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

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Abstract

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. Previous empirical studies have investigated skill demand at the worker-, firm-, and sector-level. This paper integrates intersectoral linkages and complementarities into the standard skill-biased technical change (SBTC) framework. In a simple multi-sector model, we allow skill-biased intermediate technology to raise skill bias in final production. The model predicts a multiplier effect that augments small sector-level skill bias into a large aggregate impact on skill demand. We construct a proxy for the skill bias embedded in each sector's intermediate products: input skill intensity. This variable correlates strongly with the skill share employed in final production – a novel stylized fact that points towards an intersectoral technology-skill complementarity. Together with input-output linkages, the observed complementarity reinforces skill demand along the production chain. The effect is large, accounting for more than one third of the observed skill upgrading in U.S. manufacturing.

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

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1 Introduction

As the supply of skilled workers has risen, so has the skill premium. A wealth of studies following Katz and Murphy (1992) documents a substantial increase in the demand for skilled labor over the last decades. The full magnitude of this effect, however, has not yet been explained. The usual suspects behind rising skill premia – international trade, information technology, and innovation – can account for some, but not all of the observed rise in skill demand. Much of the literature has focused on skill-biased technical change (SBTC) – a shift in production technologies that favors skilled labor. Empirical studies have investigated SBTC at the worker-, firm-, and sector-level. Linkages across sectors have been ignored so far, despite the fact that more than half of a final product's value is embedded in intermediates.

This paper extends the standard SBTC framework. Instead of one representative firm it features many sectors that purchase each other's products as intermediate inputs. The central new feature is that the skill bias of technology is not solely determined within sectors, but also has an intersectoral dimension. In the extended setup, skill-intensive (complex) intermediates require skills in their further processing or their integration into final products. 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 skill upgrading. Therefore, SBTC in one sector can increase skill demand in many other sectors, because of linkages operating through the use of intermediate products. These linkages deliver a multiplier that reinforces skill demand across firm and sector boundaries. The multiplier effect augments small sector-level SBTC into large aggregate skill bias. This can explain why within-sector studies fail to account for the observed large aggregate SBTC.

The stylized multi-sector model predicts that the proportion of skilled workers in final production increases with the skill bias of intermediate technology. The latter is a technological concept, and is not directly observable in the data. However, the model delivers a proxy: *Input skill intensity* – the weighted average share of skilled workers employed in intermediate production. We construct this measure by matching input-output tables with workforce data for 4-digit U.S. manufacturing sectors.[1] Figure 1 presents a novel stylized fact resulting from this analysis: A strong positive correlation between input skill intensity and the share of skilled workers in final production. The figure shows cross-sectional observations in 1992. In the empirical analysis, we construct a panel for 358 U.S. manufacturing sectors in 5-year intervals between 1967 and 1992. The correlation is stable over time, and is robust to the inclusion of a large number of additional controls.[2] The robust positive correlation of skilled labor shares along the production chain provides strong

[1] In the empirical analysis, input skill intensity is the weighted average share of white-collar workers employed in the production of a sector's intermediate inputs. 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] 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. We also exclude inputs from

empirical support for an intersectoral dimension of SBTC.

[Insert Figure 1 here]

In the framework introduced here, inputs from upstream sectors are not only 'intermediate' in the standard semi-manufactured sense, but also 'intermediaries' that transmit skill requirements across industries. Therefore, skill biased 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. This implies an intersectoral technology-skill complementarity (ITSC), which goes beyond the well-known within-sector complementarity between skills and technology.

What is the channel through which the ITSC works its wonders? Product innovation is one candidate. 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 complementarity, an upstream supplier that employs highly educated workers will turn out innovative intermediates. These upstream product improvements induce innovation at the downstream level, which in turn increases downstream skill demand.[3] The argument does not depend on the direction of causality; the complementarity also works from final producers to suppliers. An example is a cutting-edge downstream firm demanding innovative intermediate inputs. To supply these, upstream producers need highly skilled workers.

We present empirical evidence that argues in favor of product innovation as the ITSC channel. The argument is based on the relationship between product innovation and differentiation. Differentiated goods can be refined more readily than homogenous ones. The presence of engineers contributes to the continuous improvement of electronic components. On the other hand, crude petroleum does not change, whether it is pumped out of the ground by laborers or university graduates. Therefore, differentiated inputs are more susceptive to 'skill embedding' – their product characteristics reflect the skill intensity, or complexity, of the underlying production process. In contrast, innovations in the production of homogenous inputs improve processes rather than products, and thus have little effect on downstream skill demand.[4] Combining Rauch's (1999) classification of product differentiation with input-output tables, we construct a measure of input differentiation. We demonstrate that the ITSC is increasing in the degree of input differentiation, and is close to zero for sectors that use mainly homogenous inputs. In other words, intersectoral skill complementarities are strong when differentiated intermediates like electronic components form the link. However, when linkages work through homogenous goods like crude oil, intermediate skill intensity does not matter for

similar industries in the calculation of input skill intensity in order to address the concern that common trends drive the observed correlation.

[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] We 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.

skill shares in final production.

Finally, we investigate the contribution of the ITSC to rising skill demand. We derive an estimation strategy from a labor-demand framework that has been previously used to study the role of outsourcing and IT in skill upgrading (Feenstra and Hanson, 1999). To this familiar setup we add input skill intensity as an explanatory variable and use instruments to account for endogeneity concerns. The contribution of the ITSC is large. It explains more than one third of the increase in white-collar labor demand in U.S. manufacturing over the period 1967-92. This is similar to the contribution of IT capital and more than twice the one of outsourcing or R&D. Interestingly, the ITSC is orthogonal to previously suggested explanations of increasing skill demand – it does not dilute the explanatory power of other variables. This underlines the role of intersectoral complementarities as a new phenomenon in the SBTC literature.

The paper adds a novel angle to a large body of studies that seek to explain the remarkable increase in wage inequality in the United States starting in the 1960s.[5] Existing work can explain some of the rising inequality, but falls short of accounting for all of it. The first prominent channel is trade and its effect on international patterns of specialization (e.g., Leamer, 1996; Wood, 1998). The between-component of trade – relocating production of low-skill-intensive industries to low-skill abundant countries – contributes little to the observed skill upgrading (Berman et al., 1994; Autor, Katz, and Krueger, 1998). Within-industry effects appear to be more important. To explain this observation, 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, and paramount, channel to explain wage inequality is skill-biased technical change – technological progress that shifts labor demand in favor of highly skilled workers. Numerous studies quantify SBTC as a complementarity between capital (or technology) and skills, where computer-based information technologies (IT) play a central, although disputed role (DiNardo and Pischke, 1997; Card and DiNardo, 2002; Autor, Levy, and Murnane, 2003). So far, the empirical SBTC literature has treated technology-skill complementarities as a phenomenon within specific industries[6], within firms[7], and at the worker level.[8] 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 broader complementarity between capital equipment and skilled labor has proved con-

[5] See Autor, Katz, and Kearney (2008) for a recent review. Skill upgrading, i.e., a rise in skilled labor's share in employment and payroll, is also observed in other OECD countries (Machin and van Reenen, 1998; Berman, Bound, and Machin, 1998) as well as in developing countries (Pavcnik, 2003; Zhu, 2005).

[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 et al., 1998). Autor et al. (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) and Autor et al. (2008) 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.

troversial.[10] 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. We show below that R&D intensity can account for about 5% of skill upgrading in U.S. manufacturing. All individual contributions together explain only about half of the overall magnitude. Our results suggest that linkages across sectors can explain much of the remainder.

Input-output linkages have been investigated in an ample literature pioneered by Leontief (1936) and Hirschman (1958). A variety of studies focuses on the role of input-output multipliers in economic development. 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. Jones (2008) elaborates this point and adds the role of input complementarity. He demonstrates that input-output linkages give rise to a multiplier effect that magnifies sector-level productivity differentials. Multipliers have also been used to explain the growth in the trade share of output, or the cyclical behavior of aggregate productivity.[11] However, this paper is the first to investigate the role of intersectoral linkages for skill upgrading.

The rest of the paper is organized as follows. The next section introduces the framework of input-output linkages, innovation spillovers along the production chain, and the resulting skill complementarity. Section 3 presents a simple model that adds intermediate inputs to the standard SBTC framework. The section also derives three testable predictions. Section 4 describes the data and explains the construction of the input skill intensity measure. Section 5 reports empirical results, documenting the intersectoral technology-skill complementarity, and confirms its robustness. In addition, we derive a regression from a labor-demand framework to estimate the ITSC's contribution to skill upgrading. We address endogeneity issues by using a set of IV regressions and check instrument validity, applying weak instrument tests and overidentifying restrictions. Section 6 concludes.

