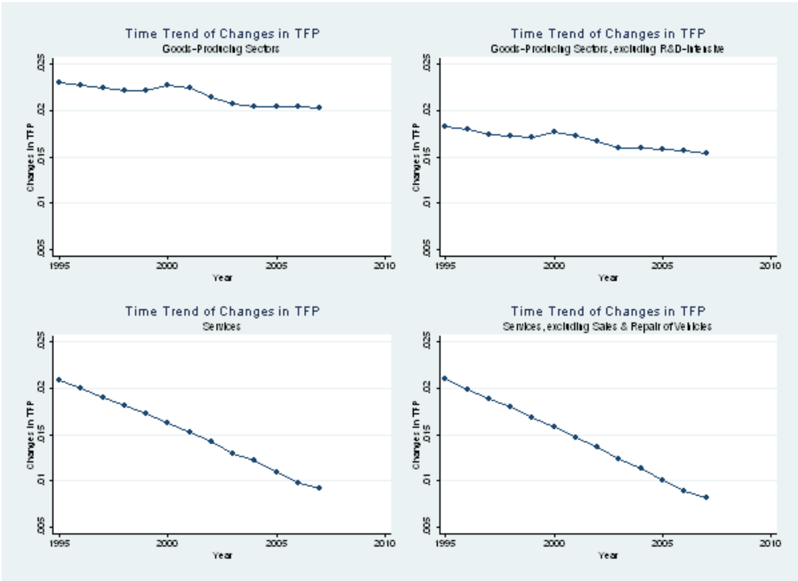
Table A.3: Sectoral Coverage, Size, and R&D Intensity

SIC-Code	Sector	Avg. Output Share	R&D Intensity
AtB	AGRICULTURE, FORESTRY & FISHING		
C	MINING & QUARRYING		
15t16	FOOD, BEVERAGES & TOBACCO	0.05	Not
17t18	Textiles and textile	0.01	Not
19	Leather, leather and footwear	0.00	Not
20	WOOD AND OF WOOD AND CORK	0.01	Not
21t22	PULP, PAPER, PRINTING & PUBLISHING	0.03	Not
23	Coke, refined petroleum & nuclear fuel	0.02	Not
24	Chemicals and chemical	0.04	Intensive
25	Rubber and plastics	0.01	Not
26	OTHER NON-METALLIC MINERAL	0.01	Not
27t28	BASIC METALS & FABRICATED METAL	0.06	Not
29	MACHINERY, NEC	0.04	Intensive
30t33	ELECTRICAL & OPTICAL EQUIPMENT	0.04	Intensive
34t35	TRANSPORT EQUIPMENT	0.05	Intensive
36t37	MANUFACTURING NEC; RECYCLING	0.01	Not
E	ELECTRICITY, GAS & WATER SUPPLY		
F	CONSTRUCTION		
50	Sale/repair of vehicles; retail sale of fuel	0.02	Not
51	Wholesale trade	0.07	Not
52	Retail trade; repair of household goods	0.05	Not
H	HOTELS & RESTAURANTS	0.03	Not
60	Other Inland transport	0.03	Not
61	Other Water transport	0.01	Not
62	Other Air transport	0.01	Not
63	Other auxiliary transport activities	0.02	Not
64	POST & TELECOMMUNICATIONS	0.03	Not
J	FINANCIAL INTERMEDIATION	0.08	Not
70	Real estate activities	0.11	Not
71t74	Renting of m&eq and other business activities	0.14	Not

Notes: Goods-producing sectors include only manufacturing sectors, i.e. from SIC code 15 to 37. Services are market services. Output shares sum up to 1.00 and refer to industry averages across countries in 2007. Classification of R&D intensity is based on OECD (2011).

