## Lecture 7 - Static Labor Demand

## References:

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The building block of labor demand is a production function

$$
f\left(x_{1}, x_{2}, \ldots x_{n}\right)
$$

where $x_{j}$ is the input of "factor" $j$ (say hours of work by some skill group). We usually assume that $f$ has constant returns to scale (CRS). This means that in a competitive industry the scale of individual firms is undefined - firms per se are unimportant. What we can measure and analyze is industry-wide demand. As you may recall in the two-input case with CRS the shape of isoquants is summarized by the elasticity of substitution. Technically this is defined as

$$
\sigma=-\frac{d \log \left(\frac{x_{1}}{x_{2}}\right)}{d \log \left(\frac{f_{1}}{f_{2}}\right)}
$$

where $f\left(x_{1}, x_{2}\right)=y$ (i.e., the derivative is along an isoquant). Since $\frac{f_{1}}{f_{2}}$ is the slope of the isoquant, this is the proportional change of the relative use of the two factors $x_{1}$ and $x_{2}$ per percent change in the slope of the isoquant (which, under cost-minimization, would be their relative factor prices).

It can be shown that

$$
\sigma=\frac{f_{1} f_{2}}{f f_{12}}
$$

A simple version of the proof follows. To begin note that with CRS, we have that $f_{1}$ and $f_{2}$ are both HD0. So

$$
\begin{aligned}
& x_{1} f_{11}+x_{2} f_{12}=0 \\
& x_{1} f_{21}+x_{2} f_{22}=0
\end{aligned}
$$

Also,

$$
f=x_{1} f_{1}+x_{2} f_{2}
$$

Now define $s$ as the slope of the isoquant at a point:

$$
\begin{aligned}
s & =\frac{f_{1}\left(x_{1}, x_{2}\right)}{f_{2}\left(x_{1}, x_{2}\right)} \\
\log s & =\log f_{1}\left(x_{1}, x_{2}\right)-\log f_{2}\left(x_{1}, x_{2}\right) \\
d \log s & =\left[\frac{f_{11}}{f_{1}}-\frac{f_{21}}{f_{2}}\right] d x_{1}+\left[\frac{f_{12}}{f_{1}}-\frac{f_{22}}{f_{2}}\right] d x_{2} \\
& =\left[-\frac{x_{2}}{x_{1}} \frac{f_{21}}{f_{1}}-\frac{f_{21}}{f_{2}}\right] d x_{1}+\left[\frac{f_{12}}{f_{1}}+\frac{x_{1}}{x_{2}} \frac{f_{12}}{f_{2}}\right] d x_{2} \\
& =\left[\frac{-f_{2} f_{21} x_{2}-f_{21} f_{1} x_{1}}{x_{1} f_{1} f_{2}}\right] d x_{1}+\left[\frac{f_{2} f_{12} x_{2}+f_{12} f_{1} x_{1}}{x_{1} f_{1} f_{2}}\right] d x_{2} \\
& =\frac{-f_{12}}{f_{1} f_{2}}\left[f_{1} x_{1}+f_{2} x_{2}\right] \frac{d x_{1}}{x_{1}}+\frac{f_{12}}{f_{1} f_{2}}\left[f_{1} x_{1}+f_{2} x_{2}\right] \frac{d x_{2}}{x_{2}} \\
& =\frac{-f_{12} f}{f_{1} f_{2}}\left[\frac{d x_{1}}{x_{1}}-\frac{d x_{2}}{x_{2}}\right]=\frac{-f_{12} f}{f_{1} f_{2}} d \log \left[\frac{x_{1}}{x_{2}}\right]=\frac{-1}{\sigma} d \log \left[\frac{x_{1}}{x_{2}}\right]
\end{aligned}
$$

Thus

$$
\frac{d \log \left[\frac{x_{1}}{x_{2}}\right]}{d \log s}=-\sigma
$$

The classic examples are Cobb-Douglas $(\sigma=1)$ and the "CES"

$$
f\left(x_{1}, x_{2}\right)=\left(\alpha x_{1}^{-\rho}+(1-\alpha) x_{2}^{-\rho}\right)^{-1 / \rho}
$$

which has $\sigma=1 /(1+\rho)$.
It is a lot easier in most cases to work with the cost function $C\left(w_{1}, w_{2}, y\right)$. With CRS this has the form

$$
C\left(w_{1}, w_{2}, y\right)=\mu\left(w_{1}, w_{2}\right) y
$$

where $\mu()$ is the "unit cost" function. We will show that:

$$
\sigma=\frac{C_{1} C_{2}}{C C_{12}} .
$$

To do so, start with Sheppard's Lemma

$$
\begin{aligned}
& x_{1}=C_{1}\left(w_{1}, w_{2}, y\right) \\
& x_{2}=C_{2}\left(w_{1}, w_{2}, y\right)
\end{aligned}
$$

Now $C_{j}$ is $H D_{0}$ in input prices, so we can write:

$$
\begin{aligned}
x_{1} & =C_{1}\left(\frac{w_{1}}{w_{2}}, 1, y\right)=g\left(\frac{w_{1}}{w_{2}}, y\right) \\
x_{2} & =C_{2}\left(\frac{w_{1}}{w_{2}}, 1, y\right)=h\left(\frac{w_{1}}{w_{2}}, y\right)
\end{aligned}
$$