2 Framework: Intersectoral Linkages and Skill Complementarity

This paper argues that intersectoral technology-skill complementarities boost skill demand. However, linkages across industries alone need not imply connected skill requirements.[12] What makes the proposed point plausible is innovation-skill complementarity *within* sectors, combined with innovation spillovers *across* sectors, through input-output linkages. Before formalizing the joint framework in a simple model, we briefly review these two concepts.

The remaining thirty percent between occupations are similar to Feenstra and Hanson's finding.

[10] This concept was first formalized by Griliches (1969). Krusell, Ohanian, Ríus-Rull, and Violante (2000) document an important contribution to skill upgrading, but Acemoglu (2002b) shows that their result disappears upon the inclusion of a linear time trend.

[11] 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.

[12] As pointed out by Jones (2008), one can have linkages without complementarity of inputs.

Intermediate linkages and innovation spillovers

Intermediate inputs account for a substantial share of overall costs. Input-output tables for the United States show that expenditure shares for intermediates are stable over time, largest in manufacturing (57%), and smallest in services (43%). The remaining costs include employee compensation (about 30%) and payments to capital (about 16%).[13] Studies of capital-skill complementarity therefore focus on a relatively small component of the final product's value. It is important to note that the approach in this paper is strictly separated from the capital-skill complementarity literature. By construction, intermediate linkages do not include investment (capital) goods.

There is substantial evidence for technological 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). Scherer identifies for about 40 industries the share of R&D that is allocated to process vs. product innovation. In this context, product innovations are by definition used outside their sector of origin, i.e., they are passed to downstream sectors or consumers in the form of improved products. Both Scherer and Pavitt confirm the overall prevalence of product innovation, accounting 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.[14] 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. In manufacturing, however, much of technical change originates 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 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. The channel also operates in the opposite direction. The literature on international spillovers and transfer of knowledge provides evidence that innovative downstream

[13]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.

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

producers foster technical progress of their upstream suppliers. For example, Blalock and Gertler (2008) 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.[15]

Adding the role of technology-skill complementarity

We currently know that innovation goes hand in hand with skilled labor.[16] In addition, much of the innovative activity creates new products that are used as intermediates in other sectors, generating 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 innovation 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 contribution in this paper 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 A Sketch Model

The informal complementarity framework above postulates that skill bias in intermediate and final production are related through input-output linkages. To develop the formal implications of this presumption, we extend the standard SBTC framework by introducing many sectors and intersectoral linkages. However, linkages alone are not sufficient for intersectoral technology-skill complementarities (ITSC). The decisive assumption is that skill biased upstream technology can lead to downstream skill bias.[17] If this is the case, the model implies a multiplier effect that augments small within-sector SBTC to large aggregate skill bias.

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

[16] The same is true for the result of innovation: product quality. As Verhoogen (2008) shows, producing high-quality goods requires skilled workers.

[17] To keep matters simple, the model features a one-directional channel – from upstream to downstream. Adding the reverse causal direction does not change the model's implications; it yields an even stronger ITSC.

The standard setup in the SBTC literature has two types of labor in a CES production function, producing one final good.[18] We extend this framework to $i = 1, ..., N$ sectors, each producing a specific good, or variety i. Within each sector, a multiplicity of firms operates under perfect competition and constant returns. We 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 we show in section 5.2 below 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 handle innovative intermediate inputs. Skill-biased technological change raises the productivity of type-H workers relative to their type-L counterparts. This *relative* skill bias is at the center of interest here. We therefore abstract from skill-neutral technological progress, assuming that all innovation raises the productivity of H workers, while the productivity of L workers remains constant.[19]

The central new feature is that SBTC not only works its wonders within the originating sector i, but can also spill over from other sectors $j \neq i$ through the intermediate input channel. In other words, high-skilled workers are not only better at handling innovation within their own sector, but are also relatively more productive in processing innovative intermediates from other sectors.

Production

A producer of good i employs low-skilled labor L_i, high-skilled labor H_i, and an aggregate of intermediate inputs $\mathcal{X}_i$. Output of good i is given by

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

where γ is a technology parameter, α is the share of value added (or aggregate labor) in production, and ϵ is the elasticity of substitution between the labor inputs. We assume $\epsilon > 1$, such that H_i and L_i are substitutes.[20] Finally, A_i denotes the skill bias of technology in sector i, as specified in more detail below, and increases in A_i correspond to SBTC.

Each sector i uses the output from all sectors $j \neq i$ as intermediate inputs. To keep matters simple, we assume that intermediates enter final production (1) according to a Leontief technology:

$$\mathcal{X}_i = \min_{j \neq i} \left\{ \frac{1}{a_{ij}} X_{ij} \right\} \tag{2}$$

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

[18]See Card and DiNardo (2002) and Violante (2006) for a review of the standard SBTC framework.

[19]This assumption is made without loss of generality. An extension with skill-neutral technical change delivers the same predictions for the relative skill bias.

[20]Empirical studies commonly pin down ϵ in the range 1.4 to 2 (Angrist, 1995; Ciccone and Peri, 2005).

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

$$X_{ij} = a_{ij}\overline{x}_i \tag{3}$$

where the effective amount of each input in sector i, $\overline{x}_i$, is determined in the optimization of production (1), 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 (3) implies that the share of input j in sector i is given by $X_{ij}/\sum_{j \neq i} X_{ij} = a_{ij}$.[21]

Next, we turn to the skill bias of technology. A_i is the relative productivity of skilled as compared to unskilled workers, or total skill bias in sector i. It consists of two components: $A_i = f\left(T_i,\ \{A_j\}_{j \neq i}\right)$. First, T_i denotes the skill bias of sector-specific technology. For example, the invention of semiconductors in the electronic components industry raised the productivity of electrical engineers who knew how to deploy this technology. T_i is exogenously given. Second, skill-biased technology in upstream production, $\{A_j\}_{j \neq i}$, also raises the productivity of skilled workers in sector i that process them. Semiconductors affected skill-specific labor productivity not only in the electronics sector itself. A large variety of other sectors – among them the previously mentioned Calculating and Accounting Equipment industry – seized the opportunities embedded in the newly available electronic components. In those sectors, too, skilled labor became relatively more productive. We now have to specify how skill-biased technology in sectors $j \neq i$, A_j, contributes to skill bias in i, A_i. A natural way to weigh the various contributions is by input shares a_{ij}. Summing over all intermediates, we can define *input skill bias*:

$$\sigma_i = \sum_{j \neq i} a_{ij} A_j \tag{4}$$

Thus, σ_i represents the weighted average skill bias embedded in intermediate inputs that are used in sector i. Using this definition, we can specify the functional form of the total skill bias in sector i:

$$A_i = T_i\ \sigma_i^{\phi_i} \tag{5}$$

The parameter $\phi_i \in [0, 1)$ indicates the strength of the ITSC, i.e., how strongly upstream SBTC influences the skill bias in downstream sectors. This can vary across sectors. If $\phi_i > 0$, the relative productivity of skilled labor in sector i increases in input skill bias. On the other hand, if $\phi_i = 0$ we are back to a standard SBTC setup, where total skill bias A_i depends only on the within-sector component T_i.

[21] This refers to units of inputs. In the empirical analysis, a_{ij} represents real expenditure shares.

Consumption

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

$$u\left(\{c_i\}_{i=1}^N\right) = \exp\left(\sum_{i=1}^N \ln c_i\right). \tag{6}$$

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

Optimization

Firms take factor and goods prices as given and choose L_i, H_i, and $\overline{x}_i$ to maximize profits from production (1) subject to (2) - (4). $\mathcal{X}_i$ in (1) 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 (3). A representative firm in sector i optimizes

$$\max_{\{L_i,H_i,\overline{x}_i\}} p_i Y_i - w_L L_i - w_H H_i - \sum_{j\neq i} p_j a_{ij}\overline{x}_i \tag{7}$$

where p_i is the price of good i. A convenient implication of the Leontief technology is that firms do not adjust intermediate input proportions if input skill bias changes, 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:

$$\frac{H_i}{L_i} = \left(\frac{\gamma}{1-\gamma}\right)^{\epsilon} \left(T_i\, \sigma_i^{\phi_i}\right)^{\epsilon-1} \left(\frac{w_L}{w_H}\right)^{\epsilon} \tag{8}$$

The relative labor demand is determined by the inverse skill premium and the parameter γ. Both are the same across sectors. In addition, within-sector skill bias T_i (including, for example, computer or high-tech equipment) and input skill bias σ_i drive up skill demand. The remaining steps of calculus are needed to close the model, but are not crucial for the intuition. They are presented in appendix A.1.

