MEASURING SKILL INTENSITY OF OCCUPATIONS WITH IMPERFECT SUBSTITUTABILITY ACROSS SKILL TYPES

Barbara Pertold-Gebicka

CERGE-EI

Charles University
Center for Economic Research and Graduate Education
Academy of Sciences of the Czech Republic
Economics Institute

WORKING PAPER SERIES (ISSN 1211-3298)
Electronic Version

421

Working Paper Series **421**
(ISSN 1211-3298)

Measuring Skill Intensity of Occupations with Imperfect Substitutability Across Skill Types

Barbara Pertold-Gebicka

CERGE-EI
Prague, October 2010

EVROPSKÝ SOCIÁLNÍ FOND
PRAHA & EU: INVESTUJEME DO VAŠÍ BUDOUCNOSTI

ISBN 978-80-7343-219-5 (Univerzita Karlova. Centrum pro ekonomický výzkum a doktorské studium)
ISBN 978-80-7344-209-5 (Národohospodářský ústav AV ČR, v.v.i.)

Measuring Skill Intensity of Occupations with Imperfect Substitutability Across Skill Types

Barbara Pertold-Gebicka*
CERGE-EI†

Abstract

In absence of a model-based measure of occupational skill-intensity, the literature on wage inequality cannot consistently track technological progress on occupational level — a key ingredient of recent theories of labor market polarization. In this paper, I use the March CPS data from 1983 to 2002 to estimate such a measure corresponding to 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, and I propose a simple strategy to obtain these. The resulting measure is used to shed light on the modified skill-biased technological change hypothesis proposed by Autor et al. (2006).

Abstrakt

Míra kvalifikační náročnosti zaměstnání umožnuje konzistentně sledovat technologický pokrok pro různě náročná zaměstnání, který je zásadním prvkem nejnovějších teorií polarizace na trhu práce. Ve svém článku využívám March CPS data z let 1983 až 2002 pro odhad této míry náročnosti zaměstnání, která odpovídá relativní produktivitě středoškolsky a vysokoškolsky vzdělaných pracovníků na jednotlivých pozicích. Za předpokladu, že substituce mezi pracovníky s různou kvalifikací je nedokonalá, měření relativní produktivity vyžaduje odhad esticity substituce. V tomto článku navrhuji jednoduchou strategii jak tohoto odhadu dosáhnout. Výsledná míra je využita pro objasnění modifikované hypotézy technologického pokroku navržené Autorem a kol. (2006).

Keywords: Occupations, skill-intensity, skill content, elasticity of labor substitution, technological progress, polarization
JEL Classification: J24, J31

*I would like to thank Alena Bicakova, David Card, Randall Filer, Stepan Jurajda, Peter Katuscak and Enrico Moretti for valuable comments and suggestions. Part of this paper was written while visiting the Department of Economics at the University of California at Berkeley and I would like to thank the department for its hospitality. All remaining errors are mine. This research was supported by the Grant Agency of the Charles University funding No. 35209.
E-mail: barbara.gebicka@cerge-ei.cz

†A joint workplace of the Center for Economic Research and Graduate Education, Charles University, Prague, and the Economics Institute of the Academy of Sciences of the Czech Republic. Address: CERGE-EI, Politickych veznu 7, Prague 11121, Czech Republic.

1 Introduction

The literature on wage inequality was able to successfully account for the majority of wage-structure shifts of the twentieth century (including the rising returns to education in face of rising educational attainment in the 1980's) by employing a framework with high and low skilled workers supplying labor to a homogenous labor market with factor-augmenting technology (Katz and Murphy, 1992; Bound and Johnson, 1992). Nevertheless, the varying extent of skill-biased technological progress (Card and DiNardo, 2002) or the recently documented earnings growth polarization (Goos and Manning, 2007; Autor et al., 2006) are not accounted for by this framework. The search for a coherent explanation for the recent trends has led researchers to analyze the labor market partitioned at the level of occupations, which allows for a natural way to introduce the differential speed of technological progress (Firpo et al., 2009). This literature, however, so far has not employed a model-based measure of occupation-specific technological progress or skill intensity.

The occupation-focused literature begun with the works of Autor et al. (2003), Goos and Manning (2007) and Autor et al. (2006), who propose a modified version of the skill-biased technological change (SBTC) hypothesis. They argue that new technologies have heterogeneous impact on workers. In particular, technologies complement workers performing nonroutine cognitive tasks and substitute for workers performing routine tasks. Also the recent work by Acemoglu and Autor (2010) stress that the mix of tasks performed by a worker defines the impact of technological progress on her productivity. Thus, to the extent that occupations capture the task content of work, the occupation-level analysis offers a key towards understanding the impact of technological change on wage structures. In the context of technological progress and the related demand for skilled labor, it is helpful to link occupations to their skill-intensity. The latter would translate the occupation-specific task mix into the demand for skills defined by an occupation-specific production function.

Currently there is no consensus on how to capture the skill-intensity of occupations and the literature offers several simple alternatives. One strategy is to rely on the description of skills, tasks 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 used in the literature in the context of income inequality and wage structures (Autor and Dorn, 2009) and overeducation (McGoldrick and Robst, 1996). The multidimensional description of occupations given by the dictionaries provides a valuable insight into the changing structure of job tasks and its relation to the observed wage structures (Firpo et al., 2009; Acemoglu and Autor, 2010). On the other hand, while capturing IT use or manual task involvement is relatively simple using occupation dictionaries, other dimensions of the SBTC are not captured systematically and in a harmonized way across occupations. For example, it is less convenient to use the O*NET for studying the implications of technological progress on the demand for educated labor in an international context, as it lacks information on occupation-specific demand for education and it is not available outside the U.S.

A clear definition of occupations' demand for skills allowing for straightforward cross-country comparability is offered by several alternative skill-intensity measures, although at the cost of being derived from the data used to investigate wage structures. Some studies of technological progress on the occupational level use employees' average years of schooling as a proxy for the skill content of occupations (Goos and Manning, 2007; Autor et al., 2006). This approach relies on a strong assumption that the employment structure of occupations correctly reflects their skill requirements and one can easily imagine violation of this assumption in occupations that are in the process of rapidly adjusting their skill requirements. Despite these shortcomings, the average years of schooling measure is also used to define occupations' demand for educated labor when studying 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) – further referred to as GH – offer a more model-based approach for defining occupation-specific demand for educated labor. Their methodology is used in this paper as a starting point for defining a measure of skill-intensity of occupations. Assuming that production technologies are homogenous within occupations, the occupation-specific relative productivity of differently skilled workers reflects the utilization of their skills, thus offering a continuous model-based measure of occupation-specific skill-intensity. GH assume perfect substitutability between differently educated workers which allows them to use the wage gap to measure the relative productivity of college and high school graduates. However, there are many studies estimating the market-wide elasticity of substitution between more and less educated labor in the U.S. to be around 1.4,[1] which requires imperfect within-occupation substitution between the two types of workers and/or outputs of individual occupations being not well substitutable.

This study generalizes the GH approach by estimating 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 I use a modification of the strategy proposed by Card (2001) to estimate their elasticity parameters. These, combined with the observed relative employment and wages, allow me to derive occupation-specific relative productivities of college and high school graduates, which provide a measure of skill-intensity of occupations. It can be used, for example, to track technological progress of individual occupations or derive the demand for educated labor within different groups of occupations. In this study I use the measure of skill-intensity of occupations to analyze the recent polarization of earnings growth in the U.S.