Also

$$
C_{11}=\frac{\partial x_{1}}{\partial w_{1}}=\frac{1}{w_{2}} g_{1}\left(\frac{w_{1}}{w_{2}}, y\right), \quad C_{21}=\frac{\partial x_{2}}{\partial w_{1}}=\frac{1}{w_{2}} h_{1}\left(\frac{w_{1}}{w_{2}}, y\right)
$$

Now fixing $y$ :

$$
\log \frac{x_{1}}{x_{2}}=\log g\left(\frac{w_{1}}{w_{2}}, y\right)-\log h\left(\frac{w_{1}}{w_{2}}, y\right)
$$

so

$$
\begin{aligned}
\sigma & =-\frac{\left(\frac{w_{1}}{w_{2}}\right) d \log \left(\frac{x_{1}}{x_{2}}\right)}{d\left(\frac{w_{1}}{w_{2}}\right)}=-\frac{w_{1}}{w_{2}}\left(\frac{g_{1}}{g}-\frac{h_{1}}{h}\right) \\
& =-\frac{w_{1}}{w_{2}}\left(\frac{w_{2} C_{11}}{g}-\frac{C_{21} w_{2}}{k}\right) \\
& =-\frac{w_{1} C_{11}}{C_{1}}+\frac{w_{1} C_{21}}{C_{2}}
\end{aligned}
$$

Now $w_{1} C_{11}+w_{2} C_{12}=0$ since $C_{1}$ is $H D_{0}$. Substituting we get

$$
\sigma=\frac{w_{1} C_{21}}{C_{2}}+\frac{w_{2} C_{12}}{C_{1}}=\frac{C_{12}\left(w_{1} C_{1}+w_{2} C_{2}\right)}{C_{1} C_{2}}=\frac{C_{12} C}{C_{1} C_{2}}
$$

using the fact that $C$ is $H D_{1}$ in input prices.

Another useful fact:

$$
\begin{align*}
\frac{\partial x_{1}}{\partial w_{2}} & =C_{12} \\
& \Rightarrow \frac{w_{2}}{x_{1}} \frac{\partial x_{1}}{\partial w_{2}}=\frac{w_{2} C_{12}}{x_{1}}=\frac{C_{12} C}{C_{1} C_{2}} \frac{w_{2} C_{2} C_{1}}{C x_{1}} \\
& =\sigma \frac{w_{2} x_{2}}{C}=\sigma s_{2} \tag{1}
\end{align*}
$$

here $s_{2}=$ input $2^{\prime} s$ cost share. Also

$$
\begin{aligned}
w_{1} \frac{\partial x_{1}}{\partial w_{1}}+w_{2} \frac{\partial x_{1}}{\partial w_{2}} & =0 \\
& \Rightarrow \frac{\partial x_{1}}{\partial w_{1}} \frac{w_{1}}{x_{1}}=-\sigma s_{2}=-\left(1-s_{1}\right) \sigma
\end{aligned}
$$

This says that in the 2-input case the output-constant elasticity of demand for an input is the product of $(1-s)$ and $\sigma$.

Finally, with more than 2 inputs we define the partial elasticity of substitution

$$
\sigma_{i j}=\frac{C_{i j} C}{C_{i} C_{j}}
$$

Note that

$$
x_{i}=C_{i}(w, y) \Rightarrow \epsilon_{i j} \equiv \frac{\partial x_{i}}{\partial w_{j}} \frac{w_{j}}{x_{i}}=C_{i j} \frac{w_{j}}{x_{i}}=\frac{C_{i j} C}{C_{i} C_{j}} \frac{w_{j} C_{i} C_{j}}{x_{i} C}=\sigma_{i j} s_{j}
$$

which is a multi-factor generalization of (1).

## Marshall's Rules

Let's consider a competitive industry with CRS and a cost function $C(w, y)=$ $\mu(w) y$. Industry output is priced at $p=\mu(w)$, and there is a downward sloping demand curve for the industry's output $y=D(p)$. We are going to show the "classic" connection between the elasticity of demand for an input by the industry and three key parameters: $\eta$ the elasticity of product demand, $\sigma_{i j}$ the partial elasticities of substitution, and $s_{j}$ the cost shares.

We start with

$$
\begin{aligned}
x_{i} & =y \mu_{i}(w) \\
& \Rightarrow \log x_{i}=\log y+\log \mu_{i}(w) \\
& \Rightarrow \frac{\partial \log x_{i}}{\partial w_{j}}=\frac{\partial \log y}{\partial \log p} \frac{d \log p}{\partial w_{j}}+\frac{\mu_{i j}(w)}{\mu_{i}(w)} \\
& =-\eta \frac{d \log \mu(w)}{\partial w_{j}}+\frac{\mu_{i j}(w)}{\mu_{i}(w)} \\
& =-\eta \frac{\mu_{j}(w)}{\mu(w)}+\frac{\mu_{i j} y C_{j} C}{\mu_{i} y C_{j} C}
\end{aligned}
$$