A proxy for input skill bias

So far we have treated input skill bias σ_i as an abstract concept. In order to take the model to the data, we need an empirical counterpart that proxies for σ_i. To derive one such candidate, we apply equations (5) and (8) to a sector $j \neq i$ and rearrange for the total skill bias in j:

$$A_j = \left(\frac{1-\gamma}{\gamma}\frac{w_H}{w_L}\right)^{\frac{\epsilon}{\epsilon-1}} \left(\frac{H_j}{L_j}\right)^{\frac{1}{\epsilon-1}} \tag{9}$$

The term in the first parentheses is constant across sectors, and the second one is proportional to $h_j \equiv H_j/(L_j + H_j)$.[22] This leads to a proxy for input skill bias:

$$\sigma_i = \sum_{j \neq i} a_{ij} A_j \sim \sum_{j \neq i} a_{ij} h_j \in [0, 1] \tag{10}$$

where the last term represents the weighted average share of skilled workers that produces sector i's intermediate inputs. We refer to this measure as *input skill intensity*. Section 5 describes its construction by combining input-output data with worker characteristics.

The symmetric case and the multiplier effect

The final theoretical step is to formally derive the multiplier of skill bias. For expositional reasons, We focus on the symmetric case of the model. This is sufficient to explain the main intuition, and is more readily compared to the standard SBTC framework. However, heterogeneity of sectors is important for testing the model's empirical predictions.

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

The first two expressions, symmetric within-sector skill bias and equal strength of ITSC in all sectors, imply $\sigma_i = \sum_{j \neq i} a_{ij} A = A$, $\forall i$.[23] Therefore, the total skill bias A is symmetric and (5) simplifies to

$$A = T^{1/(1-\phi)} \tag{11}$$

This equation describes the multiplier effect. To see how it works, we derive the wage premium at the aggregate level. Appendix A.1 shows that in the symmetric equilibrium the relative wage is given by

$$\frac{w_H}{w_L} = \frac{\gamma}{1-\gamma} \left(T^{\frac{\epsilon-1}{\epsilon}} \right)^{1/(1-\phi)} \left(\frac{L}{H} \right)^{\frac{1}{\epsilon}} \tag{12}$$

The parameter ϕ can be interpreted as the average strength of the ITSC in the economy. Note that if $\phi = 0$, the aggregate skill bias is equal to the within-sector SBTC, which corresponds to the standard model. With $\phi > 0$, however, intersectoral linkages deliver a multiplier effect. SBTC in one sector raises the skill bias in other sectors and eventually feeds back into the originating sector. This amplifies within-sector SBTC and leads to a larger aggregate bias.[24] The framework presented here can explain why SBTC observed at the aggregate level is large, while little more than half of it can be explained by sector specific drivers.

[22] We use h rather than H/L because the former is bounded between zero and one such that the resulting proxy is more readily interpreted. None of the empirical results depends on this choice – the two measures are close to linearly related over the relevant range in the dataset, with percentiles $p_1(h) = 0.093$ and $p_{99}(h) = 0.634$.

[23] See appendix A.1 for a proof.

[24] The setup here is similar to Jones' (2008) model that delivers a multiplier for productivity differences. 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 our approach,

Predictions of the model

Recall that the main assumption in the model was that skill biased upstream technology *can* lead to downstream skill bias. It does so in sectors with $\phi_i > 0$. Provided that this condition holds in a sufficiently large subset of sectors, the model implies the following three propositions that can be tested empirically.

P1. The proportion of skilled workers in sectors i, h_i, increases in within-sector skill bias T_i and in input skill intensity. The latter is defined as the weighted average share of skilled workers employed in the production of sector i's intermediate inputs.

P2. The correlation between h_i and input skill intensity can vary by sector. It is the stronger the larger ϕ_i, i.e., the larger the extent to which skill bias in upstream technology influences downstream skill bias.

P3. There is a multiplier that can augment small sector-specific SBTC to large aggregate skill bias.

The first two propositions follow from (8), and the last one from (11). Testing P1 is straightforward, using controls for within-sector skill bias from the SBTC literature and constructing the new variable *input skill intensity* by combining input-output tables with data on worker characteristics. To test P2, we split the sample by the degree of input differentiation. The underlying idea is that skill biased innovation in upstream sectors influences downstream skill bias by changing the product that links the sectors. Differentiated intermediates are more amenable to product innovation than homogenous ones. Therefore, we expect a stronger ITSC when linkages involve more differentiated intermediates. Finally, to estimate the importance of the multiplier effect in P3, we ideally want a point estimate of ϕ. However, this would require the functional forms – in particular (5) and (10) – to be correctly specified. Misspecification can cause parameter estimates to be inconsistent (e.g., White, 1982). In order to address this concern, we estimate a demand framework based on a translog cost function, which imposes very few restrictions on the shape of the corresponding production function. This approach shows that intersectoral linkages can account for about one third of the observed SBTC in U.S. manufacturing.

4 Data

This section describes the data that we use to test predictions P1-P3. 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 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.[25] 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

the intermediate input share in total output, $1 - \alpha$, is not important for the ITSC. What counts is the size of the parameter ϕ, i.e., by how much skill biased innovation embedded in intermediates, σ_i, influences the skill bias in final production, A_i. Linkages are only important for granting that sectors process each others' output. They are necessary, but not sufficient for a multiplier to exist.

[25]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.

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, we 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. We account for this by aggregating sectors, and match the resulting I-O panel to the ASM's 1987 SIC classification.[26] 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. We 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.[27]

Constructing input skill intensity

Equation (10) derives a proxy for the skill bias of technology in intermediate production. To construct this measure of skills embedded in intermediate inputs, we first obtain 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. The paper wrappings around chocolate did not become thicker in 1972. Measurement error as well as fluctuations in relative input prices, imperfectly corrected by the deflators, appear to be reasonable explanations.[28] Therefore, we use average real input shares $\bar{a}_{ij} = \sum_{t=67}^{92} a_{ij}^t$ between 1967

[26]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. We treat these data as one sector, 'paper and paperboard mills' over the full sample period. Detailed sector correspondences are available upon request.

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

[28]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.

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).[29] Input skill intensity is then defined as

$$\sigma_i^t = \sum_{j \neq i} \bar{a}_{ij} h_j^t \tag{13}$$

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.[30] We exclude inputs purchased within the same sector ($j = i$). This avoids that skilled workers employed in sector i itself enter its measure of input-embedded skills σ_i, which would bias our results.

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.[31] However, the resulting measurement error of σ_i is likely to be minor. The share of imports in non-energy intermediates during the sample period is relatively small, growing from 4% in 1967 to 13% in 1992 (see appendix A.2). 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 white-collar 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. We implement this idea by restricting the four-digit industry subscripts i and j in (13) 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 $\sigma_i^{2\mathrm{d}}$.

Table 1 provides a list of the twenty industries with the smallest and the largest increase in input skill intensity $\sigma_i^{2\mathrm{d}}$ for the period 1967-92.[32] The reported ranking seems sensible. The industries 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 white-collar employment shares. Most industries that experienced the largest increase in inputs skill intensity also appear sensible. These include

[29] This would be a strong assumption if input shares shifted systematically towards more (or less) skill intensive industries, which is not the case. In section 5.2 we 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 5.2 also provides an extended empirical analysis with time-varying input shares, showing that the ITSC is robust to this specification.

[30] 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.

[31] 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).

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

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.[33]

[Insert Table 1 here]

The measure of input differentiation

In order to identify the degree of differentiation for each sector's inputs, we use data from Rauch (1999). Rauch groups goods into 1,189 industries according to the 4-digit SITC Rev. 2 system. An industry's product is classified as being differentiated if it is neither traded on an organized exchange nor reference priced in trade publications.[34] We aggregate the Rauch data into the 358 SIC industries of our sample. This procedure yields data on the fraction of each industry's output that is differentiated.[35] Using this information, along with the input shares derived above, we define the degree of input differentiation:

$$\kappa_i = \sum_{j \neq i} \bar{a}_{ij} \; R_j^{\text{diff}} \tag{14}$$

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

We use data from Scherer (1982) to derive, for each industry, its share of R&D spent for product innovation, π_i^{prod}.[36] In the empirical analysis π_i^{prod} serves to investigate the relationship between product innovation

[33] 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, our results are robust to splitting the sample into sectors with falling and increasing overall employment.

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

[35] 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 our sample. For the remaining 56 sectors we 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, we apply equal weights when aggregating SITC industries to the SIC classification.

[36] For example, in the United States in 1982, 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 better products. The opposite holds for Industrial Electri-

and product differentiation, given by R_i^{diff} described above. In order to perform this analysis, we match our 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 we include several variables that have been previously used to explain increasing wage inequality. In the following we describe these variables briefly. Appendix A.2 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, we 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), we use lagged R&D intensity ($R\&D_{lag}$) in the regressions.[37] We use data from the BEA to construct sectoral shares of high-technology capital (*HT/K*) and office, computing & accounting equipment (*OCAM/K*).[38] Feenstra and Hanson (1999) document a substantial impact of foreign outsourcing of intermediate inputs on relative wages. We calculate their broad (OS^{broad}) and narrow (OS^{narr}) measures of outsourcing for the years and sectors included in our 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, we use OS^{narr} in most regressions, including OS^{broad} in the robustness checks.