The rest of the paper is organized as follows. Section 2 briefly explains the idea behind using occupation-specific relative productivities of differently skilled labor as a measure of skill-intensity of occupations. In the next section, I present a model of worker 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 that allow for estimation of the skill-intensity of occu-

[1] Ciccone and Peri (2005) offer a review of these studies.

pations. The next section presents the results of these estimations. In section 6, 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, can 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).

$$Y_j = \left(\alpha_{Cj} L_{Cj}^{\gamma_j} + \alpha_{Nj} L_{Nj}^{\gamma_j}\right)^{\frac{1}{\gamma_j}}, \tag{1}$$

where Y_j is the output of occupation j, L_{Cj} is the number of college graduates, L_{Nj} is the number of high school graduates employed in occupation j, and γ_j is a parameter describing the substitutability between these two labor types (the elasticity of substitution is $\sigma_j = \frac{1}{1-\gamma_j}$). In this context, $\frac{\alpha_{Cj}}{\alpha_{Nj}}$ 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, which could be attributed to the skill difference among 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 GH, 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 GH classify occupations according to the college wage premia that 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

$$\frac{\alpha_{Cjt}}{\alpha_{Njt}} = \frac{w_{Cjt}}{w_{Njt}} \left(\frac{L_{Cjt}}{L_{Njt}}\right)^{1-\gamma_j} = \frac{w_{Cjt}}{w_{Njt}} \left(\frac{L_{Cjt}}{L_{Njt}}\right)^{-\frac{1}{\sigma_j}}. \tag{2}$$

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 in order to derive the occupation-specific relative productivity.[2]

3 A model of labor allocation across occupations

In this section I outline a theoretical model describing the 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 the 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 $G(\cdot)$:

$$Y = G\left(L_1, L_2, ...L_J\right).$$

Each occupation could be described as a technology aggregating two labor types: college and high school graduates. The "output" of occupation j is labor aggregate L_j being a CES combination of college- and high school-educated labor. Occupations differ in their skill-intensity ($\frac{\alpha_{C_j}}{\alpha_{N_j}}$) and in the elasticity of substitution between college

[2]Note that setting $\gamma_j = 1$ in the occupation-specific production function (1), one gets $\frac{\alpha_{Cjt}}{\alpha_{Njt}} = \frac{w_{Cjt}}{w_{Njt}}$, as in GH, while setting $\gamma_j = -\infty$ leads to $\frac{\alpha_{Cjt}}{\alpha_{Njt}} = \frac{L_{Cjt}}{L_{Njt}}$, which is a version of the average years of schooling approach used, for example, by Autor et al. (2006).

and high school graduates ($\sigma_j = \frac{1}{1-\gamma_j}$). As before, the production function used by occupation j could be summarized in the following way:

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

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 following first-order conditions:

$$\begin{aligned} w_{Cj} &= p\frac{\partial Y}{\partial L_j}\frac{\partial L_j}{\partial L_{Cj}} = p\frac{\partial Y}{\partial L_j} L_j^{1-\gamma_j} \alpha_{Cj} L_{Cj}^{\gamma_j - 1}; \\ w_{Nj} &= p\frac{\partial Y}{\partial L_j}\frac{\partial L_j}{\partial L_{Nj}} = p\frac{\partial Y}{\partial L_j} L_j^{1-\gamma_j} \alpha_{Nj} L_{Nj}^{\gamma_j - 1}. \end{aligned}$$

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

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

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

$$\ln\left(\frac{L_{Cj}}{L_{Nj}}\right) = \sigma_j \ln\left(\frac{\alpha_{Cj}}{\alpha_{Nj}}\right) - \sigma_j \ln\left(\frac{w_{Cj}}{w_{Nj}}\right). \tag{5}$$

Equation (5) describes the relative labor demand in occupation j. It depends on the 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 a 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. Only some of these people are actually observed working in occupation j because workers differ in their occupation-specific reservation wage. This leads to the formulation of the supply of labor to occupation j as a fraction of the total size of this occupation's specific labor market:[3]

$$\begin{aligned} \ln\left(\frac{L_{Cj}}{N_{Cj}}\right) &= \beta_j \ln w_{Cj} \\ \ln\left(\frac{L_{Nj}}{N_{Nj}}\right) &= \beta_j \ln w_{Nj}. \end{aligned} \tag{6}$$

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 assumption is crucial for the model to have a closed-form solution. Despite being strong, this assumption is actually less restrictive than the relaxed assumption about $\gamma = 1$, where the labor supply can be any but equilibrium values are determined from the total demand.

The above specified supply functions can be combined into one equation describing the relative supply of labor into occupation j:

$$\ln\left(\frac{L_{Cj}}{L_{Nj}}/\frac{N_{Cj}}{N_{Nj}}\right) = \beta_j \ln\left(\frac{w_{Cj}}{w_{Nj}}\right), \tag{7}$$

which 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

[3] 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 in the model because in reality they never bind.

the equilibrium relative wages and relative employment in each occupation:

$$\begin{cases} \ln\left(\frac{w_{Cj}}{w_{Nj}}\right) = \frac{\sigma_j}{\sigma_j+\beta_j}\ln\left(\frac{\alpha_{Cj}}{\alpha_{Nj}}\right) - \frac{1}{\sigma_j+\beta_j}\ln\left(\frac{N_{Cj}}{N_{Nj}}\right) \\ \ln\left(\frac{L_{Cj}}{L_{Nj}}\right) = \frac{\sigma_j\beta_j}{\sigma_j+\beta_j}\ln\left(\frac{\alpha_{Cj}}{\alpha_{Nj}}\right) + \frac{\sigma_j}{\sigma_j+\beta_j}\ln\left(\frac{N_{Cj}}{N_{Nj}}\right) \end{cases}. \tag{8}$$

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 the production function and the shape of the 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, over 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 the total population. The relative productivity of college and high school graduates varies with the SBTC.[4] 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) can be rewritten into the following econometric model:

$$\begin{cases} \ln\left(\frac{w_{Cjt}}{w_{Njt}}\right) = c_{j0} + c_{j1}\ln\left(\frac{N_{Cjt}}{N_{Njt}}\right) + \upsilon_t + \upsilon_{jt} \\ \ln\left(\frac{L_{Cjt}}{L_{Njt}}\right) = d_{j0} + d_{j1}\ln\left(\frac{N_{Cjt}}{N_{Njt}}\right) + \mu_t + \mu_{jt} \end{cases}, \tag{9}$$

where $c_{j0} = \frac{\sigma_j}{\sigma_j+\beta_j}\ln(\alpha_j)$, $c_{j1} = -\frac{1}{\sigma_j+\beta_j}$, $\upsilon_t = \frac{\sigma_j}{\sigma_j+\beta_j}\varepsilon_t$, $\nu_{js} = \frac{\sigma_j}{\sigma_j+\beta_j}\varepsilon_{jt}$ and $d_{j0} = \frac{\sigma_j\beta_j}{\sigma_j+\beta_j}\ln(\alpha_j)$, $d_{j1} = \frac{\sigma_j}{\sigma_j+\beta_j}$, $\mu_s = \frac{\sigma_j\beta_j}{\sigma_j+\beta_j}\varepsilon_t$, $\mu_{js} = \frac{\sigma_j\beta_j}{\sigma_j+\beta_j}\varepsilon_{jt}$.

