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New Goods and Rising Skill Premium: An Empirical Investigation

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AN EMPIRICAL INVESTIGATION*

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Abstract:

This paper identifies and measures new goods in the U.S. manufacturing sector in the late 1970s and 1980s, and finds that: (*i*) The average skilled-labor intensity of new goods exceeds that of old goods by over 40%; (*ii*) even within 4-digit industries, new goods are slightly more skilled-labor intensive than old goods (by about 4%); *(iii*) new goods can account for about 30% of the increase in the relative demand for skilled labor. Therefore, new goods help explain the rising skill premium in the U.S. Furthermore, new goods provide a direct measure of technological changes so that this paper provides new evidence that technology has shifted demand in favor of skilled labor and finds that a sizeable "between" component of the rise in the relative demand for skilled labor is due to technology.

Key Words: new goods; rising skill premium; technology; average skilled-labor intensity; relative demand for skilled labor.

JEL Classification: J31 ; O30

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Section 1. Introduction

It is well-documented that the wages of skilled workers relative to unskilled workers increased steadily in the U.S. in the late 1970s and 1980s (e.g. Bound and Johnson [1992], Katz and Murphy [1992]). Meanwhile, many new products emerged in this period. Some are manufacturing products (e.g. fiber optic cables), others are service products (e.g. Windows series software); some have formidable names (e.g. NMRI: nuclear magnetic resonance imaging), but others we use every day (e.g. VCRs); some have names the mention of which immediately reminds us of "high-tech" (e.g. CT scanners), but others seem so common that we take them for granted (e.g. soft contact lens)…[1] This paper investigates the link between new goods and the rising skill premium[2] in the U.S., and finds that new goods can account for about 30% of the rise in the relative demand for skilled labor in the U.S. manufacturing sector. Therefore, new goods help explain the rising skill premium in the U.S. empirically. Furthermore, new goods provide a direct measure of technology, so that this paper finds new evidence that technology has shifted demand in favor of skilled labor.

The literature on the rising skill premium is large and growing. The consensus appears to be that the rising skill premium is driven by an increase in the relative demand for skilled labor, because the late 1970s and 1980s witnessed a considerable increase in the relative supply of skilled labor (e.g. Katz and Murphy [1992], Katz and Autor [1998]). As there are many demand-side factors (e.g. technology, trade, defense build-up…), it is desirable to know the contribution of each one, and the first cut taken in the literature is the "within-between" decomposition. The increase in skilled labor's share in the aggregate wage bill (or employment) is decomposed into a "between" component and a "within" component (e.g. Bound and Johnson [1992], Berman,

[1] More examples can be found in, for instance, Gray [1992], Zangwill [1993], Zeisset and Wallace [1998], and various case studies by the Design Center of Kobenhavn, Dansk, and the now defunct Office of Technology Assessment.

[2] Wage inequality has two components: (1) skill premium, or the wage difference between workers with different skills; (2) residual wage inequality, or the wage difference between workers with similar skills (see Katz and Autor [1998]).

Bound and Griliches [1994], Autor, Katz and Krueger [1998]). The former arises from changes in sectoral shares in the aggregate wage bill (or employment), and is interpreted to measure the contribution of between-industry product demand shifts. The latter arises from changes in skilled labor's wage-bill (or employment) shares within each sector, and is interpreted to measure the contribution of within-industry skill upgrading. The roles of the various demand-side factors are then analyzed in this within-between framework. For example, trade and defense build-up are believed to be in the "between" component,[3] and technology (e.g. skill-biased technological change or SBTC) in the "within" component. Since the "within" component is larger, technology is inferred to play a major role.

The natural next step is to measure technology directly and quantify its contribution. However, a direct measure for technology has remained elusive, and the attempts to establish a causal link between proxy variables for technology and higher wages for skilled workers have yielded mixed results. A number of studies document a strong cross-sectional correlation between the use of computers or automation technologies and higher wages or skill upgrading (e.g. Krueger [1993], Berman, Bound and Griliches [1994] and Autor, Katz and Krueger [1998]). DiNardo and Pischke [1997], however, discover an almost equally strong cross-sectional correlation between the use of pencils and higher wages for German workers, casting doubt on the inference that the use of computers leads to higher wages. In addition, Doms, Dunne and Troske [1997] find little correlation between skill upgrading and the adoption of factory automation technologies in their analysis of longitudinal plant-level data. This leads them to conclude that the cross-sectional correlation between the use of automation technologies and higher wages is due to the fact that plants with high-wage workforces are more likely to adopt these technologies.[4]

[3] Feenstra and Hanson [1999] find that trade also has a "within" component through outsourcing.

[4] Autor, Katz and Krueger [1998] find that lagged computer investment is strongly correlated with skill upgrading at the level of 2-digit industries (Table VII), and that workers' future use of computers on the job is strongly correlated with skill upgrading in the past (Table VI). While the former is consistent with the

Therefore, it seems both desirable and necessary to have a direct measure for technology (see, for instance, Berman, Bound and Machin [1998]). On the other hand, although the contribution of technology is believed to be in the "within" component *only*, the "between" component is still sizeable, and it is unclear what is driving it. Many studies examine the role of trade, and most of them find it small (e.g. Baldwin and Cain [1997]) or moderate (e.g. Feenstra and Hanson [1999])[5]. Berman, Bound and Griliches [1994] examine the role of defense build-up and also find it limited.

In this context, the contribution of this paper is as follows. First, new goods and technology are intimately related because the creation of many new products would be impossible without technological progress (e.g. personal computers), and in many cases, technology manifests its impact on the production techniques through the use of new equipment (e.g. industrial robots).[6] Thus technology (broadly interpreted) can be thought of as having two effects on the relative demand for skilled labor. The direct effect is through the creation of new goods (product innovation) with higher-than-average skilled-labor intensities. The indirect effect is to change the skilled-labor intensities of the *old* goods (process innovation). For example, the use of computers might have made the production of, say, chairs and tables, more skilled-labor intensive; this is the indirect effect. Furthermore, the production of computers themselves might also be more skilled-labor intensive than average; this is the direct effect. From this perspective, new goods provide a direct measure of technology, so that this paper finds new evidence that technology has shifted demand in favor of skilled labor. What's more, while the existing literature has mainly focused on the indirect effect of technology, this paper examines both effects.

notion that the use of computers in an industry leads to subsequent skill upgrading, the latter is consistent with the argument put forth by Doms, Dunne and Troske [1997].

[5] Other examples include Katz and Murphy [1992], Lawrence and Slaughter [1993] and Borjas, Freeman and Katz [1997]. Leamer [1996], however, finds the role of trade to be larger.

[6] Here, "technology" is to be broadly interpreted: a good idea (e.g. fast food) is a form of technological progress, as is automation.

Second, new goods are a demand-side factor, and its contribution has a sizeable "between" component because their creation expands skilled-labor intensive sectors; in other words, the role of technology is not limited to the "within" component. Therefore, the "within" and "between" components are not mutually exclusive, as the contributions of demand-side factors could show up in both. A similar point is made in Feenstra and Hanson [1999] who show that trade has a sizeable "within" component via outsourcing.

Thirdly, new goods increase the relative demand for skilled labor by using it more intensively than old goods. This is because following the creation of the new goods, 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. Since the new goods are more skilled-labor intensive, 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. Therefore, new goods can be a valid theoretical explanation for the rising skill premium if, on average, they are more skilled-labor intensive than the old goods (see Xiang [2002]). This paper finds a systematic way to identify and measure new goods in the U.S. manufacturing sector in the late 1970s and 1980s.

Finally, the contribution of new goods is quantitatively significant: the average skilled-labor intensity of new goods exceeds that of old goods by over 40%, and new goods could account for about 30% of the rise in the relative demand for skilled labor. This finding is robust to the measurement approaches and the definitions of new goods used. Furthermore, even within 4-digit industries, new goods are slightly more skilled-labor intensive than old goods (by about 4%).

Although new goods are a result of technological innovation, they represent product innovations, a concept distinct from SBTC, which is a form of process innovation (i.e. the change in the production techniques of existing products). This distinction is meaningful. For example, product and process innovations may have different welfare implications.[7] Suppose both new goods and SBTC occur with no change in total-factor productivity (TFP); then in both cases, the relative wage of unskilled workers falls. However, in the case of new goods, the welfare of unskilled workers might nonetheless increase due to an expanded set of consumer products, whereas in the case of SBTC, their welfare declines. On the other hand, from a historical point of view, the contribution of new goods might not be limited to the late 1970s and 1980s, just like SBTC.[8] For example, abundant anecdotal evidence suggests that product innovation has been an integral part of people's daily lives since the 1950s: commercial jet planes and TVs in the late 40s and 50s, liquid paper in the 50s, disposable diapers in the 60s, fast food in the late 60s and 70s, Post-It notes and video games in the 70s, VCRs in the late 70s and 80s, and CD players in the 80s[9]…

The analytical framework of the paper is straightforward. The change in the relative demand for skilled labor is decomposed into three components: the effects of new goods, and the "between" and "within" components of the old goods. The first component measures the direct effect of new goods and technology, and their indirect effect is a portion of the third component. This portion can then be identified by a regression (Berman, Bound and Griliches [1994]) and a linear decomposition (Feenstra and Hanson [1999]).

The organization of the paper is as follows. Section 2 discusses the identification of the new goods in detail, and Section 3 discusses their measurement and presents some summary statistics. Section 4 measures the direct effect of new goods and technology, and Section 5 measures their indirect effect. Finally, Section 6 concludes and discusses possible agendas for future research.

[7] See Bresnahan and Gordon [1997] or Trajtenberg [1990] for an in-depth discussion of the welfare implications of new products.
[8] See, for example, Autor and Katz [1998] and Goldin and Katz [1998] for the historical roles of SBTC.
[9] These examples are taken from Jenkins [1977], Miller and Nowak [1977], Marty [1997] and Haven [1994].

Section 2. Identification

Before the significance of new goods can be measured, they need to be identified. 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 tends to find new goods more skilled-labor intensive than they actually are, other things equal. On the other hand, looking at patent data does not work, either, because a single new product may have many patents (e.g. according to Trajtenberg [1990], the CT scanner has 456 patents scattered in over 75 patent subclasses), and there is also no good mapping between the classification of patents and the SIC (Standard Industrial Classification) system (see Trajtenberg [1990] for more details).

This paper identifies the new goods by comparing the product listings of the 1987 SIC manual and the 1972 SIC manual. 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 "*".

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. Examples include "caulking hammers"(87) vs. "calking hammers"(72), "syrup"(87) vs. "sirup"(72), "guns over 30 mm…"(87) vs. "guns more than 30 mm…"(72), "…(explosives)"(87) vs. "…(explosive)"(72) and "meal, blood"(87) vs. "blood meal"(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. Examples include "Acid oil, produced in petroleum refineries"(87) vs. "acid oil"(72), "dresses, hand knit" (87) vs. "dresses, hand knit: for the trade" (72) and "hot water heaters, household: including non-electric" (87) vs. "hot water heaters, household" (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. Examples include "cabinets, office: except wood"(87) vs. "cabinets, office: metal"(72), "menus, except lithographed or gravure printed" (87) vs. "menus, letter press and screen printing" (72) and "food containers, sanitary: except folding"(87) vs. "food containers, liquid light, sanitary" (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. Examples include "dietary supplements, dairy and nondairy base", "pregnancy test kits", "correction fluid", "multimedia education kits", "fiber optic strands", "microwave ware, plastics", "video game machines, except coin-operated" and "treadmills"…

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, as shown in Sections 4 and 5.

It is worth emphasizing 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 the population of these new products. 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.[10] On the other hand, the change of the product lists may over-represent the change of the population of products if, for whatever reason, 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”, “personal computers”, “disc players, compact”, “pagers (one-way)”, “cellular radio telephones”

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

and "cable television equipment"… Finally, more evidence can be found after the new products identified in this way are measured.

Section 3. Measurement

3.1. The Three Approaches

Ideally, the data for the new goods would consist of factor payments and output of each individual product. However, such data is difficult to come by, and so imputation is necessary. Three different approaches are taken: 4-digit counting, 4-digit matching and 5-digit matching, with the approach further down the list yielding data closer to the ideal scenario.

In the 4-digit counting approach, the imputation is based on the ratio of the number of new goods in a 4-digit (87) SIC industry to the total number of (87) SIC manual products listed for this industry, and this ratio (denoted by *ngratio*) is the proportion of industry output and factor payments assigned to the new products. For example, if 10 products are listed for an industry and 2 of them are identified as new, and the industry pays $300 to skilled workers and $200 to unskilled workers and produces $1000 worth of output, then *ngratio* is 0.2, and the output of new goods is imputed to be $200, and the payments to skilled and unskilled workers employed in the production of these new goods imputed to be $60 and $40, respectively.

