Measuring Labor Composition: A Comparison of Alternate Methodologies

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Abstract:

In productivity measurements, labor input is typically a combination of the number of hours worked and the effectiveness of each hour, which varies by type of worker. In calculating aggregate multifactor productivity, the Bureau of Labor Statistics adjusts hours worked to account for the composition of labor—which types of workers actually provided these hours. This calculation subtracts a weighted sum of the hours of different types of workers from total hours; cost shares of different classes of workers provide the relevant weights. The result is a labor composition index, which shows how much aggregate hours must be adjusted to allow for changes in the composition of the workforce.

This paper discusses two problems in calculating a labor composition index. First, what categories best identify groups of workers with different effectiveness? While workers have many demographic characteristics, under the assumption of perfect competition, the only relevant ones are those that affect marginal product. The calculation in BLS Bulletin 2426 assumes perfect markets and uses two measures of human capital—education and imputed experience—to classify workers. In addition, workers are classified by gender. There are important criticisms of this classification: education and experience are often measured badly and do not fully capture a worker's labor effectiveness; market imperfections may prevent all human capital from being fully employed in the worker's current job, thereby disrupting the equality between wages and marginal productivity.

The second problem is how to obtain hours and wage rates for each type of worker, which is necessary to calculate a weighted sum of hours. Currently, the BLS uses data from the Current Population Survey to determine actual hours for each group. Wages for each group are estimated from Mincer-type human capital wage regressions. This estimation isolates the effects of the human capital variables on wages, and excludes other characteristics of the worker or job that may affect wages. This methodology is subject to criticisms similar to those involved in the decision to disaggregate workers by education and imputed experience. Other researchers who have calculated labor composition indices have used average wages for each group or impute average wages to obtain the relevant weights. Such measures reflect actual wage differences between types of workers rather than those that can be established solely based on the education and experience of workers.

To some extent, these issues are ideological—for example, should the methodology be based on the explicit assumption of perfect markets? This paper briefly discusses such issues and then conducts an empirical comparison of alternative methodologies. I first compare the use of Mincer-type imputed wage averages to using actual wage averages. I then compare the current classification of workers by education, imputed experience and gender to a) by education, age and gender, b) by education, age and occupation, c) by education, age and industry. This paper helps support an informed discussion of the best methodology for measuring labor composition.

Introduction

Labor productivity is calculated as a ratio of output to labor input, where labor input is measured as total hours worked. This treats labor as a homogeneous input, implying that each work-hour has the same marginal productivity, or contributes the same amount to output. It is likely, however, 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.

The labor composition index adjusts the total hours worked for the composition of labor, 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. Consider the effect of the total number of hours remaining fixed over time, but the composition changing so that the hours are being performed by increasingly intelligent workers, for example. These hours, being more efficient, will result in greater output. Labor productivity would show an increase. Yet, technically, it is not the same 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 cause his work-hour to have greater or lesser effectiveness and characteristics of the job itself that affect the effectiveness of a worker's work-hour. For example, when a year passes and a worker gains an additional year of experience, this is considered a change in the input. Similarly, if the worker is replaced by another worker who has more education, this is also a change in the input. On the other hand, if a worker switches jobs with another worker, resulting in a better match quality, the input is constant, and productivity changes. In another example, the establishment might adopt teams, which would use the same inputs but increase productivity.

There have been many studies that attempt to adjust labor input for the labor composition (sometimes referred to as labor quality). They use a variety of different categorizations of workers to distinguish workers of varying effectiveness. Denison (1962) and Jorgenson and Griliches (1967) use education groups, Chinloy (1980) uses gender, class of worker, age, educational attainment and occupation, and Jorgenson, Gollop and Fraumeni (1987) uses gender, age, educational attainment, class of worker, occupation and industry. In these papers, there is little, if any, discussion of how the choice of categorizations is justified.

This paper first looks at the background evidence for whether the wage differentials observed for particular categories of workers are productivity differentials or are due to other factors. Additionally, I examine whether the composition of labor input is changing over time across these dimensions. If there are productivity differentials across two types of workers but the ratio of the hours of one type to the hours of the other type does not change over time, there is no need to take this categorization into account. If the composition is changing 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. After this discussion, I move to a comparison of various measures of the labor composition index. The current BLS methodology uses estimated wages to weight the types of labor, while other studies have used actual 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 combinations of categorizations of labor input types.

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:

$$(1) \qquad Q = A_t f(k_1, \ldots k_n, h_1, \ldots h_m)$$

where output Q is produced by n different types of capital, k_1, …k_n, by m different types of labor hours, h_1, …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 the relationship between the multifactor productivity and the growth rate of output and the growth rates of the inputs:

$$(2) \qquad \frac{\dot{A}}{A} = \frac{\dot{Q}}{Q} - (s_{k_1} k_1 + \ldots + s_{k_n} k_n + s_{h_1} h_1 + \ldots + s_{h_m} h_m)$$

where the dot notation indicates the growth rate of that variable. The partial derivatives, s_{ki} and s_{hi} represents output elasticities, or the percent change in output resulting from a one 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 share of the total wage bill that is spent on each particular type of labor.

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

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

Under a translog production function, Diewert (1976) shows that changes in input are exactly measured by changes in Tornqvist indexes. Thus, although $\frac{\dot{L}}{L}$ 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:

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

Groups of labor whose hours do not change over time relative to other groups will not affect the quality-adjusted labor input. Groups that make up a very small portion of the total economy-wide 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 (4), and the change in the unadjusted labor input, or the change in the sum of unweighted hours of all workers:

$$(5) \qquad \Delta \ln LC = \Delta \ln L - \Delta \ln H = \Delta \ln \frac{L}{H}$$

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 observed wages or, as the BLS does, replacing actual wages with imputed wages, where the imputations are obtained from a standard Mincer wage regression (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.

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[2]. 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.

[2] In fact, in the extreme, each wage rate could conceivably be considered its own "worker type", in which case the adjustment would be a weighted sum of each hour, where each is weighted by its own wage rate.

It is not necessarily the case, however, that all wage differentials represent productivity differentials. In particular, even within the competitive model[3], 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.

[3] In addition, there are several non-competitive 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.

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. Table 1 shows the average wages for age groups under 25, 25-34, 35-44, 45-54, and 55 and up, as well as for experience groups under 5, 5-14, 15-24, 25 and up, calculated from the 1984, 1994 and 2004 March Current Population Survey (CPS). 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 years shown here.

Lazear (1979), however, argues 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) consider that workers may 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 measure productivity differentials. Hellerstein, Neumark and Troske (1999) compare wage differentials to productivity differentials using matched employee establishment data and find that the size of the age wage differentials is consistent with the size of the productivity differences by age.

Figures 1 and 2 show how the composition of labor hours by age and experience groups has changed from 1984 to 2004. In the 1984 sample, nearly half the hours of work in the U.S. were performed by those ages 34 and under (those with less than 15 years of experience). By 2004, as the baby boom generation aged, this number had dropped to around 35% (30%). Thus, if we believe that age/experience wage differentials reflect productivity differences, there has been a marked shift towards a more productive labor input.

Education

Human capital theory implies that workers with more education should be more productive. Workers gain many skills through education that make them more productive workers. Table 1 confirms such a pattern of rising wages with increased education. Those with the lowest levels of education earn less than half the hourly wage of those with the most advanced degrees.

At the same time, some counter that it may not be the education itself that enhances the 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). There is some evidence of this in Table 1, where the biggest wage increases seem to come at 12 years, 16 years and 17 plus years.

