Many Sectors Meet More Skills: Intersectoral Linkages and the Skill Bias of Technology*

JOB MARKET PAPER

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Abstract

This paper presents a novel stylized fact and analyzes its contribution to the skill bias of technical change: The share of skilled labor embedded in intermediate inputs correlates strongly with the skill share employed in final production. This finding points towards an intersectoral technology-skill complementarity (ITSC). Empirical evidence suggests that the channel through which this complementarity works is product innovation driven by skilled workers. Together with input-output linkages, the observed complementarity delivers a multiplier that reinforces skill demand along the production chain. The effect is large, accounting for roughly half of the observed skill upgrading in U.S. manufacturing over the period 1967-92. The paper presents a simple multi-sector model with intermediate linkages that integrates the observed ITSC into the standard framework of skill-biased technical change. Therein, the relative productivity of skilled workers rises with the skill intensity of intermediates. A calibration exercise confirms the quantitative importance of the ITSC.

JEL: J24, J31, O14, O15, O33, C67

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1 Introduction

This paper shows that skill upgrading in one sector increases skill demand in many other sectors, because of linkages operating through the use of intermediate products. This channel has been ignored by the literature so far, despite the fact that more than half of a final product's value is embedded in intermediates. I construct a measure of input-embedded skills, matching input-output tables with workforce data for detailed U.S. manufacturing sectors. Input skill intensity is defined as the weighted average share of white-collar workers employed in the production of a sector's intermediate inputs.[1] Figure 1 presents a novel stylized fact: A strong positive correlation between input skill intensity and skills employed in final production in U.S. manufacturing.[2] I argue that this finding implies an intersectoral technology-skill complementarity (ITSC): Skills used in intermediate production are complementary to skills required in the further processing of intermediates or their integration into redesigned final products. I also show that the ITSC is quantitatively important, explaining roughly half of the increase in white-collar labor demand in U.S. manufacturing.

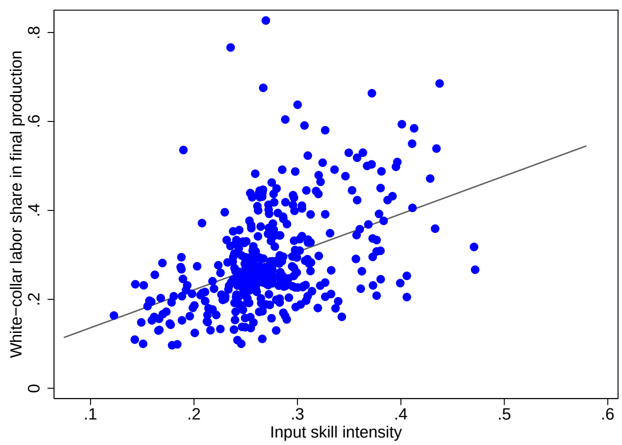

Figure 1: Skilled labor share in final production vs. input skill intensity

Notes: Data are for 358 U.S. manufacturing sectors in 1992. Input skill intensity is calculated as the weighted average share of white-collar workers employed in the production of a sector's inputs. Only inputs purchased outside a sector are taken into account. See Section 3 for a formal description and data sources, and Section 4 for regression results and robustness.

Empirical evidence suggests that this complementarity works through product innovation. Building on the seminal work by Nelson and Phelps (1966), much econometric and case-study evidence indicates that highly skilled workers are not merely more productive, but are also good innovators, adapt better to technological change, and speed the process of technological diffusion [Bartel and Lichtenberg 1987; Goldin and Katz 1998; Doms, Dunne and Troske 1997]. Because of this innovation-skill complementarity, an upstream supplier employing highly educated workers turns out innovative intermediates. Upstream product improvement induces innovation at the downstream level, which in

[1] White-collar workers – including personnel engaged in supervision, installation and servicing, professional, technological, and administrative – have been widely used to proxy for skilled labor. See in particular Berman, Bound, and Griliches (1994).

[2] The figure presents cross-sectional observations in 1992. The correlation is very similar for any other benchmark year (5-year intervals) between 1967 and 1992.

turn increases skill demand.[3] The argument does not depend on the direction of causality; the complementarity also works from producers to suppliers. An example is a cutting-edge downstream firm demanding innovative intermediate inputs, so that its upstream supplier needs highly skilled workers.

Because of the ITSC, inputs used in the production process are not only 'intermediate' in the standard semi-manufactured sense, but also 'intermediaries' that transmit skill requirements across industries. Therefore, product innovation affects labor demand not only in the corresponding firm or industry, as previous studies have argued, but also in other firms or sectors, via input-output linkages. These linkages deliver a multiplier that reinforces skill demand across firm and sector boundaries. For example, the invention and improvement of the transistor affected skill demand within and outside its sector of origin, the electronic components industry. Within this industry, the transistor enabled the production of more refined electronic parts, engineered by highly skilled workers. These innovative electronic components eventually became fundamental intermediate inputs for a large variety of other sectors, including computers, communication equipment, and controlling devices, where their integration went hand in hand with product innovation and skill upgrading. The improvement of these devices, in turn, enabled further innovation of electronic components. Innovation in the electronic components industry therefore drives skill demand in many other sectors. Eventually, it feeds back into the originating sector itself, creating a virtuous circle, or in effect a multiplier of skill upgrading.

This amplification mechanism closes an important gap in the empirical wage-inequality literature. While many variables have been shown to contribute to rising skill demand in a statistically significant way, accounting for the full scope has proved difficult. By adding the intermediate dimension, this paper shows that skill upgrading in one sector leads to rising skill demand in linked sectors, amplifying initial increases in skill demand along the production chain. It also suggests that a positive supply shock for skilled labor could lead to a rise in skill demand in the economy at large.

The empirical analysis in this paper is based on U.S. input-output data, paired with workforce characteristics from the NBER Manufacturing Industries Database at the detailed 4-digit level over the period 1967 to 1992. To quantify input skill intensity, I construct a variable that measures, for each sector, the proportion of white collar workers involved in the production of its intermediate inputs. The correlation between input skill intensity and skills in final production is stable over time and robust to the inclusion of a large number of additional controls.[4] These results are confirmed when going beyond a mere correlation analysis and using instruments to account for the endogeneity of input skill intensity and control variables. The estimated ITSC implies a multiplier of approximately 2. Consequently, an initial innovation (or shock) that causes immediate average skill upgrading of one percent translates into a total skill demand increase of about two percent (for given relative wages), as innovations and skill demand spread across sectors, reinforcing each other.

Differentiated goods can be refined more readily than homogenous ones. Crude petroleum does not change, whether it is pumped out of the ground by laborers or university graduates, while the

[3] As Scherer (1982) for the United States and Pavitt (1984) for Great Britain show, product innovation in upstream sectors serves to improve productivity and quality of output in the buying industries.

[4] These controls include sectoral fixed effects, time dummies, as well as various measures proposed in the wage inequality literature: capital intensity, shares of computer and high-tech capital, R&D intensity, and outsourcing. I also exclude inputs from kindred industries in the calculation of input skill intensity in order to address the concern that simultaneous innovations at the aggregate industry level drive the observed correlation.

presence of engineers contributes to continuous improvement of electronic components. Therefore, differentiated inputs are more susceptive to 'skill embedding.' Innovations in the production of homogenous inputs improve processes rather than products, and thus have little effect on skill demand at the subsequent downstream level. I provide evidence for this assertion, combining data on sectoral product and process innovation from Scherer (1982) with Rauch's (1999) classification of product differentiation. The constructed cross-section shows that product innovation is more pronounced in sectors that produce differentiated goods. Thus, downstream users of differentiated intermediates purchase relatively more embedded product innovation. Next, I use Rauch's (1999) classification to construct a measure of input differentiation. I demonstrate that the ITSC is increasing in the degree of input differentiation, and is insignificant for sectors that use mainly homogenous inputs. In an additional analysis, I show that skill-intensive intermediates foster productivity only in those sectors that employ skilled workers able to handle them. In the absence of final production skills, skill-intensive intermediates could even harm output per worker. Thus, input-embedded and final production skills complement each other in raising productivity.

The rest of the paper is organized as follows. Section 2 reviews the related literature and presents a framework that incorporates complementarities between product innovation, skills embedded in intermediate inputs, and skilled labor in final production. Section 3 describes the data, explaining in detail the construction of the input skill intensity measure. Section 4 reports empirical results, documenting the intersectoral technology-skill complementarity, and confirms its robustness. It also addresses endogeneity issues by using a set of IV regressions and checks instrument validity, applying weak instrument tests and overidentifying restrictions. The IV results confirm the strength and significance of my main findings. Section 5 integrates the novel stylized fact into the theoretical skill-biased technical change (SBTC) framework. I build a simple model that adds intermediate inputs to the standard SBTC setup. Therein, the relative productivity of skilled workers depends on the skills embedded in intermediates. A calibration exercise implies that the correlation of skill requirements along the production chain accounts for 50% of SBTC in U.S. manufacturing over the sample period, underscoring the potential of my framework to reconcile key facts. Section 6 concludes.

2 Motivation and Framework

As the supply of skilled workers has risen, so has the skill premium. A large body of studies following Katz and Murphy (1992) documents substantial increases in wage inequality in the United States. Skill upgrading, i.e., a rise in skilled labor's share in employment and payroll, is also observed in other OECD countries as well as in developing countries.[5] Many explanations have been offered for the rising wage inequality, but two stand out: Trade liberalization and its effects on international patterns of specialization [e.g., Leamer 1996; Wood 1998; Feenstra and Hanson 1999], and skill-biased technical change – technological progress that shifts demand toward more highly skilled workers relative to the less skilled. Numerous studies quantify SBTC as a complementarity between capital (or technology) and skill, where computer-based information technologies (IT) play a central, although disputed

[5]See Machin and van Reenen (1998), and Berman, Bound and Machin (1998) for evidence on the former; Pavcnik (2003), and Zhu (2005) on the latter group of countries.

role [DiNardo and Pischke 1997, Card and DiNardo 2002]. So far, the SBTC literature has treated technology-skill complementarities as a phenomenon within specific industries[6], within firms[7], and at the worker level[8], ignoring linkages across sectors. Some contributions add the role of complementarities among information technology, production organization, and product innovation [Milgrom and Roberts 1990] and link these to the observed increase in skill demand [Bresnahan et al. 2002].

Existing work can explain some of the rise in skill demand, but falls far short of accounting for all of it. The first prominent channel, international trade, has a between- and a within-industry component. The between-component, relocating production of low-skill-intensive industries to low-skill abundant countries, contributes little to the observed skill upgrading [Berman et al. 1994, Autor et al. 1998]. To explain the importance of observed within-industry skill upgrading, Feenstra and Hanson (1999) suggest outsourcing of low-skill intensive activities within firms or sectors. Their measure explains up to 15% of relative wage increases in U.S. manufacturing. The second group of explanations has used numerous variables to quantify the skill bias of technical change. Computers and other high-tech capital have been shown to contribute about 1/3 to the increase in white-collar labor demand in manufacturing [Feenstra and Hanson 1999, Autor et al. 1998].[9] The role of a broad capital-skill complementarity [Krusell, Ohanian, Ríus-Rull, and Violante 2000] has proved controversial. Finally, while studies document significantly positive coefficients on R&D intensity [Machin and van Reenen 1998, Autor et al. 1998], the variable itself changes relatively little over time. I show below that R&D intensity can account for about 5-10% of skill upgrading in manufacturing. All individual contributions together explain only about half of the overall magnitude.

Studies of SBTC have made the key (and limiting) assumption that complementarities are found at the individual worker, firm, or industry level. To this, I add complementarities across sectors, i.e., complementarities between input-embedded skills and skills employed in the subsequent processing of intermediates and their integration into final products. Ignoring these intersectoral linkages imposes an important limitation to the investigation of skill upgrading. This paper suggests that complementarities in the multi-sectoral structure deliver an amplification mechanism that explains more skill upgrading in U.S. manufacturing than high-tech capital, R&D intensity, or outsourcing.

[6] Berman et al. (1994) find that the rate of skill upgrading within U.S. manufacturing is strongly correlated with IT investment and R&D, and accounts for most of the demand shift towards skilled workers over the 1980s. This effect has been greater in more IT-intensive industries [Autor, Katz and Krueger 1998]. Autor, Levy and Murnane (2003) argue that computer capital substitutes for 'routine tasks' while it complements more complex 'nonroutine' tasks performed by skilled workers.

[7] Levy and Murnane (1996), Doms et al. (1997), and Bresnahan, Brynjolfsson and Hitt (2002) use broad measures of technological progress and provide evidence on firm and plant level skill-favoring demand shifts.

[8] Krueger (1993) and Autor et al. (1998) document a strong positive correlation between wages and computer use by workers. Epifani and Gancia (2006) point out scale increases as an additional channel for skill bias. See Bound and Johnson (1992) for an assessment of alternative explanations of the observed relative wage changes. Katz and Autor (1999) and Sanders and Ter Weel (2000) summarize the literature at the three levels of aggregation.

[9] These estimates are to be interpreted with caution, as they take correlation coefficients as causal effects. Autor et al. (2003) investigate computer-induced task shifts in all sectors of the U.S. economy. Their approach can explain up to sixty percent of the relative demand shift favoring college labor, but half of this impact is due to task changes within nominally identical occupations. The remaining thirty percent between occupations are similar to Feenstra and Hanson's finding.

A tale of two sectors

To illustrate my finding, I contrast the divergent experiences of two sectors. Both began with a white-collar worker share similar to the manufacturing average (24% in 1967), but took very different paths thereafter: One revolutionizing its products, while the other turned out an unchanging artifact. The first sector, Calculating and Accounting Equipment (SIC 3578), experienced major skill upgrading, with the share of white-collar workers increasing from 23% in 1967 to 58% in 1992. In contrast, this share stagnated at 20% in the second sector, Truck Trailers (SIC 3715), lagging far behind the manufacturing average that grew to 31% in 1992.[10] Table 1 shows for both sectors the six most important intermediate inputs and the white-collar labor share employed in their production.

Over the period 1967-1992, the Calculating and Accounting Equipment sector underwent major innovations, above all the switch from mechanical (wiring, metal, machines) to high-tech components (computing, electronic, and semiconductors). This transition is reflected by the changing input shares a_j in Table 1. The producers of high-tech components, in turn, experienced skill upgrading, as reflected by changes in h_j. For example, semiconductors were produced with 32% of white-collar workers in 1967 as compared to 51% in 1992. Less skill-intensive (and less innovative) inputs like wiring devices, on the other hand, were important in 1967 but nonrelevant in 1992. Therefore, skill upgrading in the Calculating and Accounting Equipment industry went hand in hand with innovation and skill upgrading in the production of its intermediate inputs. This example provides a strong case for product innovation driving skill demand in many sectors, as opposed to the commonly studied within-sector effects of process innovation. As Pavitt (1984, p.350) puts it, referring to the same sector:

> ”Innovative activities are in fact heavily concentrated on product innovation: no amount of process innovation in, for example, the production of mechanical calculators would have made them competitive with the product innovations resulting from the incorporation of the electronic chip.”

Things look different in the Truck Trailer industry, where input mix and skill intensity of input production changed little. As the lower part of Table 1 shows, input shares are very stable over time – a truck trailer in the 1990’s is not much different from one three decades earlier. Moreover, sectors supplying intermediate inputs for truck trailer production experienced minor or no skill upgrading, indicating little product innovation. Monotony of the product goes hand in hand with stagnation of the workforce composition: The white-collar labor share remained unchanged throughout 25 years.

Intermediate input linkages

While intermediate linkages play no role in the SBTC literature, studies concerned with linkages concentrate on labor productivity rather than skill bias and wage inequality. Although intermediate inputs account for more than half of all costs, the literature has not taken notice of intersectoral linkages as an explanation for skill demand. Input-output tables for the United States show that industries’ expenditure share for intermediate inputs is stable over time, largest in manufacturing (57%), and smallest in services (43%). The remaining expenditures include employee compensation (about 30%)

[10] The data are from the NBER Manufacturing Industry Database. See section 3 for details.

