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Measuring Labor Composition
A Comparison of Alternate Methodologies

Cindy Zoghi

12.1 Introduction

Productivity estimates require a measure of labor input, which is a combination of workers, number of hours they work, and effectiveness of those hours. A measure that only counts number of workers or hours ignores that some work hours produce more than others. For example, the work hour put forth by a brand new employee is not likely to produce as much output as the work hour put forth by someone who has been on the job many years. In this case, the effectiveness of the latter work hour is greater than that of the former.

A labor composition index[1] adjusts the total hours worked for the demographic composition of those hours, which requires identification of separate, heterogeneous groups of labor input whose work hours are likely to have varying effectiveness. This is particularly important when we consider changes over time in the labor input. For example, between 1984 and 2004, the share of workers with more schooling than a high school diploma increased from just over 40 percent to over 55 percent. Even given the same number of hours of work performed by the typical worker in each year, the 2004 hours, being more skilled and presumably more efficient, will result

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1. This is sometimes called a labor quality index.

in greater input, and productivity would increase. Yet, technically, it is not greater output with the same labor input. This distinction is one that we often wish to preserve in our statistics, separating the effect of increasing output with the exact same input versus increasing output with a different type of input.

There is an interesting distinction to be made here between inherent characteristics of the worker that vary the effectiveness of his or her work hour and characteristics of the job itself that alter the effectiveness. For example, when a year passes and a worker gains an additional year of experience, this changes the input. Similarly, if the worker is replaced by another with more education, this also changes the input. On the other hand, if the worker switches jobs with another worker, resulting in improved matching, the input remains unchanged, and productivity increases. In another example, the establishment might adopt teams, which would use the same inputs but increase productivity.

In this chapter, I first introduce past analysis of how to measure the labor input and discuss several suggested methods for obtaining the best input measure. I then look at the background evidence for whether particular demographic wage differentials are productivity differentials or are due to other factors. Additionally, I examine whether the composition of labor input changes over time across these dimensions. If there are productivity differentials across types of workers but the ratio of hours among them does not change over time, the hours can be aggregated without weighting. If the distribution of hours changes with respect to this categorization, and the consensus of the literature is that the wage differentials reflect differing marginal productivity, the category should be used to disaggregate the labor input, assuming it is empirically feasible. Finally, I compare various measures of the labor composition index. The current Bureau of Labor Statistics (BLS) methodology uses imputed wages to weight the types of labor, while other studies have used actual mean wages. I compare the two methodologies to determine whether estimation of wages is an improvement. I then compare how labor composition affects productivity under various categorizations of workers.

12.2 Literature Review

Beginning with the earliest discussions of the productivity "residual," researchers have recognized that a measure of labor input that merely sums all hours worked in the economy will not capture changes in the effectiveness of a work hour over time. Schmookler (1952) explained that to compare the magnitudes of an input between a pair of years and create a continuous, constant-price index requires that the input be homogeneous over time. He cited the example of the large wage differential between agricultural and nonagricultural workers and the shift in man-hours away from agriculture between 1869 and 1938 to show an important source of heterogeneity in the labor market. Similarly, Abramovitz (1956) noted that the period between 1870 and 1950 is characterized by a decrease in the labor force participation of teenagers and older men, with a compensating shift toward the employment of prime-age workers, who generally have a higher output per hour. He explained that this is likely to understate the growth of labor input and overstate productivity growth. Solow (1957, 317) summarized the issue thus: "a lot of what appears as shifts in the production function must represent improvement in the quality of the labor input, and therefore a result of real capital formation of an important kind."

As part of the exercise of national accounting, it is important to correctly measure the labor input in constant real-price terms. As explained by Jorgenson and Griliches (1967, 250), "the alteration in patterns of productive activity must be separated into the part which is 'costless,' representing a shift in the production function, and the part which represents the employment of scarce resources with alternative uses, representing movements along the production function." From the beginning of the discussion of this measurement issue, it has been acknowledged that the solution lies in a properly weighted index of disaggregated labor inputs. In fact, the ideal extreme case allows each worker to function as a unique input, by virtue of his unique set of relevant characteristics (Jorgenson, Ho, and Stiroh 2005).

Data limitations generally restricted early measures to adjusting the labor input for only one factor of worker heterogeneity. Schmookler (1952) divided the labor input into an agricultural and nonagricultural component and then took a sum of the two sectors, weighted by their respective wage rates. Denison (1962), Jorgenson and Griliches (1967) and Griliches (1970) adjusted the labor input measure for income differentials by years of education among workers, and for the income differentials between men and women. In most of these papers, the authors lamented the desirability and also the difficulty of constructing a proper index that would account for other sources of heterogeneity, such as age, occupation, industry, literacy, on-the-job training, nationality, and other such variables.

However, with the greatly improved access to the decennial Censuses, the monthly Current Population Survey, and other new data sources, more detailed categorizations of workers became possible. Denison (1974) classified workers by age groups, gender, years of schooling, average hours, and employment class, using data on worker demographics from the Current Population Survey (CPS) and the 1960 Census. Control totals were obtained from establishment-based data on hours. Gollop and Jorgenson (1980), Jorgenson, Gollop, and Fraumeni (1987), and Jorgenson, Ho, and Stiroh (2005) further disaggregated by broad occupation and industry groups using the decennial Censuses, reconciled to marginal totals from the Current Population Survey, and further controlled to establishment survey totals. The BLS (1993) divided workers by years of experience, years of education, and gender. Their unique measure of experience was derived from actual recorded experience in social security records in 1973.

Most contemporary adjustments to labor input involve replacing a simple sum of workers or worker hours with a weighted sum of the separate groups of workers or worker hours. The calculation of weights varies from study to study, however. Denison's (1974) education weights measured relative earnings of men at each education level, adjusted for differences in the composition of workers within an education group with respect to age, race, farm attachment, and geographic region. The weights were developed for 1959 and subsequently used in each period of the study, in part because he was unable to develop similar weights for other years that would be comparable. Gollop and Jorgenson (1980), Jorgenson, Gollop, and Fraumeni (1987), and Jorgenson, Ho, and Stiroh (2005) used average factor shares for each category of worker in the value of total sector compensation, using compensation rates obtained from Census wages reconciled with CPS marginal subtotals, and imputations of nonwage compensation from the National Income and Product Accounts. The BLS (1993) used estimated wage rates by type of worker from CPS wage regressions. Aaronson and Sullivan (2001) used a slightly simpler approach, estimating the growth in labor effectiveness with the growth in average predicted wages, where the wages were predicted using CPS wage regressions. Importantly, they found that differences in methodology across studies do not dramatically change the estimates of labor effectiveness.

12.3 The Labor Composition Model

The labor composition model uses a generalized production function that allows various types of labor to contribute to producing output. It can be written as:

$$Q = f(k_1, \ldots, k_n, h_1, \ldots, h_m, A_t) \tag{1}$$

where output Q is produced by n different types of capital, $k_1, \ldots, k_n$, by m different types of labor hours, $h_1, \ldots, h_m$, and by the technology available at time t, A_t.

By taking the natural logarithm of both sides, differentiating with respect to time, and rearranging terms, equation (1) can be expressed as a relationship between multifactor productivity and growth rates of output and inputs:

$$\frac{\dot{A}}{A} = \frac{\dot{Q}}{Q} - \left(s_{k_1}\frac{\dot{k}_1}{k_1} + \ldots + s_{k_n}\frac{\dot{k}_n}{k_n} + s_{l_1}\frac{\dot{h}_1}{h_1} + \ldots + s_{l_m}\frac{\dot{h}_m}{h_m} \right) \tag{2}$$

where the dot notation indicates the growth rate of that variable. The partial derivatives, s_{ki} and s_{li}, represent output elasticities, or the percent change in output resulting from a 1 percent increase in the respective input. In practice, these marginal products are unobservable. Under the assumptions of constant returns to scale and perfect competition in product and input markets, each elasticity is equal to the share of total costs paid to that input. In the case of labor, that is calculated as the product of labor's share of total costs and each type of labor's share of the total wage bill.