As with the case of age, there have been dramatic shifts in the education composition of the workforce. As Figure 3 shows, in 1984, 60% of labor hours were performed by workers with 12 years of education or less. By 2004, however, that number had fallen to approximately 45%. This is another example of a dramatic change in the composition of workers away from low-wage—and potentially low-marginal productivity—workers.

Gender

According to Blau and Kahn (2006), women's wages, which had been 60% of men's wages for much of the 1950s and 1960s, increased relative to men's in the 1980s (to 69% of men's), and that increase continued albeit much more slowly in the 1990s (to 72 % by 1999). Table 1 confirms that women earn less than men, and that the gap has narrowed between 1984 and 2004, from 68% to 74%. Hellerstein, Neumark and Troske (1999) find that although women do, in fact, have lower 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 4, the composition of hours has changed slightly toward an increasing percent of hours being worked by women. In 1984, 39.2% of total hours were performed by women. By 2004, that number had increased to 41.6%. This is an interesting case for labor composition measurement, then. There is a shift in composition toward a less-productive 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 will overstate the effect of the shift, while one that does not include women will understate it.

Industry

Table 2 compares the wages for workers in each industry, measured by the Census 1990 code for major (1-digit) industry. In 1984, wages are 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 inter-industry wage differentials represent differences across industries in amounts of unmeasured skills, non-pecuniary benefits, employee or employer bargaining power or the need for efficiency wages. Industry wage differentials are remarkably persistent over time and across countries. Krueger and Summers (1988) match 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 find that the differentials persist, and infer from this that inter-industry wage differentials are not therefore related to productivity differentials caused by unmeasured ability. Murphy and Topel (1987, 1990) use a similar methodology but find much lower differentials in their first-differenced estimates. Keane (1993), using a longer longitudinal dataset, finds that 84% 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 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) find that the patterns of interindustry wage structure are similar in highly where union avoidance is high to other areas of the country. They also find that neither time series patterns of unionization nor differences in unionization across industries provides support for this explanation of wage differentials.

The distribution of hours of work across industry has changed dramatically over the last twenty years, as Figure 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 overstate productivity.

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 5 workers with BAs and 3 workers with high school degrees—rather they hire 3 secretaries, 4 production workers and 1 manager. However, occupation codes have rather serious measurement issues. Levenson and Zoghi (2006) show 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.

Table 2 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 increased over the time period, as Figure 6 demonstrates. 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.

Union

Union workers earn approximately 20% higher wages than comparable non-union workers, according to studies by Hirsch and Macpherson (2002), and Pierce (1999). This is confirmed in Table 3, which shows that union members earn 28% more than non-union members in 1984. By 2004, however, non-union members have narrowed the wage gap quite a bit, to around 15%.

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 (1984) finds that unions in fact also increase productivity by over 20%. They attribute 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% on average in manufacturing.

The share of work hours performed by union members has decreased over the past 20 years, as Figure 7 shows. In 1984, union members accounted for 16% of work hours; by 2004 the number had dropped to around 10%. 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.

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 Table 3, where workers in the smallest establishments earn 77% the amount that workers in the largest establishments earn in 1984. The differential is somewhat lessened by 2004, however, to 89%.

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), 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 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 25 or fewer employees—from 26% to 29% 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.

Regional/Urban

There are well-known and well-documented wage differentials between geographic areas of the US, most notably the North-South differential and the inter-metropolitan wage differential. According to Table 3, workers in the South earn 91% the wages of those in the Northeast, with the gap increasing to 86% by 2004. Workers in an SMSA but outside of the central city earn the highest wages. Those outside the SMSA earn 83% as much, while those in the central city earn 91% as much in 1984. These gaps increase to 76% outside the SMSA and 88% in the central city by 2004.

These differences seem to persist even with a variety of controls. Additionally, Angel and Mitchell (1991) find increasing variation in wages across cities within geographic regions. One possible explanation is that non-pecuniary amenities may vary across regions and across cities, so that the wage does not reflect the full compensation to workers.

Figures 9 and 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.

Calculating Labor Composition Index—Mincer Wages or Actual Wages

The first step in calculating the labor composition index is to collect hours worked and average wages by categories of workers for each year, using data from the March Current Population Survey (CPS). The BLS currently uses a Mincer wage equation to estimate wages. The 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 categorization, << >>% of the cells contain 20 or more worker observations, << >>% contain 11-20, << >> % contain 6-10, and << >> contain five or fewer.

The wage model includes controls for imputed experience and its square, six indicators for years of schooling completed (0-4, 5-8, 12, 13-15, 16, 17 or more, with 9-11 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:

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

The first term inside the summation sign is the average cost share for a particular category of worker. The current methodology replaces wages in that term with imputed wages[4]. 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

[4] Put footnote here explaining which vars go into the imputed value, and which are stuck into the constant.

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 4 compares specifications of the composition-adjusted labor input rate ΔL that are closest to the current BLS methodology. The first column is the current BLS calculation, where j is defined by years of experience, seven education indicators, and separately by gender. The second column shows the methodology proposed in Zoghi (2005), which replaces an experience imputation derived from a one-time 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 wages for imputed wages in the cost shares.

The five specifications have a similar pattern over time. Labor composition growth is nearly always positive over the time period, reflecting the shifts toward workers who are older and 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 be positive. There is some indication that the rate of growth is falling 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 4. The first is the difference between the SSA-CPS experience measure and the recently proposed (Zoghi,

2004) SIPP experience measure. The former, in column 1, shows slower labor composition growth than the latter, in column 2. Since levels of experience are higher 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 11 shows the effect on multifactor productivity (MFP) growth between 1994 and 2005 when using the current methodology and the SIPP measure[6][7]. 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.

The second comparison is between the experience measures of columns 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 the lowest growth rate. It is impossible to infer from this whether this implies that important information about the effectiveness of the labor groups has been lost in the replacement of experience with age, or whether the measurement error in the experience measures biased upwards the composition effects. However, MFP growth under the current methodology is very similar to that obtained using age groups instead of any experience measure, as indicated in Figure 11.

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[5] A calculation of worker's experience using the Canadian Workplace and Employer 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] The numbers are indexed to the year 2000, so the points will always merge at that data point.
[7] These figures are calculated from the BLS preliminary MFP calculation methodology. Labor composition index numbers are those of the author and not those officially used by the BLS to calculate MFP.

The third comparison is between the use of imputed wages from Mincer wage equations and the use of actual within group average wages. Table 4 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 difference between actual wages and imputed wages is dramatic. One likely reason for this is that using individual years of predicted experience results in many more small cells at the ends of the experience distribution; these cells will have more unreliable wage averages. A comparison of columns 2 and 4 indicates that labor composition growth is somewhat higher when estimated using actual within-group average wages in the group weights, rather than the imputed wage averages from Mincer equations. Indeed, the difference is much less stark when comparing columns 3 and 5, which use age groups. In both cases, however, labor composition growth is higher with the actual average wages than with the imputed wages. Figure 12 shows the effect on MFP of using the labor composition index of column 3 versus that of column 5. MFP growth is slightly lower in the beginning of the period using actual wages, and higher toward the end. Once again, it is impossible to determine from this evidence whether actual wages pick up real compositional differences that are blurred by the imputation of wages, or whether measurement error in the estimates of average wages bias the index.

To compare other possible worker characteristics that might be included in the categorization of worker-hours, I re-estimate the labor composition index under a variety of other sets of variables. Table 5 shows the results of these calculations. Each estimation includes the five year age groups and education groups from the last column of Table 4. The first column repeats the measure of Table 4, column 5, adding gender to age and education. In the second column, broad (1 digit) occupation categories are added in place of gender; in the third, broad (1 digit) industry categories are included instead. The fourth and fifth columns use more disaggregated (2 digit) occupation and industry categories, respectively. In each case, the calculations use actual wage rates rather than the imputed ones.

