Measuring Skill Intensity of Occupations with Imperfect Substitutability Across Skill Types.

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Abstract

The literature on wage inequality lacks a consistent measure of skill-intensity of occupations. This paper proposes such a measure. Instead of using occupation-specific average educational achievement or skill wage premia, as many studies do, I employ occupation-specific relative productivities of college and high school educated. With imperfect substitution across skill types, the measurement of relative productivities requires estimation of substitution elasticities. I propose a strategy to estimate occupation-specific elasticities using the March CPS data from 1983 to 2002. I apply the resulting measure to test the modified skill-biased technological change hypothesis proposed by Autor et al. (2006).

JEL Classification: J24, J31

Keywords: Skill-intensity of occupations, elasticity of labor substitution, technological progress, polarization

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1 Introduction

Recent literature on wage inequality has achieved a consensus that not only the supply but also the demand side of the labor market is heterogeneous. A worker can produce different value added performing different jobs and the mix of jobs present in the market changes over time. That is why quantifying this heterogeneity is helpful in explaining the developments observed in the labor market.

One of these is the recent polarization of earnings growth, as documented by Autor et al. (2006) in the U.S and Goos and Manning (2007) in the UK. This pattern is illustrated in Figure 1, which plots log hourly earnings growth against wage distribution percentile in the initial year for two time periods: 1973-1988 and 1988-2004. The figure shows that the 70’s and 80’s were characterized by decreasing earnings in the low end of the distribution, but this trend was reversed in the 90’s. The pattern observed in the second period, with wage growth in the bottom and top part of the earnings distribution being faster than in the middle part, is named “polarization”.

[Figure 1 here]

Autor et al. (2008) explain the recent polarization of earnings growth by a modified version of the skill-biased technological change (SBTC) hypothesis. It assumes that new technologies have heterogeneous impact on workers – they complement workers performing nonroutine cognitive tasks, substitute for workers performing routine tasks and have little impact on workers performing nonroutine manual tasks. As nonroutine cognitive tasks are characteristic of high-skilled occupations, routine tasks are characteristic of middle-skilled occupations and nonroutine manual tasks of low-skilled occupations (Autor et al., 2006), testing the modified SBTC hypothesis involves measuring the skill contents of individual occupations. The goal of this paper is to propose a method of obtaining this measure.
Currently there is no uniform way to measure the skill-content of occupations, which I prefer to call the occupation skill-intensity. Some labor economists use the description of skills, abilities and work activities associated with individual occupations as reported in occupation dictionaries such as the Occupational Information Network (O*NET), replacing the Dictionary of Occupational Titles (DOT). This comprehensive source of information about occupations is widely cited in the literature in the context of income inequality (Autor and Dorn 2009) and overeducation (McGoldrick and Robst 1996), although it is rigid and nontransparent. Originally, the DOT was updated, on average, every 4-5 years. The O*NET is updated continuously; however, new occupation descriptions depart from the previous ones and there is no clear algorithm governing the assessment of skill requirements, which may lead to some inconsistencies across occupations.

Other studies offer more transparent approaches towards identifying the skill-intensity of occupations. Some authors use occupation-specific average years of schooling as a proxy for their skill content when analyzing the technological progress on occupational level (Goos and Manning 2007, Autor et al. 2006). This approach is easy to apply and it accounts for short-term changes in occupations’ characteristics. On the other hand, it relies on a strong assumption that the employment structure of occupations correctly reflects their skill requirements. One can easily imagine violation of this assumption in occupations quickly changing their skill requirements. Average years of schooling have also been used as an indicator of the extent to which occupations rely on college graduates in studies measuring the fraction of college graduates underutilizing their skills, i.e., working in the so called “noncollege” occupations (Pryor and Schaffer, 1997). In this line of research, Gottschalk and Hansen (2003) offer a more model-based approach for measuring the skill-intensity of occupations. They argue that the occupation-specific college - high school wage gap reflects the relative productivity of college and high school graduates and as such could be used to order occupations according to their skill intensity. Their insight is used in this paper as a point of departure for defining a consistent...
and flexible measure of the skill-intensity of occupations.

Gottschalk and Hansen (2003) propose to order occupations according to a parameter of their production function – the relative productivity of college and high school graduates. Although they focus on a binary classification of occupations into “college” (where college graduates are more productive than high school graduates) and “non-college” (where college and high school graduates are the same productive), relative productivity could be utilized in its whole continuum as a measure of the skill-intensity of occupations. The relative productivity of differently skilled workers reflects the relative utilization of skills in a given occupation’s production technology and, as such, it offers a consistent and objective measure of occupation-specific skill-intensity. In this paper I propose a generalized methodology of calculating the relative productivity of college and high school graduates within single occupations. The main feature of this approach is that differently educated workers are not treated as perfect substitutes, as is the case in Gottschalk and Hansen (2003). Although the perfect substitutability assumption significantly simplifies the analysis, it is questionable - there exist many studies estimating both the short-run and long-run elasticity of substitution between more and less educated labor in the U.S. economy to be around 1.4.\footnote{Ciccone and Peri (2005) offer a good review of these.} This is hard to obtain in the setup where the majority of occupations interchangeably use both types of workers.\footnote{Gottschalk and Hansen allow for occupations which can employ only college graduates (e.g. medical doctors or judges) by setting productivity of the other skill group to zero at these occupations.}

Generalization of the methodology proposed by Gottschalk and Hansen (2003) involves estimation of the within-occupation elasticity of substitution between high school and college graduates. Following the common practice in the literature, I assume that occupation-specific production functions are of the constant elasticity of substitution (CES) type and use a modification of the approach proposed by Card (2001) to estimate their elasticity parameters. These, combined with relative employment and wages, allow me to derive occupation-specific relative productivities of college and high school graduates.
ates. I propose to use these relative productivities as a new measure of skill-intensity of occupations. It can be used to track the technological progress of individual occupations or investigate wages and employment changes within different types of occupations. In this study I use the measure of skill-intensity of occupations to explore the mechanisms behind the recent polarization of earnings growth in the U.S.

The rest of this text is organized as follows. In the next section I present a model of workers allocation across occupations characterized by different skill-intensity. This model is further used for empirical analysis. Section 4 describes econometric procedures used to identify occupation-specific elasticities of substitution between college and high school graduates which then allows an estimation of the skill-intensity of occupations. The next section presents results of these estimations. In section 4, I use the estimated occupation-specific skill-intensities to analyze the earnings growth polarization. The last section concludes.

