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Intermediate Goods-Skill Complementarity

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Intermediate Goods–Skill Complementarity*

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Abstract

With the growing importance of intermediate goods, recent studies begin to suggest intermediate goods–skill complementarity and its potential effect on inequality. However, this possible complementarity has not yet been formally tested. This paper conducts a formal test on whether intermediate goods are complements for skilled labor. Using the panel data of 40 countries over the period 1995–2009, we estimate a two-level CES production function. Our results indicate that, at the aggregated one-sector level, the elasticity of substitution between intermediate goods and unskilled labor is significantly greater than that between intermediate goods and skilled labor. This confirms intermediate goods–skill complementarity. At the more disaggregated level, such complementarity is observed mainly in the heavy manufacturing industries and the service sector, whereas substitutability is confirmed in the primary sector and in light manufacturing industries. Moreover, intermediate goods–skill complementarity tends to be higher for industries whose shares of imported intermediate goods are higher.

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1 Introduction

The elasticity of substitution between goods or between factors is one of the most important parameters in the various fields of economics. On the elasticity of substitution between goods, many studies have argued that it is essential for understanding welfare gains from trade. Arkolakis et al. (2012), for example, showed that the welfare predictions of an important class of trade models depend only on two sufficient statistics, one of which is the trade elasticity.[1] It is one minus the elasticity of substitution between goods in Armington models.[2]

On the elasticity of substitution between factors, a number of studies have considered whether an input is more complementary with skilled or unskilled labor. This is because clarifying such complementarity/substitutability has important implications for wage inequality. In the wage inequality literature, previous studies have focused mainly on the hypothesis of capital–skill complementarity, a form of skill-biased technological change (SBTC), which was proposed by Griliches (1969).[3] Using cross-country data, Fallon and Layard (1975) formally showed evidence for this hypothesis by estimating the elasticity of substitution between capital and skilled labor and that between capital and unskilled labor. Since then, further elasticity estimations have been developed (e.g., Krusell et al., 2000; Duffy et al., 2004). Using the estimated elasticity parameters, many studies have shown that the growth in capital is quantitatively important for increased wage inequality with capital–skill complementarity (e.g., Krusell et al., 2000).[4] Moreover, upon application of capital–skill complementarity, Burstein et al. (2013) and Parro (2013) quantitatively showed that the growth in capital caused by the importing of capital goods can significantly increase wage inequality through capital–skill complementarity.[5]

Recent studies begin to suggest the effects of another possible complementarity on wage inequality. For example, Crinò (2012) utilized firm-level data for 27 transition countries and found significantly positive effects of imported inputs on the relative demand for skilled labor. This is because importing inputs leads firms to engage in high-skill intensive activities, such as the production of new and better goods and R&D/technology adoption. Similarly, using Indonesian plant-level data, Kasahara et al. (2016) showed that importing intermediate goods increased the relative demand for

[1]Trade elasticity refers to the elasticity of imports with respect to variable trade costs.

[2]The Armington models are based on the simplifying assumption that goods are differentiated by country of origin and each good enters preferences in a Dixit–Stiglitz fashion.

[3]SBTC is a change in the production technology that favors skilled over unskilled labor by increasing its relative productivity and, thus, its relative demand. Capital–skill complementarity is one of the forms of SBTC. In the production function, SBTC can be captured by such parameters as the elasticity of substitution and factor-specific productivity. For more detail, see Violante (2008).

[4]Some countries, such as Japan, have seen a decline in wage inequality over recent decades. Hara et al. (2014), for example, showed quantitatively that the decline in capital–skill complementarity in the non-manufacturing sector can account for the decline in wage inequality in Japan since the mid-1990s.

[5]In the models of Burstein et al. (2013) and Parro (2013), domestic and imported capital goods are homogeneous and thus the degree of capital–skill complementarity is the same for both capital goods.

educated workers.[6] These, when taken together with Burstein et al. (2013) and Parro (2013), imply intermediate goods–skill complementarity as another form of SBTC. Theoretically, the intermediate goods–skill complementarity hypothesis has been documented by Kurokawa (2011). It indicates that the growth in intermediate goods, due to increased imports or increased domestic production of intermediate goods, can raise wage inequality through intermediate goods–skill complementarity.[7]

In fact, as Figure 1 indicates, the ratio of intermediate goods to gross output was almost half in 1995 and has expanded since that date.[8] Specifically, it grew from 48.4 percent in 1995 to 55.8 percent in 2008 for all countries (solid line), from 47.7 percent to 52.5 percent for Organisation for Economic Co-operation and Development (OECD) countries (dashed line), and from 53.6 percent to 69.8 percent for non-OECD countries (dotted line), although it declined slightly from 2008 to 2009 for the first two cases. Thus, given the possibility of the complementarity between intermediate goods and skilled labor, the growth in intermediate goods might be another important source of increasing wage inequality.

[Figure 1 about here.]

Empirically, however, to our knowledge, unlike capital–skill complementarity, no formal test has been conducted on intermediate goods–skill complementarity.[9] More specifically, let $\sigma_{i,j}$ be the elasticity of substitution between factors i and j. Denote capital, skilled labor, unskilled labor, and intermediate goods by K, S, U, and X, respectively. Then, while we know that evidence suggested $\sigma_{K,U} > \sigma_{K,S}$ (e.g., Fallon and Layard, 1975; Krusell et al., 2000), we do not yet know the relationship between $\sigma_{X,U}$ and $\sigma_{X,S}$. Thus, it is not clear whether intermediate goods–skill complementarity exists. Without the estimated $\sigma_{X,U}$ or $\sigma_{X,S}$, we cannot also quantify the effect of the increasing use of intermediate goods on wage inequality with complementarity/substitutability.

Based on this background, this paper now formally tests whether intermediate goods are complements for skilled labor, by estimating the elasticity of substitution

[6] Empirically, our study is also related to studies of outsourcing and wage inequality. For example, Feenstra and Hanson (1999) and Hummels et al. (2014) found that outsourcing increases wage inequality between skilled and unskilled labor at the industry and firm levels, respectively. They measured outsourcing as the imports of intermediate inputs (belonging to the same industry as that of goods being produced). Noting that outsourcing generally occurs domestically as well as internationally, their analysis implies that the increase in outsourcing also leads to the use of new domestic intermediate goods.

[7] Kurokawa (2011) showed that the importing of intermediate goods increases intermediate goods and that, if intermediate goods and skilled labor are complements, wage inequality increases in both of the trading countries. His model implies that an increase in intermediate goods can also be caused by a rise in productivity or a decrease in fixed costs for firms that produce intermediate goods.

[8] The data are from the Socio Economic Accounts of the World Input-Output Database released in July 2014. In Section 2, we present a more detailed description of the data.

[9] Of course, there are empirical studies that also focused on intermediate goods, skilled, and unskilled labor. Hijzen et al. (2005) and Kiyota and Maruyama (2017), for example, estimated the price elasticities of factor demand, employing a translog functional form. None of these studies, however, provided a formal test for intermediate goods–skill complementarity.

between intermediate goods, skilled labor, and unskilled labor. More specifically, using panel data from 40 countries over the period 1995–2009, we estimate the elasticity of substitution between intermediate goods and skilled labor and that between intermediate goods and unskilled labor at the level of the aggregate sector and the level of each manufacturing industry. In this paper, we focus on the two-level CES specifications because they have been used commonly in the literature on the complementarity between capital/intermediate goods and skill.

The remainder of this paper is organized as follows. Section 2 describes the methodology and data used in this paper. Section 3 presents the results. Section 4 concludes the paper and mentions future research.

2 Methodology and Data

2.1 Methodology

2.1.1 CES production function

The hypothesis of intermediate goods–skill complementarity states that intermediate goods are more complementary with skilled labor than with unskilled labor. More formally, suppose that there are four factors of production: intermediate goods X, skilled labor S, unskilled labor U, and capital K, and that gross output Y is determined by:

$$Y = f(X, S, U, K). \tag{1}$$

Denote by $\sigma_{i,j}$ the elasticity of substitution between inputs i and j. Then intermediate goods–skill complementarity holds if:

$$\sigma_{X,U} > \sigma_{X,S}. \tag{2}$$

Its key implication is that growth in intermediate goods increases the demand for skilled labor more than the demand for unskilled labor. Therefore, intermediate goods–skill complementarity is a form of SBTC.