Table 2 reports the pairwise correlations between two measures of input skill intensity (σ_i and $\sigma_i^{2\text{d}}$) 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.

[Insert Table 2 here]

cal Equipment, where 85% of R&D was devoted to product innovation, benefitting other sectors that use electrical equipment. Appendix A.2 explains the corresponding methodology in detail.

[37]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 our results.

[38]Both technology measures are widely used in studies of wage inequality. See, in particular, Autor et al. (1998) and Feenstra and Hanson (1999). The capital stock data are likely measured with substantial error, and are often not measured directly but inferred from employment data, assuming relationships between occupations and capital-type usage. See Becker, Haltiwanger, Jarmin, Klimek, and Wilson (2006) for a discussion. This implies an upward bias of computer capital's impact on skill upgrading, stacking the odds against finding an important contribution of input skill intensity.

5 Empirical Results

Before turning to the empirical examination of the model's predictions, a word is due on causality and interpretation of the coefficients. The ITSC framework outlined in section **??** provides evidence for both causal directions; it is irrelevant for the ITSC whether we think that "downstream skill-biased innovations cause upstream innovation and skill bias" or the other way around. The model, on the other hand, assumes a causal impact of skill biased intermediate technology on the skill bias in final production. The restriction to one causal direction keeps the framework simple, while delivering the same qualitative results as a model with bi-directional causality. The model's predictions must hence be interpreted as complementarities.

Complementarity implies correlation. When analyzing predictions P1 and P2, we therefore focus on correlation coefficients. First we 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, we provide evidence suggesting that the ITSC works through product innovation, showing that its strength varies systematically with the degree of input differentiation. Finally, we examine the ITSC's importance for skill upgrading and address endogeneity issues.

5.1 Testing P1: Correlation of Skill Intensities across Sectors

This section investigates the model's first prediction: "The proportion of skilled workers in sectors i, h_i, increases in within-sector skill bias T_i and in input skill intensity σ_i." P1 follows from (8), assuming that skill biased upstream technology leads to downstream skill bias ($\phi_i > 0$) in a sufficiently large subset of sectors. Taking logs in (8) is the first step toward an estimation equation:

$$\ln\left(\frac{H_i}{L_i}\right) = const. + (\epsilon - 1)\ln(T_i) + \phi_i(\epsilon - 1)\ln(\sigma_i) + \epsilon \ln\left(\frac{w_L}{w_H}\right) \tag{15}$$

To test P1, we impose ϕ_i to be constant across sectors i. If P1 holds, we expect a positive average coefficient ϕ. Note that in addition we also need $\epsilon > 1$, i.e., H and L are substitutes.[39] Given this, we can estimate the linear equation:

$$h_{it} = \alpha_i + \alpha_t + \beta\sigma_{it} + \gamma\mathbb{T}_{it} + \varepsilon_{it} \tag{16}$$

Following the common identification strategy in the SBTC literature, we use the high-skill labor share h_i as dependent variable, which is proportional to $\ln(H_i/L_i)$.[40] On the right-hand side, α_i and α_t denote industry and time fixed effects, respectively; $\mathbb{T}_{it}$ are variables controlling for within-sector skill bias (note that γ is a vector of coefficients), σ_i is input skill intensity as calculated in (13), and ε_{it} denotes the error term, capturing measurement error and unobserved drivers of the skilled labor share. The relative wage in (15) is an aggregate variable and is therefore captured by the time dummies in (16). Controlling additionally for

[39] In a Cobb-Douglas production function with $\epsilon = 1$, technological progress favoring one factor has no impact on relative demand. Empirical studies typically find ϵ between 1.4 and 2 (Angrist, 1995; Ciccone and Peri, 2005).

[40] The proportionality is very close to linear over the relevant range in the dataset, with percentiles $p_1(h) = 0.093$ and $p_{99}(h) = 0.634$. None of the empirical results change when using $\ln(H_i/L_i)$ instead.

sector-specific relative wages does not change our results, as shown below.[41]

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.[42] 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, we now turn to using the full set of controls. The first column of Table 3 shows regression (16) with sectoral and time fixed effects. The coefficient on σ_{it} is highly significant. The number of observations represents the full sample of 6 years $\times$ 358 sectors = 2148. We 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 3 account for roughly half of the variation of h_{it} within sectors over time.

[Insert Table 3 here]

Next, we 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 significant at the 10% level.[43] We 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 our 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 our results, the coefficient of input-skill intensity is robust 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 correlation with 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.

[41] The sector-specific skill premium $w_{H,i}/w_{L,i}$ captures mostly cross-industry variation in wages, for example due to quality variation of workers. 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. See Feenstra (2004, ch. 4) for a discussion.

[42] 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). 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.

[43] This supports the critical view of Krusell et al.'s results, which disappears when a time trend is included (Acemoglu, 2002b). In fact, if we only include k^{equip} and sectoral dummies as explanatory variables in (16), 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 sector-specific real equipment data from the ASM used in our sample do not include the additional quality-adjustment that Krusell et al. apply at the aggregate level.

The last two columns of Table 3 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.[44] 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. We implement two additional ways to address the common-shock concern. Both are based on specification 3 and are not reported in the table. First, we use the 5-year lag of σ_i. 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. Second, we include time dummies at the 2-digit industry level. These absorb any industry-specific shocks to skill demand, such that the coefficient β only reflects the variation of detailed 4-digit sectors relative to the corresponding 2-digit industries. Even with this restriction, the coefficient remains highly significant and of similar magnitude, $\beta = .401$ (.185). Finally, column 6 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 30). 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.

5.2 Robustness of the Correlation

The robustness of our results to alternative measures of input skill intensity, σ_i, σ_i^{2d}, and σ_i^w has been verified in Table 3. These measures were all calculated based on constant input shares, i.e., stable linkages over time. In this section, we first show that our results are robust to including input skill intensity measures based on changing input shares. Second, we test the sensitivity and robustness of our 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, our baseline input skill intensity measures are derived based on average input shares $\bar{a}_{ij}$. Now, we use the time-varying a_{ij} to construct an alternative 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 (13), representing constant input expenditure shares with changing skilled labor shares of suppliers. Second, an input-mix component $\tau_i^t = \sum_{j \neq i} a_{ij}^t \bar{h}_j$,

[44]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.

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.[45] 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 4 shows, the coefficient of σ_i does not change when the two additional variables are used – it is still above 0.5.

[Insert Table 4 here]

Once the usual controls are included, neither τ_i nor ρ_i are significant, as shown in the second and third column of Table 4. This result was to be expected, given the noise in the input shares used to calculate these variables.[46] 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.

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 5 presents the results. Therein, we 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.

[Insert Table 5 here]

The first column of Table 5 runs the baseline regression in changes, instead of including fixed effects. All variables are in 5-year differences.[47] The corresponding coefficient on input skill intensity is very similar to the one obtained above, and is again highly significant. In column 2, we turn back to estimating levels, including fixed effects and all previously used controls. Additionally, we 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

[45]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.

[46]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, we 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.

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

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 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, $\bar{n}_t$. We derive both measures from the year-specific I-O tables. Since more 'complex' production processes require more coordination, we expect these variables to have a positive impact on demand for skilled labor. Third, we include the sector-specific skill premium, or relative wage, to capture differences in cost and quality of skilled workers across sectors. Fourth, we control for productivity by including the real value of shipments, $\ln(Y)$.[48] 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 5 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. On the other hand, neither previously suggested measure for production 'complexity' has a significant impact on skill demand.[49] 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, we 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.[50] The last two columns of Table 5 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, we use σ_i^{2d} 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 equip-

[48] 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).

[49] 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.

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

ment turns out negatively significant in the 1992 cross section.[51] In the panel, k^{equip} shows up negative and significant in some specifications. These findings together argue strongly against a broad 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.

5.3 Testing P2: Input Differentiation and Channel of the ITSC

In this section, we examine prediction P2: "The correlation between h_i and σ_i can vary by sector; it is the stronger the larger the extent to which skill bias in upstream technology influences downstream skill bias." Testing P2 hinges on the channel through which the ITSC works. In the framework analyzed here, upstream and downstream sectors are linked through intermediate products. Intermediates are thus a natural starting point to look for the ITSC channel. But how can intermediates transmit skill bias across sectors? They can do so if skilled workers (or their ideas) shape intermediate products in such a way that skills are needed in the further processing. The channel is then product innovation. The following example illustrates this point. Suppose that Exxon decides to boost productivity in oil extraction and hires a large number of engineers. More skills will shape the extraction process, but not the product – crude oil. Consequently, skill demand in a downstream refinery will be unaffected by Exxon's move. On the other hand, trained engineers inventing ever better data storage devices enabled Apple to launch the iPod – a highly skill-intensive endeavor.[52] Crude oil is a homogenous product, while data storage devices are differentiated. Our testing of P2 is built around this classification.