These sets of calculations are not wholly different from those of Table 4. This is not surprising, since age and education are the most important aspects of worker differentiation, with the other variables only contributing a lesser amount. Broad occupation indicators have the same effect on labor composition as gender does, while more detailed ones reduce labor composition somewhat. Figure 13 shows that a measure of labor composition that treats occupational differences as productivity differences yields a higher estimate of MFP growth over most of the period between 1994-2005.

Including industry variables, whether the detailed or less detailed ones, lowers the labor composition index. Recall that Figure 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 14 confirms this prediction, showing that MFP growth is mainly higher under a labor composition index that segregates workers by industry.

Conclusion

This paper 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 average wages within the group or using imputed average wages, where the imputation is derived from Mincer wage equations. Labor composition growth is higher using the actual wage averages. While wage equations introduce an additional source of potential error, average 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."

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 here, 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, higher using the SIPP measure than the SSA-CPS measure; 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. The addition of gender or occupation to age and education raise the index a bit further, while the addition of industry lowers it slightly.

This paper 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, we may choose a methodology based on its clarity 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.

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Table 1. Mean and standard deviation of wages by age, education and experience with demographic controls						
	Mean Hourly Wages			% in Excess of Imputed Wages		
	1984	1994	2004	1984	1994	2004
Age						
Age<25	5.25	5.28	5.66	12.0	18.5	17.2
Age 25-34	8.19	7.96	9.32	20.0	22.3	28.9
Age 35-44	10.10	10.01	11.72	19.2	25.1	32.8
Age 45-54	10.35	10.45	12.47	15.5	19.1	30.4
Age 55+	10.38	11.00	13.08	26.5	35.6	41.4
Experience						
Experience<5	5.06	5.07	5.24	15.1	24.7	19.2
Experience 5-14	7.69	7.54	8.53	18.8	20.4	26.5
Experience 15-24	9.61	9.61	11.36	17.5	23.8	31.6
Experience 25+	11.62	11.41	12.66	21.7	26.7	34.7
Education						
0-4 yrs school	5.78	5.36	5.59	14.3	16.5	14.0
5-8 yrs school	6.59	6.32	6.32	17.7	29.0	27.9
9-11 yrs school	5.86	5.79	5.66	15.3	26.0	19.3
12 yrs school	7.79	7.47	8.20	17.6	21.8	26.2
13-15 yrs sch.	8.40	8.25	9.51	18.8	22.5	27.8
16 yrs school	12.00	12.36	14.53	20.6	27.0	33.8
17+ yrs school	14.58	15.63	22.37	24.6	23.7	48.3
Gender						
Men	9.84	9.77	11.94	17.6	22.5	33.4
Women	6.66	7.43	8.78	20.8	25.8	27.7
Wages are adjusted for inflation, using CPI-U. Imputations are from OLS models with controls for gender, experience and its square, education, part-time and veteran indicators, region, urbanicity.						

Table 2. Mean and standard deviation of wages by major industry or occupation, with demographic controls

	Mean Hourly Wages			% in Excess of Imputed Wages		
	1984	1994	2004	1984	1994	2004
Industry						
Ag/For/Fish	5.80	8.03	6.81	-5.2	29.6	0.2
Mining	12.62	11.81	13.78	52.2	44.2	66.8
Construction	9.51	8.63	10.39	27.2	22.6	40.5
Non-Durable Manuf.	8.67	9.02	10.66	23.4	28.3	30.4
Durable Manuf.	10.05	10.56	11.45	27.4	38.0	31.9
Transp/Util.	11.07	10.53	11.89	37.0	35.2	40.5
Wholesale	9.59	9.83	11.75	20.8	29.5	36.9
Retail	6.47	6.66	8.08	3.2	6.8	14.1
Finance	9.82	10.54	14.43	32.3	38.6	63.5
Business/Repair Svc.	9.16	9.59	12.88	23.4	25.8	45.1
Personal Svc.	6.32	6.84	7.80	-1.3	8.6	9.4
Entertainment Svc.	4.96	5.55	6.32	-7.3	3.8	2.7
Professional Svc.	7.90	8.81	10.78	10.9	19.9	25.4
Occupation						
Management	12.94	12.49	16.72	42.5	43.5	64.8
Professionals	12.71	13.13	16.56	31.7	36.7	50.2
Technical	8.01	8.41	10.20	-3.7	-1.6	3.7
Sales	9.16	10.80	13.63	26.5	43.5	56.2
Administrative	4.85	5.30	5.68	-13.4	-3.0	-6.7
Services	7.49	7.70	8.66	15.6	18.8	19.3
Precision Crafts	9.74	8.75	10.62	25.1	21.6	44.8
Operators/Assemblers	8.08	7.21	9.05	20.1	14.1	28.5
Handlers/Other Laborers	8.45	8.27	8.77	19.1	22.8	17.0

Wages are adjusted for inflation, using CPI-U. Imputations are from OLS models with controls for gender, experience and its square, education, part-time and veteran indicators, region, urbanicity.

Table 3. Mean and standard deviation of wages by unionization, region, urbanicity and establishment size, with demographic controls						
	Mean Hourly Wages			% in Excess of Imputed Wages		
	1984	1994	2004	1984	1994	2004
Unionization						
Union	10.74	10.12	11.56	33.2	34.2	41.0
Non-union	8.37	8.53	10.04	13.2	19.3	25.0
Establishment Size	1989	1994	2004	1989	1994	2004
<25 employees	7.61	7.66	9.95	8.0	11.2	27.3
25-99 employees	8.22	8.31	9.92	16.1	21.1	25.9
100-499 employees	8.64	8.79	10.50	20.5	23.9	29.6
500-999 employees	9.81	8.95	11.11	33.7	26.4	35.7
1000+ employees	9.87	9.68	11.12	32.4	34.3	36.6
Region						
Northeast	8.76	9.69	11.38	20.7	33.0	36.6
Midwest	8.21	8.44	10.15	15.9	21.4	27.2
South	8.01	8.16	9.76	15.5	17.7	24.8
West	8.70	8.70	11.02	21.6	23.5	37.5
Urbanicity						
Central City	8.34	8.66	10.30	18.6	24.1	29.2
Rest of SMSA	9.18	9.65	11.67	25.1	32.1	40.3
Outside SMSA	7.60	7.66	8.88	10.6	13.2	17.8
Wages are adjusted for inflation, using CPI-U. Imputations are from OLS models with controls for gender, experience and its square, education, part-time and veteran indicators, region, urbanicity.						