In this paper, by applying Fallon and Layard (1975) and Krusell et al. (2000), we use a CES production function and linear estimation to test the intermediate goods–skill complementarity hypothesis. Our baseline functional form is:[10]

$$Y = AK^{\alpha}\left[aQ^{\rho} + (1-a)U^{\rho}\right]^{\frac{1-\alpha}{\rho}} \quad (0 < \alpha < 1, \rho < 1), \tag{3}$$

where

$$Q = \left[bX^{\theta} + (1-b)S^{\theta}\right]^{\frac{1}{\theta}} \quad (\theta < 1). \tag{4}$$

[10] Section 3.2.1 employs alternative functional forms to check the robustness of our results.

In this specification, ρ and θ govern the elasticity of substitution between intermediate goods, skilled labor, and unskilled labor. The elasticity of substitution between intermediate goods (or skilled labor) and unskilled labor $\sigma_{X,U}$ is given by $1/(1-\rho)$, while that between intermediate goods and skilled labor $\sigma_{X,S}$ is given by $1/(1-\theta)$. Then the intermediate goods–skill complementarity hypothesis $\sigma_{X,U} > \sigma_{X,S}$ holds iff $1/(1-\rho) > 1/(1-\theta)$ or $\rho > \theta$.

Here, as do Krusell et al. (2000), we have extended the three-factor CES approach of Fallon and Layard (1975) to a four-factor CES approach. In particular, we have assumed that the production function is Cobb–Douglas over capital and a CES function of the three remaining inputs.[11] While translog is a more flexible functional form than CES, we employ the CES form because the CES production function has been commonly used in the literature on the complementarity between capital/intermediate goods and skill (e.g., Fallon and Layard, 1975; Krusell et. al., 2000; Duffy et al., 2004; Kurokawa, 2011).

Suppose that the goods and factor markets are perfectly competitive.[12] Let the price of intermediate goods, the wages of skilled labor, and unskilled labor be p^X, w^S, and w^U, respectively. Then, we can obtain the following two equations from the condition that price equals marginal product:

$$\log \frac{p^X}{w^S} = \log \frac{b}{1-b} + (\theta - 1) \log \frac{X}{S}, \tag{5}$$

$$\log \frac{q}{w^U} = \log \frac{a}{1-a} + (\rho - 1) \log \frac{Q}{U}, \tag{6}$$

where

$$Q = \left[bX^\theta + (1-b)S^\theta \right]^{\frac{1}{\theta}} \tag{7}$$

and

$$q = \left[b^{\frac{1}{1-\theta}} p^{X,-\frac{\theta}{1-\theta}} + (1-b)^{\frac{1}{1-\theta}} w^{S,-\frac{\theta}{1-\theta}} \right]^{-\frac{1-\theta}{\theta}}. \tag{8}$$

Equations (5)–(8) are used to investigate the relationship between ρ and θ.

[11] To test the hypothesis of capital–skill complementarity, Krusell et al. (2000) used a production function with four factors: capital equipment, skilled labor, unskilled labor, and capital structure. It is Cobb–Douglas over the capital structure and CES for the three remaining factors. Our production function is similar to theirs in that both are Cobb–Douglas over the factor that is not of interest and CES for the three remaining factors that are of interest.

[12] As we will discuss below, the imposition of the first-order condition enables us to estimate the elasticities for all the industries without violating the basic assumptions of the CES production function. Moreover, it enables us to estimate θ and ρ without information on the user cost of capital or real capital stock, both of which are not easy to measure in a precise manner.

2.1.2 Estimating equations

By introducing country c and time t dimensions and error terms to equations (5) and (6), the regression equations are written as follows:

$$\log \frac{p_{ct}^X}{w_{ct}^S} = \gamma_c + \log \frac{b}{1-b} + (\theta - 1) \log \frac{X_{ct}}{S_{ct}} + \varepsilon_{ct}, \tag{9}$$

$$\log \frac{\hat{q}_{ct}}{w_{ct}^U} = \lambda_c + \log \frac{a}{1-a} + (\rho - 1) \log \frac{\hat{Q}_{ct}}{U_{ct}} + \mu_{ct}, \tag{10}$$

where γ_c and λ_c are the country fixed effects that control for some of the unobserved time-invariant country characteristics, such as institutional differences in labor market[13]; ε_{ct} and μ_{ct} are error terms;

$$\hat{Q}_{ct} = \left[\hat{b} X_{ct}^{\hat{\theta}} + (1-\hat{b}) S_{ct}^{\hat{\theta}}\right]^{\frac{1}{\hat{\theta}}} \tag{11}$$

and

$$\hat{q}_{ct} = \left[\hat{b}^{\frac{1}{1-\hat{\theta}}} p_{ct}^{X,-\frac{\hat{\theta}}{1-\hat{\theta}}} + (1-\hat{b})^{\frac{1}{1-\hat{\theta}}} w_{ct}^{S,-\frac{\hat{\theta}}{1-\hat{\theta}}}\right]^{-\frac{1-\hat{\theta}}{\hat{\theta}}}. \tag{12}$$

Note that equations (9) and (10) have a traditional endogeneity problem: unobserved supply shocks may affect both factor prices and factor inputs simultaneously. These equations also have an errors-in-variables problem, or, more specifically, a generated regressor problem. This is because both $\hat{Q}$ and $\hat{q}$ include estimated coefficients in equation (9) and thus equation (9) has to be estimated before equation (10).[14] To alleviate these problems, we add the following three remedies. First, to address the endogeneity problem, we employ an instrumental variable (IV) method for the estimation, where we use the lagged independent variable as an IV.

Second, to reduce the estimated coefficient bias, we take *long* differences. As Griliches and Hausman (1986) noted, the bias is reduced when long differences are utilized in the errors-in-variables problem. Taking the long differences for equation (10), we have:

$$\Delta \log \frac{\hat{q}_{ct}}{w_{ct}^U} = (\rho - 1) \Delta \log \frac{\hat{Q}_{ct}}{U_{ct}} + \Delta \mu_{ct}, \tag{13}$$

where Δ indicates the long differences (we take 5-year differences).

Finally, to obtain valid standard errors, we employ bootstrap techniques. As Redding and Venables (2004) argued, this allows us to obtain standard errors that explicitly take into account the presence of generated regressors.[15] Adding these three remedies

[13] We focus on the average $\hat{b}$ rather than the country-specific $\hat{b}_c$ that can be computed from the estimated intercept and $\hat{\gamma}_c$ This is because γ_c is not a free parameter with the constraint $\sum_c \gamma_c = 0$.

[14] In addition, the variables are not the coefficients themselves but are generated from the coefficients. It is thus infeasible to apply system equation estimation methods, such as seemingly unrelated regressions.

[15] Similarly, Brülhart and Trionfetti (2009) also employed bootstrap techniques to address the generated

enables us to estimate both the coefficients and standard errors in a precise manner.[16]

In sum, we estimate the equations (9) and (13) in the following three steps. First, we estimate equation (9), including a country fixed effect. Second, we construct $\hat{Q}$ and $\hat{q}$, using equations (11) and (12) and the estimates of $\hat{b}$ and $\hat{\theta}$. Finally, we estimate equation (13), using the information on $\hat{Q}$ and $\hat{q}$.[17] The estimation of equations (9) and (13) is based on IV methods.

2.2 Data

This paper utilizes the Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014, which cover the period from 1995 to 2009.[18] The WIOD is built on national accounts data that were developed within the Seventh Framework Program of the European Commission. The WIOD provides time-series information on the global IO tables for the EU27 countries, 13 other major countries and the rest of the world (ROW). The 13 countries include non-EU OECD member countries, including Japan and the United States, and emerging economies, including China, Indonesia, and Mexico.[19] These tables are constructed on the basis of officially published IO tables, in conjunction with national accounts and international trade statistics.

From the Socio Economic Accounts of the WIOD, we utilize the information on real intermediate inputs for X and total hours worked by skilled and unskilled workers for S and U, respectively. Following Morrow and Trefler (2017), we define skilled labor as those possessing some tertiary education. Unskilled labor is the remainder of the labor force. For the price of intermediate goods p^X, we use the price index of intermediate inputs (1995 = 100.0). The wages of skilled and unskilled labor, w^S and w^U, are calculated from the total skilled and unskilled worker compensation divided by the total

regressor problem.