Analytically, we follow a two-step process. First, we 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. We provide strong evidence for this assertion.

Product innovation and product differentiation

As described in section 4, we 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

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

[52] The story also works in the opposite direction. When Apple decides to launch the next-generation iPod it creates demand for more powerful memory devices. Both causal directions are compatible with the ITSC framework.

this number is 80% for producers of above-median differentiated goods. After this preliminary observation, we 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.[53] 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

Skill-biased innovation in one sector passes through intermediate linkages to other sectors, where it also drives innovation and skill demand. As we have seen, purchasers of differentiated inputs buy on average more innovation incorporated in their intermediates than users of homogenous ones. Therefore, input differentiation gives the degree to which skill-biased innovation can be 'embedded' in intermediates. We consequently expect a stronger ITSC when input-output linkages involve more differentiated intermediates. The corresponding measure κ_i, as described in section 4, gives the weighted average degree of input differentiation. If P2 holds, we expect a larger β in (16) for sectors with larger κ_i.

To obtain a first look at the data, we use κ_i to split the sample into sectors with below- and above-median input differentiation. Then we estimate regression (16) 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 3).

[Insert Figure 2 here]

The left panel of Figure 2 shows the partial scatterplot for the full sample, where the corresponding coefficient from regression (16) is $\hat{\beta} = .590$.[54] 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.[55] 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

[53] 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.

[54] 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, $\hat{\beta} = .558$.

[55] 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.

or different levels of outsourcing in the two subsamples. To analyze whether this concern is justified, we 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 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 make small negative (and insignificant) contributions.

Next, we include interaction terms of explanatory variables with input differentiation κ_i. This yields the following extended estimation equation:[56]

$$h_{it} = \alpha_i + \alpha_t + \beta_1 \sigma_{it} + \beta_2\, \kappa_i \times \sigma_{it} + \gamma_1 \mathbb{T}_{it} + \gamma_2\, \kappa_i \times \mathbb{T}_{it} + \varepsilon_{it} \tag{17}$$

Table 6 reports the results, using the three alternative measures for input skill intensity, σ_i (baseline), $\sigma_i^{2\text{d}}$ (excluding inputs from the same 2-digit sectors), and σ_i^w (calculated based on the high-skill wage bill share). The interactions 'input differentiation' $\times$ 'input skill intensity' 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.

[Insert Table 6 here]

5.4 Prediction 3: Importance of the ITSC

So far, we have seen that the correlation between input skill intensity and the skilled labor share in final production is highly significant and robust to the inclusion of various controls. We have interpreted this finding as evidence for an intersectoral technology-skill complementarity. Next, we turn to the importance of the ITSC for increasing skill demand. According to prediction 3, the ITSC reinforces skill demand along the production chain, which leads to the multiplier effect given in (11). Its magnitude follows from the average strength of the ITSC, ϕ. In an ideal world, we would know the exact functional form of (8) and especially (10) to pin down the true ϕ from the data. In the real world, however, models are often misspecified, and so is – almost certainly – the stylized one in this paper. Misspecification can cause inconsistent parameter estimates [White 1982]. This concern can be alleviated by using an estimation framework that imposes few restrictions on the model structure. Translog production (or cost-) functions are commonly used to allow for this flexibility.

[56] Because the framework analyzed here involves complementarity among several explanatory variables, we 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.

Following this argument, we present a framework that has been used to estimate the impact of trade and technological change on the demand for skilled labor. The underlying idea is that structural variables like R&D intensity, computer capital, or input skill intensity can shift the production function and therefore the optimal choice of skilled versus unskilled labor. Because some structural variables are arguably endogenous, we use instruments in the corresponding estimation. Our results suggest that the ITSC's contribution to skill upgrading in U.S. manufacturing is large – in the same range or even above computers and other high-tech capital.

A labor demand framework

In the following we derive a labor demand regression from a model with sector-specific technologies that are influenced by structural variables.[57] Feenstra and Hanson (1999) argue that labor demand shifting structural variables comprise fixed capital, computing equipment, and outsourcing (reflecting imported input prices). We add R&D intensity and input skill intensity to this list. The former has been identified as an important determinant of skill demand (Machin and van Reenen, 1998), while the inclusion of the latter is motivated by the empirical evidence presented above. As derived in (10), input skill intensity σ_i proxies for skill-biased technology (or complexity) embedded in a sector's intermediates. Because firms need skilled workers to handle innovative intermediates, we expect higher σ_i to go hand in hand with more demand for skilled labor in sector i.

The production function in sector i takes the form $Y_i = F_i\left(H_i, L_i;\ \sigma_i, \mathbb{T}_i\right)$ where structural variables, σ_i and $\mathbb{T}_i$, are fixed in the short run, while skilled and unskilled labor, H_i and L_i, are chosen optimally. Consequently, a firm in sector i minimizes its wage bill $w_H H_i + w_L L_i$ subject to the corresponding production technology, taking as given high-skill and low-skill wages, w_H and w_L, as well as input skill intensity σ_i and other structural variables $\mathbb{T}_i$. This yields the short-run cost function: $C_i\left(w_H, w_L; \sigma_i, \mathbb{T}_i, Y_i\right)$. Next, we need to choose a functional form. The translog cost function is a convenient choice, as it imposes no a-priori restrictions on elasticities of substitution and returns to scale.[58] We then use Shephard's Lemma, which states that the derivative of the cost function with respect to w_H gives the demand for skilled labor, H_i. This final step is the centerpiece of the demand framework – it enables us to analyze factor demand by examining the properties of the first derivative of the cost function. As shown in Feenstra (2004, ch. 4), we obtain the estimation equation

$$\triangle h_{it}^{w} = \alpha + \beta \triangle \ln \sigma_{it} + \gamma \triangle \ln \mathbb{T}_{it} + \delta \triangle \ln Y_{it} + \eta \triangle \ln \left(\frac{w_{H,t}}{w_{L,t}}\right) + \varepsilon_{it} \qquad (18)$$

where $h_i^w = (w_H H_i)/(w_H H_i + w_L L_i)$ is the wage bill share of skilled (white-collar) workers. This equation says that the relative demand for skilled labor, represented by its cost share, depends on the structural variables σ_i and $\mathbb{T}_i$, and on the relative wage. Intuitively, for a given relative wage, structural variables shift

[57] For a more detailed exposition see Katz and Murphy (1992) and Feenstra (2004, ch. 4).

[58] See Kim (1992) for a general treatment of the translog function. In order to derive the estimation equation below, we have to assume that the translog cost function is homogenous of degree one in wages.

the relative demand for the two types of labor, as captured by the coefficients β and γ.

Contributions without input skill intensity

The first specification of Table 7 presents an estimation of (18), following the strategy outlined in Feenstra and Hanson (1999). Input-skill intensity is not yet included in the regression. The structural variables $\mathbb{T}_{it}$ comprise all previously used drivers of skill demand (see Table (3)). In addition, (18) implies that we also have to control for the real value of shipments, $\ln Y_{it}$, and the relative wage $(w_{H,t})/(w_{L,t})$. In the data, the latter varies across i because of cross-industry variation in wages, for example due to quality variation of workers.[59] Multiplying each regression coefficient by the 1967-92 change in the corresponding variable (shown in the first column) gives each structural variable's contribution to the increase in the white-collar wage share. If we divide this number by the total change in the white-collar wage bill share 1967-92 (0.0727), we obtain percentage contributions. In the first specification, high-tech capital contributes about 12% to overall skill upgrading, and outsourcing (broad and narrow) delivers another 17%. Both numbers are in the ranges documented by Feenstra and Hanson (1999) for the period 1979-90.[60] While the coefficient of R&D intensity is large, its contribution to rising skill demand is not. This is because R&D intensity itself increased relatively little. Broad capital is roughly skill neutral, with the positive contribution of structures offsetting the negative impact of equipment. Overall, the results in the first column of Table 7 replicate previous findings and confirm the empirical gap in explaining skill demand increases.[61]

[Insert Table 7 here]

Endogeneity of input skill intensity

Before including σ_i in regression (18), we have to carefully discuss its endogeneity. In the intersectoral complementarity framework presented in the previous sections, causality could run in either direction – from upstream to downstream skill intensity (σ_i to h_i), or the other way around.[62] But now we treat σ_i as a structural variable that can shift the demand for skilled labor in downstream sectors. We must therefore find instruments that explain skill upgrading at the upstream level but do not have an impact on downstream skill demand other than through intermediate linkages. To derive candidates for such instruments, we restate the

[59] Results are very similar when relative wages are dropped from the regressions. See footnote 41 for a more detailed discussion.