2 The measure of skill-intensity

Within-occupation relative productivity of college and high school graduates, where college graduates represent highly skilled labor and high school graduates represent less skilled labor, could be used as a proxy for occupation-specific skill-intensity. Let me illustrate this point using a relatively general occupation-specific production function – the constant elasticity of substitution (CES) aggregate of college- and high school-educated labor, as specified in Equation (1).

\[ Y_j = \left( \alpha_{C_j} L_{C_j}^{\gamma_j} + \alpha_{N_j} L_{N_j}^{\gamma_j} \right)^{\frac{1}{\gamma_j}}, \]

where \( Y_j \) is the output of occupation \( j \), \( L_{C_j} \) is the number of college graduates, \( L_{N_j} \) is the number of high school graduates employed in occupation \( j \), and \( \gamma_j \) is a parameter describing substitutability between these two labor types (the elasticity of substitution is \( \sigma_j = \frac{1}{1-\gamma_j} \)). In this context, \( \frac{\alpha_{C_j}}{\alpha_{N_j}} \) describes the occupation-specific relative productivity of
differently educated workers. In occupations where this parameter assumes high values, college graduates are much more productive than high school graduates, what could be attributed to the skill difference between differently educated workers. That is why $\frac{\alpha_{Cj}}{\alpha_{Nj}}$ describes the skill-intensity of an occupation. It tells us how crucial college-gained skills are for the tasks performed within a specific occupation.

Under the simplifying assumption made by Gottschalk and Hansen (2003), i.e. when the elasticity of substitution between college and high school graduates is infinite ($\gamma_j = 1$), $\frac{\alpha_{Cj}}{\alpha_{Nj}}$ is fully reflected in the relative wage of the two education groups. This is why Gottschalk and Hansen (2003) classify occupations according to college wage premia which they pay. The perfect substitutability assumption is, however, questionable. One could easily come up with examples of occupations where the elasticity of substitution between college and high school graduates is zero (e.g. medical doctors) or where it is highly limited (e.g. financial advisors). Relaxing the infinite elasticity of substitution assumption (i.e. allowing for $\gamma_j < 1$) and rearranging the first order conditions for firms’ profit maximization problem gives

$$\frac{\alpha_{Cj}}{\alpha_{Nj}} = \frac{w_{Cj\ell}}{w_{Nj\ell}} \left( \frac{L_{Cj\ell}}{L_{Nj\ell}} \right)^{1-\gamma_j} = \frac{w_{Cj\ell}}{w_{Nj\ell}} \left( \frac{L_{Cj\ell}}{L_{Nj\ell}} \right)^{-\frac{1}{\gamma_j}}. \quad (2)$$

Thus, in the setup where college and high school graduates are allowed to be imperfect substitutes, one needs to know the elasticity of substitution between them to derive the occupation-specific relative productivity.\(^4\)

\(^3\)Note that parameters $\alpha_{Cj}$ and $\alpha_{Nj}$ capture both the relative income shares and productivities of college and high school graduates. What actually matters, is their relative value, $\frac{\alpha_{Cj}}{\alpha_{Nj}}$ (see Card and DiNardo, 2002, for a more detailed discussion), so one could write $Y_j = F_j \left( \alpha_j L_{Cj} + L_{Nj} \right)^{\frac{1}{\gamma_j}}$. I keep the notation as presented in the text to be consistent with Gottschalk and Hansen (2003).

\(^4\)Note that setting $\gamma_j = 1$ in the occupation-specific production function (1) one gets $\frac{\alpha_{Cj}}{\alpha_{Nj}} = \frac{w_{Cj\ell}}{w_{Nj\ell}}$, as in Gottschalk and Hansen (2003), while setting $\gamma_j = -\infty$ leads to $\frac{\alpha_{Cj}}{\alpha_{Nj}} = \frac{L_{Cj\ell}}{L_{Nj\ell}}$, which is a version of the average years of schooling approach used, for example, by Autor et al. (2006).
3 Theoretical model of labor allocation across occupations

In this section I outline a theoretical model describing allocation of differently skilled labor across occupations characterized by different skill-intensity and different substitutability between skill types. The model explains why observationally similar people are found in different (and differently paying) occupations. It also provides a baseline for an econometric specification used to estimate occupation-specific elasticity of substitution between college and high school graduates.

3.1 Demand for labor

Let us assume that the economy produces one uniform good which sells at price $p$. This good is produced using $J$ different occupations with production technology described by a twice-differentiable function $G(\cdot)$:

$$Y = G(L_1, L_2, ..., L_J).$$

Each occupation could be described as a technology aggregating two labor types: college and high school graduates. The “output” of occupation $j$ is a labor aggregate $L_j$ being a CES combination of college- and high school-educated labor. Occupations differ in their skill-intensity ($\frac{C_j}{N_j}$) and the elasticity of substitution between college and high school graduates ($\sigma_j = \frac{1}{1 + \gamma_j}$). The production function used by occupation $j$ could be summarized in the following way:

$$L_j = (\alpha_{Cj}L_{Cj}^{\gamma_j} + \alpha_{Nj}L_{Nj}^{\gamma_j})^{\frac{1}{\gamma_j}}, \tag{3}$$

where $L_{Cj}$ and $L_{Nj}$ are the amounts of college- and high school-educated labor employed in occupation $j$.

In a competitive market, under the above-specified functions, wages of each education group in occupation $j$ should be equal to their marginal products, as expressed by the
first-order conditions:

\[ w_{Cj} = p \frac{\partial Y}{\partial L_j} \frac{\partial L_j}{\partial L_{Cj}} = p \frac{\partial Y}{\partial L_j} L_j^{1-\gamma_j} \alpha_{Cj} L_{Cj}^{\gamma_j-1} \]

\[ w_{Nj} = p \frac{\partial Y}{\partial L_j} \frac{\partial L_j}{\partial L_{Nj}} = p \frac{\partial Y}{\partial L_j} L_j^{1-\gamma_j} \alpha_{Nj} L_{Nj}^{\gamma_j-1} \]

These equations lead to the formulation of the relative wage of college and high school graduates in occupation \( j \):

\[ \frac{w_{Cj}}{w_{Nj}} = \frac{\alpha_{Cj}}{\alpha_{Nj}} \left( \frac{L_{Nj}}{L_{Cj}} \right)^{1-\gamma_j}, \quad (4) \]

which, after rearrangement and substitution of \( \sigma_j = \frac{1}{1-\gamma_j} \), gives

\[ \ln \left( \frac{L_{Cj}}{L_{Nj}} \right) = \sigma_j \ln \left( \frac{\alpha_{Cj}}{\alpha_{Nj}} \right) - \sigma_j \ln \left( \frac{w_{Cj}}{w_{Nj}} \right). \quad (5) \]

Equation (5) describes the relative labor demand in occupation \( j \). It depends on relative wages of the two education groups, their relative productivities and the elasticity of labor substitution within occupation \( j \).