[16]We also try different estimation methods: 1) estimate equations (3) and (4) based on a nonlinear estimation method or generalized method of moments as was employed by Duffy et al. (2004); 2) utilize the Bartik (1991) instrument, following Oberfield and Raval (2014); 3) employ a command provided by Erickson et al. (2017) for implementing the estimators in Erickson et al. (2014) that use the information contained in the higher-order cumulants of the observable variables. However, the estimated substitution elasticities violate the basic assumptions of the CES production function (i.e., $\hat{\theta} < 1$ and $\hat{\rho} < 1$). Indeed, such problems are often observed in the literature (e.g., Duffy et al., 2004; Koesler and Schymura, 2015). Therefore, the current version of our study employs the three remedies as described above.

[17]Equation (13) includes neither country fixed effects nor constant term due to the long differences.

[18]The WIOD and all satellite accounts are available at http://www.wiod.org. The satellite accounts include the National IO Tables, the Socio Economic Accounts (i.e., data on employment, capital stocks, and so on) and the Environmental Accounts. Although the latest version of the Socio Economic Accounts was released in February 2018, we utilize the earlier version because the latest version does not distinguish between skilled and unskilled workers. For a detailed description of the database construction, see Dietzenbacher et al. (2015).

[19] The list of countries in the WIOD is as follows. The European Union: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, the Netherlands, Poland, Portugal, Romania, the Slovak Republic, Slovenia, Spain, Sweden, and the United Kingdom. North America: Canada and the United States. Latin America: Brazil and Mexico. Asia and the Pacific: China, India, Japan, South Korea, Australia, Taiwan, Turkey, Indonesia, and Russia. The regional classification follows Timmer (2012, Table 1).

hours worked by skilled and unskilled workers, respectively.

Table 1 presents the annual average growth rate of inputs from 1995 to 2009 for the aggregated one sector and the three sectors: Primary, Manufacturing, and Services.[20] Note that, for the ease of explanation, we use the word "sector" at the level of the aggregated one sector and the three sectors while using the word "industry" at the level of each manufacturing industry. To obtain the growth of inputs, we first aggregate factors into the one sector or the three sectors and then calculate the annual average growth rate for each factor. Table 1 indicates that the input of intermediate goods and that of skilled labor relative to unskilled labor both increased at the aggregate one-sector level. At the three-sector level, the input of intermediate goods declined while that of skilled labor relative to unskilled labor increased in Primary. In contrast, the input of intermediate goods and that of skilled labor relative to unskilled labor increased in Manufacturing and Services. It is worth mentioning that in Manufacturing, the growth in capital stock is accompanied by an increase in the input of skilled labor relative to unskilled labor, which is consistent with capital–skill complementarity.

[Table 1 about here.]

Table 1 also shows the annual average growth rate of inputs from 1995 to 2009, by manufacturing industry. In 10 out of 14 industries, the growth rate of intermediate goods indicates the same sign as that of skilled labor relative to unskilled labor. These results seem to suggest intermediate goods–skill complementarity. However, these findings are based on simple descriptive statistics. To address this issue further, the next section now turns to the econometric analysis.

3 Estimation Results

3.1 Main results

Table 2 indicates the results for the aggregated one sector and the aggregated three sectors: Primary, Manufacturing, and Services. To estimate the equations at the aggregate level, we aggregate nominal and real inputs into one sector or the three sectors, and compute factor prices at the aggregate level.[21]

We highlight five findings. First, the estimated parameters satisfy all the parameter restrictions. Table 2 indicates that all of the $\hat{b}, \hat{\theta}$, and $\hat{\rho}$ are between zero and one. Second, on average, the intermediate goods are complements for skilled labor. As the aggregated one-sector results indicate, $\hat{\theta} = 0.051$ while $\hat{\rho} = 0.178$, and thus

[20] For the industry classification, see Appendix A.1.

[21] In our regression analysis, the number of observations is 560 (= 40 countries × 14 years, due to the use of the lagged independent variable as an IV). Note that Wald statistics rather than F-statistics are reported for the first-stage results because we employ bootstrapped standard errors (i.e., significance levels are computed using z-statistics rather than t-statistics).

$\hat{\rho} - \hat{\theta} = 0.127 > 0$, which is significantly greater than zero at the 10 percent level (the p-value of the z test is 0.052).[22] That is, the elasticity of substitution between intermediate goods and unskilled labor, which is given by $1/(1-\hat{\rho})$, is 1.22. It is significantly greater than that between intermediate goods and skilled labor of 1.05, which is given by $1/(1-\hat{\theta})$.

[Table 2 about here.]

Third, $\hat{\rho} - \hat{\theta}$ is significantly negative for Primary while significantly positive for Manufacturing and Services. This result implies that intermediate goods and skilled labor are substitutes in Primary whereas they are complements in Manufacturing and Services. Note that the complementarity between intermediate goods and skilled labor is higher in Services than in Manufacturing.

Fourth, even though $\hat{\rho} - \hat{\theta}$ is the lowest in Primary of the three sectors, it does not necessarily mean that Primary has the smallest $\hat{\rho}$. Rather, Table 2 indicates that Primary has the largest $\hat{\rho}$ $(= 0.189)$. Its $\hat{\theta}$ $(= 0.337)$, however, is also the largest of the three sectors. Thus, the substitutability between intermediate goods and skilled labor in Primary comes from its large elasticity of substitution between intermediate goods and skilled labor relative to the other two sectors.

Finally, our results also imply that the elasticity of substitution between skilled and unskilled labor, which is given by $1/(1-\hat{\rho})$, is 1.22 for the aggregated one-sector level, 1.23 for Primary, 1.18 for Manufacturing, and 1.21 for Services. These estimates are in line with the estimates in the literature. For example, Autor et al. (1998) argued that the elasticity of substitution between skilled and unskilled labor is likely to be between one and two, although our estimates are slightly lower than "most estimates" in the neighborhood of 1.5 (Johnson, 1997, p. 44).

Table 3 presents the estimation results, by manufacturing industry.[23] In five industries, intermediate goods and skilled labor are substitutes while they are complements in the other nine industries. The results indicate that complementarity between intermediate goods and skilled labor tends to be observed in heavy manufacturing industries such as Transportation Equipment while substitutability tends to be observed in light manufacturing industries such as Leather & Footwear. A caution, however, may be needed because $\hat{\rho} - \hat{\theta}$ is insignificant in some industries.

In summary, the estimation results indicate that, on average, intermediate goods were complements for skilled labor for the period between 1995 and 2009.[24] Although

[22] Following the study by Clogg et al. (1995), we employ the z test to compare regression coefficients between models, where the z-statistics is computed as $z = \left(\hat{\rho} - \hat{\theta}\right) / \sqrt{\sigma_{\hat{\rho}}^2 + \sigma_{\hat{\theta}}^2}$.

[23] For some industries, the number of observations is slightly smaller due to the availability of data.

[24] Our results may be affected by the global financial crisis because the ratio of intermediate goods to gross output declined sharply in 2009 (Figure 1). To address this concern, we restrict our sample to before 2009. We find that our main messages continue to hold even when we restrict the sample to the period before the global financial crisis.

its impact would be heterogeneous across industries, overall the results suggest the growing use of intermediate goods as an alternative, complementary factor of increasing wage inequality. It is important to note that, at the aggregate level, the degree of intermediate goods–skill complementarity differs across countries because of differences in industry structures. Even though we confirm intermediate goods–skill complementarity for 40 countries on average, intermediate goods and skilled labor could be substitutes rather than complements for some countries.

[Table 3 about here.]

3.2 Discussion

3.2.1 Alternative specifications

In the baseline specification, we employ a two-level CES production function where intermediate goods and skilled labor are aggregated by the CES functional form, and then this CES composite is aggregated with unskilled labor by the other CES function. It is natural to ask whether our results continue to hold when we employ an alternative functional form: the intermediate goods and unskilled labor are aggregated by the CES functional form, and then this CES composite is aggregated with skilled labor by the other CES function:

$$Y = AK^{\alpha}\left[aQ^{\rho} + (1-a)S^{\rho}\right]^{(1-\alpha)/\rho}, \tag{14}$$

where

$$Q = \left[bX^{\theta} + (1-b)U^{\theta}\right]^{1/\theta}. \tag{15}$$

When we employ this functional form, we expect that $\hat{\rho} - \hat{\theta} < 0$ if intermediate goods are complements with skilled labor. We also employ this specification and test whether $\hat{\rho} - \hat{\theta} < 0$ holds to check the robustness of our results.

