Industry estimates of the elasticity of substitution and the rate of biased technological change between skilled and unskilled labor

William F. Blankenau*
Kansas State University

Steven P. Cassou†
Kansas State University

August 21, 2008

Abstract

We estimate the elasticity of substitution between skilled and unskilled labor and the pace of skill-biased technological change at the industry level. The data is compiled from the March extract of the Current Population Survey from 1968-2006. Industry information provided by the survey is used to group workers into 13 industry categories and education levels are used to dichotomize workers as skilled or unskilled. We construct measures of the ratio of skilled to unskilled employment and the ratio of skilled to unskilled wages in each industry. Using a relationship implied by profit maximizing behavior on the part of representative firms, this data generates estimates of structural parameters. We find considerable differences across industries in the elasticity of substitution between skilled and unskilled labor. Furthermore, while most industries have experienced skill-biased technological change, the pace of this change has varied widely across industries.

JEL Classification: D240, E250, J240,O150.

*Department of Economics, 327 Waters Hall, Kansas State University, Manhattan, KS, 66506, (785) 532-6340, Fax:(785) 532-6919, email: blankenw@ksu.edu.

†Corresponding Author - Department of Economics, 327 Waters Hall, Kansas State University, Manhattan, KS, 66506, (785) 532-6342, Fax: (785) 532-6919, email: scassou@ksu.edu.

1 Introduction

In most economic work, skill levels provide the foundation for a worker's productivity and wages. This foundation provides a link between wages and technology through which the wage structure illuminates features of the production process. Both labor economists and macroeconomists commonly use this linkage to estimate production function parameters. Our paper contributes to this literature by extending the standard aggregated empirical analysis to industry level regressions. Our focus is on estimating the elasticity of substitution between skilled and unskilled labor and the rate of skill-biased technological progress. Despite the paper's obvious extension to common labor economic regressions, the paper is also motivated by advances in macroeconomics where good estimates of production function parameters at the industry level are important for addressing new areas of research with disaggregated economic models.

The need for industry level production function estimates in macroeconomics has arisen as a result of the successful integration of human capital into macroeconomic analysis. Important work by Romer (1987, 1990) and Lucas (1988) began this process by focusing attention on the role of human capital in growth and development. With the role of human capital now widely recognized, macroeconomists are now extending the human capital paradigm to distinguish types of labor inputs and differences in production capabilities across industries. For instance, some attention is focused on two pronounced trends across labor types in the aggregate economy. First, the average share of the population considered skilled (by a variety of measures) has increased steadily and secondly there has been a long term upward trend in the wage premium for skilled workers. To say anything meaningful about the causes or consequences of these trends requires disaggregation of labor into skilled and unskilled types. Recent work of this sort includes Krusell, et al. (2000), Acemoglu (2002) and Blankenau and Cassou (2006).

In a similar vein, persistent trends in the industrial composition of output has directed research toward models which can accommodate sectoral trends. For example Kongsamut, Rebelo, and Xie (2001) build a model consistent with a persistent reallocation of labor from agriculture to manufacturing and services. More recently, Ngai and Pissarides (2006) and Blankenau and Cassou (2008) build models where sectoral trends result from differences in technological changes across industries.

Work of this sort highlights that new insights into aggregate economic behavior can be gained from disaggregating labor inputs by skill level and disaggregating output by sector. The purpose of this paper is to contribute to this research program by estimating production parameters in a disaggregated setting. We estimate these parameters in an environment where skilled and unskilled labor are imperfectly substitutable labor inputs, and production is specified at the most disaggregated level for which a consistent time series data could be compiled. The data is constructed from the March extract of the Current Population Survey from 1968-2006. We use industry information in the survey to group workers into the 13 industry categories used by the Department of Commerce and dichotomize workers as skilled or unskilled according to education levels. We then construct time series of the ratio of skilled to unskilled employment and the ratio of skilled to unskilled wages in each industry. Similar to Katz and Murphy (1992), we use a relationship implied by profit maximizing behavior to estimate structural parameters of industry level production functions.

We find that the elasticity of substitution calculated from aggregate data tends to underestimate this substitutability. Nine of 13 industries have elasticities in excess of that measured by Katz and Murphy (1992). Only three are considerably smaller. In fact, we find that for some industries, we cannot reject the null hypothesis of perfect substitutability. Since significant modeling simplifications often arise when technology can be expressed as a Cobb-Douglas combination of inputs, we also test whether elasticities of substitution are significantly different from one (the Cobb-Douglas case). Here we find mixed results. While point estimates of the elasticity are nearly uniformly in excess of one, the difference is often not significant. The key message of our elasticity estimates is that there is considerable difference across industries. In general, skilled services and manufacturing stand out as having lower elasticities.

We also find that skill-biased technological change is widespread. Point estimates suggest that technology is biased toward skilled labor in 12 of 13 industries and the finding is statistically significant in most. While the direction of this change is fairly consistent, the pace varies considerably across industries. In general, skilled services and manufacturing have experienced the most rapid changes while unskilled services have experienced the least.

In what follows, we first specify the empirical model in Section 2. While it shares features with the specification in Katz and Murphy (1992), there are also differences and, for completeness, we provide the full derivation. In Section 3, we discuss the compilation of the data. This is similar to the constructions used by Katz and Murphy (1992) as well as Krusell, et al. (2000), and Blankenau (1999). The key distinction here is the industry level specification. A discussion of the results follows in Section 4. In this section we first recreate the Katz and Murphy (1992) aggregate estimate. We then discuss and demonstrate the appropriateness of an instrumental variable approach when considering the disaggregated industry level regressions. This section also provides the key estimates and a sensitivity analysis. Section 5 concludes.

2 The empirical model

In this section we describe the economic theory behind the empirical model. This theory begins from the optimization problem for the firm. Since our objective ultimately is to estimate labor elasticities for different industries, we will include industrial differences from the start by using the subscript i to specify an industry. It is assumed that each industry consists of many identical representative firms which combine capital, skilled labor and unskilled labor to produce a distinct good. Furthermore, the production functions for firms in the different industries are assumed to have the same CES form but parameters of this function may differ by industry and can change through time which is indexed by t. Output of a firm from industry i at time t is a Cobb-Douglas combination of capital, $K_{i,t}$, and a labor aggregate, $L_{i,t}$, scaled by a labor augmenting technology parameter, $A_{i,t}$. The relative importance of capital is determined by $\alpha_{i,t} \in (0,1)$ so that the production function is given by

$$Y_{i,t} = K_{i,t}^{\alpha_{i,t}} \left(A_{i,t} L_{i,t}\right)^{1-\alpha_{i,t}}.$$

