NEW GOODS AND THE RELATIVE DEMAND FOR SKILLED LABOR*

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Abstract:

This paper provides data on the output and factor payments of new goods for every 4-digit industry in the U.S. manufacturing sector in the late 1970s and 1980s. For the entire manufacturing sector, the new goods' average skilled-labor intensity exceeds the old goods' by over 40%, and new goods can account for about 30% of the increase in the relative demand for skilled labor. Since new goods provide a direct measure of technology, this paper offers new evidence that technology has shifted demand in favor of skilled labor, consistent with the technology-skill-complementarity hypothesis (*JEL* J31, O30).

Section 1. Introduction

An integrated part of human life has always been technology and innovation, without which we would still be riding horse-carts to work. In the late 1970s and 1980s, many new products burst into life, such as fiber optic cables, Windows series software, VCRs and soft contact lens. This paper identifies the new goods within the U.S. manufacturing sector during this period and studies how they affect the relative demand for skilled labor by measuring their outputs and factor payments. This question is interesting because the late 1970s and 1980s saw an increase in the skill premium in the U.S.,[1] and new goods provide a direct measure of technology.

The increase in the skill premium (i.e. relative wage of skilled labor to unskilled labor) is well documented, and so is the increase in the relative supply of skilled labor.[2] Thus the relative demand for skilled labor must have increased. Furthermore, the empirical SBTC literature shows that the majority of the increase in the relative demand for skilled labor is through within-industry skill upgrading (e.g. the changes in skilled labor's wage-bill shares within each industry), and concludes that skill-biased technical changes (SBTC) play a major role.[3] But what are the sources of SBTC? This question is tackled in a recent literature on the direction of technological changes: SBTC could be endogenous responses to other exogenous shocks.[4] For example, in Acemoglu (1998), the increase in the relative supply of skilled labor offers a larger market for skilled-labor-complementing machines and makes it more profitable to invent them ("directed technical change"); in Thoenig and Verdier (2003), trading with developing countries increases the likelihood of imitation and leads to increased adoption of skilled-labor intensive technologies that are also hard to imitate ("defensive skill-upgrading"). In both examples, the induced technological changes might increase the relative demand for skilled labor by so much that the skill premium could increase.

Both strands of literature posit the technology-skill-complementarity hypothesis: technology increases the relative demand for skilled labor as a factor of production. However, finding empirical support for this hypothesis is challenging. The attempts to establish a causal link between proxy variables for technology and higher wages for skilled workers have yielded mixed results (Krueger, 1993, DiNardo and Pischke, 1997).[5] This highlights the need for a direct measure of technology (Berman, Bound, and Machin, 1998). What variables could provide the link between technology and the relative demand for skilled labor?

New goods are one such variable. In many cases, new goods embed technology (e.g. the light bulb); in many other cases, new goods and technology are two sides of the same coin (e.g. the steam engine and the industrial-age power technology). Historical examples include the Bessemer steel furnace, the telegraph, the airplane, and the TV, and recent examples are PC's, industrial robots, CD players, and CAT and MRI scanners.[6] Many endogenous growth models model technological progress as the introduction of new goods (e.g. Grossman and Helpman, 1991, Acemoglu and Zilibotti, 2001). Thus new goods provide a direct measure of technology. On the other hand, new goods can be identified and their factor demands measured by their outputs and factor payments. Since the production of every new good generates labor demand, a comprehensive list of them is necessary to study their effects on the labor demand of the U.S. manufacturing sector. This paper identifies and measures new goods for every 4-digit SIC industry. Since some new goods appear in skilled-labor intensive industries and others appear in unskilled-labor intensive industries, the new goods' average skilled-labor intensity over the entire manufacturing sector needs to be calculated and compared with the old goods'.

To preview the findings, the new goods' average skilled-labor intensity for the entire manufacturing sector exceeds the old goods' by over 40%. The industries with more new goods also tend to be skilled-labor intensive, more active in R&D activities and have higher shares of investment in computers. The new goods' contribution is about 30% of the rise in the relative demand for skilled labor, the bulk of which is due to the new goods in the most R&D intensive 2-digit industries---28 (chemicals), 35 (machinery), 36 (electronics), 37 (transportation) and 38 (instruments). This provides new evidence that technology shifts demand in favor of skilled labor, and is consistent with the technology-skill-complementarity hypothesis.

An alternative view on the role of technology is the Nelson-Phelps hypothesis: the creation and/or adaptation of technologies require more skilled labor.[7] In the context of new goods, this means that new goods require more skilled labor to invent, whereas the technology-skill-complementarity hypothesis means that once they are invented, the production of new goods increases the relative demand for skilled labor. This paper studies the factor demands by the new goods' production only and so does not investigate the Nelson-Phelps hypothesis.[8] Next, the new goods identified in this paper might reflect both product and process innovations as the two types of innovations can be intertwined in many instances. Since product and process innovations often have similar theoretical implications for the skill premium (e.g. Acemoglu, 2002a), distinguishing product innovation from process innovation is beyond the scope of this paper. Also, this paper identifies the new goods during the late 1970s and 1980s, and so does not investigate whether the relative demand for skilled labor had accelerated since the 1950s.[9] Finally, this paper does not argue that new goods are the whole story for the increase in the skill premium, or that new goods encompass every aspect of technology. New goods are *one* channel through which technology affects the relative demand for skilled labor.

This paper is organized as follows. Section 2 discusses the new goods' average skilled-labor intensity and relates it to the literature. Sections 3 and 4 describe the new goods' identification and measurement. Section 5 presents the new goods' descriptive statistics and section 6 calculates their contribution to the increase in the relative demand for skilled labor. Section 7 concludes.

Section 2 Average Skilled-labor Intensity

The manner in which new goods affect the relative demand for skilled labor depends on how the new goods' average skilled-labor intensity over the entire manufacturing sector compares with the old goods'. Let z index the manufacturing industries, $b(z)$ denote industry z's share in aggregate consumption expenditure and $\theta_s(z)$ ($\theta_u(z)$) denote the share of skilled (unskilled) labor's income in industry z's output. Then the average skilled-labor intensity (denoted by μ) is:[10]

$$(1) \qquad \mu = \frac{\Sigma_z b(z)\theta_s(z)}{\Sigma_z b(z)\theta_u(z)}$$

The numerator is the average of skilled-labor's income shares ($\theta_s(z)$) weighted by the industries' consumption shares ($b(z)$), and it represents the demand for skilled labor. Likewise, the denominator is the weighted average of unskilled-labor's income shares and represents the demand for unskilled labor. Thus the average skilled-labor intensity represents the relative demand for skilled labor. Theoretically, if the new goods' average skilled-labor intensity exceeds the old goods', they tend to increase the relative demand for skilled labor and so the skill premium.

First, consider a supply-demand framework in the empirical SBTC literature.[11] Suppose new goods are the only exogenous change. Then demand is shifted away from all the old goods towards them, so that the production of the old goods contracts, releasing both skilled and unskilled labor. If the new goods' average skilled-labor intensity is higher than the old goods', they demand a higher proportion of skilled labor compared with the factors released by the old sectors, creating excess relative demand for skilled labor and pushing up its relative wage.

Next, consider the models on the direction of technological changes. One example is Acemoglu (2003a).[12,13] There are 2 types of machines: type-S is produced by skilled labor only, and type-U by unskilled labor only. Each type has many symmetric varieties that are never obsolete, and new varieties keep being invented by profit-seeking monopolists. At equilibrium, the number of type-S varieties, n_s, grows at the same rate as the number of type-U varieties, n_u, so that n_s/n_u is fixed. Suppose the relative supply of skilled labor increases. More units can then be produced for each type-S variety relative to type-U varieties. Since each unit is sold for a profit, this market-size effect makes it more profitable to invent type-S machines and could lead to n_s/n_u being higher at the new equilibrium. This increase could be so large that the skill premium increases. Thus, the increase in the relative supply of skilled labor in the 1970s may have led to the increase in skill premium in the 1980s.

In this model, n_s/n_u represents the relative demand for skilled labor at a given moment in time. Because the varieties are symmetric, type-S machines are produced using only skilled labor and type-U machines only unskilled labor, n_s/n_u is proportional to the average skilled-labor intensity as defined in equation (1). Because the new type-S and type-U varieties are just as skilled-labor intensive as the old ones, for n_s/n_u to increase, the new machines invented in a given period must contain a higher fraction of type-S varieties than the existing stock of machines. In other words, the new goods' average skilled-labor intensity must exceed the old goods'.