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, σ_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 σ_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

[4] 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 on others.

wages 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 and Murphy, 1992; Card and 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 captures 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. Estimating this variable using fitted values for a multinomial logit model 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 (Griliches and Mason, 1972).

Finally, the disturbance terms from the relative wage and relative employment equations for a 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-equation system of seemingly unrelated regressions (SUR).

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

$$\begin{cases} \ln\left(\frac{w_{Cjt}}{w_{Njt}}\right) = c_{j0} + c_{j1} \ln\left(\frac{N_{Cjt}}{N_{Njt}}\right) + c_{j2}t + \zeta_{jt} \\ \ln\left(\frac{L_{Cjt}}{L_{Njt}}\right) = d_{j0} + d_{j1} \ln\left(\frac{N_{Cjt}}{N_{Njt}}\right) + d_{j2}t + \xi_{jt} \end{cases}, \tag{10}$$

where $c_{j2}t + \zeta_{jt} = v_t + v_{jt}$ and $d_{j2}t + \xi_{jt} = \mu_t + \mu_{jt}$, with ζ_{jt} and ξ_{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 the 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 $\widehat{c_{j1}}$ and $\widehat{d_{j1}}$. These estimates are further used to calculate the elasticity of substitution between more and less educated labor: $\widehat{\sigma_j} = -\frac{\widehat{d_{j1}}}{\widehat{c_{j1}}}$. Finally, one can combine $\widehat{\sigma_j}$'s estimated separately for each occupation with occupation-specific estimates of college wage premium and relative employment to calculate the relative productivities as

$$\frac{\widehat{\alpha_{Cjt}}}{\alpha_{Njt}} = \frac{w_{Cjt}}{w_{Njt}}\left(\frac{L_{Cjt}}{L_{Njt}}\right)^{-\frac{1}{\widehat{\sigma_j}}}. \tag{11}$$

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 the 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.[5] Due to a limited number of observations offered by March CPS, three consecutive years had to be merged to obtain sample sizes large enought to allow the data-hungry occupation-level analysis to be conducted. 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 years 1983 - 2000. This

[5] 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.

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 any interesting phenomena in the labor market.

In order to make my analysis comparable to GH, 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), GH and I concentrate on recent school leavers defined as individuals with 10 or less years of potential labor market experience.[6] 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). Re-coding 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

[6]Potential labor market experience is calculated as $age - years\ of\ schooling - 6$.

3-digit categories to ensure sufficient sample sizes.[7]

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 measurement error associated with predicting the size of such a labor market might be correlated with the observed number of employees, i.e., in times economicall favourable for a given occupation we might overestimate the size of this occupation's labor market. 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

[7] Gottschalk and Hansen (2003) offer a detailed description of occupational coding and aggregation.

labor market conditions. These predispositions (proxied by observable demographic and other characteristics) determine the probabilities (π_{ij}) of choosing 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 π_{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.[8]

Once "neighboring" occupations are defined for each occupation at each education level, the multinomial logit model of occupational choice is estimated. For each employed individual[9] with a 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[10] which controls for the predictable shifts in occupation attractiveness. The estimated equation is as follows:

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

where the dependent variable equals one if an individual i works in occupation j at time t, X_{it} contains individual demographic characteristics and regional dummies,

[8]See Peracchi and Welch (1995) for a description of the matching procedure.

[9]The unemployed are not taken into account in this study. It is supposed to have a negligible effect on the results because I analyze relatively highly educated individuals.

[10]Note that here I allow for a quadratic time here, in contrast to a linear trend in system 10.

t is the time trend, and η_{it} captures individual unobservable effects. This approach allows us to estimate the importance of each characteristic for working in occupation j's labor market given the expected labor market conditions (proxied by the time trend). The estimate of β is then used to predict the individual-specific probability of working in each occupation $\widehat{\pi_{ij}}$ cleared of time effects. The year-specific sum of these fitted values represents occupation j's specific labor market in the given year. This measure could be thought of as the number of people who 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 extent. 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 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 the labor market of occupation j. 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 a 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:

$$\begin{aligned} N_{Cjt} &= T_{Ctj} \times L_{Ct} \\ N_{Njt} &= T_{Ntj} \times L_{Nt}, \end{aligned}$$

where T_{Ctj} and T_{Ntj} are the j-th columns of matrices T_{Ct} and T_{Nt}, and L_{Ct} and L_{Ct} 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.[11] Nevertheless, they are based on different assumptions and are disturbed by different factors: the overlapping markets measure is identified with occupation switchers, while the probabilistic measure is defined with the stayers. Thus, I use one measure to instrument for the other to reduce the measurement error bias when estimating the system 10.

6 Skill-intensity estimates

This section presents step-by-step results leading towards the estimation of occupation-specific skill-intensities. 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.

Estimation of the substitution elasticities using the system of equations (10) can be implemented for occupations employing significant amounts of both labor types, which in this study are defined as occupations with at least 10% of employees having only a high school diploma and at least 5% of employees being college graduates. Occupations where college and university graduates constitute the wide majority of employees are treated as licensed occupations (i.e., occupations where holding a degree is required by law), which implies an elasticity of substitution between

[11] The correlation between these two measures is 0.855.

college and high school graduates of zero.[12] Occupations where hardly any college graduates are employed are treated as not attractive for highly educated workers, which implies perfectly inelastic labor supply and does not allow for estimation of the within-occupation substitution elasticities.[13] For the remaining 73 occupations, the system (10) is estimated and the estimates of c_{j1} and d_{j1} are recorded.

For many occupations c_{j1} is found not to be 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 found to be finite and positive. The full list of the estimates of substitution elasticities ($\widehat{\sigma}_j = -(\widehat{d}_{j1}/\widehat{c}_{j1})$) and the respective standard errors obtained using the delta method is reported in the first column of Table 1 in the Appendix. Note that only 28 of all 90 analyzed occupations are characterized by the 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 the elasticity of substitution between different labor types is crucial when analyzing the skill-intensity of occupations.

While I am not aware of any other study estimating the occupation-specific substitution elasticities, I can only compare my estimates to previous economy-wide

[12] These occupations include achitects, biological and life scientists, health diagnosing occupations, judges, lawyers, postsecondary teachers, secondary school teachers, elementary school teachers, special education teachers, and speech therapists.