The labor aggregate is a constant elasticity of substitution combination of skilled labor, $S_{i,t}$, and unskilled labor, $U_{i,t}$, given by

$$\begin{array}{lll} L_{i,t} = \left[\gamma_{i,t} S_{i,t}^{1-\rho_{i,t}} + \left(1-\gamma_{i,t}\right) U_{i,t}^{1-\rho_{i,t}}\right]^{\frac{1}{1-\rho_{i,t}}} & \text{if} & \rho_{i,t} \neq 1, \\ L_{i,t} = S_{i,t}^{\gamma_{i,t}} U_{i,t}^{1-\gamma_{i,t}} & \text{if} & \rho_{i,t} = 1, \end{array}$$

where $\rho_{i,t} > 0$ and $0 \leq \gamma_{i,t} \leq 1$. Under this formulation the elasticity of substitution is given by $\frac{1}{\rho_{i,t}}$ and $\gamma_{i,t}$ is related to the share of income received by the two types of labor inputs.[1]

Firms are assumed to maximize profits and to participate in competitive markets. This implies that wages will be equal to the marginal revenue product of the labor inputs. Letting $p_{i,t}$ denote the price of a unit of production, the skilled wage in industry i is thus given by

$$w_{i,t}^{s} = p_{i,t}\left(1-\alpha_{i,t}\right) K_{i,t}^{\alpha_{i,t}} A_{i,t}^{1-\alpha_{i,t}} \left[\gamma_{i,t} S_{i,t}^{1-\rho_{i,t}} + \left(1-\gamma_{i,t}\right) U_{i,t}^{1-\rho_{i,t}}\right]^{\frac{1-\alpha_{i,t}}{1-\rho_{i,t}}-1} \gamma_{i,t} S_{i,t}^{-\rho_{i,t}},$$

and the unskilled wage is

$$w_{i,t}^{u} = p_{i,t}\left(1-\alpha_{i,t}\right) K_{i,t}^{\alpha_{i,t}} A_{i,t}^{1-\alpha_{i,t}} \left[\gamma_{i,t} S_{i,t}^{1-\rho_{i,t}} + \left(1-\gamma_{i,t}\right) U_{i,t}^{1-\rho_{i,t}}\right]^{\frac{1-\alpha_{i,t}}{1-\rho_{i,t}}-1} \left(1-\gamma_{i,t}\right) U_{i,t}^{-\rho_{i,t}}.$$

For our purposes it is the ratio of these wage rates that is of interest. Letting $\omega_{i,t} \equiv \frac{w_{i,t}^{s}}{w_{i,t}^{u}}$ and $s_{i,t} \equiv \frac{S_{i,t}}{U_{i,t}}$, the ratio of the wage rate of a skilled worker to that of an unskilled worker is given by

$$\omega_{i,t} = \tilde{\gamma}_{i,t} s_{i,t}^{-\rho_{i,t}}. \tag{1}$$

where $\tilde{\gamma}_{i,t} \equiv \frac{\gamma_{i,t}}{1-\gamma_{i,t}}$. The parameter $\tilde{\gamma}_{i,t}$ determines the relative importance of skilled labor in production, and because it is related to $\gamma_{i,t}$, we refer to it as the 'relative

[1] When $\rho_{i,t} = 1$, γ_{it} is exactly equal to the share income received by skilled labor.

skill share.' One advantage of formulating things in terms of ratios is the succinct relationship between wages and labor inputs. Differences in the wage ratio across time and across industries depend only on differences in the ratio of skilled workers to unskilled workers employed, differences in the relative skill share, and differences in elasticities. Other items such as prices, capital employed, and the technology scalar affect skilled and unskilled wages symmetrically and drop out in computing the ratio.

Our goal is to determine the extent to which elasticities differ across industries and relative skill shares differ by time and industry. Toward this end, we take the natural log of both sides of (1) to arrive at

$$\ln \omega_{i,t} = \ln \tilde{\gamma}_{i,t} - \rho_{i,t} \ln s_{i,t}. \tag{2}$$

For our empirical specification, we take $\omega_{i,t}$ and $s_{i,t}$ as observable and assume $\ln \omega_{i,t}$ is measured with error, $\varepsilon_{i,t}$, which is normally distributed with mean 0 and a constant, common variance σ^2. We allow an industry specific time trend in $\tilde{\gamma}_{i,t}$ by assuming

$$\ln \tilde{\gamma}_{i,t} = \beta_{1,i} + \beta_{2,i} t, \tag{3}$$

so that $\beta_{2,i}$ is the growth rate of the relative skill share. This also has the interpretation as the rate of skill-biased technological progress. Putting (3) and the error term into (2) gives

$$\ln \omega_{i,t} = \beta_{1,i} + \beta_{2,i} t + \beta_{3,i} \ln s_{i,t} + \varepsilon_{i,t}. \tag{4}$$

where $\beta_{3,i} = -\rho_{i,t}$.

3 The Data

The data comes from two sources which store different years of the Current Population Survey data. Data for 1968-1991 comes from Current Population Surveys: March Individual Level Extracts, 1968-1992, Second ICPSR Version.[2] Data for 1992-2006 is from the March Supplement of the Current Population Survey.[3] In these surveys,

[2] This data is published by the Inter-University Consortium of Political and Social Research in 1999 and was overseen by Chief Investigator, Robert Moffit who was at the University of Michigan at the time.

[3] This data was extracted using Data Ferret (dataferrett.census.gov).

individual level data is available on age, gender, years of schooling, industry of employment, data useful for estimating the hourly wage and the CPS weight for each individual. Although there are general levels of consistency from one year of data to the next, the coding does have some changes over time which lead to processing challenges. In the remainder of this section, we describe how the data is processed for this study.

We use measures of years of schooling to classify individuals as skilled or unskilled. We follow a common professional practise of coding individuals with 12 or fewer years of schooling as unskilled and individuals with 16 or more years of school as skilled, while individuals with 13-15 years of schooling are excluded from the analysis. In the data from 1968 to 1991, we use variable 67, "Year of education completed," and in the data from 1992-2006 we use variable a_hga, "Years of education". In the earlier set of data, things are organized exactly as we need it and the coding is straight forward. However, in the later data set, exact years of education are not recorded. Instead codes for education levels are used. In this data there is a mapping where, for example, 39 means high school degree and 40 means some college but no degree, etc. In this case, we take everyone with a college degree or more to be skilled and everyone with a high school degree or less to be unskilled. Those with some college but no degree or associate degrees are interpreted to be like individuals with 13-15 years of schooling in the earlier sample and are excluded.

Coding an individual's industry of employment proves to be the most challenging of the data processing activities, because of large differences in the way the CPS coded industries across time. In general, 48 to 52 industries are defined each year. But using these narrow industry classifications presents a number of problems. First, the same set of narrowly defined industries are not used in each time period. Secondly, when we construct wage ratios as defined below, there is insufficient data for many industries to complete the calculation. Because of this, we map the many industries into just thirteen broad industry classifications which are currently used by the U.S.

Commerce Department in constructing, for example, GDP by industry.[4] Table A1 in the appendix shows how we reconcile the different classifications.[5] We choose this classification due to its widespread usage and as a means to avoid arbitrary groupings. However, one deviation from this grouping is required. The Commerce Department groups educational services and health care in the same industry. Our empirical specification described above derives from an assumption of profit maximizing behavior. It is unlikely that this specification is valid in analyzing the education sector since schools have objectives unrelated to profits and employees in schools, particularly teachers or professors, often pursue these professions with some disregard for wage scales in alternative professions with similar education backgrounds. Because of this we exclude education from this sector.