Table 1: Two sectors: Intermediate input shares and skills used in intermediate production

Calculating and Accounting Equipment (SIC 3578)

	1967		1992	
Input (j)	a_j	h_j	a_j	h_j
Electronic computing equipment	.018	.419	.364	.663
Miscellaneous electronic components	.055	.267	.232	.358
Semiconductors & related devices	.021	.322	.095	.507
Wiring devices	.116	.249	.000	.285
Office machines	.110	.284	.000	.500
Metal stampings	.038	.172	.068	.237

Truck Trailers (SIC 3715)

	1967		1992	
Input (j)	a_j	h_j	a_j	h_j
Motor vehicle parts & accessories	.237	.180	.201	.217
Aluminum rolling & drawing	.122	.208	.144	.241
Blast furnaces & steel mills	.150	.186	.115	.230
Tires & inner tubes	.065	.230	.121	.183
Fabricated rubber products	.039	.255	.053	.265
Sawmills & planing mills, general	.030	.088	.037	.146

Notes: Data from U.S. Input-Output tables and the NBER Manufacturing Industry Database. See section 3 for details. a_j: The respective sector's expenditure share for input j (relative to total expenditures for manufacturing inputs purchased outside the same sector); ordered by average importance in 1967/92. h_j: Share of white-collar workers in production of input j

and payments to capital (about 16%).[11] Studies arguing that a capital-skill complementarity is responsible for skill upgrading therefore focus on a relatively small component of the final product's value.[12] The approach applied in this paper is strictly separated from the capital-skill complementarity literature. While the latter analyzes SBTC related to capital (or investment) goods, my analysis is based on intermediate input-output linkages that by construction do not include investment.

The importance of input-output linkages for economic development has been investigated in an ample literature pioneered by Leontief (1936) and Hirschman (1958). Ciccone (2002) shows that small increasing returns at the firm level can translate into large effects on aggregate income when industrialization goes hand in hand with the adoption of intermediate-input intensive technologies. In a recent contribution, Jones (2007) analyzes this point more deeply, underlining the role of linkages

[11] These two, together with the minor component 'Indirect business tax and nontax liability' make up value added (on average 47% of all expenditures). All percentage values are derived from the 1992 U.S. input-output table from the Bureau of Economic Analysis. Numbers are very similar in other years.

[12] The hypothesis of capital-skill complementarity has been formalized by Griliches (1969). Krusell et al. (2000) argue that the stock of capital equipment, measured in efficiency units, is complementary to skilled labor, accounting for much of the variations in the skill premium over the last 30 years. This result has been challenged because it disappears upon the inclusion of a time trend, which is the case in my analysis, as well.

and complementarities to explain large cross-country income differences. In his paper, input-output linkages give rise to a multiplier effect in production that augments productivity differentials; the latter are in turn explained by complementarities along the production chain. Multipliers have also been used to explain the growth in the trade share of output, or the cyclical behavior of aggregate productivity.[13] However, this paper is the first to investigate the role of intersectoral linkages for skill upgrading.

Innovation linkages across sectors

Linkages across industries alone need not imply connected skill requirements.[14] What makes the proposed point plausible is the (above discussed) innovation-skill complementarity *within* sectors, combined with strong empirical evidence showing that innovation is transmitted *across* sectors through input-output linkages.

Research from the 1980's provides substantial evidence for technology linkages across sectors. Scherer (1982) using U.S. patent data, and Pavitt (1984) using British innovation data, implement a methodology first proposed by Schmookler (1966). They construct what can be considered the technological equivalent of an input-output table, identifying sectoral R&D expenditures, as well as the amount of each sector's R&D that is passed to other sectors in the form of product-embedded innovation. In this context, product innovations are by definition used outside their sector of origin, and process innovations are used inside their sector. For example, in the United States 86% of all R&D expenditures in the Lumber and Wood sector improved production processes, and only 14% of innovations left this sector in the form of improved products. The opposite holds for Industrial Electrical Equipment, where 85% of R&D was devoted to product innovation, benefitting sectors that use electrical equipment. Both Scherer and Pavitt confirm the overall prevalence of product innovations, which account for 73.8 percent of total R&D outlays in the USA, and 75.3 percent in Great Britain. Therefore, the majority of innovations influence product characteristics and design outside their sector of origin.[15] How does this pattern of production and use of innovations compare with recent contributions to the SBTC literature that analyze innovation- and capital-skill complementarities solely *within* sectors? These studies assume that technology is created by R&D within a sector, or that it is capital-embodied, entering the sector through investment. For non-manufacturing sectors, where technical change comes mainly through the purchase of equipment, these assumptions are realistic. Within manufacturing, however, much of technical change is originating outside of a given sector and enters the sector through intermediate inputs. As Scherer (1982, p.227) emphasizes:

> ”If [a new product] is a producer good or intermediate sold externally, it serves to improve output/input relationships or the quality of output in the buying industries. With a new turbojet engine product, for example, the R&D is performed in the aircraft engine industry, but the productivity effect often shows up in lower energy consumption or

[13] Yi (2003) shows that small decreases in tariff barriers multiply up to large trade increases when intermediates are traded several times during the production process. Basu (1995) argues that intermediate goods act as a multiplier for price stickiness, augmenting little firm-level rigidity to a large economy-wide price inflexibility.

[14] As pointed out by Jones (2007), one can have linkages without complementarity of inputs.

[15] Scherer (1982) also provides evidence that most productivity benefits are realized by R&D using, rather than product R&D-originating industries.

> faster, quieter, and more reliable operation of equipment used by the quite distinct airlines industry. [...] to assume that the productivity-enhancing effect occurs solely within the R&D-performing industry [...] is more wrong than right, since three-fourths of all industrial R&D is devoted to new or improved products, as distinguished from processes."

This discussion underlines the existence of innovation spillovers from upstream suppliers to downstream final producers, via intermediate linkages. Does this channel exist in the opposite direction, too? That is, do innovative final producers demand cutting-edge intermediates? At the national level, this specific causal relationship is empirically difficult to separate from agglomeration economies, due to the proximity of production activities.[16] However, the literature on international spillovers and transfer of knowledge provides evidence that innovative downstream producers foster technical progress of their upstream suppliers. For example, Blalock and Gertler (2002) document vertical spillovers in the case of foreign investment in Indonesia: Subsidiaries of multinational enterprises provide technological knowledge to their local intermediate suppliers in order to reduce prices and increase competition in upstream markets.[17]

Adding the role of technology-skill complementarity

We currently know that innovation goes hand in hand with skilled labor. Moreover, innovative activity generates spillovers along the production chain. So far, these two facts have been treated separately in the literature. Combining them yields an intersectoral technology-skill complementarity. The interactions of innovations and skills run in both directions, and across sectors, reinforcing one another. Individually and collectively, innovations in sectors related through input-output (I-O) linkages increase the relative demand for skilled labor (H/L) as summarized below:

$$\begin{array}{ccc}
\underline{\text{Upstream}} & & \underline{\text{Downstream}} \\
\text{Product Innovation}_j & \Leftrightarrow & \text{Product Innovation}_i \\
\updownarrow & \text{I-O linkages} & \updownarrow \\
(H/L)_j & & (H/L)_i
\end{array}$$

Closest to my contribution are the complementarity frameworks proposed by Milgrom and Roberts (1990) and Bresnahan et al. (2002), where the adoption of IT, work organization, product innovation, and skill upgrading reinforce each other within, but not across firms.

3 Data

Data on worker characteristics, wages, value of shipment, and real capital (equipment and structures) at the 4-digit SIC level are from the NBER-CES Manufacturing Industry Database. These data are

[16] Besides technological spillovers and intermediate input linkages, Marshall's (1927) three major sources of agglomeration also include labor pools. Robbins (2006) identifies knowledge spillovers that spread across U.S. states and vary in magnitude depending on distance and technologies.

[17] For a theoretical framework see Rodríguez-Clare (1996). Keller (2004) and Koo (2005) summarize the literature on international and local technology spillovers.

collected from various years of the Annual Survey of Manufacturing (ASM), and have been widely used to investigate the determinants of the rise in U.S. wage inequality.[18] This database classifies employment in two broad categories: production and non-production workers. The former are 'workers engaged in fabricating, processing, assembling, inspecting, and other manufacturing', while the latter are 'personnel, including those engaged in supervision, installation and servicing of own product, sales, delivery, professional, technological, administrative, etc.' According to this classification, non-production workers are involved in innovative activities, the focus of this paper. As noted by Berman et al. (1994), the production/non-production classification closely mirrors the distinction between blue- and white-collar occupations from the Current Population Survey, which in turn closely reflects educational levels as high school vs. college. In the following, I refer to non-production (white-collar) workers as high-skilled labor H and to production (blue-collar) workers as low-skilled labor L.

The Bureau of Economic Analysis' (BEA) Input-Output Use Tables specify expenditures of each industry i for intermediate inputs purchased from industry j. The BEA provides U.S. input-output (I-O) data at the 4-digit SIC level in 5 year periods between 1967 and 1992. For some sectors, the level of aggregation or coverage changes over time. I account for this by aggregating sectors, and match the resulting I-O panel to the ASM's 1987 SIC classification.[19] This yields a panel of 358 manufacturing industries over the period 1967-1992. For each industry, the panel contains production and non-production employment and wages, value of shipment with the corresponding deflator (1987=1), real capital equipment and structures (all from the ASM), and the purchases of industry i from sector j (from the BEA I-O data). All figures provided in the BEA's I-O Use Tables are in nominal dollars. I use the shipment deflators provided by the ASM to calculate, for every manufacturing industry i, its real expenditures for inputs from each manufacturing industry j in year t, X_{ij}^t.[20]

Constructing the measure of input skill intensity

To construct a measure of skills embedded in intermediate inputs, I first derive intermediate input shares from the real I-O expenditure data X_{ij}^t. Let $X_i^t = \sum_{j \neq i} X_{ij}^t$ represent total expenditures for manufacturing inputs purchased by industry i outside the same industry in period t. The time-varying intermediate input shares are then given by $a_{ij}^t = X_{ij}^t / X_i^t$. These exhibit substantial fluctuations over time, mostly due to one-time outliers in the six benchmark years. For example, in 1967 'Paperboard containers and boxes' accounted for 3.4% of the manufacturing inputs in the 'Chocolate and cacao products' sector. This number more than quadrupled 5 years later (13.4%), stabilizing at 6.5% thereafter until 1992. Another example is 'Communication equipment', used in 'Guided missiles and space vehicles' production. The corresponding a_{ij} grows from 4% in 1967 to 47% in 1977, then falling back to 5% in 1992. There is no reason to believe that these numbers reflect physical input shares. Measurement error as well as fluctuations in relative input prices, imperfectly corrected

[18]Examples include Berman et al. (1994), Autor et al. (1998), and Feenstra and Hanson (1999). See Bartelsman and Grey (1996) for a documentation of these data.

[19]For example, paper mills (SIC 2621) and paperboard mills (SIC 2631) are available separately in the I-O data until 1982, but aggregated from 1987 on. I treat these data as one sector, 'paper and paperboard mills' over the full sample period. Detailed sector correspondences are available upon request.

[20]Bartelsman and Grey (1996) use the same method to derive real material (or input) costs.

by the deflators, appear to be reasonable explanations.[21] Therefore, I use average real input shares $\bar{a}_{ij} = \sum_{t=67}^{92} a_{ij}^t$ between 1967 and 1992 as a baseline. This approach can be interpreted to reflect an underlying Cobb-Douglas technology that keeps expenditure shares constant over time (or a Leontief that has the same effect under stable relative prices).[22] Input skill intensity is then defined as

$$\sigma_i^t = \sum_{j \neq i} \bar{a}_{ij} h_j^t \tag{1}$$

where $h_j^t \equiv H_j^t/(H_j^t + L_j^t)$ denotes the share of white-collar workers employed in the production of input j.[23] I exclude inputs purchased within the same sector ($j = i$) for two reasons. First, this avoids that skilled workers employed in sector i itself enter its measure of skill intensity σ_i, which would bias my results. Second, I am concentrating on product innovation entering a sector via intermediates purchased from outside, rather than process innovation generated within a sector.

A potential concern arises because inputs X_{ij} (and thus input shares a_{ij}) contain imports from abroad, while the corresponding skill shares h_j are measured in U.S. sectors.[24] However, the resulting measurement error of σ_i is likely to be minor. The share of imports in non-energy intermediates during my sample period is relatively small, growing from 4% in 1967 to 13% in 1992 (see Appendix A1). Moreover, most U.S. imports of intermediates in this period were sourced from other OECD countries with similar skill intensities. Finally, having a noisy measure of input skill intensity creates attenuation bias against finding skill complementarities across sectors.

By construction $\sigma_i \in [0, 1]$ is the weighted average share of non-production workers involved in the production of sector i's intermediate manufacturing inputs. An alternative measure of input skill intensity is obtained by excluding those inputs that are purchased from the same two-digit SIC industry as the good being produced. I implement this idea by restricting the four-digit industry subscripts i and j in (1) to be outside the same two-digit SIC industry. This measure addresses the concern that skill upgrading may happen simultaneously in similar industries, which would imply a correlation of input and final production skill intensities when similar sectors buy each other's inputs. The resulting measure is labeled σ_i^{2d}.

Table 2 provides a list of the twenty industries with the smallest and the largest increase in input skill intensity σ_i^{2d} for the period 1967-92.[25] The reported ranking seems sensible. The industries

[21] Out of the about 128,000 $i \times j$ input shares, 7,000 are nonzero throughout the sample period. Their average coefficient of variation over the six sample benchmark years is 0.67. Less than 1/3 have a time trend that is significant at the 10% level.

[22] This would be a strong assumption if input shares shifted systematically towards more (or less) skill intensive industries. This is not the case. In section 4.2 I use the time-varying a_{ij} to decompose input skill intensity into input-mix and skill-mix components. This analysis shows that practically all the increase in input skill intensity between 1967 and 1992 is due to skill upgrading in input production at constant input shares (skill mix), rather than changing input shares (input mix). Section 4.2 also provides an extended empirical analysis with time-varying input shares, showing that the ITSC is robust to this specification.

[23] Alternatively, σ_i^w can be calculated, using wage-bill instead of employment shares: $h_j^w \equiv w_{H,j}H_j/(w_{H,j}H_j + w_{L,j}L_j)$, where $w_{H,j}$ and $w_{L,j}$ denote white- and blue-collar wages, respectively. Regression results change only very little when using σ_i^w.

[24] Unfortunately, the BEA provides import matrices only from 1997 on. But even these numbers are approximations and do not include the source country. Actual data on the domestic/imported content of an industry's intermediate inputs are, for the most part, not available. Import matrix estimates are typically based on the assumption that the share of imports in total domestic consumption of a commodity applies to each industry that uses the commodity (proportionality assumption).

[25] The sectoral *levels* of input skill intensity are not important for my empirical results – they are taken up by fixed effects in the regressions. Thus, I report changes rather than levels. The ranking is similar when based on the measure σ_i.

with smallest changes (or declines) in input skill intensity are mainly textile and food industries. These tend to use primary inputs, which in turn changed little or dropped in terms of non-production employment shares. Most industries that experienced the largest increase in inputs skill intensity also appear sensible. These include various electronic, computing, and communication equipment, as well as aircraft and space industries, all of which intensively use high-tech inputs that experienced innovation and skill-upgrading throughout the last decades.[26]

Table 2: The twenty industries with smallest and largest change in input skill intensity

Smallest change in σ_i^{2d} 1967-92		Largest change in σ_i^{2d} 1967-92	
$\triangle\sigma_i^{2d}$	Industry description	$\triangle\sigma_i^{2d}$	Industry description
-.045	Leather tanning & finishing	.074	Carbon black
-.023	Tire cord & fabrics	.074	Ceramic wall & floor tile
-.022	Yarn mills & finishing of textiles	.075	Watches, clocks, & parts
-.011	Women's hosiery, except socks	.075	Photographic equipment & supplies
.001	Carpets & rugs	.076	Paperboard containers & boxes
.006	Cordage & twine	.076	Primary aluminum
.009	Thread mills	.076	Primary nonferrous metals
.010	Knit fabric mills	.077	Ordnance & accessories
.020	Hosiery	.079	Steel pipe & tubes
.021	Manufactured ice	.079	Search & navigation equipment
.021	Footwear cut stock	.080	Aircraft
.025	Leather gloves & mittens	.081	Wood preserving
.026	Knitting mills	.082	Paper & paperboard mills
.027	Schiffli machine embroideries	.082	Calculating & accounting equipment
.027	Malt beverages	.086	Typesetting
.028	Truck trailers	.089	Instruments to measure electricity
.028	Mobile homes	.090	Pulp mills
.028	Bottled & canned soft drinks	.091	Electronic computing equip.
.029	Frozen fruits & vegetables	.093	Guided missiles & space vehicles
.029	Fertilizers, mixing only	.111	Electromedical equipment

Note: Reported input skill intensities are rounded from seven digits to three digits.