Tables 4 and 5 present the estimation results of our alternative specification. The results indicate that $\hat{\rho} - \hat{\theta} > 0$ for Primary while $\hat{\rho} - \hat{\theta} < 0$ for All, Manufacturing, and Services, although insignificant for All and Services. At the level of each manufacturing industry, $\hat{\rho} - \hat{\theta}$ is significantly negative in most of the heavy manufacturing industries. Therefore, our main messages are mostly unchanged even when we employ this alternative specification.

[Table 4 about here.]

[Table 5 about here.]

Another concern may be the effect of SBTC other than intermediate goods–skill complementarity. We have so far focused on intermediate goods–skill complementarity; however, that is only one form of SBTC. One may thus argue that omitting the effect of other SBTC could cause some biases in our regression analysis. To address this issue, we introduce factor-specific productivity that can also capture SBTC.[25] Equation (4) in the production function is now as follows:

$$Q = \left[bX^{\theta} + \varphi(1-b)S^{\theta} \right]^{\frac{1}{\theta}}, \tag{16}$$

where φ is a skill-specific productivity parameter that captures the effect of SBTC other than intermediate goods–skill complementarity. As can be seen, a rise in φ increases the relative productivity of skilled labor without the growth in intermediate goods. Then, the equations (9), (11), and (12) can be rewritten as follows:

$$\log \frac{p^X_{ct}}{w^S_{ct}} = \gamma_c + \log \frac{b}{1-b} - \log \varphi_t + (\theta - 1) \log \frac{X_{ct}}{S_{ct}} + \varepsilon_{ct}, \tag{17}$$

$$\hat{Q} = \left[\hat{b} X^{\hat{\theta}}_{ct} + \hat{\varphi}_t (1-\hat{b}) S^{\hat{\theta}}_{ct} \right]^{\frac{1}{\hat{\theta}}}, \tag{18}$$

and

$$\hat{q}_{ct} = \left[\hat{b}^{\frac{1}{1-\hat{\theta}}} p_{ct}^{X,-\frac{\hat{\theta}}{1-\hat{\theta}}} + [\hat{\varphi}_t(1-\hat{b})]^{\frac{1}{1-\hat{\theta}}} w_{ct}^{S,-\frac{\hat{\theta}}{1-\hat{\theta}}} \right]^{-\frac{1-\hat{\theta}}{\hat{\theta}}}, \tag{19}$$

respectively. We use the log of time trend, $\log(\text{trend}_t)$, to estimate φ_t. Therefore, $-\log \varphi_t = \xi \log(\text{trend}_t)$, where ξ is the estimated coefficient of $\log(\text{trend}_t)$.[26]

Tables 6 and 7 present the regression results, substituting equations (17), (18), and (19) to (9), (11), and (12), respectively, to control for the effect of other SBTC. There are two notable findings. First, in all industries except for one manufacturing industry (i.e., Coke, Refined Petroleum & Nuclear Fuel), the parameter $\hat{\xi}$ is significantly negative, which in turn means that the parameter $\hat{\varphi}_t$ is significantly positive. This result suggests that the effect of other SBTC might not be negligibly small in the increases in demand for skilled labor in almost all industries.

[Table 6 about here.]

[Table 7 about here.]

Second, the results are qualitatively similar to the main results, even after we control for the effect of other SBTC. All the coefficients of $\hat{\rho} - \hat{\theta}$ indicate the same signs as those in Tables 2 and 3 except for two manufacturing industries (i.e., Food, Beverages & Tobacco; Pulp, Paper, Printing & Publishing), although they are insignificant in these two industries. These results suggest that our main messages generally continue to hold even when the analysis takes into account the effect of SBTC other than intermediate goods–skill complementarity.

[25]See footnote 3.

[26]Thus, $\hat{\varphi}_t$ is obtained from $\exp(-\hat{\xi} \log(\text{trend}_t))$.

3.2.2 Results for OECD countries

One may be concerned that our analysis covers not only developed countries such as the United States and Japan but also developing countries such as China and India whose production technology could be different from that of developed countries. Although 30 out of 40 countries in our sample consist of the OECD members, the estimation of the elasticity parameters could be affected by the differences between developed and developing countries.[27] To address this concern, we reestimate equations (9) and (13), restricting the sample to 30 OECD countries.[28]

Tables 8 and 9 present the regression results. There are three notable findings. First, at the aggregated one-sector level in Table 8, we continue to confirm the complementarity between intermediate goods and skilled labor because $\hat{\rho} - \hat{\theta} = 0.283 > 0$ (p-value is 0.000). Second, at the aggregated three-sector level, all the signs of $\hat{\rho} - \hat{\theta}$ are exactly the same as those presented in Table 2. $\hat{\rho} - \hat{\theta}$ continues to be negative for Primary while significantly positive for Manufacturing and Services.

[Table 8 about here.]

[Table 9 about here.]

Finally, at the level of each manufacturing industry (Table 9), most of the signs of $\hat{\rho} - \hat{\theta}$ are the same as those presented in Table 3, although the significance levels are slightly different. Only two manufacturing industries (i.e., Wood, Products of Wood & Cork; Pulp, Paper, Printing & Publishing) present different signs. These results together suggest that our main results continue to hold even when we restrict the sample to OECD countries.

3.2.3 Effects of imported intermediate goods

One may be further concerned about the difference between the effects of domestic intermediate goods and those of imported intermediate goods. While we have not distinguished domestic from imported intermediate goods, recent studies such as Crinò (2012) and Kasahara et al. (2016) found that importing intermediate goods increases the demand for skilled labor. They argue that using imported intermediate goods in production can mean the adoption of more sophisticated technology (SBTC) and thus increases the demand for skilled labor.[29] Our results thus might be stronger if we had

[27] For example, Fallon and Layard (1975) presented results, separating countries into richer and poorer countries.

[28] This reestimation excludes the following 10 non-OECD countries: Brazil, Bulgaria, China, Cyprus, India, Indonesia, Malta, Romania, Russia, and Taiwan. For the whole sample countries, see footnote 19. Even when we restrict our sample to the non-OECD countries, estimation results are similar to the baseline results. However, we have less significant results, possibly due to the small sample (only 10 countries).

[29] If a change in production function due to the introduction of imported intermediate goods is interpreted as technological change, the Kurokawa (2011) model has provided a simple representation of the import-induced SBTC.

focused on imported intermediate goods. Unfortunately, however, it is difficult to address this issue directly for the following two reasons. First, information on the price of imported intermediate goods is not available. Second, incorporating domestic and imported intermediate goods separately to the CES function will result in a more complex functional form, which has never been used in the literature.[30]

Nevertheless, we can at least investigate whether the industries that have a higher ratio of imported intermediate goods to total intermediate goods tend to indicate higher intermediate goods–skill complementarity (i.e., higher $\hat{\sigma}_{X,U} - \hat{\sigma}_{X,S}$ or higher $\hat{\rho} - \hat{\theta}$). Indeed, Figure 2 illustrates this relationship. Using the ratio of intermediate goods to total intermediate goods from the WIOD, we compute its average over the period between 1995 and 2009, for each of the 14 manufacturing industries.[31]

[Figure 2 about here.]

Figure 2 clearly indicates that for industries whose shares of imported intermediate goods are higher, intermediate goods–skill complementarity tends to be higher. In other words, the extent to which intermediate goods are complements for skilled labor relative to unskilled labor tends to be higher. The correlation coefficient between the share of imported intermediate goods and $\hat{\rho} - \hat{\theta}$ is 0.419. The slope of the linear regression is 0.439, which is significant at the 10 percent level. While only indicative, the result suggests that imported intermediate goods play an important role in the complementarity between intermediate goods and skilled labor.

4 Concluding Remarks

In light of the increasing importance of intermediate inputs and its potential effects on inequality, this paper formally tested whether intermediate goods are complements for skilled labor by estimating the elasticity of substitution between intermediate goods, skilled labor, and unskilled labor. We used a two-level CES production function and the panel data of 40 countries over the period 1995–2009. Our major findings are fourfold. First, at the aggregated one-sector level, the elasticity of substitution between intermediate goods and unskilled labor is significantly greater than that between intermediate goods and skilled labor. This confirms intermediate goods–skill complementarity. Second, at the more disaggregated level, however, such complementarity is observed mainly in the heavy manufacturing industries and the service sector. In the primary sector and the light manufacturing industries, we confirmed substitutability

[30] As mentioned in footnote 5, domestic and imported capital goods are not differentiated in the models of Burstein et al. (2013) and Parro (2013). Therefore, how to incorporate domestic and imported capital goods separately into the production function is also an important subject for future investigation.