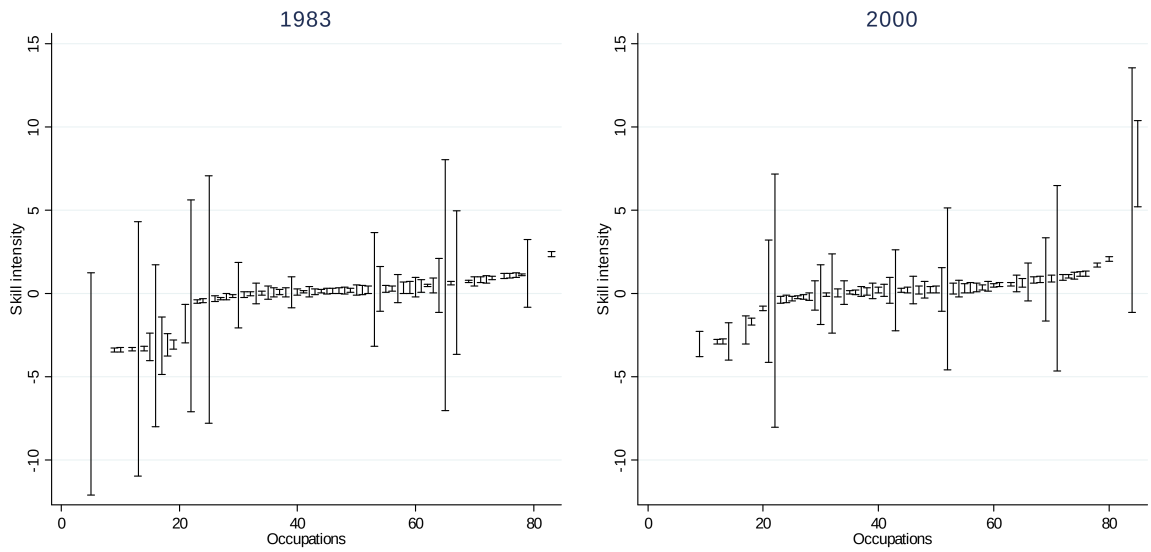
[13] These occupations include cashiers, food preparation and service occupations, freight, stock, material handlers, and service stations occupations, mail and message distributing occupations, mechanics and repairers, vehicle and industrial machinery, transportation and material moving occupations, waiters and waitresses.

measures. These estimate the elasticity of substitution between differently educated workers to be between 1 and 3 (Ciccone and Peri, 2005). My finite estimates of the within-occupation elasticity of substitution between college and high school graduates are of the same order of magnitude – they vary from 0.5 to 10, with the median of 2.7. Occupations with the highest substitution elasticities include artists, sales workers, record processing and service occupations. They involve jobs that can be well performed by college and high school graduates. Occupations with the lowest, but still finite, elasticity of substitution include more specialistic jobs like legal assistants, purchasing agents or insurance specialists. It is intuitive to think about these jobs as not equally performed by college and high school graduates. Further specialistic occupations like therapists, health assistants and some management related occupations are found to have the elasticity of substitution between college and high school graduates equal to zero, while among the occupations characterized by perfect substitutability, we can find all types of office and administrative occupations, and among those with no substitutability we can find further specialistic 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 are assigned the relative productivity of college and high school graduates equal to the relative employment, and occupations with infinite substitution elasticity are assigned the relative productivity equal to the college – high school wage premium. While it is difficult to present here all 1620 estimates (90 occupations in 18 years), point estimates of occupation-specific skill intensity for the years 1983 and 2000 (the first and last year of the sample) are presented in columns 4 and 5 of Table 1 in the Appendix and visualized in Figure 1 together with the estimated confidence intervals. The full list of this measure is available from the author upon request.

Note that a great majority of occupations experienced an upgrade in their skill intensity between 1983 and 2000, which is consistent with skill-biased technological

Figure 1: Distribution of skill-intensity across occupations.

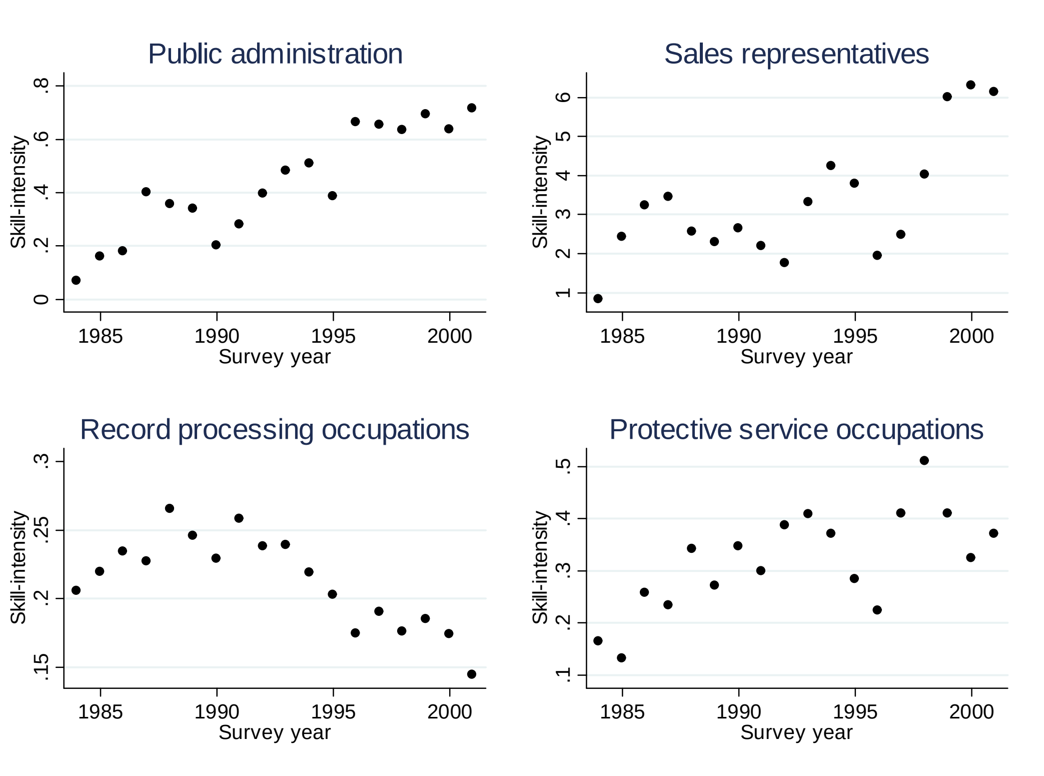


change hypothesis. Nevertheless, some occupations became significantly less skill intensive during the analyzed period. This mainly concerns the occupations involving high precision mechanical tasks, like records processing, laboratory technicians and farm occupations, that originally required high skills but gradually become substituted by machines. There is also a group of occupations in which the relative productivity of college and high school graduates remained constant. The most interesting trends in occupation-specific skill-intensities are presented in Figure 2.

Note the extensive increase in the skill intensity among public administration officers and sales representatives. These occupations used to be relatively un-intensive in college skills in the mid 1980's but popularization of personal computers increased their skill requirements. The opposite trend is observed in records processing occupations which are an example of occupations where computers substituted skilled labor. Finally, the bottom right panel of Figure 2 presents protective service occupations which were not affected by the recent technological progress.

It is interesting to see how the new measure of occupation-specific skill intensity corresponds to job characteristics reported by occupation dictionaries. Such a comparison is presented in Figure 3, which plots the nonroutine tasks index and manual

Figure 2: Evolution of log of skill-intensity in selected occupations (1983-2000).