Table 4. Labor composition index under different specifications: imputed vs. actual wages and imputed experience vs. age groups					
	I	II	III	IV	V
1984-2004	9.5%	11.9%	9.4%	16.4%	11.0%
1984	0.918	0.895	0.92	0.852	0.906
1985	0.923	0.902	0.925	0.862	0.912
1986	0.926	0.908	0.927	0.865	0.915
1987	0.928	0.922	0.927	0.874	0.916
1988	0.935	0.921	0.933	0.878	0.921
1989	0.94	0.921	0.939	0.888	0.93
1990	0.946	0.917	0.944	0.884	0.935
1991	0.957	0.93	0.955	0.894	0.948
1992	0.969	0.944	0.968	0.912	0.962
1993	0.973	0.95	0.972	0.921	0.966
1994	0.979	0.962	0.978	0.937	0.973
1995	0.984	0.973	0.983	0.957	0.978
1996	0.986	0.981	0.985	0.973	0.983
1997	0.989	0.986	0.989	0.976	0.986
1998	0.993	0.991	0.993	0.989	0.992
1999	0.999	0.998	0.999	0.995	0.999
2000	1	1	1	1	1
2001	1.007	1.008	1.007	1.008	1.009
2002	1.011	1.011	1.011	1.012	1.014
2003	1.011	1.011	1.012	1.013	1.014
2004	1.013	1.014	1.014	1.016	1.016
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

Table 5. Labor composition index under different categorizations: age & occupation, education and industry, occupation and industry, age, education and industry					
	I	II	III	IV	V
1984-2004	11.0%	11.0%	8.95%	9.8%	8.8%
1984	0.906	0.9	0.915	0.909	0.925
1985	0.912	0.906	0.918	0.914	0.926
1986	0.915	0.911	0.919	0.919	0.929
1987	0.916	0.917	0.921	0.925	0.928
1988	0.921	0.928	0.929	0.936	0.934
1989	0.93	0.927	0.933	0.939	0.941
1990	0.935	0.934	0.936	0.943	0.948
1991	0.948	0.945	0.945	0.954	0.955
1992	0.962	0.958	0.954	0.967	0.962
1993	0.966	0.961	0.958	0.969	0.966
1994	0.973	0.968	0.966	0.975	0.971
1995	0.978	0.976	0.974	0.979	0.98
1996	0.983	0.977	0.979	0.984	0.982
1997	0.986	0.983	0.985	0.983	0.989
1998	0.992	0.988	0.99	0.99	0.995
1999	0.999	0.998	1	0.999	1.003
2000	1	1	1	1	1
2001	1.009	1.001	1.006	0.999	1.005
2002	1.014	1.005	1.013	1.005	1.009
2003	1.014	1.006	1.014	1.005	1.009
2004	1.016	1.01	1.02	1.007	1.013
Age	yes	yes	yes	yes	yes
Educ	yes	yes	yes	yes	yes
Gender	yes	no	no	no	no
1 Dig. occ	no	yes	no	no	no
1 Dig. ind.	no	no	yes	no	no
2 Dig. occ	no	no	no	yes	no
2 Dig. ind	no	no	no	no	yes

Figure 1. Distribtion of Hours Worked, by Age Group

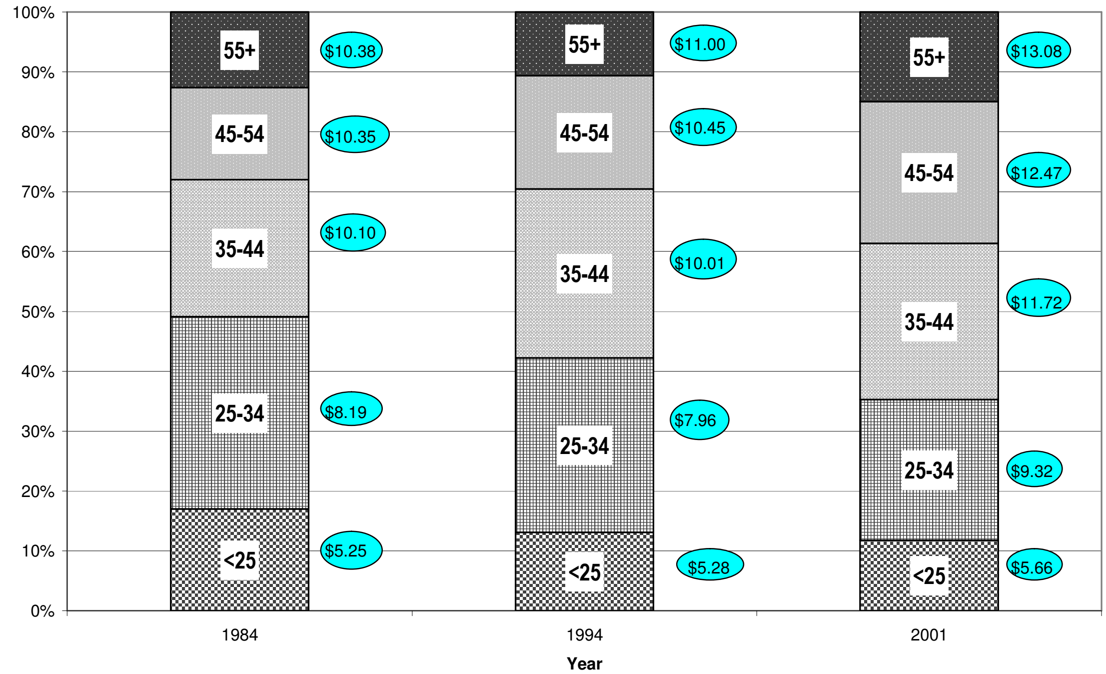


Figure 2. Distribution of Hours Worked, by Years Experience (SIPP)