Therefore

$$
\begin{aligned}
w_{j} \frac{\partial \log x_{i}}{\partial w_{j}} & =\frac{w_{j} \mu_{j}(w) y}{\mu(w) y}+\frac{w_{j} C_{i j} C_{j} C}{C_{i} C_{j} C} \\
& =-\eta \frac{w_{j} C_{j}}{C}+\sigma_{i j} \frac{w_{j} C_{j}}{C} \\
& =-\eta s_{j}+\sigma_{i j} s_{j} \\
& =\epsilon_{i j}-\eta s_{j}
\end{aligned}
$$

Now let's consider the own-price effect:

$$
\frac{\partial \log x_{i}}{\partial \log w_{i}}=\epsilon_{i i}-\eta s_{i} .
$$

Finally, consider the 2-input case, so $\epsilon_{i i}=-\left(1-s_{i}\right) \sigma$. Then

$$
\frac{\partial \log x_{i}}{\partial \log w_{i}}=-\left(\eta s_{i}+\sigma\left(1-s_{i}\right)\right)
$$

which says that in the 2-input case the own-price demand elasticity is a combination of the final product demand elasticity (a "scale" effect) and the elasticity of substitution (a "substitution" effect).

To understand the scale effect, note that when $p=M C=\mu(w)$

$$
\begin{aligned}
\frac{\partial \log p}{\partial w_{j}} & =\frac{\mu_{j}(w)}{\mu(w)} \\
w_{j} \frac{\partial \log p}{\partial w_{j}} & =\frac{w_{j} \mu_{j}(w) y}{\mu(w) y}=\frac{w_{j} x_{j}}{C}=s_{j}
\end{aligned}
$$

Thus when $w_{j}$ rises by $1 \%$, industry selling price rises by $s_{j} \%$, and this chokes off demand by $\eta s_{j} \%$.

The "standard model" of the demand side in labor economics is one in which all firms have CRS and pay the same prices for all factors. In this model firms per se do not matter: in fact the number and size of firms is indeterminant. In trade theory and IO there is considerable interest in models with a lot of heterogeneity across firms (e.g., Melitz, 2003). In these models different firms have different levels of productivity. Less productive firms survive because they produce differentiated products which consumers are willing to buy (though less productive firms are smaller). On the labor side, all firms pay the same wages, so the heterogeneity in firms does not matter directly. An important and growing area of work in labor economics focuses on the impact of firms. The starting point for this work is the recognition that "who you work for matters". See the presentation for the "Vancouver School of Economics" in Sept. 2013 (on the class web site) that tries to summarize some of the older ideas and new thrusts in this area.

## Some Functional Forms

Cobb Douglas - often used for modeling labor and capital in contexts where the assumption that $\sigma=\sigma_{K L}=1$ is not too crazy:

$$
y=f(K, L)=A L^{\alpha} K^{1-\alpha}
$$

Note that labor's share is $\alpha$ which is constant. This used to be approximately correct. However, over the 2000 's, labor's share has fallen from the "historical" value of about $65 \%$ to about $58 \%$. See Fleck, Glaser and Sprague, "The

Compensation-Productivity Gap": A Visual Essay" Monthly Labor Review January 2011 (Figure 5 is attached). Note that in any CRS 2-input production function

$$
\begin{aligned}
f\left(x_{1}, x_{2}\right) & =x_{1} f\left(1, x_{2} / x_{1}\right)=x_{1} g\left(x_{2} / x_{1}\right) \\
& \Rightarrow f\left(x_{1}, x_{2}\right) x_{1}=g\left(x_{2} / x_{1}\right) .
\end{aligned}
$$

In the C-D case we get

$$
y / L=A(K / L)^{1-\alpha}
$$

which says that with fixed $A$ "labor productivity" ( $y / L$, the average product of labor) is a concave function of $K / L$. With C-D we get

$$
\frac{\partial y}{\partial L}=\alpha A(K / L)^{1-\alpha}
$$

so marginal product is just a constant times average product. These equations are widely used as a starting point for understanding productivity trends.
$C E S$ - often used to study high/low skill labor:

$$
f\left(x_{1}, x_{2}\right)=\left(\alpha x_{1}^{-\rho}+(1-\alpha) x_{2}^{-\rho}\right)^{-1 / \rho} .
$$

Many textbooks (e.g. Silberberg) have a section on the derivation of the CES from the differential equation

$$
\frac{d \log \left(\frac{x_{1}}{x_{2}}\right)}{d \log \left(\frac{f_{1}}{f_{2}}\right)}=-\sigma, \quad \text { a constant }
$$

a problem that was solved by Arrow et al (ReStat, 1961). With the CES as defined here:

$$
\sigma=\frac{1}{1+\rho}
$$

CES with $\rho=0$ is Cobb Douglas. CES with $\rho \rightarrow-1$ (from above) has $\sigma \rightarrow \infty$ which is the linear isoquant case. CES with $\rho \rightarrow \infty$ has $\sigma \rightarrow 0$, which is Leontief.

## Relative Demand and the Relative Wage Structure

The "demand-supply and wage inequality" literature operates with two key assumptions:
(1) at any point in time there is a national production function $y=f\left(K, L_{1}, L_{2}, \ldots\right)$ that determines the relative productivity of different skill groups
(2) supply of each skill group is predetermined (and hence exogenous to "current technoology shocks").