In both types of models, there can be many new goods, some in skilled-labor intensive industries and others in unskilled-labor intensive ones. This is also the case in the data. Intuitively, if "more" new goods appear in skilled-labor intensive industries, new goods tend to increase the relative demand for skilled labor. The average skilled-labor intensity as defined by equation (1) formalizes this intuition. Since the production of every new good generates labor demand, in order to measure the relative demand for skilled labor in manufacturing, the average needs to be taken over all manufacturing industries.

Section 3 Identification

To study the impacts of new goods on the relative demand for skilled-labor, both the data on industries' output and factor payments and the data on new goods' outputs and factor payments are needed. The industries' data is readily available (see the Data Appendix for a list of the sources). In particular, the factor payments data comes from the NBER-CES Database (Bartelsman and Gray, 1996), and following Berman, Bound, and Griliches (1994), non-production workers are classified as skilled labor, and production workers are classified as unskilled labor.[14] This paper's contribution is to construct the data on new goods' outputs and factor payments. The rest of this section and section 4 discuss how the construction is done.

The first step is to identify the new goods. A case study of a few industries is inadequate, not only because every new product matters for the relative demand for skilled labor, but also because the choice of industries might create bias. For instance, choosing skilled labor-intensive industries might over-estimate the new goods' average skilled-labor intensity for the manufacturing sector. On the other hand, looking at patent data does not work, either, because a single new product may have many patents, and there is no good mapping between the classification of patents and the Standard Industrial Classification (SIC) system.[15]

This paper identifies the new goods by comparing the product listings of the 1987 SIC manual and the 1972 SIC manual. The SIC system classifies establishments by type of activity in which they are engaged, and underlies all establishment-based Federal economic statistics classified by industry. For each 4-digit industry, the SIC manuals contain a few lines of description and a list of the products the industry produces. When the manual was revised in 1987, new entries appeared in the list, and these new entries are candidates for identification as new products. Take industry 3357, "drawing and insulating of nonferrous wire", as an example. In the 1972 SIC manual, the list of products is:

Automative and aircraft wire and cable, nonferrous;

Cable, nonferrous: bare, insulated, or armored-*mfpm*;

Coaxial cable, nonferrous;

Communication wire and cable, nonferrous;

Magnetic wire, insulated;

Shipboard cable, nonferrous

Signal and control cable, nonferrous

Weatherproof wire and cable, nonferrous

Wire, nonferrous: bare, insulated, or armored-*mfpm*

whereas the list in the 1987 SIC manual is longer:

*Apparatus wire and cord: made in wire-drawing plants

Automative and aircraft wire and cable, nonferrous;

Cable, nonferrous: bare, insulated, or armored-*mfpm*;

Coaxial cable, nonferrous;

Communication wire and cable, nonferrous;

*Cord sets, flexible: made in wiredrawing plants

*Fiber optic cable

Magnetic wire, insulated;

Shipboard cable, nonferrous

Signal and control cable, nonferrous

Weatherproof wire and cable, nonferrous

*Wire cloth, nonferrous: made in wiredrawing plants

*Wire screening, nonferrous: made in wiredrawing plants

Wire, nonferrous: bare, insulated, or armored-*mfpm*

The five new entries in the 1987 manual are marked here with a star "*".

The 1987 SIC revision has 2 main objectives: 1. to take into account the technological change and economic growth and decline of individual industries; 2. to maintain the continuity of major Federal statistical series based on the SIC classification system. Changes were unlikely to be made for the sole purpose of obtaining more detailed statistical information on specific products, but were more likely to be accepted if they maintained the structure and historical continuity of the existing classification. To be recognized as an industry, a group of establishments must have economic significance measured in terms of numbers of establishments, employment, payroll, value added and volume of business (value of shipments or receipts). The industries that were growing rapidly but not large enough were also more likely to be recognized as new SIC industries. Therefore, the 1987 SIC revision is likely to be a conservative process and reflect the new goods that were growing rapidly and/or had much economic significance. Since the economic significance of the new goods that were not represented is likely to be limited, so is the bias caused by not having these new goods in the analysis.

One concern is whether the identification process undercounts new goods for unskilled-labor intensive industries. This would happen if fewer SIC manual products are listed for unskilled-labor intensive industries so that the identification process is less likely to pick up new goods for these industries; i.e. the industries' product counts are positively correlated with their skilled-labor intensities. But this is not the case in the data. Column 2 of Table 1 reports the 2-digit industries' product counts normalized by gross output and column 3 reports their skilled-labor intensities, calculated as the ratios of skilled labor's compensations to unskilled labor's compensations. These two variables have a correlation coefficient of –0.13 (insignificant) at the 2-digit level and –0.06 (insignificant) at the 4-digit level.

Among the 11,809 manufacturing products listed in the 1987 manual, 8,311 have identical entries in the 1972 manual. The remaining 3,498 products can be classified into 4 groups. A product is in Group 1 if the spelling of its name is close to an entry in the 72 SIC manual, and the difference in spelling does not justify having them as different products (e.g. "s*y*rup"(87) vs. "s*i*rup"(72)). This group has 1,383 products. As regards the products in Group 2, their names are identical to some 72-SIC-manual entries except for clarifications (e.g. "acid oil, produced in petroleum refineries"(87) vs. "acid oil"(72)). There are 791 products in this group. Group 3 contains the products that have minor differences in their names with some 72-SIC-manual entries (e.g. "cabinets, office: except wood"(87) vs. "cabinets, office: metal"(72)). A total of 499 products are in this group. Finally, Group 4 contains the remaining 825 products, which have major differences in their names (e.g. "pregnancy test kits", "fiber optic strands" and "treadmills"). A random selection of 5% of these 825 products is listed in the Data Appendix.[16]

The purpose of the classification is to try to control for measurement errors. First, a product could have different but equivalent names, as those in Group 1, and it is inappropriate to identify one name as representing a different product from the other. Second, an 87-SIC-manual entry could have a new name because its name was modified for the purpose of clarification. If this is the case, then the entry should not be considered as representing a new product. Group 2 is meant to include all the products that fall into this category. For the remaining products, they could have new names either because they are new entries, or because their names are modified. In the latter case, the entry seems less likely to represent a new product, and Group 3 contains the products that seem to fall into this category. Given these considerations, the most accurate definition of new goods is to include only the products in Group 4 (the narrow definition). Having the products in both Groups 3 and 4 as new goods (the broad definition) yields similar results.

Note that the purpose of the exercise is not to identify each and every one of the new manufacturing products, but to get a reasonable proxy to their population. The logic is simply that, if the product list of an SIC manual is a good representation of the population of products in the U.S. economy at one point in time, then the change in the underlying population should be well reflected in the change of the lists.[17] This change might over-represent the change of the population of products if products are not consistently named in the two lists. This issue is at least partially addressed by the classification and robustness checks mentioned earlier. Furthermore, anecdotal evidence suggests that many of the products in Group 4 are indeed new. Examples include those in section 1 and above, plus “positron emission tomography (PET) scanner”, “cellular radio telephones” and “cable television equipment”… Finally, even more evidence is provided in section 5.

Section 4 Measurement

With the new goods identified, the next step is to measure their factor payments and outputs. Ideally, we would collect these data for each individual new good. However, such data is hard to come by, and so imputation is necessary. Three different approaches are taken. In the increasing order of their accuracy, they are 4-digit counting, 4-digit matching and 5-digit matching.

For each 4-digit 87 SIC industry, the 4-digit counting approach calculates the new goods’ shares in product counts (i.e. the numbers of SIC manual products), denoted by *ng-counting*, and then assigns a fraction of industry output and factor payments to the new products that is equal to *ng-counting*. For example, suppose 10 products are listed for an industry and 2 of them are identified as new. Then *ng-counting* is 0.2. Suppose, in addition, that the industry pays $300 to skilled workers and produces $1000 of output. Then 20% of the output and skilled-labor payment, or $200 and $60, are assigned to new goods.

The variable *ng-counting* is likely to be positively correlated with the new goods' shares in the industry output and factor payments. Besides, the variable *ng-counting* is easy to construct. Thus when the broad definition of new goods is used, the 4-digit counting approach is chosen. In this case, the new goods' shares in product counts are denoted by *ng-broad.* However, the imputation of new goods' factor payments and outputs in this approach is likely to be subject to measurement errors, unless the value of output does not vary across SIC manual products within the same industry, and neither do skilled-labor intensities.