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

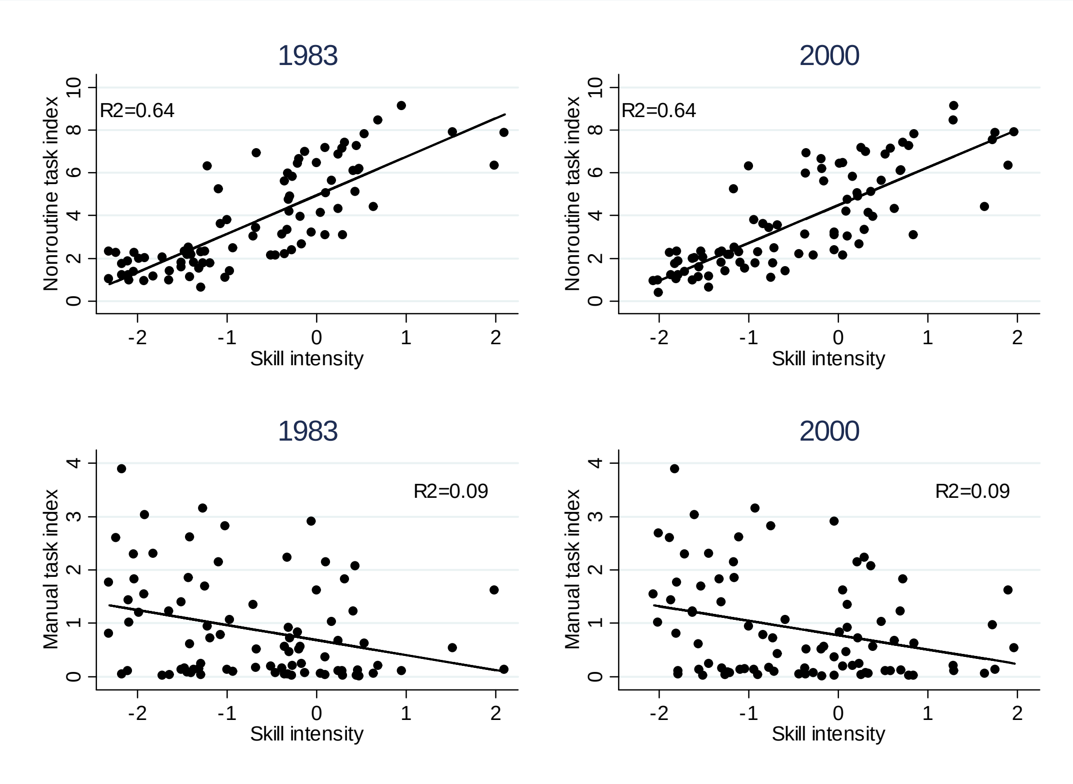
tasks index, as derived from the DOT, against the skill-intensity.

Note that there is a strong positive correlation between the nonroutine tasks index and the measure of skill-intensity, but hardly any relationship is observed between the manual tasks index and the measure of skill-intensity. This is intuitive as the productivity advantage of college graduates should come from their ability to perform nonroutine tasks while performance in manual tasks should not depend on level of education.

7 Applications of the measure of skill-intensity of occupations

The measure of skill-intensity of occupations derived in this study can be used, for example, to track the technological progress of individual occupations or derive the de-

Figure 3: Comparison of the measure of skill-intensity with the DOT routine and manual task index.

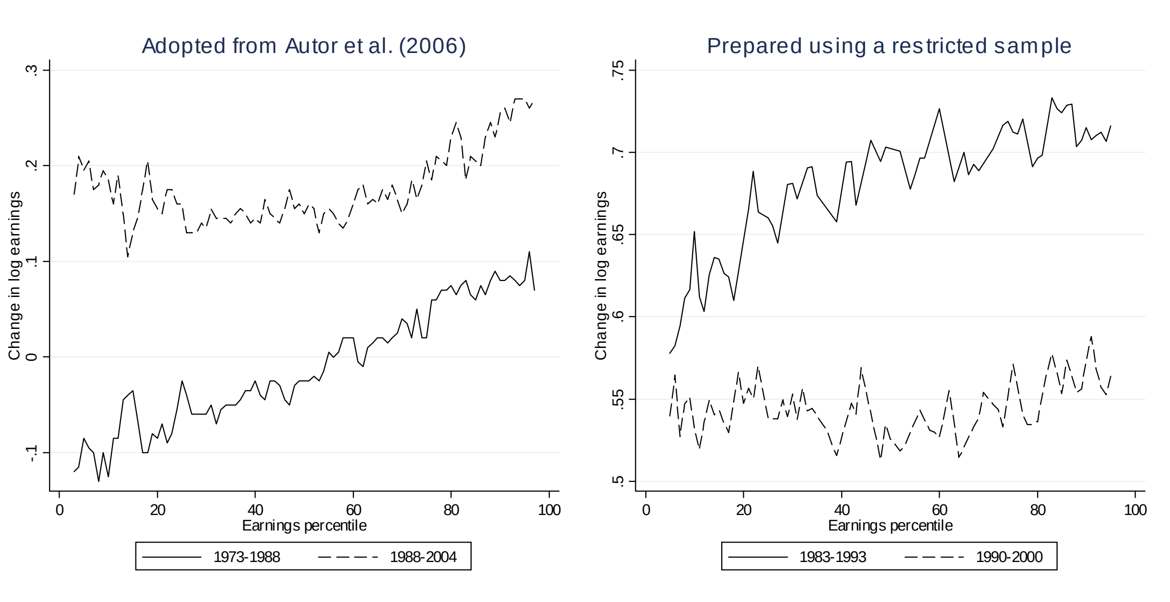


mand for educated labor within different types of occupations. This section presents another application: an analysis of the recent polarization of earnings growth in the U.S.

7.1 Polarization of earnings growth

The pattern in earnings growth changes 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, which is known as earnings growth polarization, was documented by Autor at al. (2006). This observation is especially interesting when contrasted with earlier periods when earnings at the low end of the distribution were falling and those at the top end were increasing, which is illustrated in the left panel of Figure 4, adopted from Autor et al. (2006). The same pattern, although with higher growth rates for the whole distribution, is present in the sub-sample of the U.S. labor force investigated in this study, i.e., among college and high school graduates with no more than 10 years of labor market experience, as presented in the right panel of Figure 4.

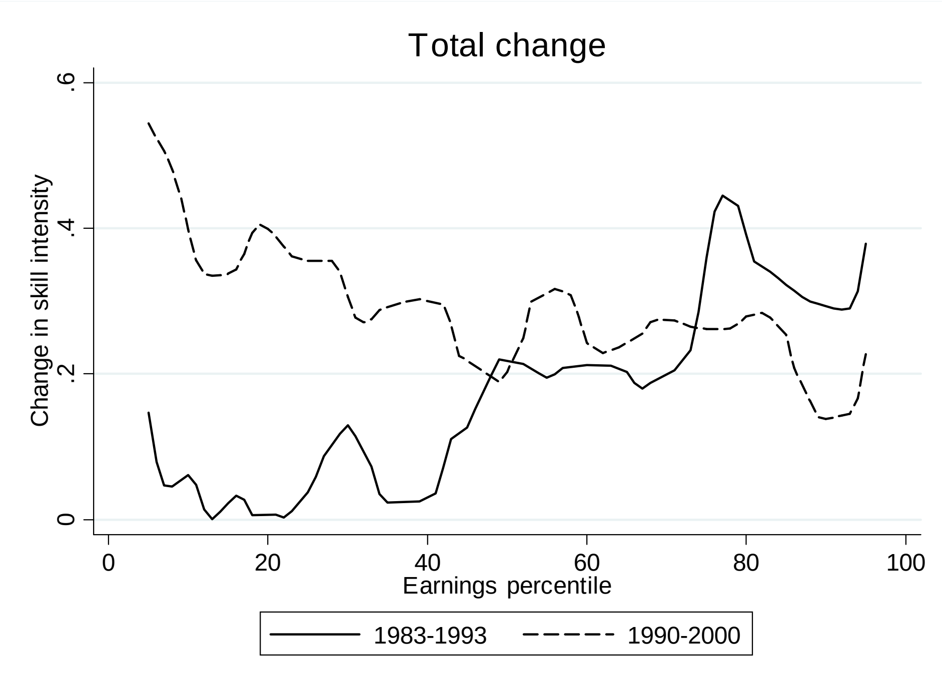
Figure 4: Changes in log earnings by earnings percentile.