This approach is straightforward and it seems plausible to expect that as *ngratio* gets higher, new goods account for a higher proportion of the industry output and factor payments. However, this approach assumes that: (1) the value of output does not vary across products within the same industry (Assumption 1); (2) the shares of factor payments in output do not vary across products within the same industry and neither do skilled-labor intensities (Assumption 2). Both assumptions are likely to fail, and therefore imposing them leads to measurement errors.

The 4-digit matching approach controls for the measurement errors caused by imposing Assumption 1 by matching the new goods (SIC manual products) to the 7-digit products in the 1992 Census of Manufactures (CM) and Current Industrial Report (CIR). Because the (gross) output (i.e. value of shipments) data of these 7-digit products is available, the new goods' output need not be imputed anymore. Then for each (4-digit) industry, the variable *ngratio* can be computed as the share of new goods in this industry's (gross) output, and the new goods' factor payments can be imputed in the same way as in the 4-digit counting approach but using this new definition of *ngratio*. Matching products between two different sources (SIC manuals and CM/CIR) might introduce additional measurement errors, and so the following two paragraphs briefly discuss the 92 CM/CIR coding system and the matching process. For more details, see the data appendix (Appendix 1).

The coding system of the 92 CM/CIR is based on the SIC classification system as defined by the 87 SIC manual. The manufacturing products are each assigned a 7-digit code and then grouped into product classes (the first 5 digits of the 7-digit codes), and product classes are grouped into industries (the first 4 digits) so that the coverage of the group is progressively narrower with the successive addition of digits (see Table 3.1 for an example). The body of 7-digit codes in the 92 CM/CIR has about 11,000 items, a disaggregation level comparable to that of the product listing of the 87 SIC manual.

As a result, the matching 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. For instance, "Heads-up display (HUD) systems, aeronautical" is matched to "Airborne navigation heads-up display (hud) systems" (CIR 3812269), and "Optical scanning devices, computer peripheral equipment" matched to five CIR products: "computer optical scanning bar code devices" (3577114), "computer optical scanning OCR equipment" (3577116), "computer optical flat bed scanners" (3577118), "computer optical hand held scanners" (3577122) and "other computer optical scanning devices other than bar code or OCR devices" (3577124). However, such a straightforward matching by product names is not always feasible, and the help of the industry analysts at the U.S. Census Bureau was sought (for about 250 out of 825 products). For example, "Hydrostatic drives (transmission)" is matched to "Aerospace-type hydraulic fluid power motor packages, motor/gearbox, motor/valve, motor/generator, and similar combination units" (CIR 3594687). Therefore the additional measurement errors that the matching process introduces are likely to be much less severe than those caused by imposing Assumption 1.

Unfortunately, the most disaggregated factor payments data in the 92 CM is at the 5-digit (product class) level, and so the measurement errors caused by imposing Assumption 2 can only be partially controlled for by having *ngratio* as the share of the new goods in the gross output of a product class and then imputing the new goods' factor payments within the product classes. In other words, the skilled-labor intensities could vary across (5-digit) product classes within the same (4-digit) industry, but they are identical for all the (7-digit) products within the same product class. This is the 5-digit matching approach. Although this is the most accurate of the three approaches, it is not always feasible because each CM uses a different coding system at the 5- and 7-digit levels,[11] and CM data is available only every five years (years ending in 2 and 7). Therefore, most of the empirical analysis is based on 4-digit matching, and robustness checks using the other two approaches are performed whenever possible. As will become clear, these three approaches generate similar results, which is perhaps surprising given their differences.

3.2. Indirect Evidence for Identification

Measuring the new goods provides a piece of indirect evidence for their identification. A remarkable feature of many new products is that the first couple of years after their introduction are often characterized by declining prices and rising sales in quantity, probably due to increasing supply (see Gordon [1990] for the case of electrical appliances such as VCRs[12], microwave ovens and TV sets, Trajtenberg [1990] for head CAT scanners, and Brynjolfsson [1997] for mainframe computers). Do the new goods identified in Section 2 also have this property? The answer is a

[11] The CM coding system at the 4-digit level is defined by the SIC manual. However, since the SIC manual does not define 5- and 7-digit codes, a set of them is created for each CM and can change substantially from one CM to another.
[12] An illustrative 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.

clear "yes." Assuming that *ngratio* is time-invariant, and using the 4-digit matching data, Figure 3.1 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 3.2 shows that during this period, the new goods' share in real manufacturing net output (i.e. value added) steadily increases.

3.3 Some Summary Statistics of *ngratio*

First, as reported in Table 3.2, *ngratio* is positive for 257 out of 458 4-digit (87 SIC) industries,[13] suggesting that new goods are widespread. For each 2-digit industry group, the numbers of 4-digit industries with some new goods are reported in the 3rd column of Table 3.3, and the total numbers of 4-digit industries in the 2nd column. New goods are present in all 2-digit industry groups except 21, tobacco and related products.

Second, *ngratio* has a large variation with a mean of 0.11 and a standard deviation of 0.18 (see Table 3.2), and this feature also holds for all 2-digit industry groups except 21 (see the 4th column of Table 3.3). In all cases, the standard deviations of *ngratio* normalized by the means exceed 1. For the sake of comparison, the normalized standard deviation for the uniform distribution over [0,1] is about 0.58. To further illustrate the point, Figure 3.3 plots the histogram of *ngratio* for the 4-digit industries in industry group 38. The numbers of observations at both ends of the distribution are large.

Thirdly, new goods tend to be concentrated in large industries because they account for 7% (825/11,809) of the number of manufacturing products listed in the 87 SIC manual but roughly 12% of the manufacturing (nominal) net output in 1992 (see the last column of Table 3.4). Also, the correlation coefficient between *ngratio* and (nominal) net output is about 0.04 (see Table 3.5).

Finally, *ngratio* is strongly and positively correlated with the skilled-labor intensity, measured as the ratio of non-production workers' (skilled labor) compensation to production workers' (unskilled labor) compensation (see, for instance, Berman, Bound and Griliches [1994]

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[13] Industries 2064 (candy) and 2067 (chewing gum) are merged.

for the justification of having non-production (production) workers as skilled (unskilled) labor).[14] The correlation coefficient is a significant 0.26 for 1992, as shown in Table 3.6. To further illustrate the point, Figure 3.4 plots the skilled-labor intensities of the 4-digit industries against *ngratio* for 1992. Also plotted is the regression line with the skilled-labor intensity as the dependent variable, and its slope is about 0.9 (significant). This suggests that new goods tend to be concentrated in skilled-labor intensive industries.[15]

These properties are robust to both the measurement approaches used and to the end years chosen. When the 4-digit counting approach is used, new goods appear in 257 of the 458 4-digit industries with a mean of 0.10 and a standard deviation of 0.16 (Table 3.2). For 1992, the correlation coefficient between *ngratio* and net output is 0.07 (Table 3.5) while that between *ngratio* and skilled-labor intensities is a significant 0.33 (Table 3.6). When the 5-digit matching approach is used, new goods appear in 492 of the 1250 5-digit product classes,[16] have a mean of 0.10 and a standard deviation of 0.23. The correlation coefficient between *ngratio* and output is 0.04, while that between *ngratio* and skilled-labor intensities is 0.08. The variations of *ngratio* under both measurement approaches are also large within each 2-digit industry group, as reported in the rest of Table 3.3. On the other hand, while using either the 4-digit matching or the 4-digit

[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] In Figure 3.4, (1) to show the details better, only the observations with skilled-labor intensities below 3 are included (this excludes 5 observations); (2) above the regression line is a collection of high-skilled-labor-intensity and high-*ngratio* industries from industry groups 35 (industrial machinery and equipment), 36 (electronic and other electric equipment) and 38 (instruments and related products), and below the regression line is a collection of high-*ngratio* industries with medium to low skilled-labor intensities from such industry groups as 20 (food and kindred products) and 30 (rubber and miscellaneous plastics products).

[16] This is a mixture of 1201 5-digit classes, 48 4-digit industries and 1 aggregation group of 5-digit product classes. Among the 1449 5-digit product classes in the 1992 CM, 75 have their data withheld, and 48 4-digit industries contain at least one of them. All the 5-digit product classes in these 48 4-digit industries are dropped, and the rest combined with these 48 4-digit industries. On the other hand, product classes 32297 and 32298 are aggregated to be consistent with the 1993 CIR.

counting approach but using 87, 89 or 94 as the end years, similar results are obtained, as shown in the rest of Tables 3.4 ~ 3.6.

Section 4. The Direct Effect of Technology: New Goods

Two frameworks can be used to measure the contribution of new goods to the increase in the relative demand for skilled labor. Framework A is based on the standard within-between decomposition using wage bills (e.g. Berman, Bound and Griliches [1994]) and (indirectly) measures the relative demand for skilled labor by its share in the aggregate wage bill. Framework B is based on the theoretical framework of Xiang [2002] and (directly) measures the relative demand for skilled labor by calculating the average skilled-labor intensity. Although these two frameworks yield similar results as far as the effects of new goods are concerned, Framework A might under-estimate the contribution of between-industry product demand shifts because it makes the inference without using any information on sectoral output. The structure of Framework A and its results are presented first, followed by the structure and results of Framework B. The differences between these two frameworks are also discussed.

4.1. Framework A: Structure

Denote skilled labor's share in the aggregate wage bill by μ^w. 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 the wage bill of sector z. Then (see Appendix 2 for its derivation):

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

It is standard in the literature to decompose the change in μ^w into the following two components:

(2) $$\Delta\mu^w = G^w_{btw} + G^w_{wthn}$$

$$G^w_{btw} = \Sigma_z \Delta m(z)\ \overline{\theta_s^w(z)} \text{ and } G^w_{wthn} = \Sigma_z \Delta\theta_s^w(z)\ \overline{m(z)}$$

where a bar over a term represents averaging over time. The "between" component (G^w_{btw}) adds up the changes in the sectoral shares in the aggregate wage bill ($\Delta m(z)$) holding constant skilled labor's wage-bill shares within each sector, and is meant to measure the contribution of between-industry product demand shifts. The "within" component (G^{w}_{wthn}) adds up the changes in skilled labor's wage-bill shares for all the sectors $(\Delta\theta_s^{w}(z))$ holding constant each sector's share in the aggregate wage bill, and is meant to measure the contribution of within-industry skill upgrading.

When new goods are present, the change in μ^w can be decomposed into the contribution of the new goods (denoted by G_n^{w}) and the contribution of the old goods; then applying (2) to the latter yields the "between" and "within" components of the old goods (denoted by $G^{w}_{o,btw}$ and $G^{w}_{o,wthn}$ respectively) (see Appendix 2 for the derivation of (3)):

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

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

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

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

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

While (4.2) and (4.3) are a straightforward application of (2) to the old goods, (4.1) merits more discussion. Suppose new goods were the only change between period 0 and period 1, and for a sector *z*, its share in the aggregate wage bill (*m(z)*) also 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)*,[17] 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 against which the "complementarity" between this old good and the new goods is measured. That is to say, after the arrival of the new goods, an old good, *z*, is a "complement" of the new goods if its consumption share exceeds $\rho^w m(z)|_{t=0}$ (i.e., its consumption share has declined by proportionately less than the average of all the old goods). Likewise, good *z* is a "substitute" for the new goods if its consumption share falls below $\rho^w m(z)|_{t=0}$ (i.e. its consumption share has declined by proportionately 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,[18] Equation (4.1) correctly measures the effects of the new goods.[19,20] However, Equation (4.1) tends to over (under)-

[17] The ideal measurement of this exogenous decline requires knowledge of the change in the demand for each individual old good.

[18] To be rigorous, for each old good *z,* let $\varepsilon(z) \equiv b(z)|_{t=1} - \rho^w b(z)|_{t=0}$, where *b(z)* denotes good *z*'s consumption share. Then $\varepsilon(z)$ is the complementarity between *z* and the new goods, and when the complementarities of all the old goods are uncorrelated with their skilled-labor intensities, $\Sigma_z^{old}\varepsilon(z)\theta_s^w(z)|_{t=0} = 0$. This condition is satisfied when the representative consumer has CES (Constant Elasticity of Substitution) preferences. For more details, see Xiang [2002].

[19] Notice 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). Thus it is unclear whether and how the *share of contribution* of each component is biased. This caveat also applies to (7)~(9.3).