[60] The contribution of high-tech capital is at the lower end of Feenstra and Hanson's findings, which is likely due to the longer time horizon in our sample, starting in 1963. In other specifications (see columns 2 and 3), however, the number is closer to the usually reported roughly one third.

[61] Even with a larger contribution of high-tech capital – say the commonly reported 30% – the overall explained increase would barely exceed one half. This corresponds to the total skill demand increase explained by previous studies that we derived in section **??**.

[62] As a first pass at the issue, we use a Granger causality test. The usual cavaets apply – time precedence and causality are two distinct concepts. We 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). All lags are 5 years; both regressions include all lagged control variables used in Table 3, sectoral dummies, and the lag of the left-hand side variable.

ITSC in a simultaneous equations model:

$$h_{it} = \alpha_{1,i} + \beta_1 \sigma_{it} + \gamma_1 \mathbb{T}_{it} + \varepsilon_{1,it} \tag{19}$$

$$\sigma_{it} = \alpha_{2,i} + \beta_2 h_{it} + \gamma_2 \mathbb{T}_{j\neq i,t} + \varepsilon_{2,it} \tag{20}$$

The first equation represents the upstream-downstream direction of the ITSC, estimating the impact of input skill intensity on final production skill demand. $\mathbb{T}_{it}$ is the usual set of within-sector control variables. The second equation describes the opposite causal direction – from final producers i to intermediate suppliers $j \neq i$.[63] Slightly abusing notation, denote elements of $\mathbb{T}$ by T. Individual within-sector control variables that affect the skill demand in intermediate production, $T_{j\neq i,t}$, are constructed in a similar fashion as σ_{it}:

$$T_{j\neq i,t} = \sum_{j\neq i} \bar{a}_{ij} T_{jt} \tag{21}$$

For example, let T_{jt} be R&D intensity 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 $T_{j\neq i,t}$ thus represents weighted average R&D intensity of sector i's suppliers. The same methodology applies to computer and high-tech capital as well as outsourcing. All are summarized as $\mathbb{T}_{j\neq i,t}$.[64]

Deriving the reduced form for σ_{it} from (19) and (20) gives the first stage of an instrumental variable (IV) regression, with $\mathbb{T}_{j\neq i,t}$ as instruments for σ_{it}:

$$\sigma_{it} = \tilde{\alpha} + \tilde{\gamma}_1 \mathbb{T}_{it} + \tilde{\gamma}_2 \mathbb{T}_{j\neq i,t} + \tilde{\varepsilon}_{it} \tag{22}$$

Writing this in changes, we could use $\triangle\mathbb{T}_{j\neq i,t}$ to instrument for $\triangle\sigma_{it}$ in (18). Being conservative, we use the 5-year lags, $\triangle\mathbb{T}_{j\neq i,t-5}$, as instruments.[65] This alleviates the concern that downstream SBTC might lead to more computer use or R&D in supplying upstream industries. Apple developing the next-generation iPod can raise R&D in firms supplying solid state drives – in the same time period, but not 5 years earlier. Intuitively, the identification strategy says that rising R&D and computer use in an upstream sector can drive innovation and skill upgrading there, which leads to downstream sectors demanding more skills in order to process the innovative intermediates.

The exclusion restriction is that instruments $\triangle\mathbb{T}_{j\neq i,t-5}$ influence $\triangle\sigma_{it}$ but are uncorrelated with $\triangle h^w_{it}$ after controlling for $\triangle\mathbb{T}_{it}$ in the second stage, i.e., in (18). For this restriction to hold we have to assure that (i) lagged changes in high-tech capital, outsourcing, or R&D at the upstream level influence upstream

[63] These two equations can be used to quantify the bias that arises when we interpret the OLS coefficient β from equation (16) 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 (16).

[64] The set $\mathbb{T}_{j\neq i}$ that we use in the IV regressions comprises $(HT/K)_{j\neq i}$, $(OCAM/K)_{j\neq i}$, $OS^{\text{narr}}_{j\neq i}$, $OS^{\text{broad}}_{j\neq i} - OS^{\text{narr}}_{j\neq i}$, and $(R\&D)_{j\neq i}$.

[65] Recall that the manufacturing industry panel has 5-year intervals. Using the contemporaneous $\triangle\mathbb{T}_{j\neq i,t}$ gives similar results but is more amenable to endogeneity concerns.

skill demand and (ii) do only have an impact on downstream skill demand through the intermediate linkage channel. The first part is well-founded, as our own and other previous findings in the literature show. In addition, note that variations in high-tech capital or R&D across sectors may also capture variations in (unobserved) innovative activity. This poses no problem to $\triangle\mathbb{T}_{j\neq i,t-5}$ as instruments – to the contrary: it is in line with the innovation - skill channel, which is at the core of the ITSC.

Despite being less evident, it is reasonable to argue that the instruments also fulfill the second requirement. Recall that the set $\mathbb{T}$ denotes *within*-sector drivers of SBTC that should have no direct impact on skill demand in other sectors. For example, it is hard to maintain that more computers in intermediate production lead to higher skill demand in final production for reasons different from an innovation-skill channel – especially because any intersectoral computer-compatibility channel would be captured by computers showing up as a control variable in the second stage regression (18). A similar argument holds for outsourcing and R&D. This rules out a direct impact of the instruments $\triangle\mathbb{T}_{j\neq i,t-5}$ on $\triangle h^w_{it}$. But what about common trends? More specifically, the concern is that changes in high-tech capital, outsourcing, or R&D can be correlated across upstream and downstream industries, in particular if the production chain involves similar industries. This could lead to $\triangle\mathbb{T}_{j\neq i,t-5}$ influencing $\triangle h^w_{it}$ because both correlate with $\triangle\mathbb{T}_{it}$. Including the downstream variables $\triangle\mathbb{T}_{it}$ in the second stage regression (18) controls for this channel. Summing up, we are able to alleviate the most serious concerns regarding $\triangle\mathbb{T}_{j\neq i,t-5}$ as instruments for $\triangle\sigma_{it}$. However, it is important to mention that the instruments are not completely satisfactory. Endogeneity remains a concern if three things come together: unobserved shocks or innovations hit similar industries simultaneously, these industries are linked through intermediates, and the shocks influence changes in skill demand and the $\mathbb{T}$-variables over a long horizon (>5 years). Empirically, we have the means to shed light on this concern using overidentification restrictions. The results are encouraging (see below).

Endogeneity of control variables

Having addressed the endogeneity of σ_{it}, we turn to the same concern for other structural variables in the demand framework – the within-sector drivers of SBTC, $\mathbb{T}_{it}$. Most importantly, endogeneity is an issue for high-tech capital as well as for R&D intensity. To tackle the potential bias, we use an approach outlined in Wooldridge (2002, ch. 11). Under sequential exogeneity, we can use lagged levels of $\mathbb{T}_{it}$ as instruments for $\triangle\mathbb{T}_{it}$, which gives consistent estimates and is similar in spirit to Arellano and Bond (1991). Sequential exogeneity implies that if we run regression (18) in levels, then after the structural variables ($\mathbb{T}_{it}$ and σ_{it}) and sectoral fixed effects have been controlled for, no past values of $\mathbb{T}_{it}$ or σ_{it} affect the expected value of h^w_{it}. To see whether this holds, we include the 5- and 10-year lags of all structural variables in (18), estimated in levels. None is significant at the 10% level, with the exception of the 10-year lag of $R\&D$. This suggests that sequential exogeneity is a reasonable assumption for the structural variables in our demand framework. As suggested in Wooldridge (2002, ch. 11), we thus use the 5- and 10-year lags of high-tech capital and R&D intensity to instrument for the contemporaneous 5-year changes. Sequential exogeneity also delivers the 5- and 10-year lags of σ_{it} as additional instruments for $\triangle\sigma_{it}$.[66]

Results with input skill intensity

Following this discussion, we now turn to the IV estimation results. The second specification in Table 7 adds instrumented input skill intensity to the regression. As the number of observations in column 2 reflects, the choice of instruments – lagged changes $\triangle\mathbb{T}_{j\neq i,t-5}$ – loses an additional time period (with one already lost due to first differencing). The IV coefficient of input skill intensity is highly significant and smaller than in the OLS specification.[67] This makes sense, given that we expect an upward bias of OLS estimates (see footnote 63). Input skill intensity contributes more than one third to the overall increase of the white collar wage bill share in U.S. manufacturing. This is large – about as much as previous estimates assign to computers, and double the contribution of outsourcing or R&D. Interestingly, input skill intensity is orthogonal to other proposed drivers of SBTC. The latter remain largely unchanged when adding $\triangle\sigma_{it}$ to the regression. Thus, technology-skill complementarity across sectors is not a spurious phenomenon that withdraws explanatory power from other variables; rather, the ITSC is an additional driver of skill upgrading.