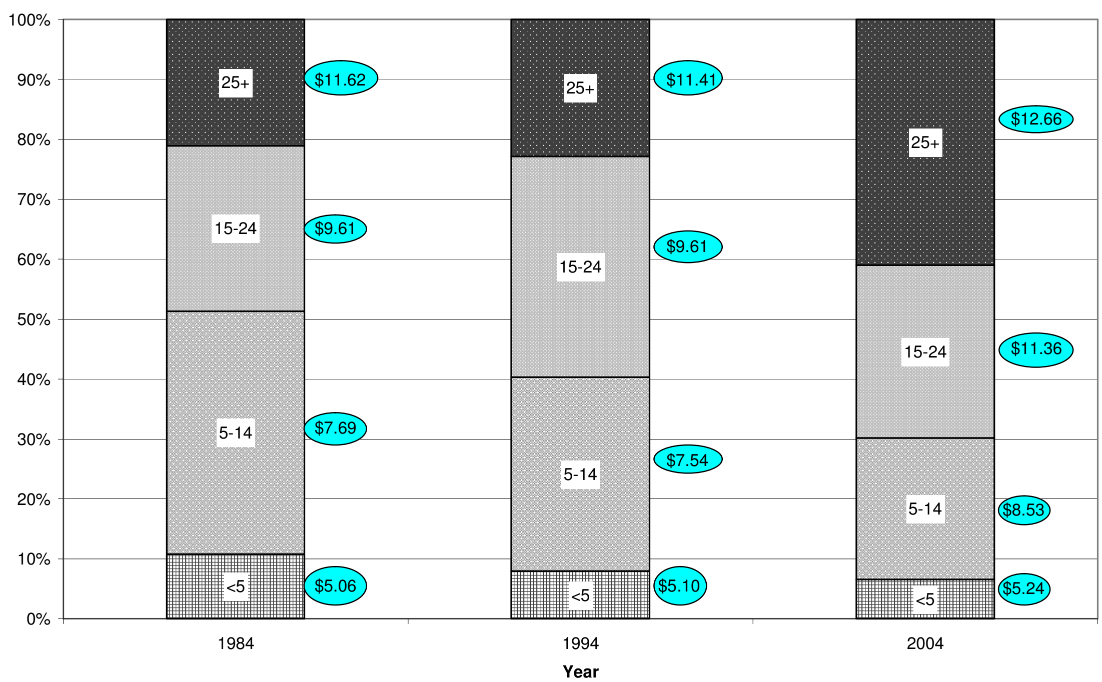


Figure 3. Distribution of Hours Worked, by Education

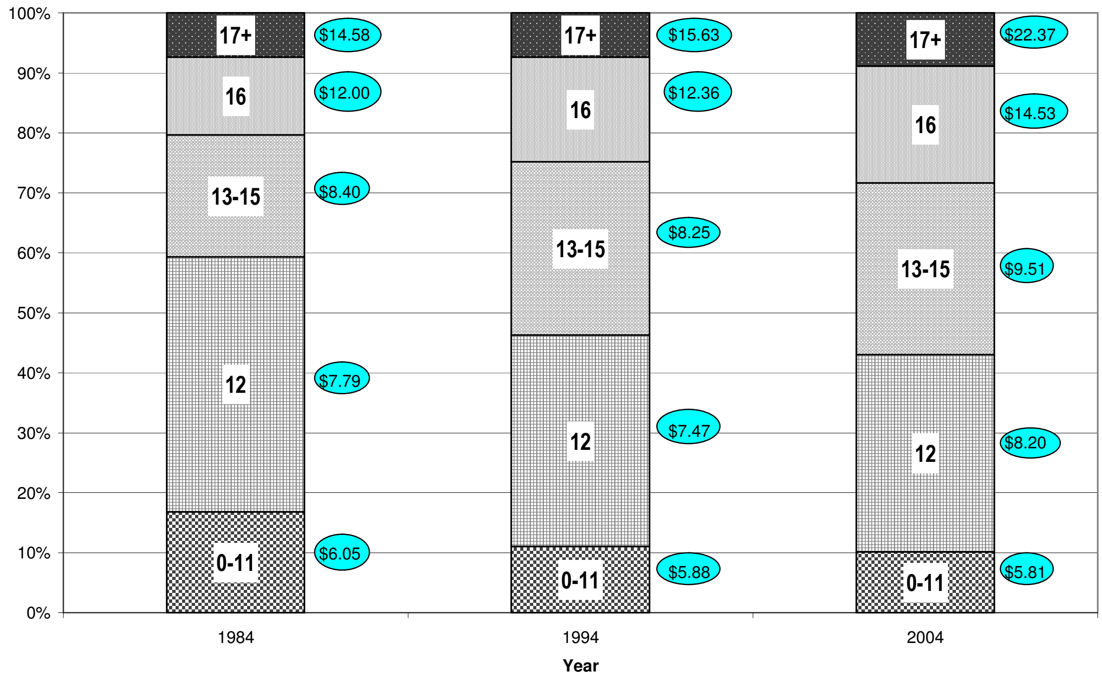


Figure 4. Distribution of Hours Worked, by Gender

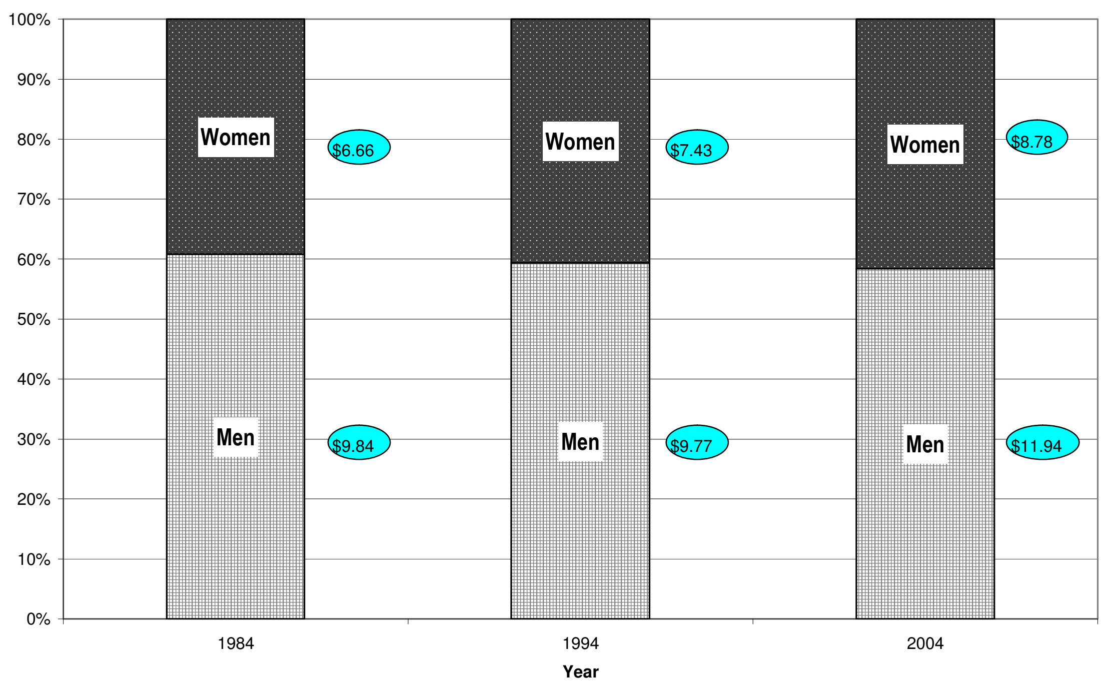


Figure 5. Distribution of Hours Worked, by Industry

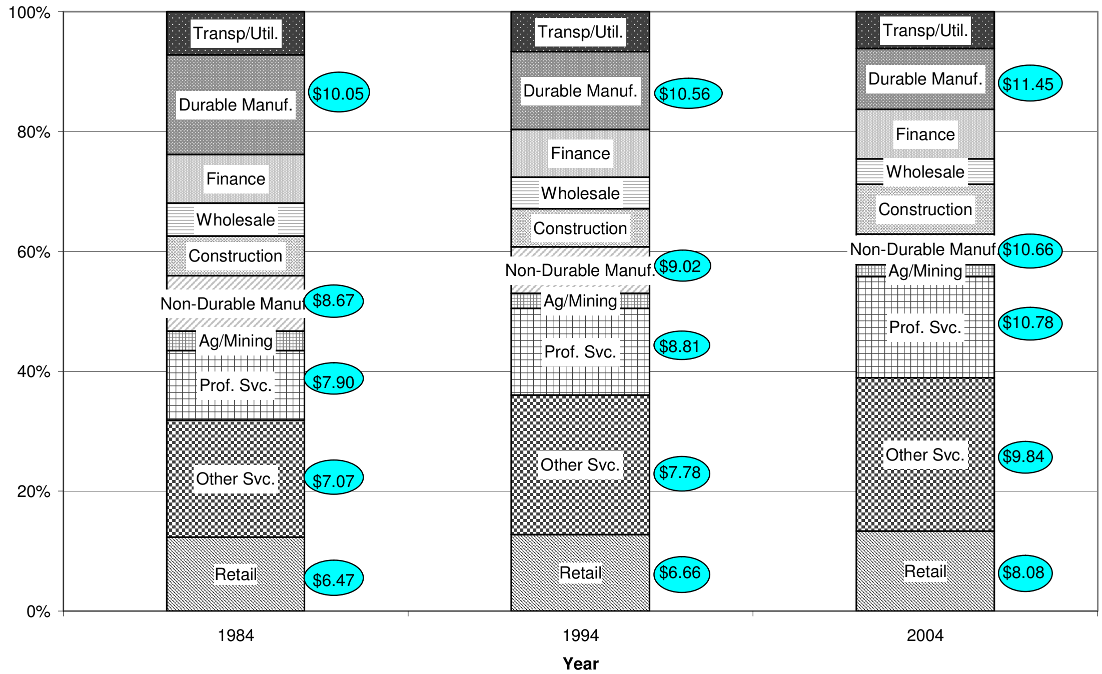


Figure 6. Distribution of Hours Worked, by Occupation