[20] Notice that in an open economy, Equation (4.1) might not fully capture the general equilibrium effects of new goods since they could show up in (4.2). 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 [2002] 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 (4.2). Therefore, (4.1) (as well as (8.1) and (9.1)) 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, (4.1) (as well as (8.1) and (9.1)) tends to under-estimate the contribution of the new goods. Capturing the full general equilibrium effects of new goods is difficult (e.g., one needs data on new goods in the rest of the U.S. economy and the rest of the world).

estimate the effects of the new goods if the complementarities of the old goods are positively (negatively) correlated with their skilled-labor intensities.

4.2 Framework A: Results

First, Table 4.1 reports the results of a standard within-between decomposition using (2). For the four periods this paper is primarily interested in (79-87, 79-89, 79-92 and 79-94), the contributions of the "between" component are 42%, 42%, 34% and 32%, respectively. In other words, about 37% of the increase in the relative demand for skilled labor (measured as skilled labor's share in the aggregate wage bill, μ^w) is due to the "between" component. This result is similar to the literature (e.g., Berman, Bound and Griliches [1994], Katz and Autor [1998]).

Second, Table 4.2 reports the contribution to the rise in μ^w by the new goods and the other two components of Equation (3) for the same four periods, 79-87, 79-89, 79-92 and 79-94. The 1st panel uses the 4-digit matching approach. On average, new goods account for about 26% of the increase in the relative demand for skilled labor, and about 25% for the period 79-92. Similar results are obtained when the other measurement approaches are used. With the 4-digit counting approach, the contribution of new goods rises slightly to 28% on average and 26% for the period 79-92 (the 2nd panel), and with the 5-digit matching approach, it is 27% for the period 79-92 (the 3rd panel). The result is also robust to the definitions of new goods used. The last panel of Table 4.2 reports the results obtained by using the broad definition of new goods and the 4-digit counting approach. The contribution of new goods rises to 35% on average, and 33% for the period 79-92. On the other hand, the contribution of exogenous product demand shifts (the "between" component) of the old goods is about 20%, 18%, and 22% on average (the 1st, 2nd and 4th panels), and that of exogenous changes in the production techniques (the "within" component) of the old goods about 54%, 54% and 43% on average[21]. Summarizing the results in a sketch, about 30% (26% - 35%) of the rise in the relative demand for skilled labor can be attributed to

[21] Equations (4.2) and (4.3) are difficult to implement using the 5-digit matching approach 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).

new goods, 20% to product demand shifts among old goods, and 50% to changes in the production techniques of the old goods.

Comparing these numbers (obtained using Equations (3) ~ (4.3) so that the contribution of new goods has been identified) with the results of the within-between decomposition in Table 4.1 (obtained using Equation (2) so that new goods and old goods are all mixed together), about 17% of the increase in the relative demand for skilled labor inside the latter's "between" component, or nearly half of the "between" component itself, can be attributed to new goods. Because new goods provide a direct measure for technology, this says that the contribution of technology has a sizeable "between" component. On the other hand, about 13% of the increase in the relative demand for skilled labor inside the "within" component (of Equation (2)) can be attributed to new goods.[22]

4.3. Framework B: Structure

It can be shown (Xiang [2002]) that the relative demand for skilled labor (denoted by μ) equals the average skilled-labor intensity when there are two or more factors of production:

$$\mu = \frac{\Sigma_z b(z)\theta_s(z)}{\Sigma_z b(z)\theta_u(z)} \qquad (5)$$

where *b(z)* is sector *z*'s share in aggregate consumption expenditure and $\theta_s(z)$ ($\theta_u(z)$) the share of skilled (unskilled) labor's income in sector *z*'s output. The numerator of the right-hand side of (5) is the average of the income shares of skilled labor ($\theta_s(z)$) weighted by the sectoral consumption shares (*b(z)*), and this weighted average represents the demand for skilled labor. Likewise, the denominator of the right-hand side of (5) is the average of the income shares of unskilled labor ($\theta_u(z)$) weighted by the sectoral consumption shares (*b(z)*), and this weighted average represents the demand for unskilled labor. Thus the ratio of these two weighted averages, or the average

[22] In the standard within-between decomposition (Equation (2)), the "between" component includes the exogenous product demand shifts between the old goods and the new goods, and the "within" component includes sectoral changes in the production techniques caused by the changes in the mix of products. Thus the effects of new goods are present in both components.

skilled-labor intensity, equals the relative demand for skilled labor. In other words, because labor demand is generated by the production of consumption or intermediate goods, the relative demand for skilled labor is the average intensity of its usage in production.

Denote the numerator and denominator of the right-hand side of (5) by D_s and D_u, respectively (i.e. $D_s \equiv \Sigma_z b(z)\theta_s(z)$, $D_u \equiv \Sigma_z b(z)\theta_u(z)$ and $\mu = D_s/D_u$). Then the log change of μ can be approximated as:[23]

(6) $$\Delta ln\mu = \Delta lnD_s - \Delta lnD_u \cong \Delta D_s/D_{s,0} - \Delta D_u/D_{u,0}$$

Similar to (3)~(4.3), both ΔD_s and ΔD_u can be decomposed into the effects of the new goods $(\Delta D_{x,n})$ and the "between" and "within" components of the old goods $(\Delta D_{x,o}^{btw}$ and $\Delta D_{x,o}^{wthn}$, respectively), with similar intuition:

(7) $$\Delta D_x = \Delta D_{x,n} + \Delta D_{x,o}^{btw} + \Delta D_{x,o}^{wthn}\ ;\ x = s,\ u$$

(8.1) $$\Delta D_{x,n} = \Sigma_z^{new} b(z)\theta_x(z) + \Sigma_z^{old}[\rho b(z)]\theta_x(z)|_{t=0} - \Sigma_z^{old} b(z)\theta_x(z)|_{t=0};\ x=s,\ u$$

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

(8.2) $$\Delta D_{x,o}^{btw} = \Sigma_z^{old}\Delta b(z)\ \overline{\theta_x(z)}\ ;\ \Delta b(z) = b(z)|_{t=1} - \rho b(z)|_{t=0};\ x=s,u$$

(8.3) $$\Delta D_{x,o}^{wthn} = \Sigma_z^{old}\Delta\theta_x(z)\ \overline{b(z)}\ ;\ \overline{b(z)} = (b(z)|_{t=1} + \rho b(z)|_{t=0})/2;\ x=s,u$$

These three components' contributions towards the change in the relative demand for skilled labor are then:

(9.1) $$G_n = \Delta D_{s,n}/(D_{s,0}) - \Delta D_{u,n}/(D_{u,0})$$

(9.2) $$G_{o,btw} = \Delta D_{s,o}^{btw}/(D_{s,0}) - \Delta D_{u,o}^{btw}/(D_{u,0})$$

(9.3) $$G_{o,wthn} = \Delta D_{s,o}^{wthn}/(D_{s,0}) - \Delta D_{u,o}^{wthn}/(D_{u,0})$$

In this framework ((5)~(9.3)), the contribution of the new goods (G_n) depends critically on their average skilled-labor intensity, μ_n:

[23] The approximation ensures that the contributions of all the components (i.e. the left-hand sides of (9.1) ~ (9.3) below) add up to 1.

(10.1) $$\mu_n \equiv \frac{\Sigma_z^{new} b(z)\theta_s(z)}{\Sigma_z^{new} b(z)\theta_u(z)}$$

The intuition is, if new goods were the only change between period 0 and period 1, the total relative demand for skilled labor in period 1 (denoted by μ_i) would be:

(10.2) $$\mu_i = \frac{\Sigma_z^{new} b(z)\theta_s(z) + \Sigma_z^{old}[\rho b(z)]\theta_s(z)|_{t=0}}{\Sigma_z^{new} b(z)\theta_u(z) + \Sigma_z^{old}[\rho b(z)]\theta_u(z)|_{t=0}}$$

Clearly, μ_i can be thought of as the average of the average skilled-labor intensities of the new goods (the ratio of the first terms in the numerator and denominator) and of the old goods (the ratio of the second terms in the numerator and denominator). Thus new goods tend to increase the relative demand for skilled labor if their average skilled-labor intensity exceeds that of the old goods, and the more it does so, the larger is the contribution of the new goods. On the other hand, in μ_i, the average skilled-labor intensities of the new goods and of the old goods are weighted by the total consumption shares of these two groups of goods ($\Sigma_z^{new} b(z)$ and $\Sigma_z^{old} \rho b(z)|_{t=0}$, respectively); thus as the total consumption share of the new goods gets higher, μ_i gets closer to μ_n and the contribution of the new goods increases because μ_n exceeds the average skilled-labor intensity of the old goods by over 40% (see Section 4.4).

The main difference between Frameworks A and B is not how they measure the relative demand for skilled labor. In fact, Appendix 2 shows that μ^w (in Equation (1), Framework A) is a monotonic transformation of μ (in Equation (5), Framework B):

(11) $$\mu^w = \mu/(1+\mu)$$

Rather, the main difference is how Frameworks A and B infer the contribution of exogenous (between-industry) product demand shifts: Framework B does so by explicitly using the information on sectoral output (see, for example, Equation (8.2) with ρ = 1) whereas Framework A uses only the information on labor compensation (see, for example, Equation (2)). Suppose that exogenous product demand shifts are absent (so that there is no change in sectoral output). Then

Framework A would attribute a negative contribution to these demand shifts if the skilled-labor intensive industries see a decline in their skilled-labor payments, but Framework B would not make the same mistake (see Appendix 3 for a numerical example). Therefore when exogenous product demand shifts happen alongside within-industry skill upgrading, Framework A might under-estimate the contribution of the former due to this downward bias (see Appendix 3 for a numerical example), which arises because Framework A makes the inference without using any information on sectoral output.

Another difference between Frameworks A and B is that Framework B is more informative. With more than two factors of production, is skill upgrading due to an increase in the demand for skilled labor, a decrease in the demand for unskilled labor, or both, or neither? The answer is difficult to find using Framework A, but not so using Framework B (see Section 4.4).

4.4. Framework B: Results

The 2nd ~ 4th columns of Table 4.3 show that averaging across the end years 87, 89, 92 and 94, new goods account for about 12% of manufacturing apparent consumption,[24] regardless of the measurement approaches used (the 1st, 2nd and 4th panels). This number is similar to the new goods' share in manufacturing net output (see Section 3.3 or Table 3.4). However, under the broad definition, the share of new goods in manufacturing apparent consumption increases to about 19% (the 3rd panel).

The 5th ~ 7th columns of Table 4.3 report the average skilled-labor intensities of the new goods and the old goods and their differences. The 1st panel shows that when the 4-digit matching approach is used, the average skilled-labor intensity of the new goods (about 0.9) exceeds that of the old goods (about 0.6) by about 40%, consistent with the finding of Section 3.3 that new goods tend to be concentrated in large and skilled-labor intensive industries. This result is robust to both the measurement approaches and the definitions of new goods used. When the 4-digit counting or

[24] Apparent consumption equals gross output – exports + imports. The use of apparent consumption is to be consistent with the theory, though using net output yields similar results.

5-digit matching approach is used (the 2nd and 4th panels), the average skilled-labor intensity of the new goods approaches 1 and exceeds that of the old goods by about 50%. When the broad definition of new goods and the 4-digit counting approach are used (the 3rd panel), the average skilled-labor intensity of the new goods falls to about 0.8, exceeding that of the old goods by about 30%.

Clearly, the new goods are much more skilled-labor intensive than the old goods within the manufacturing sector. Does this relation also hold within 4-digit industries? The investigation of this question is possible with the 5-digit matching approach. The left panel of Table 4.4 reports summary statistics for five variables for the 257 4-digit industries with some new goods: the share of new goods in apparent consumption, the average skilled-labor intensities of the new goods and old goods, and their differences, both weighted (by sectoral shares of apparent consumption) and un-weighted. As shown in the last two columns (of the left panel), the means of both weighted and un-weighted differences are about 0.035, or 4% of the mean of the average skilled-labor intensities of the old goods for the 257 industries (0.86). The last two rows show that for 117 out of the 257 4-digit industries, new goods are more skilled-labor intensive than old goods, and less for 92 industries. This implies that new goods are slightly more skilled-labor intensive than old goods even within the 4-digit industries.

One reason that the result is not strong could be that the most dis-aggregated labor compensation data is at the 5-digit product class level, still not dis-aggregated enough to distinguish the skilled-labor intensities of the new goods from those of the old goods: if both new goods and old goods are present in a product class, they will appear to have the same skilled-labor intensities because of the imputation. To see whether this matters, the right panel of Table 4.4 looks only at those 4-digit industries with at least one new 5-digit product class (i.e. *ngratio* = 1 for the product class). The result is slightly stronger. For the 25 industries that meet the criterion, the mean of the average skilled-labor intensities of the new goods exceeds that of the old goods by about 0.05 when un-weighted, and by 0.06 when weighted, or 6.5% and 7.9% of the mean of the average skilled-labor intensities of the old goods for the 25 industries (0.76). However, the results are still weak: the differences have large standard deviations (about 0.3), and for only 10 industries out of 25 do the average skilled-labor intensities of the new goods exceed those of the old goods.