Note: The left panel is adapted from Autor et al. (2006); the right panel is obtained using the sample of young college and high school graduates described in Section 5.

Recent literature explains the changes in the growth profile documented above by the varying impact that new technologies have on different job tasks (Autor and Dorn, 2009; Firpo et al., 2009; Acemoglu and Autor, 2010). In particular, it is argued that modern technologies complement workers performing nonroutine cognitive tasks and substitute for workers performing routine tasks. Assuming that the task content of work is homogenous within occupations, this statement can be verified using the measure of skill-intensity of occupations defined in this article. Recall that the skill-intensity is defined as the within-occupation relative productivity of college and high school graduates and, as such, it measures occupation-specific skill bias. If changes in earnings inequality observed in the last decades of the twentieth century are indeed driven by heterogeneous impact of technologies on different occupations, plotting changes in the average skill-intensity of occupations employing workers from each percentile of the earnings distribution should reveal patterns similar to those in Figure 4.

Figure 5: 1983-1993 and 1990-2000 changes in the log occupational skill-intensity by earnings percentile.



Note: This figure plots total changes in log of average skill-intensity of occupations performed by young college and high school graduates from each percentile of the earnings distribution. Log of skill intensity is defined as $ln(\frac{\alpha_{Cjt}}{\alpha_{Njt}}) = ln(\frac{w_{Cjt}}{w_{Njt}}) - \frac{1}{\sigma_j} ln(\frac{L_{Cjt}}{L_{Njt}})$.

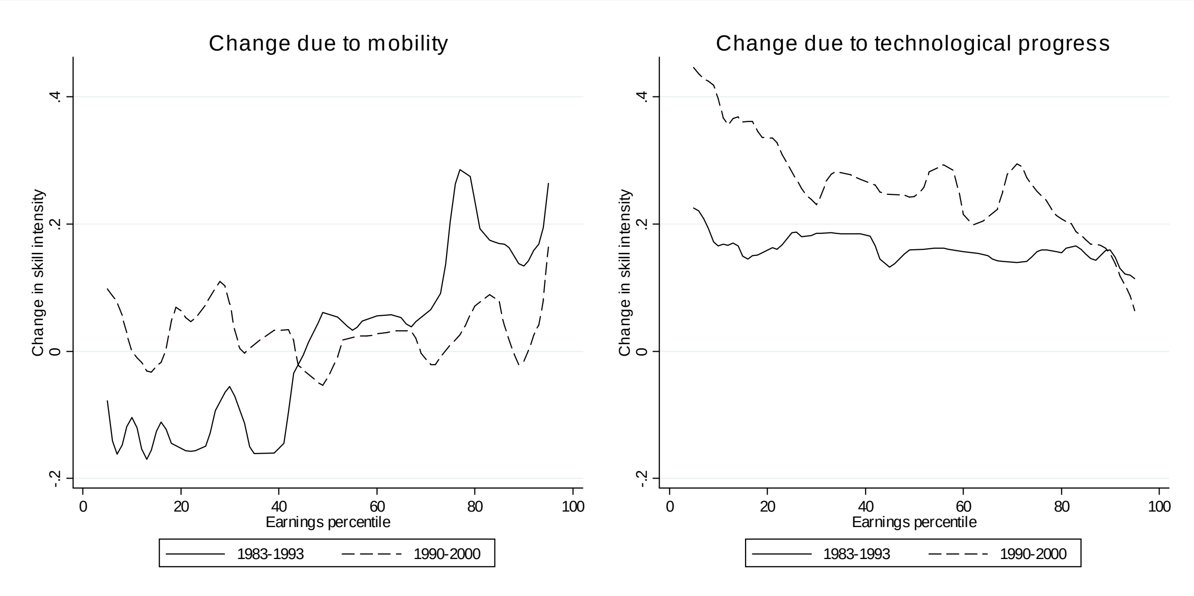
In the above figure we observe that between 1983 and 1993 workers from the lower part of the earnings distribution did not experience any significant change in the average skill-intensity of the occupations in which they were employed, while workers with above median earnings experienced a strong skill-biased technological progress. Interestingly, between 1990 and 2000 the growth 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 much more spectacular improvement in the skill-intensity of occupations in which they were employed.

The increase in skill-intensity of occupations employing workers from the lower part of the earnings distribution could be in part responsible for the earnings growth polarization.

To better understand the nature of patterns observed in Figure 5, let me decompose the difference in skill-intensity of occupations where workers from each percentile of earnings distribution are employed into occupation-specific technological progress and mobility (of workers across occupations and of occupations across earnings percentiles). Worker mobility happens when fewer people become employed in certain types of occupations (e.g., low skill-intensive) and more of them find employment in other types of occupations (e.g., high skill-intensive), and thus we observe shifts in the skill intensity of occupations employing the reallocated workers. Occupation-earnings mobility happens when certain type sof occupations pay relatively more (or less) than they used to pay (e.g., due to changes in total factor productivity) and thus shift to a different earnings percentile. By fixing the skill-intensity of all 90 occupations at their initial level (i.e., at the level from 1983 or 1990, respectively) one can observe the changes in average skill-intensity of occupations performed by workers from different percentiles of the earnings distribution which are just due to mobility. In other words, occupation-specific skill intensities are forced to be constant and thus any changes observed in the distribution of skill-intensities over the earnings distribution have to be attributed to workers' and occupation-earnings mobility. Changes due to shifts in occupation-specific skill-intensity constitute the difference between the total changes depicted in Figure 5 and changes due to mobility, i.e., this is the residual variation. The resulting decomposition is pictured in the two panels of Figure 6.

When abstracting from occupation-specific technological progress, which is presented in the left panel of Figure 6, the pattern of skill-intensity changes observed across the earning distribution in the 1980's is to a great extent preserved; however, the pattern from the 1990's disappears. We observe that during the 1980's the occupation mix for the bottom 40% of earners shifted towards less skill-intensive occupations, while the occupation mix for the top 30% of earners shifted towards more

Figure 6: A decomposition of 1983-1993 and 1990-2000 changes in log occupational skill-intensity by earnings percentile.