A more accurate approach is 4-digit matching. It improves on the 4-digit counting approach by measuring the new goods' (gross) output (i.e. value of shipments) directly. First, match every new good (SIC manual products) to the 7-digit products in the 1992 Census of Manufactures (CM) and Current Industrial Report (CIR).[18] Next, for each 4-digit industry, sum over the outputs of the 7-digit products that this industry's new goods are matched to. This produces the new goods' total output for this industry, so that their share in industry output, denoted by *ng-matching*, can be calculated. Finally, assign a fraction of industry factor payments to the new goods that is equal to *ng-matching*.

The following provides a simplified example. "Heads-up display (HUD) systems, aeronautical", a new good in industry 3812 (search and navigation equipment), is matched to "Airborne navigation heads-up display (hud) systems" (CIR 3812269). The output of this new good is then looked up in the 92 CIR: $158.3 million. Repeat this process for all the other new goods in industry 3812 to obtain their total outputs, $12.08 billion. Since the output of industry 3812 is $35.27 billion, *ng-matching* equals 0.34. Thus out of this industry's $7.54 billion payments to skilled workers, 34%, or $2.58 billion, is assigned to new goods.

Compared with the 4-digit counting approach, the 4-digit matching approach is likely to considerably reduce measurement errors. First, the output of new goods is measured rather than imputed. This controls for the measurement errors caused by assuming that output doesn't vary across products within the same industry. Furthermore, for a given industry, compared with the new goods' share in product counts, their share in output is likely to be a better predictor of their share in factor payments. Thus imputing the new goods' factor payments using *ng-matching* is likely to be subject to less measurement errors than using *ng-counting*. The majority of the analysis in this paper uses the 4-digit matching data.

However, the 4-digit matching approach assumes that new goods have the same skilled-labor intensities as old goods within each 4-digit industry, and so some measurement errors are likely to remain. Since 4-digit industries might hide important elements of the change in the demand for skilled labor (Bernard and Jensen, 1997), these measurement errors might be important.

The 5-digit matching approach tries to control for these measurement errors by utilizing the factor payments data at the 5-digit product class level, the most disaggregated factor payments data in 92 CM. The construction is very similar to the 4-digit matching approach, but is carried out at the 5-digit product class level: for each 5-digit product class, calculate the new goods' share in output, denoted by *ng-matching5*, and then assign a fraction of factor payments to new goods that is equal to *ng-matching5*. Thus the skilled-labor intensities of new goods could differ from old goods within a 4-digit industry.

Although 5-digit matching is likely to be the most accurate approach, it is not always available.[19] However, all three approaches, 4-digit counting, 4-digit matching and 5-digit matching, generate similar results, which is perhaps surprising given the differences in their construction. This also suggests that measurement errors are not having an excessively large impact on the results.

Table 2 lists the summary statistics of the various measures of new goods discussed in this section. The next section provides more descriptive statistics of these measures.

Section 5 Descriptive Statistics

In Table 1, column 4 lists *ng-counting*, the new goods' shares in product counts, by 2-digit industries. New goods are present in all 2-digit industries except 21 (tobacco), suggesting that they are widespread. Column 5 shows the new goods' shares in output, *ng-matching*. Compared with *ng-counting*, *ng-matching* is larger for most 2-digit industries, with 27 (printing) and 30 (rubber & plastics) as major exceptions. This suggests that the 4-digit counting approach tends to underestimate the new goods' shares in industry outputs. Column 6 shows *ng-broad*, the new goods' shares in product counts when the broad definition is used. Since the broad definition has more products as new goods, *ng-broad* is larger than *ng-counting* and *ng-matching* in most cases. The 5-digit matching data is not shown because at the 2-digit level it is the same as *ng-matching*.

These different measures of new goods are all highly correlated. For example, the correlation coefficient between *ng-counting* and *ng-matching* is 0.80 (significant) at the 2-digit level, and 0.79 (significant) at the 4-digit level. This helps explain why these measures all generate similar results. For the entire manufacturing sector, new goods account for about 12% of the nominal output when measured by *ng-matching*, and about 19% when measured by *ng-broad*.

As shown by columns 3 and 5, the 2-digit industries with more new goods tend to be more skilled-labor intensive. The correlation coefficient between *ng-matching* and skilled-labor intensities is 0.42 (p value = 0.06) at the 2-digit level, and becomes 0.26 (significant) at the 4-digit level.[20] Figure 1 plots the 4-digit industries' skilled-labor intensities against *ng-matching* for 1992.[21] The slope coefficient of the fitted regression line is about 0.9 (significant).

Measuring the new goods provides some evidence for their identification. First, many new products experience declining prices and rising sales in quantity in the first couple of years after their introduction, probably due to increasing supply.[22] This is also the case for the new goods identified in this paper. Assuming that *ng-matching* is time-invariant, Figure 2 shows that the average price of the new goods falls between 1979 and 1994 despite a clear upward trend of the average price of the entire manufacturing sector. Figure 3 shows that during this period, the new goods' share in real manufacturing (net) output steadily increases. Next, a lot of technology and innovation are the fruits of research and development efforts (e.g. Acemoglu 2002b), and so the industries with more R&D activities should introduce more new technologies and innovation. Then if new goods provide a direct measure of technology, more new goods should be observed for the industries more active in R&D. This is indeed the case in the data. Column 6 of Table 1 shows the ratios of private R&D expenditures to net sales---a measure of the intensity of R&D activities---by 2-digit industries,[23] and Figure 4 plots these ratios against *ng-matching* with the fitted regression line. The correlation coefficient between R&D intensities and *ng-matching* is a significant 0.59, and the regression line has a slope coefficient of 0.24 (significant). Finally, column 7 of Table 1 shows the computers' shares in investment by 2-digit industries, and this variable is also positively correlated with *ng-matching*: the correlation coefficient is 0.41 (p value = 0.08) at the 2-digit level and 0.13 (significant) at the 4-digit level. Since an industry's share of investment in computers' is a useful indicator of how much new technology and innovation it introduces, this positive correlation provides more evidence that new goods are a direct measure of technology.

Note that among the 2-digit industries with lots of new goods (*ng-matching* > 0.10), while some are highly skilled-labor intensive, such as 35 (machinery), 36 (electronics) and 38 (instruments), quite a few have medium-to-low skilled-labor intensities, such as 20 (food), 23 (apparel) and 30 (rubber & plastics). To see whether or not new goods increase the relative demand for skilled labor within the manufacturing sector, it is necessary to compare new goods' average skilled-labor intensity, taken over the entire manufacturing sector, with the old goods'.

Using equation (1), columns 2 and 3 of Table 3 calculate the average skilled-labor intensities of the new goods and the old goods for the entire manufacturing sector. Column 4 reports their differences. The consumption share of a good, *b(z)*, is measured as its share in apparent consumption (gross output + imports – exports).[24] When *ng-matching* is used, the new goods' average skilled-labor intensity is 0.93 for 1992 and 0.87 on average over the years 87, 89, 92 and 94, whereas the old goods' average skilled-labor intensity is 0.64 for 1992 and 0.61 on average. For the entire manufacturing sector, the new goods' average skilled-labor intensity is about 40% higher than the old goods'. When *ng-counting* is used, the new goods' average skilled-labor intensity approaches 1 and exceeds the old goods' by about 50%. When the broad definition of new goods is used (*ng-broad*), the new goods' average skilled-labor intensity falls to about 0.8, exceeding the old goods' by about 30%.

In these calculations, the new goods' skilled-labor intensities are assumed to be the same as the old goods' within 4-digit industries. To see how much the results change if this assumption is relaxed, the 5-digit matching data, *ng-matching5*, can be used. Within each of the 257 4-digit industries with some new goods, the new goods' and old goods' average skilled-labor intensities are calculated. Across these industries, the mean for the new goods is 0.89, the mean for the old goods is 0.86, and their difference is about 4%.[25] This suggests that allowing the skilled-labor intensities to vary between new goods and old goods within 4-digit industries tends to strengthen the results, but not by much. This is confirmed by comparing the calculations using *ng-matching5* with those using the 4-digit matching data. When *ng-matching5* is used, the new goods' average skilled-labor intensity is 0.96 for 1992, slightly higher than the 4-digit matching result of 0.93.

To summarize, the new goods' average skilled-labor intensity for the entire manufacturing sector exceeds the old goods' by over 40% (30% ~ 52%). This difference is close to 50% for 1992 when the most accurate measurement approach, 5-digit matching, is used. This suggests that new goods tend to increase the relative demand for skilled labor.