In summary, based on variations across the 4-digit industries, the average skilled-labor intensity of the new goods exceeds that of the old goods by over 40% (30% ~ 52%). Notice that this difference is close to 50% if we use the narrow definition of new goods and 5-digit matching, the most accurate measurement approach, for the year 1992. Within the 4-digit industries with some new goods, the mean of the average skilled-labor intensities of the new goods slightly exceeds that of the old goods by about 4%.

The contributions of the new goods and the other components in Equation (7) can be calculated using (9.1) ~ (9.3), and the results are reported in Table 4.5. The numbers are very close to the results of Framework A (see Section 4.2 or Table 4.2). The 1st (2nd) panel shows that new goods account for about 26% (28%) of the increase in the relative demand for skilled labor when the 4-digit matching (counting) approach is used. Their contribution is 27% for the period 79-92 when the 5-digit matching approach is used (the 3rd panel), and rises to 36% when the broad definition of new goods and the 4-digit counting approach are used (the last panel). On the other hand, the "between" component of the old goods is about 20%, 18%, and 16% (the 1st, 2nd and last panels), and the "within" component of the old goods about 54%, 54% and 48%. Therefore, about 30% (26% - 36%) of the rise in the relative demand for skilled labor can be attributed to new goods, 20% to product demand shifts of the old goods, and 50% to changes in the production techniques of the old goods.

Finally, Table 4.6 presents the results of a within-between decomposition based on Framework B obtained by having $\rho = 1$ in Equations (8.2), (8.3), (9.2) and (9.3) and applying them to all the goods for the same six periods as in Table 4.1. The consumption share of a product is measured as its share in total net output (value-added) rather than in apparent consumption.[25] For the period 59-73, the "between" component accounts for about 12% of the total change, contrasting with the –41% in Table 4.1, and suggesting that Framework A underestimates the contribution of exogenous product demand shifts. This also happens for the period 73-79, as the contribution of the "between" component is 29% in Framework A but 54% in Framework B. However, for the periods this paper is primarily interested in (79-87, 79-89, 79-92 and 79-94), the decomposition results based on Framework B (Table 4.6) are very similar to Framework A (Table 4.1). Table 4.6 also illustrates that Framework B is more informative than Framework A. In every period, the demand for unskilled labor decreases (see the row labeled "Du") and the magnitude of the decrease is much larger than that of the change in the demand for skilled labor (see the row "Ds"), suggesting that the increase in the *relative* demand for skilled labor is driven by the decrease in the demand for unskilled labor.

Section 5. The Indirect Effect of Technology

The indirect effect of technology is measured by regressing skill upgrading on proxy variables for technology, controlling for structural variables (e.g. capital deepening) and other skill-upgrading contributors (e.g. outsourcing), the same as in the literature (e.g. Berman, Bound and Griliches [1994], Feenstra and Hanson [1999]). The twist of this section is to run the regression for the old goods and to attempt to address the endogeneity of capital deepening. Although this approach might not be able to distinguish causality from correlation[26] (see, for

[25] Using apparent consumption (total output – exports + imports) yields very similar results except for 59-73, in which case the relative demand for skilled labor *de*creases, and both the "within" and "between" components (0.017 and –0.0171) are very large compared with the total change (-0.000155). The reason is probably that 1959 and 1973 belong to different trade regimes. The early 1960s marked the accession to the General Agreement on Tariffs and Trade (GATT) of many newly independent developing countries, and in February 1965, Part IV on Trade and Development was adopted. The additional chapter of the GATT required developed countries to accord high priority to the reduction of trade barriers on products of developing countries (source: http://www.wto.org/english/thewto_e/minist_e/min96_e/chrono.htm). This could have led U.S. imports of unskilled-labor intensive manufactured goods to outgrow domestic gross output and exports.

[26] Addressing this issue is beyond the scope of this paper.

example, DiNardo and Pischke [1997] and Doms, Dunne and Troske [1997]), it allows us to identify the portion of skill upgrading "explained" by each regressor, netting out the effects of all the other regressors. In particular, there is some reassurance in finding that new goods matter for skill upgrading, even after controlling for various structural variables and proxy variables for technology.

5.1. Exogenous Capital Deepening

When capital is a fixed input, the following regression (weighted by $\overline{m^{old}(z)}$ in (4.3)) can be run for the *old* goods:

(12) $$\Delta\theta_s^w(z) = \alpha + \beta_1 \Delta ln(K/Y(z)) + \beta_2 \Delta lnY(z) + \beta_3 X_1 + \beta_4 X_2 + \varepsilon(z)$$

where X_1 contains the variables measuring the use of new technology by sector *z* (e.g. computer investment), and X_2 other factors that could lead to changes in the production techniques of the old goods (e.g. outsourcing). The dependent variable in (12), skill upgrading, adds up to the "within" component of the old goods ($G^w_{o,wthn}$ in (4.3)) in Framework A when weighted by $\overline{m^{old}(z)}$, and a linear decomposition identifies the contribution of each regressor.

The 2nd column of Table 5.1 reports the results of running (12) for the old goods only, and the left panel of Table 5.2 lists the summary statistics for the variables used. Notice that in contrast to the literature, capital deepening *($\Delta ln(K/Y)$)* has an insignificant coefficient of –0.03. (Running (12) for all the goods, however, yields similar results to the literature, as shown in the 3rd column of Table 5.1.) The other coefficients (see the 2nd column of Table 5.1 again) have the same signs as in Feenstra and Hanson [1999], with computer investment and outsourcing being statistically significant with coefficients of 0.016 and 0.42, respectively. The 11th column of Table 5.1 reports the "contributions" of each regressor in "explaining" the weighted mean of the dependent variable (i.e. skill upgrading of the old goods). For instance, the weighted mean of computer investment is 6.2 with a coefficient of 0.016, and so the part "explained" by computer investment is about 0.10 (6.2 × 0.016). Since the mean of skill upgrading of the old goods is about 0.20, the "contribution" of computer investment is about 51%. Altogether, the technology proxies (see Table 5.1 for the definitions of these variables) "explain" 84% of the mean of the dependent variable: 51% from computer investment, 12% from investment in office machines, and 21% from investment in "high-tech" capital. Outsourcing explains 11%, and the rest is attributed to output, capital deepening and the constant. The estimated contribution of outsourcing is comparable to Feenstra and Hanson [1999] while that of the technology proxies are higher than in that study. Because the dependent variable adds up to the "within" component of the old goods whose contribution is about 50% of the increase in the relative demand for skilled labor (see Section 4.2 or Table 4.2), the indirect effect of technology is about 42% (84% × 50%) of this increase. Together, new goods and technology proxies account for over 70% (30% plus 42%) of the increase in the relative demand for skilled labor.

The regression (12) also enables us to measure the contribution of new goods using the following simplistic approach. New goods could increase the relative demand for skilled labor either by expanding skilled-labor intensive sectors relative to unskilled-labor intensive ones at constant skilled-labor intensities, or by contributing to within-industry skill upgrading. The first component (the "between" component) can be calculated using Equation (4.1) but having the skilled-labor intensities of the *old* goods in the first term, and the second component (the "within" component) calculated by adding the variable *ngratio* into regression (12), running (12) for all the goods, and then computing the contribution of *ngratio*. Although theoretically unjustified, this alternative approach could be useful as a robustness check for Framework A.

As reported in the left panel of Table 5.3, the first component of the contribution of new goods is about 17% on average, and 14% for the period 79-92. On the other hand, the 4th column of Table 5.1 reports the results of running (12) for all the goods with *ngratio* added to the right hand side. This variable has a coefficient of 0.55 (significant) and a weighted mean of 0.12; i.e. new goods "explain" about 30% of the dependent variable (see the last column of Table 5.1). Because the dependent variable adds up to the "within" component of Equation (2), the second component of the contribution of new goods is about 20% (30% × 66%) of the increase in the relative demand for skilled labor for the period 79-92, and 19% on average (30% × 63%). Put these two components together, and the total contribution of the new goods is about 34% (of the increase in the relative demand for skilled labor) for the period 79-92 and 36% on average, comparable to the results of Framework A (see Section 4.2 or Table 4.2).

5.2. Endogenous Capital Deepening

Given the long horizon of the analysis (over 10 years), it seems appropriate to believe that firms have a long enough time to adjust their capital stocks. Then the capital-net-output-ratio at period 0 (k_0) can be used to instrument for capital deepening. Use a log form to be consistent with (12) and add $(lnk_0)^2$ to capture possible non-linearity:

(13) $$\Delta lnk = \alpha + \beta_1 lnk_0 + \beta_2 (lnk_0)^2 + \gamma_1 X_1 + \gamma_2 X_2 + \varepsilon_1$$

where X_1 and X_2 have the same meanings as in (12). The idea behind (13) is that capital deepening arises from firms' adjusting their actual capital stocks at period 0 to their desired levels of capital stocks at period 1, which are affected by technological changes and other factors such as outsourcing. The term $\beta_1 lnk_0$ corresponds to the firms' period-0 capital stocks (thus $\beta_1 < 0$ is expected), and the term $\gamma_1 X_1 + \gamma_2 X_2$ corresponds to the firms' desired levels of capital stocks. Implementing (13) amounts to using lnk_0 and $(lnk_0)^2$ as instruments for capital deepening (Δlnk) in (12).

The 5^{th} ~ 7^{th} columns of Table 5.1 report the results of the instrumental-variable (IV) estimation of (12) under three specifications: for the old goods only and for all goods with and without the variable *ngratio* as a regressor. When (12) is run for all goods without *ngratio* as a regressor, the coefficient of capital deepening changes a lot, from a significant 0.15 (3^{rd} column of Table 5.1) using OLS to an insignificant –0.08 using IV (6^{th} column), and a version of the Hausman test (see Davidson and MacKinnon [1993], Chapter 7) rejects the null hypothesis that the estimates based on OLS and IV are the same.[27] The story is similar when (12) is run for all the goods with *ngratio* as a regressor, but different when (12) is run for the old goods only: the results of OLS and IV are similar, and the coefficient of capital deepening is statistically indistinguishable from 0 under both OLS and IV (the 2nd and 5th columns of Table 5.1). On the other hand, the coefficients of the other regressors are similar under OLS and IV for all three specifications. Finally, the 8th ~ 10th columns of Table 5.1 report the results of running (13) under the same three specifications. In all three cases, β_1 is negative and significant.

An alternative approach to the IV estimation is to adopt the same translog specification as in (12) but without fixed inputs. Then imposing the zero-profit condition (the total cost is not observed, but it equals total sales when profits are zero) and the constant-returns-to-scale assumption (otherwise output appears on both sides of the regression) yields:

$$\Delta\theta_x(z) = \alpha' + \beta_3{}'X_1 + \beta_4{}'X_2 + \varepsilon'(z);\ x = s, u \tag{14}$$

where X_1 and X_2 have the same meanings as in (12) and (13). When weighted by $\overline{b(z)}$ in Equation (8.3), the dependent variables in (14) add up to the "within" components of the old goods ($\Delta D_{x,o}^{wthn}$) in Framework B.

Notice that the translog specification without fixed inputs would have the price of capital as a regressor; this variable is absent from (14) because it is difficult to measure accurate (see Berman, Bound and Griliches [1994]). Thus compared with (12), although (14) takes the endogeneity of capital deepening into account, it might miss useful information about changes in the price of capital contained in capital deepening; i.e. (14) is not necessarily a better specification than (12).

Table 5.4 reports the results of running (14) for the old goods only (see the columns labeled with "Old Goods"), and the right panel of Table 5.2 lists the summary statistics for the variables

[27] Allowing the error terms in (12) and (13) to be correlated within 2-digit industry groups (see Feenstra and Hanson [1999]), or dropping the shares of office equipment and high-tech capital and using White hetereoskedacity-consistent standard errors, yield qualitatively similar results. In both cases, the estimated coefficients remain the same; however, because of larger standard errors, the Hausman tests fail to reject the null hypothesis.

used. 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 the "within" component of the old goods. The calculation is done by subtracting a regressor's coefficient in the unskilled-labor equation from its coefficient in the skilled-labor equation, multiplying the difference by the regressor's mean, and then dividing the product by the difference of the mean of the dependent variables. For instance, the coefficient of computer investment is about –0.00075 in the skilled-labor equation and –0.0096 in the unskilled-labor equation, and its mean is about 4.9. Thus the part of skill upgrading of the old goods attributable to computer investment is about 0.05 ((0.0096-0.00075) ×4.9). Since the means of the income shares of skilled and unskilled labor are 0.01 and –0.18, respectively, the contribution of computer investment is about 23% (0.05/(0.01+0.18)).