[31] The intermediate goods in SEA include taxes and international transportation margins. Because these items are not reported by country, we compute the share of imported intermediate goods, excluding these items.

between the intermediate goods and skilled labor. Third, our main results stand up to several robustness checks. Finally, intermediate goods–skill complementarity tends to be higher for industries whose shares of imported intermediate goods are higher.

Although its impact would be heterogeneous across industries, our results suggest that researchers might want to consider the growing use of intermediate goods as an alternative, complementary factor of increasing wage inequality. Moreover, using the estimated elasticity parameters, applied general equilibrium models or structural estimations would be able to quantify the impact of the growth of intermediate goods (e.g., through the increased imports of intermediate goods) on wage inequality.[32] Thus, there would be further development of quantitative analysis of intermediate goods and skills.

Several further steps can be taken for future research. First, as mentioned above, it is essential to quantify the extent to which intermediate goods–skill complementarity affects wage inequality, based upon a quantitative analysis. Our estimated elasticity parameters will be helpful for such quantitative analysis. Second, it is important to ask whether the complementarity between intermediate goods and skilled labor is stronger than the complementarity between capital stock and skilled labor. Third, it would be interesting to examine whether our results would be stronger if we were to focus on imported intermediate goods. To address the second and third issues, however, we would need to develop a more complex functional form of the CES production function, which possibly requires additional parameter constraints.[33] Finally, the search for more appropriate modeling and empirical strategies is another important but challenging step. These issues will be explored in the next stage of our research.

References

Arkolakis, Costas, Arnaud Costinot, and Andrés Rodríguez-Clare. 2012. "New Trade Models, Same Old Gains?" *American Economic Review*, 102(1): 94–130.

Atolia, Manoj and Yoshinori Kurokawa. 2016. "The Impact of Trade Margins on the Skill Premium: Evidence from Mexico." *Journal of Policy Modeling*, 38(5): 895–915.

[32] Using Mexican data, Atolia and Kurokawa (2016) quantified the impact of trade in intermediate goods on wage inequality with intermediate goods–skill complementarity. Because of the uncertainty about the elasticities, however, they did a sensitivity analysis for several values of the elasticity parameters.

[33] Alternatively, it may be possible to address this issue by employing a translog production function. Note, however, that most of the quantitative analysis relies on the CES production function rather than a translog production function because it is not easy to incorporate the translog production function into a simple general equilibrium framework. Moreover, it requires information on factor prices, which is available for intermediate goods as a whole but not usually for domestic and imported intermediate goods separately.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*, 113(4): 1169–213.

Bartik, Timothy J. 1991. "Who Benefits from State and Local Economic Development Policies?" Manuscript, W.E. Upjohn Institute for Employment Research.

Brülhart, Marius and Federico Trionfetti. 2009. "A Test of Trade Theories When Expenditure is Home Biased." *European Economic Review*, 53(7): 830–45.

Burstein, Ariel, Javier Cravino, and Jonathan Vogel. 2013. "Importing Skill-Biased Technology." *American Economic Journal: Macroeconomics*, 5(2): 32–71.

Clogg, Clifford C., Eva Petkova, and Adamantios Haritou. 1995. "Statistical Methods for Comparing Regression Coefficients Between Models." *American Journal of Sociology*, 100(5): 1261–93.

Crinò, Rosario. 2012. "Imported Inputs and Skill Upgrading." *Labour Economics*, 19(6): 957–69.

Dietzenbacher, Erik, Bart Los, Robert Stehrer, Marcel P. Timmer and Gaaitzen J. de Vries. 2013. "The Construction of World Input–Output Tables in the WIOD Project." *Economic Systems Research*, 25(1): 71–98.

Duffy, John, Chris Papageorgiou, and Fidel Perez-Sebastian. 2004. "Capital–Skill Complementarity? Evidence from a Panel of Countries." *Review of Economics and Statistics*, 86(1): 327–44.

Erickson, Timothy, Colin Hua Jiang, and Toni M. Whited. 2014. "Minimum Distance Estimation of the Errors-in-variables Model Using Linear Cumulant Equations." *Journal of Econometrics*, 183: 211–21.

Erickson, Timothy, Robert Parham, and Toni M. Whited. 2017. "Fitting the Errors-in-Variables Model Using High-Order Cumulants and Moments." *Stata Journal*, 17(1): 116–29.

Fallon, P. R. and Richard Layard. 1975. "Capital–Skill Complementarity, Income Distribution, and Output Accounting." *Journal of Political Economy*, 83(2): 279–301.

Feenstra, Robert C. and Gordon H. Hanson. 1999. "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-90." *Quarterly Journal of Economics*, 114(3): 907–40.

Griliches, Zvi. 1969. "Capital–Skill Complementarity." *Review of Economics and Statistics*, 51(4): 465–68.

Griliches, Zvi and Jerry A. Hausman. 1986. "Errors in Variables in Panel Data." *Journal of Econometrics*, 31(1): 93–118.

Hara, Naoko, Munechika Katayama, and Ryo Kato. 2014. "Rising Skill Premium? The Roles of Capital–Skill Complementarity and Sectoral Shifts in a Two-Sector Economy." Bank of Japan Working Paper Series No. 14-E-9.

Hijzen, Alexander, Holger Görg, and Robert C. Hine. 2005. "International Outsourcing and the Skill Structure of Labor Demand in the United Kingdom." *Economic Journal*, 115(506): 860–78.

Hummels, David, Rasmus Jørgensen, Jakob Munch, and Chong Xiang. 2014. "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data." *American Economic Review*, 104(6): 1597–629.

Johnson, George. 1997. "Changes in Earnings Inequality: The Role of Demand Shifts." *Journal of Economic Perspectives*, 11(2): 41–54.

Kasahara, Hiroyuki, Yawen Liang, and Joel Rodrigue. 2016. "Does Importing Intermediates Increase the Demand for Skilled Workers? Plant-level Evidence from Indonesia." *Journal of International Economics*, 102: 242–61.

Kiyota, Kozo, and Sawako Maruyama. 2017. "ICT, Offshoring, and the Demand for Part-time Workers: The Case of Japanese Manufacturing." *Journal of Asian Economics*, 48: 75–86.

Koesler, Simon and Michael Schymura. 2015. "Substitution Elasticities in a Constant Elasticity of Substitution Framework – Empirical Estimates Using Nonlinear Least Squares." *Economic Systems Research*, 27(1): 101–21.

Krusell, Per, Lee E. Ohanian, Jose-Victor Rios-Rull, and Giovanni L. Violante. 2000. "Capital–Skill Complementarity and Inequality: A Macroeconomic Analysis." *Econometrica*, 68(5): 1029–53.

Kurokawa, Yoshinori. 2011. "Variety–Skill Complementarity: A Simple Resolution of the Trade–Wage Inequality Anomaly." *Economic Theory*, 46(2): 297–325.

Morrow, Peter M. and Daniel Trefler. 2017. "Endowments, Skill-biased Technology, and Factor Prices: A Unified Approach to Trade." NBER Working Paper Series, No. 24078, National Bureau of Economic Research (NBER).

Oberfield, Ezra and Devesh Raval. 2014. "Micro Data and Macro Technology." Manuscript, Princeton University.