The measure of input differentiation

In order to identify the degree of differentiation for each sector's inputs, I use data from Rauch (1999). Rauch groups goods into 1,189 industries according to the 4-digit SITC Rev. 2 system. An indus-

[26]Pulp Mills and Paper & Paperboard Mills do not seem to fit this pattern. Part of the increase in input skill intensity is explained by their dependence on Industrial Chemicals (about 1/4 of all inputs), which experienced skill upgrading from 35 to 44 percent. However, another part is due to accounting, rather than real skill upgrading in input production. Both industries depend heavily on inputs from Logging, with the corresponding input shares 36 and 28 percent, respectively. The non-production labor share in Logging rose from 4.4% to 17.0%. A possible explanation for this increase is offered by the Occupational Employment Statistics from the Bureau of Labor Statistics, which provides detailed occupation data from 1999 on. According to these data Logging involved about 22 percent of employment in transportation activities in 1999. The ASM classifies transportation as non-production labor. The rising importance of transportation is relative rather than absolute, because overall employment in Logging fell. Because few sectors depend on inputs from Logging, this problem is an isolated one. Moreover, my results are robust to splitting the sample into sectors with falling and increasing overall employment.

try's product is classified as being differentiated if it is neither traded on an organized exchange nor reference priced in trade publications.[27] I aggregate the Rauch data into the 358 SIC industries of my sample. This procedure yields data on the fraction of each industry's output that is differentiated.[28] Using this information, along with the input shares derived above, I define the degree of input differentiation:

$$\kappa_i = \sum_{j \neq i} \bar{a}_{ij} \; R_j^{\text{diff}} \tag{2}$$

where R_j^{diff} is the proportion of input j that is classified as differentiated. The measure κ_i is therefore the weighted average share of a sector's inputs (purchased outside the same sector) that are differentiated. This variable is similar to Nunn's (2007) measure of relationship specificity; but Nunn uses Rauch's classification in a different context, showing that countries with good contract enforcement specialize in the production of goods that require relationship-specific investments.

Data on product innovation

I use data from Scherer (1982) to derive, for each industry, its share of R&D spent for product innovation, π_i^{prod}.[29] In the empirical analysis π_i^{prod} serves to investigate the relationship between product innovation and product differentiation, given by R_i^{diff} described above. In order to perform this analysis, I match my 4-digit SIC code to Scherer's 36 manufacturing industries and aggregate R_i^{diff} to this level of detail, using sectoral shipments as weights. The resulting sample includes π_i^{prod} and R_i^{diff} for 34 manufacturing sectors (2 observations of π_i^{prod} are missing). π_i^{prod} has mean .66 and standard deviation .27. The share of product innovation is smallest in primary industries like wood products, ferrous metals, or petroleum, and largest in various machinery and equipment industries, including photo, medical instruments, communication and construction equipment.

Additional control variables

In the empirical analysis I include several variables that have been previously used to explain increasing wage inequality. In the following I describe these variables briefly. Appendix A.1 provides more detail. Krusell et al. (2000) argue that the stock of capital equipment is complementary to skilled labor. To control for this capital-skill complementarity, I include real equipment and real structures per worker, k^{equip} and k^{struct}, respectively. Data on research and development (R&D) intensity are from the National Science Foundation (NSF). Following Autor et al. (1998), I use lagged R&D intensity ($R\&D_{lag}$) in the regressions.[30] I use data from the BEA to construct sectoral shares of high-

[27] Rauch provides liberal and conservative estimates. I use the former, but none of the results presented in the following depend on this choice.

[28] Nunn (2007) describes the construction of a crosswalk from the 4-digit SITC to the BEA's 1987 4-digit SIC classification. He kindly shared his data. These aggregate into 302 sectors of my sample. For the remaining 56 sectors I use a correspondence from 4-digit SITC to 4-digit SIC provided by Pamela Lowry (downloadable from Jon Haveman's Industry Trade page). Like Nunn, I apply equal weights when aggregating SITC industries to the SIC classification.

[29] Appendix A.1 explains the corresponding methodology in detail.

[30] The first (lagged) period is 1963, implying a 4-year lag. All other lags are 5 years. Because industrial R&D intensity tends to be persistent over time, working with lagged or contemporaneous R&D makes very little difference to the nature of the results.

technology capital (*HT/K*) and office, computing & accounting equipment (*OCAM/K*).[31] Feenstra and Hanson (1999) document a substantial impact of foreign outsourcing of intermediate inputs on relative wages. I calculate their broad (OS^{broad}) and narrow (OS^{narr}) measures of outsourcing for the years and sectors included in my sample. Feenstra and Hanson argue that the narrow measure – from within the same two-digit industry – best captures the idea of outsourcing. For example, the import of steel by a U.S. automobile producer is normally not considered as outsourcing, while it is common to think of imported automobile parts by that company as outsourcing. Following this reasoning, I use OS^{narr} in most regressions, including OS^{broad} in the robustness checks.

Table 3 reports the pairwise correlations between two measures of input skill intensity (σ_i and σ_i^{2d}) and the most prominent control variables. As in most of the following analyses, these correlations are obtained after controlling for industry and time fixed effects. The two measures of input skill intensity are highly correlated with one another, and are also correlated with control variables commonly used in the SBTC literature. Industries using skill-intensive intermediates tend to be capital and R&D intensive, employ high-tech capital, and outsource the production of their intermediates.

Table 3: Correlations between input skill intensity and control variables

	Input skill intensity		Capital per worker		High-Tech	R&D/ sales	Out-sourcing
Measure	σ_i	σ_i^{2d}	k^{equip}	k^{struct}	HT/K	$R\&D_{lag}$	OS^{narr}
σ_i	1						
σ_i^{2d}	.66***	1					
k^{equip}	.12***	.15***	1				
k^{struct}	.05**	.07***	.70***	1			
HT/K	.20***	.14***	-.03	-.01	1		
$R\&D_{lag}$	.18***	.13***	-.01	.03	.39***	1	
OS^{narr}	.13***	.11***	.05**	.04*	.03	.10***	1

Notes: Reported numbers are pairwise correlation coefficients, controlling for sector and time fixed effects.
Key: *** significant at 1%; ** 5%; * 10%.

4 Empirical Results

Complementarity implies correlation. It is irrelevant for the ITSC whether we think that ”downstream skills and innovation cause upstream innovation and skills” or the other way around. If new technology and skills are complements along the production chain, skill upgrading at one level affects innovation and skill demand in both directions, upstream and downstream. Thus, the complementarity theory can be investigated in either causal direction. I follow the common identification strategy in the SBTC literature and use the high-skill labor share, h_i, as dependent variable.

[31] Both technology measures are widely used in studies of wage inequality. See, in particular, Autor et al. (1998) and Feenstra and Hanson (1999). The former discuss the limited reliability of the capital stock data that are likely measured with substantial error and in some cases not measured directly but inferred from employment data.

First I show that the novel fact presented in the introduction is not an artifact: the correlation between input skill intensity and final production skills is robust to a variety of additional controls and specifications. After this, I examine endogeneity issues.

4.1 Correlation of Skill Intensities across Sectors

A first look at the data was provided above by Figure 1, plotting a cross-section of h_i against σ_i, where both variables are calculated in 1992. The corresponding regression, including a constant term, yields a highly significant coefficient: $\beta = .957$, with a (robust) standard error of .101. Two concerns arise. First, the observed correlation may be due to unobserved sectoral characteristics that drive both skill demand and input skill intensity.[32] Second, when using a panel, the correlation between h_{it} and σ_{it} may be spurious, driven by a general trend of skill upgrading. To address these concerns, I now turn to using the full panel, controlling for time and sectoral fixed effects. In addition, I control for variables that have been previously identified as influencing h_i. I estimate the following equation

$$h_{it} = \alpha_i + \alpha_t + \beta\sigma_{it} + \gamma Z_{it} + \varepsilon_{it} \tag{3}$$

where α_i and α_t denote industry and time fixed effects, respectively; Z_{it} are control variables, and ε_{it} denotes the error term, capturing measurement error and unobserved drivers of the skilled labor share. The first column of Table 4 shows regression (3) with sectoral and time fixed effects. The coefficient is now smaller, but still highly significant. The number of observations represents the full sample of 6 years $\times$ 358 sectors = 2148. I report two frequently used measures for the goodness of fit: One including the variation explained by sectoral fixed effects (R^2), and the other assessing the model's fit after accounting for sectoral dummies (R^2 within). The former is close to one, while the latter implies that the regressions presented in Table 4 account for roughly half of the variation of h_{it} within sectors over time.

Next, I control for capital endowments as determinants of skill upgrading. Krusell et al. (2000) find a strong positive impact of capital equipment on skill demand for the aggregate U.S. economy. As column 2 shows, this finding is not reproduced at the detailed industry level; the coefficient on k^{equip} has the wrong sign and is insignificant at the 10% level.[33] I also include capital structures, which are skill-neutral in the setup of Krusell et al. (2000), and on the verge of influencing skill upgrading significantly in my sample. The share of high-tech capital correlates significantly positively with the proportion of skilled labor, resembling the well-documented complementarity. This variable has more explanatory power than the alternative measure that only includes office, computing, and accounting equipment. Finally, and most important for my results, the coefficient of input-skill intensity is robust

[32] One such story would be that both skill-intensity of sectors and the inputs they use are 'naturally given' (e.g., determined by technological history) and independent of innovative activity. Suppose that 'ancient' sectors are low-skill intensive, buying mainly 'ancient' inputs, while 'modern' sectors employ skilled workers and purchase 'modern' inputs. This would yield the observed correlation in the absence of intersectoral technology-skill complementarities.

[33] This supports the critical view of Krusell et al.'s results, which disappears when a time trend is included. In fact, if I only include k^{equip} and sectoral dummies as explanatory variables in (3), the coefficient on k^{equip} is positive and highly significant. As soon as other controls or time dummies are included, the coefficient becomes insignificant. Note, however, that sectoral capital equipment data from the ASM used in my sample do not include the quality-adjustment that Krusell et al. apply at the aggregate level.

Table 4: Final production skills, input skill intensity, and controls. Dependent variable is h_{it}.

Input skill measure	Baseline: σ_i				σ_i^{2d}	σ_i^{w}
	(1)	(2)	(3)	(4)	(5)	(6)
Input skill intensity: σ_i	.834***	.658***	.558***	.665***	.502***	.548***
	(.156)	(.145)	(.126)	(.066)	(.170)	(.148)
Structures per worker: k^{struct}		.259*	.191	.249**	.232*	.175
		(.134)	(.117)	(.120)	(.122)	(.118)
Equipment per worker: k^{equip}		-.114*	-.0992	-.168**	-.103	-.0687
		(.067)	(.062)	(.070)	(.064)	(.061)
High-Tech capital: HT/K		.716***	.600***	.410***	.618***	.614***
		(.134)	(.151)	(.125)	(.150)	(.153)
Office equipment: $OCAM/K$		-.0692	.0102	.0576	.0371	.016
		(.294)	(.316)	(.324)	(.308)	(.316)
R&D intensity $R\&D_{lag}$			.401**	.322*	.461***	.363**
			(.163)	(.193)	(.158)	(.163)
Outsourcing: OS^{narr}			.146***	.122**	.161***	.139***
			(.050)	(.051)	(.053)	(.048)
Sector fixed effects	yes	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	no	yes	yes
R^2	.97	.98	.98	.98	.98	.98
R^2 (within)	.50	.55	.57	.56	.56	.57
Observations	2148	2148	2089	2089	2083	2089

Notes: Clustered standard errors (by sector) in parentheses. Key: *** significant at 1%; ** 5%; * 10%. All regressions are weighted by sectors' average share in total manufacturing employment 1967-92.

to the inclusion of capital controls. The same holds when further controls are included, as shown in column 3. The sample size is now 2089 due to missing observations in the outsourcing measure. Both lagged R&D intensity and outsourcing have a significantly positive impact on skilled labor in final production, which confirms previous findings (Machin and van Reenen 1998, Feenstra and Hanson 1999). Column 4 shows the results without time dummies. As expected, because of the general skill upgrading over time, the coefficient of input skill intensity is now slightly bigger. Remarkably, the coefficient of capital equipment is now significantly negative, providing further evidence against a capital-skill complementarity.

The last two columns of Table 4 present regression results for alternative measures of input skill intensity, including all controls. In column 4, σ_i^{2d} is used, excluding inputs purchased within the same 2-digit industries. This specification addresses the concern that common trends or technology shocks may drive skill upgrading in similar industries, biasing β upwards when these industries are linked via input-output relationships. The more conservative measure comes along with a cost: σ_i^{2d} discards a substantial part of intersectoral linkages, since sectors purchase on average 35% of their inputs within the same 2-digit category.[34] Therefore, σ_i^{2d} is a more noisy measure of input skill intensity and likely subject to attenuation bias. However, the coefficient β is only slightly smaller than in the previous specifications and still highly significant. An additional way to address the common-shock concern is

[34] One sector, 'Special product sawmills' (SIC 2429) purchases all inputs within the same 2-digit category. The corresponding σ_i^{2d} is therefore missing in all 6 benchmark years, leaving 2083 observations.

using the 5-year lag of σ_i (not reported in the table). The coefficient on $\sigma_{i,t-5}$ is highly significant, .366 (.095), with all other coefficients very similar to those reported in columns 3 and 5. This finding mitigates the common-shock concern – to maintain it, one would have to argue that downstream skill demand reacts half a decade later than its upstream counterpart to the same shock. Finally, column 5 uses σ_i^w, where skills in input production are measured with the wage-bill, instead of the labor share of skilled workers (see footnote 23). Berman et al. (1994) propose the wage-bill share as an alternative measure of skill demand, because it also captures skill upgrading within either category – production or non-production workers. The results obtained with σ_i^w are very similar to the ones with σ_i.

4.2 Robustness of the Correlation

The robustness of my results to alternative measures of input skill intensity, σ_i, σ_i^{2d}, and σ_i^w has been included in Table 4. These measures were all calculated based on constant input shares, i.e., stable linkages over time. In this section, I first show that my results are robust to including input skill intensity measures based on changing input shares. Second, I test the sensitivity and robustness of my estimates to alternative specifications.

Input skill intensity with changing input shares

Because input shares a_{ij} vary substantially over time, mostly due to one-time outliers, my baseline input skill intensity measures are derived based on average input shares $\bar{a}_{ij}$. Now, I use the time-varying a_{ij} to construct the input skill intensity measure $S_i^t = \sum_{j \neq i} a_{ij}^t h_j^t$. This variable can be decomposed into three parts. First, a skill component σ_i^t, as defined in (1), representing constant input expenditure shares with changing skilled labor shares of suppliers. Second, an input-mix component $\tau_i^t = \sum_{j \neq i} a_{ij}^t \bar{h}_j$, reflecting varying input shares with constant skilled labor shares of suppliers. This variable grows over time if sector i switches its input mix towards more skill intensive intermediates. Finally, a covariance component $\tau_i^t = \sum_{j \neq i}(a_{ij}^t - \bar{a}_{ij})(h_j^t - \bar{h}_j) - \sum_{j \neq i} \bar{a}_{ij}\bar{h}_j$, which grows if sector i switches its input mix towards sectors whose skill intensity rises over time.[35] Note that $S_i^t = \sigma_i^t + \tau_i^t + \rho_i^t$. The skill component σ_i is by far the most important contributor to increases in S_i^t between 1967 and 1992. The weighted average of S_i^t increases from 21.2 to 27.6 percent. Of this 6.4% rise, 6.2% are due to σ_i, 1.3% to τ_i, and -1.1% to ρ_i. As Table 5 shows, the coefficient of σ_i does not change when the two additional variables are used – it is still above 0.5.

Once the usual controls are included, neither τ_i nor ρ_i are significant, as shown in the second and third column of Table 5. This result was to be expected, given the noise in the input shares used to calculate these variables.[36] Similarly, we expect attenuation bias and therefore a smaller coefficient when using the composite skill intensity S_i. Columns 4 and 5 show this result with and without time dummies. The coefficients on S_i are, however, still highly significant.

[35] The term $\sum_{j \neq i} \bar{a}_{ij}\bar{h}_j$ is a constant for each sector i and does not influence estimation results in the presence of sectoral fixed effects.

[36] Less than 1/3 of all input shares have a time-trend that is significant at the 10% level. In an additional check not presented here, I calculate τ_i and ρ_i using changing input shares when the time-trend is significant, and average shares otherwise. Under this method, τ_i is significant at the 5% level when all controls are included, while the coefficient of σ_i remains unchanged.

Table 5: Input skill intensity with time-varying input shares. Dependent variable is h_{it}.