### 3.2 Supply of labor

Let us assume now that there are \( N_{Cj} \) college-educated workers and \( N_{Nj} \) high school-educated workers who could potentially supply labor to occupation \( j \) (\( N_{Cj} \) and \( N_{Nj} \) describe labor markets specific to occupation \( j \)). The notion of occupation-specific labor markets, introduced by Card (2001), is used to accommodate the observation that a worker usually looks for employment in specific occupation, however she has some flexibility to switch occupations as a reaction to productivity shocks affecting the labor market. In this context, \( N_{Cj} \) and \( N_{Nj} \) capture all workers who would supply labor to occupation \( j \) under favorable labor market conditions. Just some of these people are actually observed working in occupation \( j \) because workers differ in their occupation-specific reservation wage. This leads to formulation of the supply of labor to occupation
log as a fraction of the total size of this occupation’s specific labor market.\textsuperscript{5}
\begin{align}
\ln \left( \frac{L_{Cj}}{N_{Cj}} \right) &= \beta_j \ln w_{Cj} \\
\ln \left( \frac{L_{Nj}}{N_{Nj}} \right) &= \beta_j \ln w_{Nj}.
\end{align}

Log-linear aggregate labor supply functions are commonly used when describing the
supply of workers to different units of production, usually occupations (Card 2001,
Gottschalk and Hansen 2003). The occupation-specific elasticity of labor supply, \( \beta_j > 0 \),
represents workers’ aggregate preferences towards occupation \( j \). It is assumed to be the
same for each education group within the occupation-specific labor market. This as-
sumption is crucial for the model to have a closed-form solution. Despite being strong,
this assumption is less restrictive than the relaxed assumption about \( \gamma = 1 \).

The above specified supply functions can be combined into one equation describing
the relative supply of labor into occupation \( j \):
\begin{equation}
\ln \left( \frac{L_{Cj}}{L_{Nj}} \cdot \frac{N_{Cj}}{N_{Nj}} \right) = \beta_j \ln \left( \frac{w_{Cj}}{w_{Nj}} \right). \tag{7}
\end{equation}

The relative supply of labor to occupation \( j \) depends on the relative wages of the
two education groups and the occupation-specific elasticity of labor supply.

3.3 Equilibrium

Equations (5) and (7) describe the relative demand and supply of labor for occupation
\( j \). Equalizing supply with demand and rearranging, one arrives at a system capturing
the equilibrium relative wages and relative employment in each occupation:
\begin{equation}
\begin{aligned}
\ln \left( \frac{w_{Cj}}{w_{Nj}} \right) &= \frac{\sigma_j}{\sigma_j + \beta_j} \ln \left( \frac{\alpha_{Cj}}{\alpha_{Nj}} \right) - \frac{1}{\sigma_j + \beta_j} \ln \left( \frac{N_{Cj}}{N_{Nj}} \right) \\
\ln \left( \frac{L_{Cj}}{L_{Nj}} \right) &= \frac{\sigma_j \beta_j}{\sigma_j + \beta_j} \ln \left( \frac{\alpha_{Cj}}{\alpha_{Nj}} \right) + \frac{\sigma_j}{\sigma_j + \beta_j} \ln \left( \frac{N_{Cj}}{N_{Nj}} \right). \tag{8}
\end{aligned}
\end{equation}

\textsuperscript{5}Let me note that \( \frac{L_{Cj}}{N_{Cj}} \) and \( \frac{L_{Nj}}{N_{Nj}} \) are restricted not to exceed 1, which is not captured by the presented
functions. I do not incorporate these restrictions, because in reality they never bind.
Let us note that both relative wages and relative employment depend on occupation-specific supply factors (total relative amounts of college- and high school-educated workers in occupation-specific labor markets) and demand factors (relative productivity of college and high school graduates). The shape of these dependencies is described jointly by the occupation-specific elasticity of labor supply and the elasticity of substitution between the two labor types.

The system derived above describes how the observed occupation-specific employment structure and wages depend on the relative number of college and high school graduates ready to supply labor to that occupation. These formulas strongly rely on the functional forms assumed, i.e. on the shape of production function and the shape of labor supply. Nevertheless, the CES production function and the log-linear supply function are the functional forms most widely used in the context of labor-labor substitutability and occupational choice; as such, they constitute a good baseline for this study. Observing occupation-specific labor allocation, relative wages and the structure of this occupation’s labor market, one can use the derived system to estimate the elasticity of substitution between more and less educated labor as well as the occupation-specific elasticity of labor supply.

4 Econometric approach

Under the assumption that the occupation-specific elasticities of substitution between college and high school graduates and the elasticities of labor supply do not change over time, I can use the above presented model to estimate them. To do so, let me analyze an economy, as described in the previous section, in several consecutive periods (subscribed by \( t \)). In each period the occupation-specific supply and demand factors are different. The relative amounts of college- and high school-educated workers in occupation-specific labor markets vary with the socio-demographic structure of the population, current popularity of occupations and the fraction of college graduates in total population. The
relative productivity of college and high school graduates varies with the SBTC. These movements of the relative supply and demand curves lead to the observation of different equilibrium values of occupation-specific relative wages and employment which can be used to estimate the system of equations as presented in (8).

To completely specify the model, let me decompose the (unobserved) variation in the relative productivity of labor into three components: occupation-specific (characteristic of a given occupation, constant over time), year-specific (common for all occupations) and occupation-year specific effects. It is usual to assume that the occupation-specific component is deterministic, while the other two are stochastic (Card 2001), which can be expressed as

\[
\ln \left( \frac{\alpha_{Cjt}}{\alpha_{Njt}} \right) = \ln(\alpha_j) + \varepsilon_t + \varepsilon_{jt}.
\]

Using this notation, the system (8) could be rewritten into the following econometric model:

\[
\begin{align*}
\ln \left( \frac{w_{Cjt}}{w_{Njt}} \right) &= c_{j0} + c_{j1} \ln \left( \frac{N_{Cjt}}{N_{Njt}} \right) + v_t + v_{jt}, \\
\ln \left( \frac{L_{Cjt}}{L_{Njt}} \right) &= d_{j0} + d_{j1} \ln \left( \frac{N_{Cjt}}{N_{Njt}} \right) + \mu_t + \mu_{jt},
\end{align*}
\]

where

\[
c_{j0} = \frac{\sigma_j}{\sigma_j+\beta_j} \ln(\alpha_j), \quad c_{j1} = -\frac{1}{\sigma_j+\beta_j}, \quad v_t = \frac{\sigma_j}{\sigma_j+\beta_j} \varepsilon_t, \quad \nu_{js} = \frac{\sigma_j}{\sigma_j+\beta_j} \varepsilon_{jt},
\]

and

\[
d_{j0} = \frac{\sigma_j \beta_j}{\sigma_j+\beta_j} \ln(\alpha_j), \quad d_{j1} = \frac{\sigma_j}{\sigma_j+\beta_j}, \quad \mu_s = \frac{\sigma_j \beta_j}{\sigma_j+\beta_j} \varepsilon_t, \quad \mu_{js} = \frac{\sigma_j \beta_j}{\sigma_j+\beta_j} \varepsilon_{jt}.
\]

This model describes the simultaneous determination of occupation-specific relative wages and relative employment as a function of the relative numbers of college- and high school-educated workers in occupation-specific labor markets in a given time period \(t\). Note that the occupation-specific elasticity of substitution between college and high school graduates, \(\sigma_j\), could be expressed as

\[
\sigma_j = \frac{d_{j1}}{c_{j1}}.
\]

Thus, consistent estimation of \(c_{j1}\) and \(d_{j1}\) allows for the identification of \(\sigma_j\). Before turning to the estimation, however, one has to acknowledge several important features of the model and data used in the analysis.