The same basic setup is used to address the effects of immigration on the wages of different groups, at both the national and local levels. Under assumptions (1) and (2), the structure of the relative demand for different skill groups entirely determines the relative wage structure. The key questions are: how are skill groups defined?
how do we parameterize the degree of substitutability between groups? how does capital fit in?

We will discuss the "standard" theoretical framework for this analysis, which makes 3 assumptions:

1. $y=f\left(K, h\left(L_{1}, L_{2} \ldots\right)\right)$ with $\quad f(K, L)=A L^{\alpha} K^{1-\alpha}$
2. the return to capital $(r)$ is exogenous
3. $h\left(L_{1}, L_{2} \ldots\right)$ has a nested CES structure

Under the first two assumptions, we have

$$
\begin{aligned}
\frac{\partial y}{\partial K} & =(1-\alpha) A L^{\alpha} K^{-\alpha}=r \\
& \Rightarrow K=L\left(\frac{(1-\alpha) A}{r}\right)^{1 / \alpha} \quad \text { and } \quad \frac{y}{K}=\frac{r}{(1-\alpha)}
\end{aligned}
$$

This means that $K$ adjusts to match the overall supply of "labor units" $L$, keeping $y / K$ constant, and keeping $K / L$ on a trend path that is driven by the rate of growth of t.f.p. Figures 2 and 3 from Ottaviano and Peri (2011) suggest this is a reasonable assumption at the national level. At the local level (or for "small open economies" that take the price of capital as exogenous) these assumptions are even more plausible. Substituting for $K$ we get

$$
y=A L^{\alpha} K^{1-\alpha}=A^{1 / \alpha}\left(\frac{1-\alpha}{r}\right)^{\frac{1-\alpha}{\alpha}} L
$$

which is linear in $L$. Thus, under these assumptions we can ignore capital. ${ }^{1}$
To analyze the effects of relative supply or relative technology changes (i.e., the part of technology embedded in $h()$ ) we need to specify the labor aggregator function. A good starting point is a 2 -group CES model:

$$
L=h\left(L_{1}, L_{2}\right)=\left(\theta_{1} L_{1}^{\frac{\sigma-1}{\sigma}}+\theta_{2} L_{1}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}
$$

where $\theta_{1}$ and $\theta_{2}$ are possibly trending over time. ${ }^{2}$ The marginal product of group 1 is

$$
h_{1}\left(L_{1}, L_{2}\right)=\theta_{1} L_{1}^{\frac{-1}{\sigma}}\left(\theta_{1} L_{1}^{\frac{\sigma-1}{\sigma}}+\theta_{2} L_{1}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}}=\theta_{1} L_{1}^{\frac{-1}{\sigma}} L^{\frac{1}{\sigma}} .
$$

Likewise

$$
h_{2}\left(L_{1}, L_{2}\right)=\theta_{2} L_{2}^{\frac{-1}{\sigma}} L^{\frac{1}{\sigma}},
$$

[^0]and assuming $w_{1} / w_{2}=h_{1} / h_{2}$ (i.e., MRTS=relative wage) we have:
$$
\log \frac{w_{1}}{w_{2}}=\log \frac{\theta_{1}}{\theta_{2}}-\frac{1}{\sigma} \log \frac{L_{1}}{L_{2}}
$$

The slope of the relative demand curve is $-\frac{1}{\sigma}$, which is 0 if the two types are perfect substitutes, and something larger otherwise. This simple model is widely used to discuss "skill biased technical change" (SBTC).

In the "traditional" SBTC literature (e.g., Katz and Murphy, 1992) it is assumed that

$$
\log \frac{\theta_{1 t}}{\theta_{2 t}}=a+b t+e_{t}
$$

leading to a model for the relationship of relative wages to relative supplies:

$$
\begin{equation*}
\log \frac{w_{1 t}}{w_{2 t}}=a+b t-\frac{1}{\sigma} \log \frac{L_{1 t}}{L_{2 t}}+e_{t} . \tag{2}
\end{equation*}
$$

Freeman (1976) and Katz and Murphy (1992) estimate models of this form, using 2 "types" of labor - high-school equivalents and college equivalents. Dropouts are assumed to be perfect substitutes for HS graduates with a relative efficiency of (roughly) $70 \%$. Post-graduates are assumed to be perfect substitutes for college graduates with a relative efficiency of (roughly) $125 \%$. People with $1-3$ years of college are assumed to represent $1 / 2$ unit of HS labor and $1 / 2$ unit of college labor. (There are different conventions about whether supply should be based on the total numbers of adults in each education group, or total employees. There are also different ways to combine men and women). The "magic number" is $\frac{1}{\sigma}=0.7$, which implies $\sigma=1.4$ (See KM, equation 19, page 69). It has turned out to be hard to get a model like (1) to work as well as it did in KM's study (and in Freeman, 1976) when the sample is extended to the 1990s and 2000's. Katz and Goldin (2008) present some estimates that have trend breaks in the last two decades and manage to get estimates in the range of $\frac{1}{\sigma}=0.7$.