The instruments for $\triangle\sigma_{it}$ 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, we can test for their endogeneity using the Sargan-Hansen test of overidentifying restrictions. The corresponding p-value is .78. We therefore do not reject instrument exogeneity.

Next, we turn to specification 3, instrumenting for several endogenous structural 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. 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. Stock and Yogo (2002) provide a framework that allows testing the hypothesis of weak instruments in this case. The null hypothesis is that instrument quality is below one of four levels. The last row of Table 7 reports the critical value for the highest quality level, corresponding to a maximum IV bias of 5% because of weak instruments. The Stock and Yogo framework allows for models with up to three endogenous variables. Therefore, we instrument (in addition to σ_{it}) for those two controls for which endogeneity is the most serious concern: high-tech capital and R&D intensity.[68] The results for all structural variables, including input skill intensity, are very similar to the previous specification – with the exception of high-tech

[66] Our second stage estimation results do not depend on whether or not we use these additional instruments, but they contribute to instrument quality and provide additional overidentification restrictions (see below).

[67] See, in particular, regression (3) in Table 5, which also uses h^w_{it} as dependent variable.

[68] R&D intensity can be instrumented with one more time lag without losing an additional time period of observations, because the R&D data include 1963.

capital that now has a larger coefficient. The p-values for the overidentification test is again well above the rejection level. Finally, instruments are close to the highest quality level according to the Stock and Yogo test.[69] Altogether, the results reported in Table 7 support to role of the ITSC as an additional – up to now neglected – phenomenon in the SBTC literature that can explain a large fraction of skill upgrading in U.S. manufacturing.

6 Conclusion

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, focusing on within-sector skill bias, has failed to account for the full scope of skill upgrading in recent decades. This paper extends the standard SBTC framework, presenting a simple multi-sector model that features linkages operating through the use of intermediate products. In this setup, skill biased intermediate technology can create skill bias in final production, because skill-intensive (complex) intermediates require skills in their further processing. Consequently, SBTC in one sector increases skill demand in many other sectors, which delivers a multiplier that reinforces skill demand along the production chain.

To identify this novel mechanism, we derive a proxy for the skill bias in intermediate production from theory: *Input skill intensity*, which measures the skills embedded in a sector's intermediate inputs. We construct this variable by combining product flows from input-output tables with worker characteristics from the Annual Survey of Manufactures. Input skill intensity correlates strongly with final production skills, i.e., skilled labor 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. The presented evidence implies an intersectoral technology-skill complementarity (ITSC) that amplifies within-sector skill bias and spreads its impact across sectors.

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.

Empirical evidence suggests that the ITSC works through product innovation. The corresponding argument involves two steps. First, we show that product innovation is more pronounced in sectors producing differentiated goods. Thus, downstream industries using differentiated intermediates purchase relatively more embedded innovation. Second, we construct a measure of input differentiation and show that the ITSC is stronger among sectors linked through differentiated intermediates. Both steps together imply that the ITSC increases when involving more innovative intermediates.

The ITSC contributes in an important way to the observed increase in skill demand over the last decades. The estimation strategy follows from a framework that has been previously used in the skill demand context.

[69]The critical value for the second quality level, corresponding to a maximum IV bias of 10%, is 10.01.

Feenstra and Hanson (1999) apply the same method to study the importance of IT capital and outsourcing for skill upgrading. Our setup controls for these, and in addition for other previously suggested drivers of SBTC: capital equipment and R&D intensity. To this familiar list we add input skill intensity, using instruments to account for endogeneity concerns. The results reproduce previous findings for the control variables – together they can account for about half of the rise in skill demand. The ITSC closes most of the remaining empirical gap. Its contribution is large, explaining more than one third of increasing skill demand in U.S. manufacturing between 1967 and 1992. This is similar to the importance of IT capital and more than twice the one of outsourcing or R&D. Remarkably, the ITSC is orthogonal to previously suggested explanations of skill upgrading, which underlines its role as a new phenomenon in the SBTC literature.

Interestingly, the multiplier identified in this paper can also help to reconcile theoretical SBTC models with the data. In order to generate the observed upward-sloping relationship between relative skill supply and the skill premium, these models need a large elasticity of substitution between skilled and unskilled labor.[70] The multiplier effect identified here reinforces endogenous skill bias: Skill-complementary technology affects not only the sectors that use it directly, but also has an indirect impact on downstream sectors that handle the corresponding products as intermediates. Therefore, smaller elasticities are sufficient to generate increasing skill premia in response to growing supply of skilled labor.

The present paper documents the novel stylized fact of intersectoral technology-skill complementarities in U.S. manufacturing. An important topic for further investigation is whether the ITSC is a broad phenomenon, extending to linkages beyond this sector. In addition, the ITSC opens the door for analyzing other 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.

Appendix

A.1 Solving the Model

Production side

Firms' optimization with respect to H_i and L_i yields the relative demand for skilled workers, shown in (8). The FOC with respect to $\overline{x}_i$ gives sector i's demand for effective units of each intermediate input j, x_{ij}, as a function of total output and goods prices:

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

[70] See for example Acemoglu (1998, 2002b, 2007); Acemoglu and Zilibotti (2001), and in particular Acemoglu (2002a). These models require an elasticity larger than 2, while empirical studies commonly find smaller values (see Angrist, 1995; Ciccone and Peri, 2005).

In the following, we use these conditions to derive the demand for each factor and the marginal cost of production, which equals the product price under perfect competition. Rearranging (8) and substituting for H_i in (1) yields

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

and similarly for H_i:

$$H_i = \left(\frac{w_H}{\gamma}\right)^{-\epsilon} \left(T_i \ \sigma_i^{\phi}\right)^{\epsilon-1} \Omega_i^{\epsilon} \ (\overline{x}_i)^{-\frac{1-\alpha}{\alpha}} \ (Y_i)^{\frac{1}{\alpha}} \tag{A.3}$$

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

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

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:

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

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:

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

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:

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

$$H_i = \alpha \left(\frac{\gamma}{w_H}\right)^{\epsilon} \left(T_i \ \sigma_i^{\phi}\right)^{\epsilon-1} \Omega_i^{\epsilon-1} \left(\frac{\overline{p}_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{\Omega_i}{\alpha}\right)^{\alpha} Y_i \tag{A.9}$$

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.[71]

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

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

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

Demand side and market clearing

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 (6) 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

$$c_{L,i} = \frac{w_L}{Np_i} \quad \text{and} \quad c_{H,i} = \frac{w_H}{Np_i} \tag{A.12}$$

Let $C_i = Lc_{L,i} + Hc_{H,i}$ 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:

$$L = \sum_{i=1}^{N} L_i \tag{A.13}$$

$$H = \sum_{i=1}^{N} H_i \tag{A.14}$$

and

$$Y_i = C_i + X_{\bullet i},\ \forall i. \tag{A.15}$$

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 production in other sectors.

[71] Recall that $\overline{x}_i$ reflects also the total amount of inputs used in sector i, which follows from (3) 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.

Equilibrium with symmetric technology

We can now derive the quantities for the symmetric case described in definition 1. First, (4) becomes $\sigma_i = 1/(N-1)\sum_{j\neq i} A_j$, which together with (5) implies $A_i = A,\ \forall i$.[72] Plugging this result into (A.4) yields $\Omega_i = \Omega, \forall i$. Next, using $\overline{p}_i = 1/(N-1)\sum_{j\neq i} p_j$ in (A.11) implies $p_i = p, \forall i$.[73] Consequently, $\overline{p}_i = p, \forall i$. Because of price symmetry, final demand (A.12) 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 (12).

Finally, we show that goods markets clear. This is not as straightforward as with value-added-only production, and checking that this condition holds provides a verification of the model setup. We use 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 (A.12) and is given by

$$C_i = c_{L,i}L + c_{H,i}H = \frac{w_L L + w_H H}{Np}, \tag{A.16}$$

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

$$X_{\bullet i} = \sum_{j\neq i} \frac{1}{N-1}\overline{x}_j = \left(\frac{p}{1-\alpha}\right)^{1-\alpha}\left(\frac{\Omega}{\alpha}\right)^{\alpha}\frac{1-\alpha}{p(N-1)}\sum_{j\neq i} Y_j^S = \frac{(1-\alpha)}{N-1}\sum_{j\neq i} Y_j^S \tag{A.17}$$

where the first equality follows from (3) and the last one from (A.11). Next, we replace Y_j^S using the symmetric expression for the expenditure share, $\alpha p Y_j^S = (w_L L + w_H H)/N$ in all sectors $j \neq i$. Therefore, total demand for each good i is given by

$$Y_i^D = C_i + X_{\bullet i} = \frac{w_L L + w_H H}{Np} + \frac{(1-\alpha)}{\alpha(N-1)}\sum_{j\neq i}\frac{w_L L + w_H H}{Np} = \frac{1}{\alpha}\frac{w_L L + w_H H}{Np}. \tag{A.18}$$

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:

$$p_i Y_i^S = w_L L_i + w_H H_i + \sum_{j\neq i} p_j X_{ij} \tag{A.19}$$

where the last term is equal to $\overline{p}_i\overline{x}_i$. Under symmetry, and using (A.7) together with the labor expenditure

[72] The proof is by contradiction. Suppose $A_i \neq A_j$ for at least one pair $j \neq i$. We can order the A_i such that (without loss of generality) $A_1 > A_2 \geq A_3 \geq ... \geq A_N$. Then $A_1 = \left(\sum_{j\neq 1} 1/(N-1)A_j\right)^{\phi} T < A_1^{\phi}T$ and therefore $A_1^{1-\phi} < T$. Similar steps lead to $A_N^{1-\phi} > T$. Consequently, $A_1 < A_N$, which contradicts the ordering.