Input skill measure	σ_i		σ_i^{2d}	S_i	
	(1)	(2)	(3)	(4)	(5)
Input skill intensity					
Skill component: σ_i / σ_i^{2d}	.832***	.562***	.511***		
	(.150)	(.124)	(.161)		
Input mix component: τ_i / τ_i^{2d}	.110	.068	-.011		
	(.077)	(.061)	(.079)		
Covariance component: ρ_i / ρ_i^{2d}	.725*	.236	.224		
	(.389)	(.394)	(.466)		
All together: $S_i = \sigma_i + \tau_i + \rho_i$				.189***	.325***
				(.059)	(.049)
Controls	no	yes	yes	yes	yes
Sector fixed effects	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	no
R^2	.97	.98	.98	.97	.97
R^2 (within)	.51	.57	.56	.56	.53
Observations	2090	2089	2083	2089	2089

Notes: Clustered standard errors (by sector) in parentheses. Key: *** significant at 1%; ** 5%; * 10%. All regressions are weighted by sectors' average share in total manufacturing employment 1967-92. Controls include the following variables: Structures per worker (k^{struct}), Equipment per worker (k^{equip}), High-Tech capital (HT/K), Office and computer capital ($OCAM/K$), R&D intensity ($R\&D_{lag}$), and Outsourcing (OS^{narr}).

Alternative specifications and further controls

Alternative specifications comprise running the regression in changes, including further controls, and restricting the sample to single years, analyzing cross-sections rather than a panel. Table 6 presents the results. Therein, I include the computer capital share $OCAM/K$ and the *difference* between high-tech and computer capital share ($HT/K - OCAM/K$), which represents the fraction of capital services derived from various high-technology assets other than office, computing and accounting machinery. Feenstra and Hanson (1999) suggest this specification, and a similar one for outsourcing: the difference between the broad and narrow measures $OS^{\text{broad}} - OS^{\text{narr}}$, representing the intermediate inputs from outside the two-digit purchasing industry that are sourced from abroad.

The first column of Table 6 runs the baseline regression in changes, instead of including fixed effects. All variables are in 5-year differences.[37] The corresponding coefficient on input skill intensity is very similar to the one obtained above, and again highly significant. In column 2, I turn back to estimating levels, including fixed effects and all previously used controls. Additionally, I control for various other variables that potentially drive skill demand. First, broad outsourcing (as difference to narrow). Second, two measures of the 'complexity' of production processes: the variety of inputs used in production, measured as one minus the Herfindahl index of input concentration for each industry ($1 - H_{it}$). This variable is used as a measure of a good's 'complexity' by Blanchard and Kremer (1997) to explain the decline of output when bargaining breaks down along the production chain. The other measure for production 'complexity' is an indicator function for the number of inputs, proposed

[37] R&D intensity is also calculated in actual differences, rather than differences of the lagged variable.

Table 6: Robustness analysis. Dependent variable is h_i.

Input skill measure	σ_i		σ_i^w	σ_i^{2d}	
	(1)	(2)	(3)‡	(4)	(5)
	Changes	Additional Controls	Wage bill	1967 only	1992 only
Input skill intensity: σ_i / σ_i^{2d} / σ_i^w	.621***	.468***	.574***	.562*	.467***
	(.062)	(.123)	(.201)	(.324)	(.139)
Structures per worker: k^{struct}	.255*	.291**	.353***	- .557	.941***
	(.136)	(.121)	(.135)	(1.317)	(.337)
Equipment per worker: k^{equip}	-.0872	-.107*	-.266***	.580	-.383**
	(.090)	(.064)	(.090)	(1.442)	(.176)
Office equipment: $OCAM/K$	.107	.588	.481	3.884***	4.637***
	(.165)	(.380)	(.492)	(1.306)	(.460)
High-Tech capital: difference $(HT/K - OCAM/K)$	.124	.579***	.490***	4.238***	2.011***
	(.109)	(.152)	(.186)	(.898)	(.497)
R&D intensity $R\&D_{lag}$	.323**	.268	.468***	1.077	.144
	(.161)	(.165)	(.181)	(1.027)	(.364)
Outsourcing: OS^{narr} (narrow)	.0651*	.159***	.157**	-.650**	.0768
	(.039)	(.045)	(.069)	(.313)	(.100)
Outsourcing (broad): difference $(OS^{\text{broad}} - OS^{\text{narr}})$		.0944*		-.0369	.0781
		(.055)		(.570)	(.129)
Many inputs: $I_i^{n_i > \bar{n}}$		.00177		.00892	.0352***
		(.005)		(.026)	(.012)
Input variety: $(1 - H_i)$		-.00155		-.0837	.0385
		(.014)		(.107)	(.042)
Relative wage: $\ln(w_{H,i}/w_{L,i})$		-.0493***			
		(.017)			
Real shipments: $\ln(Y_i)$		.00912**			
		(.004)			
Value added share		.0330*			
		(.017)			
Sector fixed effects	no	yes	yes	no	no
Time fixed effects	no	yes	yes	no	no
R^2	.17	.98	.97	.24	.71
R^2 (within)	-	.59	.55	-	-
Observations	1731	2089	2089	328	356

‡ The dependent variable in (3) is the non-production wage bill share: $h_i^w \equiv w_{H,i}H_i/(w_{H,i}H_i + w_{L,i}L_i)$.
Notes: Robust standard errors in parentheses (for (1) - (3) clustered by sector). Key: *** significant at 1%; ** 5%; * 10%. Regressions (1) and (2) are weighted by sectors' average share in total manufacturing employment 1967-92; (3) by the average share in total manufacturing wage bill 1967-92; (4) and (5) by the sector's employment in 1967 and 1992, respectively. All variables in (1) represent 5-year differences (in this case, R&D intensity is $R\&D_t - R\&D_{t-5}$.), while levels are used in the remaining regressions.

by Nunn (2007). $I_{it}^{n_{it}>\bar{n}_t}$ equals one if the number of inputs n_{it} used in industry i in year t is greater than the median number of inputs used in all industries, $\bar{n}_t$. I derive both measures from the year-specific I-O tables. Since more 'complex' production processes require more coordination, I expect these variables to have a positive impact on demand for skilled labor. Third, I include the sector-specific skill premium, or relative wage, to capture differences in the cost of skilled workers across sectors.[38] Fourth, I control for productivity by including the real value of shipments, $\ln(Y)$.[39] This variable addresses the concern that productivity increases may be the driver of skill upgrading in final, as well as input production. Finally, the share of value added in total cost (derived from the BEA I-O data) controls for the overall importance of labor and capital (as opposed to intermediate inputs) in production. Service-oriented sectors generally have a larger value added share, and also a higher proportion of white-collar labor.

The inclusion of further control variables shown in column 2 of Table 6 changes neither the size nor the high statistical significance of the coefficient on input skill intensity. The last three additional controls are significant and have the expected sign. Interestingly, the positive and significant coefficient of real shipments, $\ln(Y_i)$, confirms Epifani and Gancia's (2006) hypothesis that the scale of production may be skill-biased. On the other hand, neither measure for production 'complexity' has a significant impact on skill demand.[40] The additional outsourcing measure has the expected positive sign and is significant at the 10% level. Column 3 presents the regression with the non-production wage-bill share as dependent variable. This measure is frequently used as an alternative to the purely labor based measure, as it also captures skill upgrading *within* either occupational category (Berman et al. 1994). The wage-bill regression confirms magnitude and significance of the ITSC effect.

In all panel regressions presented so far, I address the concern of inconsistent standard errors due to serially correlated observations by accounting for correlation within sectors across time (i.e., by clustering standard errors). Bertrand, Duflo and Mullainathan (2004) argue that this correction alone may not fully solve the problem and suggest collapsing the time series information into single periods as a further correction.[41] The last two columns of Table 6 implement this additional consistency check, presenting cross-sectional regressions for the first and the last benchmark year of the sample, 1967 and 1992. Fixed effects cannot be used in this specification, raising the concern that unobserved characteristics, like similarity of sectors, drive the correlation between input skill intensity and the skilled labor share in final production . To address this concern, I use $\sigma_i^{2\mathrm{d}}$ as the input skill intensity measure, excluding linkages within 2-digit industries. The corresponding coefficient is of the same magnitude as observed before, significant in 1967, and highly significant in 1992. Most control variables also confirm the previous findings. Capital equipment turns out negatively significant in

[38]Because of its endogeneity with skill demand, this variable is usually not included in regressions where the dependent variable is the share of skilled workers. Here, I merely use it as a control for possible cross-sectoral variations in the cost of labor classified as 'non-production' in the ASM. For example, a sector employing 30% delivery and sales personnel likely faces different non-production labor costs than one with 30% engineers.

[39]Feenstra and Hanson (1999) use this control variable. Results are very similar when using the natural logarithm of value added, as in Bresnahan et al. (2002).

[40]The two complexity measures vary little over time, such that the inclusion of sector fixed effects eliminates much of their variation. In fact, when running the same regression without sector dummies, the effect of $I_i^{n_i>\bar{n}}$ is positive and significant.

[41]Long time series (15 periods and more) are a major contributing factor to Bertrand et al.'s concern. Since my panel involves only 6 periods, the concern is likely of minor importance, given that I am already controlling for serial correlation.

the 1992 cross section.[42] In the panel, k^{equip} shows up negative and significant in some specifications. These findings together argue strongly against a broad capital (equipment)-skill complementarity. The more narrow high-tech capital variable, however, shows up significantly positive in the cross-section, as well. Finally, production 'complexity', measured by $I_i^{n_i > \bar{n}}$, has a significantly positive impact on skill demand in the 1992 cross-section.

4.3 Investigating the Channel of the ITSC

In this section, I investigate the hypothesis that the ITSC works through product innovation. I follow a three-step process. First, I show that sectors producing differentiated products spend relatively more R&D for product innovation, while producers of homogenous goods concentrate on innovating their own processes. This suggests that differentiated products embody more innovation than homogenous ones. Therefore, sectors using differentiated products as intermediates purchase relatively more embodied product innovation, which leads to the second step: If the ITSC works through product innovation, we expect it to be stronger for sectors that use relatively more differentiated inputs. Finally, I turn to the impact of skills on productivity – the outcome of innovation. I show that innovative intermediates, measured by their skill content, raise productivity only if they meet skilled workers knowing to handle them. Consequently, skills in intermediate and final production complement each other in fostering innovation and productivity.

Product Innovation and Product Differentiation

As described in section 3, I derive sectoral shares of R&D expenditures used for product innovation, π_i^{prod}, from Scherer's (1982) data, and match them to Rauch's (1999) data on product differentiation. This gives π_i^{prod} together with the share of products classified as differentiated, R_i^{diff}, for 34 manufacturing industries. The median of R_i^{diff} in this sample is .84. The 17 industries turning out goods with below-median product differentiation spend on average 53% of R&D for inventing new products (as opposed to processes), while this number is 80% for producers of above-median differentiated goods. After this preliminary observation, I turn to the simple regression $\pi_i^{\text{prod}} = \delta_0 + \delta_1 R_i^{\text{diff}} + \varepsilon_i$, where the last variable represents an error term. The corresponding estimate is positive and highly significant: $\delta_1 = .416$ with a robust standard error of .127 and R^2 of 0.27.[43] These findings suggest that differentiated products are more susceptive to product innovation, such that they are more readily reshaped by the innovative minds of skilled workers.

Input Differentiation and ITSC

When skilled workers improve their products, the innovation passes through intermediate linkages to other sectors, where it also drives innovation and skill demand. As we have seen, purchasers of differentiated inputs buy more innovation incorporated in their intermediates than users of homogenous

[42] This finding is robust and also appears when only capital structures and equipment are included in the regression.

[43] The result is practically identical when using Rauch's (1999) conservative estimate to construct R_i^{diff}. Outliers are not an issue, and even excluding the 9 sectors that produce only differentiated products ($R_i^{\text{diff}} = 1$) leaves the remaining ones with a significantly positive δ_1 (at p=0.1).

ones. Consequently, we expect a stronger ITSC when input-output linkages involve more differentiated intermediates. The corresponding measure κ_i gives the weighted average degree of input differentiation, as described in section 3. To obtain a first look at the data, I use this measure to split the sample into sectors with below- and above-median input differentiation. Then I estimate regression (3) for the two subsamples and report the results in Figure 2 in the form of partial scatter plots. The vertical axis shows the variation in the skilled labor share h_i to be explained by input skill intensity σ_i, after controlling for fixed effects and statistically significant control variables (all controls that were significant in at least one specification in Table 4).

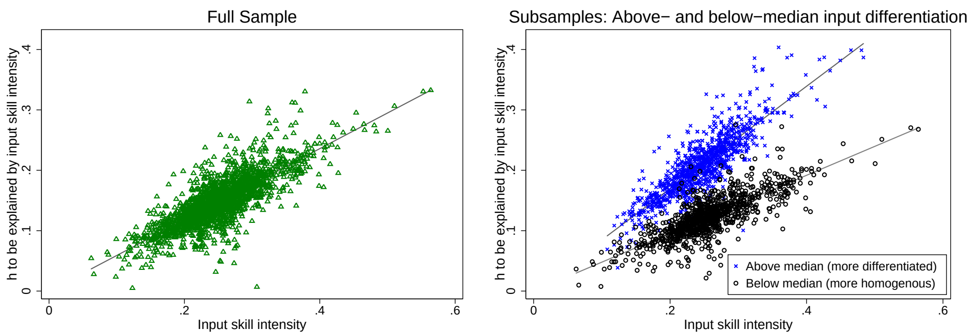

Figure 2: Partial scatter plots: Skilled labor share (h_{it}) vs. input skill intensity (σ_{it})

Notes: The measure of input differentiation is calculated as in (2), yielding a median of .52. The vertical axis shows $h_{it} - (\hat{\alpha}_i + \hat{\alpha}_t + \hat{\gamma} Z_{it})$; notice that $\hat{\beta}\sigma_{it}$ does not appear in this equation. In the left panel, coefficient estimates $\hat{\alpha}_i$, $\hat{\alpha}_t$, and $\hat{\gamma}$ are obtained by estimating (3) for the full sample (2089 obs.), with the controls Z_{it} comprising k^{struct}, k^{equip}, HT/K, $R\&D_{lag}$, and OS^{narr}. In the right panel, the same methodology is applied for the two subsamples including sectors with above-median input differentiation (1040 obs.) and below-median input differentiation (1049 obs.).

The left panel of Figure 2 shows the partial scatterplot for the full sample, where the corresponding coefficient from regression (3) is $\hat{\beta} = .590$.[44] This plot also shows that the positive correlation between input skill intensity and final production skills is a broad phenomenon, not driven by outliers. The right panel repeats the exercise for two subsamples, one with sectors purchasing relatively homogenous inputs (below-median κ_i) and the other comprising sectors that use more differentiated inputs (above-median κ_i). These first results are in favor of the hypothesis that the ITSC is stronger for sectors using more differentiated inputs than for those using more homogenous ones; the corresponding coefficients are $\hat{\beta}^{\text{diff}} = .848$ and $\hat{\beta}^{\text{hom}} = .479$, respectively.[45] In addition, the two subsamples have different final production skill shares. Sectors using more differentiated inputs are on average more skill intensive ($\bar{h}^{\text{diff}} = .286$ vs. $\bar{h}^{\text{hom}} = .245$). This is what we expect, given that differentiated inputs incorporate more product innovation. However, the difference in final production skill shares could also be due to different endowments like high-tech capital or different levels of outsourcing in the two subsamples. To analyze whether this concern is justified, I use the Blinder-Oaxaca decomposition, splitting the mean outcome differential (predicted $\bar{h}^{\text{diff}} - \bar{h}^{\text{hom}}$) into one part that is due to

[44] To ease graphical exposition, the regressions in Figure 2 use equal weights for each sector. The estimated coefficient is very similar when weighted by employment shares, $\hat{\beta} = .558$.

[45] A more detailed analysis, using quintiles of input differentiation κ_i, confirms this result: $\hat{\beta}$ increases with each quintile of κ_i and is highly significant for all except the first one.

differences in endowments in the two subsamples, one part that is due to differences in coefficients (after accounting for fixed effects), and a third part that is due to interaction between coefficients and endowments. This decomposition shows that the different final production skill shares in the two subsamples are entirely due to differences in coefficients, while endowments and interaction have small negative (and insignificant) contributions.

Next, I include interaction terms of explanatory variables with input differentiation κ_i.[46] Table 7 reports the results, using the three alternative measures for input skill intensity, σ_i (baseline), σ_i^{2d} (excluding inputs from the same 2-digit sectors), and σ_i^w (calculated based on the high-skill wage bill share). The interactions 'input skill intensity' $\times$ 'input differentiation' are positive and highly significant, implying that the ITSC grows with the degree of input differentiation. Moreover, the coefficient on input skill intensity (β_1) becomes small and insignificant when the usual controls are included. This indicates that the ITSC is not present for a (hypothetical) sector using only homogenous inputs ($\kappa_i = 0$). To see this, note that the marginal effect of input skill intensity on final production skills is given by $\partial h_i / \partial \sigma_i = \beta_1 + \beta_2 \kappa_i$. On average, this effect is slightly larger than above, where input differentiation was not controlled for.[47]

Table 7: Interaction of input skill intensity with input differentiation. Dependent variable is h_{it}.