A few findings are noticeable. First, the changes in the income shares of skilled labor are more difficult to explain than those of unskilled labor with a lower R^2 (about 0.04 versus 0.07). Second, most regressors have larger coefficients for the skilled-labor equation than for the unskilled-labor equation, suggesting that they tend to increase the relative demand for skilled labor. This suggests that technology proxies make positive contributions to the skill upgrading of the old goods, consistent with the finding of Section 5.1, and that they do so mainly by reducing the demand for unskilled labor, consistent with the finding of Section 4.4. Finally, the technology proxies account for about 43% of the "within" component of the old goods (23% from computer investment, 1% from office equipment, and 19% from high-tech capital), less than in Framework A. Because the "within" component of the old goods accounts for about 50% of the increase in the relative demand for skilled labor (see Section 4.4 or Table 4.5), the technology proxies account for about 22% of this increase (43% × 50%). Together, new goods and technology proxies account for over 50% (30% plus 22%) of the rise in the relative demand for skilled labor.

As in Section 5.1, a simple robustness check can be done for Framework B, in which the contribution of the new goods is found by combining a "between" component and a "within" component. The "between" component is calculated using Equation (8.1) but having the skilled-labor intensities of the *old* goods in the first term, and the "within" component calculated by adding *ngratio* to regression (14) and running (14) for all the goods. Again, this approach is useful only as a robustness check because it is not theoretically justified. As shown in the right panel of Table 5.3, the "between" component of the contribution of new goods is about 20% on average and 17% for the period 79-92. On the other hand, running (14) for all the goods and with *ngratio* added to the right hand side yields[28] a coefficient for *ngratio* of about –0.022 (insignificant) for the skilled-labor equation (see the 4th column of Table 5.4) and –0.21 (significant) for the unskilled-labor equation (the 7th column). Thus new goods "explain" about 10% of skill-upgrading, and the "within" component of their contribution is about 7% of the overall increase in the relative demand for skilled labor (10% × 67%) for the period 79-92, and 6% on average (10% × 63%). Put the "within" component and the "between" component together, and the total contribution of the new goods is about 24% for the period 79-92, and 26% on average, comparable to the results of Framework B (see Section 4.4 or Table 4.5).

Section 6. Conclusion and Discussion

New goods tend to increase the relative demand for skilled labor if their average skilled-labor intensity is higher than old goods. This paper systematically identifies and measures the new goods in the U.S. manufacturing sector and finds that their average skilled-labor intensity exceeds the old goods by over 40% and they account for about 30% of the increase in the relative demand for skilled labor. Furthermore, even within 4-digit industries, new goods are slightly more skilled-

[28] The regression is weighted by the average of net output. Using the average of apparent consumption as weights yields qualitatively similar results: the coefficient of *ngratio* is –0.24 (significant) for the skilled-labor equation, and –0.34 (significant) for the unskilled-labor equation, and the contribution of new goods drops to about 6% (5.744%) of skill upgrading. This puts the total contribution of new goods at about 22% for the 79-92, and 24% on average.

labor intensive than old goods (by about 4%). Therefore, new goods help explain the rising skill premium in the U.S. between the late 1970s and the late 1980s/early 1990s. This finding is robust to the definitions of the new goods (the narrow definition and the broad definition), the measurement approaches (4-digit counting, 4-digit matching and 5-digit matching) and the analytical frameworks (Frameworks A and B) used.

This paper also finds that the indirect effect of technology is about 40% of the rise in the relative demand for skilled labor using Framework A, and about 20% using Framework B. Together, new goods and technology explain over 70% of the rise in the relative demand for skilled labor using Framework A, and over 50% using Framework B.

The exercise in this paper highlights the importance of direct measurement. As demand-side factors could show up in both the "within" and "between" components (e.g., trade shows up in the "within" component through outsourcing, and technology in the "between" component through new goods), it is inadequate to infer their contributions based on the within-between decomposition alone. On the other hand, the "within" component of the old goods still accounts for about 50% of the increase in the relative demand for skilled labor, suggesting that the indirect effect of technology is important. Therefore it seems worthwhile to search for a direct measure of it and establish a causal link between this measure and the within-industry skill upgrading of the old goods. Finally, it is also interesting to search for the cause of technological change: why does technology increase the relative demand for skilled labor? The first step is theory. For example, Acemoglu [1998] shows that the increase in the relative supply of skilled labor could lead to SBTC. The natural next step would be related empirical work.

Appendix 1: Data

A1.1. A List of the Data Sources

Most data sources use the 87 SIC classification system. Those using the 72 SIC classification system are converted into the 87 system using the concordance at the NBER website (http://www.nber.org/nberces/).

Output, price indices and factor payments (4-digit 87 SIC): NBER-CES Manufacturing Industry Database (formerly known as the NBER Productivity Database *a la* Bartelsman and Gray [1996]), available at http://www.nber.org/nberces/.

Imports and exports (4-digit 72 SIC): NBER Trade Database (Feenstra [1996], Feenstra [1997]), the same as used in Feenstra and Hanson [1999] and provided by Gordon H. Hanson.

New technology and outsourcing variables (4-digit 72 SIC): the same as used in Feenstra and Hanson [1999] and provided by Gordon H. Hanson.

Output and factor payments (5-digit 92 CM, 87 SIC): U.S. Census Bureau, Economic Census 1992-Disc 1J (CD-EC92-1J). The 92 CM covers all establishments with one or more paid employees primarily engaged in manufacturing as defined in the 87 SIC manual.

Shipment values (i.e. gross output) (7-digit 92 CM/CIR, 87 SIC): CD-EC92-1J and U.S. Census Bureau, CIR 1993 publications, various issues, available at http://www.census.gov/cir/www/alpha.html. The CIR is conducted annually (sometimes monthly or quarterly) for a selected number of manufacturing industries, and its data tied to and not duplicated in the CM conducted in the same year (e.g. the entry 3577100 in the 92 CM ("Computer peripheral (input/output) equipment, n.e.c., except parts, attachments, and accessories") is a "tieline" to the 29 7-digit products in the 92 CIR starting with "35771"). Notice that the data for 1992 in the 93 CIR publications is used because the 93 publications revise the 1992 data in the 92 publications.

A1.2. More Details about the Matching Process

A.1.2.1. 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. For instance, "Ice buckets, plastics: except foam" and "Picnic jugs, plastics", both new, are matched to "Plastics picnic jugs, cooler chests, and ice buckets (except foam)" (CM 3089621). Since "Ice chests or coolers, portable, plastics: except insulated or foam plastics", an old good (Group 3), is the only other SIC manual product in industry 3089 that can be matched to the CM product 3089621, each of the two SIC manual new goods is assigned 1/3 of the CM product's shipment value.

A.1.2.2. Missing data

This occurs when a 7-digit CM/CIR product has its shipment data withheld to avoid disclosing individual manufacturers. This product is then aggregated with other 7-digit products whenever possible.

Sometimes the aggregation group is given in the CM/CIR (e.g. "Tampons" (CM 2676151) and "Sanitary napkins, including maternity pads" (CM 2676114) are lumped together), and other times it is created by imputing the total shipment value of all the 7-digit products with missing data within a 5-digit product class (e.g. "Fabric softener" (CM 2842341) is aggregated with "Cat litter, except natural and untreated materials" (CM 2842390)). The SIC products are then re-matched to the aggregation groups thus formed. In both examples above, the SIC manual new good ("tampon" and "fabric softener" respectively) has half the aggregation group's shipment.

A1.2.3. Really difficult matching

This can be due to (1) in the case of **A1.2.1**, it is difficult to find all the SIC manual products that can be matched to the single CM/CIR product (e.g. "caprolactam" is matched to "miscellaneous cyclic and acyclic chemicals and chemical products" (CM 2869700), and there are 166 products listed in the 87 SIC manual for industry 2869); (2) the matching is straightforward, yet the shipment data of the CM/CIR product is withheld and cannot be easily imputed. In both cases, the relevant SIC manual product is matched to its 4-digit industry, and gets its *ngratio* using the 4-digit counting approach (for 90 out of 825 products).

A1.2.4. Establishment-based data versus product-based data

In the 92 CM, the 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 and "reflect both the primary and secondary activities of the establishments classified in those industries," and the latter is product-based and reflects "shipments by all producers, regardless of the industry in which they are classified" (pp. X, U.S. Census Bureau, 92 CM, General Summary (MC-92-S-1)). In the calculation of *ngratio*, the product-based outputs of new goods are divided by the product-based industry or product-class total outputs.

A1.2.5. CIR output versus CM output

The total gross outputs of 92 CIR products do not always equal their 92 CM tieline entries, and the deviation 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 *ngratio*'s of the new goods matched to 92 CIR are calculated using the CIR totals.

Appendix 2

A2.1. Derivation of (1)

Let $W(z)$ and $W_s(z)$ be the total and skilled-labor wage bills of industry z; then $m(z) = W(z)/\Sigma_z W(z)$ and $\theta_s^w(z) = W_s(z)/W(z)$. Thus $\Sigma_z m(z)\theta_s^w(z) = \Sigma_z[W(z)/\Sigma_z W(z)][W_s(z)/W(z)] = \Sigma_z[W_s(z)/\Sigma_z W(z)] = \Sigma_z W_s(z)/\Sigma_z W(z) = \mu^w$.

A2.2. Derivation of (3)

First, notice that by (4.2) and (4.3), $G^{w}_{o,btw} + G^{w}_{o,wthn} = \Sigma_z^{old}\theta_s^{w}(z)m(z)|_{t=1} - \Sigma_z^{old}[\rho^{w}m(z]\ \theta_s^{w}(z)|_{t=0}$ (see the Appendix of Berman, Bound and Griliches [1994]). Then by (4.1), $G_n^{w} + G^{w}_{o,btw} + G^{w}_{o,wthn} = \Sigma_z^{new}m(z)\ \theta_s^{w}(z) + \Sigma_z^{old}\theta_s^{w}(z)m(z)|_{t=1} - \Sigma_z^{old}\ m(z)\ \theta_s^{w}(z)|_{t=0}$. By (1), the first two terms add up to $\mu^{w}|_{t=1}$, and the last term is $-\mu^{w}|_{t=0}$. Thus $\Delta\mu^{w} = G_n^{w} + G^{w}_{o,btw} + G^{w}_{o,wthn}$.

A2.3. Derivation of (11)

Let $y(z)$ be the output of sector z; then $W_x(z) = \theta_x(z)\ y(z),\ x=s,\ u\ \ \forall z$, and $b(z) = y(z)/\Sigma_z y(z)$. Thus $\Sigma_z\theta_x(z)b(z) = \Sigma_z[W_x(z)/y(z][y(z)/\Sigma_z y(z] = \Sigma_z W_x(z)/\Sigma_z y(z)$ for $x = s,\ u,\ \mu = \Sigma_z\theta_s(z)b(z)/\ \Sigma_z\theta_u(z)b(z) = \Sigma_z W_s(z)/\Sigma_z W_u(z)$, and $1 + \mu = \Sigma_z W(z)/\Sigma_z W_u(z)$. Thus $\mu/(1+\mu) = \Sigma_z W_s(z)/\Sigma_z W(z) = \mu^{w}$.

Appendix 3

To see why Framework A might inaccurately measure the contribution of product demand shifts, notice that labor compensation is all that is needed for the calculation of G^{w}_{btw} in Equation (2) and output does not matter. In other words, Framework A infers the contribution of exogenous demand shifts without using any information on sectoral output.

Example 1 in Table A1 illustrates how this could matter. There are three industries, 1~3, whose labor compensations, outputs and skilled-labor intensities are listed for period 0 (before the change) and period 1 (after the change). Industry 1 is the least skilled-labor intensive, and industry 3 the most skilled-labor intensive. Between periods 0 and 1, the only changes are that the skilled-labor compensation of industry 3 decreases from 20 to 19 while that of industry 1 increases from 10 to 12, and the latter dominates so that the relative demand for skilled labor (i.e. μ) increases from 1 to 1.014. Notice that there is no change in these industries' outputs; i.e. the change in μ is due entirely to within-industry skill upgrading, and exogenous product demand shifts are absent. However, G^{w}_{btw} is negative and sizable (its ratio to $\Delta\mu^{w}$ is –0.91) because industry 3's share in total labor compensation declines ($\Delta m(3) = -0.0086$) and this decrease receives a large weight ($\overline{\theta_s^{w}(3)} = 0.66$) as industry 3 is skilled-labor intensive. In other words, Framework A attributes a negative contribution to exogenous product demand shifts even though such shifts are absent.