Section 6 New Goods' Contribution to the Relative Demand for Skilled Labor

6.1 Decomposition

To quantify the new goods' contribution to the relative demand for skilled labor, consider the framework of the commonly-used wage-bill decomposition in the literature (e.g. Berman, Bound, and Griliches, 1994), which measures the relative demand for skilled labor by its share in the aggregate wage bill, μ^w.[26] Let z index the sectors, $m(z)$ denote sector z's share in the aggregate wage bill, and $\theta_s^w(z)$ denote skilled labor's share in sector z's wage bill. Then:

(2) $$\mu^w = \Sigma_z m(z)\theta_s^w(z)$$

The change in μ^w can be decomposed into the following two components:

(3) $$\Delta\mu^w = G^w_{btw} + G^w_{wthn}\ ;\ G^w_{btw} = \Sigma_z\Delta m(z)\ \overline{\theta^w_s(z)} \text{ and } G^w_{wthn} = \Sigma_z\Delta\theta_s^w(z)\,\overline{m(z)}$$

where a bar over a term represents averaging over time. The "between" component G^w_{btw} measures between-industry product demand shifts $(\Delta m(z))$, holding constant the industries' production techniques. The "within" component G^w_{wthn} measures within-industry skill upgrading $(\Delta\theta_s^w(z))$, holding constant the industries' shares in the aggregate wage bill. When new goods are present, the change in μ^w can be decomposed into the contribution of the new goods, G_n^w, and the "between" and "within" components of the old goods, $G^w_{o,btw}$ and $G^w_{o,wthn}$:

(4) $$\Delta\mu^w = G_n^w + G^w_{o,btw} + G^w_{o,wthn}$$

(5.1) $$G_n^w = \Sigma_z^{new} m(z)\ \theta_s^w(z) + \Sigma_z^{old}[\rho^w m(z)]\ \theta_s^w(z)|_{t=0} - \Sigma_z^{old} m(z)\ \theta_s^w(z)\,|_{t=0}$$

where $\rho^w = 1 - \Sigma_z^{new} m(z)$

(5.2) $$G^w_{o,btw} = \Sigma_z^{old}\Delta m^{old}(z)\ \overline{\theta^w_s(z)}\ ;\text{ where } \Delta m^{old}(z) = m(z)|_{t=1} - \rho^w m(z)|_{t=0}$$

(5.3) $$G^w_{o,wthn} = \Sigma_z^{old}\Delta\theta_s^w(z)\,\overline{m^{old}(z)}\ ;\text{ where } \overline{m^{old}(z)} = (m(z)|_{t=1} + \rho^w m(z)|_{t=0})/2$$

While equations (5.2) and (5.3) are a straightforward application of (3) to the old goods, equation (5.1) merits more discussion. Suppose new goods were the only change between period 0 and period 1, and a sector z's share in the aggregate wage bill ($m(z)$) measures its share in aggregate consumption expenditure. Then following the creation of the new goods, the aggregate consumption share of the old goods declines from 1 to ρ^w $(= 1 - \Sigma_z^{new} m(z))$. Thus the relative demand for skilled labor would have 2 parts: that generated by the new sectors (the 1st term on the right-hand side) and that by the old sectors (the 2nd term). The old sectors have contracted (by ρ^w) because demand is shifted away from them towards the new goods (holding constant the old goods' prices). Finally, the 3rd term is simply μ^w at period 0.

Although in this thought experiment, the demand for each old good is assumed to decline exogenously by the same proportion (ρ^w), this assumption is not as strong as it seems. For an old good z, think about $\rho^w m(z)|_{t=0}$ as a benchmark for its "complementarity" with the new goods: it is a "complement" ("substitute") of the new goods if its consumption share is higher (lower) than $\rho^w m(z)|_{t=0}$; i.e., its consumption share has declined by proportionately less (more) than the average of all the old goods. As long as the complementarities between the old goods and the new goods are uncorrelated with the skilled-labor intensities of the old goods,[27] equation (5.1) correctly measures the effects of the new goods.[28,29] However, equation (5.1) tends to over (under)-estimate the effects of the new goods if the complementarities of the old goods are positively (negatively) correlated with their skilled-labor intensities.

Columns 5 ~ 7 of Table 3 report the results of the wage-bill decomposition using equation (3). The "between" component accounts for about 34% of the increase in the relative demand for skilled labor for 79-92 and 37% on average over 79-87, 79-89, 79-92 and 79-94. This result is similar to the literature. Column 8 reports the contributions of the new goods. When *ng-matching* is used, new goods account for about 25% of the increase in the relative demand for skilled labor for the period 79-92 and 26% on average over 79-87, 79-89, 79-92 and 79-94. When *ng-counting* is used, the contribution of new goods rises slightly to 26% for 79-92 and 28% on average. When the broad definition of new goods is used (*ng-broad*), the contribution of new goods rises to 33% for 79-92 and 35% on average. Finally, when the 5-digit matching data is used, the new goods' contribution is 27% for 79-92. This is higher than the 4-digit matching result of 25%, suggesting that allowing the skilled-labor intensities to vary between new goods and old goods within 4-digit industries tends to strengthen the results, though not by much. Column 9 reports the contribution of the "between" component of the old goods: it is about 20%, 18%, and 22% on average over the four periods (the 1st, 2nd and 3rd panels). Column 10 reports the contribution of the "within" component of the old goods: it is about 54%, 54% and 43% on average. To summarize, about 30% (26% - 35%) of the rise in the relative demand for skilled labor can be attributed to new goods, 20% to product demand shifts among old goods, and 50% to changes in the production techniques of the old goods.

Note that since the creation of new goods shifts demand away from all the old goods towards them, the expansion of skilled-labor intensive industries relative to unskilled-labor intensive ones is an important channel through which new goods increase the relative demand for skilled labor. To highlight the importance of this channel, let the new goods and old goods have the same skilled-labor intensities within 3-digit industries. The new goods' contributions are but slightly reduced to about 21% for 79-92 and 23% on average (24.74%, 23.52%, 21.25% and 22.71% for 79-87, 79-89, 79-92 and 79-94). Since new goods provide a direct measure of technology, technology could affect skilled-labor demand through between-industry product demand shifts. This channel might have been overlooked in the empirical SBTC literature.[30]

Finally, since new goods provide a direct measure of technology, their 30% contribution provides new evidence that technology shifted demand in favor of skilled labor during the late 1970s and 1980s. To highlight the point that new goods' contribution can be attributed to technology, column 11 of Table 3 reports the contribution of the new goods from R&D intensive industries, the five 2-digit industries with the highest R&D-to-net-sale ratios---28 (chemicals), 35 (machinery), 36 (electronics), 37 (transportation) and 38 (instruments).[31] When *ng-matching* is used, the contribution of these "R&D intensive" new goods is almost as large as all the new goods combined, reaching 23% for 79-92 and 25% on average. Using the other measurement approaches yields similar results: the "R&D intensive" new goods account for the bulk of the new goods' contribution to the increase in the relative demand for skilled labor.

6.2 Correlation with Skill Upgrading: Regression Analysis

The main purpose of this sub-section is to show that new goods are positively correlated with skill upgrading even after controlling for various other factors. The regressions could also be robustness checks for the analysis based on decomposition.

Adding new goods into the commonly-used skill-upgrading regression in the literature (e.g. Berman, Bound, and Griliches, 1994, Feenstra and Hanson, 1999) with capital as a fixed input:

$$\Delta\theta_s^w(z) = \alpha + \beta_1\Delta ln(K/Y(z)) + \beta_2\Delta lnY(z) + \beta_3X_1 + \beta_4X_2 + \gamma\, ng\text{-}matching + \varepsilon(z) \quad (6)$$

where $\Delta ln(K/Y(z))$ is capital deepening, $\Delta lnY(z)$ is the change in industry output, X_1 is the industry shares of investment in computers and high-tech equipment, X_2 is outsourcing (a measure of industry imports of intermediate inputs), and *ng-matching* is new goods' share in industry output. The dependent variable is within-industry skill upgrading. Column 4 of Table 4 shows that running (6) without *ng-matching* yields similar results to the literature: all independent variables have positive coefficients, some of which are significant (e.g. capital-deepening, computers' shares in investment). Columns 2 and 3 list the summary statistics of the variables used in the regression. Column 5 shows that when *ng-matching* is included in (6), its coefficient is a significant 0.55. Thus new goods are positively correlated with skill upgrading even after controlling for the various factors represented by the other independent variables in (6).[32]

Although having *ng-matching* in (6) might not be theoretically justified, it could be useful as part of a simplistic robustness check for the decomposition-based analysis. New goods could increase the relative demand for skilled labor by: 1. expanding skilled-labor intensive sectors relative to unskilled-labor intensive ones at constant skilled-labor intensities; or 2. by contributing to within-industry skill upgrading. To calculate the first component, let new goods have the skilled-labor intensities of the old goods in equation (5.1). When *ng-matching* is used, this component is about 17% of the increase in the relative demand for skilled labor on average and 14% for 79-92.[33] To calculate the second component, column 6 of Table 4 reports how much each regressor in (6) "explains" the (weighted) mean of the dependent variable (i.e. skill upgrading). Since *ng-matching* has a mean of 0.12 and a coefficient of 0.55, the part "explained" by new goods is about 0.066 (0.12 × 0.55), or about 30% of skill-upgrading. Because skill-upgrading accounts for about 66% of the increase in the relative demand for skilled labor for 79-92 and 63% on average (see Table 3), the second component of new goods' contribution is about 20% (30% × 66%) of this increase for 79-92, and 19% on average (30% × 63%). Put these two components together, new goods account for about 34% (14% + 20%) of the increase in the relative demand for skilled labor for 79-92 and 36% (17% + 19%) on average. These numbers are comparable to the results based on decomposition.