First, consider the endogenous nature of occupation-specific labor markets. As a result of a positive skill-biased productivity shock affecting occupation \(j\), relative wages

\[\text{Note, that according to the modified version of the SBTC, the technological progress might have positive influence on the relative productivity in some occupations while having a negative effect in other.}\]
and relative employment of college graduates in this occupation increase. At the same
time, however, more college graduates enter this occupation-specific labor market, as
they see a possibility of high returns to education. Due to this effect, the OLS estimates
of $c_{j1}$ and $d_{j1}$ are likely to be biased upwards. In the existing literature, such a problem
is commonly dealt with by assuming that the time evolution of relative productivity is
log-linear (Katz & Murphy 1992, Card & DiNardo 2002, Autor et al. 2008), i.e. that
$\varepsilon_t + \varepsilon_{jt}$ can be approximated by a linear time trend. Although this does not capture all
the unobservable shocks to relative labor productivity, it capturing the ones that can be
anticipated by workers and thus might influence the structure of the occupation-specific
labor market.

Second, the explanatory variable $\frac{N_{Cjt}}{N_{Njt}}$, is not directly observable in the data. Estimat-
ing this variable introduces a measurement error satisfying the classical error-in-variables
(CEV) assumptions. To mitigate this problem, I rely on two alternative approaches to
estimate the sizes of occupation-specific labor markets. As discussed in the next section,
the measurement errors of these estimates are uncorrelated. In the final estimation one
measure is used as an instrument for the other to reduce the attenuation bias (Ashen-
filter and Krueger, 1994).

Finally, the disturbance terms from the relative wage and relative employment equa-
tions for single occupation are expected to be correlated between themselves, as they are
both derived from the stochastic part of the relative productivity, $\varepsilon_t + \varepsilon_{jt}$. While this
feature does not invalidate the estimates of the model coefficients, taking it into account
can greatly improve the estimation efficiency. Thus, I estimate the elasticity parameters
of each occupation using a 2-equations system of seemingly unrelated regressions (SUR).

Taking into account the above-discussed properties, the final econometric model is
specified in the following way:

$$
\begin{align*}
\ln \left( \frac{w_{Cjt}}{w_{Njt}} \right) &= c_{j0} + c_{j1} \ln \left( \frac{N_{Cjt}}{N_{Njt}} \right) + c_{j2} t + c_{j3} t^2 + \zeta_{jt} \\
\ln \left( \frac{L_{Cjt}}{L_{Njt}} \right) &= d_{j0} + d_{j1} \ln \left( \frac{N_{Cjt}}{N_{Njt}} \right) + d_{j2} t + d_{j3} t^2 + \xi_{jt}
\end{align*}
$$

(10)
where $c_{j2t} + \zeta_{jt} = v_t + v_{jt}$ and $d_{j2t} + \xi_{jt} = \mu_t + \mu_{jt}$, with $\zeta_{jt}$ and $\xi_{jt}$ being uncorrelated with the true value of $\ln\left(\frac{N_{Cjt}}{N_{Njt}}\right)$. When estimating this model, I use an estimate of the relative size of occupation-specific labor market, $\ln\left(\frac{N_{Cjt}}{N_{Njt}}\right)^A$, which is instrumented by an alternative measure, $\ln\left(\frac{N_{Cjt}}{N_{Njt}}\right)^B$. The whole system is estimated using the SUR approach.

Under the assumption that predictable shocks to occupation-specific relative labor productivity follow a linear trend and the measurement errors in the two estimates of occupation-specific labor markets are uncorrelated, the above presented approach leads to consistent estimation of $\hat{c}_{j1}$ and $\hat{d}_{j1}$. These estimates are further used to calculate the elasticity of substitution between more and less educated labor: $\hat{\sigma}_j = -\frac{\hat{d}_{j1}}{\hat{c}_{j1}}$. Finally, one can combine $\hat{\sigma}_j$’s estimated separately for each occupation with occupation-specific estimates of college wage premium and relative employment to calculate the relative productivities as:

$$\frac{\hat{\alpha}_{Cjt}}{\hat{\alpha}_{Njt}} = \frac{w_{Cjt}}{w_{Njt}} \left(\frac{L_{Cjt}}{L_{Njt}}\right)^{-\frac{1}{\hat{\sigma}_j}}.$$  \hfill (11)

This is the measure used in this study to define the skill-intensity of occupations.

## 5 Data and measurement issues

The data used in this study come from 1983-2002 March Supplement to the Current Population Survey (March CPS), which means that I observe earnings for the years 1982 through 2001. This is the longest time span with consistent occupational coding, which is crucial for my analysis.\(^7\) Due to a limited number of observations offered by March CPS, three consecutive years had to be merged to obtain sample sizes allowing the data-hungry occupation-level analysis. This means that data used to analyze year $t$ are composed of $t-1$, $t$ and $t+1$ March CPS samples. Thus, I can effectively analyze

\(^7\)In 1983 CPS started to use the 1980 Census occupation codes. These were later substituted by 1990 Census occupation codes which, however, introduced only minor changes. The 2000 Census occupational classification introduced to CPS in 2003 differs substantially from the previous ones.
years 1983 - 2000. This time period covers the decade of rapid increase in the college-high school wage gap as well as the later slowdown in the rate of growth of this gap. Thus, it should be enough to capture the interesting phenomena in the labor market.

In order to make my analysis comparable to Gottschalk and Hansen (2003), I apply the same restrictions to the data as these authors do. Only male and female workers with at least a high school diploma and no more than a college degree are included in the sample. I do not construct college equivalents and high school equivalents, as many studies do. Instead, I focus on occupational allocation of college graduates with no higher degree as compared to high school graduates not having a college diploma. To avoid the issue of imperfect substitutability between experience groups, as discussed by Card and Lemieux (2001), I concentrate on recent school leavers defined as individuals with 10 or less years of potential labor market experience. Both full time and part time workers are included in the sample to ensure a sufficient number of observations. However, self-employed individuals are excluded from the sample as are those with reported working hours per week of zero or above 98. The earnings measure used in this analysis is the log of weekly earnings defined as yearly wage and salary income divided by weeks worked last year. Earnings are expressed in 2000 dollars.