Note: The left panel illustrates changes in the log of average skill-intensity of occupations due to different composition of occupations performed by workers from each percentile of earnings distribution; the right panel illustrates changes in average skill-intensity due to technological change. Figures were obtained using the sample of young college and high school graduates described in Section 5. The log of skill intensity is defined as $ln(\frac{\alpha_{Cjt}}{\alpha_{Njt}}) = ln(\frac{w_{Cjt}}{w_{Njt}}) - \frac{1}{\sigma_j} ln(\frac{L_{Cjt}}{L_{Njt}})$.

skill intensive occupations. Interestingly, no changes in the occupation mix were observed in the 1990's, which suggests that neither workers were changing occupations nor occupations were switching places in the earnings distribution (or these two neutralized each other). On the other hand, when plotting changes in the skill-intensity driven purely by occupation-specific technological progress, only the relationship observed in the latter period is mimicked. The right panel of Figure 6 shows that in the 1980's occupations employing workers from all earnings percentiles experienced the same technological progress, on average, while in the 1990's, occupations employing the bottom earners were subject to much larger increase in their skill-intensity than other occupations. This suggests that the differences between 1983-1993 and 1990-2000 periods can be attributed to the changing nature of the technological progress. Specifically, in the earlier period across-the-board computerization concurred with strong reallocation of the top earners towards more computerized occupations, as there appeared more work opportunities involving complex tasks (for example, the demand for IT specialist increased). The least earning (and, supposedly, the least skilled) workers moved towards less skill-intensive occupations either because they were substituted by machines or because they did not know how to operate them. In the later stages of computerization these effects were not observed because the young labor force was already prepared to meet new technologies. During this time we observe an above-average increase in the skill-intensity of occupations employing the least earning workers, which could be caused by gradual computerization of simple job tasks.

How to reconcile the above findings with the modified SBTC hypothesis? As argued above, the mobility of workers across occupations documented in the 1980's could be driven by the heterogeneous impact of technologies on different job tasks; and the fast growing skill-intensity of occupations employing the least earning workers could be caused by technological improvement of simple job tasks.

8 Conclusion

In this study I propose a model-based approach for determining the skill-intensity of occupations. This measure can be used to track technological progress on the occupational level — a key ingredient of recent theories of labor market polarization. I argue that a good proxy for occupation-specific skill-intensity is the relative productivity of college and high school graduates. This parameter of the 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 σ_j. Relaxing this one is a challenge for future 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.

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. in this study could be, with some care, also applied in other countries.

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) for the UK and Autor et al. (2009) for the U.S. The presented results are in line with the hypothesis proposed by Autor that the technological change in the 1980's had a positive effect on the high earners, while in the 1990's also the low end of the earnings distribution benefited from it. This paper also brings new evidence about the changing nature of the technological progress. I show that in the earlier phase technological progress was equally distributed across occupations from all the earnings distribution, 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 reallocation and the least paying occupations experienced a greater technological progress. The observed reallocation of workers across occupations is in line with Acemoglu and Autor (2010), who argue that the technological progress changed the task composition of occupations and thus their demand for skills.

References

[1] Acemoglu, D., Autor, D. (2010) Skills, tasks and technologies: implications for employment and earnings. In: Ashenfelter, O., Card, D. (Eds.), Handbook of labor economics, vol. 4, Amsterdam: Elsevier, forthcoming.

[2] Autor D., Dorn, D. (2009) This job is "getting old": Measuring changes in job opportunities using occupational age structure. American Economic Review Papers and Proceedings 99(2), 45-51.

[3] Autor, D., Katz, L., Kearney, M. (2006) The polarization of the U.S. labor market. American Economic Review 96(2), 189–194.

[4] Autor, D., Katz, L., Kearney, M. (2008) Trends in U.S. wage inequality: Revising the revisionists. The Review of Economics and Statistics 90(2), 300–323.

[5] Autor, D., Levy, F., Murnane, R. (2003) The skill content of recent technological change: An empirical exploration. Quarterly Journal of Economics 118(4), 1279-1334.

[6] Bound, J., Johnson, G. (1992) Changes in structure of wages in 1980's: An evaluation of alternative explanations, American Economic Review 82, 371-92.

[7] Card, D., 2001. Immigrant inflows, native outflows and the local labor market impacts of higher immigration. Journal of Labor Economics 19(1), 22-64.

[8] Card, D., DiNardo, J. (2002) Skill-biased technological change and wage inequality: some problems and puzzles. Journal of Labor Economics 20(4), 733-783.

[9] Card, D., Lemieux, T. (2001) Can falling supply explain the rising return to college for younger men? A cohort-based analysis. The Quarterly Journal of Economics 116(2), 705-746.

[10] Ciccone, A., Peri, G. (2005) Long-run substitutability between more and less educated workers: Evidence from U.S. states, 1950–1990. The Review of Economics and Statistics 87(4), 652 - 663.

[11] Firpo, S., Fortin, N., Lemieux, T. (2009) Occupational tasks and changes in the wage structure. UBC Working Paper.

[12] Goos, M., Manning, A. (2007) Lousy and lovely jobs: The rising polarization of work in Britain, The Review of Economics and Statistics 89(1),118-133

[13] Gottschalk, P., Hansen, M. (2003) Is the proportion of college workers in noncollege jobs increasing? Journal of Labor Economics 21(2), 449-471.

[14] Griliches, Z., Mason, W.M. (1972) Education, income, and ability, The Journal of Political Economy 80(3), S74-S103.

[15] Handel, M. (2000) Trends in direct measures of job skill requirements. Levy Economics Institute Working Paper No. 301.

[16] Jeager, D. (1997) Reconciling the old and new Census Bureau education questions: Recommendations for researchers. Journal of Business & Economic Statistics 15(3), 300-309.

[17] Katz, L., Murphy, K. (1992) Changes in relative wages, 1963-1987: Supply and demand factors. The Quarterly Journal of Economics 107(1), 35-78.

[18] Kezdi, G. (2003) Imported technology and increasing demand for skill: The case of Hungary, mimeo, Central European University.

[19] Larrimore, J., Burkhauser, R., Feng, S., Zayatz, L. (2008) Consistent cell means for topcoded incomes in the public use March CPS (1976-2007). Journal of Economic and Social Measurement 33(2-3), 89-128.

[20] McGoldrick, K.M , Robst, J. (1996) Gender differences in overeducation: A test of the theory of differential overqualification. American Economic Review 86(2), 280-84.

[21] Meyer, P., Osborne, A. (2005) Proposed category system for 1960-2000 Census occupations. U.S. Bureau of Labor Statistics Working Paper No. 383.

[22] Peracchi, F., Welch, F. (1995). How representative are matched cross-sections? Evidence from the Current Population Survey. Journal of Econometrics 68, 153-179.

[23] Pryor, F., Schaffer, D. (1997) Wages and the university educated: a paradox resolved. Monthly Labor Review 120(7), 3-14.

Table 1: Estimates of occupation-specific elasticities of substitution between college and high school graduates and the imputed relative productivities.