Finally, given the long horizon of the analysis (over 10 years), firms might have a long enough time to adjust their capital stocks. When capital is not a fixed input, adopting the same translog specification as in (6) but without fixed inputs yields the following pair of regressions: [34]

(7) $$\Delta\theta_x(z) = \alpha' + \beta_3'X_1 + \beta_4'X_2 + \gamma'\, ng\text{-}matching + \varepsilon'(z);\ x = s, u$$

where X_1, X_2 and *ng-matching* have the same meanings as in (6). The dependent variables are the log differences in the income shares of skilled and unskilled labor, in order to facilitate calculating the contribution of the regressors to within-industry skill upgrading.

Columns 7 and 8 of Table 4 list the summary statistics of the variables used in the regressions. Columns 9 and 10 show that the coefficient of *ng-matching* is about –0.022 (insignificant) in the skilled-labor equation ($x = s$ in equation (7)) and –0.21 (significant) in the unskilled-labor equation ($x = u$ in (7)). Thus the conditional correlation between new goods and skill-upgrading is also positive in regressions (7). On the other hand, since *ng-matching* has a mean of about 0.12, the part of skill-upgrading attributable to new goods is about 0.023 ((0.21-0.022) × 0.12). Since the means of the dependent variables are –0.012 and –0.23, respectively, new goods account for about 10% (0.023/(0.23 – 0.012)) of skill-upgrading. Thus the second component of new goods' contribution is about 7% of the increase in the relative demand for skilled labor (10% × 67%) for 79-92 and 6% on average (10% × 63%). As a result, the total contribution of the new goods is about 21% (14% + 7%) for the period 79-92, and 23% (17% + 6%) on average, [35] comparable to the results based on decomposition.

Section 7 Conclusion and Discussion

This paper provides data on the output and factor payments of new goods for every 4-digit industry in the U.S. manufacturing sector in the late 1970s and 1980s. The industries with more new goods also tend to be skilled-labor intensive, more active in R&D activities and have higher shares of investment in computers. New goods are also positively correlated with skill upgrading even after controlling for various factors such as capital deepening and computers' shares in investment. For the entire manufacturing sector, the new goods' average skilled-labor intensity exceeds the old goods' by over 40%. New goods' contribution is about 30% of the increase in the relative demand for skilled labor, the bulk of which is due to the new goods in the most R&D intensive 2-digit industries---28 (chemicals), 35 (machinery), 36 (electronics), 37 (transportation) and 38 (instruments). Since new goods provide a direct measure of technology, these findings offer new evidence that technology has shifted demand in favor of skilled labor. This is consistent with the technology-skill-complementarity hypothesis put forth by both the empirical SBTC literature and the literature about the directions of technological change.

Finally, this paper finds that the production of new goods increases the relative demand for skilled labor, and it remains a distinct possibility that new goods require more skilled labor to invent (e.g. Dinopoulos and Segerstrom, 1999). Thus the new goods' overall effects on skilled-labor demand might be even larger than what this paper has found. Also, this paper primarily uses factor payments data at the 4-digit SIC level so that new goods' skilled-labor intensities are assumed to be the same as old goods within 4-digit SIC industries. Going down to the 5-digit SIC level strengthens the results, but not by much. It is interesting to see whether using more dis-aggregated data might generate even stronger results.

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Data Appendix

A1 Data Sources

1. Output, price indices and factor payments (4-digit 87 SIC): NBER-CES Manufacturing Industry Database (Bartelsman and Gray, 1996). **2. Imports, exports**, i**ndustry shares of investment in computers and high-tech. equipment and outsourcing** (4-digit 72 SIC): the same as used in Feenstra and Hanson (1999) and provided by Gordon H. Hanson. The trade data is based on Feenstra (1996, 1997). **3. R&D-to-net-sale ratios** (2-digit 87 SIC): NSF survey in Research and Development in Industry, 1992 (NSF 95-324), Tables A-17 and A-18. **4. Output and factor payments** (5-digit 92 CM, 87 SIC): U.S. Census Bureau, Economic Census 1992-Disc 1J (CD-EC92-1J). **5. Shipment values (i.e. gross output)** (7-digit 92 CM/CIR, 87 SIC): CD-EC92-1J and U.S. Census Bureau, CIR 93 publications, various issues. CIR 93 is used because it contains the revised data for the year 1992. Finally, the data in 72 SIC is concorded into 87 SIC using the concordance at the NBER website (http://www.nber.org/nberces/).

A2 More Details About Matching

(a) More than one SIC manual product matched to a single CM/CIR 7-digit product: all the SIC manual products within the same 4-digit industry, new or old, are checked, the total number of matches recorded, and each SIC manual new good is assigned a fraction of the CM/CIR product's shipment value equal to the inverse of that number. **(b) Missing data**: the 7-digit CM/CIR product whose data is missing is aggregated with other 7-digit products whenever possible. The new goods are then re-matched to the aggregation groups thus formed and have their shipments calculated as in **(a)**. **(c) Really difficult matching**: this is due to: (1). in the case of **(a)**, it is hard to find all the SIC manual products that can be matched to the single CM/CIR product; (2). in the case of **(b)**, the missing data is hard to impute. In both cases, the new good's output is calculated using the 4-digit counting approach (for 90 out of 825 products).

A3 Consistency Issues

(a) In the 92 CM, the total gross output of an (4-digit) industry or (5-digit) product class does not equal the sum of all its (7-digit) products because the former is establishment-based but the latter is product-based. The new goods' outputs are product-based and so their output shares are calculated using the product-based totals. **(b)** The total gross outputs of 92 CIR products do not always equal their corresponding 92 CM entries. This is probably due to sampling issues (e.g. differences in sample coverage, different treatment of late responses, etc.), according private conversation with U.S. Census Bureau staff. The output shares of the new goods matched to 92 CIR are calculated using the CIR totals.

A4 A Random Selection of 5% of the Narrow-Definition New Goods

Industry	Product Name
2026	Half and half-mfg
2043	Granola, except bars and clusters-mfg
2096	Cheese curls and puffs-mfg
2099	Tofu, except frozen desserts-mfg
2339	Gowns, hospital: surgical and patient mfpm-mfg
2339	Warmup suits: women's, misses', and juniors' -mfpm-mfg
2341	Chemises: women's, misses', children's, and infants'-mfpm-mfg
2369	Jogging suits: girls', children's, and infants'-mfpm-mfg
2522	Panel furniture systems, office: except wood-mfg
2796	Color separations for printing-mfg
2796	Flexographic plates, preparation of-mfg
2819	Tungsten carbide powder, except abrasives or by metallurgical process-mfg
2835	Enzyme and isoenzyme diagnostic reagents-mfg
2842	Window cleaning preparations-mfg
3088	Water closets, plastics-mfg
3089	Bathware, plastics: except plumbing fixtures-mfg
3089	Microwave ware, plastics-mfg
3111	Exotic leathers-mfg
3269	Ceramic articles for craft shops --mfg
3357	Apparatus wire and cord: made in wire drawing plants-mfg
3462	Nuclear power plant forgings, ferrous: not made in rolling mills-mfg
3463	Missile forgings, nonferrous: not made in hot-rolling mills-mfg
3491	Valves, nuclear-mfg
3492	Hose fittings and assemblies, fluid. power: metal-mfg

3524	Seeders, residential lawn and garden-mfg
3545	Blanks tips and. inserts: cutting tools mfg
3545	Threading toolholders-mfg
3553	Presses, woodworking: particleboard, hardboard, medium density fiberboard. (MDF)
3556	Fish and shellfish processing machinery mfg
3571	Personal computers-mfg
3577	Decoders, computer peripheral equipment-mfg
3585	Air-conditioners, motor vehicle-mfg
3663	Cameras, television-mfg
3663	Pagers (one-way)-mfg
3671	Photomultiplier tubes-mfg
3674	Photoconductive cells-mfg
3674	Thyristors-mfg
3695	Video recording tape, blank-mfg
3812	Air traffic control radar systems and equipment-mfg
3812	Light reconnaissance and surveillance systems and equipment-mfg
3821	Ovens, laboratory-mfg
3826	Mass spectroscopy instrumentation-mfg
3826	Polarographic: equipment-mfg
3829	Rain gauges-mfg
3829	Restitution apparatus, Photogrammetrical-mfg
3829	Wind direction indicators-mfg
3841	Surgical stapling devices-mfg

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[1] See, e.g. Berman, Bound, and Machin (1998) for changes in skill premia outside of U.S.