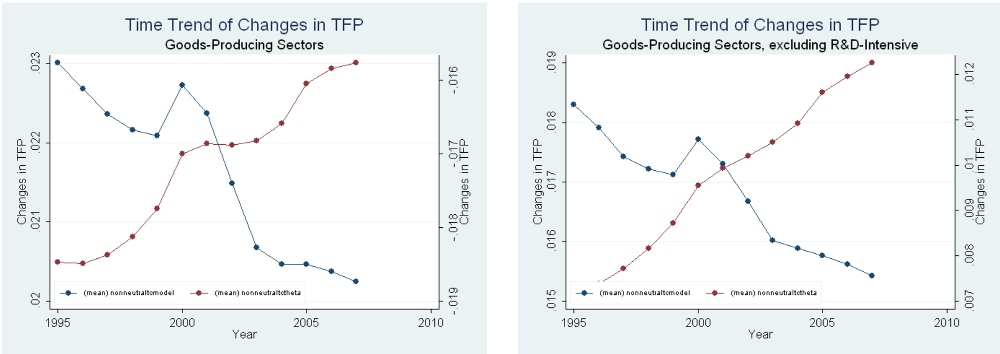
AppendixB. Figures

Figure B.1: Changes in TFP, by Goods-Producing and Services Sectors



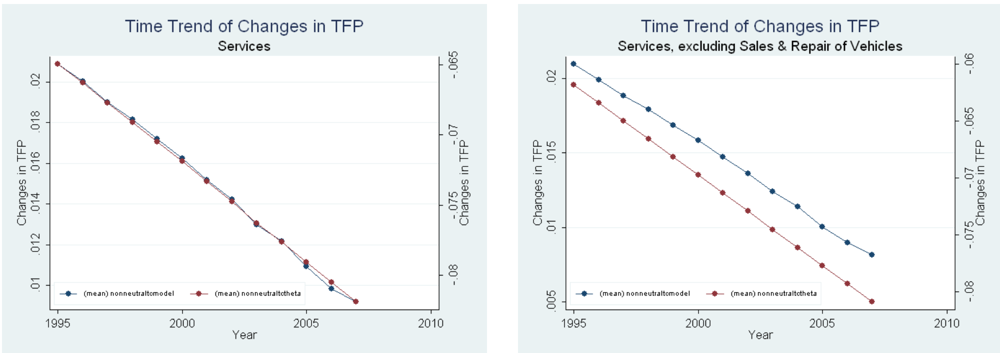
Notes: Goods-producing sectors include only manufacturing sectors. Services are market services. Changes in TFP reflect the partial derivative of the estimated TFP residual with respect to time.

Figure B.2: Changes in TFP, by Goods-Producing Sectors



Notes: Goods-producing sectors include only manufacturing sectors. Changes in TFP reflect the partial derivative of the estimated TFP residual with respect to time. Averages are across sectors by year. *Source:* Author's calculations.

Figure B.3: Changes in TFP, by Services



Notes: Services are market services. Changes in TFP reflect the partial derivative of the estimated TFP residual with respect to time. Averages are across sectors by year. *Source:* Author's calculations.

AppendixC. Theoretical Underpinning: Extension

For illustration of the mechanism between intermediate inputs, technological change, and output, the relationship is modeled in a simple version of the original Romer model (Romer, 1990), which is a modified version of the product variety model presented in Aghion and Howitt (2009). It is assumed that there is a continuum of intermediate inputs x_i (i.e. no distinct separation into high-tech and non-high-tech), whereas the total amount of intermediate inputs produced resembles the total amount of final goods used in the production of intermediate inputs, X_t:

$$X_t = \int_0^{M_t} x_i di \tag{C.1}$$

and that final output is produced under perfect competition given the simplified production function

$$Y_t = L_t^{1-\alpha} X_t^{\alpha} \tag{C.2}$$

where Y_t is output and L resembles a fixed supply labor. The final good is used for consumption and investment (in producing blueprints). Its only other use is in producing intermediate products. The rational behind the production function incorporates the degree of intermediate inputs X_t as the economy's aggregate productivity parameter, which determines the economy's long-run growth rate. Hence it represents a stock of embodied technological change. More inputs raise the economy's production potential because a given stock of new inputs is allowed to be spread over a larger number of uses. Each intermediate input is monopolized by the person who created it, hence new innovations result from R&D investments by researchers who are motivated by the prospect of such monopoly rents and thus act as monopolists in the production of intermediate inputs.

Regarding labor supply it is assumed that there is a fixed number L of households, whereas no one has a demand for leisure time, so each person offers labor inelastically (i.e. independently of the wage rate). The household's utility each period depends only on consumption, c, according to an isoelastic function:

$$u(c) = \frac{c^{1-\epsilon}}{1-\epsilon}, \epsilon > 0 \tag{C.3}$$

with ϵ resembling the substitution parameter between present and future consumption. Furthermore, the household discounts utility using a constant rate of time preference, ρ. This means that in the steady state the growth rate of output, g, and the interest rate, r, must obey the Euler equation, which can be written as

$$g = \frac{r-\rho}{\epsilon} \tag{C.4}$$

Regarding the monopolist, he seeks to maximize the flow of profits, which are measured in units of the final good:

$$\Pi_i = p_i x_i - x_i \tag{C.5}$$

where p_i is the price in units of the final good. As shown in equation C.5 the monopolist's output equals the revenue (price times quantity) and his costs. Since the price of an input in a perfectly competitive industry is the value of its marginal product, it can be formulated

$$\frac{\partial Y_t}{\partial x_i} = \alpha L_t^{1-\alpha} x_i^{\alpha-1} = p_i \tag{C.6}$$

Therefore the monopolist's profit is calculated according to

$$\Pi_i = \alpha L^{1-\alpha} x_i^{\alpha} - x_i \tag{C.7}$$

Maximizing his profit, the monopolist will choose x in such way that it obeys the the first-order condition

$$\frac{\partial \Pi_i}{\partial x_i} = \alpha^2 L^{1-\alpha} x_i^{\alpha-1} - 1 = 0 \tag{C.8}$$

Form this follows that the equilibrium quantity will be the same constant in every sector i:

$$x = L\alpha^{\frac{2}{1-\alpha}} \tag{C.9}$$

and so will the equilibrium profit flow:

$$\Pi = \frac{1-\alpha}{\alpha} L\alpha^{\frac{2}{1-\alpha}} \tag{C.10}$$

To see how the mechanism affects output growth, it is assumed that output changes proportionally with inputs:

$$g = \frac{dY_t}{dt}\frac{1}{Y_t} = \frac{dX_t}{dt}\frac{1}{X_t} \tag{C.11}$$

Modeling the driving forces of inputs, it is supposed that inputs grow at a rate that depends on the amount R, which is the final output that is used in research (note, there is not explicit modeling of sectors characterized by *different* Rs). Alternatively, the output of research in each period is the flow of blueprints allowing new inputs to be developed; hence, changes in the production of inputs are determined according to

$$\frac{dX}{dt} = \lambda R \tag{C.12}$$

where λ is a (positive) parameter indicating the productivity of the research.