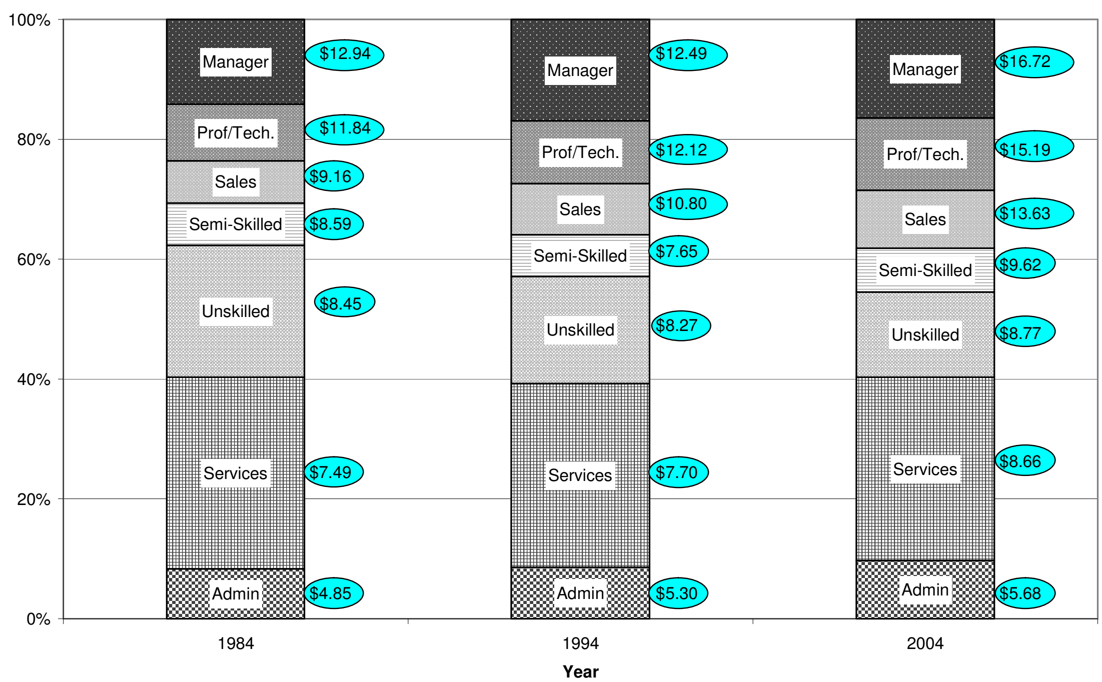


Figure 7. Distribution of Hours Worked, by Unionization

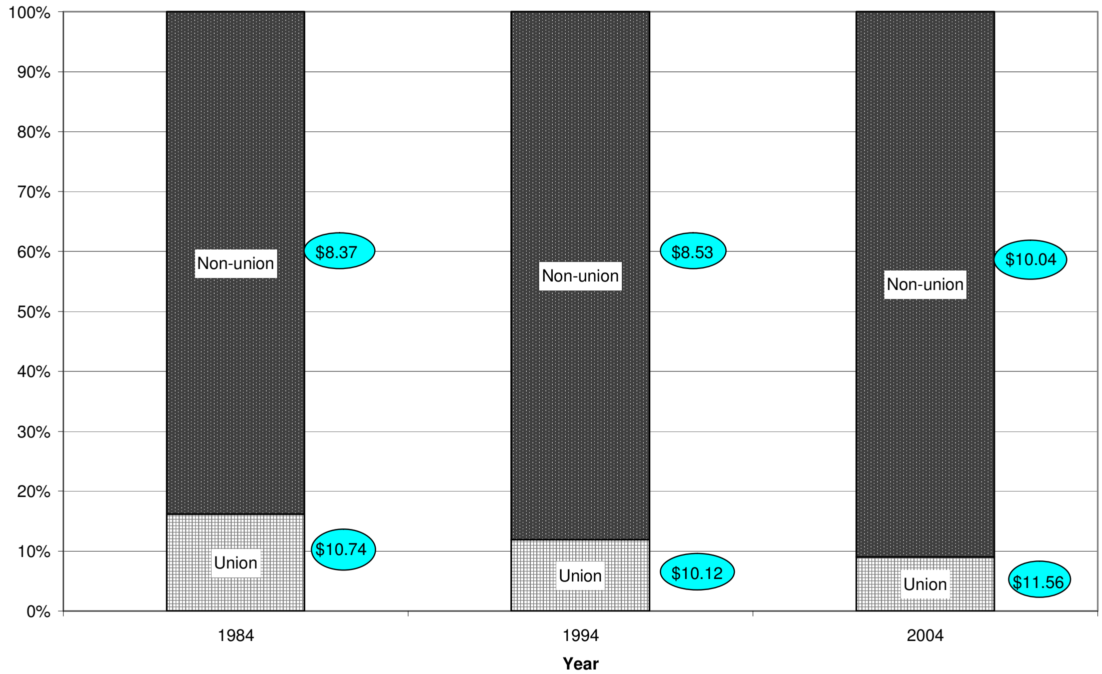


Figure 8. Distribution of Hours at Work, by Establishment Size

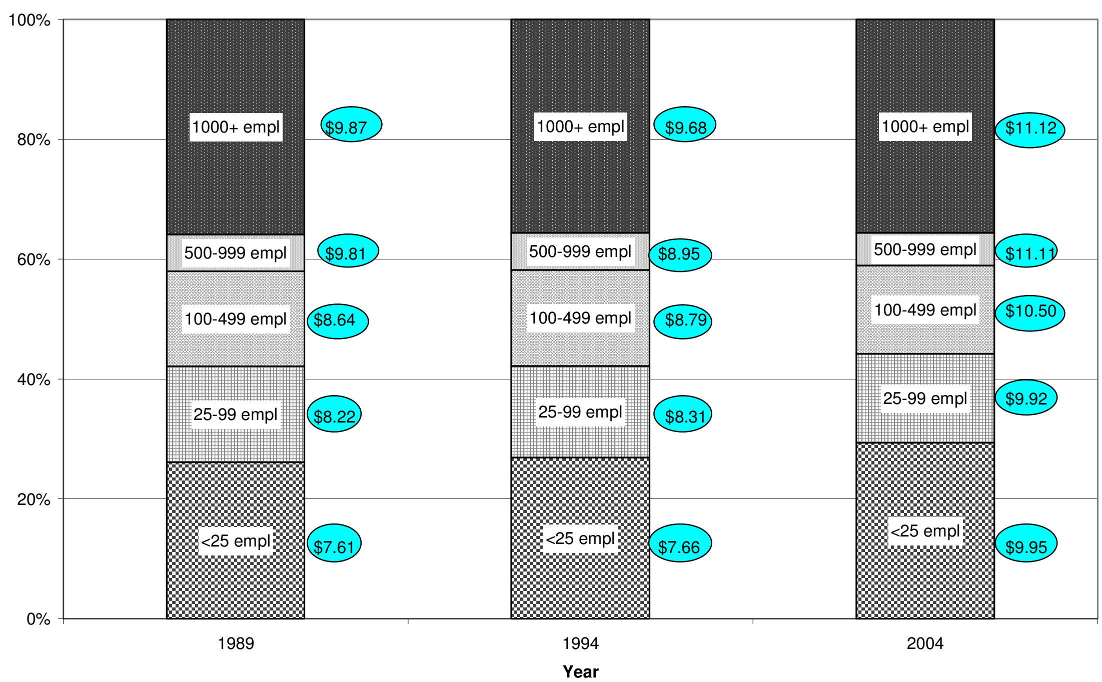


Figure 9. Distribution of Hours Worked, by Region

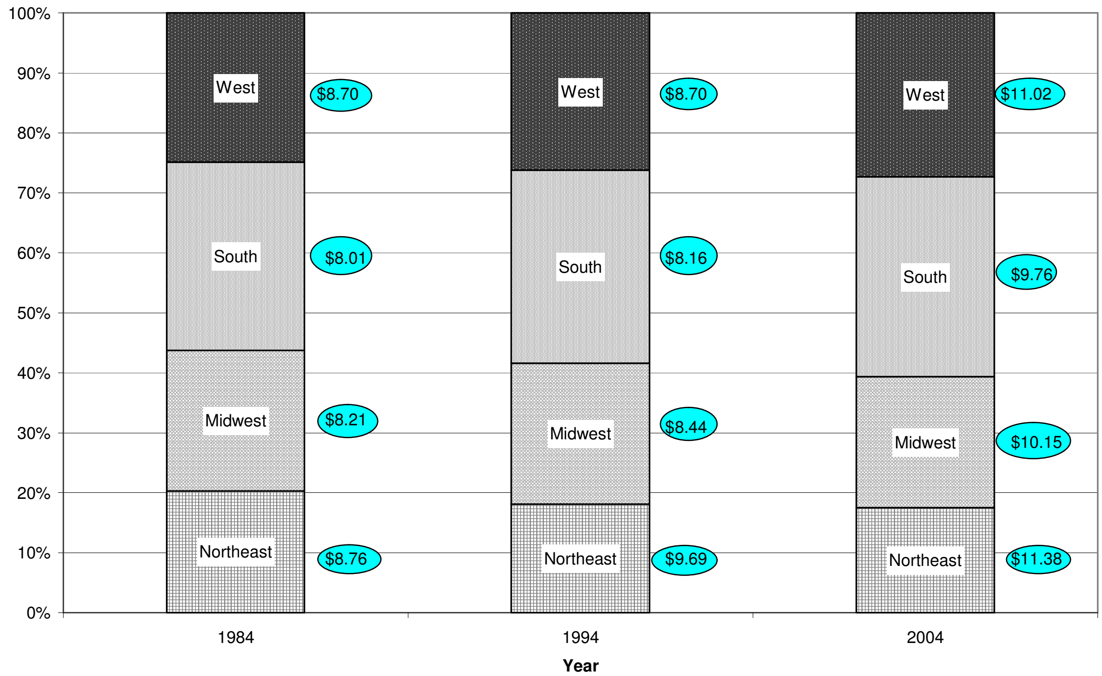