[2] e.g. Bound and Johnson (1992), Katz and Murphy (1992). Note that this paper does not tackle residual wage inequality (i.e. the wage difference between workers with similar skills), a potentially important component of the overall wage inequality (e.g. Katz and Autor, 1999).

[3] e.g. Berman, Bound, and Griliches (1994), Autor, Katz, and Krueger (1998). See Acemoglu (2002b) for a recent survey. Also, see Feenstra and Hanson (1999) for the role of outsourcing, and Lawrence and Slaughter (1993), Borjas, Freeman, and Katz (1997) and Leamer (1996) for the role of trade.

[4] See also Acemoglu (2001, 2002a, b, 2003a, b) and Acemoglu and Zilibotti (2001).

[5] See also Autor, Katz, and Krueger (1998) and Doms, Dunne, and Troske (1997).

[6] For more examples, see Mokyr (1990), Gray (1992) and the case studies by the now defunct Office of Technology Assessment.

[7] E.g. Nelson and Phelps (1966), Aghion and Howitt (1998), Dinopoulos and Segerstrom (1999). See Acemoglu (2002b) for a more detailed discussion on these two views of technology.

[8] This is because the factor payments data is establishment-based and exclude headquarter activities, which might include lots of research and development.

[9] See, for example, Acemoglu (2002b) and Card and DiNardo (2002).

[10] This is an extension of equation (28) in Katz and Autor (1999) to the general case of constant-returns-to-scale and multiple factors. See, for example, Xiang (2002a) for the derivation.

[11] E.g. Katz and Autor (1999). See also Xiang (2002a).

[12] This horizontal innovation model is isomorphic to the vertical innovation model of Acemoglu (1998). Acemoglu (2002a) argues that horizontal and vertical innovation models often generate similar results.

[13] The Thoenig and Verdier (2003) story of "defensive skill upgrading" can be told along similar lines: assume that quality improvements can only be made to new varieties of machines and machines are never obsolete, let type-S machines have higher production costs and be harder to imitate, and let the exogenous change be increased opportunity of imitation (e.g. trading with developing countries).

[14] Berman, Bound, and Griliches (1994) show that the production/non-production worker distinction closely mirrors the distinction between blue- and white-collar occupations, which, in turn, closely reflect an educational classification of high school/college. Krueger (1997) shows that the raw correlation between average education and the share of production workers is –0.61 at the 1980 three-digit Census Industry Classification level.

[15] E.g., the CT scanner has 456 patents scattered in over 75 patent subclasses (Trajtenberg, 1990).

[16] The complete list is available at http://www.mgmt.purdue.edu/faculty/cxiang/.

[17] Private conversation with staff members of the U.S. census Bureau confirms that this approach is a sensible way to identify new products.

[18] The matching process is feasible although non-trivial. It is feasible because the product coding system of the 92 CM/CIR is based on the 87 SIC manual, and oftentimes the matching is straightforward. When a straightforward matching is not feasible, the help of the industry analysts at the U.S. Census Bureau was sought (for about 250 out of 825 products). See the Data Appendix for more details.

[19] This is because each CM uses a distinct coding system at the 5- and 7-digit levels, and this system can change substantially from one CM to another. Plus, CM data is available only every five years.

[20] These two correlation coefficients are not as different as they seem since 0.26 is less than one standard deviation away from 0.42.

[21] To show the details better, only the observations with skilled-labor intensities below 3 are included. This excludes 5 observations.

[22] One anecdote in Gordon (1990) is that the price of a "Type B" VCR fell from $1500 to $600 between 1982 and 1985, and then to $275 in 1986. Other examples include microwave ovens and TV sets (Gordon, 1990), head CAT scanners (Trajtenberg, 1990) and mainframe computers (Brynjolfsson, 1997).

[23] A "*" indicates that the R&D data is merged for two or more industries. The merging is for 20 with 21, 22 with 23, 24 with 25, 29 with 13, and 27 with 31 and 39. Using the total (federal plus private) R&D expenditures yields similar results.

[24] Measuring consumption shares as shares in net output yields very similar results.

[25] This difference is about 7% within 3-digit industries and 14% within 2-digit industries.

[26] An alternative framework can be developed based on equation (1), and it produces similar results, as shown in the working paper version of this paper (Xiang, 2002b).

[27] To be rigorous, the "complementarity" between an old good z and the new goods is $\varepsilon(z) \equiv b(z)|_{t=1} - \rho^{w} b(z)|_{t=0}$, where $b(z)$ denotes good z's consumption share. If the old goods'

complementarities are uncorrelated with their skilled-labor intensities, $\Sigma_z^{old}\varepsilon(z)\theta_s^w(z)|_{t=0} = 0$. This holds when the representative consumer has CES (Constant Elasticity of Substitution) preferences. For more details, see Xiang (2002a).

[28] Note that the relative demands for skilled labor at periods 0 and 1 are not measured at the same prices. Addressing this issue is difficult because it requires information on the $m(.)$'s and $\theta_s^w(.)$'s of the new goods at the period-0 prices. However, all the 3 components of $\Delta\mu^w$ are biased in the same direction (e.g. downward if the elasticities of substitution of consumption and production are larger than 1). This helps alleviate the concern because the analysis focuses on the *share of contribution* of the individual components.

[29] Note that in an open economy, equation (5.1) might not fully capture the general equilibrium effects of new goods since they could show up in (5.2). For example, suppose U.S. (North) trades with some developing country (South), both countries specialize, all the new goods appear in the North, and their average skilled-labor intensity equals the old goods. This leads to an increase in the relative demand for North's products and thus its factor services, so that North's factors become more expensive, and the least skilled-labor intensive North goods cease to compete with the imports. Thus North contracts its range of production into more skilled-labor intensive sectors, raising the relative demand for skilled labor (see Xiang, 2002a for more details). Thus, although $G_n^w = 0$ in this case, the positive contribution of new goods shows up as $G_{o,btw}^w > 0$, in (5.2). Therefore, (5.1) captures only the "domestic factor market effects" of the new goods in the U.S. manufacturing sector. Furthermore, if the U.S. is a developed country, developed countries are abundant in skilled-labor, and more new goods appear in developed countries, (5.1) tends to under-estimate the contribution of the new goods. Capturing the full general equilibrium effects of new goods is beyond the scope of this paper.

[30] Suppose new technology is the introduction of computers. The empirical SBTC literature emphasizes that the use of computers could make the production of, say, chairs and tables, more

skilled-labor intensive, and might have overlooked the following additional channel: the production of computers themselves could have a higher average skilled-labor intensity.

[31] This is not to say that the new goods of the other industries have little to do with technology: e.g. the 2003 Campbell soup boasts "cold-blend" technologies and "cold-swell" starch that help retain the soup's flavors while it is heated (Wall Street Journal, A1, July 30, 2003).

[32] This finding cannot be interpreted as strong evidence that new goods lead to within-industry skill upgrading because (6) might fail to distinguish causality from correlation (DiNardo and Pischke, 1997).

[33] They are 18.67%, 17.12%, 14.39% and 16.39% for 79-87, 79-89, 79-92 and 79-94. The results are stronger when the decomposition based on equation (1) is used: 17% for 79-92 and 20% on average (Xiang, 2002b).