Assuming that research is perfectly competitive with free entry then the flow of profit from research activities must be equal to zero. Each blueprint is worth Π/r, which reflects the present value of the profit flow, Π, discounted at the market interest rate, r. Hence, the flow of profit from research is

$$(\Pi/r)\lambda R - R \tag{C.13}$$

which just resembles revenues (price, Π/r), times output, λR) minus costs (R). For this to be zero, a rate of interest is needed that satisfies the subsequent research-arbitrage equation:

$$r = \lambda \Pi \tag{C.14}$$

That is, the rate of interest must equal the flow of profit that an innovating sector can receive per unit invested in research. Substituting equation (C.14) into equation (C.4) yields

$$g = \frac{\lambda \Pi - \rho}{\epsilon} \tag{C.15}$$

Further substituting equation (C.10) in equation (C.15) yields the following expression for the equilibrium growth rate:

$$g = \frac{\lambda \frac{1-\alpha}{\alpha} L \alpha^{\frac{2}{1-\alpha}} - \rho}{\epsilon} \tag{C.16}$$

where output growth positively depends on productivity of research, λ, and the size of the economy, L.

In the outlined innovation-based growth model, innovations take place with the same average frequency in all intermediate sectors, measured by the parameter R. In reality, however, some sectors are persistently more innovative than others and thus show different R&D intensities. Because of this, I explicitly account for different R&D intensities by sectors and their intermediate inputs produced, which are high-tech and non-high-tech inputs. From this follows

$$\frac{dH}{dt} = \lambda_h R_h \tag{C.17}$$

$$\frac{dM}{dt} = \lambda_n R_n \tag{C.18}$$

where H resembles high-tech inputs (produced by R&D-intensive sectors with λ_h and R_h) and M is non-high-tech inputs (produced by non-R&D-intensive sectors with λ_n and R_n).

Allowing for differences in R&D intensities by sectors introduces the mechanism of biases in technological change. This is because differences in sectoral R&D intensities often originate from their size. This is as it is more profitable to innovate in a larger sector because a successful innovator has a larger market there. Hence, technological change tends to be biased more toward larger sectors than smaller ones. Regarding the size of sectors, measured as sectoral output share in total output, Table A.3 shows that R&D-intensive sectors indeed belong to those sectors with the highest output shares in goods-producing sectors.

Relaxing the assumption of constant returns to scale in equation (C.2) and extending the production function by introduction of capital and separation of X into H and M yields

$$Y_t = (K_t^{\alpha} L_t^{\beta})^{1-\theta_1-\theta_2} H_t^{\theta_1} M_t^{\theta_2} \tag{C.19}$$

with intermediate inputs substituting for value added reflected by the substitution parameters θ_1 and θ_2. H and M again represent a stocks of embodied technological change that drives output growth, whereas H is assumed to incorporate a higher fraction of technology as these input are produced by R&D-intensive sectors. A confirmation of the positive effect of both types of intermediate inputs is shown in the regression results in Table 1, where the proxy for technological change is excluded from the regression (column II). However, the *direct* impact of H on output is much lower than for M.

Now, besides assuming that technological change is entirely embodied in intermediate inputs, technological change as measured by A can also be modeled explicitly. Presuming that A is Hicks neutral and thus is affecting all inputs equally, equation (C.19) can be formulated according to

$$Y_t = A(K_t^{\alpha} L_t^{\beta})^{1-\theta_1-\theta_2} H_t^{\theta_1} M_t^{\theta_2} \tag{C.20}$$

whereas there is no bias in technological change toward specific input factors. Instead, allowing for technology biases equation (C.19) can be modeled with specific technology parameters for all input factors explicitly

$$Y_t = [(A_K K_t)^{\alpha}(A_L L_t)^{\beta}]^{1-\theta_1-\theta_2}(A_H H_t)^{\theta_1}(A_M M_t)^{\theta_2} \tag{C.21}$$

Since A_H and A_M reflect the technology biases toward high-tech and non-high-tech inputs, a positively (negatively) estimated coefficient suggests input-augmenting (-saving) technological change, whereas especially the augmentation in high-tech inputs serves as confirmation of the embodied hypothesis of high-tech inputs (hypothesis H_A). The different sectoral productivity parameters of research, measured as λ, and which are assumed to be time invariant in nature, may introduce an endogeneity issue between Y_t and H and M. However, by applying fixed-effects estimation methods this endogeneity issue is mitigated as such unobserved individual heterogeneity is purged from the regression.

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