Card and Lemieux (2001) generalize the 2-skills model by introducing a nested CES:

$$
\begin{align*}
h(.) & =\left(\theta_{H} H^{\frac{\sigma-1}{\sigma}}+\theta_{L} L^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}  \tag{3}\\
H & =\left(\sum_{j} \alpha_{j} H_{j}^{\frac{\sigma_{A}-1}{\sigma_{A}}}\right)^{\frac{\frac{\sigma_{A}}{\sigma_{A}-1}}{}} \\
L & =\left(\sum_{j} \beta_{j} L_{j}^{\frac{\sigma_{A}-1}{\sigma_{A}}}\right)^{\frac{\sigma_{A}}{\sigma_{A}-1}}
\end{align*}
$$

Here $H_{j}$ is the number of workers in the "high" education group in age group $j$, and similarly $L_{j}$ is the number of workers in the "low" education group in age
group $j$. The new parameter $\sigma_{A}$ measures the degree of substitutability across age (or experience) groups (which is implicitly set to infinity in the traditional SBTC literature). This model is motivated by the observation (CL, Figures I, II) that in US, UK and Canada the rise in the college high-school wage gap is mainly driven by changes for young workers, and by the realization that since the late 1970s the relative growth rate in educational attainment of consecutive cohorts has stalled in all 3 countries (CL, Figure III). The argument in CL is that the "twisting" of the age profile of relative returns in their Figure II was caused by the slowdown in the growth of relative supply among young workers that is slowly working its way through the age distribution.

Differentiating (2) w.r.t. $L_{j}$ and $H_{j}$ and re-arranging terms it is easy to derive a generalization of (1) of the form:

$$
\begin{equation*}
\log \frac{w_{j t}^{H}}{w_{j t}^{L}}=\log \frac{\theta_{H t}}{\theta_{L t}}+\log \frac{\alpha_{j}}{\beta_{j}}-\frac{1}{\sigma} \log \frac{H_{t}}{L_{t}}-\frac{1}{\sigma_{A}}\left(\log \frac{H_{j t}}{L_{j t}}-\log \frac{H_{t}}{L_{t}}\right) \tag{4}
\end{equation*}
$$

(CL, equation 8 b ). This says that for age group $j$ the percentage gap in wages between $H$ and $L$ workers in period $t$ depends on $\log \frac{\theta_{H t}}{\theta_{L t}}$, the aggregate index of "skill biased" tech-change, on the aggregate relative supply of $H$ and $L$ workers, $\log \frac{H_{t}}{L_{t}}$, on an age-group specific relative productivity effect $\log \frac{\alpha_{j}}{\beta_{j}}$ (which we are assuming in (3) does not vary over time) and on the deviation between the relative supply of $H$ workers in age group $j$ and the overall relative supply. There are a number of interesting implications of (3):

1. if $\log \frac{H_{j t}}{L_{j t}}-\log \frac{H_{t}}{L_{t}}$ is constant over time then the Freeman-Katz-Murphy model is still OK, and provides a valid estimate of $\frac{1}{\sigma}$. Empirically the relative supply gaps were pretty stable over time in the US until the late 1970s which may explain why Freeman's analysis looks so good.
2. the relative supply of educated workers in age group $j$ is (largely) determined by the choices when the people who are currently age $j$ were finishing school. That suggests a simple model like:

$$
\log \frac{H_{j t}}{L_{j t}}=\lambda_{t-j}+\phi_{j}
$$

where $\lambda_{c}$ is a cohort effect (and we measure age by years since age 20, and index cohorts by the calendar year they reached age 20) and $\phi_{j}$ is an age effect that is constant across cohorts and time. Substituting this into (3) yields a model with age, time and cohort effects:

$$
\begin{equation*}
\log \frac{w_{j t}^{H}}{w_{j t}^{L}}=\log \frac{\theta_{H t}}{\theta_{L t}}+\log \frac{\beta_{j}}{\alpha_{j}}-\frac{1}{\sigma_{A}} \phi_{j}-\left(\frac{1}{\sigma}-\frac{1}{\sigma_{A}}\right) \log \frac{H_{t}}{L_{t}}-\frac{1}{\sigma_{A}} \lambda_{t-j} \tag{5}
\end{equation*}
$$

Notice that the cohort effects drop out if $\frac{1}{\sigma_{A}}=0$ : so evidence of cohort effects is simple evidence of imperfect substitution across age groups.
3. Using (2) the relative wage of any 2 age groups $\left(j, j^{\prime}\right)$ in the same education class can be written as:

$$
\begin{aligned}
\log \frac{w_{j t}^{H}}{w_{j^{\prime} t}^{H}} & =\log \frac{\alpha_{j}}{\alpha_{j^{\prime}}}-\frac{1}{\sigma_{A}}\left(\log \frac{H_{j t}}{H_{j^{\prime} t}}\right) \\
\log \frac{w_{j t}^{L}}{w_{j^{\prime} t}^{L}} & =\log \frac{\beta_{j}}{\beta_{j^{\prime}}}-\frac{1}{\sigma_{A}}\left(\log \frac{L_{j t}}{L_{j^{\prime} t}}\right) .
\end{aligned}
$$