I deal with earnings censoring by assigning the cell means of earnings to the top-coded individuals. Starting in 1996, the cell-means are reported in the March CPS, while the cell-means for years 1983-1995 are calculated by Larrimore et al. (2008). Recoding of occupations due to the switch from the 1980 to the 1990 Census occupational classification is done according to the scheme proposed by Meyer and Osborne (2005). Finally, for the earlier years, when March CPS reported the years spent in education instead of the highest degree obtained, I use the sample the individuals having 12-17 years of education (Jeager, 1997). Those with 16 or 17 years of education are assumed to be college graduates. Occupations are defined on a 3-digit level. However, some of the 3-digit categories had to be merged with other 3-digit categories to ensure sufficient

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8Potential labor market experience is calculated as age – years of schooling – 6.
5.1 Relative wages and relative employment measures

To calculate the relative wages of college and high school graduates, I use the regression adjusted wages of individuals. The controls included in the log-wage regressions, widely used to estimate returns to college, are experience, gender, race, education, full-time work status, and dummies for years $t - 1$ and $t + 1$.

Relative employment is calculated as the ratio of the numbers of college and high school graduates observed in a given occupation in a given year weighted by individual sample weights.

5.2 Occupation-specific labor markets

Occupation-specific labor markets, $N_{Cjt}$ and $N_{Njt}$, are not directly observed in the data. They are composed of all workers who would supply labor to occupation $j$ in period $t$ if the labor market conditions were favorable enough. As one never knows what fraction of potential employees actually supplies labor to occupation $j$, it is not possible to measure the sizes of occupation-specific labor markets precisely and the disturbance here is probably correlated with the observed numer of employees – in times good for a given occupation we might overestimate. To mitigate the effect of measurement error, I rely on two alternative approaches to estimate $N_{Cjt}$ and $N_{Njt}$. First, I draw on Card (2001), who proposes to consider an individual’s occupation as a probabilistic outcome that depends on her underlying characteristics. Let me call the obtained variable as the probabilistic measure. Second, I construct transition matrices which define overlaps between occupation-specific labor markets. to obtain the overlapping markets measure.

Card’s (2001) idea is that individuals with a given education level choose which occupation labor market to enter based on their predispositions and the expected labor market conditions. These predispositions (proxied by observable demographic and other characteristics) determine the probabilities ($\pi_{ij}$) to choose each occupation given the expectations. Under these assumptions, the number of people who could potentially work in occupation $j$ at time $t$ can be expressed as the sum of $\pi_{ij}$’s across the active population.

The probability of working in occupation $j$ should be estimated against all other occupations, as these are competing choices. An obvious choice in this context is to apply the multinomial logit. This model is, however, very computationally demanding and difficult to track when the number of possible choices is large. While Card (2001) dealt with 6 broad occupational categories, this study analyses 90 3-digit occupations. To overcome this problem, I propose that for each occupation the so called “neighboring” occupations are defined. These are all occupations from which we observe a significant number of workers switching to occupation $j$ and to which workers from occupation $j$ switch. To find these occupations, I look at occupation-switchers observed in the matched panel subsamples of March CPS.\(^{10}\)

Once “neighboring” occupations are defined for each occupation at each education level, the multinomial logit model of occupational choice is estimated. For each individual with given education level, I estimate the probability of choosing occupation $j$ from among all the “neighboring” occupations as a function of her demographic characteristics such as gender, age and race, as well as the region where she lives and a quadratic time trend which controls for the predictable shifts in occupation attractiveness. The estimated equation is as follows:

$$prob(occ_{it} = j) = G (X_{it} \beta + \psi_1 t + \psi_2 t^2 + \eta_{it}) ,$$

where the dependent variable equals one if an individual $i$ works in occupation $j$

\(^{10}\)See Peracchi and Welch (1995) for a description of the matching procedure.
at time $t$, $X_{it}$ contains individual demographic characteristics and regional dummies, $t$ is the time trend, and $v_{it}$ captures individual unobservable effects. This approach allows us to estimate the importance of each characteristics for working in occupation $j$’s labor market given the expected labor market conditions (proxied by the time trend). The estimate of $\beta$ is then used to predict individual-specific probability to work in each occupation $\tilde{\pi}_{ij}$ cleared of time effects. The year-specific sum of these fitted values represents the occupation $j$’s specific labor market in the given year. This measure could be thought of as the number of people that would work in occupation $j$ in year $t$ if the productivity shocks experienced by this occupation exactly followed the expected trend. As such, this measure is independent of yearly deviations from the quadratic trend which drive the variation in relative wages and relative quantities of labor actually employed in a given occupation.

The alternative measure of occupation-specific labor markets is based on aggregate trends rather than individual predispositions. It assumes that occupation-specific labor markets overlap to a well-defined extend. One can understand the overlap between two occupations’ markets as the fraction of people employed in occupation $k$ who belong to occupation’s $j$ labor market. Knowing these fractions one can easily calculate the sizes of occupation-specific labor markets as the sum of employment in all occupations weighted by the respective overlaps.

Assuming that the extent of the cross-occupational overlap of the labor markets is follows a quadratic time trend (with slight variations caused by year-specific shocks), I can use the pooled data from the whole time period covered in this study to construct education-specific transition matrices, $T_{Ct}$ and $T_{Nt}$, whose elements in the $k$-th row and $j$-th column represent the average fraction of workers in occupation $k$ who move to occupation $j$ within a year. The elements of these matrices are treated as proxies for the fraction of workers observed in occupation $k$ who also belong to occupation’s $j$ labor market. That is why the elements on the diagonal are set to be 1.
With the transition matrices in hand, one can retrieve the total number of college and high school graduates ready to supply labor to each occupation \( j \) by observing employment in all 90 occupations. Under the assumptions stated above, the occupation-specific labor market at time \( t \) can be defined as the weighted sum of all workers with given education level employed in each occupation in the given year. The weights are composed of the elements of the \( j \)-th columns of the education-specific transition matrices:

\[
N_{Cjt} = T_{Ctj} \times L_{Ct}, \\
N_{Njt} = T_{Ntj} \times L_{Nt},
\]

where \( T_{Ctj} \) and \( T_{Ntj} \) are the \( j \)-th columns of matrices \( T_{Ct} \) and \( T_{Nt} \), and \( L_{Ct} \) and \( L_{Nt} \) are the horizontal vectors of employment of college and high school graduates in all \( J \) occupations in year \( t \).

The two approaches to measure \( N_{Cjt} \) and \( N_{Njt} \) result in similar estimates of occupation-specific labor markets. Nevertheless, as they are based on different assumptions and are disturbed by different factors, I use the overlapping markets measure to instrument for the probabilistic measure to reduce the measurement error bias when estimating the system 10.

6 Empirical implementation

In this Section, I present step-by-step results leading towards the estimation of occupation-specific skill-intensity. As explained in Section 4, the main challenge of this analysis, and the main contribution of this study, is the estimation of occupation-specific elasticities of substitution between college and high school graduates.