Input skill measure	σ_i			σ_i^{2d}	σ_i^w
	(1)	(2)	(3)	(4)	(5)
Input skill intensity (β_1):	.293*	.118	.046	-.071	.018
σ_i / σ_i^{2d} / σ_i^w	(.152)	(.154)	(.158)	(.240)	(.219)
Inp. skill intensity $\times$ inp. differentiation (β_2):	1.118***	1.147***	1.284***	1.325***	1.213***
$\sigma_i \times \kappa_i$ / $\sigma_i^{2d} \times \kappa_i$ / $\sigma_i^w \times \kappa_i$	(.317)	(.334)	(.312)	(.449)	(.389)
Implied coefficient: $\hat{\beta} = \hat{\beta}_1 + \hat{\beta}_2 \bar{\kappa}$	.907***	.747***	.751***	.657***	.684***
Controls	no	yes	yes	yes	yes
Sector fixed effects	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	no	yes	yes
R^2	.97	.98	.98	.98	.98
R^2 (within)	.53	.59	.58	.58	.59
Observations	2148	2089	2089	2083	2089

Notes: Clustered standard errors (by sector) in parentheses. Key: *** significant at 1%; ** 5%; * 10%. All regressions and the mean $\bar{\kappa}$ are weighted by sectors' average share in total manufacturing employment 1967-92. Controls include: Structures per worker (k^{struct}), equipment per worker (k^{equip}), high-tech capital (HT/K), R&D intensity ($R\&D_{lag}$), and outsourcing (OS^{narr}), as well as their interactions with input differentiation: $k^{\text{struct}} \times \kappa_i$, $k^{\text{equip}} \times \kappa_i$, $HT/K \times \kappa_i$, $R\&D_{lag} \times \kappa_i$, and $OS^{\text{narr}} \times \kappa_i$. Weighted average input differentiation is $\bar{\kappa} = .549$.

[46] Because the framework analyzed here involves complementarity among several explanatory variables, I also interact the control variables with input differentiation. This addresses the concern that the $\sigma_i \times \kappa_i$ interaction alone might capture other effects related to product differentiation. This is the case, for example, if the processing of differentiated intermediates is more R&D intensive, or if outsourcing is more pronounced for differentiated inputs, influencing skill demand through these channels. Input differentiation κ_i is not included in the regressions, as it is captured by sectoral fixed effects.

[47] An interesting and robust finding is that the interaction term 'high-tech capital' $\times$ 'input differentiation' is negative and highly significant, while the coefficient on 'high-tech capital' is significantly positive and of the same magnitude (not reported in Table 7). Therefore, high-tech capital explains much of the skill demand in sectors using homogenous inputs, but little in sectors using differentiated inputs.

Productivity and ITSC

Now I turn to the relationship between productivity and skills. Because of the well-documented innovation-skill complementarity, we expect sectors with a high proportion of skilled workers to be more productive. However, this holds only for the right mix of complementary inputs [Milgrom and Roberts 1990, Bresnahan et al. 2002]. When skilled workers meet an environment without the potential for production improvements, their innovative potential is wasted. On the other hand, computers or innovative intermediates are squandered when there are no skills to handle them.[48] It is only when skills meet an innovative environment that ideas and productivity flourish. Following this argument, I examine the interaction between input-embedded skills σ_{it}, reflecting innovative intermediates, and final production skills h_{it} in regressions with productivity measures as dependent variable. I run the following regression, expecting a positive coefficient on the interaction term.

$$prd_{it} = \alpha_i + \alpha_t + \beta_1 h_{it} + \beta_2 \sigma_{it} + \beta_3 h_{it} \times \sigma_{it} + \gamma Z_{it} + \varepsilon_{it} \tag{4}$$

where prd_{it} denotes productivity, measured by value added per worker (in natural logarithm) or alternatively by total factor productivity (TFP).[49] Z_{it} stands for the controls used above, and also includes the interactions of high-tech capital with h_{it} and σ_{it}. As always, sector and time dummies (α_i, α_t) are included, and ε_{it} denotes the error term. The results are presented in Table 8.

Table 8: Productivity and skills. Dependent variable is productivity.

Productivity measure:	ln(value added per worker)					TFP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Skilled labor share: h_i	.006		.058	.834***	-1.904***	-2.421***	-2.577***
	(.286)		(.293)	(.179)	(.693)	(.910)	(.899)
Input skill intensity: σ_i	.672	.675		-.025	-1.840**	-2.455**	-1.982*
	(.503)	(.535)		(.382)	(.812)	(.981)	(1.061)
Interaction: $\sigma_i \times h_i$					6.748***	8.824**	9.600***
					(2.089)	(3.610)	(3.567)
Controls	yes	yes	yes	yes	yes	yes	yes
Interaction Controls	no	no	no	no	yes	yes	yes
Sector fixed effects	yes	yes	yes	no	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	yes	yes	no
R^2 (within)	.97	.97	.97	.90	.97	.16	.11
Observations	2089	2089	2089	2089	2089	2089	2089

Notes: Clustered standard errors (by sector) in parentheses. Key: *** significant at 1%; ** 5%; * 10%. All regressions are weighted by sectors' average share in total manufacturing employment 1967-92. Controls include: Structures per worker ($\ln(k^{\text{struct}})$), Equipment per worker ($\ln(k^{\text{equip}})$), high-tech capital (HT/K), R&D intensity ($R\&D_{lag}$), and outsourcing (OS^{narr}). Interaction controls include: $h_i \times HT/K$ and $\sigma_i \times HT/K$.

As column 1 shows, neither input-embedded nor final production skills correlate significantly with productivity. Columns 2 and 3 verify that this is not a consequence of collinearity between σ_i and h_i;

[48] Massive inflows of modern Western capital to the Polish economy in the early 1970's failed to raise industrial productivity – partially due to the lack of technical personnel [Terrell 1992].

[49] I use the 5-factor TFP index (1987=1) from the NBER Manufacturing Industry Database. See Bartelsman and Gray (1996) for a documentation. Results are also very similar when using the natural logarithm of shipments per worker to measure productivity.

neither is significant by itself. Column 4 uses more cross-sectoral variation by dropping industry fixed effects. In this case, h_i is highly significant, but subject to the concern that unobserved sector-specific characteristics drive both productivity and skill demand. Next, the significantly positive interaction term $\sigma_i \times h_i$ in column 5 explains why σ_i and h_i alone are insignificant: innovative inputs, reflected by their embedded skills, raise productivity only if they are combined with skilled labor to process them. The marginal effect of input skill intensity on productivity is given by $\partial prd_{it}/\partial\sigma_{it} = \beta_2 + \beta_3 h_{it}$, with the weighted average of h_{it} equal to .279, and the corresponding 10$^{\text{th}}$ and 90$^{\text{th}}$ percentile given by .147 and .420, respectively.[50] Therefore, a 1% increase in σ_{it} *lowers* value added per worker by 0.9% when industry i has few skilled workers (10$^{\text{th}}$ percentile), leaves it unchanged in an average industry i, and *raises* value added per worker by 0.9% if i employs many skilled workers (90$^{\text{th}}$ percentile). This finding provides further support for product innovation as the ITSC channel: Skills in intermediate and final production together foster innovation and raise productivity. Finally, columns 6 and 7 confirm that this result is neither an artifact of the chosen productivity measure (it is obtained when using TFP, as well) nor dependent on the inclusion of time dummies.

4.4 Endogeneity and Causal Direction

In my intersectoral complementarity framework, causality can run in either direction – from upstream to downstream skill intensity (σ_i to h_i), or the other way around. Now I go beyond the mere correlation analysis and account for this endogeneity. As a first pass at the issue, I use a Granger causality test. The usual cavaets apply – time precedence and causality are two distinct concepts.[51] I find Granger causality in both directions – stronger in the upstream-downstream direction, where the coefficient on lagged σ_i is .179 (.054); and weaker in the opposite direction with a coefficient on lagged h_i of .033 (.015).[52] Next, I represent the ITSC by a simultaneous equations model, where our aim is to estimate β_1.

$$h_{it} = \alpha_{1,i} + \beta_1\sigma_{it} + \gamma_1 Z_{it} + \varepsilon_{1,it} \tag{5}$$

$$\sigma_{it} = \alpha_{2,i} + \beta_2 h_{it} + \gamma_2 Z_{j\neq i,t} + \varepsilon_{2,it} \tag{6}$$

The first equation represents the upstream-downstream direction of the ITSC, estimating the impact of input skill intensity on final production skill demand. The latter is also influenced by the usual control variables Z_{it}. The second equation represents the impact of the final producer skill share on skill demand of intermediate suppliers $j \neq i$.[53] Control variables that affect the skill demand in

[50] While prd_{it} is specified in logs, σ_{it} and h_{it} are already percentages. Thus, the marginal effect can be interpreted as the elasticity of value added per worker with respect to input skill intensity.

[51] The Granger causality definition does not allow to discover true causal structures via data analysis, without substantive theory. It is best thought of as an attempt at specifying a necessary condition for a causal relation.

[52] Both regressions include all (5-year lagged) control variables used in Table 4, sectoral dummies, and the (5-year) lag of the left-hand side variable.

[53] These two equations can be used to quantify the bias that arises when we interpret the OLS coefficient β from regression (3) as a causal influence of σ_{it} on h_{it}, not taking into account the reverse relationship. The covariance between σ_{it} and $\varepsilon_{1,it}$ is given by $\beta_2/(1-\beta_1\beta_2)Var(\varepsilon_{1,it})$, and the corresponding bias in β is equal to this covariance divided by $Var(\sigma_{it})$. The Granger causality test suggests that the feedback from h_{it} to σ_{it} is small in comparison to the opposite direction. We thus expect that β_2 is small, which yields a small positive bias of the OLS coefficient in (3).

intermediate production, $Z_{j\neq i,t}$, are constructed in a similar fashion as σ_{it}:

$$Z_{j\neq i,t} = \sum_{j\neq i} \bar{a}_{ij} Z_{jt} \tag{7}$$

For example, let Z_{jt} represent outsourcing of intermediate supplier j. We expect this variable to affect $\sigma_{it} = \sum_{j\neq i} \bar{a}_{ij} h_{jt}$ through its impact on h_{jt}. The same holds for all suppliers $j \neq i$. In this example $Z_{j\neq i,t}$ therefore represents weighted average outsourcing of sector i's suppliers. The controls for capital equipment and structures, computer and high-tech capital, and R&D intensity are calculated using the same methodology. All are summarized as $Z_{j\neq i,t}$ in the following. In order to address the concern of correlations due to industry similarities, I exclude all j that fall into the same 2-digit category as i in the calculation of $Z_{j\neq i,t}$.

We want to estimate β_1, the effect of input skill intensity on skill demand in final production. The first step is to derive the reduced form for σ_{it} from (5) and (6). This gives the first stage of an instrumental variable (IV) regression, with $Z_{j\neq i,t}$ being the instruments for σ_{it}. For now, I concentrate on an estimation that excludes a causal impact of h_{it} on σ_{it}. The exclusion restriction is that the instruments $Z_{j\neq i,t}$ influence σ_{it} but are uncorrelated with h_{it} once we control for Z_{it}. This assumption is reasonable if we use again outsourcing as an example, which we know has a positive impact on the skilled labor share. If sector i purchases mainly products from high-outsourcing sectors j, we expect σ_{it} to be high. Moreover, we would neither expect outsourcing in upstream industries to directly influence skill demand of downstream producers, nor a reverse causal relation, with h_{it} influencing outsouring of suppliers $j \neq i$.[54] For the remaining instruments, especially computer- and high-tech capital, as well as R&D intensity, endogeneity is potentially a concern. Innovation and skills in final production may not only create demand for skills at the intermediate stage, as represented in (6), but also for high-tech equipment or R&D. I therefore begin by using only the two outsourcing measures in the results presented in Table 9.

Having addressed the endogeneity of σ_{it}, there is one more concern we need to deal with – some of the controls Z_{it} are not strictly exogenous. I use two approaches to tackle the potential bias. First, under sequential exogeneity, the corresponding inconsistency is bounded and of the order T^{-1}, with T denoting the number of periods in the panel [Wooldridge 2002, ch. 11].[55] This holds for the fixed effects estimator that is therefore preferable to first differencing when no instruments are used for Z_{it}. The regressions in columns 1 and 2 of Table 9 use this methodology, instrumenting only for σ_{it}. While this method does not exclude the concern of biased estimates, the inconsistency is bounded. However, we do not need to settle with inconsistent estimators. Columns 3 - 5 implement the second approach to estimating equation (5) under sequential exogeneity: apply first differencing and then use lagged levels of Z_{it} as instruments for $\triangle Z_{it}$ [Wooldridge 2002, ch. 11]. This gives consistent estimates and is similar in spirit to Arellano and Bond (1991).

[54] A potential concern might be that outsourcing in upstream and downstream industries is correlated (even if we restrict attention to upstream and downstream sectors that differ at the 2-digit level). The fact that downstream outsourcing is included in Z_{it} in (5) controls for this channel.

[55] Sequential exogeneity in regression (5) implies that after Z_{it}, σ_{it}, and sectoral fixed effects have been controlled for, no past values of Z_{it} affect the expected value of h_{it}. When including the 5- and 10-year lags of all Z_{it} in (5), none is significant at the 10% level, with the exception of the 5-year lag of $R\&D_{lag}$. This suggests that sequential exogeneity is a reasonable assumption.

The first column in Table 9 shows that the IV coefficient on input skill intensity, β_1, is highly significant and of the same magnitude as estimated above. The two outsourcing instruments are highly significant – the corresponding F-statistic of the exclusion hypothesis is well above the rule of thumb threshold of 10 recommended by Staiger and Stock (1997) to avoid weak instrument concerns. The additional test of weak instruments based on Stock and Yogo (2002) confirms this result. This test becomes especially useful in models with more than one endogenous variables and is discussed in more detail below. Since the number of instruments is larger than one, I can test for their endogeneity using Hausman's (1983) test. The implied overidentifying restriction cannot be rejected for any of the specifications (the corresponding p-values are given at the bottom of the table).

Table 9: Two-stage least square regressions. Dependent variable is h_{it}.

	Levels		Changes, Instruments for controls		
	(1)	(2)	(3)	(4)	(5)
Input skill intensity: σ_i	.618***	.550***	.486***	.540***	.434***
	(.171)	(.123)	(.127)	(.111)	(.118)
Structures per worker: k^{struct}	.252**	.280**	.190*	.196*	.746
	(.123)	(.122)	(.104)	(.103)	(.457)
Equipment per worker: k^{equip}	-.155***	-.173***	-.024	-.0361	-.268*
	(.058)	(.061)	(.069)	(.068)	(.137)
High-Tech capital: HT/K	.462*	.523**	.411***	.461***	.577***
	(.239)	(.220)	(.154)	(.155)	(.186)
R&D intensity $R\&D_{lag}$	.32	.379*	.798***	.728**	.535**
	(.199)	(.198)	(.308)	(.300)	(.269)
Outsourcing: OS^{narr}	.127**	.135**	.0519	.0537	.0327
	(.052)	(.055)	(.039)	(.037)	(.128)
Relative wage: $\ln(w_{H,i}/w_{L,i})$		-.0590***			-.0869***
		(.017)			(.028)
Sector fixed effects	yes	yes	no	no	no
R^2	.98	.98	.17	.18	.22
R^2 (within)	.56	.57	-	-	-
Observations	2083	2083	1398	1398	1369
First stage regressions					
Instruments for σ_i	OS	All $Z_{j\neq i}$	OS	All $Z_{j\neq i}$	All $Z_{j\neq i}$
F-test for significance	63.0	64.6	24.3	46.5	37.5
Instrumented control variables:‡			[HT/K, $R\&D$]		All
p-value overidentifying restrictions	0.86	0.25	0.49	0.66	0.30
Stock and Yogo weak IV F-statistic	333.9	165.1	23.5	20.9	-
(Critical value for highest IV quality)	(19.9)	(19.9)	(17.4)	(18.9)	-

Notes: Clustered standard errors (by sector) in parentheses. Key: *** significant at 1%; ** 5%; * 10%. All regressions are weighted by sectors' average share in total manufacturing employment 1967-92. All variables in (1) and (2) are in levels, while 5-year differences are used in regressions (3)-(5). In the latter, R&D intensity is $R\&D_t - R\&D_{t-5}$. OS represents the instruments $OS^{\text{narr}}_{j\neq i}$ and $OS^{\text{broad}}_{j\neq i}$. The 5- and 10-year lags of σ_{it} are used as additional instruments in (3)-(5), and the instruments $Z_{j\neq i}$ are in five-year differences.
‡ Instruments are the 5- and 10-year lags of of each instrumented control variable. R&D intensity is additionally instrumented with the 15-year lag.