Thus the coefficient $\frac{1}{\sigma_{A}}$ can be estimated by relating the relative wages of different age groups in the same education class to their relative supplies, and a set of relative efficiency parameters. CL get estimates for $\frac{1}{\sigma_{A}}$ in the range of 0.2 or a little smaller (see also Ottaviano and Peri, 2011). (Note too that it would be pretty easy to have different values for $\sigma_{A}$ for the different education groups).
4. How do you estimate a 2-level nested CES? As you can see from (3), this is somewhat complicated by the fact that the aggregate supply indexes $H_{t}$ and $L_{t}$ are "model-based": you need to know the parameters $\alpha_{j}, \beta_{j}$ and $\sigma_{A}$ to construct these indexes. An easy way is to proceed in two steps. Step 1 focuses on estimating $\sigma_{A}$, using observation 3 above. Notice that once you normalize one of the efficiency parameters for each education group (e.g., $\alpha_{1}=\beta_{1}=1$ ) you also get estimates of $\alpha_{j}$ and $\beta_{j}$ for the other groups. Using these and the estimate of $\sigma_{A}$ we construct the "effective" supply indexes:

$$
\begin{aligned}
H_{t} & =\left(\sum_{j} \alpha_{j} H_{j t}^{\frac{\sigma_{A}-1}{\sigma_{A}}}\right)^{\frac{\sigma_{A}}{\sigma_{A}-1}} \\
L_{t} & =\left(\sum_{j} \beta_{j} L_{j t}^{\frac{\sigma_{A}-1}{\sigma_{A}}}\right)^{\frac{\sigma_{A}}{\sigma_{A}-1}} .
\end{aligned}
$$

If you examine expressions like these you will see that when $\frac{1}{\sigma_{A}} \approx 0.2$ the exponents inside the parentheses are numbers like 0.8 and the numbers outside are numbers like 1.25. In this range

$$
H_{t} \approx \sum_{j} \alpha_{j} H_{j t}, \quad L_{t} \approx \sum_{j} \beta_{j} L_{j t}
$$

So sometimes people "cheat" by using simple supply aggregates rather than "model consistent" aggregates.

In the second step we estimate (3) on age-group/time-period observations, using the estimates of $H_{t}$ and $L_{t}$, and some assumption on the time series process for $\log \frac{\theta_{H t}}{\theta_{L t}}$. This yields estimates of $\frac{1}{\sigma}$ and $\frac{1}{\sigma A}$. The latter can be compared to the estimate obtained in the first step to provide a consistency check of the process. In general, with multiple nests, we can proceed in the same way: start at the
lowest level of aggregation and estimate the lowest-level substitution parameter, and the relative efficiency parameters, then construct the supply indexes for the next level and work backwards up the nesting structure.
5. Anderson and Moroney (1994) show that when you have a nested CES, the Allen partial elasticity of substitution ${ }^{3}$ between two inputs in the same nest is related to the within-nest substitution effect and the between-nest effect. In the contex of (2) they show that for any two age groups $i$ and $j$ with high education:

$$
\sigma_{i, j}^{\text {Allen }}=\frac{1}{s_{H}}\left(\sigma_{A}-s_{L} \sigma\right)
$$

and for any two groups with low education

$$
\sigma_{i, j}^{\text {Allen }}=\frac{1}{s_{L}}\left(\sigma_{A}-s_{H} \sigma\right)
$$

where $s_{L}$ and $s_{H}$ are the cost shares of the $L$ and $H$ groups. If $\sigma_{A}$ is small relative to $\sigma$ this means that two groups in the same nest can be complements (which cannot happen in a 1-level CES, where all groups are substitutes). In a two-nest model like CL's, $\sigma_{A}$ is quite a bit smaller than $\sigma$ and so people in the same education group in different age classes are Allen-complements, which might make economic sense.

## II. Generalizations of the 2-nest model.

a) Multiple education classes.

One immediate issue that arises in thinking about (3) is whether we need more education groups. For example, with $K$ education groups we get:

$$
\begin{align*}
h(.) & =\left(\sum_{k=1}^{K} \theta_{k} E_{k}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}  \tag{6}\\
E_{k} & =\left(\sum_{j} \alpha_{j}^{k} E_{k j}^{\frac{\sigma_{A}-1}{\sigma_{A}}}\right)^{\frac{\sigma_{A}}{\sigma_{A}-1}}
\end{align*}
$$

where $E_{k}$ represents the supply of people in education group $k$. Let's consider 2 groups $k=1$ and $k=2$. Then a variant of (3) will imply a model for the relative wages of people of age group $j$ in education groups 1 and 2 of the form:

$$
\begin{equation*}
\log \frac{w_{j t}^{2}}{w_{j t}^{1}}=\log \frac{\theta_{2 t}}{\theta_{1 t}}+\log \frac{\alpha_{j}^{2}}{\alpha_{j}^{1}}-\left(\frac{1}{\sigma}-\frac{1}{\sigma_{A}}\right) \log \frac{E_{2 t}}{E_{1 t}}-\frac{1}{\sigma_{A}} \log \frac{E_{2 j t}}{E_{1 j t}} \tag{7}
\end{equation*}
$$

Suppose however that we've made a mistake and groups 1 and 2 are really perfect substitutes. Then the relative wages of people of age group $j$ in groups

[^1]1 and 2 should be constant:

$$
\log \frac{w_{j t}^{2}}{w_{j t}^{1}}=k
$$

(potentially we could allow $k$ to vary by age group). This provides a way to think about how to define the right grouping structure: we group together workers whose relative wages are constant over time (or across local markets, if we are focusing on spatial variation in wages).