The hourly wage rate is not provided in the CPS data. However, a wage rate can be calculated from other data. To do this, data on income is divided by data on hours worked. For income, we use the reported wages & salary income.[6] We then take the number of weeks worked last year and estimate hours per week. Computation of the number of weeks worked requires some special data processing since 1968-1975 does not provide a specific number for weeks worked but instead uses a code which grouped people into broader numbers of weeks. For these years we calculate weeks worked as the midpoint of the range of weeks each code covered. Finally, there occasionally appears to be inconsistencies between the number of weeks worked and income, with some people having large incomes despite having worked very little. We decided to exclude people who worked less than 200 hours per year which is roughly one tenth of a year. The hourly wage is then found by taking the wage & salary income and dividing by the product of weeks worked and hours per week.

[4] See, for example, http://www.bea.gov/industry/iedguide.htm.

[5] For the 1968-1991 period, the variable used for industry categorization is v57 labeled "Industry." For 1991-2002 the variable indicating industry is a_dtind. For 1992-2002 this variable is labeled "Current Status-Industry Detailed Recode" and for 2003-2006 it is labeled "Industry and Occupation-Main Job Detailed Industry."

[6] In our first pass with the data we added wage and salary income to self employment income to get an income measure. However, the self employment income often didn't seem consistent with the number of hours worked and resulted in occasional wild outliers. Since self employment income was a relatively small set of individuals, we focus on wage and salary income for our income measure.

To calculate the wage rate for each industry at each date we follow the procedure used by Krusell, et al. (2000) on aggregate data. Our procedure differs from theirs only to the extent that the sample is partitioned one step further into industry categories. In what follows, we describe the procedure for a particular industry. The first step is to segregate the sample into industries. Next, all individuals for whom all data is available are put into groups by demographic characteristics. The groups are characterized by gender and age. For age, we put individuals into one of nine groups: ages (16-25), (26-30), (31-35), (36-40), (41-45), (46-50) (51-55), (56-60), (61-70). Along with gender then, this gives 18 demographic groups. Each agent in each group is also indexed as either skilled or unskilled as discussed above. The wage for a particular group is simply the average wage of individuals in that group. Finally, the overall wage used in the study is calculated as the average wage across the 18 demographic groups.

To be more concrete, the skilled wage for group $m \in \{1, 2, ...18\}$ in industry i at time t $\left(w^s_{m,i,t}\right)$ is found using

$$w^s_{m,i,t} = \frac{\sum\limits_{j \in m, e=s} \chi_{j,i,t} w_{j,i,t}}{\sum\limits_{j \in m, e=s} \chi_{j,i,t}},$$

where $w_{j,i,t}$ is the wage of individual j in industry i at time t and $\chi_{j,i,t}$ is a weight. The notation $j \in m$ selects only individuals in demographic group m and $e = s$ indicates that only individuals considered skilled are included. We carry out the calculations using two weighting schemes, one where $\chi_{j,i,t}$ is the CPS weight assigned to this particular individual and one where the weight is simply equal to 1. Similarly, the corresponding unskilled wage is

$$w^u_{m,i,t} = \frac{\sum\limits_{j \in m, e=u} \chi_{j,i,t} w_{j,i,t}}{\sum\limits_{j \in m, e=u} \chi_{j,i,t}}.$$

where $e = u$ indicates that only individuals considered unskilled are included.

Next, industry wage rates are computed using an unweighted average of the wage ratios for each group. However, one selection criteria comes into play for this calculation. For some of the early years, the number of individuals who fall into some of the 18 groups turns out to be small and this makes the cell averages sensitive to a single individual. To avoid influencing the results due to a miscode, we screen out groups with fewer than 5 individuals in either the skilled or unskilled subgroup. Thus in practise, the averages for a few years turn out to be computed from somewhat fewer than 18 groups. Specifically, to find the wage ratio for an industry, we take the average of the ratio of skilled wages to unskilled wages across those groups with a sufficient number of both skilled and unskilled workers. Letting J be the number of such groups (usually 18) we get

$$\omega_{i,t} = \frac{1}{J} \sum_{m \in \{1,2..J\}} \frac{w^s_{m,i,t}}{w^u_{m,i,t}}.$$

We compute the ratio of skilled workers to unskilled workers in a similar fashion. In particular, the total skilled and unskilled labor input in group m of industry i at time t, ($l^s_{m,i,t}$ and $l^u_{m,i,t}$) are calculated as

$$l^s_{m,i,t} = \sum_{j \in m, e=s} \chi_{j,i,t} l_{j,i,t}; \quad l^u_{m,i,t} = \sum_{j \in m, e=u} \chi_{j,i,t} l_{j,i,t} \quad ,$$

where $l_{j,i,t}$ is the total number of hours worked by individual j in industry i at time t. Then the ratio of hours is found using the same scheme used for the wage ratio and is given by

$$s_{i,t} = \frac{1}{J} \sum_{m \in \{1,2..J\}} \frac{l^s_{m,i,t}}{l^u_{m,i,t}}.$$

After compiling the raw data in this fashion, the transformed data used in the regression analysis are presented in Figures 1 and 2 below. These figures are organized into two groups with those in Figure 1 representing industries which have a relatively high skilled work force at the end of the sample period and those in Figure 2 representing industries which have a relatively low skilled work force at the end of the sample period. In particular, let $s_{i,39}$ indicate the skill ratio for industry i in the final period of the sample.[7] Then, Figure 1 plots the 5 industries with $s_{i,39} > 1$, which we will refer to as the skilled industries, while Figure 2 plots the 8 industries

[7] Note, $t = 39$ in 2006.

with $s_{i,39} < 1$. In these figures, the solid line is the wage ratio $\omega_{i,t}$ and the units are given on the left axis while the dashed line is the skill share ratio $s_{i,t}$ and its units are given on the right.

Put Figures 1 and 2 around here.

These figures show that in each industry except mining, $s_{i,t}$ has increased steadily while in all but public administration and agriculture $\omega_{i,t}$ also shows a clear upward trend. Since $s_{i,t}$ and $\omega_{i,t}$ comprise the data for regression (4), it is useful here to consider how these trends relate to the coefficients $\beta_{2,i}$ and $\beta_{3,i}$. If $\beta_{2,i}$ were restricted to zero in order to eliminate the time trend, the jointly upward trending data series would assure that the coefficient in a regression of $\omega_{i,t}$ on $s_{i,t}$ $\left(\beta_{3,i}\right)$ would be positive. However, in this case, $\beta_{3,i}$ would have double duty, capturing both changes in technology and substitutability of the inputs. By including a time trend in the standard regression, $\beta_{2,i}$ captures the changing technology and $\beta_{3,i}$ captures substitutability.

In the following section, it is shown that with $\beta_{2,i}$ included, its value is typically positive; the relative skill share grows through time. Notice from Figures 1 and 2 that high skilled industries tend to have more strongly trending data for both variables, but especially for the labor share ratio $s_{i,t}$. In the regressions that follow, this is manifest by larger time trend coefficients. Thus the rate of skill-biased technological change tends to be higher for skilled industries.