Column 2 shows that the results change only little when I use all $Z_{j\neq i,t}$ as instruments for input skill intensity and additionally control for the relative wage (to capture differences in skilled labor costs across sectors, as argued in footnote 38.) In addition to upstream outsourcing (broad and narrow) and capital (equipment and structures), the instruments $Z_{j\neq i,t}$ now also include upstream R&D intensity and computer and high-tech capital, for which a reverse causal relationship could be a more serious concern. This is confirmed by the smaller p-value for the over-identifying restriction, bringing the hypothesis of instrument exogeneity closer to (though still well above) the rejection level.

Next, I turn to columns 3 - 5, instrumenting for several endogenous variables. The Staiger and Stock (1997) rule of thumb for avoiding weak instruments refers to models with one endogenous variable. In models with two or more endogenous variables, instruments can be weak despite being very significant in each first-stage regression.[56] Stock and Yogo (2002) provide a framework that allows testing the hypothesis of weak instruments in this case. The null hypothesis is that the quality of the instruments is below one of four levels. The last row of Table 9 reports the critical value for the highest quality level, corresponding to a maximum 2SLS bias of 5% because of weak instruments. The Stock and Yogo (2002) framework allows for models with up to three endogenous variables. Therefore, I first instrument (in addition to σ_{it}) those two controls for which endogeneity is the most serious concern: high-tech capital and R&D intensity. Columns 3 and 4 show the results. While the former uses only upstream outsourcing ($OS^{\text{broad}}_{j\neq i}$ and $OS^{\text{narr}}_{j\neq i}$), the latter applies all instruments $Z_{j\neq i,t}$ for σ_{it}.[57] Results are very similar for both approaches, and the coefficients for σ_{it} and high-tech capital do not differ from previous results (but now also high-tech capital is highly significant). The coefficient of R&D intensity is larger than before and also highly significant. As the number of observations reflects, the choice of instruments – using 5- and 10-year lagged levels of Z_{it} as instruments for $\triangle Z_{it}$ – loses an additional time period (with one already lost due to first differencing). The p-values for the overidentification test are well above the rejection levels, suggesting that instrument endogeneity is not a serious concern. Finally, instruments are of the highest quality level according to the Stock and Yogo test.[58]

Column 6 establishes what one might refer to as a 'brute force' estimation. It uses 5- and 10-year lags to instrument for (the changes of) all control variables, including the relative wage. For this case, with seven endogenous variables, weak instrument tests are not available, and the results are to be interpreted with caution.[59] Interpreting column 6 as a robustness check, we see that it affects neither the magnitude nor the significance of input skill intensity's impact on final production skills.

4.5 The Multiplier Effect and the ITSC's Contribution to Skill Upgrading

So far, we have seen that the correlation between input skill intensity and skilled labor share in final production is highly significant and robust to the inclusion of various control variables. I have also

[56] This is because endogenous explanatory variables predicted by the instruments may be close to collinear, which makes it difficult to separate the effect of each individual one.

[57] The notes of Table 9 provide a listing of all instruments used. R&D intensity can be instrumented with one more time lag without using an additional time period of observations, because the R&D data include 1963.

[58] The relatively low R^2 is not an indication for bad model fit. In 2SLS, the model's residuals are computed over a set of regressors different from those used to fit the model. Therefore, it is often the case that the distribution of the 2SLS parameter estimates is very well approximated by its asymptotic distribution, while the R^2 is low or even negative.

[59] Individual F-statistics from the first-stage regressions for k^{struct} and OS^{narr} are below 10, suggesting weak instruments. All other F-statistics are well above this threshold (37.5 for σ_{it}, as shown in the table).

shown that the OLS estimates are good proxies for the causal impact of upstream skill intensity on final production skills. Next, I turn to the importance of the implied ITSC for skill upgrading. The point estimate for β is in the range of 0.5-0.6. Regarding its interpretation, recall that both h_{it} and σ_{it} reflect proportions. Therefore, a positive coefficient means that an increase of the average manufacturing sector's input skill intensity by 1% (relative to the sector's average over time and the manufacturing average in the respective period) goes hand in hand with a β percent increase of the sector's skilled labor share in final production (again, relative to the manufacturing and sector-specific average). Skill upgrading in one sector creates skill demand in many other sectors via intermediate linkages, and finally feeds back into the originating sector.

In order to derive the overall multiplier of this feedback mechanism, let us consider the simple case where manufacturing consists of only two equally sized sectors, A and B. These are small relative to the economy, hiring labor at given skill-specific wages. Suppose that both purchase each other's output for intermediate use. Therefore, one sector's high-skill labor share is the other's input skill intensity: $\sigma_A = h_B$ and $\sigma_B = h_A$.[60] Finally, let the technology-skill complementarity between both sectors reflect the manufacturing average estimated above. Now let sector B accomplish a product innovation that comes along with skill upgrading $\triangle h_B = 1\%$. Sector A incorporates the improved intermediate from B and innovates its own product, which implies skill upgrading of β percent: $\triangle h_A = \beta \cdot 1\%$. Sector B, in turn, profits from the improved product A, which stimulates further innovation and skill demand $\triangle h'_B = 1\% + \beta \cdot \triangle h_A = (1+\beta^2) \cdot 1\%$. This virtuous circle continues, yielding total skill upgrading $\triangle h_A = 1\% \cdot \beta/(1-\beta^2)$ and $\triangle h_B = 1\% \cdot 1/(1-\beta^2)$. Therefore, the initial innovation-skill shock to sector B increases average manufacturing skill demand by 0.5%, and its amplification via ITSC leads to total skill upgrading of $\triangle h = 0.5 \cdot \triangle h_A + 0.5 \cdot \triangle h_B = 0.5\% \cdot 1/(1-\beta)$. Given the point estimates for β, the multiplier is large. At given relative wages, an initial innovation coming along with average skill upgrading of 1 percent is amplified to raise skill demand by $1/(1-\beta)$ percent, more than doubling the initial shock.

Following this discussion, we expect an important contribution of the ITSC to overall skill upgrading in U.S. manufacturing. To investigate this point, I repeat two of the previous regressions (OLS and IV) and multiply the corresponding coefficients by the mean change in each variable.[61] This gives each variable's contributions to skill upgrading – the percentage of the total average change in the nonproduction labor share ($\triangle h = 5.86\%$ from 1967-92) due to each of the independent variables, as shown in Table 10. Specification 1 uses levels of all variables and derives contributions from the observed correlations, while specification 2 uses 5-year differences and applies instruments (as discussed in the previous section). Input skill intensity is responsible for about half of manufacturing skill upgrading, followed by high-tech capital that contributes about 1/3. The latter is at the upper end of the 8-32 percent found by Feenstra and Hanson (1999) for the period 1979-90. Outsourcing accounts for roughly one tenth in specification 1, which is also in line with the estimates by Feenstra and Hanson (1999), and for less in specification 2. While the coefficient of R&D intensity is large, its contribution to increasing white-collar labor demand is not. This is because R&D intensity itself

[60] Section 5 presents a more general model with N sectors. The associated multiplier is the same as in the two-sector case, as shown in Appendix A.3.

[61] I revert to the specifications shown in column (4) of Table 4 and Table 9. Note that these do not include time dummies, since we want to account for changes over time.

increased little. Overall capital is roughly skill neutral, with the positive contribution of structures offsetting the negative impact of equipment.

Table 10: Contribution of several variables to skill upgrading. Dependent variable is h_{it}.

		Levels		Changes + IV for σ_i, HT/K, $R\&D$			
		(1)		(2)		(3)	
	Mean Change	Regression	Contribution	Regression	Contribution	Regression	Contribution
Input skill intensity: σ_i	.0519	.660*** (.074)	58.5%	.540*** (.111)	47.8%		
Structures per worker: k^{struct}	.0109	.249** (.120)	4.6%	.196* (.103)	3.6%	.195* (.117)	3.6%
Equipment per worker: k^{equip}	.0331	- .168** (.069)	-9.5%	- .036 (.068)	-2.0%	.061 (.073)	3.4%
High-Tech capital: HT/K	.0442	.436** (.189)	32.9%	.461*** (.155)	34.8%	.305* (.171)	23.0%
R&D intensity $R\&D_{lag}$	.0093	.32 (.200)	5.1%	.728** (.300)	11.5%	1.111*** (.355)	17.6%
Outsourcing: OS^{narr}	.0460	.122** (.051)	9.6%	.054 (.037)	4.2%	.035 (.039)	2.7%
Sector fixed effects		yes		no		no	
R^2 (after FE)		.56		.18		.01	
Observations		2089		1398		1402	

Notes: Mean changes refer to the period 1967-92. The mean change in the dependent variable h is .0586. All regressions and means are weighted by sectors' average share in total manufacturing employment 1967-92. Clustered standard errors in parentheses. Key: *** significant at 1%; ** 5%; * 10%. 'Contribution' gives the proportion of the observed mean change in h explained by the respective variable. In (2), σ_i, HT/K, and $R\&D_{lag}$ are instrumented as in column 4 of Table 9 – see this table for details on instruments used and related tests. In (3), instruments specific to σ_i are left out in the first stage.

Finally, specification 3 excludes σ_i and its instruments from the estimation. Interestingly, the remaining contributions of individual variables change only slightly and add up to about 50%, as they did in the previous specifications, leaving the gap to be explained by σ_i. This confirms that input skill intensity is not merely picking up explanatory power from other variables. Altogether, the results reported in Table 10 suggest that the ITSC accounts for a larger share of skill upgrading in manufacturing than any other previously proposed explanation.

5 A Sketch Model

This section integrates my empirical findings into the analytical SBTC framework. The standard setup has two types of labor in a CES production function, producing one final good.[62] I add intermediate input linkages and skill-complementarity across many sectors, as motivated by the empirical evidence presented above. In order to concentrate on the main mechanism, I present a static model, abstracting from intertemporal dynamics and endogenous skill supply. The economy is composed of $i = 1, ..., N$ sectors, each producing a specific good, or variety i. The number of sectors is fixed. Within each

[62] See Card and DiNardo (2002) for a review of the standard SBTC framework.

sector, a multiplicity of firms operates under perfect competition and constant returns. I focus on a representative firm for each sector i, making zero profits. Each good i is used for final consumption and as intermediate input in sectors $j \neq i$ with constant input shares. This Leontief technology is at the heart of input-output tables, and section 4.2 has shown that constant input shares are a reasonable assumption.

The economy is populated by L low skilled individuals, working in production, and H high-skilled individuals that coordinate production and innovate products. The skill intensity of inputs is defined as the weighted average share of high-skilled workers employed in their production, resembling the empirical part of the paper. High-skilled workers are relatively more productive in processing skill intensive inputs. This setup is similar in spirit to Kremer's (1993) O-Ring theory. Kremer assumes that production involves the completion of n tasks, each performed by a worker of skill level q_i in one and the same firm. Output is proportional to $\prod_{i=1}^{n} q_i$, implying a strong complementarity of workers' skill levels. In this framework, a high skilled worker performing task i is most productive in firms that employ high-q workers in all other tasks, too. The model presented here can be thought of as a multi-sector version of the O-Ring theory. Kremer's tasks are my intermediate inputs – final products contain intermediates from various sectors instead of being entirely manufactured in one firm.[63] Innovations and quality of skilled workers are embedded in the goods they produce. In my setup, Kremer's *within*-firm skill complementarity works its wonders *across* firms along the production chain. High skilled workers in sector N are the more productive relative to the unskilled, the more innovative their inputs are, i.e., the more skills are embedded in the $N-1$ input varieties that they process.

Another related model endogenizes the direction of technical change [Acemoglu 1998, 2002 and 2007, Acemoglu and Zilibotti 2001]. Therein, an increasing number of skilled workers implies a larger market and demand for skill-complementary technologies, inducing skill-biased technological change. However, this channel lacks empirical support, as it is hard to pin down a robust relationship between demand factors and R&D intensity [Cohen and Levin 1989].[64] In a more recent contribution, Ngai and Samaniego (2007) find that neither TFP growth nor R&D intensity are related to demand factors in equilibrium, arguing that technical progress is largely a supply-driven phenomenon. They draw this conclusion from a calibrated multi-sector model of productivity growth with knowledge generation and spillovers as the driving factors. This is similar in spirit to my model, where innovations and skill demand are also supply driven. However, neither the model of Ngai and Samaniego nor the one pioneered by Acemoglu feature intersectoral linkages or skill complementarities across sectors. Furthermore, in Acemoglu's setup a relative increase in the amount of skill-complementary technologies yields decreasing incentives to develop more of them, since their relative price falls.[65] In my model, increasing skill intensity in one sector *augments* the skill bias in other sectors connected through intermediate linkages.

[63] The infamous O-Ring itself is not a product of the space vehicle industry (SIC 3761), but of the gaskets, packing, and sealing devices sector (SIC 3053).

[64] Some studies argue explicitly against demand-driven innovation [Nelson and Winter 1977].

[65] The overall strength of the skill bias results from a trade-off between this price effect and the market size effect, with the elasticity of substitution between skilled and unskilled labor playing a crucial role. This parameter is of secondary importance for my results.

5.1 Production and Consumption

There are N types of goods produced in this economy, each by a representative firm in its corresponding sector i. A producer of good i employs low-skilled labor L_i, high-skilled labor H_i, and an aggregate of intermediate inputs $\mathcal{X}_i$, specified in more detail below. Output of good i is given by

$$Y_i = A_i \left[\gamma_i \left[e^{\,\phi_i \sigma_i}\ H_i \right]^{\frac{\epsilon-1}{\epsilon}} + (1-\gamma_i) \left[L_i \right]^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}\alpha} (\mathcal{X}_i)^{1-\alpha} \tag{8}$$

where $\epsilon > 0$ is the elasticity of substitution between the labor inputs, γ_i is a sector-specific technology parameter, and α is the share of value added (or aggregate labor) in production. Finally, σ_i denotes the skill intensity of intermediate inputs that enter the production of i, and ϕ_i reflects the strength of the ITSC. If $\phi_i > 0$, *overall* productivity of sector i increases in input skill intensity σ_i, which reflects the spillover of innovations embedded in intermediates produced by skilled workers. Moreover, when $\phi_i > 0$, the *relative* productivity of high-skilled workers increases with σ_i, reflecting skill complementarities along the production chain. Therefore, a sector purchasing skill intensive intermediates will employ relatively more skilled workers. If $\phi_i = 0$ we are back to a standard SBTC production function, in a setup with intermediate inputs. This way of modeling the ITSC is a shortcut, aimed at providing a simple calibratable model. A micro-founded model is in the works [Voigtländer 2007].

Each sector i uses the products from all sectors $j \neq i$ as intermediate inputs. To keep matters simple, I assume that intermediates enter final production (8) according to a Leontief technology:

$$\mathcal{X}_i = \min_{j \neq i} \left\{ \frac{1}{a_{ij}} X_{ij} \right\} \tag{9}$$

where X_{ij} is the amount of input j used in the production of good i, and $a_{ij} \in (0,1)$ is the corresponding input requirement. High a_{ij} indicate that much of input j is needed in the production of product i. Sectors do not use their own output as intermediate: $a_{ii} = 0$, but use a positive amount of all others: $a_{ij} > 0$, $\forall j \neq i$; and a_{ij} is normalized such that $\sum_{j \neq i} a_{ij} = 1$. Let the fraction $x_{ij} \equiv X_{ij}/a_{ij}$ denote the effective units of input j. When optimizing production, the representative firm i chooses the same amount of each effective input j, such that $x_{ij} = \overline{x}_i$, $\forall j$. Consequently, the total amount of input i used by sector j is given by

$$X_{ij} = a_{ij} \overline{x}_i \tag{10}$$

where the effective amount of each input in sector i, $\overline{x}_i$, is determined in the optimization of production (8), with $\mathcal{X}_i = \overline{x}_i$. A convenient feature is that $\overline{x}_i$ also gives the total amount of intermediates used, $\sum_{j \neq i} X_{ij} = \overline{x}_i$. Equation (10) implies that the share of input j in sector i is given by $X_{ij} / \sum_{j \neq i} X_{ij} = a_{ij}$. Final piece of the model's production side is the skill intensity of inputs, which is defined in concordance with the empirical analysis:

$$\sigma_i = \sum_{j \neq i} a_{ij} h_j \tag{11}$$

where h_j is the high-skill labor share employed in the production of input j. Thus, $\sigma_i \in [0,1]$ represents the weighted average share of high-skill workers employed in the production of all intermediate inputs used in sector i.

All agents have the same preference structure, independent of their skill level. Skill-specific wages w_L and w_H are the only source of income. There is no investment. A representative consumer draws utility from the consumption c_i of all N goods according to the Cobb-Douglas preferences

$$u\left(\{c_i\}_{i=1}^N\right) = \exp\left(\sum_{i=1}^N \ln c_i\right). \tag{12}$$

This formulation of utility is convenient because it delivers constant and equal final expenditure shares in equilibrium.