Having obtained the structure of occupation-specific labor markets according to the algorithm outlined above, I proceed to the estimation of system 10 for each of the occupational categories where more than 5% and less than 90% of the employees have at least a college degree. Occupations where college and university graduates constitute the wide
majority of employees are treated as licensed occupation (i.e. occupations where holding a degree is required by law), which implies an elasticity of substitution between college and high school graduates of zero.\textsuperscript{11} Occupations where hardly any college graduates are employed are assumed to be exclusively high school occupations, which also implies an elasticity of substitution of zero.\textsuperscript{12} For the remaining 73 occupations system 10 is estimated and the estimates of $c_{j1}$ and $d_{j1}$ are recorded.

For many occupations $c_{j1}$ is found to be not statistically different from zero. These are plausible values. The parameter $c_{j1}$ is expected to be zero for occupations where college and high school graduates are perfect substitutes ($\sigma_j = \infty$) or where workers supply labor perfectly elastically ($\beta_j = \infty$). In the latter case, $d_{j1}$ should also be zero, while in the former, $d_{j1}$ is expected to be one. This property can be used to distinguish between the two cases. Additionally, $d_{j1}$ is expected to be zero (but $c_{j1}$ significant and negative) for occupations where it is impossible to substitute between college and high school graduates ($\sigma_j = 0$). For all other occupations, the substitutability between workers with different education levels is positive and finite. The full list of the estimates of elasticities of substitution between college and high school graduates ($\sigma_j = -(d_{j1}/c_{j1})$) is reported in the first column of Table 1. One should note that only 28 of all analyzed occupations are characterized by an elasticity of substitution between college and high school graduates being non-zero and finite. These are, however, the occupations for which skill (or educational) requirements are often discussed – Sales workers, Record processing occupations, or Computer technicians, etc. – which strengthens the argument that elasticity of substitution between different labor types is crucial when analyzing the

\textsuperscript{11}These occupations include Architects, Biological and life scientists, Elementary school teachers, Health diagnosing occupations, Judges, Lawyers, Postsecondary teachers, Secondary school teachers, Special education teachers, and Speech therapists.

\textsuperscript{12}These occupations include Cashiers, Food preparation and service occupations, Freight, stock, material handlers, and service stations, Mail and message distributing occupations, Mechanics and repairers, vehicle and industrial machinery, Transportation and material moving occupations, Waiters and waitresses.
skill-intensity of occupations.

The estimated elasticities of substitution are further used to calculate occupation-time specific relative productivities of college and high school graduates – the measure of the skill-intensity of occupations. These are calculated for each occupation-year cell separately according to Equation (11). Occupations with zero elasticity of substitution between the two worker types were assigned the relative productivity of college and high school graduates of infinity (when more than 90% of the employees have at least a college degree) or zero (when less than 5% of the employees have at least a college degree). While it is difficult to present here all 1620 estimates (90 occupations in 18 years), let me present the most interesting findings in the figure below.

[Figure 2 here]

One should note that the majority of occupations have undergone a significant skill-upgrading. This concerns mainly those occupations where communication skills (e.g. knowledge of foreign languages) plays an important role, i.e., for example, Public administration and Sales representatives. There is also a group of occupations in which the relative productivity of college and high school graduates remained constant during the 1990’s. These are represented by Protective service occupations in Figure 2. Finally, some occupations experienced a decline in skill intensity. These involve computationally demanding tasks which were previously done by men, but recently have been substituted by technology.

For reference, point estimates of occupation-specific skill intensity for the years 1984 and 2001 (first and last year of the sample) are presented in columns 3 and 4 of table 1. A full list of this measure is available from the author upon request.
7 Applications of the measure of skill-intensity of occupations

The measure of skill-intensity of occupations derived in this study has multiple applications. This section shortly presents one of them: an analysis of recent polarization of earnings growth in the U.S.

7.1 Polarization of earnings growth

Polarization of earnings growth in the U.S. has been documented by Autor (2006) as a pattern observed in the last decade of the 20th century when the wage growth in the bottom and top part of the earnings distribution was faster than in the middle part. This observation is especially interesting when contrasted with earnings growth in earlier periods when the earnings at the low end of the distribution were falling and in the top end of the distribution increasing. Similar patterns, although with naturally higher growth rates, can be recognized in the sub-sample of the U.S. labor force investigated in this article, i.e. among college and high school graduates with no more than 10 years of labor market experience, as presented in Figure 3.

[Figure 3 here]

The above figure displays changes in log earnings of American population with at least a high school degree over two 10-year periods. The left panel was constructed using the average skill-intensity of occupations performed by individuals from each percentile of earnings distribution in the beginning and end year of the respective time interval, while the right panel shows a smoothened relationship. It is clearly visible in both graphs that between 1984 and 1994 earnings in the 5th to 25th percentile of earnings distribution grew much slower than earnings of the median worker and earnings in the 75th to 95th percentile of earnings distribution grew much faster. On the other hand,
between 1991 and 2000 earnings in both the 5th to 25th percentile and the 75th to 95th percentile of earnings distribution grew faster than the earnings in the middle of the distribution.

The change in the growth profile documented in Figure 3 can be understood by analyzing the impact of technological change, as measured by the skill-intensity, on occupations performed by workers along the earnings distribution in each of the considered time periods. Employing the occupation-year specific skill-intensities estimated in Section 6, the left panel of Figure 4 plots the changes in log of average skill-intensity \( \ln(\frac{\text{avg}}{\text{median}}) \) of occupations performed by workers in different percentiles of the earnings distribution.

[Figure 4 here]

We observe that between 1984 and 1994 workers with below median earnings experienced only about a 0.1 change in the log of average skill-intensity of occupations in which they were employed, while workers with above median earnings experienced a strong skill-biased technological progress. Interestingly, between 1991 and 2001 the change in skill-intensity of occupations performed by the top 50% of earners was roughly the same as in the previous period, while people with below median earnings experienced a significant improvement in the skill-intensity of occupations in which they were employed. To better understand the nature of these differences, I fix the skill-intensity of individual occupations at their initial level (i.e. from year 1984 or 1991, respectively) and analyze the changes in average skill-intensity of occupations performed by workers from different percentiles of earnings distribution which are just due to their reallocation across occupations. This is pictured in the right-hand panel of Figure 4. When abstracting from occupation-specific technological progress, the pattern observed in the 1980’s is preserved, however the pattern from the 1990’s disappears.
This exercise suggests that in the 1980’s the technological change affected mainly the top-earners, which might have resulted in a widening of the earnings gap between the richest and the poorest. Additionally, we can see that this technological change affected equally all the occupations performed by workers from the continuum of earnings distribution. The difference between the above median and below median earners should be attributed to the change in the mix of occupations performed by these workers – the top earners shifted towards more skill-intensive occupations. On the other hand, in the 1990’s those earning the least were "catching up" with the skill-intensity of occupations, which might have led to a slight narrowing of income inequality. Interestingly, in the later period of my analysis the difference between the below and above median earners was solely caused by changes in the skill-intensity of occupations – the occupations performed by the least-earning workers experienced the strongest skill-biased technological progress.