With the time trend accounting for the jointly rising data, there is an inverse residual relationship between $s_{i,t}$ and $\omega_{i,t}$. In the regressions below, this results in negative $\beta_{3,i}$ estimates. This is as expected. Controlling for technology, an increase in relative skill should drive down its relative wage. This negative coefficient on $s_{i,t}$ is then inverted and multiplied by minus one to yield an elasticity of substitution estimate. The negative $\beta_{3,i}$ estimates are required to generate theoretically plausible elasticity estimates. Thus without controlling for time trends, the data could not yield reasonable elasticity estimates.

Another feature that stands out in the figures for leisure services and agriculture is a noticeable decline in the wage share ratio in the first few years. We suspect there were some changes in the way the commerce department was coding data in these industries. Given this suspicion, we run the regressions using a subsample in which the first few years were left out. That analysis produces largely the same results as we report below and since our view is that more data is better than less, we report results only over the full sample.

4 Results

The results of our empirical analysis is divided into three subsections. In the first subsection we show that our procedures are able to replicate the standard elasticity estimates found when using aggregate data. In the second subsection, we present our results on the industry level regressions. This section begins by following an estimation procedure analogous to the aggregate regression and shows that such a procedure does not produce very reasonable estimates. Next, an instrumental variables regression procedure is used and results which appear consistent with the aggregate results are presented and discussed. Finally, the third subsection evaluates the instrumental variable results by running similar regressions using different sets of instruments and shows that the baseline estimates are broadly robust to alternative instruments.

4.1 Aggregate Results

Aside from the disaggregation into industry level data and a few minor coding details, the methodology we use to process the data is widely used by the profession, such as in Katz and Murphy (1992) or Krussel et al. (2000). As a first check that everything is in order, we run an aggregate regression. The results of this regression are presented in the first line of Table 1.[8]

Table 1 organizes the results so that the most interesting results are presented in Columns 3-5. Column 3 presents the estimate of the coefficient on the time trend and

[8] These results, and all subsequent results, are based on using $\chi_{j,i,t}$ weights in the wage ratio and share ratio calculations equal to 1. The results using weights equal to the CPS weights were virtually identical and are thus not presented.

Column 4 presents the estimate of the coefficient on the share ratio. This share ratio is easily mapped into an elasticity value and the elasticity is presented in Column 5. Columns 2-4 present both parameter estimates and t-statistics for various tests. The parameter estimates are presented without parenthesis while the t-statistics are presented in parenthesis. Columns 2 and 3 have one set of parenthesis which presents the standard t-statistic on the null that the parameter is equal to zero. Column 4 presents two sets of parenthesis. The first parenthesis presents the standard t-statistic on the null that the parameter is equal to zero while the second parenthesis presents the t-statistic on the null that the parameter is equal to minus one. This later null is of interest because if the parameter equals minus one, then the elasticity is equal to the Cobb-Douglas production elasticity.

Put Table 1 around here.

The first line of Table 1 shows the aggregate regression results are quite similar to results found by Katz and Murphy (1992) or Krussel et al. (2000). For instance, Katz and Murphy (1992) found point estimates for the coefficient on s equal to -0.709 while we have -0.716. These measures translate to elasticity estimates of 1.41 for Katz and Murphy (1992) and 1.396 for us. On the other hand, although Krussel et al. (2000) run a slightly different empirical model, they report an elasticity estimate of 1.67. Similarly our time trend coefficient of 0.037 is comparable with the Katz and Murphy (1992) coefficient on the time trend of 0.031. Using our interpretation of the time trend parameter, this suggests that the growth rate of the relative skill share has been similar across the time periods.

The ability to replicate the aggregate results suggests that small differences between our coding procedures and the procedures used by others is not impacting the estimation results in any significant way and lets us move on to the more interesting industry level regressions with confidence.

4.2 Industry-specific regressions

The remainder of Table 1 presents results carried out on industry level regressions. In this table we break the industry level regressions into two panels with the top panel presenting estimates using an OLS estimation procedure on (4) and the second panel presenting results of an instrumental variable estimation procedure. Before we discuss the superior instrumental variable regression estimates, we will first discuss the inferior findings using the OLS procedure. One of the purposes of presenting these OLS estimates is to show that simply running regressions analogous to the aggregate regressions does not work very well.

In the top panel of Table 1, Column 4 shows the point estimates of the share ratio coefficients. These coefficients are related to the elasticity of substitution which is reported in the last column of the table. A striking feature of the elasticity measures is that each positive measure is much larger than the 1.396 estimate for the aggregate model. The smallest estimate is 2.217, the largest is over 500, and the median is 7.988. Qualitatively, this result can be reconciled by noting that when one industry experiences an increase in the wage ratio, it may respond by hiring the most appropriate unskilled labor from another industry. This is a margin unavailable to the economy as whole which constrains the aggregate elasticity estimate. Thus we would expect that industry specific elasticities would, on average, exceed the aggregate elasticity. However, quantitatively, the results are more suspect. In general the elasticity estimates are outside the range of elasticity estimates in the literature.[9] While we expect that the elasticities would tend to be larger overall, we would also expect that for some industries, the elasticity would be smaller than the 1.4 estimated for the economy overall. In addition, the negative elasticity estimate for Public Administration is of even greater concern. As negative elasticities violate basic economic principles, we take this result not as an elasticity estimates but rather as evidence of a methodological failing or of serious data problems for this industry.

[9] Aside from the estimates mentioned above, Hamermesh (1993) summarizes some similar estimates.

In the top panel of Table 1, Column 3 shows that point estimates of the relative skill share growth rate are positive for all 13 industries. These values exceed 0 with 95% confidence or more in 9 of these industries.[10] Collectively, these results suggest that skill-biased technological change is widespread rather than confined to a few industries. However, it is interesting to note that for each industry, the growth rate estimate is smaller than for the aggregate industry. On average, these are only about a third as large. As we see below, this oddity is corrected when we employ the instrumental variable approach.

Given these questionable results from the industry level OLS regressions, it seems reasonable to sort out why this may arise at the industry level yet not be a problem at the aggregate level. One potential problem with the industry level regressions is that they do not account for the endogeneity of s_i. In the aggregate regression, it is reasonable to assume that skill ratios drive wage ratios within a period, rather than wages driving skill levels, because the aggregate supply of skill can adjust to wage changes only in the longer term. However, at the industry level the movement of skill across industries in response to wage changes can be more immediate. Thus high skilled wages in industry i may induce firms to shift hiring toward unskilled workers which means there potentially is endogeneity between ω_i and s_i. To control for this potential endogeneity, we adopt an instrumental variable approach. Fortunately, the data provides us with a natural instrument. Let s_a be the skill ratio for the aggregate economy. Then s_a and s_i should be correlated as an increase in skill is spread through the economy. However, as s_a can adjust only slowly to wages, it can be taken as fixed within a period and thus unresponsive to wage changes. Furthermore, the wage ratio in a particular industry, which is small relative to the overall economy, should not be expected to influence s_a in a quantitatively important way even longer term.