Assuming that the labor input is separable from capital, an aggregate labor input equation can be derived:

$$\frac{\dot{L}}{L} = s_{h_1}\frac{\dot{h}_1}{h_1} + \ldots + s_{h_m}\frac{\dot{h}_m}{h_m} \tag{3}$$

where s_{hi} is the share of the total wage bill that is spent on each particular type of labor. Under a translog production function, Diewert (1976) showed that changes in input are exactly measured by changes in Tornqvist indexes. Thus, although $\dot{L}/L$ is the instantaneous rate of change in composition-adjusted labor input, it can be replaced by annual rates of change, measured with a Tornqvist index as the difference in the natural logarithm of successive observations, with the weights equal to the mean of the factor shares in the corresponding pair of years:

$$\Delta\ln L = \sum_j \frac{1}{2}[s_{h_j}(t) + s_{h_j}(t-1)]\Delta\ln h_j. \tag{4}$$

Groups that make up a very small portion of the total wage bill will not have much impact on the labor input measure.

Changes in the index of labor composition, LC, are defined as the difference between the change in composition-adjusted labor input given in equation (4), and the change in the sum of unweighted hours:

$$\Delta\ln \mathrm{LC} = \Delta\ln L - \Delta\ln H = \Delta\ln\frac{L}{H}. \tag{5}$$

In practice, estimation of the labor composition index requires a count of the number of hours worked by each type of worker, as well as cost share weights for each type of worker. Cost share weights may be calculated using either actual mean observed wages, as in Denison (1974); Gollop and Jorgenson (1980); Jorgenson, Gollop, and Fraumeni (1987); and Jorgenson, Ho, and Stiroh (2005); or, as BLS (1993) does, replacing actual wages with imputed wages, where the imputations are obtained from a standard Mincer wage regression (see BLS 1993, Appendix E).

The key components for identifying distinct categories of workers are evident from equation (4). The group must have a different output elasticity from other workers in theory, which should be evidenced in the data by a wage differential for that group. Additionally, it should experience changing hours relative to other groups. In the next section, we discuss several potential groups in the context of wage differentials and hours change.

12.4 Wage Differentials

The basic neoclassical model assumes perfect competition, profit maximizing firms, and homogeneous workers. This results in equal wages across all workers. The human capital model relaxes the assumption of homogeneous workers, recognizing that workers can vary in their innate abilities, as well as in their human capital investments. As a result, wages will not be equal across heterogeneous worker types. Rather, wage differentials will reflect differences in the marginal productivity of workers. This suggests that a logical categorization is one that separates types of workers that obtain different wages. The literature on wage differentials is vast, and suggests some interesting categories of workers along the dimension of education, experience, gender, race, unionization, geographic location, establishment size, and other characteristics of both the worker and the workplace.

It is not necessarily the case, however, that all wage differentials represent productivity differentials. In particular, even within the competitive model,[2] there are other explanations for persistent wage differentials between groups of homogeneous workers. The theory of equalizing differences (Rosen 1986; Brown 1980) hypothesizes that wages are adjusted down (up) to account for the amenity (disamenity) of working at a particular job, which equalizes the total monetary and nonmonetary benefits across jobs, keeping the workers indifferent between them. This would result in workers of equal marginal productivity being offered different wages, depending on their job.

Another well-discussed explanation for wage differentials is the efficiency wage theory, in which managers have an incentive to pay workers above the market-clearing wage rate in order to improve the efficiency of the workers or of the organization as a whole. There are several examples of this. If managers pay workers a high wage, the workers face greater potential loss if they become unemployed. This gives the worker an extra incentive to work hard so she will not lose her high-paying job. Note carefully here, that the worker paid in excess is not intrinsically any different from another worker with the same abilities and human capital investments who earns the equilibrium wage rate—it is the same input, but she is induced to work more efficiently. Thus, it is not a different input, but a productivity enhancement. Other reasons for paying in excess of the market-clearing wage rate include reducing turnover and attracting a higher quality pool of workers from which to fill vacancies. In both cases, the labor input is constant, but the wage differentials would be related to increased productivity for the establishment.

2. In addition, there are several noncompetitive models that generate wage differentials. Since the theoretical model relies on perfect competition in the labor market to generate the result that elasticities can be empirically estimated by cost shares, these are not considered here.

12.4.1 Age/Experience

Traditional human capital models (i.e., Mincer 1974) predict that as workers age, they gain experience and skills that make them more productive, and wages rise accordingly. Productivity may decrease again later in life as health concerns begin to affect performance in many jobs. Figure 12.1 shows the average wages and annual hours worked by workers in age groups under twenty-five, twenty-five to thirty-four, thirty-five to forty-four, forty-five to fifty-four, and fifty-five and up, and figure 12.2 repeats for experience groups under five, five to fourteen, fifteen to twenty-four, and twenty-five and up, calculated from the 1984, 1994, and 2004 March CPS. Experience is imputed from experience regression coefficients obtained from the Survey of Income and Program Participation (SIPP) as described in Zoghi (2006). The pattern of increasing wages early in life/career followed by a slowdown later in life/career is confirmed in the data. The effect has gotten stronger over the twenty-year period shown here.

Lazear (1979), however, argued that the age-wage differential may not be an accurate measure of the productivity differentials between age groups, because firms may make implicit long-term incentive contracts with workers to pay wages below the value of marginal product when workers are young and above it when workers are older. Similarly, Loewenstein and Sicherman (1991) considered that workers might prefer such wage profiles in order to force their savings for consumption later in life. Again, this would imply that the age-wage differentials do not accurately measure productivity differentials. However, Hellerstein, Neumark, and Troske (1999) compared wage differentials to productivity differentials using matched employee establishment data and found that the size of the age-wage differentials is consistent with the size of the productive differences by age.

The composition of labor hours by age and experience groups has changed dramatically from 1984 to 2004. In the 1984 sample, nearly half the hours of work in the United States were performed by those ages thirty-four and under (those with less than fifteen years of experience). By 2004, as the baby boom generation aged, this number had dropped to around 35 percent (30 percent). Thus, if we believe that age/experience wage differentials reflect productivity differences, there has been a marked shift toward a more productive labor input.

12.4.2 Education

Human capital theory implies that workers with more education gain skills that should make them more productive. Figure 12.3 shows a pattern of rising wages with increased education consistent with this theory. Those with the lowest levels of education earn less than half the hourly wage of those with the most advanced degrees.

Some counter that it may not be the education itself that enhances the

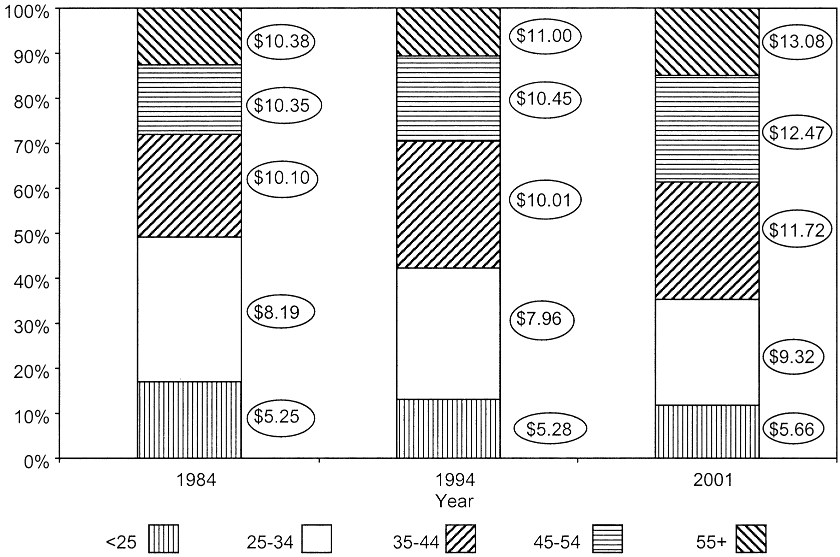

Fig. 12.1 Distribution of hours worked, by age group

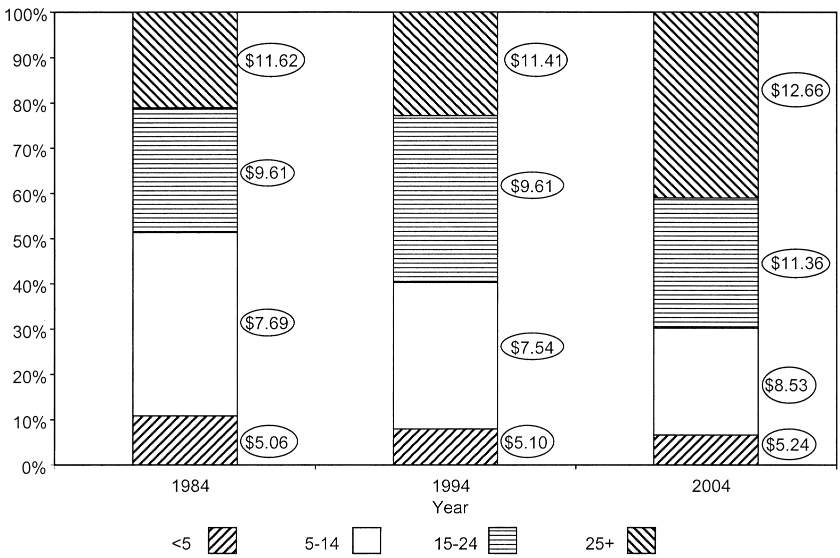

Fig. 12.2 Distribution of hours worked, by years experience (SIPP)