Due to this downward bias, Framework A might under-estimate the contribution of exogenous product demand shifts when they happen alongside within-industry skill upgrading, and this is illustrated in Example 2 in Table A1. In Example 2, the within-industry skill upgrading is identical to that in Example 1, and the shift in product demands is in favor of industry 3 so that its labor compensation and output expand by the same proportion (1%) (compared with the numbers in period 1 in Example 1). Because industry 3 is the most skilled-labor intensive, the contribution of product demand shifts should be positive (μ is 1.016 in period 1 instead of 1.014 as in Example 1). However, Framework A fails to identify this positive contribution because it is eclipsed by the downward bias that is illustrated in Example 1: the between component is still negative with a large magnitude (about 75% of $\Delta\mu^{w}$).

In contrast, Framework B makes the correct inference in both examples because it takes the changes in output into account. In Example 1, the between component of Framework B is 0 because the industries' shares in total output remain unchanged ($\Delta b(z) = 0$ for $z = 1, 2, 3$). In Example 2, Framework B identifies the positive contribution of product demand shifts (the between component is 8.6% of $\Delta\mu$) by picking up the expansion of industry 3 as its share in total output increases ($\Delta b(3) = 0.0022$).

Reference:

Acemoglu, Daron, "Why do New Technologies Complement Skills? Directed Technical Change and Wage Inequality", *Quarterly Journal of Economics*, CXIII [1998], pp1055-1089.

Autor, David H., Katz, Lawrence F. and Krueger, Alan B. "Computing Inequality: Have Computers Changed the Labor Market", *Quarterly Journal of Economics*, CXIII [1998], 1169-1213.

Baldwin, Robert E. and Cain, Glen G., "Shifts in US Relative Wages: The Role of Trade, Technology and Factor Endowments", NBER working paper #5934, 1997.

Bartelsman, Eric J. and Wayne Gray, 1996, "The NBER Manufacturing Productivity Database", NBER technical working paper #205.

Berman, Eli, Bound, John, and Machin, Stephen, "Implications of Skilled-biased Technological Change: International Evidence", *Quarterly Journal of Economics*, CXIII[1998], 1245-1279.

Berman, Eli, Bound, John, and Griliches, Zvi, "Changes in the Demand for Skilled Labor with U.S. Manufacturing: Evidence from the Annual Survey of Manufactures", *Quarterly Journal of Economics*, [1994], 367-397.

Borjas, George J., Freeman, Richard B. and Katz, Lawrence F., "How Much Do Immigration and Trade Affect Labor Market Outcomes?", *Brookings Papers on Economic Activitity* [1997], 1-90.

Bound, John and Johnson, George, "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations", *American Economic Review*, 83(3) [1992], pp371-392.

Bresnahan, Timothy F. and Gordon, Robert J. [1997] edt. "The Economics of New Goods", published by the University of Chicago Press.

Brynjolfsson, Erik [1997], "Comment" (on "From Superminis to Supercomputer" by Shane M. Greenstein) in "The Economics of New Goods", edited by Timothy F. Bresnahan and Robert J. Gordon, University of Chicago Press.

Davidson, Russel and MacKinnon, James G, [1993], "Estimation and Inference in Econometrics", Oxford University Press.

DiNardo, John and Pischke, Jorn-Steffen, "The Returns to Computer Use Revisited: Have Penncils Changed the Wage Structure too?", *Quarterly Journal of Economics*, CXII[1997], 291-303.

Doms, Mark, Dunne, Timothy and Troske, Kenneth R., "Workers, Wages and Technology", *Quarterly Journal of Economics* CXII [1997], 253-290.

Feenstra, Robert C., [1996], "U.S. Imports, 1972-1994, with State Exports and Other U.S. Data", NBER working paper #5515.

Feenstra, Robert C., [1997], "U.S. Exports, 1972-1994, with State Exports and Other U.S. Data", NBER working paper #5990.

Feenstra, Robert E. and Hanson, Gordon, "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990", *Quarterly Journal of Economics*, 114(3), [1999], pp907-940.

Goldin, Claudia and Lawrence F. Katz, "The Origin of Technology-Skill Complementarity", *Quarterly Journal of Economics*, 113(3), August, 1998, pp 693-732.

Gordon, Robert J. [1990], "The Measurement of Durable Goods Prices", University of Chicago Press.

Gray, Maureen B., "Consumer Spending on Durables and Services in the 1980s", *Monthly Labor Review, May 1992*, pp18-26.

Haven, Kendall [1994], "Marvels of Science: 50 Fascinating 5-Minute Reads", published by Libraries Unlimited, Inc. Englewood, Colorado.

Jenkins, Alan [1977], "The Forties", published by London: Heinemann.

Katz, Lawrence F. and Autor, David H. [1998], "Changes in the Wage Structure and Earnings Inequality", a chapter in Handbook of Labor Economics (eds.: Orley Ashenfelter and David Card), Armsterdam, North-Holland, forthcoming.

Katz, Lawrence F. and Murphy, Kevin M., "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *Quarterly Journal of Economics*, 107(1) [1992], pp35-78.

Kobenhavn: Dansk, Design Center, "Success via Design", [1992].

Kruger, Alan B. "How Computers have Changed the Wage Structure: Evidence from Microdata, 1984-1989", *Quarterly Journal of Economics*, CVIII[1993], pp33-60.

Krueger, Alan B. "Labor Market Shifts and the Price Puzzle Revisited", Industrial Relations Section Working Paper #375, Princeton University, 1997.

Lawrence, Robert Z. and Slaughter, Matthew J., "International Trade and American Wages in the 1980s: Giant Sucking Sound or Small Hiccup?", *Brookings Papers on Economic Activity* [1993], 161-226.

Leamer, Edward ,1996, "In Search of Stolper-Samuelson Effects on US Wages", NBER working paper # 5427.

Marty, Myron A. [1997], "Daily Life in the United States, 1960-1990: Decades of Discord", published by Westport, Connecticut: Greenwood Press.

Miller, Douglas T. and Nowak, Marion [1977], "The Fifties: the Way We Really Were", 1st edition, published by Garden City, New York: Doubleday.

Office of Technology Assessment, case studies, various issues. Available at: http://www.wws.princeton.edu/~ota/ns20/legacy_n.html.

Office of Management and Budget, Standard Industrial Classification Manual, 1972, 1977 supplement, and 1987.

Trajtenberg, Manuel [1990], "Economics Analysis of Product Innovation: The Case of CT Scanners", Harvard University Press.

U.S. Census Bureau, 1992 Census of Manufactures, Subject Series, General Summary (MC-92-S-1). Available at http://www.census.gov/prod/www/abs/manu-min.html.

U.S. Census Bureau, 1993 Current Industrial Report publications, various issues. Available at http://www.census.gov/cir/www/alpha.html.

U.S. Census Bureau, Economic Census 1992-Disc 1J (CD-EC92-1J).

Xiang, Chong, [2002], "New Goods and Rising Skill Premium: A Theoretical Investigation", RSIE working paper #478, the University Of Michigan, 2002.

Zangwill, Willard I., "Lightning Strategy for Innovation: How the World's Best Firms Create New Products", Lexington Books, an Imprint of Macmillan, Inc., New York [1993].

Zeisset, Paul T. and Wallace, Mark E., "How NAICS Will Affect Data Users", the Bureau of Census website: http://www.census.gov/epcd/naicsusr.html.