An interesting application is to the classification of lower-education groups. One view is that dropouts and high school graduates are 2 different skill groups. An alternative (widely used in the SBTC literature) is that dropouts and HS grads are perfect substitutes. The latter implies that the HS graduation premium is constant (over time and across markets) - a prediction that seems remarkably true. See Figure 6 from "Is the New Immigration Really So Bad?", Ottaviano and Peri (forthcoming, Table 5), and Goldin and Katz (2008, chapter 8). This has important implications for interpreting the effect of immigration, since many immigrants ( $50 \%$ or more) have very low education. If they compete with a broader skill group that includes HS graduates their effect (especially on natives with less than a high school education) is substantially diffused.
b) Immigration

A second important application of the relative supply-demand apparatus is to the analysis of the effects of immigration. George Borjas (QJE, 2003) used a variant of the CL model with 4 education groups (dropouts, HS grads, some college, $\mathrm{BA}+$ ) and argued that immigration has had a pretty big effect on the wages of the least-educated natives. (He estimates a model like (5), then does some simulations, accounting for the presence of immigrants in various education and age cells. He focuses on simulations in which the capital stock is fixed and imposes an estimate of $\sigma$ across four education groups - assumptions that arguably over-state the effects of immigration). More recent work, including Ottaviano and Peri (forthcoming) has differed from Borjas in 3 ways:

1. in the simulations capital is allowed to vary endogenously
2. in the estimation, careful attention is paid to the number and definition of education groups
3. a third substitution parameter - between immigrants and natives with the same age and education - is introduced and estimated.

Ottaviano and Peri extend the 2 -level model to a 3 -level model:

$$
\begin{align*}
h(.) & =\left(\sum_{k=1}^{K} \theta_{k} E_{k}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \\
E_{k} & =\left(\sum_{j} \alpha_{j}^{k} E_{k j}^{\frac{\sigma_{A}-1}{\sigma_{A}}}\right)^{\frac{\sigma_{A}}{\sigma_{A}-1}} \\
E_{k j} & =\left(\sum_{n=1}^{2} \lambda_{n}^{k j} E_{k j, n}^{\frac{\sigma_{n}-1}{\sigma_{n}}}\right)^{\frac{\sigma_{n}}{\sigma_{n}-1}} \tag{8}
\end{align*}
$$

Here $E_{k j, n}$ is the number of natives $(n=1)$ or immigrants $(n=2)$ in educationage cell $k j$. Using this structure is easy to show that the relative wage of immigrants versus natives in a particular cell is given by:

$$
\log \frac{w_{k j 2, t}}{w_{k j 1, t}}=\log \frac{\lambda_{2}^{k j}}{\lambda_{1}^{k j}}-\frac{1}{\sigma_{n}} \log \frac{E_{k j, 2 t}}{E_{k j, 1 t}}
$$

Models that ignore the final nest are implicitly assuming $\sigma_{n}=\infty$. Ottaviano and Peri (Table 2) provide estimates of $\frac{1}{\sigma_{n}}$ in the range of 0 to -.09. They get larger estimates for low-educated groups (-.07 to -.09), and smaller estimates for highly educated groups (close to 0 for college grads). One can easily think of explanations for this pattern. While $\frac{1}{\sigma_{n}}$ is small, it turns out to matter for simulating the net effects of immigration, since even a modest value for $\frac{1}{\sigma_{n}}$ implies that more of the impact of immigrants in a given skill (age/education) group is concentrated among immigrants, and less "spills over" to natives.

Ottaviano and Peri give a general version of a nested CES model with $N$ nests $n=1 \ldots N$ (their equation 6 ), and show the associated generalization of equation (3). They also show the general expressions for the implied effects of a change in the supply of 1 type of workers on the level of wages for workers of other types. When the nests are ordered so the intra-nest substitution elasticities are strictly increasing (so the top nest has the smallest value of $\sigma_{n}$ ) they show that an increase in the supply of one type at the bottom of the nesting structure has a negative effect on all groups who are in the same type in nest 1 , and a positive effect on all groups who are in the opposite type in nest 1. (The "top nest" dominates).

Exercise: derive Ottaviano and Peri's expressions (9) and (10).

## II. Modeling Labor Demand with a Traded Sector

The analysis of the effects of relative supply on relative demand is substantially different when an economy has the possibility of "exporting" some (or all) of its excess labor in some skill group. A full analysis of the various trade models would take many lectures - it is worthwhile to read through Johnson and Stafford's Handbook paper at some point.