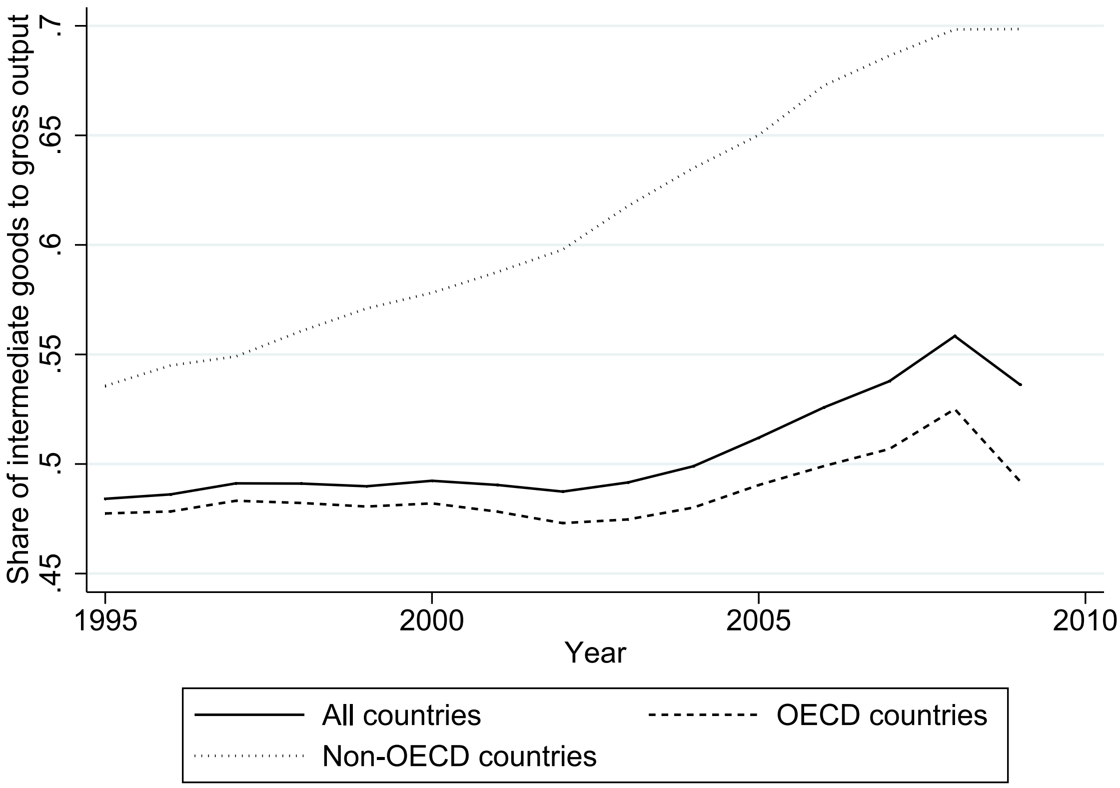
Parro, Fernando. 2013. "Capital–Skill Complementarity and the Skill Premium in a Quantitative Model of Trade." *American Economic Journal: Macroeconomics*, 5(2): 72–117.

Redding, Stephen and Anthony J. Venables. 2004. "Economic Geography and International Inequality." *Journal of International Economics*, 62(1): 53–82.

Timmer, Marcel P. ed. 2012. "The World Input–Output Database (WIOD): Contents, Sources and Methods." WIOD Working Paper Number 10, University of Groningen.

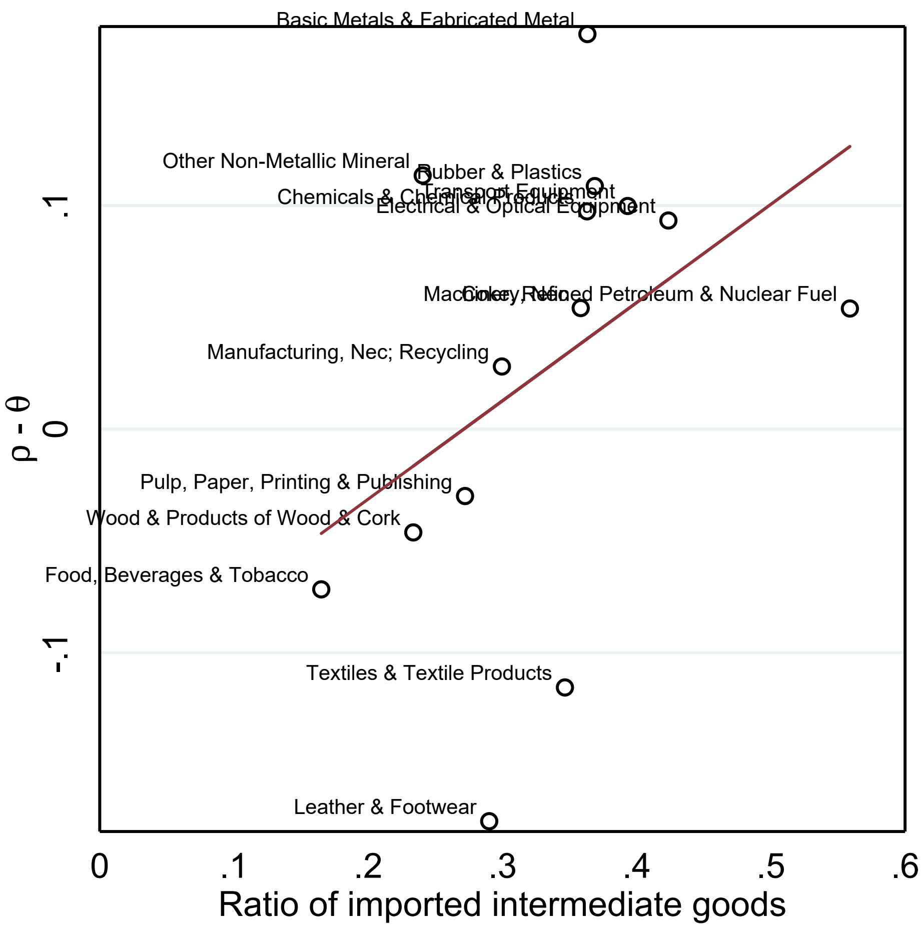
Violante, Giovanni L. 2008. "Skill-Biased Technical Change." in Steven Durlauf and Lawrence E. Blume (eds.), *The New Palgrave Dictionary of Economics*, London: Palgrave Macmillan.

Figure 1: Ratio of Intermediate Goods to Gross Output, 1995–2009



Notes: Solid, dashed, and dotted lines indicate the ratio of intermediate goods to gross output for all countries, OECD countries, and non-OECD countries, respectively.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

Figure 2: Relationship between $\hat{\rho} - \hat{\theta}$ and Imported Intermediate Goods: Manufacturing Industries



Notes: The solid line indicates the fitted value: $\hat{y} = -0.119(0.077) + 0.439(0.209)x$, where $\hat{y}$ is $\hat{\rho} - \hat{\theta}$ and x is the ratio of imported intermediate goods to total intermediate goods, and figures in parentheses are heteroskedasticity-robust standard errors. $N = 14$ and $R^2 = 0.175$.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

Table 1: Annual Average Growth Rates of Inputs from 1995 to 2009,
by Aggregate Sector and by Manufacturing Industry

Sector / industry	Intermediate goods	Skilled workers	Unskilled workers	Capital stock
All	0.019	0.037	0.000	-0.006
Primary	-0.009	0.032	-0.026	-0.006
Manufacturing	0.013	0.027	-0.015	0.001
Services	0.022	0.039	0.010	-0.007
Food, Beverages & Tobacco	-0.006	0.027	-0.016	-0.010
Textiles & Textile Products	-0.037	-0.001	-0.048	-0.028
Leather & Footwear	-0.063	-0.024	-0.069	-0.029
Wood & Products of Wood & Cork	-0.006	0.026	-0.016	0.010
Pulp, Paper, Printing & Publishing	0.002	0.031	-0.010	0.004
Coke, Refined Petroleum & Nuclear Fuel	0.003	0.017	-0.024	-0.001
Chemicals & Chemical Products	0.013	0.029	-0.012	0.001
Rubber & Plastics	0.021	0.041	0.001	0.019
Other Non-Metallic Mineral	0.002	0.020	-0.022	-0.003
Basic Metals & Fabricated Metal	0.003	0.037	-0.004	-0.006
Machinery, Nec	0.008	0.024	-0.020	0.004
Electrical & Optical Equipment	0.038	0.035	-0.006	0.013
Transport Equipment	0.025	0.039	-0.004	0.017
Manufacturing, Nec; Recycling	0.007	0.032	-0.010	0.018

Notes: The annual average growth rate is the mean of the annual average growth rates of the sample countries. For the sectoral classification, see Appendix A.1.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

Table 2: Estimated Elasticities, by Aggregate Sector

Sector	$\hat{b}$	$\hat{\theta}$	N Wald	$\hat{\rho}$	N Wald	$\hat{\rho}-\hat{\theta}$
All	0.843	0.051	560	0.178	360	0.127
	[0.040]	[0.073]	185.3	[0.028]	244.2	(0.052)
Primary	0.772	0.337	560	0.189	360	-0.148
	[0.071]	[0.073]	539.7	[0.029]	256.9	(0.019)
Manufacturing	0.952	0.033	560	0.152	360	0.119
	[0.014]	[0.051]	195.3	[0.025]	254.0	(0.019)
Services	0.783	0.031	560	0.175	360	0.144
	[0.029]	[0.042]	204.3	[0.034]	238.5	(0.004)

Notes: Figures in brackets indicate standard errors that are based on 100 bootstrap replications. Figures in parentheses are the p-values of the z test. Wald indicates the first-stage Wald statistics.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