Figure 10. Distribution of Hours, by Urbanicity

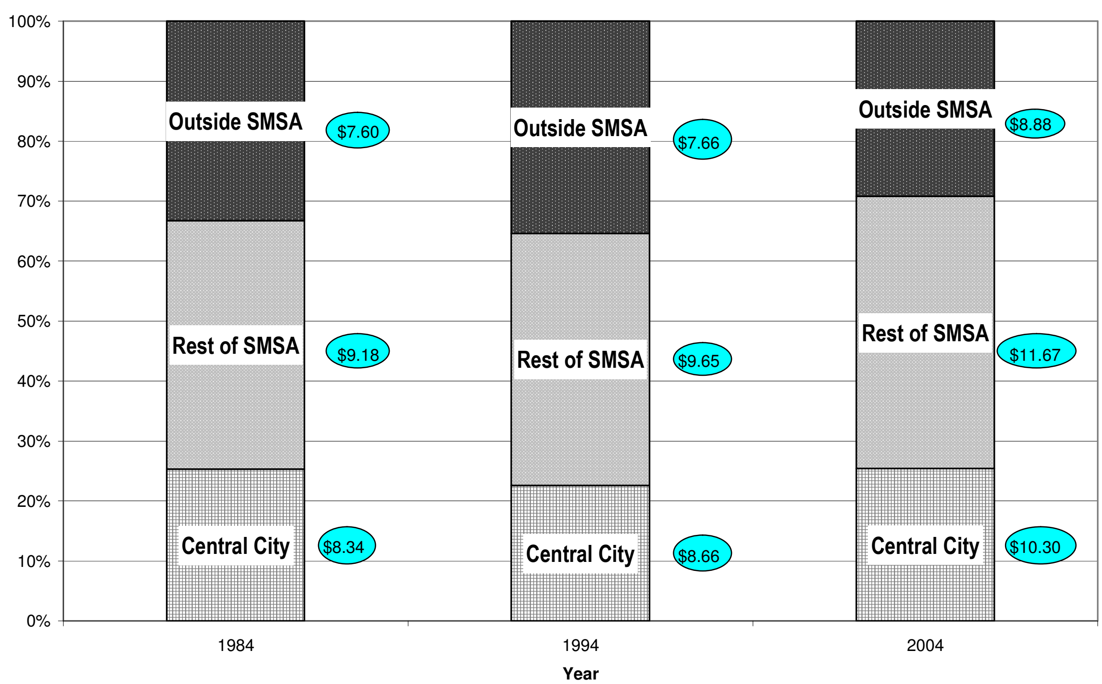


Figure 11. MFP Growth with Experience Imputations/ Age in Labor Composition

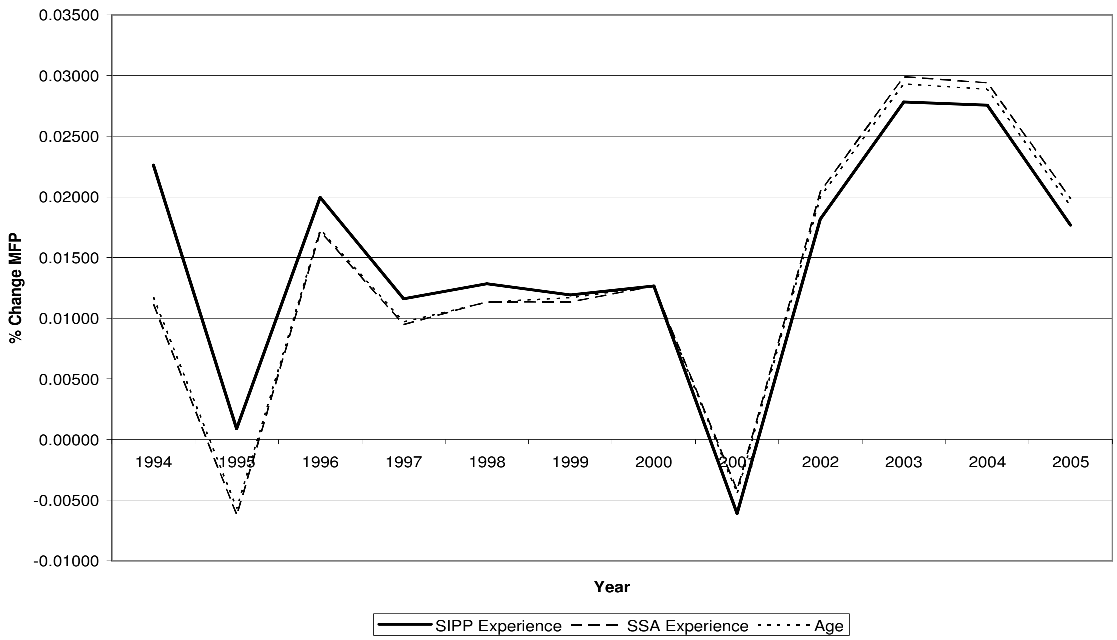


Figure 12. MFP Growth with Actual/Imputed Wages in Labor Composition Index

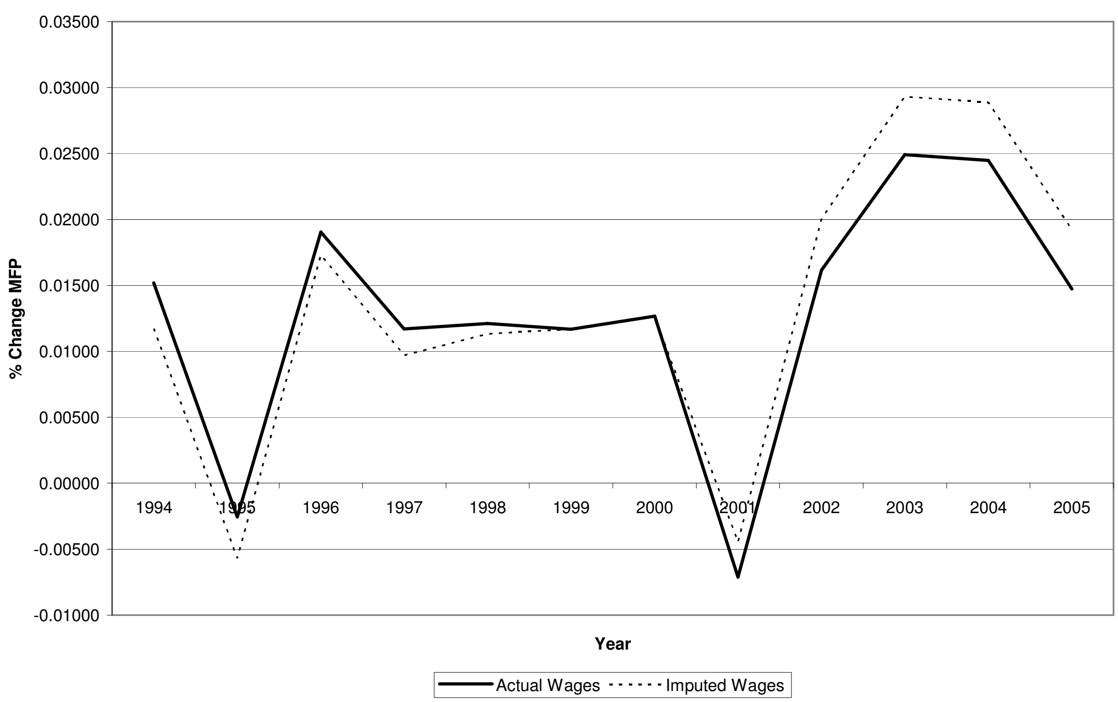


Figure 13. MFP Growth Under Different Labor Composition Worker Groups