Occupation group	$\widehat{\sigma_j}$	St.err($\widehat{\sigma_j}$)	$ln\widehat{\frac{\alpha_{Cjt}}{\alpha_{Njt}}}_{1983}$	$ln\widehat{\frac{\alpha_{Cjt}}{\alpha_{Njt}}}_{2000}$
Securities and financial services sales occupations	∞	n/a	0.157	0.447
Supervisors, production occupations	∞	n/a	0.278	0.377
Painters, sculptors, and photographers	∞	n/a	0.054	0.343
Extractive and precision production occupations	∞	n/a	-3.136	0.316
Engineers, n.e.c.	∞	n/a	0.264	0.310
Managers, marketing and advertising	∞	n/a	0.415	0.300
Miscellaneous financial officers	∞	n/a	0.250	0.299
Other mechanics and repairers	∞	n/a	0.052	0.293
Miscellaneous professional specialty occupations	∞	n/a	0.260	0.284
Material recording, scheduling, & distributing clerks	∞	n/a	0.249	0.281
Financial managers	∞	n/a	0.351	0.224
Engineering technologists and technicians	∞	n/a	0.102	0.209
Stenographers and typists	∞	n/a	0.140	0.184
General office clerks	∞	n/a	0.174	0.181
Administrative support occupations	∞	n/a	0.194	0.178
Public administration	∞	n/a	0.069	0.713
Secretaries	∞	n/a	0.087	0.112
Farm occupations	∞	n/a	0.475	0.084
Nursing aides	∞	n/a	-3.301	-2.887
Handlers and laborers	∞	n/a	-3.346	-2.899
Cleaning and building service occupations	∞	n/a	-3.096	-3.019
Median	∞	n/a	0.157	0.224

Occupation group	$\widehat{\sigma_j}$	St.err($\widehat{\sigma_j}$)	$ln\widehat{\frac{\alpha_{Cjt}}{\alpha_{Njt}}}_{1983}$	$ln\widehat{\frac{\alpha_{Cjt}}{\alpha_{Njt}}}_{2000}$
Sales workers, retail	9.719	5.293	0.100	0.251
Writers, artists, and related workers	7.212	3.337	0.172	-0.074
Service occupations, n.e.c.	6.788	2.379	-0.135	-0.184
Records processing occupations, except financial	6.333	2.030	0.231	0.133
Financial records processing occupations	5.337	3.060	-0.268	-0.250
Carpenters, electricians, and painters	5.299	2.446	-3.077	-0.451
Mathematical and computer scientists	5.231	1.956	0.277	0.409
Sales occupations, advertising & other services	5.103	2.236	0.225	0.520
Construction trades, n.e.c.	4.910	2.968	-0.381	-0.189
Miscellaneous managers and administrators	4.501	1.837	0.151	0.274
Public relations specialists, announcers	4.456	1.127	0.192	0.211
Designers	4.452	1.902	0.055	0.233
Health technologists and technicians	3.609	2.110	-0.429	-0.304
Personnel, training, and labor relations specialists	3.312	1.767	0.054	0.275
Computer equipment operators	3.176	1.820	-0.508	-0.191
Prekindergarten and kindergarten teachers	2.937	1.789	0.350	0.473
Clinical laboratory technologists and technicians	2.807	1.194	0.178	0.153
Cooks	2.783	1.267	-3.201	-2.877
Computer programmers	2.589	0.920	0.139	0.268
Fabricators and assemblers, production occs.	2.162	0.686	-3.387	-1.091
Real estate sales occupations	1.691	0.677	-0.355	-0.195
Supervisors, administrative support occupations	1.642	0.669	-0.511	-0.628
Insurance adjusters, examiners, & investigators	1.618	0.564	-0.267	-0.346
Insurance sales occupations	1.382	0.489	-0.278	-0.041
Accountants and auditors	1.033	0.453	0.520	0.942
Child-care workers	0.920	0.425	-2.038	-2.277
Purchasing agents and buyers	0.585	0.255	-1.182	-1.364
Legal assistants	0.498	0.173	-1.302	-1.357
Median	2.718	1.778	-0.201	-0.129

Occupation group	$\widehat{\sigma_j}$	St.err($\widehat{\sigma_j}$)	$ln\widehat{\frac{\alpha_{Cjt}}{\alpha_{Njt}}}_{1983}$	$ln\widehat{\frac{\alpha_{Cjt}}{\alpha_{Njt}}}_{2000}$
Editors and reporters	0	n/a	0.741	1.035
Social workers	0	n/a	0.487	0.735
Electrical and electronic engineers	0	n/a	0.680	0.712
Therapists, n.e.c.	0	n/a	0.574	0.704
Recreation and religious workers	0	n/a	0.709	0.640
Registered nurses	0	n/a	0.431	0.585
Teachers, not elsewhere classified	0	n/a	0.555	0.512
Technicians, n.e.c.	0	n/a	0.450	0.481
Sales representatives, commodities except retail	0	n/a	0.179	0.641
Miscellaneous management-related occupations	0	n/a	0.394	0.441
Counselors, librarians, archivists, and curators	0	n/a	0.006	0.364
Real estate managers	0	n/a	0.361	0.342
Health assessment and treating occupations	0	n/a	0.731	0.321
Supervisors and proprietors, sales occupations	0	n/a	0.260	0.286
Police and detectives	0	n/a	0.189	0.231
Science technicians	0	n/a	0.299	0.227
Sales-related occupations	0	n/a	0.208	0.208
Drafting occupations & surveying and mapping	0	n/a	0.222	0.191
Miscellaneous adjusters and investigators	0	n/a	0.217	0.189
Protective service occupations	0	n/a	0.155	0.357
Agricultural, forestry, fishing, and hunting occupations	0	n/a	0.114	0.121
Information clerks	0	n/a	0.097	0.105
Dental assistants and health aides	0	n/a	0.152	0.085
Machine operators	0	n/a	-3.314	-2.957
Median	0	n/a	0.217	0.227

Note: The second and third columns of this table presents the estimated elasticity of substitution between college and high school graduates followed by its standard error calculated using the delta method. For occupations with zero or infinite elasticity of substitution, the standard errors are unavailable because the substitution elasticity is inferred from the observed properties of occupations rather than estimated from the data. Columns 4 and 5 present logs of the estimated relative productivities of college and high school graduates in years 1983 and 2000.

Working Paper Series
ISSN 1211-3298
Registration No. (Ministry of Culture): E 19443

Individual researchers, as well as the on-line and printed versions of the CERGE-EI Working Papers (including their dissemination) were supported from the European Structural Fund (within the Operational Programme Prague Adaptability), the budget of the City of Prague, the Czech Republic's state budget and the following institutional grants:

- Center of Advanced Political Economy Research [Centrum pro pokročilá politicko-ekonomická studia], No. LC542, (2005-2010);
- Economic Aspects of EU and EMU Entry [Ekonomické aspekty vstupu do Evropské unie a Evropské měnové unie], No. AVOZ70850503, (2005-2010);
- Economic Impact of European Integration on the Czech Republic [Ekonomické dopady evropské integrace na ČR], No. MSM0021620846, (2005-2011);

Specific research support and/or other grants the researchers/publications benefited from are acknowledged at the beginning of the Paper.

Published by
Charles University in Prague, Center for Economic Research and Graduate Education (CERGE)
and
Economics Institute ASCR, v. v. i. (EI)
CERGE-EI, Politických vězňů 7, 111 21 Prague 1, tel.: +420 224 005 153, Czech Republic.
Printed by CERGE-EI, Prague
Subscription: CERGE-EI homepage: http://www.cerge-ei.cz

Phone: + 420 224 005 153
Email: office@cerge-ei.cz
Web: http://www.cerge-ei.cz

The paper is available online at http://www.cerge-ei.cz/publications/working_papers/.

ISBN 978-80-7343-219-5 (Univerzita Karlova. Centrum pro ekonomický výzkum
a doktorské studium)
ISBN 978-80-7344-209-5 (Národohospodářský ústav AV ČR, v. v. i.)

CERGE-EI
P.O.BOX 882
Politických vězňů 7
111 21 Praha 1
Czech Republic
http://www.cerge-ei.cz