In the lower panel of Table 1, we present the industry level estimates using an instrumental variable regression approach where the aggregate share ratio, s_a, is used as an instrument to control for endogeneity. In this set of regressions, the elasticity

[10] The one tailed 95% critical value is 1.645.

estimates are more in line with expectations. For three industries, elasticity measures are quite large: agriculture, construction, and other services. Notice that for these three industries we were unable to reject the null hypothesis of no technological change. These results are plausible. It is the nature of construction and agriculture that college education is not required for the majority of the tasks completed. While skill is undoubtedly needed for many tasks in these industries, the requisite skill is not often imparted by colleges. Thus it is not measured by our methodology. This explains both why technology has not changed to favor college educated workers in these industries and why workers without college degrees can substitute relatively easily for those with college degrees. For the social services industry, we suspect that budget concerns have forced agencies to respond to rising skilled wages by relying more heavily on workers without college degrees.

For the remaining industries we get elasticity estimates of 5.376 or less. Considering all industries, the median elasticity is 2.234. This is again higher than for the aggregate case but now the difference is smaller. Since the point estimate of the elasticity for 'Information' is less than one, labor inputs in this industry are estimated to be more complementary than in the Cobb-Douglas case. For all other estimates, the estimate exceeds one so that factors in these industries are estimated to be more substitutable than in the Cobb-Douglas case. However, for Manufacturing, Financial Services, Professional Services as well as Information it is not possible to reject the null that these coefficients are greater than minus one (i.e. more substitutable than the Cobb-Douglas production case).

The widespread nature of skill-biased technological change is also confirmed. Column 3 shows that all point estimates of the time trend parameter are positive with the exception of agriculture which is very close to 0. Again 9 are greater than 0 at the 95% confidence level. The main difference along these lines is the magnitude of the growth rate point estimates. Now four of the 9 industries have growth rates that exceed the economy wide estimate and the average is about 80% of the economy wide estimate. Furthermore, the relative rankings are more in line with expectations. In the earlier regression, for example, the information and financial services industries appear to have had among the slowest lower rates of technological change. In the new estimates, these industries are estimated to have experienced the fastest rates.

Table 1 shows that there are broad differences in both the elasticity of substitution between skilled and unskilled labor as well as the rate of skill-biased technological change. However, one further question is whether these differences are statistically significant. Table 2 shows the results of a variety of Wald tests for various nulls about whether the coefficients across industries are equal. This table is organized into two panels with the top panel showing results on various share coefficient tests and the lower panel showing results on various time trend coefficient tests.

Let us first focus on the share coefficient tests. The first row of Table 2 shows a test statistic of 26.692 for the null that all industries have the same share coefficient. This test statistic is distributed χ^2 with 12 degrees of freedom and has a 95% critical value of 21.026. Based on this comparison, we are able to reject the null that all of the coefficients are equal. Since these coefficients are not equal and they map into the elasticities of substitution, this test provides evidence that the elasticities of substitution are not equal across industries. In addition to this test, a restricted estimation of the model is carried out in which all share coefficients are constrained to be equal. This estimation results in a constrained elasticity estimate of 3.574 which is somewhat higher than the median value of the individual estimates, but given the skewness of the elasticities with the larger values being much larger, this value seems to be about right.

Put Table 2 around here.

We also carry out three tests for whether the share coefficients for various groups of industries are equal. We call these groups, non-services, skilled services and unskilled services. In a final categorization, we consider all services jointly. The non-service group consists of Agriculture, Mining, Construction and Manufacturing, the skilled services consists of Financial Services, Professional Services, Health Services and Public Administration and the unskilled services consists of Wholesale and Retail Trade, Transportation, Information, Leisure Services and Other Services.[11] Table 2 shows that we are unable to reject the null that the share coefficients are equivalent within any of these groupings. As one would expect, the skilled services have the lowest elasticity of substitution while the non-services have the highest elasticity of substitution.

Finally, we explore whether there are differences in the rates of skill-biased technological change across industries. This is investigated by testing various nulls that the coefficients on the time trends are equal. The nulls are organized like the share coefficient nulls in that we carry out a test over all industries, the three subindustry groupings, and all services. The results of these tests are reported in the second panel of Table 2. These tests mostly reject the null of equal rates of skill-biased technological progress. The only case in which equal skill-biased technological progress is not rejected is in the skilled services. Interestingly, this industry group has the highest point estimate for the rate of skill-biased technological progress with a value of 3.5%. This is the only point estimate which approaches the 3.7% value found in the aggregate regression.

4.3 Alternative instruments

Despite the success of using the aggregate share ratio as an instrument, it is worthwhile to explore whether other instruments yield different results. One common strategy is to use lagged values of the various variables in the regression. In our case, this would suggest using lagged values of the industry share ratio or the lagged values of the industry wage ratio.

Table 3 presents results for instrumental variables estimates based on a number of alternative sets of instruments. In addition to the baseline instrument of the aggregate share ratio, the table also includes results for the following four groups of instruments: (1) The aggregate share ratio, the lagged value of the industry share

[11] We allocated the services between skilled and unskilled services based on the proportion of their labor force that was skilled at the beginning of the sample period.

ratio and the lagged value of the industry wage ratio; (2) the aggregate share ratio and the lagged value of the industry share ratio; (3) the aggregate share ratio and the lagged value of the industry wage ratio; and (4) the lagged value of the industry share ratio and the lagged value of the industry wage ratio.

Put Table 3 around here.

Table 3 is organized a bit differently than Table 1 so as to present all five regressions in a relatively small table. To do this, the results for the constant terms are not presented, nor are the implied elasticity values or the t-statistics and each regression is written so as to run down a single column. Although the t-statistics were omitted, Table 3 does report the results of various t-tests by using the following convention. The dagger symbol, †, next to a coefficient indicates the null for a test that the coefficient equals zero is rejected at the 95% level and a double dagger symbol, ‡, next to a coefficient indicates the null for a test that the coefficient equals minus 1 is rejected at the 95% level. Since the second null is only interesting for the share ratio coefficient, it is not presented for the time trend coefficients. In addition, Table 3 reports the baseline instrumental variable regression reported in Table 1 in the second column for easy comparison.

Table 3 shows that, for the most part, the coefficient estimates do not vary much under the alternative instrument selections. This further reinforces that the correct estimation procedure to use is an instrumental variables approach and that straight OLS estimation does not produce good estimates.

5 Summary and Conclusions

In this work, we provide industry level estimates of production function parameters in which skilled and unskilled labor are used as inputs. In particular, we estimate the elasticity of substitution between these two labor inputs and the rate of skill-biased technological progress. We find that the elasticity of substitution calculated from aggregate data tends to underestimate this substitutability. We suspect that this arises because at the industry level, skilled labor can move across industries in response to wages, dampening the responsiveness of input ratios to wage ratios. In our instrumental variable estimation, nine of 13 industries have elasticities in excess of that measured by Katz an Murphy (1992). Only three are considerably smaller. In some industries, we cannot reject the null hypothesis of perfect substitutability. We typically find that point estimates of substitutability exceed one (the Cobb-Douglas case) and are often significantly larger than one. We show that there are considerable differences in elasticities across industries and in general, skilled services and manufacturing stand out as having lower elasticities. We do not find evidence of significant elasticity differences when we group industries by type.