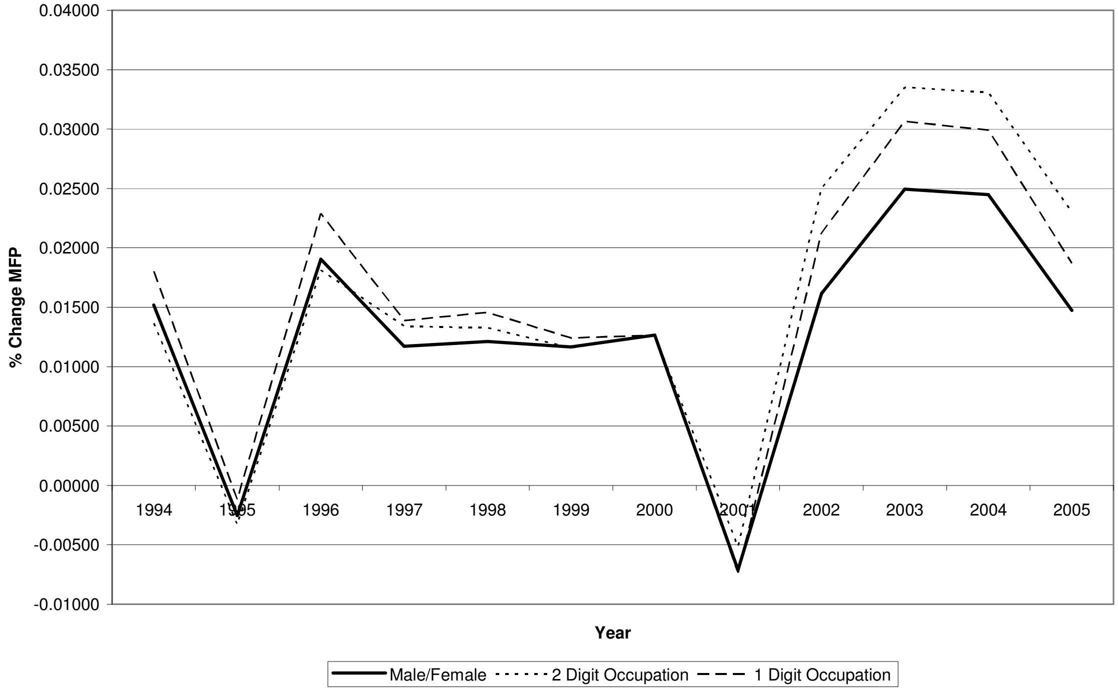
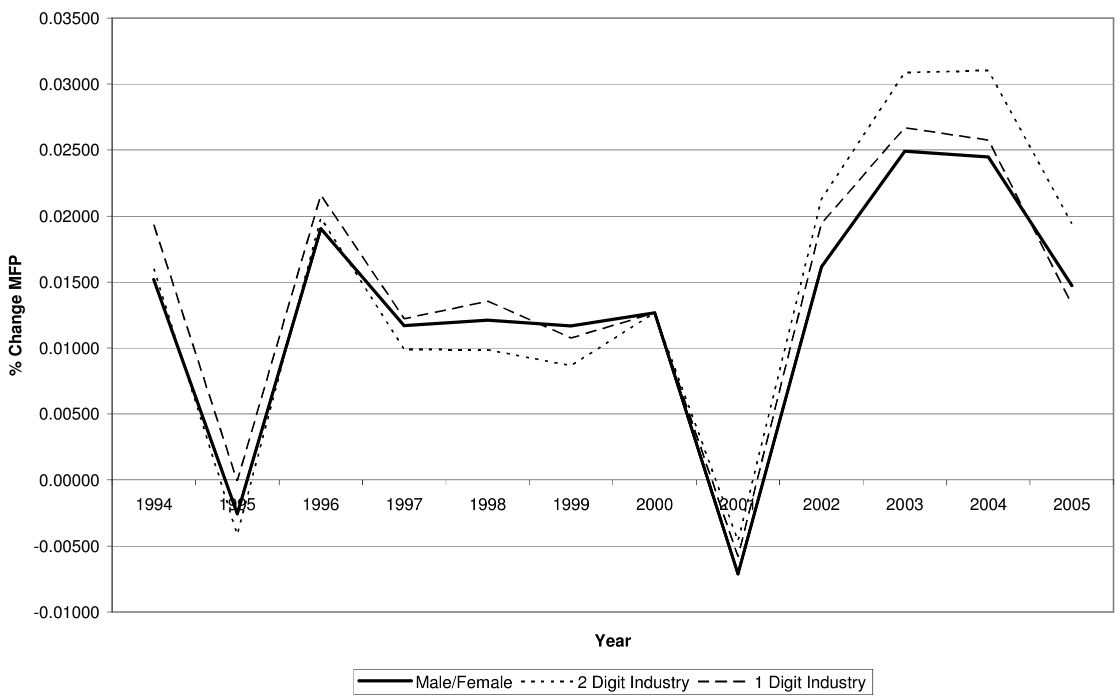


Figure 14. MFP Growth Under Different Labor Composition Groups



Appendix Table A. 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	--	.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]
No. Obs.	30794	28558	40115	27573	26539	37582
R^2	.3705	.3283	.3214	.2099	.2353	.2567