5.2 Linkages, Complementarities, and Multipliers

The economic environment in my model is similar to Jones' (2007) setup involving intermediate linkages and complementarity. There, too, final goods are used for consumption and as intermediate inputs, simultaneously. Jones needs the assumption that goods are complements in both production and consumption in order to obtain a closed-form solution. My approach achieves this result with a more natural formulation of preferences but the stronger assumption of no input substitutability. Both Jones' and my model deliver a multiplier that reinforces productivity differences and skill demand, respectively. The multiplier channel, however, is different. In Jones' paper, higher intermediate productivity leads to more output, which feeds back into the production of intermediates. The share of intermediate goods in total revenue is therefore crucial for the size of the multiplier. In my approach, the intermediate input share in total output, $1-\alpha$, is not important for the ITSC. What counts is the average proportion of skills embedded in inputs, σ_i, together with the strength of cross-sectoral complementarity given by ϕ_i. Linkages are only important for granting that sectors process each others' output. They are necessary, but not sufficient for skill complementarities across sectors. If $\phi_i \sigma_i = 0$, there is no intersectoral skill complementarity despite the existence of intermediate linkages. Provided that $\phi_i > 0$, my model delivers a skill demand multiplier. Suppose that H increases exogenously relative to L and that initially only firms in sector j react by employing more high-skilled workers. Skill upgrading in sector j increases σ_i for all $i \neq j$, which leads to higher productivity of skilled workers and thus augmented skill demand in these sectors, as well. The consequence is a virtuous circle of skill upgrading in the whole economy.

5.3 Optimization and the Symmetric Case

Firms take factor and goods prices as given and choose L_i, H_i, and $\overline{x}_i$ to maximize profits from production (8) subject to (9) - (11). $\mathcal{X}_i$ in (8) is replaced by $\overline{x}_i$ because of the Leontief technology related to intermediate inputs. The total cost of intermediates is $\sum_{j\neq i} p_j X_{ij}$, with X_{ij} given by (10). A representative firm in sector i optimizes

$$\max_{\{L_i, H_i, \overline{x}_i\}} p_i Y_i - w_L L_i - w_H H_i - \sum_{j\neq i} p_j a_{ij} \overline{x}_i \tag{13}$$

where p_i is the price of good i. A convenient implication of the Leontief technology is that firms do not adjust input proportions if input skill intensities change, that is, firms take σ_i as given. Setting the ratio of the two labor types' marginal product equal to the ratio of their wages and rearranging yields the relative demand for skilled labor:

$$\frac{H_i}{L_i} = \left(\frac{\gamma_i}{1-\gamma_i}\right)^{\epsilon} \left(e^{\phi_i \sigma_i}\right)^{\epsilon-1} \left(\frac{w_L}{w_H}\right)^{\epsilon} \tag{14}$$

The relative labor demand is determined by sector-specific characteristics γ_i (including, for example, computer equipment and outsourcing), input skill intensity, and relative wages. This result will become important in the calibration of the model. The remaining steps of calculus for the production side are needed to close the model, but not crucial for the intuition. They are presented in Appendix A.2.

On the demand side, let $c_{L,i}$ and $c_{H,i}$ denote labor-type specific consumption of good i. Low-skilled and high-skilled individuals maximize (12) subject to their budget constraints $\sum_{i=1}^{N} p_i c_{L,i} \leq w_L$ and $\sum_{i=1}^{N} p_i c_{H,i} \leq w_H$, respectively. This yields the skill-specific demand functions

$$c_{L,i} = \frac{w_L}{N p_i} \quad \text{and} \quad c_{H,i} = \frac{w_H}{N p_i} \tag{15}$$

Let $C_i = L c_{L,i} + H c_{H,i}$ denote total *final* demand, and $X_{\bullet i} = \sum_{j \neq i} X_{ji}$ total *intermediate* demand for good i. We can now specify the three market clearing constraints that the economy faces:

$$L = \sum_{i=1}^{N} L_i \tag{16}$$

$$H = \sum_{i=1}^{N} H_i \tag{17}$$

and

$$Y_i = C_i + X_{\bullet i}, \ \forall i. \tag{18}$$

The first two constraints assume that the economy is endowed with an exogenously given amount of each type of labor, and that both are fully employed. The last market clearing constraint says that each sector's output is completely used up in final consumption and as an intermediate input for other sectors' production.

For expositional reasons, I present only the symmetric case of the model. This is sufficient to explain the main intuition, and more readily compared to the standard SBTC framework. However, heterogeneity of sectors is important in the calibration, as it provides the variation needed to identify the key parameter ϕ.

Definition 1 *The symmetric case of the model is characterized by all sectors having the same technology, that is,* $A_i = A$, $\gamma_i = \gamma$, $\phi_i = \phi$, $\forall i = 1, ..., N$; *and* $a_{ij} = 1/(N-1), \forall j \neq i$.

The last expression in the definition says that each sector uses the same proportion of all other sectors' products as intermediate inputs. Appendix A.2 shows that in the corresponding symmetric equilibrium the relative wage is given by

$$\frac{w_H}{w_L} = \frac{\gamma}{1-\gamma} \left(e^{\phi h}\right)^{\frac{\epsilon-1}{\epsilon}} \left(\frac{L}{H}\right)^{\frac{1}{\epsilon}} \tag{19}$$

where h is the proportion of high-skilled workers in the economy. This result is an extension of the standard expression in the SBTC literature, which is recovered if $\phi = 0$, i.e., in the absence of

ITSC. The empirical evidence presented above argues strongly for $\phi > 0$. In this case, an increase in H relative to L has two effects. First, the standard downward pressure on the relative wage due to the increased relative supply. Second, the ITSC effect, working in the opposite direction: The newly employed skilled workers foster product innovation in their own sectors, which in turn drives innovation in all other sectors and raises the relative productivity of skilled workers. The second effect therefore raises skill demand and the relative wage. Next, I calibrate the model in order to investigate the strength of the ITSC effect and see how the model performs in explaining the observed relative wage trend in U.S. manufacturing.

5.4 Calibration

In the symmetric equilibrium shown in (19), ϕ represents the average strength of the ITSC in the model economy. In order to calibrate this parameter, I use my panel of manufacturing sectors. First, I derive equation (14) in logarithmic form:

$$\ln\left(\frac{H_i}{L_i}\right) = \ln\left(\frac{\gamma_i}{1-\gamma_i}\right) + (\epsilon - 1)\phi_i\sigma_i + \epsilon \ln\left(\frac{w_L}{w_H}\right) \tag{20}$$

The left-hand side variable is now the relative demand, rather than the skilled labor share analyzed in previous regressions. On the right-hand side, γ_i reflects sector-specific characteristics driving skill demand, i.e., the previously used sectoral fixed effects and control variables. The inverse relative wage in (20) represents the economy-wide skill premium. I use two approaches to address the endogeneity of this variable. First, capture the economy-wide changes by time-dummies, and second, use instruments. The latter also accounts for sector-specific wage endogeneity.[66] A variety of studies pin down the elasticity of substitution between high- and low-skilled labor, ϵ, in the range 1.5 to 2 [Angrist 1995, Ciccone and Peri 2005]. In (20) we can only identify the term $\beta_i \equiv (\epsilon - 1)\phi_i$. However, for a given ϵ, ϕ_i can be recovered. Following the empirical findings reported above, we expect $\beta_i \geq 0$ and increasing in the degree of input differentiation in sector i. The identifying regression is:

$$\ln\left(\frac{H_{it}}{L_{it}}\right) = \alpha_i + \alpha_t + \beta_i\sigma_{it} + \gamma Z_{it} + \varepsilon_{it} \tag{21}$$

where α_i and α_t are sector and time fixed effects, Z_{it} are control variables, and ε_{it} denotes the error term. There are two ways to estimate the economy-average ITSC parameter ϕ. First, identify it directly by constraining $\beta_i = \beta, \forall i$ and weighting by sectoral employment. The corresponding results are shown in column 1 (using OLS) and columns 3, 5, and 6 (using instruments) of Table 11. Instruments and control variables are the same as in section 4.4; the previous discussion of control variable endogeneity and potential bias applies here, as well. Columns 5 and 6 show that the two approaches to deal with the relative wage – time dummies and instruments – yield similar coefficients β.[67] Second, take into account that β_i varies with input differentiation κ_i and include the corresponding interaction: $\beta_1\sigma_i + \beta_2\sigma_i\kappa_i$ (using the interaction term $Z_{j\neq i} \times \kappa_i$, to instrument for $\sigma \times \kappa_i$). In this case, the average effect is $\beta = \beta_1 + \beta_2\bar{\kappa}$, where $\bar{\kappa}$ is average input differentiation, weighted by sectoral employment. Columns 2 and 4 show the corresponding results, with the derived coefficient larger as

[66] See footnote 38 for a discussion. I also address the endogeneity of controls as in section 4.4.

[67] Since Stock and Yogo's (2002) weak instrument test is only available for up to three endogenous regressors, I instrument (in addtion to σ_i and the relative wage) for the one for which endogeneity is of greatest concern: high-tech capital.

compared to the first method. As reported in the bottom of the table, instruments pass all the relevant tests.[68] Overall, the estimates of β lie in the range 2.5-5. I use the IV estimate of column 3, $\beta \approx 3.2$, as a baseline, and also include the lower and upper bounds in the calibration.

Table 11: Calibration of the ITSC parameter ϕ. Dependent variable is $\ln(H_i/L_i)$.

	Levels				Changes	
	OLS	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Input skill intensity (β_1):	2.670***	1.088	3.160*	1.886	2.736***	2.557***
σ_i	(.629)	(1.095)	(1.666)	(2.008)	(1.014)	(.604)
Inp skill intens. $\times$ inp diff. (β_2):		4.045*		5.872**		
$\sigma_i \times \kappa_i$		(2.065)		(2.888)		
Implied coefficient: $\hat{\beta} = \hat{\beta}_1 + \hat{\beta}_2 \bar{\kappa}$		3.309***		5.110***		
Relative wage: $\ln(w_{H,i}/w_{L,i})$						-0.677***
						(.155)
Controls	yes	yes	yes	yes	yes	yes
Sector fixed effects	yes	yes	yes	yes	no	no
Time fixed effects	yes	yes	yes	yes	yes	no
R^2 (after FE)	.56	.57	.56	.57	.22	.27
Observations	2089	2089	2083	2083	1398	1398
First stage regressions						
Instruments for: σ_i			All $Z_{j\neq i}$	All $Z_{j\neq i}$,	All $Z_{j\neq i}$	OS
$\sigma_i \times \kappa_i$				$Z_{j\neq i} \times \kappa_i$		
Instrumented control variables:‡					HT/K	HT/K,
						$\ln(w_H/w_L)$
p-value overidentifying restrictions			0.88	0.13	0.22	0.20
Stock and Yogo weak IV F-statistic			39.0	26.9	22.7	15.9
(Critical value for highest IV quality)			(19.9)	(19.8)	(19.1)	(15.2)

Notes: Clustered standard errors (by sector) in parentheses. Key: *** significant at 1%; ** 5%; * 10%. All regressions and the mean $\bar{\kappa}$ are weighted by sectors' average share in total manufacturing employment 1967-92. Controls include the following variables: Structures per worker (k^{struct}), Equipment per worker (k^{equip}), High-Tech capital (HT/K), R&D intensity ($R\&D_{lag}$), and Outsourcing (OS^{narr}). In columns 2 and 4, also the interactions of the control variables with input differentiation κ_i are included. Weighted average input differentiation is $\bar{\kappa} = .549$. All variables in (1)- (4) are in levels, while 5-year differences are used in regressions (5) and (6). See the notes below Table 9 for details on instruments.
‡ Instruments are the 5- and 10-year lags of of each instrumented control variable.

Figure 3 shows the results of the calibrated model, depicting the skill premium given by (19). In the absence of other factors driving skill demand (γ_i constant), the model with $\phi = 0$ predicts a sharp decline in w_H/w_L when the high-skill labor share h grows. In the figure, I refer to this as the standard model, meaning a CES production function with skilled and unskilled labor. The ITSC model uses $\phi = 3.2$, corresponding to $\beta = 3.2$ and $\epsilon = 2$.[69] In the ITSC baseline case, the decline of the skill premium is much more moderate. The upper bound of the calibration implies increasing relative wages over a wide range of h, and the lower bound lies still substantially above the standard model. The right panel of Figure 3 compares the model predictions with the observed skill premium

[68]The overidentification test in the IV interaction specification (column 4) is close to rejection. I do not take a stand on the corresponding estimate and only use it as an upper bound.

[69]Results are very similar when using $\epsilon = 1.5$ and $\phi = 3.2/0.5 = 6.4$.

in U.S. manufacturing. While the weighted average share of skilled workers rose from 24.7 to 30.6 percent between 1967 and 1992, the skill premium returned to its previous value of 1.56 after a small initial decline. Following the common convention, I refer to skill bias as the difference between the standard model's predicted decline and the observed stagnation of the relative wage. The calibrated ITSC model explains about half of the observed skill bias. This confirms the results of the empirical analysis in section 4, where high-tech capital, R&D intensity, and outsourcing explained the remaining skill upgrading.

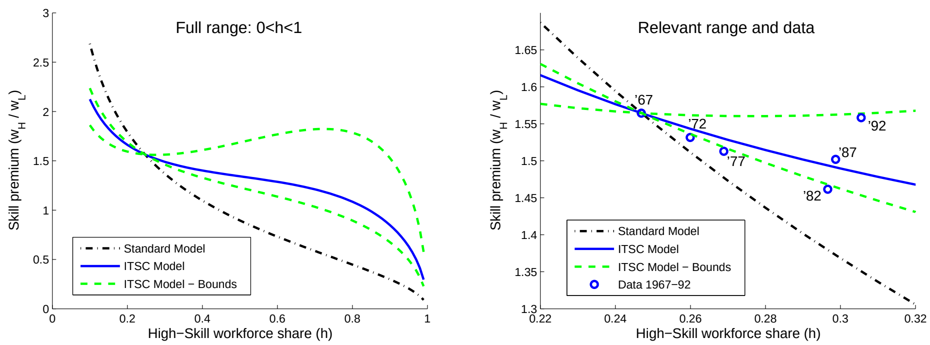

Figure 3: Calibrated ITSC model vs. standard model and data

Notes: The data in the right panel represent the weighted average share of white-collar workers in U.S. manufacturing 1967-92, derived from the NBER Manufacturing Industry Database, using total sectoral employment as weights. The parameter γ is normalized such that the model matches the data in 1967. The elasticity of substitution between skilled and unskilled labor is $\epsilon = 2$.

6 Conclusions

While intermediate inputs account for more than half of a final product's value, intersectoral linkages have been ignored as a source of skill bias. Existing empirical work on rising wage inequality has failed to account for the full scope of skill upgrading in recent decades. This paper presents strong evidence for an intersectoral technology-skill complementarity (ITSC). The ITSC amplifies initial shocks or innovations that increase skill demand, spreading their impact across sectors. I provide empirical evidence suggesting that the ITSC works through product innovation. The innovative activity of skilled workers in one sector improves products used in many other sectors, stimulating innovation and skill demand along the production chain. The result is a self-enforcing circle of skill upgrading that eventually feeds back into the originating sector. Overall, the ITSC can account for about 50% of the skill upgrading in U.S. manufacturing between 1967 and 1992. The remaining half is explained by previously suggested within-sector drivers of skill demand, including high-tech capital, R&D intensity, and outsourcing.

To identify this novel mechanism, I construct a measure for the skills embedded in a sector's intermediate inputs. This input skill intensity correlates with final production skills, i.e., skills employed in the further processing of intermediates. The correlation is robust to the inclusion of numerous control variables previously suggested in the SBTC literature, as well as to using a more conservative measure of input skill intensity, discarding linkages between similar sectors. These results are confirmed by an estimation strategy that goes beyond the mere correlation, using instruments to account for the bi-directional causality between upstream and downstream skill requirements and the endogeneity of control variables.

The ITSC does not come as a surprise. It combines the well-documented findings of a technology-skill complementarity *within* sectors with technological spillovers *across* sectors. The concept of multipliers due to intermediate linkages is also a well-established one. It has been used in studies explaining productivity differences or rising world trade, but not in the SBTC literature. Two empirical findings suggest that the ITSC works through product innovation performed by skilled workers. First, the ITSC is stronger when involving differentiated intermediates, more readily reshaped by innovative minds. I show that product innovation is more pronounced in sectors producing differentiated goods. Thus, downstream industries using differentiated intermediates purchase relatively more embedded innovation. Constructing a measure of input differentiation, I then provide evidence for a stronger ITSC among sectors linked through differentiated intermediates. Second, productivity regressions show that skills in intermediate and final production complement each other in driving TFP and output per worker. Skill-intensive intermediates raise productivity only if they meet final production skills knowing to handle them. These findings suggest that upstream skills foster intermediate product innovation, which in turn augments skill demand and productivity in final production.