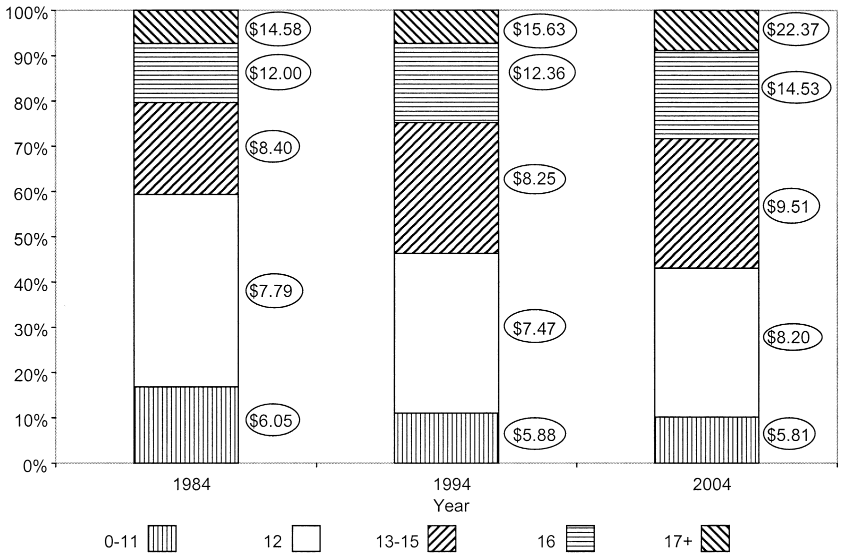

Fig. 12.3 Distribution of hours worked, by education

skills of the worker, but rather that workers with a certain skill level obtain an education in order to signal their skill to employers (Spence 1973). In either case, however, educational differentials are likely to be correlated with productivity differentials. This fits in closely with the idea that there are "sheepskin effects," or disproportionate effects to obtaining a particular degree, above and beyond the effect of the number of years of education that it takes to obtain such a degree (Hungerford and Solon 1987; Belman and Heywood 1991).

As with the case of age, there have been large shifts in the education composition of the workforce. As figure 12.3 shows, in 1984, 60 percent of labor hours were performed by workers with twelve years of education or less. By 2004, however, that number had fallen to approximately 45 percent. This is another example of a shift in the composition of workers away from low-wage—and potentially low-marginal productivity—workers.

12.4.3 Gender

According to Blau and Kahn (2006), women's wages, which had been 60 percent of men's wages for much of the 1950s and 1960s, increased relative to men's in the 1980s (to 69 percent of men's), and that increase continued, albeit much more slowly, in the 1990s (to 72 percent by 1999). Figure 12.4 confirms that women earn less than men, and that the gap has narrowed between 1984 and 2004, from 68 percent to 74 percent. Hellerstein, Neumark, and Troske (1999) found that although women do, in fact, have lower

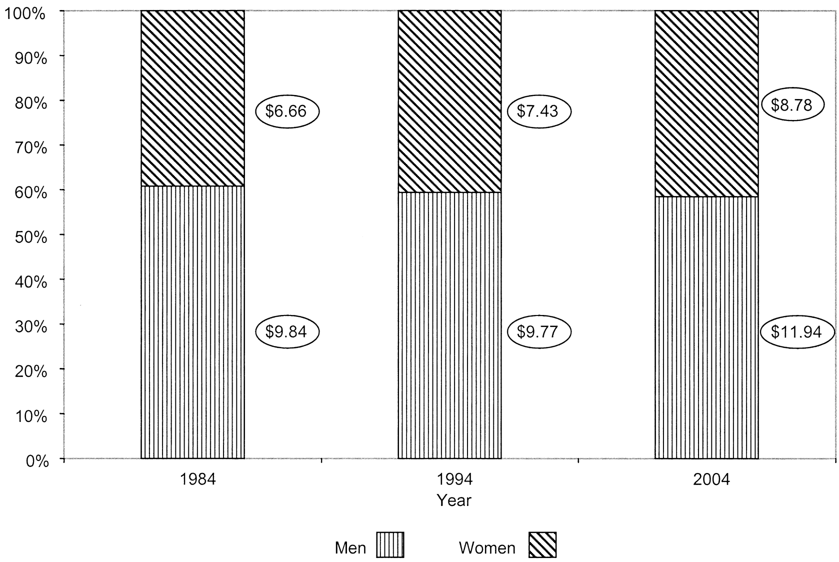

Fig. 12.4 Distribution of hours worked, by gender

productivity than men, the wage gap is much larger than would be suggested by these productivity differentials. Thus, a large part of the wage differential measures discrimination.

Another motivation used for segregating workers by gender is that the returns to other characteristics may vary across gender. For example, women's returns to age or potential experience are likely to be lower than men's, since women are more likely to have been out of the labor market for some of that time. Additionally, women's returns to education may be different, if the types of jobs they hold are more or less likely to value education than the types of jobs men hold.

In figure 12.4, the composition of hours has changed slightly toward an increasing percent of hours being worked by women. In 1984, 39.2 percent of total hours were performed by women. By 2004, that number had increased to 41.6 percent. This is an interesting case for labor composition measurement. There is a shift in composition toward a lower-paid type of worker; however, since only part of the wage differential is believed to be productivity-related, a labor composition measure that includes women as a category of worker may overstate the effect of the shift, while one that does not include women may understate it.

12.4.4 Industry

Figure 12.5 compares the wages for workers in each industry, measured by the Census 1990 code for major (one-digit) industry. In 1984, wages were

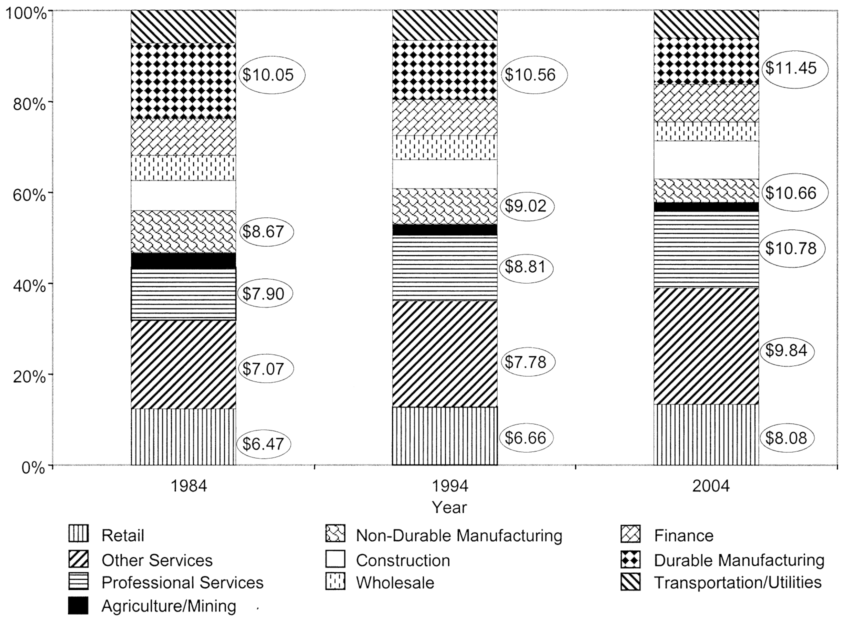

Fig. 12.5 Distribution of hours worked, by industry

highest in mining, transportation and utilities, and durable manufacturing, with the lowest wages found in personal and entertainment services. By 2004, finance and business services moved to the top of the list, along with mining.