[34] Two more assumptions are imposed: 1. profits are zero, so that the total cost equals total sales; 2. constant returns to scale, so that output does not appear on both sides of the regression. Also, the price of capital is absent from (7) because it is difficult to measure accurate (Berman, Bound, and Griliches, 1994). Thus (7) is not necessarily a better specification than (6) because it might miss useful information about changes in the price of capital contained in capital deepening.

[35] When the decomposition based on equation (1) is used, the new goods' total contribution is 24% for 79-92 and 26% on average (Xiang, 2002b). See also note 33.

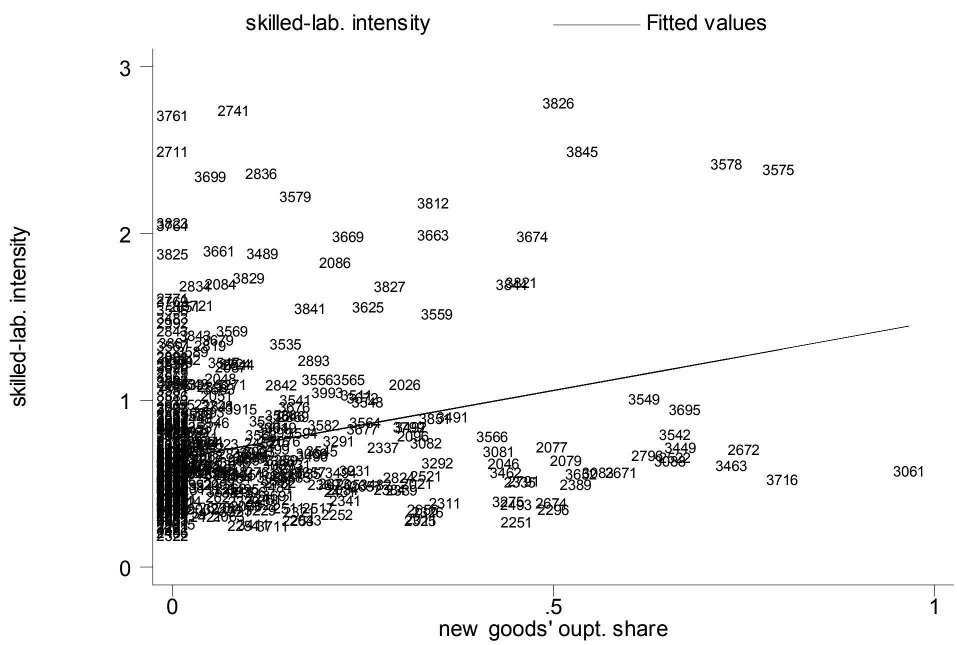

Figure 1 Correlation between *ng-matching* and Skilled-Labor Intensity

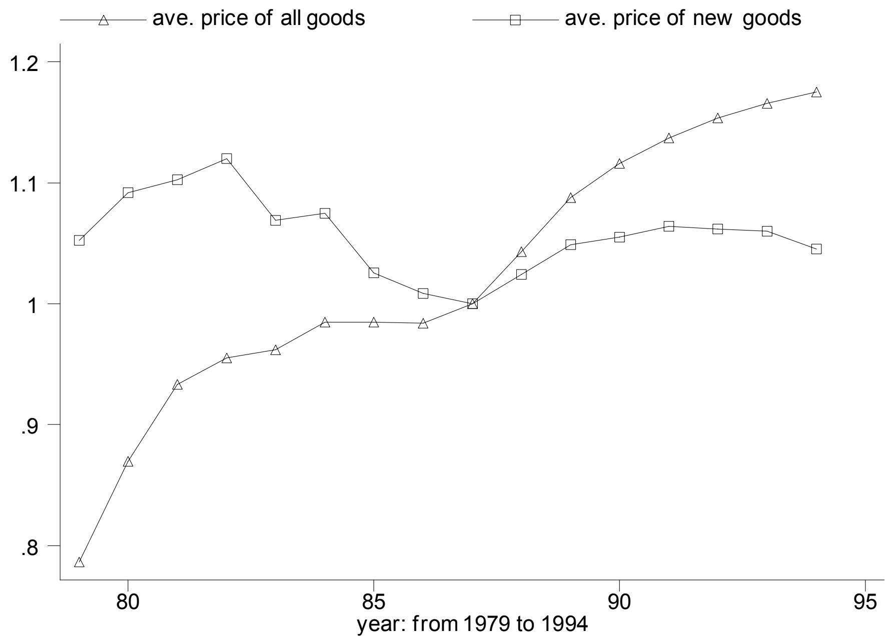

Figure 2 The Price Movements of New Goods: 79-94

Notes to Figure 2:

The average prices are the averages of the industrial price deflators (1987 = 1) weighted by net outputs (value-added).