Skill-biased technology is wide-spread and occurs in nearly every industry. However, the pace of this change differs considerably by industry and even within industry groupings. In general, skilled services and manufacturing have experienced the most rapid changes while unskilled services have experienced the least. Only in agriculture has technology advanced in a skill-neutral manner.

These findings fill a gap in the empirical labor literature because they provided industry-level estimates previously unavailable. We also hope that the estimates will be useful to macroeconomists as they build and calibrate disaggregated models of the macroeconomy.

References

[1] Acemoglu, D., 2002. Directed technical change. Review of Economic Studies 69, 781-810.

[2] Beaudry, P. and van Wincoop, E., 1996. The intertemporal elasticity of substitution: An exploration using a US panel of state data. Economica 63, 495-512.

[3] Blankenau, W., 1999. A welfare analysis of policy responses to the skilled wage premium. Review of Economic Dynamics 2, 820-849.

[4] Blankenau, W. and Cassou, S. P., 2006. Labor market trends with balanced growth. Journal of Economic Dynamics and Control 30, 807-842.

[5] Blankenau, W. and Cassou, S. P., 2008. Industrial dynamics and the neoclassical growth model. Forthcoming in Economic Inquiry.

[6] Hamermesh, D., 1993. Labor Demand. Princeton University Press.

[7] Katz, L. and Murphy, K., 1992. Changes in relative wages, 1963-1987: Supply and demand factors. Quarterly Journal of Economics 107, 35-78.

[8] Kongsamut, P., Rebelo, S. and Xie, D., 2001. Beyond balanced growth. Review of Economic Studies 68, 869-882.

[9] Krusell, P., Ohanian, L. E., Ríos-Rull, J. and Violante, G.L., 2000. Capital-skill complementarity and inequality: A macroeconomic analysis. Econometrica 68, 1029-1053.

[10] Krueger, A. B., 1993. How computers have changed the wage structure: Evidence from microdata, 1984-1989. Quarterly Journal of Economics 108, 33-60.

[11] Lucas, R. E., Jr., 1988. On the mechanics of economic development. Journal of Monetary Economics 22, 3-42.

[12] Ngai, L. and C. Pissarides, 2007. Structural change in a multi-sector model of growth. American Economic Review 97, 429-443.

[13] Romer, P., 1987. Growth based on increasing returns due to specialization. American Economic Review 77, 56-62.

[14] Romer, P., 1990. Endogenous technological change. Journal of Political Economy 98, S71-S102.

Table 1 - Baseline regression results

	Constant	Time Trend	Share Ratio		Elasticity
Industry Agg	-0.999 (-5.14)	0.037 (8.69)	-0.716 (-7.16)	(2.83)	1.396
Breakdown by industry using own share ratios					
Financial Ser	0.286 (1.27)	0.009 (1.21)	-0.002 (-0.01)	(6.32)	566.078
Public Admin	0.361 (1.48)	0.002 (0.29)	0.002 (0.02)	(7.57)	-436.845
Professional Ser	0.168 (1.56)	0.017 (3.71)	-0.266 (-2.07)	(5.72)	3.766
Health Ser	0.339 (2.14)	0.017 (2.93)	-0.137 (-0.95)	(6.01)	7.318
Information	0.005 (0.03)	0.011 (1.87)	-0.085 (-0.89)	(9.59)	11.817
Leisure Ser	0.134 (1.44)	0.007 (3.20)	-0.232 (-3.36)	(11.12)	4.311
Agriculture	0.217 (1.36)	0.004 (1.47)	-0.125 (-2.22)	(15.51)	7.988
Manufacturing	-0.498 (-1.20)	0.025 (3.25)	-0.284 (-2.03)	(5.12)	3.527
Other Ser	0.208 (0.68)	0.007 (1.46)	-0.056 (-0.46)	(7.73)	17.861
Whole/Retail	-0.920 (-2.77)	0.026 (4.83)	-0.451 (-3.71)	(4.51)	2.217
Transportation	-0.366 (-1.67)	0.012 (3.38)	-0.252 (-3.08)	(9.16)	3.970
Construction	-0.017 (-0.05)	0.010 (1.89)	-0.065 (-0.57)	(8.17)	15.296
Mining	0.074 (0.87)	0.013 (8.73)	-0.114 (-2.39)	(18.62)	8.780
Breakdown by industry using aggregate share ratio as an instrument					
Financial Ser	-0.936 (-1.11)	0.051 (1.78)	-0.866 (-1.46)	(0.23)	1.155
Public Admin	-0.464 (-0.78)	0.030 (1.51)	-0.448 (-1.39)	(1.71)	2.234
Professional Ser	-0.379 (-1.75)	0.040 (4.36)	-0.938 (-3.55)	(0.23)	1.066
Health Ser	0.052 (0.19)	0.028 (2.78)	-0.400 (-1.62)	(2.44)	2.501
Information	-2.702 (-2.66)	0.097 (3.02)	-1.463 (-2.83)	(-0.90)	0.684
Leisure Ser	-0.194 (-0.76)	0.013 (2.54)	-0.486 (-2.48)	(2.62)	2.056
Agriculture	0.487 (1.58)	-0.000 (-0.05)	-0.028 (-0.26)	(8.81)	35.482
Whole/Retail	-1.108 (-2.34)	0.029 (3.80)	-0.520 (-3.00)	(2.77)	1.923
Manufacturing	-1.768 (-2.29)	0.048 (3.40)	-0.711 (-2.74)	(1.11)	1.406
Other Ser	0.295 (0.49)	0.006 (0.62)	-0.021 (-0.09)	(4.09)	46.974
Transportation	-0.405 (-1.15)	0.013 (2.25)	-0.267 (-2.02)	(5.57)	3.750
Construction	-0.151 (-0.26)	0.012 (1.38)	-0.110 (-0.58)	(4.65)	9.048
Mining	-0.049 (-0.26)	0.014 (5.67)	-0.186 (-1.75)	(7.67)	5.376

Table 2 - Test of equal coefficients across industries

	Elasticity	Wald Stat	χ^2 Critical value
All industries have equal elasticities	3.574	26.692	21.026 ($df = 12$)
All non-services have equal elasticities	6.578	6.058	7.815 ($df = 3$)
All unskilled services have equal elasticities	2.700	8.314	9.488 ($df = 4$)
All skilled services have equal elasticities	1.614	2.711	7.815 ($df = 3$)
All services have equal elasticities	2.326	13.067	15.507 ($df = 8$)
	Time Trend	Wald Stat	
All industries have equal time trends	0.015	36.921	21.026 ($df = 12$)
All non-services have have equal time trends	0.012	12.918	7.815 ($df = 3$)
All unskilled services have equal time trends	0.016	11.025	9.488 ($df = 4$)
All skilled services have equal time trends	0.035	1.194	7.815 ($df = 3$)
All services have equal time trends	0.020	19.407	15.507 ($df = 8$)