The above findings shed new light on the understanding of the skill-biased technological progress and its impact on individual workers’ earnings over time. It seems that in the earlier decades the skill-biased technological progress was uniformly distributed across occupations, while in the later years it affects more the least paying occupations. This is not fully consistent with Autor’s modified skill-biased technological change hypothesis which assumes that recent technological progress is neutral towards workers performing the least-paying jobs, who are assumed to perform manual nonroutine tasks. Nevertheless, my findings support the statement that the impact of technological change in the 1980’s was different from that in the 1990’s. In the earlier decade new technologies strongly favored the top-earning workers (or, better to say, the top-earning workers moved to occupations employing these new technologies), while in the later decade they increased the productivity of workers over the whole earnings distribution.
8 Conclusion

In this study I propose a methodology for determining the skill-intensity of occupations. This measure is useful for explaining the evolution of wage inequality, analyzing the occupational allocation of labor, assessing the benefits of education, and in many other applications. I argue that a good proxy for occupation-specific skill-intensity is the relative productivity of college and high school graduates. This parameter of production function captures the importance of college-gained skills for the tasks performed within a specific occupation.

When proposing a new measure of skill-intensity of occupations, I relax the assumption of the elasticity of substitution between college and high school graduates being the same across occupations, but still assume that occupation-specific substitution elasticities do not change over time. Keeping the elasticity constant over time is one of the identifying assumptions of the econometric model used to estimate $\sigma_j$. Relaxing this one would be the next step of research.

When estimating occupation-specific relative productivities, it is important to take into account the elasticity of substitution between college and high school graduates. This parameter in many studies is $ex\ ante$ assumed to be infinite. I estimate the elasticity of substitution between differently educated workers and find that many occupations are characterized by imperfect substitutability between college and high school graduates. Not taking that into account would bias the estimates of relative productivities.

The proposed measure of skill-intensity of occupations has multiple applications. This paper discusses one of them. I show that the measure of skill-intensity could be used to analyze the recently observed polarization of earnings growth, as documented by Goos and Manning (2007) in the UK and Autor et al. (2006) in the U.S. The presented results confirm the hypothesis proposed by Autor that the technological change in the 1980’s affected mainly the high earners, while in the 1990’s it also affected the rest of the earnings distribution. They also bring new evidence about the changing nature of the
technological progress. In the earlier phase it was equally distributed across occupations, but high earners sorted to more skill-intensive occupations and low earners sorted to less skill-intensive occupations. In the latter phase there was no further re-allocation and the least paying occupations experienced a stronger technological progress.

Finally, let me acknowledge the fact that estimating skill-intensity of occupations is a data hungry process. This limits the application of the methodology developed in this study to economies which have sizeable worker-level data. An alternative solution would be to take advantage of the findings of Kezdi (2003) who shows that the skill-bias in Hungary follows global skill-biased changes. Extrapolating these findings would suggest that the occupation-specific relative productivity of college and high school graduates (occupation-specific skill-bias) is similar in all open economies. Thus, skill intensities calculated for the U.S. could be, with some care, applied also in other countries.
References


Figure 1: Changes in occupational wages by occupational wage percentile.

Note: Adapted from Autor et al. (2006)

Figure 2: Evolution of log of skill-intensity in selected occupations (1983-2001).

Note: Log of skill intensity is defined as $\ln(\frac{C_{jt}}{N_{jt}}) = \ln(\frac{w_{C_{jt}}}{w_{N_{jt}}}) - \frac{1}{\sigma_j} \ln(\frac{L_{C_{jt}}}{L_{N_{jt}}})$. 

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Figure 3: 1984-1994 and 1991-2001 changes in log earnings by earnings percentile.

Note: The left panel pictures raw data; right panel pictures smoothened lines. Figures obtained using the sample of young college and high school graduates described in Section 5.

Figure 4: 1984-1994 and 1991-2001 changes in log occupational skill-intensity by earnings percentile

Note: The left panel illustrates total changes in average skill-intensity of occupations performed by workers from each percentile of the earnings distribution; the right panel illustrates changes in average skill-intensity due to different composition of occupations performed by workers from each percentile of earnings distribution. Figures were obtained
using the sample of young college and high school graduates described in Section 5. Log of skill intensity is defined as

$$\ln\left(\frac{w_{C_{jt}}}{w_{N_{jt}}}\right) = \ln\left(\frac{w_{C_{jt}}}{w_{N_{jt}}}\right) - \frac{1}{\sigma^2} \ln\left(\frac{L_{C_{jt}}}{L_{N_{jt}}}\right).$$
Table 1: Estimates of occupation-specific elasticities of substitution between college and high school graduates and the imputed relative productivities.