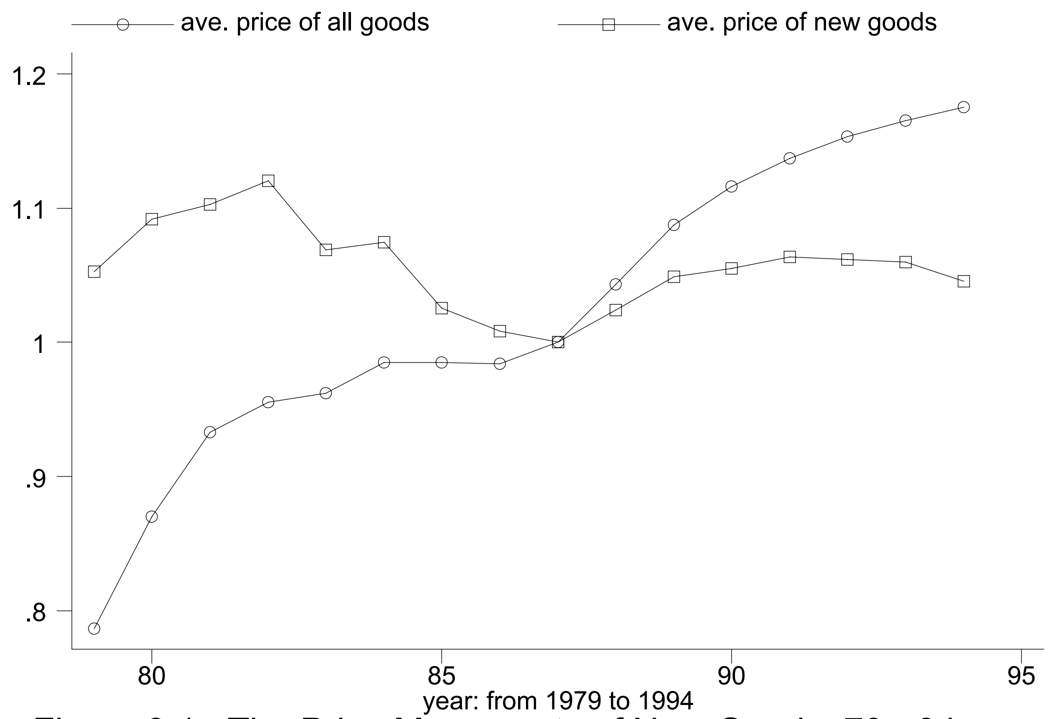

Figure 3.1.: The Price Movements of New Goods: 79 - 94

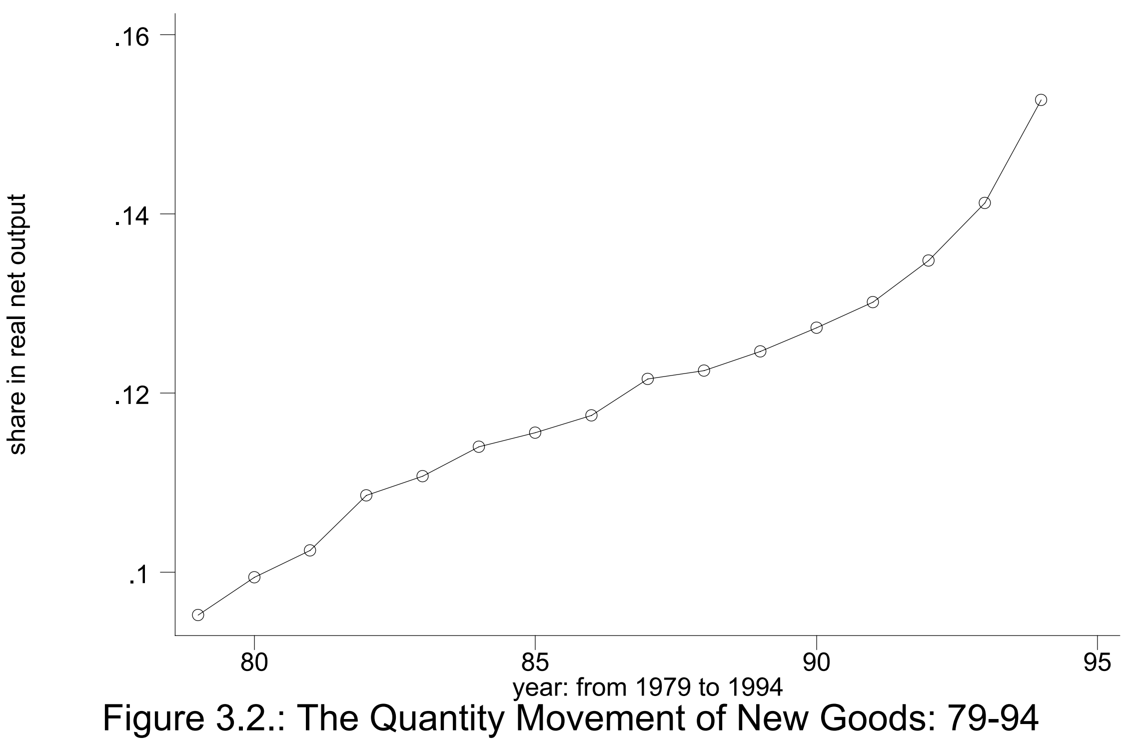

Figure 3.2.: The Quantity Movement of New Goods: 79-94

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

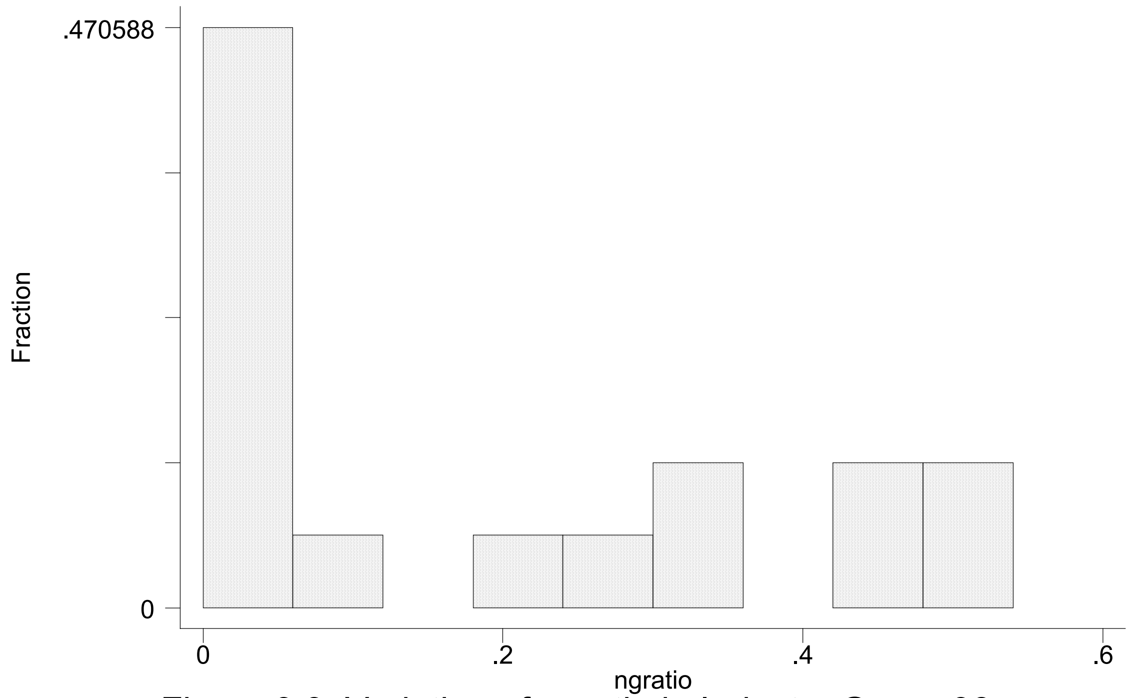

Figure 3.3. Variation of ngratio in Industry Group 38

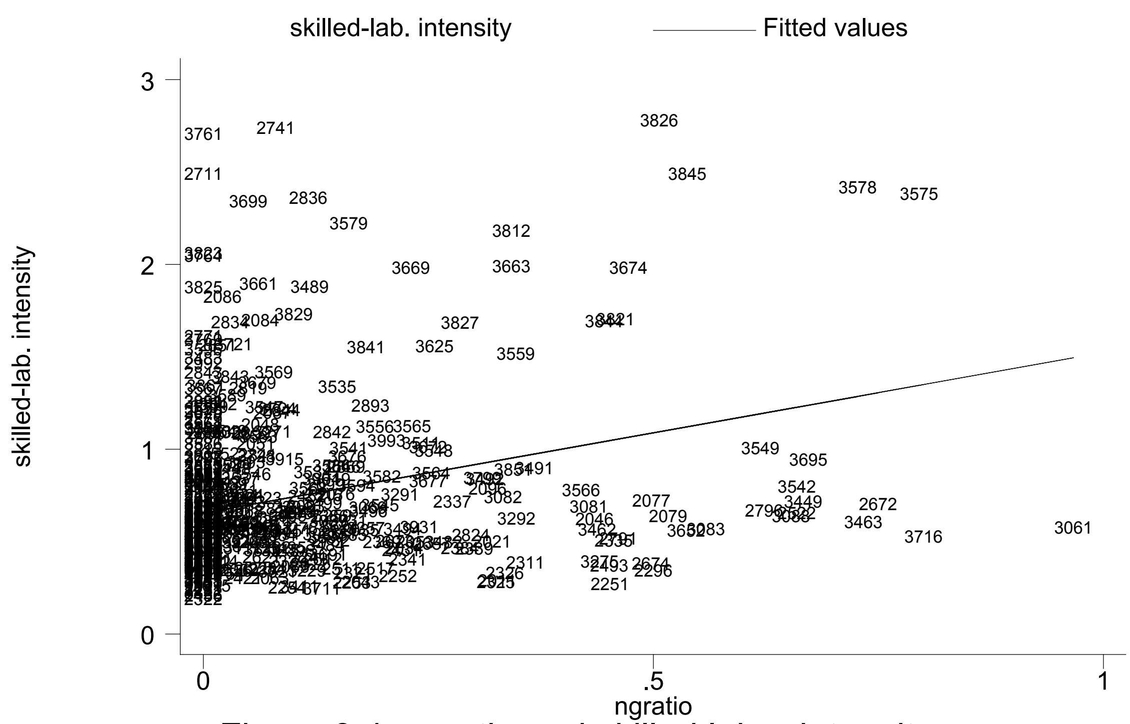

Figure 3.4: ngratio and skilled labor intensity

Table 3.1. Example of The 92 CM Coding System

Code	Level of Dis-aggregation	Description/Name
2835	Industry	Diagnostic Substances
28352	Product Class	Diagnostic substances, in vivo
2835220	Product	In vivo radioactive reagents (both diagnostic and therapeutic)

Table 3.2 **Some Summary Statistics of *ngratio***

Method	Obs	Positive obs.	Mean	Std. Dev.	Min	Max	Std.Dev./Mean
4-digit matching	458	257	0.108	0.177	0	1	1.64
4-digit counting	458	257	0.103	0.162	0	1	1.57
5-digit matching	1250	492	0.103	0.228	0	1	2.21

Table 3.3 **Variation of *ngratio***

2-digit Industry Groups	4-digit matching			4-digit counting			5-digit matching		
	obs. #	positive obs. #	std.dev./mean	obs. #	positive obs. #	std.dev./mean	obs. #	positive obs. #	std.dev./mean
20 (food)	48	35	1.26	48	35	1.01	120	54	1.91
21 (tobacco)	4	0	-	4	0	-	4	0	-
22 (textile)	23	9	1.80	23	9	1.98	67	12	2.61
23 (apparel)	31	19	1.14	31	19	1.11	75	24	1.94
24 (wood)	17	7	2.26	17	7	2.06	59	25	2.30
25 (furniture)	13	8	1.46	13	8	1.01	36	19	1.96
26 (paper)	17	11	1.81	17	11	1.21	42	16	2.09
27 (printing)	14	10	1.46	14	10	1.09	58	24	2.33
28 (chemicals)	29	15	2.36	29	15	2.76	92	36	2.89
29 (petroleum)	5	2	1.64	5	2	1.89	6	2	1.83
30 (rubber/plastics)	15	8	1.33	15	8	1.23	56	32	1.65
31 (leather)	11	2	2.41	11	2	2.26	12	2	2.57
32 (clay/glass)	26	8	2.14	26	8	2.20	43	12	2.41
33 (metal: primary)	26	5	2.61	26	5	2.65	70	7	4.32
34 (metal: fabricated)	38	23	1.65	38	23	1.67	128	51	2.15
35 (machinery)	51	40	1.30	51	40	1.24	146	77	1.78
36 (electronics)	37	22	1.51	37	22	1.33	109	39	2.03
37 (transportation)	18	11	1.92	18	11	1.99	42	17	2.00
38 (instruments)	17	12	1.09	17	12	1.43	36	18	1.79
39 (miscellaneous)	18	10	1.49	18	10	1.45	49	25	2.65

Table 3.4 New Goods' Shares in Manufacturing Net Output (Nominal)

End year	Manufacturing ($Million)	New Goods ($Million)	Share
87	1165732	141703	12.16%
89	1308103	156828	11.99%
92	1425207	171479	12.03%
94	1605981	199726	12.44%

Table 3.5 Correlation between *ngratio* and Net Output (Nominal)

	4-digit matching		4-digit Counting		5-digit matching	
End year	Correlation Coefficient	Significance level	Correlation Coefficient	Significance Level	Correlation Coefficient	Significance Level
87	0.05	0.29	0.07	0.13	-	-
89	0.04	0.37	0.06	0.23	-	-
92	0.04	0.35	0.07	0.14	0.04	0.15
94	0.06	0.22	0.07	0.12	-	-

Table 3.6 Correlation between *ngratio* and Skilled-labor Intensities

	4-digit matching		4-digit Counting		5-digit matching	
End year	Correlation Coefficient	Significance Level	Correlation Coefficient	Significance Level	Correlation Coefficient	Significance Level
87	0.23	0.00	0.32	0.00	-	-
89	0.24	0.00	0.31	0.00	-	-
92	0.26	0.00	0.33	0.00	0.082	0.0038
94	0.22	0.00	0.30	0.00	-	-

Table 4.1 **Decomposition Using Equation (2) (Framework A)**

Period	Overall	Components		Shares (%)	
		Within	Between	Within	Between
53-73	0.007	0.0101	-0.0029	141.00%	-41.00%
73-79	0.018	0.0125	0.0050	71.39%	28.61%
79-87	0.059	0.0346	0.0247	58.37%	41.63%
79-89	0.064	0.0375	0.0269	58.21%	41.79%
79-92	0.076	0.0505	0.0259	66.11%	33.89%
79-94	0.063	0.0428	0.0205	67.81%	32.47%

Table 4.2 **New Goods' Contribution to the Increase in The Relative Demand for Skilled Labor (Framework A)**

Periods	Overall	Components			Shares (%)		
		G_n^w	$G_{o,btw}^w$	$G_{o,wthn}^w$	G_n^w	$G_{o,btw}^w$	$G_{o,wthn}^w$
		4-digit matching					
79-87	0.059	0.017	0.013	0.030	27.96%	22.13%	49.91%
79-89	0.064	0.017	0.015	0.032	26.36%	23.73%	49.91%
79-92	0.076	0.019	0.014	0.043	24.55%	18.58%	56.87%
79-94	0.063	0.017	0.010	0.037	26.42%	15.14%	58.44%
		4-digit counting					
79-87	0.059	0.017	0.012	0.030	29.27%	20.35%	50.38%
79-89	0.064	0.018	0.014	0.032	27.64%	22.05%	50.31%
79-92	0.076	0.020	0.013	0.044	25.98%	16.88%	57.14%
79-94	0.063	0.018	0.008	0.037	28.19%	13.14%	58.67%
		5-digit matching					
79-92	0.075	0.020	-	-	27.21%	-	-

Table 4.2 (Continued)

Periods	Overall	Components G_n^{w}	Components $G_{o,btw}^{w}$	Components $G_{o,wthn}^{w}$	Shares (%) G_n^{w}	Shares (%) $G_{o,btw}^{w}$	Shares (%) $G_{o,wthn}^{w}$
4-digit counting, Broad Definition							
79-87	0.059	0.022	0.014	0.023	36.86%	23.89%	39.25%
79-89	0.064	0.023	0.016	0.026	34.97%	25.37%	39.66%
79-92	0.076	0.025	0.016	0.036	32.65%	20.53%	46.82%
79-94	0.063	0.022	0.012	0.030	34.13%	18.40%	47.47%

Table 4.3 New Goods' Share in Apparent Consumption and Average Skilled-labor Intensity

Year	New Goods' Share in Apparent Consumption: Total ($Million)	New goods Share (%) ($Million)		Average Skilled-labor Intensity: New	Old	Difference
4-digit matching						
87	2629441	305133	11.60%	0.82	0.60	38.31%
89	2923315	337951	11.56%	0.84	0.61	38.50%
92	3090464	370416	11.99%	0.93	0.64	43.47%
94	3495058	431767	12.35%	0.87	0.60	44.44%
4-digit counting						
87	2629441	296948	11.29%	0.87	0.59	46.75%
89	2923315	329283	11.26%	0.88	0.61	46.08%
92	3090464	365181	11.82%	0.97	0.64	51.25%
94	3495058	421341	12.06%	0.91	0.60	52.08%

Table 4.3 (Continued)