There is a long history of debate on whether interindustry wage differentials represent differences in amounts of unmeasured skills, nonpecuniary benefits, employee or employer bargaining power, or the use of efficiency wages. Industry wage differentials are remarkably persistent over time and across countries. Krueger and Summers (1988) matched CPS workers across months to look at the industry differentials for job changers, using first-differencing to remove the effect of unobserved worker characteristics. They found that the differentials persist, and inferred from this that interindustry wage differentials are not, therefore, related to productivity differentials caused by unmeasured ability. Murphy and Topel (1987, 1990) used a similar methodology but found much lower differentials in their first-differenced estimates. Keane (1993), using a longer longitudinal data set, found that 84 percent of the wage differential is attributed to unobserved worker characteristics. One problem with these studies, however, is that they assume that the worker's skills are equally valuable after he or she changes industry, which is not likely to be the case.

Alternative explanations for the interindustry wage differentials have not been met with much empirical success. Brown (1980), Smith (1979), Brown and Medoff (1989), and others have been unable to find evidence that wage differentials are due to differences across industries in on-the-job hazards or other job attributes. Testing a model by Dickens (1986) of the relationship between unionization threat and wage differentials, Krueger and Summers (1988) and Dickens and Katz (1986) found that the patterns of interindustry wage structure are similar in geographic areas where union avoidance is high relative to other areas of the country. They also found that neither time series patterns of unionization nor differences in unionization across industries provide support for this explanation of wage differentials.

The distribution of hours of work across industry has changed enormously over the last twenty years, as figure 12.5 indicates. Employment has fallen in manufacturing and transportation and utilities, and has risen in the service industries. Unlike the patterns we see for experience and education, this suggests a shift away from higher-wage jobs—if these wage differentials reflect productivity differences across workers in different industries, not including industry in a labor composition measure will understate productivity.

12.4.5 Occupation

Occupation codes are intended to classify different skill sets (or amounts of human capital types) needed to perform different jobs. Thus, occupations are in some sense the most natural unit of segregation of workers. In addition, employers do not hire five workers with BAs and three workers with high school degrees—rather, they hire three secretaries, four production workers, and one manager. However, occupation codes have rather serious measurement issues. Levenson and Zoghi (2006) showed that there is considerable variation in skills even within occupation codes, and that the extent of variation is not uniform across occupation. White-collar occupations are much more varied than pink-collar and blue-collar ones.

Figure 12.6 shows that the wages of managers and professionals is significantly higher than that of other occupations, and administrative workers earn the least of all occupations. The relative differences in wages has changed only slightly over time, with technical workers earning slightly more relative to other groups in 2004 than they did in 1984, and handlers earning less in relative terms in 2004 than in 1984. The share of work hours performed by managers and professionals has also increased over the time period. The share of work done by the lowest skill group—handlers and other laborers, has fallen. This indicates a shift toward high-wage workers, which may indicate increasing efficiency per man-hour.

12.4.6 Union

Union workers earn approximately 20 percent higher wages than comparable nonunion workers, according to studies by Hirsch and Macpherson (2002) and Pierce (1999). This is confirmed in figure 12.7, which shows that union members earn 28 percent more than nonunion members in 1984. By

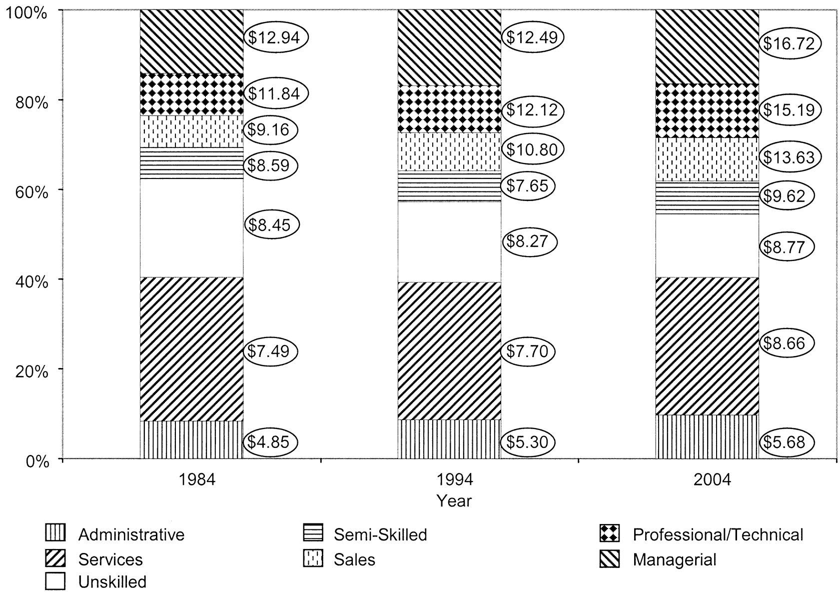

Fig. 12.6 Distribution of hours worked, by occupation

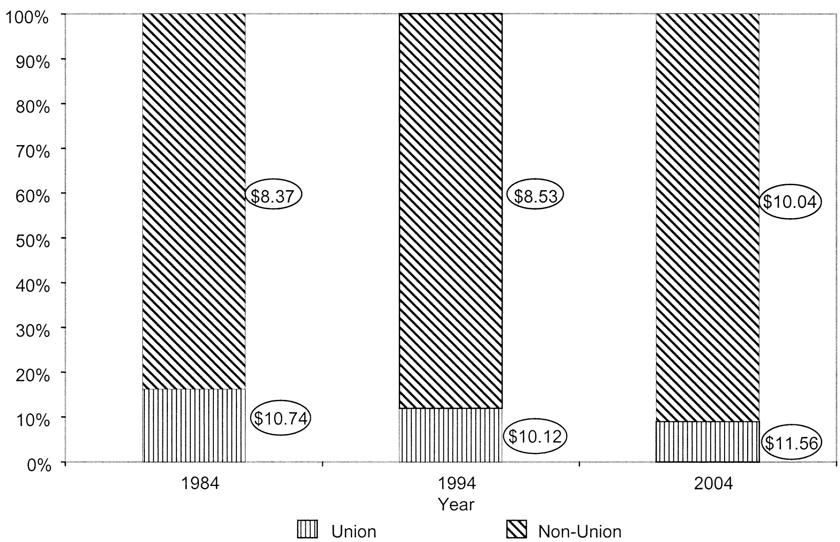

Fig. 12.7 Distribution of hours worked, by unionization

2004, however, nonunion members have narrowed the wage gap quite a bit, to around 15 percent.

While one may infer from the wage differential that unions prevent markets from operating freely, and use the bargaining power to raise wages in excess of marginal productivity, early work by Freeman and Medoff (1982, 1984) found that unions in fact also increase productivity by over 20 percent. They attributed this to the increased union voice making workers more satisfied with their jobs and less likely to be absent or quit. Meta-analysis of other studies (Doucouliagos and Laroche 2003) suggests that taking all studies into account there is a near zero relationship between unions and productivity, although there are positive and significant productivity differentials of 10 percent on average in manufacturing.

The share of work hours performed by union members has decreased over the past twenty years, as figure 12.7 shows. In 1984, union members accounted for 16 percent of work hours; by 2004 the number had dropped to around 10 percent. If higher wages of union workers indicate their higher marginal productivity, such a shift away from unionized work hours would indicate a labor composition shift that decreased productivity.