In order to integrate my empirical findings into the SBTC framework, I extend the standard model featuring skilled and unskilled labor in a CES production function, adding intermediate inputs in a setup with N sectors. Therein, the *relative* productivity of skilled workers grows with skills embedded in intermediate inputs, reflecting the complementarity of skills along the production chain. Moreover, *overall* productivity increases with input skill intensity, reflecting the innovative activity of skilled workers in intermediate production. An increase in the number of skilled workers has two effects on the skill premium: The standard downward pressure due to increased supply, and an ITSC effect, pushing in the opposite direction. The latter works through the complementarity of skills along the production chain. Once the newly available skills are employed in one sectors, they raise the relative productivity of skilled labor in other sectors through intermediate linkages, augmenting skill demand. The calibrated model accounts for half of the observed skill bias in U.S. manufacturing, confirming the previous estimation results.

The present paper documents the novel stylized fact of an ITSC and applies it to the skill bias of technical change. In addition, the ITSC opens the door for analyzing other important questions from an intermediate-linkage angle. One example is the observed prevalence of North-North trade. Standard models of international trade predict that the skill-abundant North should specialize in skill-intensive production, importing low-skill intensive goods from the South. The ITSC, on the other hand, suggests that skill intensive Northern production requires high-quality skill-intensive intermediates, purchased in the North. Another potential application is the observation that TFP growth rates differ widely and persistently across industries [Ngai and Samaniego 2007]. The ITSC, working through product innovation, can explain this fact. Some sectors purchase more innovation embedded in their intermediates than others. Innovative intermediates, in turn, foster final product improvements. Therefore, heterogeneity in intermediate input requirements could lead to persistent variations in sectoral TFP growth. Finally, an important topic for further investigation is whether the ITSC is a broad phenomenon, extending to linkages beyond the manufacturing sector.

Appendix

A.1 Data Sources and Construction of Variables

Product innovation

Scherer (1982) provides data on R&D expenditures broken down into product and process innovation for 36 manufacturing sectors, broadly equivalent to the 2-digit level. In this context, a new process is defined as a technical improvement in a firm's own production methods, while a new product is an improvement sold to other business enterprises or consumers. Scherer uses data from the Federal Trade Commission's Line of Business survey for 1974 to construct a match between industrial invention patents and the underlying R&D expenditures. He also derives, for each patent, its industry of origin and industries using the invention. Based on these data, Scherer implements a methodology first proposed by Schmookler (1966): Constructing a matrix similar to an input-output table, with industries performing R&D and originating inventions comprising the rows, and industries (including end consumers) using those inventions comprising the columns. Each element in the matrix represents the flow of technology from an originating industry to a using one. Diagonal elements indicate process technology. I use this table to derive, for each industry, its share of R&D spent for product innovation, π_i^{prod}, as the sum of off-diagonal elements divided by total R&D expenditures (row-sum).

Additional control variables

The capital measure in efficiency units used by Krusell et al. (2000) is only available at the aggregate U.S. level. Thus, I use the 4-digit SIC figures from the Manufacturing Industry Database for real capital equipment and structures.[70] The National Science Foundation (NSF) provides company and other (except Federal) research and development (R&D) expenditures as a percentage of sales by industry. This R&D proportion is commonly referred to as R&D intensity.[71] The NSF data cover 24 industries that I match to the 358 industries of my sample.[72] The weighted mean of R&D intensity for my sample increases from 2.12 percent in 1963 to 3.28 percent in 1992.

In order to control for computer equipment and other high-technology capital, I use detailed data on private nonresidential fixed assets from the BEA. These data distinguish capital by asset type for 21 (approximately two-digit) NAICS manufacturing industries, which I match to the 358 industries of my panel. I derive the real net capital stock by asset type and industry (in 2000 dollars) from the current-cost capital stock and the chain-type quantity index. Following Berndt, Morrison, and Rosenblum (1992), who use an earlier version of this dataset, I define high-technology capital to include

[70] See Bartelsman and Gray (1996) for a documentation of these data and the corresponding investment deflators.

[71] See, for example, Autor et al. (1998), who work with the same NSF data as used here. Machin and Van Reenen (1998) use R&D intensity in an industry-level panel for several OECD countries and report substantial positive effects on the growth of high-skill employment and wage-bill shares.

[72] The corresponding crosswalk from the 24 NSF industries to the 358 SIC industries of my sample is available upon request. Due to missing observations in the NSF data, several imputations and interpolations were required.

office, computing and accounting machinery; communications equipment; scientific and engineering instruments; and photocopy and related equipment. From this number I calculate the share of high-technology capital in the total capital stock for each industry (*HT/K*). The weighted average of this broad measure increases from 1.2 percent in 1967 to 3.2 percent in 1982, and 6.0 percent in 1992. A frequently used, more narrowly defined measure includes only the share of office, computing and accounting equipment in the capital stock (*OCAM/K*). This variable is 0.4 percent in 1967, 0.8 percent in 1982, and then increases to 2.0 percent in 1992.

Feenstra and Hanson (1999) derive, for each 4-digit SIC industry, a proxy for imported intermediate inputs from trade data. Expressing this measure relative to total expenditure on non-energy intermediates in each industry gives their broad measure of foreign outsourcing. The narrow measure considers only inputs that are purchased from the same 2-digit SIC industry as the good being produced. While the broad measure includes all imported intermediates, the narrow measure restricts attention to the outsourcing of production activities that could have been performed by the respective industry within the United States. I calculate both measures of outsourcing for the years and sectors included in my sample, using data on U.S. imports and exports by 4-digit SIC industries from the Center for International Data at UC Davis together with the above described input-output data.[73] The weighted averaged broad (narrow) measure increases from 4.4 (2.4) percent in 1967 to 8.6 (3.9) percent in 1982 and 13.4 (6.6) percent in 1992.

A.2 Equilibrium for the Symmetric Case

Firms' optimization with respect to H_i and L_i yields the relative demand for skilled workers, shown in (14). The first order condition (FOC) for $\overline{x}_i$ gives sector i's demand for effective units of each intermediate input j, x_{ij}, as a function of total output and goods prices:

$$x_{ij} = \overline{x}_i = \frac{(1-\alpha)p_i Y_i}{\sum_{j\neq i} p_j a_{ij}},\ \forall j \tag{A.1}$$

In the following, I use these FOC to derive the demand for each factor and the marginal cost of production, which equals the product price under perfect competition. Rearranging (14) and substituting for H_i in (8) yields

$$L_i = \left(\frac{w_L}{1-\gamma_i}\right)^{-\epsilon} \Omega_i^{\epsilon}\ (\overline{x}_i)^{-\frac{1-\alpha}{\alpha}} \left(\frac{Y_i}{A_i}\right)^{\frac{1}{\alpha}} \tag{A.2}$$

and similarly for H_i:

$$H_i = \left(\frac{w_H}{\gamma_i}\right)^{-\epsilon} \left(e^{\phi_i \sigma_i}\right)^{\epsilon-1} \Omega_i^{\epsilon}\ (\overline{x}_i)^{-\frac{1-\alpha}{\alpha}} \left(\frac{Y_i}{A_i}\right)^{\frac{1}{\alpha}} \tag{A.3}$$

where Ω_i is the cost of the H_i-L_i labor composite, given by

$$\Omega_i = \left[\gamma_i^{\epsilon} w_H^{1-\epsilon} \left(e^{\phi_i \sigma_i}\right)^{\epsilon-1} + (1-\gamma_i)^{\epsilon} w_L^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}} \tag{A.4}$$

[73] I construct a crosswalk to match the 450 manufacturing industries from the trade database to the 358 industries of my sample. The correspondences are available upon request. Feenstra and Hanson use nominal input shares when calculating the outsourcing measure. My results are robust to using both nominal and real input shares.

The next steps lead to factor demand as linear functions of Y_i. Multiplying (A.2) and (A.3) by the respective wages and adding up yields the total cost of labor in sector i:

$$w_L L_i + w_H H_i = \Omega_i \left(\overline{x}_i\right)^{-\frac{1-\alpha}{\alpha}} \left(\frac{Y_i}{A_i}\right)^{\frac{1}{\alpha}} \tag{A.5}$$

The FOC of producers' optimization also yield the standard result that the expenditure share for labor is α, i.e., $w_L L_i + w_H H_i = \alpha p_i Y_i$. Plugging this into (A.1) gives

$$\frac{w_L L_i + w_H H_i}{\overline{p}_i \overline{x}_i} = \frac{\alpha}{(1-\alpha)} \tag{A.6}$$

where $\overline{p}_i \equiv \sum_{j \neq i} a_{ij} p_j$ is the effective (or weighted average) input price. Plugging (A.6) into (A.5) yields the demand for effective units of each input as a function of factor prices and output:

$$\overline{x}_i = \frac{1}{A_i} \frac{1-\alpha}{\overline{p}_i} \left(\frac{\overline{p}_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{\Omega_i}{\alpha}\right)^{\alpha} Y_i \tag{A.7}$$

Using this result together with (A.2) gives the demand for low-skilled labor L_i; and together with (A.3) for high-skilled labor H_i, as functions of factor prices and output:

$$L_i = \frac{1}{A_i} \alpha \left(\frac{1-\gamma_i}{w_L}\right)^{\epsilon} \Omega_i^{\epsilon-1} \left(\frac{\overline{p}_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{\Omega_i}{\alpha}\right)^{\alpha} Y_i \tag{A.8}$$

$$H_i = \frac{1}{A_i} \alpha \left(\frac{\gamma_i}{w_H}\right)^{\epsilon} \left(e^{\phi_i \sigma_i}\right)^{\epsilon-1} \Omega_i^{\epsilon-1} \left(\frac{\overline{p}_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{\Omega_i}{\alpha}\right)^{\alpha} Y_i \tag{A.9}$$

We can now derive the total cost of production, TC_i, by multiplying (A.7) - (A.9) with the corresponding factor prices and adding up.[74]

$$TC_i = \frac{1}{A_i} \left(\frac{\overline{p}_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{\Omega_i}{\alpha}\right)^{\alpha} Y_i \tag{A.10}$$

Due to perfect competition within sectors and constant returns to scale in production, representative firms make zero profits, implying $p_i Y_i = TC_i$. Therefore, the price of good i is given by

$$p_i = \frac{1}{A_i} \left(\frac{\overline{p}_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{\Omega_i}{\alpha}\right)^{\alpha}. \tag{A.11}$$

We can now derive the quantities for the symmetric case described in Definition 1. First, from (11): $\sigma_i = 1/(N-1) \sum_{j \neq i} h_j$; the input skill intensity of sector i is equal to the average skill intensity of production in all other sectors. Plugging this result into (14) and using $H_i/L_i = h_i/(1-h_i)$ gives:

$$\frac{h_i}{1-h_i} = \left(\frac{\gamma}{1-\gamma}\right)^{\epsilon} \left(e^{\phi \sigma_i}\right)^{\epsilon-1} \left(\frac{w_L}{w_H}\right)^{\epsilon} \tag{A.12}$$

This equation implies that $h_i = h = H/(H+L), \forall i$.[75] Plugging this into (A.4) yields $\Omega_i = \Omega, \forall i$. Moreover, the input skill intensity is equal to the average high-skill labor share in each sector: $\sigma_i =$

[74] Recall that $\overline{x}_i$ reflects also the total amount of inputs used in sector i, which follows from (10) and the normalization $\sum_{j \neq i} a_{ij} = 1$. The total cost of intermediate inputs is equal to $\sum_{j \neq i} p_j X_{ij} = \sum_{j \neq i} p_j a_{ij} \overline{x}_i = \overline{p}_i \overline{x}_i$, i.e., weighted average input price times total amount of inputs used.

[75] To prove this result, note that $h = [(N-1)/N]\sigma_i + [1/N]h_i$. Now suppose that sector i uses more than the average skilled labor share, $h_i > h$. Then $\sigma_i < h$. However, (A.12) requires that $\sigma_i > h$ in order to have $h_i > h$. A similar contradiction arises when we suppose $h_i < h$.

$h, \forall i$. Next, using $\overline{p}_i = 1/(N-1)\sum_{j\neq i} p_j$ in (A.11) implies $p_i = p, \forall i$.[76] Consequently, $\overline{p}_i = p, \forall i$. Because of price symmetry, final demand (15) is also symmetric, and so are factor demands (A.7)-(A.9). Thus, $L_i = L/N$, $H_i = H/N$, and $Y_i = Y/N$, where Y is total (intermediate and final) output of the economy. Dividing (A.9) by (A.8) in the symmetric case gives equation (19).

Finally, I show that goods markets clear, using the superscripts D for demand and S for supply. Total demand for each good i has a final and an intermediate component: $Y_i^D = C_i + X_{\bullet i}$. The former derives from (15) and is given by

$$C_i = c_{L,i}L + c_{H,i}H = \frac{w_L L + w_H H}{Np}, \tag{A.13}$$

while the latter is composed of the demand for sector i's output from all other $N-1$ sectors:

$$X_{\bullet i} = \sum_{j\neq i} \frac{1}{N-1}\overline{x}_j = \frac{1}{A}\left(\frac{p}{1-\alpha}\right)^{1-\alpha}\left(\frac{\Omega}{\alpha}\right)^{\alpha}\frac{1-\alpha}{p(N-1)}\sum_{j\neq i} Y_j^S = \frac{(1-\alpha)}{N-1}\sum_{j\neq i} Y_j^S \tag{A.14}$$

where the first equality follows from (10), and the last one from (A.11). In order to join these two equations, I replace Y_j^S using the symmetric expression for the labor expenditure share, $\alpha p Y_j^S = (w_L L + w_H H)/N$ for all sectors $j \neq i$. Therefore, total demand for each good i is given by

$$Y_i^D = C_i + X_{\bullet i} = \frac{w_L L + w_H H}{Np} + \frac{(1-\alpha)}{\alpha(N-1)}\sum_{j\neq i}\frac{w_L L + w_H H}{Np} = \frac{1}{\alpha}\frac{w_L L + w_H H}{Np}. \tag{A.15}$$

The total demand for i is therefore a multiple $1/\alpha$ of the corresponding final demand. With $\alpha = 0.5$, doubling final demand means quadrupling total demand. Under perfect competition, in each sector i total sales equal total expenditures for labor and intermediates:

$$p_i Y_i^S = w_L L_i + w_H H_i + \sum_{j\neq i} p_j X_{ij} \tag{A.16}$$

where the last term is equal to $\overline{p}_i \overline{x}_i$. Under symmetry, and using (A.7) together with the labor expenditure share to replace $\overline{p}_i \overline{x}_i$, (A.16) yields total supply for each i

$$Y_i^S = \frac{1}{\alpha}\frac{w_L L + w_H H}{Np}, \tag{A.17}$$

which equals total demand given by (A.15).

A.3 The Multiplier in the Model with N Sectors

In section 4.5 I derived the multiplier of skill upgrading for the two-sector case. Now suppose that an exogenous innovation arrives in sector i, augmenting skill demand by δ_i. The total change in sector i's high-skilled labor share is then given by $\triangle h_i^T = \triangle h_i^E + \delta_i$, where $\triangle h_i^E$ denotes the endogenous component due to the multiplier effect. This is driven by changes in i's input skill intensity:

$$\triangle h_i^E = \beta \sum_{j\neq i} a_{ij} \triangle h_j^T \tag{A.18}$$

[76] The proof is similar to the one in the previous footnote. Define the average price as $p = [(N-1)/N]\overline{p}_i + [1/N]p_i$ and suppose that sector i charges more, $p_i > p$. Then $\overline{p}_i < p$, which implies that sector i has a lower intermediate input price, but charges more for its final product than the economy average, therefore making positive profits. This would attract competitors charging lower prices until $p_i = p$.

where the sum corresponds to $\triangle\sigma_i$, and β is the strength of the ITSC, as estimated in section 4. Now suppose symmetry, such that $h_i = h_j = h$, $\delta_i = \delta_j = \delta$ and $a_{ij} = 1/(N-1)$. Then (A.18) simplifies to $\triangle h^E = \beta(\triangle h^E + \delta)$, which implies

$$\triangle h^E = \frac{\beta}{1-\beta}\delta \quad \text{and} \quad \triangle h^T = \frac{1}{1-\beta}\delta. \tag{A.19}$$

Therefore, an exogenous innovation coming along with skill-upgrading of 1 percent increases the skilled labor share by $1/(1-\beta)$ percent in the long run.

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