Table 3: Estimated Elasticities, by Manufacturing Industry

Industry	$\hat{b}$	$\hat{\theta}$	N and Wald	$\hat{\rho}$	N and Wald	$\hat{\rho}-\hat{\theta}$
Food, Beverages & Tobacco	0.9993	0.137	560	0.065	360	-0.072
	[0.0003]	[0.075]	332.3	[0.025]	191.6	(0.182)
Textiles & Textile Products	0.9983	0.233	560	0.118	360	-0.116
	[0.0007]	[0.073]	324.8	[0.038]	187.5	(0.080)
Leather & Footwear	0.9967	0.383	545	0.208	350	-0.175
	[0.0014]	[0.081]	311.9	[0.053]	186.0	(0.034)
Wood, Products of Wood	0.9989	0.162	560	0.116	360	-0.046
& Cork	[0.0003]	[0.059]	243.0	[0.019]	154.7	(0.226)
Pulp, Paper, Printing	0.9989	0.126	560	0.096	360	-0.030
& Publishing	[0.0004]	[0.076]	268.6	[0.026]	162.5	(0.355)
Coke, Refined Petroleum	0.9993	0.268	528	0.322	332	0.054
& Nuclear Fuel	[0.0003]	[0.060]	782.2	[0.062]	0.3	(0.266)
Chemicals	0.9995	0.060	560	0.157	360	0.097
& Chemical Products	[0.0002]	[0.054]	412.1	[0.028]	356.1	(0.056)
Rubber & Plastics	0.9994	0.041	560	0.150	360	0.109
	[0.0002]	[0.039]	340.2	[0.032]	310.9	(0.015)
Other Non-Metallic Mineral	0.9994	0.000	560	0.113	360	0.113
	[0.0002]	[0.045]	225.2	[0.032]	271.1	(0.021)
Basic Metals	0.9995	0.008	560	0.185	360	0.177
& Fabricated Metal	[0.0002]	[0.059]	984.5	[0.040]	262.6	(0.007)
Machinery, Nec	0.9989	0.115	560	0.169	360	0.054
	[0.0003]	[0.046]	524.1	[0.023]	440.5	(0.145)
Electrical	0.9991	0.107	560	0.200	360	0.093
& Optical Equipment	[0.0003]	[0.065]	225.4	[0.039]	318.1	(0.111)
Transport Equipment	0.9994	0.049	560	0.149	360	0.100
	[0.0002]	[0.050]	275.7	[0.029]	273.9	(0.042)
Manufacturing, Nec;	0.9992	0.054	560	0.082	360	0.028
Recycling	[0.0002]	[0.054]	371.4	[0.046]	374.3	(0.346)

Notes: Figures in brackets indicate standard errors that are based on 100 bootstrap replications. Figures in parentheses are the p-values of the z test. Wald indicates the first-stage Wald statistics.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

Table 4: Estimated Elasticities, by Aggregate Sector: Alternative Specification

Sector	$\hat{b}$	$\hat{\theta}$	N Wald	$\hat{\rho}$	N Wald	$\hat{\rho}-\hat{\theta}$
All	0.650	0.171	560	0.126	360	-0.045
	[0.043]	[0.058]	157.4	[0.036]	236.5	(0.258)
Primary	0.558	0.163	560	0.616	360	0.453
	[0.031]	[0.054]	154.1	[0.049]	534.8	(0.000)
Manufacturing	0.749	0.183	560	0.039	360	-0.144
	[0.041]	[0.051]	191.6	[0.030]	226.5	(0.007)
Services	0.623	0.136	560	0.133	360	-0.003
	[0.050]	[0.072]	157.3	[0.029]	230.5	(0.486)

Notes: Figures in brackets indicate standard errors that are based on 100 bootstrap replications. Figures in parentheses are the p-values of the z test. Wald indicates the first-stage Wald statistics.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

Table 5: Estimated Elasticities, by Manufacturing Industry: Alternative Specification

Industry	$\hat{b}$	$\hat{\theta}$	N and Wald	$\hat{\rho}$	N and Wald	$\hat{\rho} - \hat{\theta}$
Food, Beverages & Tobacco	0.9980	0.089	560	0.063	360	-0.026
	[0.0004]	[0.048]	122.3	[0.035]	197.5	(0.330)
Textiles & Textile Products	0.9959	0.153	560	0.152	360	-0.002
	[0.0008]	[0.060]	178.6	[0.045]	201.2	(0.491)
Leather & Footwear	0.9953	0.226	545	0.292	350	0.066
	[0.0009]	[0.072]	190.8	[0.054]	204.5	(0.232)
Wood, Products of Wood	0.9963	0.157	560	0.086	360	-0.072
& Cork	[0.0006]	[0.039]	121.4	[0.030]	157.3	(0.075)
Pulp, Paper, Printing	0.9962	0.140	560	0.062	360	-0.078
& Publishing	[0.0007]	[0.051]	137.7	[0.041]	156.1	(0.115)
Coke, Refined Petroleum	0.9978	0.324	528	0.266	332	-0.058
& Nuclear Fuel	[0.0007]	[0.052]	1017.3	[0.071]	1.4	(0.254)
Chemicals	0.9965	0.226	560	0.012	360	-0.214
& Chemical Products	[0.0009]	[0.053]	328.1	[0.029]	291.1	(0.000)
Rubber & Plastics	0.9964	0.153	560	0.048	360	-0.104
	[0.0008]	[0.049]	223.5	[0.027]	258.6	(0.032)
Other Non-Metallic Mineral	0.9959	0.155	560	-0.031	360	-0.186
	[0.0009]	[0.055]	223.4	[0.031]	194.1	(0.002)
Basic Metals	0.9966	0.163	560	0.036	360	-0.127
& Fabricated Metal	[0.0012]	[0.091]	245.5	[0.032]	219.3	(0.095)
Machinery, Nec	0.9951	0.195	560	0.093	360	-0.102
	[0.0008]	[0.041]	537.0	[0.031]	308.2	(0.024)
Electrical	0.9958	0.225	560	0.103	360	-0.122
& Optical Equipment	[0.0009]	[0.052]	287.6	[0.048]	222.4	(0.042)
Transport Equipment	0.9968	0.162	560	0.028	360	-0.134
	[0.0005]	[0.037]	286.5	[0.034]	237.0	(0.004)
Manufacturing, Nec;	0.9963	0.111	560	0.041	360	-0.070
Recycling	[0.0007]	[0.060]	425.6	[0.044]	233.1	(0.174)

Notes: Figures in brackets indicate standard errors that are based on 100 bootstrap replications. Figures in parentheses are the p-values of the z test. Wald indicates the first-stage Wald statistics.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

Table 6: Estimated Elasticities, by Aggregate Sector: Controlling for other SBTC

Sector	$\hat{b}$	$\hat{\theta}$	$\hat{\xi}$	N and Wald	$\hat{\rho}$	N Wald	$\hat{\rho}-\hat{\theta}$
All	0.862	0.047	-0.018	560	0.226	320	0.179
	[0.027]	[0.052]	[0.003]	549.9	[0.027]	316.7	(0.001)
Primary	0.885	0.210	-0.031	560	0.193	320	-0.017
	[0.042]	[0.063]	[0.006]	626.9	[0.035]	260.1	(0.408)
Manufacturing	0.955	0.041	-0.014	560	0.187	320	0.146
	[0.013]	[0.049]	[0.003]	572.9	[0.025]	295.1	(0.004)
Services	0.800	0.026	-0.011	560	0.249	320	0.223
	[0.033]	[0.049]	[0.003]	534.9	[0.031]	335.2	(0.000)

Notes: Figures in brackets indicate standard errors that are based on 100 bootstrap replications. Figures in parentheses are the p-values of the z test. Wald indicates the first-stage Wald statistics.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

Table 7: Estimated Elasticities, by Manufacturing Industry: Controlling for other SBTC