12.4.7 Establishment Size

There is much evidence that wages are higher at larger plants as well as larger firms, with the differentials being as large as that between men and women (Mellow 1982; Brown and Medoff 1989; Doms, Dunne, and Troske 1997; Oi and Idson 1999). The pattern is confirmed in figure 12.8, where workers in the smallest establishments earn 77 percent of the amount that

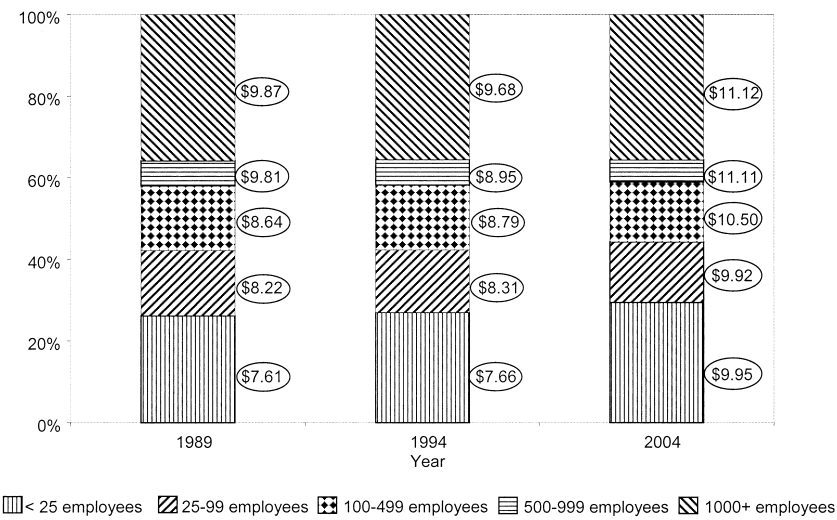

Fig. 12.8 Distribution of hours at work, by establishment size

workers in the largest establishments earn in 1984. The differential is somewhat lessened by 2004, however, to 89 percent.

Evidence shows that large employers demand more productive workers, as measured by observable worker characteristics (see, for example, Personick and Barsky 1982). Thus it is possible that workers with high unobserved ability select into large establishments as well, which would indicate that the establishment-size wage differential represents productivity differentials. Adjustments for selection bias (Brown and Medoff 1989; Abowd and Kramarz 2000; Evans and Leighton 1989; Idson and Feaster 1990) are unable to eliminate the wage differentials, suggesting that the wage differential does not represent differences in unobserved worker characteristics.

Some alternative theories for the establishment-size wage differential focus on compensating differentials for the increased risk of unemployment when employed at small establishments, differences in monitoring costs between small and large establishments, and whether efficiency wages might be paid in large establishments to reduce shirking. Additionally, however, the job performed in a large firm may be different from the same job performed in a small firm, since larger firms may use capital more intensively, may use newer technologies, may have a more constant stream of customers, may organize its workers differently (as in teams), or may be more likely to train workers. It seems likely from the bulk of the evidence that workers in large firms earn higher wages because they are more productive, although whether that is a characteristic of the worker or the job that worker is in is less clear.

Figure 12.8 indicates that the distribution of hours across different-sized establishments has changed slightly over time. There has been a small increase in the work hours performed in the smallest establishments—those with twenty-five or fewer employees—from 26 percent to 29 percent between 1984 and 2004. The hours have shifted to these small establishments mainly from the middle-sized establishments—those with between 25 and 999 employees. If the marginal productivity of workers is lower in small establishments, as wage differentials signify, omitting this category from labor composition leads to understating productivity growth.

12.4.8 Regional/Urban

There are well-known and well-documented wage differentials between geographic areas of the United States, most notably the North-South differential and the intermetropolitan wage differential. According to figure 12.9, workers in the South earn 91 percent of the wages of those in the Northeast, with the gap increasing to 86 percent by 2004. Figure 12.10 shows that workers in a Standard Metropolitan Statistical Area (SMSA) but outside of the central city earn the highest wages. Those outside the SMSA earn 83 percent as much, while those in the central city earn 91 percent as much in 1984. These gaps increase to 76 percent outside the SMSA and 88 percent in the central city by 2004. Angel and Mitchell (1991) also find

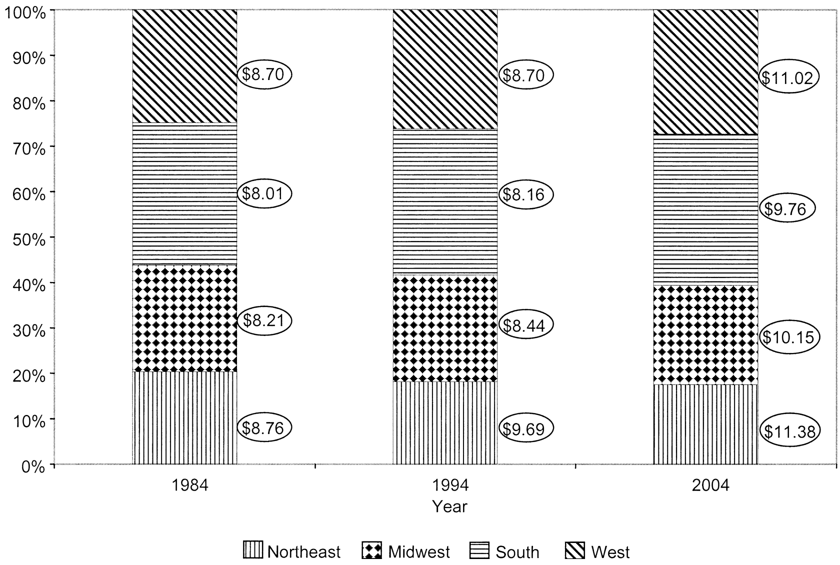

Fig. 12.9 Distribution of hours worked, by region

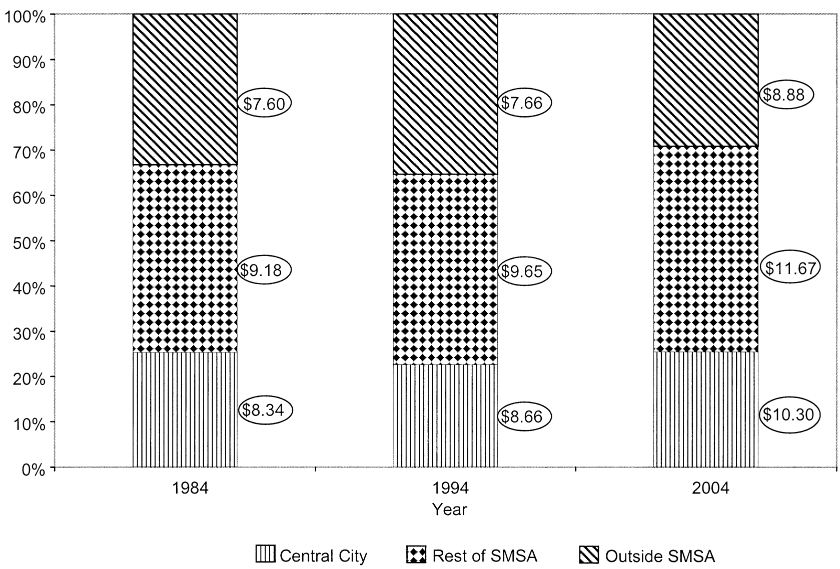

Fig. 12.10 Distribution of hours, by urbanicity

increasing variation in wages across cities within geographic regions. One possible explanation is that nonpecuniary amenities may vary across regions and across cities, so that the wage does not reflect the full compensation to workers.

Figures 12.9 and 12.10 show that the distribution of hours has shifted away from the Midwest and the Northeast somewhat, with the West increasing its hours worked. Employment has increased in the SMSA outside the central city, and has decreased outside the SMSA. A comparison of these shifts with the patterns of wage differentials does not clearly indicate which way productivity might be affected by including geographic variables in the labor categorization. The shift away from the rural areas might be interpreted as a shift away from low productivity workers, while the shift away from the Northeast might be considered a shift away from higher productivity workers according to the wage differentials.

Many of the aforementioned wage differentials are interesting potential sources of productivity differentials, and there are many others as well. In this chapter, I will restrict attention to those that are most closely linked to likely productivity differentials, and that have the most dramatic changes over time. Further, the variable must be measured consistently over time. Thus, I begin with education and age or experience as the most important baseline categories, and then consider the addition of gender, occupation, or industry independently. I leave further explorations of the effects of other categorizations to future research.