Year	New Goods' Share in Apparent Consumption: Total ($Million)	New goods ($Million)	Share (%)	Average Skilled-labor Intensity: New	Old	Difference
	4-digit counting, broad definition					
87	2629441	482402	18.35%	0.77	0.59	29.99%
89	2923315	532871	18.23%	0.78	0.60	29.89%
92	3090464	583313	18.87%	0.84	0.64	31.93%
94	3495058	670456	19.18%	0.79	0.60	33.15%
	5-digit matching					
92	3090464	365715	11.83%	0.96	0.64	48.81%

Table 4.4 Average Skilled-labor Intensity Within 4-digit Industries

	All industries with *ngratio* > 0					All industries with at least one new product class				
	New goods' Share in Apparent Consumption	Average skilled Labor intensities: New goods	Old goods	Difference: Un-weighted	Weighted	New goods' Share in Apparent Consumption	Average skilled Labor intensities: New goods	Old goods	Difference: Un-weighted	Weighted
Mean	0.19	0.89	0.86	0.035	0.035	0.37	0.81	0.76	0.050	0.060
Std. Dev.	0.20	0.76	0.75	0.203	0.199	0.25	0.60	0.40	0.286	0.309
Min	0.00022	0.14	0.21	-1.019	-1.019	0.06	0.30	0.30	-0.297	-0.297
Max	0.99	6.85	6.77	1.052	1.052	0.99	3.02	2.23	0.943	0.943
Positive #.	257	257	458	117	117	25	25	458	10	10
Negative #.	0	0	0	92	92	0	0	0	15	15

Table 4.5 New Goods' Contribution to the Increase in The Relative Demand for Skilled Labor (Framework B)

Periods	Overall	Components			Shares (%)		
		G_n	$G_{o,btw}$	$G_{o,wthn}$	G_n	$G_{o,btw}$	$G_{o,wthn}$
		4-digit matching					
79-87	0.23	0.061	0.046	0.122	26.81%	20.05%	53.15%
79-89	0.24	0.063	0.053	0.127	25.88%	21.69%	52.43%
79-92	0.30	0.075	0.062	0.164	24.87%	20.55%	54.57%
79-94	0.22	0.064	0.039	0.121	28.42%	17.50%	54.08%
		4-digit counting					
79-87	0.23	0.066	0.040	0.123	28.76%	17.43%	53.81%
79-89	0.24	0.067	0.047	0.128	27.69%	19.44%	52.87%
79-92	0.30	0.080	0.056	0.165	26.47%	18.74%	54.79%
79-94	0.22	0.069	0.035	0.121	30.59%	15.52%	53.89%
		5-digit matching					
79-92	0.29	0.079	-	-	27.10%	-	-
		4-digit counting, broad definition					
		G_n	$G_{o,btw}$	$G_{o,wthn}$	G_n	$G_{o,btw}$	$G_{o,wthn}$
79-87	0.23	0.084	0.036	0.109	36.58%	15.82%	47.60%
79-89	0.24	0.086	0.043	0.113	35.55%	17.77%	46.68%
79-92	0.30	0.102	0.053	0.146	33.92%	17.70%	48.39%
79-94	0.22	0.086	0.031	0.108	38.38%	13.69%	47.93%

Table 4.6 Decomposition (Framework B)

Period		**59-73**	**73-79**	**79-87**	**79-89**	**79-92**	**79-94**
	$\Delta ln\mu$	0.028	0.071	0.238	0.250	0.290	0.224
	ΔD_s	-0.0186	-0.0065	0.0105	0.0068	0.0079	-0.0056
Changes	ΔD_s^{wthn}	-0.0173	-0.0073	0.0027	0.0004	0.0028	-0.0100
	ΔD_s^{btw}	-0.0013	0.0008	0.0078	0.0064	0.0051	0.0045
	ΔD_u	-0.0474	-0.0338	-0.0423	-0.0521	-0.0604	-0.0683
	ΔD_u^{wthn}	-0.0436	-0.0239	-0.0313	-0.0387	-0.0448	-0.0555
	ΔD_u^{btw}	-0.0037	-0.0098	-0.0110	-0.0134	-0.0157	-0.0125
Shares	Within	88.47%	45.74%	59.02%	61.08%	66.59%	22.47%
	Between	11.53%	54.26%	40.98%	38.92%	33.41%	35.73%

Notes: Obtained by having $\rho = 1$ in Equations (8.2), (8.3), (9.2) and (9.3) and applying them to all the goods

Table 5.1 Regression (79-92) (12)

Dependent variable: skill upgrading

	OLS			IV			2nd stage			Contribution	
Regressors	**Old Goods**	**All Goods**	**All Goods**	**Old Goods**	**All Goods**	**All Goods**	**Old Goods**	**All Goods**	**All Goods**		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δlnk	-0.031	0.147	0.146	0.003	-0.083	-0.086				-1.54%	5.31%
	(0.049)	(0.058)	(0.056)	(0.097)	(0.094)	(0.093)					
ΔlnY	0.077	0.367	0.280	0.092	0.288	0.202				2.77%	28.96%
	(0.037)	(0.040)	(0.041)	(0.029)	(0.027)	(0.029)					
Comp. Investment	0.016	0.013	0.013	0.016	0.015	0.015	-0.008	-0.011	-0.009	50.82%	36.77%
(Share)	(0.0025)	(0.0027)	(0.0026)	(0.0025)	(0.0027)	(0.0026)	(0.0033)	(0.0034)	(0.0032)		
Office machinery	0.306	0.556	0.327	0.265	0.857	0.639	1.960	1.714	1.847	11.63%	11.22%
(Share)	(0.35)	(0.37)	(0.36)	(0.41)	(0.41)	(0.40)	(0.40)	(0.42)	(0.39)		
High-tech cap.	0.337	0.201	0.305	0.341	0.163	0.258	-0.083	0.109	-0.017	21.39%	17.46%
(Share)	(0.28)	(0.30)	(0.28)	(0.28)	(0.30)	(0.29)	(0.32)	(0.33)	(0.29)		
Out-sourcing	0.425	0.317	0.351	0.404	0.450	0.484	0.678	0.648	0.623	11.37%	8.48%
	(0.20)	(0.22)	(0.21)	(0.21)	(0.22)	(0.21)	(0.23)	(0.24)	(0.23)		
Constant	0.007	-0.043	-0.082	0.008	-0.044	-0.076	-0.090	-0.094	-0.017		
	(0.027)	(0.029)	(0.028)	(0.028)	(0.030)	(0.018)	(0.033)	(0.034)	(0.033)		
ngratio			0.549			0.487			-0.745		29.52%
			(0.09)			(0.18)			(0.09)		
lnk_0							-0.255	-0.303	-0.288		
							(0.032)	(0.033)	(0.030)		
$(lnk_0)^2$							0.061	0.046	0.059		
							(0.039)	(0.041)	(0.038)		
Adj. R^2	0.16	0.32	0.37	0.16	0.31	0.36	0.25	0.25	0.36		
Hausman test				F=0.14	F = 6.77	F=7.16					
(Significance level)				(0.71)	(0.0096)	(0.0077)					

Notes: 1. weighted by the average of total labor compensation in 79 and 92, and standard errors are in the brackets

2. *ngratio* uses 4-digit matching

Table 5.2 Summary Statistics

Regression (12)

Variable	Old goods only Mean	Old goods only Std. Dev.	All goods Mean	All goods Std. Dev.
Skill upgrading	0.20	0.31	0.22	0.37
Δlnk	0.096	0.37	0.079	0.39
ΔlnY	0.071	0.47	0.22	0.55
Comp. Investment. (Share)	6.20	6.04	6.26	6.08
Office machinery (Share)	0.074	0.065	0.075	0.066
High-tech cap. (Share)	0.12	0.078	0.12	0.079
Out-sourcing	0.052	0.071	0.052	0.070
ngratio			0.12	0.17

Regression (14)

Variable	Old goods only Mean	Old goods only Std. Dev.	All goods Mean	All goods Std. Dev.
$\Delta\theta_s(z)$	0.010	0.35	-0.012	0.28
$\Delta\theta_u(z)$	-0.18	0.29	-0.23	0.26
Comp. Investment. (Share)	4.88	5.46	6.07	6.17
Office machinery (Share)	0.060	0.057	0.070	0.064
High-tech cap. (Share)	0.12	0.070	0.13	0.077
Out-sourcing	0.055	0.075	0.055	0.074
ngratio			0.12	0.18

Table 5.3 Robustness check: the "between" component of new goods

(4-digit matching)

Periods	Equation (4.1) (Framework A) Overall	Equation (4.1) (Framework A) New goods	Equation (4.1) (Framework A) Share (%)	Equation (8.1) (Framework B) Overall	Equation (8.1) (Framework B) New goods	Equation (8.1) (Framework B) Share (%)
79-87	0.059	0.011	18.67%	0.23	0.045	19.79%
79-89	0.064	0.011	17.12%	0.24	0.046	18.92%
79-92	0.076	0.011	14.39%	0.30	0.052	17.24%
79-94	0.063	0.010	16.39%	0.22	0.056	24.97%

Table 5.4 Regression (79-92) (14)

Regressor	Skilled-labor equation			Unskilled-labor equation			Contribution		
	Old Goods Only	**All Goods**	**All with *ngratio***	**Old Goods Only**	**All Goods**	**All with *ngratio***	**Old Goods Only**	**All Goods**	**All with *ngratio***
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Comp. Investment.	-0.0007	-0.00152	-0.00146	-0.0096	-0.0088	-0.0082	23.26%	20.01%	18.69%
(Share)	(0.0032)	(0.0023)	(0.0024)	(0.0027)	(0.0021)	(0.0021)			
Office machinery	-0.021	0.799	0.805	-0.056	0.44	0.50	1.11%	11.37%	9.67%
(Share)	(0.42)	(0.31)	(0.31)	(0.33)	(0.28)	(0.28)			
High-tech cap.	0.27	0.046	0.041	-0.035	-0.11	-0.17	18.77%	9.17%	11.93%
(Share)	(0.32)	(0.26)	(0.25)	(0.27)	(0.22)	(0.22)			
Out-sourcing	-0.93	-0.611	-0.610	-0.82	-0.66	-0.65	-3.32%	1.16%	0.88%
	(0.22)	(0.19)	(0.19)	(0.18)	(0.17)	(0.17)			
Constant	0.036	-0.031	-0.029	-0.077	-0.16	-0.14	60.18%	58.29%	48.61%
	(0.032)	(0.026)	(0.028)	(0.026)	(0.024)	(0.025)			
ngratio			-0.022			-0.21			10.21%
			(0.073)			(0.066)			
Adj. R^2	0.031	0.052	0.050	0.066	0.075	0.0935			

Notes: 1. weighted by the average of real net output in 79 and 92, and standard errors are in the brackets
2. *ngratio* uses 4-digit matching

Table A1 The Inaccuracy of Framework A

Example 1

	Industry	**Unskilled Labor Payments**	**Skilled Labor Payments**	**Output**	**Skilled Labor Intensity**	**Framework A** $\overline{\theta_s^w}$	**Framework A** $\Delta m(z)$	**Framework B** $\overline{\theta_s}$	**Framework B** $\overline{\theta_u}$	**Framework B** $\Delta b(z)$
Period 0	3	10	20	100	2	0.66	-0.0086	0.195	0.1	0
(μ=1)	2	40	40	100	1	0.5	-0.0041	0.4	0.4	0
	1	20	10	100	0.5	0.35	0.0127	0.11	0.2	0
Period 1	3	10	19	100	1.9	Between	-0.0032	Between	0	
(μ=1.014)	2	40	40	100	1	$\Delta\mu_w$	0.0035	$\Delta\mu_u$	0.014	
	1	20	12	100	0.6	Share (%)	-91.16%	Share (%)	0	

Example 2

	Industry	**Unskilled Labor Payments**	**Skilled Labor Payments**	**Output**	**Skilled Labor Intensity**	**Framework A** $\overline{\theta_s^w}$	**Framework A** $\Delta m(z)$	**Framework B** $\overline{\theta_s}$	**Framework B** $\overline{\theta_u}$	**Framework B** $\Delta b(z)$
Period 0	3	10	20	100	2	0.66	-0.0070	0.195	0.1	0.0022
(μ=1)	2	40	40	100	1	0.5	-0.0052	0.4	0.4	-0.0011
	1	20	10	100	0.5	0.35	0.0122	0.11	0.2	-0.0011
Period 1	3	10.1	19.19	101	1.9	Between	-0.0029	Between	0.0013	
(μ=1.016)	2	40	40	100	1	$\Delta\mu_w$	0.0039	$\Delta\mu_u$	0.0155	
	1	20	12	100	0.6	Share (%)	-75.25%	Share (%)	8.56%	