Table 3 - Results based on lagged instruments

	Baseline	Agg-Own-Wg	Agg-Own	Agg-Wg	Own-Wg
			Share Ratio Coefficient		
Financial Ser	-0.866	-0.517	-0.639	-0.552	-0.536
Public Admin	-0.448 ‡	-0.183 ‡	-0.179 ‡	-0.331 ‡	-0.133 ‡
Professional Ser	-0.938 †	-0.461 †‡	-0.484 †‡	-0.906 †	-0.435 †‡
Health Ser	-0.400 ‡	-0.354 ‡	-0.414 †‡	-0.361 †‡	-0.637 †
Information	-1.463 †	-0.591 †‡	-0.624 †‡	-1.091 †	-0.246 ‡
Leisure Ser	-0.486 †‡	-0.374 †‡	-0.385 †‡	-0.302 †‡	-1.217 †
Agriculture	-0.028 ‡	0.014 ‡	-0.003 ‡	0.048 ‡	-0.108 ‡
Manufacturing	-0.711 †	-0.558 †‡	-0.584 †‡	-0.590 †‡	-0.597†
Other Ser	-0.021 ‡	-0.161 ‡	-0.151 ‡	-0.060 ‡	-0.266 ‡
Whole/Retail	-0.520 †‡	-0.492 †‡	-0.497 †‡	-0.511 †‡	-0.429 †‡
Transportation	-0.267 †‡	-0.240 †‡	-0.238 †‡	-0.255 †‡	-0.245 †‡
Construction	-0.110 ‡	-0.048 ‡	-0.080 ‡	-0.049 ‡	0.015 ‡
Mining	-0.186 †‡	-0.044 ‡	-0.069 ‡	-0.100 ‡	-0.031 ‡
			Time Trend Coefficient		
Financial Ser	0.051 †	0.035	0.041 †	0.036	0.036
Public Admin	0.030 †	0.014	0.014	0.024	0.011
Professional Ser	0.040 †	0.024 †	0.025 †	0.040 †	0.023 †
Health Ser	0.028 †	0.026 †	0.029 †	0.026 †	0.037 †
Information	0.097 †	0.043 †	0.045 †	0.075 †	0.021
Leisure Ser	0.013 †	0.013 †	0.013 †	0.011 †	0.035 †
Agriculture	-0.000	-0.001	0.000	-0.002	0.005
Manufacturing	0.048 †	0.040 †	0.042 †	0.042 †	0.042 †
Other Ser	0.006	0.011	0.011	0.007	0.015 †
Whole/Retail	0.029 †	0.028 †	0.028 †	0.029 †	0.025 †
Transportation	0.013 †	0.012 †	0.012 †	0.013 †	0.013 †
Construction	0.012	0.009	0.011 †	0.009	0.007
Mining	0.014 †	0.013 †	0.013 †	0.014 †	0.013 †

6 Appendix

Table A.1 - Disaggregated Industry mapping

D.O.C. Category	1968- 1971	1972- 1982	1983- 1988
Agriculture, forestry, fishing, and hunting	Agriculture Forestry and fisheries	Ag. production Agricultural services Forestry and fisheries	Agriculture Forestry & fisheries
Mining	Mining	Mining	Mining
Construction	Construction	Construction	Construction
Manufacturing	All manufacturing 21 industries	All manufacturing 24 industries	All manufacturing 24 industries
Wholesale & retail trade	Wholsale trade Eating & drinking places Other retail trade	Wholsale trade Eating & drinking places Other retail trade	Wholesale trade Retail trade
Transportation	Railroads & rail express services Other trans.	Railroads & rail express services Other trans.	Transportation
Information	Communications	Communications	Communications
Financial Activities	Banking & other finance Insurance & real estate	Banking & other finance Insurance & real estate	Banking & other finance Insurance & real estate
Professional and business services	Business services Other professional services	Business services Other professional services	Business services Other professional services
Educational and health services	Medical and other health services Hospitals Educational services	Medical . exc hospitals Hospitals Educational services	Health services exc hospitals Hospitals Educational services
Leisure & hospitality	Entertainment & recreation services	Entertainment & recreation services	Entertainment & recreation services
Other services	Utilities and san. serv. Private hshld serv. Repair services Personal services Welfare and religious	Other pub utilities Private hshld serv. Repair services Personal services Welfare and religious	Other pub utilities Private hshld serv. Repair services Personal services Social services
Public administration	Postal service Fed. pub. admin. State. pub. admin. Local pub. admin.	Postal Other federal State Local	Public administration

Table A.1 (continued) - Disaggregated Industry mapping

D.O.C. Category	1989-1991	1992-2002	2003-2004
Agriculture, forestry, fishing, and hunting	Other agriculture Agricultural services Forestry and fisheries	Other agriculture Agricultural services Forestry and fisheries	Agriculture Forestry, logging, fishing, hunting, & trapping
Mining	Mining	Mining	Mining
Construction	Construction	Construction	Construction
Manufacturing	All manufacturing 24 industries	All manufacturing 24 industries	All manufacturing 16 industries
Wholesale & retail trade	Wholesale trade Retail trade	Wholsale trade Eating & drinking places & other retail trade	Wholsale trade Retail trade Accomodation Food services & drinking places
Transportation	Transportation	Transportation & warehousing	Transportation
Information	Communications	Communications	*
Financial Activities	Banking & other finance Insurance & real estate	Banking & other finance Insurance & real estate	Finance Insurance Real estate Rent, lease serv.
Professional and business services	Business services Other professional services	Business services Other professional services	Prof. & tech. serv. Mgmt. of comp. Admin & support Membership assn.
Educational and health services	Health services exc hospitals Hospitals Educational serv.	Health services exc hospitals Hospitals Educational serv.	Health services exc hospitals Hospitals Educational serv.
Leisure & hospitality	Entertainment & recreation serv.	Entertainment & recreation serv.	Arts, entertain. & recreation
Other services	Utilities and san. Private hshld serv. Auto & repair Personal services Social services	Utilities and san. Private hshld serv. Auto & repair Personal services Social services	Waste Mgmt Utilities Social assistance Repair & maint. Private hshld serv. Personal services
Public administration	Public administration	**	Public administration

*Publishing, Motion picture, Broadcasting, Internet publishing & broadcasting, Telecommunications Internet service & data processing, Other information services. ** Justice, public order, safety, Admin. of human resource progs., National service and internanional affairs, Other public admin.