Industry	$\hat{b}$	$\hat{\theta}$	$\hat{\xi}$	N and Wald	$\hat{\rho}$	N and Wald	$\hat{\rho} - \hat{\theta}$
Food, Beverages & Tobacco	0.9996	0.059	-0.025	560	0.085	320	0.026
	[0.0002]	[0.065]	[0.004]	387.4	[0.034]	168.0	(0.363)
Textiles & Textile Products	0.9992	0.119	-0.033	560	0.107	320	-0.012
	[0.0003]	[0.070]	[0.004]	363.0	[0.044]	150.6	(0.441)
Leather & Footwear	0.9985	0.277	-0.037	545	0.198	311	-0.078
	[0.0007]	[0.080]	[0.005]	305.3	[0.055]	116.6	(0.209)
Wood, Products of Wood	0.9992	0.126	-0.025	560	0.122	320	-0.004
& Cork	[0.0002]	[0.044]	[0.004]	315.3	[0.023]	110.2	(0.470)
Pulp, Paper, Printing	0.9993	0.073	-0.024	560	0.096	320	0.023
& Publishing	[0.0002]	[0.060]	[0.004]	391.2	[0.028]	148.6	(0.366)
Coke, Refined Petroleum	0.9992	0.269	0.011	528	0.360	295	0.091
& Nuclear Fuel	[0.0004]	[0.063]	[0.009]	780.1	[0.064]	0.3	(0.155)
Chemicals	0.9995	0.061	-0.010	560	0.184	320	0.123
& Chemical Products	[0.0002]	[0.056]	[0.004]	773.2	[0.029]	361.8	(0.026)
Rubber & Plastics	0.9994	0.044	-0.013	560	0.177	320	0.133
	[0.0002]	[0.053]	[0.004]	572.3	[0.030]	266.2	(0.014)
Other Non-Metallic Mineral	0.9995	0.003	-0.011	560	0.177	320	0.175
	[0.0002]	[0.056]	[0.005]	429.3	[0.028]	293.5	(0.003)
Basic Metals	0.9996	0.000	-0.005	560	0.251	320	0.250
& Fabricated Metal	[0.0002]	[0.063]	[0.003]	910.5	[0.040]	255.4	(0.000)
Machinery, Nec	0.9989	0.139	-0.018	560	0.199	320	0.060
	[0.0004]	[0.060]	[0.005]	1094.6	[0.022]	464.4	(0.172)
Electrical	0.9991	0.150	-0.019	560	0.224	320	0.074
& Optical Equipment	[0.0006]	[0.101]	[0.007]	564.0	[0.031]	356.2	(0.242)
Transport Equipment	0.9995	0.067	-0.015	560	0.168	320	0.101
	[0.0002]	[0.047]	[0.005]	424.2	[0.028]	278.3	(0.033)
Manufacturing, Nec;	0.9993	0.043	-0.010	560	0.112	320	0.069
Recycling	[0.0002]	[0.050]	[0.004]	461.7	[0.038]	253.7	(0.134)

Notes: Figures in brackets indicate standard errors that are based on 100 bootstrap replications. Figures in parentheses are the p-values of the$z$ test. Wald indicates the first-stage Wald statistics.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

Table 8: Estimated Elasticities, by Aggregate Sector: OECD Countries

Sector	$\hat{b}$	$\hat{\theta}$	N Wald	$\hat{\rho}$	N Wald	$\hat{\rho} - \hat{\theta}$
All	0.899	-0.093	420	0.190	270	0.283
	[0.024]	[0.055]	861.2	[0.047]	1283.4	(0.000)
Primary	0.654	0.391	420	0.255	270	-0.136
	[0.146]	[0.115]	779.3	[0.029]	1078.2	(0.126)
Manufacturing	0.960	-0.033	420	0.189	270	0.222
	[0.011]	[0.048]	490.2	[0.036]	1445.6	(0.000)
Services	0.829	-0.064	420	0.180	270	0.245
	[0.026]	[0.038]	1042.0	[0.058]	1175.3	(0.000)

Notes: Figures in brackets indicate standard errors that are based on 100 bootstrap replications. Figures in parentheses are the p-values of the$z$ test. Wald indicates the first-stage Wald statistics.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

Table 9: Estimated Elasticities, by Manufacturing Industry: OECD Countries

Industry	$\hat{b}$	$\hat{\theta}$	N and Wald	$\hat{\rho}$	N and Wald	$\hat{\rho}-\hat{\theta}$
Food, Beverages & Tobacco	0.9993	0.094	420	0.047	270	-0.047
	[0.0005]	[0.103]	824.4	[0.038]	758.7	(0.335)
Textiles & Textile Products	0.9985	0.159	420	0.053	270	-0.106
	[0.0010]	[0.120]	468.7	[0.045]	814.1	(0.204)
Leather & Footwear	0.9948	0.412	405	0.213	260	-0.199
	[0.0040]	[0.139]	161.4	[0.050]	358.0	(0.089)
Wood, Products of Wood	0.9990	0.104	420	0.152	270	0.048
& Cork	[0.0005]	[0.095]	539.6	[0.023]	1013.2	(0.312)
Pulp, Paper, Printing	0.9993	-0.001	420	0.083	270	0.083
& Publishing	[0.0004]	[0.105]	396.8	[0.032]	899.7	(0.225)
Coke, Refined Petroleum	0.9992	0.261	401	0.329	255	0.068
& Nuclear Fuel	[0.0005]	[0.084]	533.4	[0.074]	233.1	(0.271)
Chemicals	0.9994	0.057	420	0.247	270	0.190
& Chemical Products	[0.0003]	[0.068]	524.7	[0.037]	1035.7	(0.007)
Rubber & Plastics	0.9991	0.067	420	0.200	270	0.133
	[0.0003]	[0.065]	789.5	[0.039]	1242.8	(0.039)
Other Non-Metallic Mineral	0.9995	-0.045	420	0.150	270	0.195
	[0.0002]	[0.059]	678.9	[0.036]	827.7	(0.002)
Basic Metals	0.9992	0.059	420	0.261	270	0.202
& Fabricated Metal	[0.0004]	[0.077]	484.1	[0.050]	767.3	(0.013)
Machinery, Nec	0.9985	0.133	420	0.213	270	0.080
	[0.0005]	[0.049]	1240.4	[0.025]	1124.6	(0.074)
Electrical	0.9992	0.056	420	0.218	270	0.161
& Optical Equipment	[0.0003]	[0.070]	400.0	[0.043]	963.8	(0.025)
Transport Equipment	0.9993	0.067	420	0.202	270	0.134
	[0.0003]	[0.053]	434.7	[0.031]	966.2	(0.014)
Manufacturing, Nec;	0.9991	0.043	420	0.155	270	0.112
Recycling	[0.0003]	[0.056]	1183.5	[0.044]	1129.9	(0.058)

Notes: Figures in brackets indicate standard errors that are based on 100 bootstrap replications. Figures in parentheses are the p-values of the$z$ test. Wald indicates the first-stage Wald statistics.
Source: Socio Economic Accounts of the World Input-Output Database (WIOD) released in July 2014.

A Appendix

A.1 Industry Classification

Table A1: Industry Classificatoin

Code	Industry	Aggregate
1	Agriculture, Hunting, Forestry & Fishing	Primary
2	Mining & Quarrying	Primary
3	Food, Beverages & Tobacco	Manufacturing
4	Textiles & Textile Products	Manufacturing
5	Leather & Footwear	Manufacturing
6	Wood & Products of Wood & Cork	Manufacturing
7	Pulp, Paper, Printing & Publishing	Manufacturing
8	Coke, Refined Petroleum & Nuclear Fuel	Manufacturing
9	Chemicals & Chemical Products	Manufacturing
10	Rubber & Plastics	Manufacturing
11	Other Non-Metallic Mineral	Manufacturing
12	Basic Metals & Fabricated Metal	Manufacturing
13	Machinery, Nec	Manufacturing
14	Electrical & Optical Equipment	Manufacturing
15	Transport Equipment	Manufacturing
16	Manufacturing, Nec; Recycling	Manufacturing
17	Electricity, Gas & Water Supply	Services
18	Construction	Services
19	Sale, Maintenance & Repair of Motor Vehicles & Motorcycles; Retail Sale of Fuel	Services
20	Wholesale Trade & Commission Trade, Except of Motor Vehicles & Motorcycles	Services
21	Retail Trade, Except of Motor Vehicles & Motorcycles; Repair of Household Goods	Services
22	Hotels & Restaurants	Services
23	Inland Transport	Services
24	Water Transport	Services
25	Air Transport	Services
26	Other Supporting & Auxiliary Transport Activities; Activities of Travel Agencies	Services
27	Post & Telecommunications	Services
28	Financial Intermediation	Services
29	Real Estate Activities	Services
30	Renting of M&Eq & Other Business Activities	Services
31	Public Admin & Defence; Compulsory Social Security	Services
32	Education	Services
33	Health & Social Work	Services
34	Other Community, Social & Personal Services	Services

Note: Aggregate industries are based on our own classification.

Source: Socio Economic Accounts of the World Input–Output Database (WIOD) released in July 2014.