12.5 Calculating Labor Composition Index—Mincer Wages or Actual Wages

The first step in calculating the labor composition index is to collect hours worked and weights by categories of workers for each year, using data from the March Current Population Survey (CPS). The BLS (1993) currently uses a Mincer wage equation to estimate wages. One reason for this is that when hours are divided into the many distinct categories of workers, the cell sizes are often quite small. Under the current BLS categorization, more than one-fourth of the cells contain fewer than five worker observations and more than one-third of the cells contain fewer than ten. Another reason for using estimated wages is to restrict differentials to that part attributable to productivity-related human capital variables.

The wage model includes controls for imputed experience and its square; six indicators for years of schooling completed (zero to four, five to eight, twelve, thirteen to fifteen, sixteen, seventeen or more, with nine to eleven omitted to avoid multicollinearity); an indicator for part-time status, for veteran status, a set of seven indicators for region (Northeast, Mid-Atlantic, East North Central, South Atlantic, East South Central, West South Central, and Mountain, with Pacific omitted); and indicators for whether in the central city or in the rest of the SMSA. The models are estimated separately for men and women, to allow the coefficients to vary by gender.

Once hours and wages are collected and/or estimated, the growth in the composition-adjusted labor input is:

$$\Delta L = \sum_{j=1}^{J} \left\{ \frac{1}{2} \left[\frac{\hat{w}_{jt} * h_{jt}}{\sum_{j=1}^{J} \hat{w}_{jt} * h_{jt}} + \frac{\hat{w}_{jt+1} h_{jt+1}}{\sum_{j=1}^{J} \hat{w}_{jt+1} h_{jt+1}} \right] * \ln\left(\frac{h_{jt+1}}{h_{jt}} \right) \right\}.$$

The first term inside the summation sign is the average cost share for a particular category of worker, given the imputed wage rate.[3] Thus, rather than a simple sum of hours growth rates, this is a weighted sum, where the weights are the average labor cost shares. Labor composition growth makes up the difference between this composition-adjusted labor input growth and the unadjusted input growth, which is measured as:

$$\Delta H = \ln \frac{\sum_{j=1}^{J} h_{jt+1}}{\sum_{j=1}^{J} h_{jt}}.$$

Table 12.1 compares specifications of the labor composition index that are closest to the current BLS methodology. The first column is the current BLS calculation, where categories are jointly defined by years of experience, seven education indicators, and gender. The second column shows the methodology proposed in Zoghi (2006), which replaces an experience imputation derived from a onetime Social Security Administration-Current Population Survey (SSA-CPS) match with an experience imputation derived from a repeated SIPP experience regression. Alternative versions are shown in column (3), which uses age groups in place of any imputed experience, and columns (4) and (5), which repeat columns (2) and (3), substituting actual median wage rates for each type of worker for imputed wages in the cost shares.[4]

The five specifications have a similar pattern over time. Labor composition growth is nearly always positive in each year over the time period, reflecting the shifts toward workers who are older, more experienced, and who have more education. Since these are the groups that experience high wages, it is natural that a labor composition index that only categorizes workers by these factors will increase. There is some indication that the rate of growth falls slightly over time, although it is difficult to tell whether this is driven by one or two outliers.

There are three important comparisons to consider in table 12.1. The first is the difference between the SSA-CPS experience measure and the recently proposed (Zoghi 2006) SIPP experience measure. The former, in column (1),

3. The equation $\hat{w}_{jt} = \hat{\alpha}_t + \hat{\beta}_1 \, Experience_{jt} + \hat{\beta}_2 \, Yrs.school_{jt}$ is estimated separately for each gender. The effects of all other wage equation variables are collapsed into the intercept term, α_t.

4. These numbers look fairly similar when using mean wage rates, as in other studies; however, the volatility of the wage rates is greatly reduced.

Table 12.1 **Labor composition index under different specifications: Imputed vs. actual (median) wages and imputed experience vs. age groups**

	(1)	(2)	(3)	(4)	(5)
1984–2004	9.5%	11.8%	9.5%	11.3%	10.4%
1984	.926	.907	.928	.911	.919
1985	.929	.912	.931	.912	.923
1986	.929	.925	.930	.922	.923
1987	.937	.924	.937	.922	.929
1988	.942	.924	.943	.923	.939
1989	.947	.920	.948	.918	.945
1990	.958	.932	.958	.933	.958
1991	.969	.945	.971	.948	.970
1992	.973	.951	.974	.952	.974
1993	.979	.962	.978	.964	.979
1994	.984	.973	.983	.974	.983
1995	.986	.982	.985	.983	.986
1996	.989	.986	.989	.986	.989
1997	.993	.991	.992	.992	.993
1998	.999	.998	.999	.998	.999
1999	1.000	1.000	1.000	1.000	1.000
2000	1.008	1.011	1.009	1.012	1.010
2001	1.016	1.019	1.017	1.019	1.017
2002	1.019	1.022	1.020	1.022	1.021
2003	1.020	1.026	1.021	1.022	1.022
2004	1.022	1.025	1.023	1.024	1.023
Wage	imputed	imputed	imputed	actual	actual
Experience	SSA impute	SIPP impute	no	SIPP impute	no
Age	no	no	yes	no	yes
Education	yes	yes	yes	yes	yes
Gender	yes	yes	yes	yes	yes

shows slower labor composition growth than the latter, in column (2). Since experience grows faster under the SIPP measure, this is an expected result. It seems likely that the two measures form an upper and lower bound for the actual experience of workers in today's labor market.[5] Figure 12.11 shows the effect on multifactor productivity (MFP) growth between 1987 and 2005 when using the current methodology and the SIPP measure.[6] The productivity growth using the SIPP labor composition measure is somewhat higher in the first half of the period, and slightly lower toward the end than under the current methodology, but overall matches the current methodology.

The second comparison is between the experience measures of columns

5. A calculation of worker's experience using the Canadian Workplace and Employee Survey yields age-experience profiles somewhat lower than those from the SIPP, and higher than those of the SSA-CPS, suggesting that the former is an overestimate of true experience and the latter is an underestimate.

6. These figures are calculated from the published BLS MFP index and labor composition index numbers.

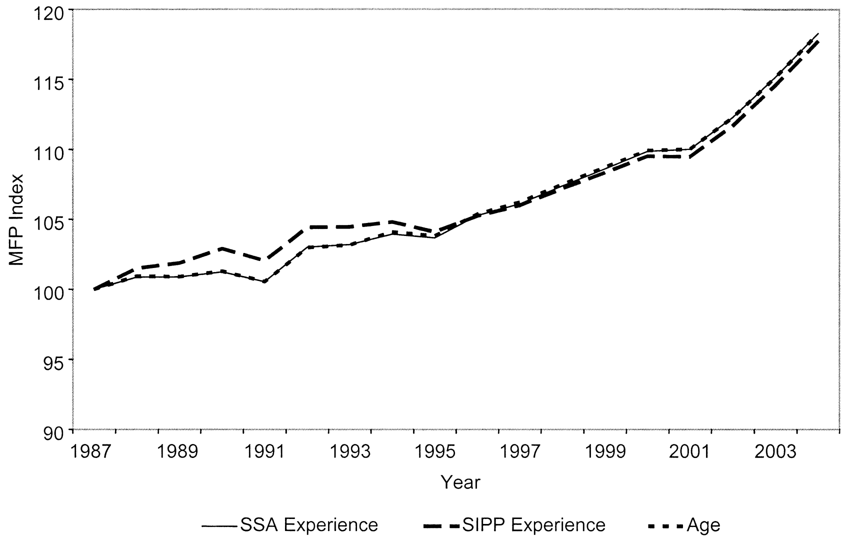

Fig. 12.11 MFP index with experience imputations/age in labor composition

(1) and (2), and a labor composition index calculated without using experience at all, but rather replacing it with age groups, as in column (3). This eliminates the measurement error that is inherent in both experience measures, and to a certain extent, any experience measure. Calculating the index in this way yields a growth rate that is quite similar to the SSA-CPS experience measure. It is impossible to be certain from this result whether important information about worker effectiveness has been lost in the replacement of experience with age, or whether the measurement error in the SIPP experience measure biased upwards the composition effects. It seems likely, however, that both are affecting the growth rate, and that a growth rate calculated with perfectly measured experience would lie somewhere between these two estimates. The MFP growth under the current methodology is nearly identical to that obtained using age groups instead of any experience measure, as indicated in figure 12.11.