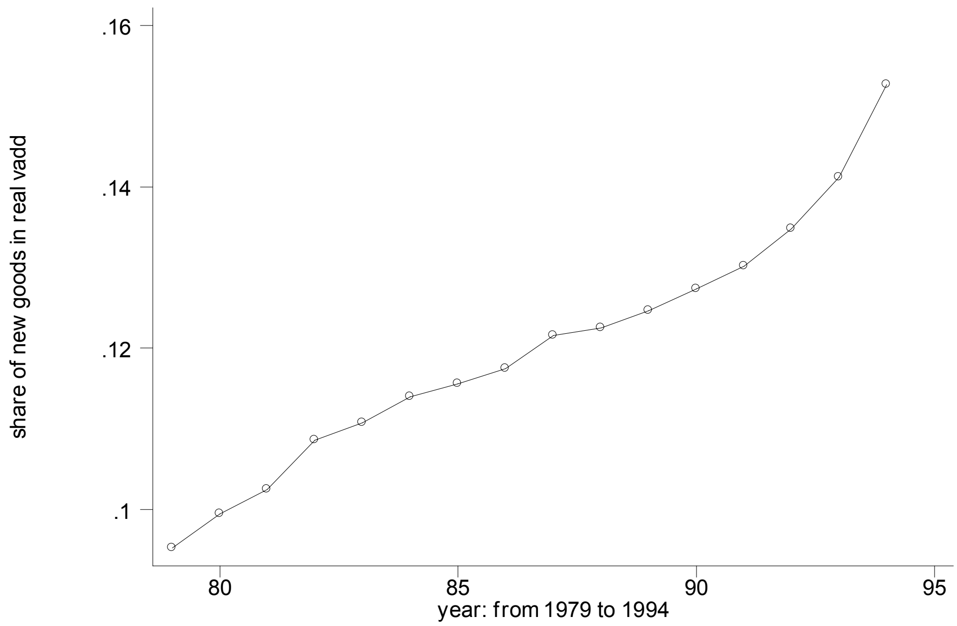

Figure 3 The Quantity Movement of New Goods: 79-94

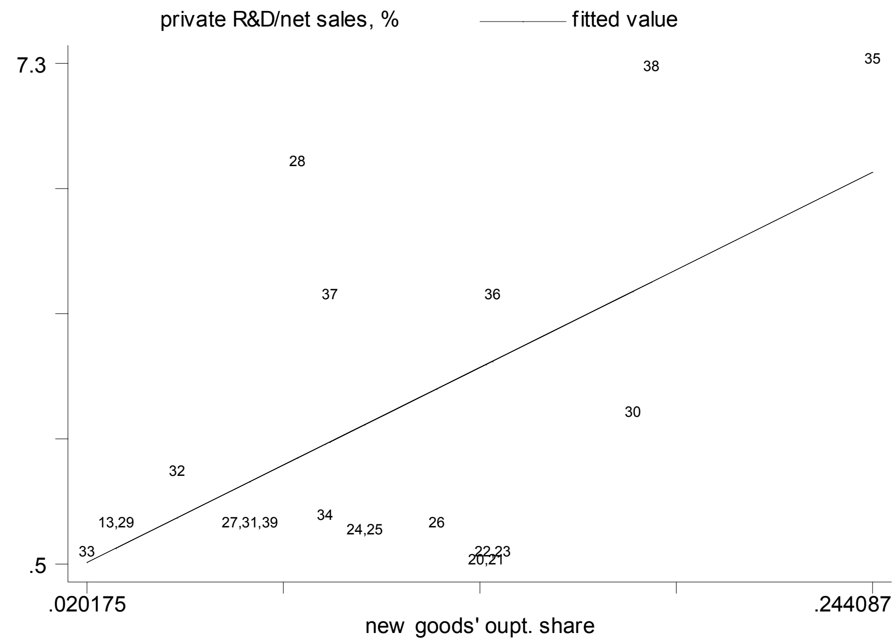

Figure 4 Correlation between *ng-matching* and R&D Intensity

Table 1 Descriptive Statistics by 2-digit Industries

Industries	Prod. Cnts. /Oupt.	Skilled Lab. Int.	*ng-counting*	*ng-matching*	*ng-broad*	% net sale in R&D	% invest. in computers
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
20 (food)	1.68	0.525	0.13	0.133	0.25	0.5*	2.31
21 (tobacco)	0.23	0.573	0	0	0	0.5*	6.17
22 (textile)	8.79	0.324	0.029	0.047	0.066	0.6*	1.98
23 (apparel)	5.88	0.430	0.128	0.189	0.257	0.6*	5.95
24 (wood)	4.18	0.360	0.050	0.065	0.085	0.9*	1.63
25 (furniture)	4.97	0.509	0.092	0.173	0.244	0.9*	4.81
26 (paper)	2.15	0.465	0.070	0.127	0.115	1.0	1.79
27 (printing)	1.51	1.111	0.091	0.078	0.254	1.0*	11.27
28 (chemicals)	4.09	1.052	0.042	0.088	0.055	5.9	2.75
29 (petroleum)	0.47	0.699	0.028	0.028	0.099	1.0	1.47
30 (rubber/plastics)	2.94	0.537	0.219	0.183	0.269	2.5	2.77
31 (leather)	19.34	0.444	0.016	0.015	0.043	1.0*	8.61
32 (clay/glass)	8.82	0.462	0.020	0.040	0.038	1.7	3.64
33 (metal: primary)	2.67	0.413	0.033	0.025	0.079	0.6	2.43
34 (metal: fabricated)	5.61	0.557	0.078	0.090	0.123	1.1	4.61
35 (machinery)	4.53	1.070	0.103	0.271	0.148	7.3	10.75
36 (electronics)	2.85	1.020	0.122	0.167	0.185	4.1	9.68
37 (transportation)	0.79	0.556	0.076	0.081	0.095	4.1	6.00
38 (instruments)	5.52	1.675	0.144	0.191	0.173	7.2	12.32
39 (miscellaneous)	12.5	0.800	0.065	0.078	0.075	1.0*	8.13

Notes to Table 1:

All data used is for 1992. See the Data Appendix for the data sources. Column 2 lists the numbers of SIC manual products normalized by gross outputs ($billion). Column 3 lists the skilled-labor intensities, calculated as the ratios of skilled labor's (non-production workers') compensations to unskilled labor's (production workers') compensations. Column 4 lists the new goods' shares in product counts (the 4-digit counting approach). Column 5 lists the new goods' shares in outputs (the 4-digit matching approach). Column 6 lists the new goods' shares in product counts using the broad definition of new goods. Column 7 lists the private R&D-to-net-sale ratios. A "*" indicates that the R&D data is merged for two or more 2-digit industries. The merging is for 20 with 21, 22 with 23, 24 with 25, 29 with 13, and 27 with 31 and 39. Column 8 shows computers' shares in total investment.

Table 2 Summary Statistics

Variable Name	Nos. Obs.	Nos. Positive Obs.	Mean	Std. Dev.	Min.	Max.
ng-matching (4-digit matching)	458	257	0.108	0.177	0	1
ng-counting (4-digit counting)	458	257	0.103	0.162	0	1
ng-broad (broad definition)	458	257	0.176	0.231	0	1
ng-matching5 (5-digit matching)	1250	492	0.103	0.228	0	1

Notes to Table 2:

The industries 2064 (candy) and 2067 (chewing gum) are merged.

Table 3 New Goods' Average Skilled-Labor Intensity and Contribution to the Relative Demand for Skilled-Labor

	Ave. Skill.-Labor Intensity			**Wage-bill Decomp.**			**Contribution of**			
							New Gd.	Old Gd.		R&D Int.
End Year	New Gd.	Old Gd.	Diff.	Overall	Within	Between		Between	Within	New Gd.
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
87				0.059	58.37%	41.63%				
89				0.064	58.21%	41.79%				
92				0.076	66.11%	33.89%				
94				0.063	67.81%	32.47%				
	4-digit matching (*ng-matching*)						4-digit matching (*ng-matching*)			
87	0.82	0.6	38.31%				27.96%	22.13%	49.91%	27.28%
89	0.84	0.61	38.50%				26.36%	23.73%	49.91%	25.60%
92	0.93	0.64	43.47%				24.55%	18.58%	56.87%	23.21%
94	0.87	0.6	44.44%				26.42%	15.14%	58.44%	25.36%
	4-digit counting (*ng-counting*)						4-digit counting (*ng-counting*)			
87	0.87	0.59	46.75%				29.27%	20.35%	50.38%	25.13%
89	0.88	0.61	46.08%				27.64%	22.05%	50.31%	23.47%
92	0.97	0.64	51.25%				25.98%	16.88%	57.14%	21.56%
94	0.91	0.6	52.08%				28.19%	13.14%	58.67%	23.40%
	broad definition (*ng-broad*)						broad definition (*ng-broad*)			
87	0.77	0.59	29.99%				36.86%	23.89%	39.25%	34.12%
89	0.78	0.6	29.89%				34.97%	25.37%	39.66%	32.05%
92	0.84	0.64	31.93%				32.65%	20.53%	46.82%	28.85%
94	0.79	0.6	33.15%				34.13%	18.40%	47.47%	30.65%
	5-digit matching (*ng-matching5*)						5-digit matching (*ng-matching5*)			
92	0.96	0.64	48.81%				27.21%	-	-	25.24%

Notes to Table 3:

The calculation of the average skilled-labor intensity is based on equation (1). The wage-bill decomposition is based on equation (3). The contributions of new goods and the two components of old goods are calculated using equations (4) – (5.3). The "R&D intensive" new goods are those in the five 2-digit industries with the highest R&D-to-net-sale ratios (see Table 1): 28 (chemicals), 35 (machinery), 36 (electronics), 37 (transportation) and 38 (instruments). When the 5-digit matching data is used, the between and within components of the old goods cannot be calculated using equations (5.2) and (5.3) because the data for periods 1 and 0 are at different levels of dis-aggregation (the former 5-digit product classes and the latter 4-digit industries).

Table 4 New Goods' Correlation with Skill Upgrading: Regression Analysis

	Using equation (6)					Using equation (7)				
Variable Names	**Mean**	**Std. Dev.**	**Coefficients**		**Contribution**	**Mean**	**Std. Dev.**	**Coefficients**		**Contribution**
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dep. Variables										
Skill Upgrading	0.22	0.37								
$\Delta\theta_s(z)$						-0.012	0.28			
$\Delta\theta_u(z)$						-0.23	0.26			
Indep. Variables										
Cap. Deepening	0.079	0.39	0.147	0.146	5.31%					
			(0.06)	(0.06)						
Change in Output	0.22	0.55	0.367	0.280	28.96%					
			(0.04)	(0.04)						
Comp. Investment	6.26	6.08	0.013	0.013	36.77%	6.07	6.17	-0.000146	-0.0082	18.69%
(Share)			(0.00)	(0.00)				(0.0024)	(0.0021)	
Office machinery	0.075	0.066	0.556	0.327	11.22%	0.07	0.064	0.805	0.5	9.67%
(Share)			(0.37)	(0.36)				(0.31)	(0.28)	
High-tech cap.	0.12	0.079	0.201	0.305	17.46%	0.13	0.077	0.041	-0.17	11.93%
(Share)			(0.30)	(0.28)				(0.25)	(0.22)	
Out-sourcing	0.052	0.07	0.317	0.351	8.48%	0.055	0.074	-0.61	-0.65	0.88%
			(0.22)	(0.21)				(0.19)	(0.17)	
Constant			-0.043	-0.082				-0.029	-0.14	48.61%
			(0.03)	(0.03)				(0.03)	(0.03)	
ng-matching	0.12	0.17		0.549	29.52%	0.12	0.18	-0.022	-0.21	10.21%
				(0.09)				(0.07)	(0.07)	
Adjusted R^2			0.32	0.37				0.05	0.0935	

Notes to Table 4:

The regression (6) is weighted by the average of total labor compensation in 79 and 92, and standard errors are in the brackets. The regression (7) is weighted by the average of real net output in 79 and 92, and standard errors are in the brackets. Column 9 reports the results of the skilled-labor equation (i.e. by having $x = s$ in equation (7)). Column 10 reports the results of the unskilled-labor equation (i.e. by having $x = u$ in equation (7)).