<table>
<thead>
<tr>
<th>Occupation group</th>
<th>$\tilde{\sigma}_j$</th>
<th>$\ln \frac{\tilde{\alpha}<em>{Cj}}{\tilde{\alpha}</em>{Nj}}_{1984}$</th>
<th>$\ln \frac{\tilde{\alpha}<em>{Cj}}{\tilde{\alpha}</em>{Nj}}_{2001}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Securities and financial services sales occupations</td>
<td>$\infty$</td>
<td>0.157</td>
<td>0.447</td>
</tr>
<tr>
<td>Supervisors, production occupations</td>
<td>$\infty$</td>
<td>0.278</td>
<td>0.377</td>
</tr>
<tr>
<td>Painters, sculptors, and photographers</td>
<td>$\infty$</td>
<td>0.054</td>
<td>0.343</td>
</tr>
<tr>
<td>Extractive and precision production occupations</td>
<td>$\infty$</td>
<td>-3.136</td>
<td>0.316</td>
</tr>
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<td>Engineers, n.e.c.</td>
<td>$\infty$</td>
<td>0.264</td>
<td>0.310</td>
</tr>
<tr>
<td>Managers, marketing and advertising</td>
<td>$\infty$</td>
<td>0.415</td>
<td>0.300</td>
</tr>
<tr>
<td>Miscellaneous financial officers</td>
<td>$\infty$</td>
<td>0.250</td>
<td>0.299</td>
</tr>
<tr>
<td>Other mechanics and repairers</td>
<td>$\infty$</td>
<td>0.052</td>
<td>0.293</td>
</tr>
<tr>
<td>Miscellaneous professional specialty occupations</td>
<td>$\infty$</td>
<td>0.260</td>
<td>0.284</td>
</tr>
<tr>
<td>Material recording, scheduling, &amp; distributing clerks</td>
<td>$\infty$</td>
<td>0.249</td>
<td>0.281</td>
</tr>
<tr>
<td>Financial managers</td>
<td>$\infty$</td>
<td>0.351</td>
<td>0.224</td>
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<td>Engineering technologists and technicians</td>
<td>$\infty$</td>
<td>0.102</td>
<td>0.209</td>
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<td>Stenographers and typists</td>
<td>$\infty$</td>
<td>0.140</td>
<td>0.184</td>
</tr>
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<td>General office clerks</td>
<td>$\infty$</td>
<td>0.174</td>
<td>0.181</td>
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<td>Administrative support occupations</td>
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<td>0.194</td>
<td>0.178</td>
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<td>Public administration</td>
<td>$\infty$</td>
<td>0.069</td>
<td>0.113</td>
</tr>
<tr>
<td>Secretaries</td>
<td>$\infty$</td>
<td>0.087</td>
<td>0.112</td>
</tr>
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<td>Farm occupations</td>
<td>$\infty$</td>
<td>0.475</td>
<td>0.084</td>
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<tr>
<td>Nursing aides</td>
<td>$\infty$</td>
<td>-3.301</td>
<td>-2.887</td>
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<td>Handlers and laborers</td>
<td>$\infty$</td>
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<td>-2.899</td>
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<td>Cleaning and building service occupations</td>
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<td>-3.019</td>
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<td>Sales workers, retail</td>
<td>9.719</td>
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<td>Writers, artists, and related workers</td>
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<td>Service occupations, n.e.c.</td>
<td>6.788</td>
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<td>-0.184</td>
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<td>Records processing occupations, except financial</td>
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<td>-0.033</td>
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<td>Financial records processing occupations</td>
<td>5.337</td>
<td>-0.268</td>
<td>-0.250</td>
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<td>Occupation group</td>
<td>$\tilde{\sigma}_j$</td>
<td>$\frac{\ln \alpha_{jN}}{\sigma_{Nj}}$ 1984</td>
<td>$\frac{\ln \alpha_{jN}}{\sigma_{Nj}}$ 2001</td>
</tr>
<tr>
<td>-------------------------------------------------------</td>
<td>---------------------</td>
<td>---------------------------------------------</td>
<td>---------------------------------------------</td>
</tr>
<tr>
<td>Carpenters, electricians, and painters</td>
<td>5.299</td>
<td>-3.077</td>
<td>-0.451</td>
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<tr>
<td>Mathematical and computer scientists</td>
<td>5.231</td>
<td>0.277</td>
<td>0.409</td>
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<tr>
<td>Sales occupations, advertising &amp; other services</td>
<td>5.103</td>
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<td>0.520</td>
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<td>Construction trades, n.e.c.</td>
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<td>-0.189</td>
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<td>Miscellaneous managers and administrators</td>
<td>4.501</td>
<td>0.151</td>
<td>0.274</td>
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<td>Public relations specialists, announcers</td>
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<td>0.211</td>
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<td>Designers</td>
<td>4.452</td>
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<td>0.233</td>
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<td>Health technologists and technicians</td>
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<td>-0.304</td>
</tr>
<tr>
<td>Personnel, training, and labor relations specialists</td>
<td>3.312</td>
<td>0.054</td>
<td>0.275</td>
</tr>
<tr>
<td>Computer equipment operators</td>
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<td>-0.191</td>
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<td>Prekindergarten and kindergarten teachers</td>
<td>2.937</td>
<td>0.350</td>
<td>0.473</td>
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<tr>
<td>Clinical laboratory technologists and technicians</td>
<td>2.807</td>
<td>0.178</td>
<td>0.153</td>
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<td>Cooks</td>
<td>2.783</td>
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<td>-2.877</td>
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<td>Computer programmers</td>
<td>2.589</td>
<td>0.139</td>
<td>0.268</td>
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<td>Fabricators and assemblers, production occs.</td>
<td>2.162</td>
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<td>Real estate sales occupations</td>
<td>1.691</td>
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<td>-0.195</td>
</tr>
<tr>
<td>Supervisors, administrative support occupations</td>
<td>1.642</td>
<td>-0.511</td>
<td>-0.628</td>
</tr>
<tr>
<td>Insurance adjusters, examiners, &amp; investigators</td>
<td>1.618</td>
<td>-0.267</td>
<td>-0.346</td>
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<td>Insurance sales occupations</td>
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<td>Child-care workers</td>
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<td>Purchasing agents and buyers</td>
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<td>-1.364</td>
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<td>Legal assistants</td>
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<td>Editors and reporters</td>
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<td>Social workers</td>
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<td>Occupation group</td>
<td>$\hat{\sigma}_j$</td>
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<td>$\ln \frac{\alpha_{CJ}}{\alpha_{NJ}}_{2001}$</td>
</tr>
<tr>
<td>---------------------------------------------------------------------------------</td>
<td>-----------------</td>
<td>-----------------------------------------------</td>
<td>-----------------------------------------------</td>
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<td>Therapists, n.e.c.</td>
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<td>0.704</td>
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<td>Recreation and religious workers</td>
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<td>Sales representatives, commodities except retail</td>
<td>0</td>
<td>0.379</td>
<td>0.461</td>
</tr>
<tr>
<td>Miscellaneous management-related occupations</td>
<td>0</td>
<td>0.394</td>
<td>0.441</td>
</tr>
<tr>
<td>Counselors, librarians, archivists, and curators</td>
<td>0</td>
<td>0.006</td>
<td>0.364</td>
</tr>
<tr>
<td>Real estate managers</td>
<td>0</td>
<td>0.361</td>
<td>0.342</td>
</tr>
<tr>
<td>Health assessment and treating occupations</td>
<td>0</td>
<td>0.731</td>
<td>0.321</td>
</tr>
<tr>
<td>Supervisors and proprietors, sales occupations</td>
<td>0</td>
<td>0.260</td>
<td>0.286</td>
</tr>
<tr>
<td>Police and detectives</td>
<td>0</td>
<td>0.189</td>
<td>0.231</td>
</tr>
<tr>
<td>Science technicians</td>
<td>0</td>
<td>0.299</td>
<td>0.227</td>
</tr>
<tr>
<td>Sales-related occupations</td>
<td>0</td>
<td>0.208</td>
<td>0.208</td>
</tr>
<tr>
<td>Drafting occupations &amp; surveying and mapping</td>
<td>0</td>
<td>0.222</td>
<td>0.191</td>
</tr>
<tr>
<td>Miscellaneous adjusters and investigators</td>
<td>0</td>
<td>0.217</td>
<td>0.189</td>
</tr>
<tr>
<td>Protective service occupations</td>
<td>0</td>
<td>0.155</td>
<td>0.157</td>
</tr>
<tr>
<td>Agricultural, forestry, fishing, and hunting occupations</td>
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<td>0.114</td>
<td>0.121</td>
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<tr>
<td>Information clerks</td>
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<td>0.097</td>
<td>0.105</td>
</tr>
<tr>
<td>Dental assistants and health aides</td>
<td>0</td>
<td>0.152</td>
<td>0.085</td>
</tr>
<tr>
<td>Machine operators</td>
<td>0</td>
<td>-3.314</td>
<td>-2.957</td>
</tr>
</tbody>
</table>

Note: The second column of this table presents the estimated elasticity of substitution between college and high school graduates. Columns 3 and 4 present logs of the estimated relative productivities of college and high school graduates in years 1984 and 2001.