The third comparison is between the use of imputed wages from Mincer wage equations and the use of actual within-group median wages. Table 12.1 shows two such comparisons, the first between columns (2) and (4) and the second between columns (3) and (5). In the first instance, which uses the experience imputation, the growth rate is slightly slower when weights are derived from actual median wages than when they are derived from imputed wages. The case for the two models that use age groups has the opposite effect. The growth rate is nearly 1 percent higher when using actual wages when workers are disaggregated by age group rather than years of imputed experience. Once again, actual wages measure something somewhat different from imputed wages. The former include all sources of wage differentials, and the latter only include those due to experience and education; both are subject to some form of measurement error. In other words, this does not imply that either approach is correct or incorrect, but merely signifies that the simpler method of calculating weights from median wage rates can be used without a dramatic change in the labor composition index. Figure 12.12 shows that there is not a tremendous effect on MFP of using the labor composition index of column (3) versus that of column (5). The MFP index is slightly lower, using actual median wages rather than imputed ones.

To compare other possible worker characteristics that might be included in the categorization of worker hours, I reestimate the labor composition index under a variety of other sets of variables. Table 12.2 shows the results of these calculations. Each estimation includes the five-year age groups and education groups from the last column of table 12.1. The first column shows the labor composition index if only age and education are taken into account as sources of worker heterogeneity. The second column repeats the measure of table 12.1, column (5) with labor disaggregated by gender, age, and education. In the third column, broad (one-digit Census) occupation categories are added in place of gender; in the fourth, broad (one-digit Census) industry categories are included instead. The fifth and sixth columns use more disaggregated (two-digit Census) occupation and industry categories, respectively. In each case, the calculations use actual median wage rates rather than the imputed ones.

Age and education are clearly the demographic features of workers that have increased the growing effectiveness of hours the most over the 1980s

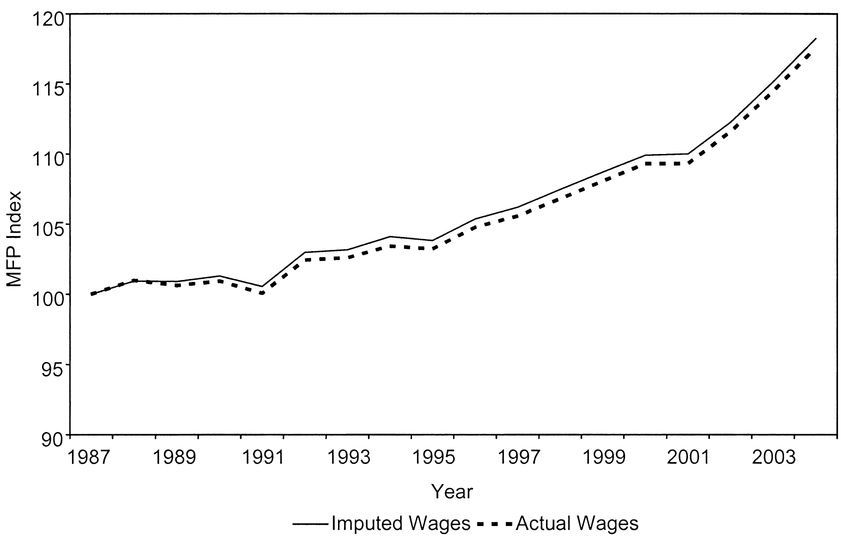

Fig. 12.12 MFP index with actual/imputed wages in labor composition index

Table 12.2 Labor composition index under different categorizations: Age, education and gender, occupation or industry (weights are median wage rates)

	(1)	(2)	(3)	(4)	(5)	(6)
1984–2004	11.4%	10.4%	11.2%	8.4%	10.4%	6.6%
1984	.910	.919	.909	.934	.918	.954
1985	.916	.923	.917	.936	.922	.956
1986	.918	.923	.921	.938	.924	.951
1987	.929	.929	.932	.947	.933	.961
1988	.933	.939	.936	.952	.937	.964
1989	.940	.945	.940	.957	.940	.967
1990	.954	.958	.953	.962	.943	.972
1991	.967	.970	.966	.973	.955	.977
1992	.972	.974	.968	.974	.961	.978
1993	.976	.979	.975	.980	.967	.980
1994	.980	.983	.982	.986	.972	.981
1995	.985	.986	.983	.991	.981	.986
1996	.989	.989	.989	.996	.991	.994
1997	.992	.993	.992	.995	.994	.995
1998	.999	.999	.997	1.001	1.000	1.004
1999	1.000	1.000	1.000	1.000	1.000	1.000
2000	1.011	1.010	1.012	1.010	1.008	1.006
2001	1.018	1.017	1.011	1.012	1.007	1.014
2002	1.023	1.021	1.016	1.016	1.012	1.020
2003	1.023	1.022	1.018	1.017	1.017	1.015
2004	1.024	1.023	1.021	1.018	1.022	1.020
Age	yes	yes	yes	yes	yes	yes
Education	yes	yes	yes	yes	yes	yes
Gender	no	yes	no	no	no	no
1 Dig. occ.	no	no	yes	no	no	no
1 Dig. ind.	no	no	no	yes	no	no
2 Dig. occ.	no	no	no	no	yes	no
2 Dig. ind.	no	no	no	no	no	yes

and 1990s. Distributional changes by either occupation or industry have worked against the increasing effectiveness of labor, although much more so for industry than for occupation. Figure 12.13 shows that a measure of labor composition that treats occupational differences as productivity differences yields a higher estimate of MFP growth over 1989 to 1997 and 2001 forward. Recall that figure 12.5 showed that industry compositional changes have favored lower-wage workers over the past twenty years. This indicates that, assuming industry wage differentials reflect productivity differentials, omitting industry from the labor composition calculation might have resulted in an understatement of productivity growth in the 1980s and 1990s. Figure 12.14 confirms this prediction, showing that MFP growth is significantly higher under a labor composition index that segregates workers by industry.

While it is especially interesting that a categorization of workers by indus-

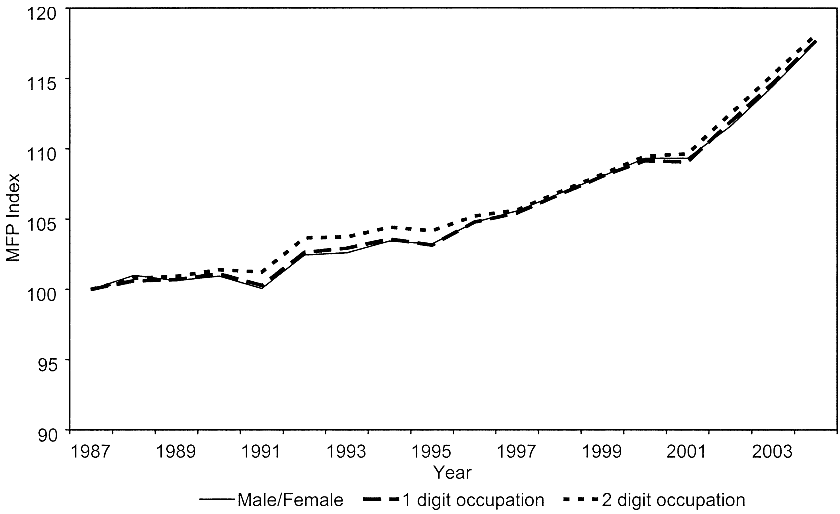

Fig. 12.13 MFP index under different labor composition worker groups

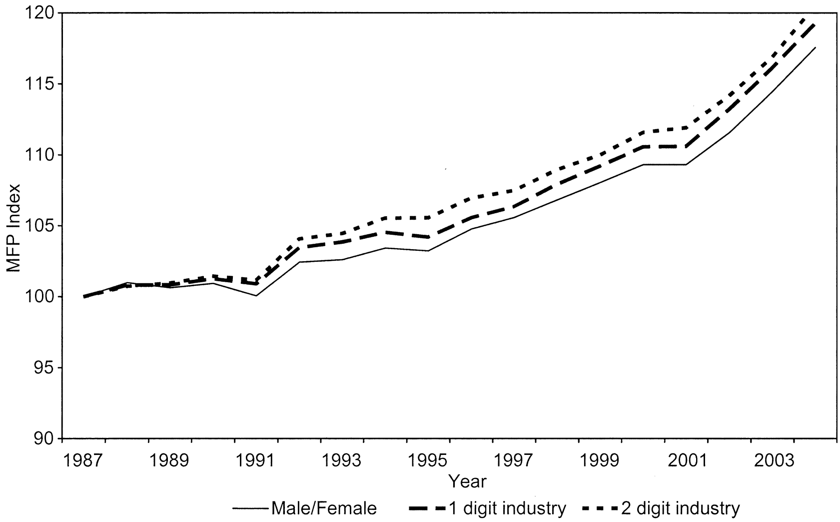

Fig. 12.14 MFP index under different labor composition groups

try or occupation would yield a lower labor composition index and more unexplained residual productivity, it is not at all clear that a worker who maintains his same characteristics and human capital becomes a different input when he moves to a new job in a different industry. Although his movement may, in fact, shift the aggregate production function, we may or may not want to include this effect with more traditional changes in the quantity and effectiveness of labor input. A natural compromise is that followed by Jorgenson, Gollop, and Fraumeni (1987), of considering separately the industry effects as a "reallocation of labor input."