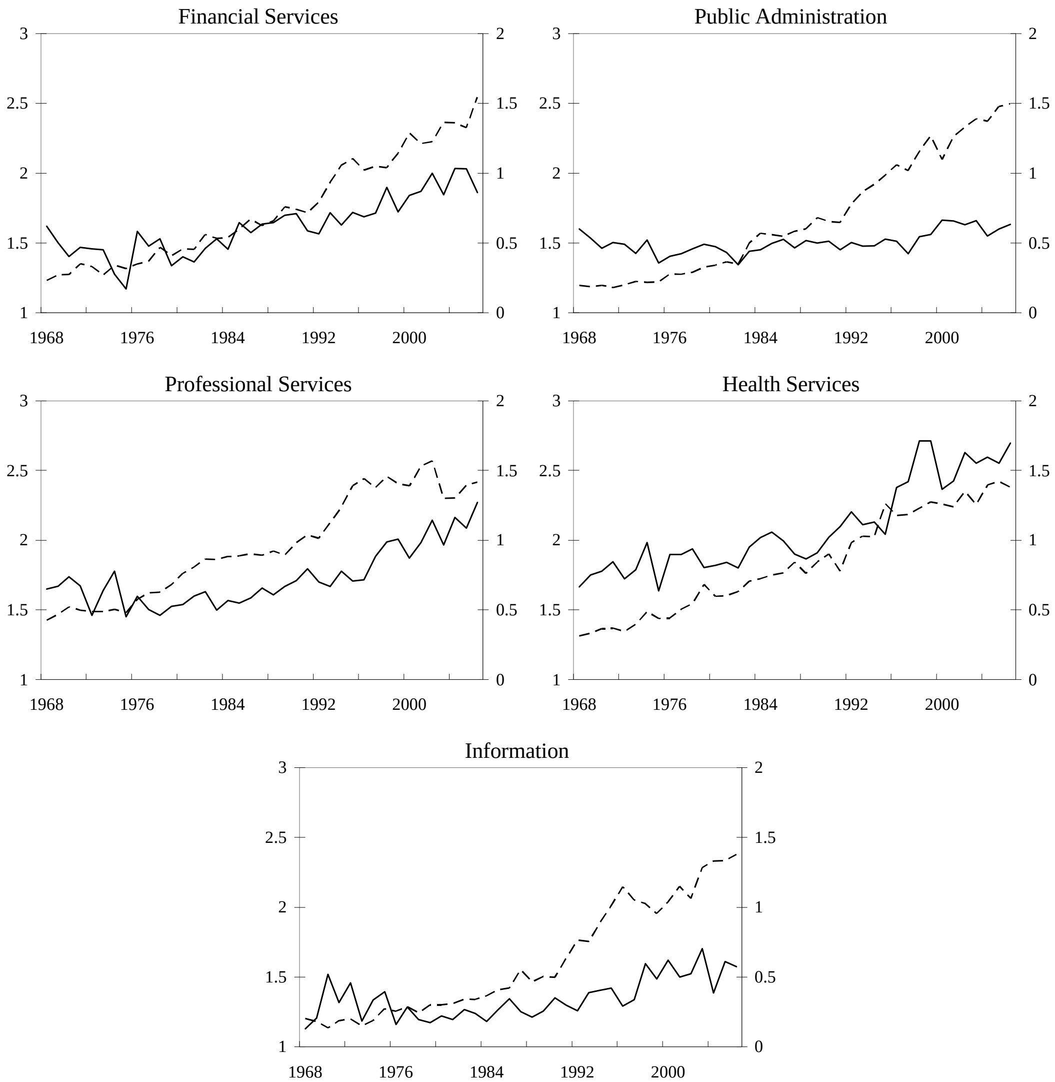

Figure 1: Higher skilled industry. The solid lines show ω_t and the units are given on the left. The dashed lines show s_t and the units are given on the right.

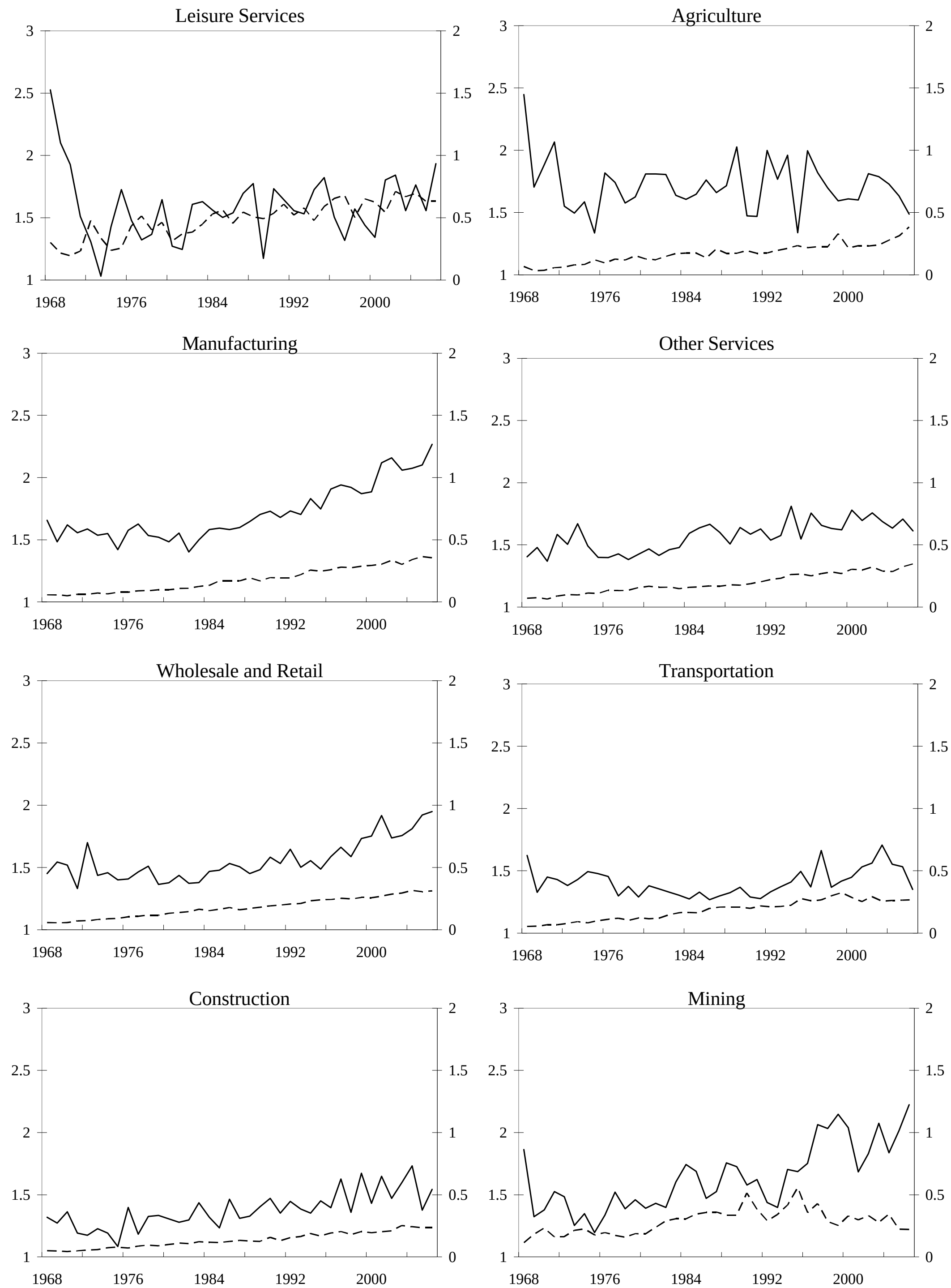

Figure 2: Lower skilled industries. The solid lines show ω_t and the units are given on the left. The dashed lines show s_t and the units are given on the right.