[73] To prove this, 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 $p_i = p$.

share to replace $\overline{p}_i \overline{x}_i$, (A.19) yields total supply for each i

$$Y_i^S = \frac{1}{\alpha} \frac{w_L L + w_H H}{Np}, \tag{A.20}$$

which equals total demand given by (A.18).

A.2 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. We 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, we use the 4-digit SIC figures from the Manufacturing Industry Database for real capital equipment and structures.[74] 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.[75] The NSF data cover 24 industries that we match to the 358 industries of our sample.[76] The weighted mean of R&D intensity for our 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, we use detailed data on private nonresidential fixed assets from the BEA. These data distinguish capital by asset type for 21 (ap-

[74] See **?** for a documentation of these data and the corresponding investment deflators.

[75] 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.

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

proximately two-digit) NAICS manufacturing industries, which we match to the 358 industries of our panel. We 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, we define high-technology capital to include office, computing and accounting machinery; communications equipment; scientific and engineering instruments; and photocopy and related equipment. From this number we 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. We calculate both measures of outsourcing for the years and sectors included in our 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.[77] 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.

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

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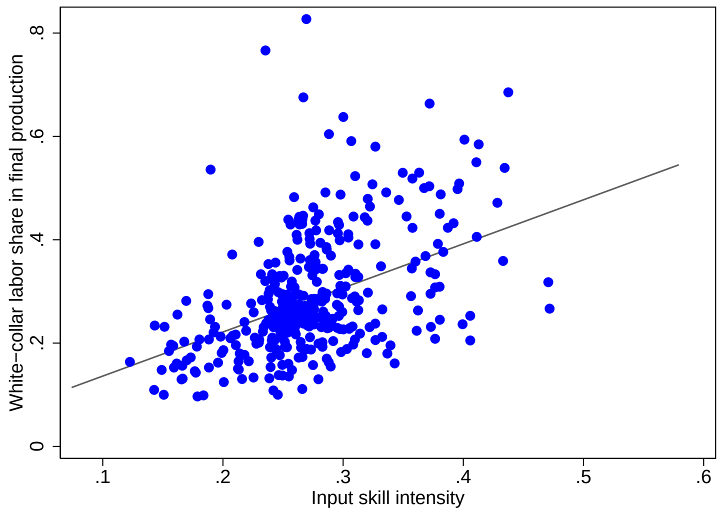

Figure 1: Skilled labor share in final production vs. input skill intensity

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 4 for a formal description and data sources, and Section 5 for regression results and robustness.

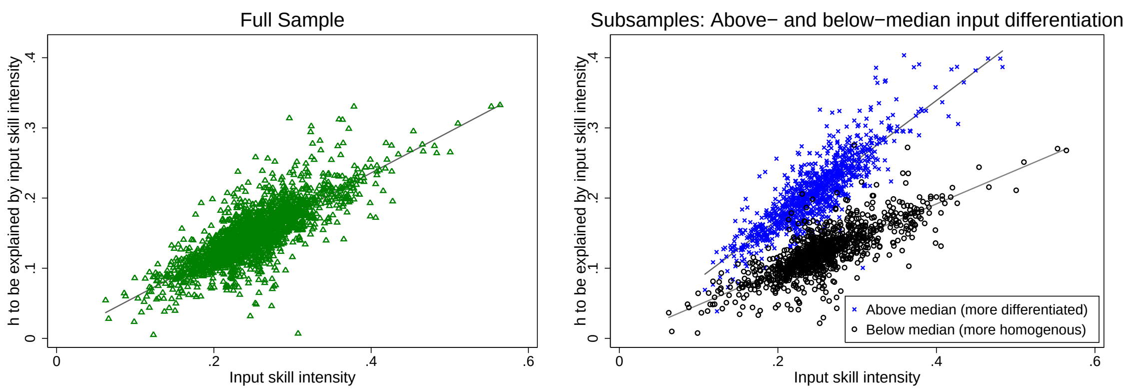

Figure 2: Partial scatter plots: Skilled labor share (h_{it}) vs. input skill intensity (σ_{it})

Notes: The measure of input differentiation is calculated as in (14), yielding a median of .52. The vertical axis shows $h_{it} - (\hat{\alpha}_i + \hat{\alpha}_t + \hat{\gamma}\mathbb{T}_{it})$; 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 (16) for the full sample (2089 obs.), with the controls $\mathbb{T}_{it}$ 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.).

Table 1: 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

Source: Author's calculations.

Table 2: 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%.

Table 3: 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.

Table 4: 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}).

Table 5: 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 $(OS^{broad} - OS^{narr})$		.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.

Table 6: 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***
$\sigma_i \times \kappa_i$ / $\sigma_i^{\text{2d}} \times \kappa_i$ / $\sigma_i^w \times \kappa_i$	(.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 $\bar{\kappa} = .549$.

Table 7: Contribution to skill upgrading. Dependent variable is the white-collar wage bill share h^w_{it}.

		(1)		(2)		(3)	
	Change '67-'92	Regres-sion	Contri-bution	Regres-sion	Contri-bution	Regres-sion	Contri-bution
Input skill intensity: $\triangle\sigma_i$ *instrumented*	.0546			.485*** (.098)	36.4%	.499*** (.093)	37.5%
Structures per worker: $\triangle k^{\text{struct}}$	.0120	.281 (.220)	4.7%	.196 (.140)	3.2%	.190 (.129)	3.1%
Equipment per worker: $\triangle k^{\text{equip}}$	.0383	-.0679 (.110)	-3.6%	-.0858 (.082)	-4.5%	-.0741 (.070)	-3.9%
High-Tech capital: $\triangle HT/K$ *instrumented in (3)*	.0469	.189* (.115)	12.2%	.299*** (.097)	19.3%	.423** (.190)	27.3%
R&D intensity $\triangle R\&D$ *instrumented in (3)*	.0108	.442*** (.164)	6.6%	.221 (.134)	3.3%	.26 (.242)	3.9%
Outsourcing: $\triangle OS^{\text{narr}}$	.0470	.103** (.043)	6.7%	.0838** (.037)	5.4%	.0816** (.038)	5.3%
Outs.: $\triangle(OS^{\text{broad}} - OS^{\text{narr}})$	.0571	.136*** (.047)	10.7%	.0508 (.056)	4.0%	.0358 (.049)	2.8%
Total Contribution:			37.2%		67.1%		75.9%
Additional Controls:							
Real shipments: $\triangle\ln(Y)$		-.012* (.007)		-.012*** (.004)		-.010** (.005)	
Relative wage: $\triangle\ln(w_H/w_L)$		.101*** (.015)		.118*** (.012)		.115*** (.012)	
Observations		1731		1402		1402	
First stage regressions: ‡							
F-test for significance of IV for σ_i				43.6		35.4	
Instrumented control variables:						HT/K, $R\&D$	
individual F-test for IV						51.5, 15.3	
p-value overidentifying restrictions				.78		.79	
Stock and Yogo weak IV F-statistic				43.5		15.2	
Critical value for highest quality IV				19.9		17.8	

Notes: The first column gives the change of each variable's weighted (by industry wage bill) average over the period 1967-92. The change in the dependent variable h^w is .0727. All regressions are run in 5-year changes and are weighted by sectors' average share in the manufacturing wage bill 1967-92. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and intra-sector correlation. Key: *** significant at 1%; ** 5%; * 10%. Regressions (2) and (3) are estimated using two-step feasible efficient GMM. 'Contribution' gives the proportion of the observed change in h^w explained by the respective variable.

‡ Instruments are the 5- and 10-year lags of each instrumented variable. In addition, $\triangle\sigma_i$ is instrumented with the 5-year lag of $\triangle\mathbb{T}_{j\neq i}$ (see text). $\triangle R\&D$ also uses its 15-year lag.