12.6 Conclusion and Recommendations

This chapter explores various possible ways to estimate a labor composition index. One methodological choice is whether to measure the weights for each worker group using actual median wages within the group or using imputed wages, where the imputation is derived from Mincer wage equations. Labor composition growth is not dramatically different using the actual median wage rates. While wage equations introduce an additional source of potential error, median wage rates may differ between groups for more reasons than just differences in the defined characteristics. As a result, there is an inherent trade-off between the efficiency of the wage measures and the clarity of the conceptual basis for the wage differentials. It is not possible to determine ex post which measure is "right;" however, it seems preferable to use the simpler median wage rates, given the narrow difference between the two measures.

The second methodological choice is which set of variables to use to identify distinct worker groups, each of which has a different expected marginal productivity. Again, while we can examine ex post the effects of including different sets of variables, the set of variables must be determined ex ante, using our economic reasoning to assess whether marginal productivity differences are likely to exist between the groups under the set of assumptions of the labor composition model. A brief survey of the economic literature on this subject unfortunately suggests that there remains uncertainty as to which wage differentials represent productivity differentials. As a result, it becomes an empirical question whether the variable adds to or distorts our understanding of labor composition change. While the assumption that labor markets are competitive should be our guiding principle, it might prove better to leave an uncertain and poorly measured portion of the labor composition change in the multifactor productivity residual.

Using experience and education yields a mainly positive labor composition index, since experience and education increase the wages—and, hopefully productivity—of the worker. The two experience measures considered here result in fairly different estimates of labor composition, which is higher using the SIPP measure than the SSA-CPS measure. This is not surprising, since the SSA measure is likely to understate true experience and the SIPP measure may overstate it. Replacing the experience variable with five-year age groups results in lower labor composition growth. It is likely that an index derived from a perfectly measured experience variable would lie somewhere between these two outcomes. As neither experience imputation is well measured, and no other experience measure exists that can be used here, it seems reasonable to use the simpler and more transparent age group variable.

The addition of gender to age and education lowers the index slightly, as does the addition of either broad or detailed occupation groups. Disaggregating workers by industry, broad or detailed, significantly lowers the labor composition index, reflecting changes in the industry distribution of workers away from high-wage manufacturing jobs. While this is an important shift to capture, it seems inappropriate to lump this together with the effects of changes in age, gender, or education, as it is arguable whether such distributional shifts reflect changes in the magnitude or effectiveness of the labor input.

This chapter is meant to be exploratory in nature. The purpose of the empirical section is to determine how important the choice of labor composition methodology is to the calculation of multifactor productivity. If using real wages or imputed measures, or altering the set of variables that differentiate workers does not affect our productivity estimate greatly, it is desirable to select a methodology based on its clarity, simplicity, and adherence to the theoretical precepts. If, on the other hand, productivity estimates are greatly different depending on which methodology is chosen, then it is important to be cautious and understand what price we pay with our choice of methodology, and what implicit assumptions we are making.

Appendix

Table 12A.1 Determinants of wages

	Men			Women		
	1984	1994	2004	1984	1994	2004
Experience	.059[1]	.054[1]	.045[1]	.040[1]	.040[1]	.039[1]
Experience^2	–.001[1]	–.001[1]	–.001[1]	–.001[1]	–.001[1]	–.001[1]
0–4 yrs. school	–.261[1]	–.249[1]	–.177[1]	–.127[1]	–.073	–.168[1]
5–8 yrs. school	–.099[1]	–.101[1]	–.124[1]	–.076[1]	–.128[1]	–.117[1]
12 yrs. school	.192[1]	.149[1]	.164[1]	.176[1]	.143[1]	.178[1]
13–15 yrs. sch.	.243[1]	.242[1]	.330[1]	.324[1]	.289[1]	.346[1]
16 yrs. school	.557[1]	.573[1]	.671[1]	.508[1]	.587[1]	.656[1]
17+ yrs. school	.599[1]	.737[1]	.954[1]	.678[1]	.816[1]	.909[1]
Part-time	–.180[1]	–.137[1]	–.210[1]	–.151[1]	–.132[1]	–.125[1]
Veteran	.007	.001	–.003	n.a.	.014	.050
Northeast	.013	.119[1]	.053[1]	.016	.090[1]	.068[1]
Mid-Atlantic	–.022[5]	.057[1]	.001	–.016	.070[1]	–.022
E. No. Central	–.019[10]	.034[1]	–.005	–.045[1]	–.017	–.035[1]
So. Atlantic	–.084[1]	–.032[5]	–.052[1]	–.062[1]	–.017	–.054[1]
E. So. Central	–.083[1]	–.016	–.039[5]	–.138[1]	–.079[1]	–.115[1]
W. So. Central	–.016	–.038[5]	–.051[1]	–.063[1]	–.077[1]	–.098[1]
Mountain	.010	–.003	–.015	–.027	–.017	–.038[1]
Central city	.025[1]	.009	.024[5]	.102[1]	.086[1]	.091[1]
Rest of SMSA	.130[1]	.123[1]	.116[1]	.112[1]	.158[1]	.150[1]
Number of Observations	30,794	28,558	40,115	27,573	26,539	37,582
R^2	.3705	.3283	.3214	.2099	.2353	.2567

Notes: Coefficients from log wage regression using March CPS data. Experience is imputed from coefficients on a SIPP experience regression as described in Zoghi (2006). n.a. = not applicable.

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Comment Stephanie Aaronson

In "Measuring Labor Composition: A Comparison of Alternate Methodologies," Cindy Zoghi examines the sensitivity of measured labor composition growth to changes in the method of computation. This is an interesting exercise for several reasons. Most obviously, the measure of labor composition provides information on how the productive capacity of our workforce is changing over time and also provides a framework for forecasting the growth in labor composition. In addition, in a growth accounting framework such as that used by the Bureau of Labor Statistics (BLS), MFP growth is the residual, so a change in the measurement of labor composition affects the path of MFP growth.

At the outset Zoghi describes her criteria for choosing a methodology:

> If [the methodology] does not affect our productivity estimates greatly, it is desirable to select a methodology based on its clarity, simplicity, and adherence to the theoretical precepts. If, on the other hand, productivity estimates are greatly different depending on which methodology is chosen, then it is important to be cautious and understand the price we pay with our choice of methodology and the implicit assumptions we are making.

I would probably reword this a bit. I would say that the methodology should match up with theoretical precepts to the extent possible. Having taken that into account, I then agree that clarity and simplicity are desirable features of a model. In addition, since Zoghi's work appears to be aimed at providing guidance to the BLS on how they might change their calculation of labor composition, there are two other criteria that I believe should be taken into account. The first issue is timeliness. As it is, the BLS typically publishes the official multifactor productivity data for a given year with a lag of about one and one-fourth years (so for instance, the MFP data for 2006 were released at the end of March 2008). The wait can be longer if there has been a comprehensive revision to the National Income and Product Accounts (NIPAs)—an event that will become more frequent when the Bureau of Economic Analysis (BEA) institutes flexible annual revisions. In recognition of the long wait, a few years ago the BLS began to produce a preliminary

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