The classic Hecksher-Olin (HO) model assumes that each industry uses a different combination of input factors, and that the number of traded industries is at least as big as the number of input factors. In this setting there is a region of relative factor endowments (the cone of diversification) such that changes in relative supply of different skill groups have no effect on wages but are simply accomodated by shifts in the size of different sectors. Card and Lewis try to evaluate the importance of inter-industry shifts in "absorbing" different fractions of high school dropouts across different urban labor markets using the following setup. Let $N_{c}^{d}$ represent the number of dropout workers in city $c$, and let $N_{c}$ represent the total number of workers in the city. Then the share of dropout workers in city $c$ is:

$$
\begin{aligned}
s_{c}^{d} & =\frac{N_{c}^{d}}{N_{c}} \\
& =\frac{1}{N_{c}} \sum_{i} N_{i c}^{d} \\
& =\sum_{i} \frac{N_{i c}^{d}}{N_{i c}} \times \frac{N_{i c}}{N_{c}} \\
& =\sum_{i} \lambda_{i c} s_{i c}^{d}
\end{aligned}
$$

where $N_{i c}^{d}$ is the number of dropouts employed in industry $i$ in city $c, N_{i c}$ is total employment in industry $i$ and city $c, \lambda_{i c}$ is industry $i^{\prime} s$ employment share in city $c$, and $s_{i c}^{d}$ is the "dropout intensity" of industy $i$ in city $c$. In the HO case $s_{i c}^{d}=s_{i}^{d}$ : dropout intensity is constant across cities and all that varies is the share of the different industries. Its not hard to form the decomposition:

$$
\begin{aligned}
s_{c}^{d}-s^{d} & =\sum_{i}\left(\lambda_{i c}-\lambda_{i}\right) s_{i}^{d}+\sum_{i}\left(s_{i c i}^{d}-s_{i}^{d}\right) \lambda_{i}+\sum_{i}\left(\lambda_{i c}-\lambda_{i}\right)\left(s_{i c i}^{d}-s_{i}^{d}\right) \\
& =B_{c}+W_{c}+I_{c}
\end{aligned}
$$

where $B_{c}$ is the "between industry" component of adjustment, $W_{c}$ is the "within industry" component of adjustment, and $I_{c}$ is the "interaction effect". CardLewis estimate these components for each city using 2000 census data. Then they consider regression models of the form

$$
\begin{aligned}
B_{c} & =a^{B}+b^{B}\left(s_{c}^{d}-s^{d}\right)+e_{c}^{B} \\
W_{c} & =a^{W}+b^{W}\left(s_{c}^{d}-s^{d}\right)+e_{c}^{W} \\
I_{c} & =a^{I}+b^{I}\left(s_{c}^{d}-s^{d}\right)+e_{c}^{I}
\end{aligned}
$$

By construction $b^{B}+b^{W}+b^{I}=1$. So we can think of $b^{B}$ as the "share" of the total absorption of the excess fraction of dropout workers in city $c$ that is attributable to between-industry shifts. Its also useful to plot $B_{c}, W_{c}, I_{c}$ against $s_{c}^{d}-s^{d}$. See figures 11-13 from Card-Lewis. The estimates across 150 larger

MSA's are:

$$
\begin{aligned}
b^{B} & =.22 \\
b^{W} & =.76 \\
b^{I} & =.02
\end{aligned}
$$

Card-Lewis also show that out of the 0.22 total between-industry component 0.09 comes from agriculture, 0.05 from textiles and apparel, and 0.03 from lowskill services. (You may be surprised to learn that agriculture is important for MSA-level employment. However, many MSA's are counties with a substantial agricultural presence (like Sonoma County and other counties in CA and TX). Arguably the variation in dropout shares accounted by agriculture represents reverse causality: because there is more agriculture in some areas, low-skilled workers are drawn to the areas.

## Other Models

Kuhn and Wooten (1991) consider a model with 3 factors (think of these as 2 types of labor and capital) and 3 goods, 2 of which are traded and one of which is non-traded. We'll outline a simplified version of their model with:

2 sectors: one traded, one untraded
2 types of labor
capital, which is freely mobile at an exogenous price.
In this model the tradeable sector can adjust to partially export away excess supplies of one of the types of labor.

Supply of both types of labor is perfectly inelastic: the total supply of unskilled labor is $N_{u}$, while the total supply of skilled labor is $N_{s}$. In addition to labor, industry 1 and industry 2 use capital, which is available at an exogenous price $r$. Both industries are assumed to have constant returns to scale and to be perfectly competitive. The cost functions of the two industries depend on the wages of unskilled and skilled labor, $w_{u}$ and $w_{s}$, and on the price of capital:

$$
\begin{aligned}
& C^{1}\left(w_{u}, w_{s}, r, y_{1}\right)=y_{1} c^{1}\left(w_{u}, w_{s}, r\right) \\
& C^{2}\left(w_{u}, w_{s}, r, y_{2}\right)=y_{2} c^{2}\left(w_{u}, w_{s}, r\right)
\end{aligned}
$$

where $c^{1}$ and $c^{2}$ are the unit cost functions. Finally, it is assumed that both unskilled and skilled workers have Cobb-Douglas preferences, and that unskilled workers spend a fraction $\alpha_{u}$ of their income on the local good, while skilled workers spend a fraction $\alpha_{s}$ on the local good.

Equilibrium in the labor market requires:

$$
\begin{aligned}
y_{1} c_{u}^{1}\left(w_{u}, w_{s}, r\right)+y_{2} c_{u}^{2}\left(w_{u}, w_{s}, r\right) & =N_{u} \\
y_{1} c_{s}^{1}\left(w_{u}, w_{s}, r\right)+y_{2} c_{s}^{2}\left(w_{u}, w_{s}, r\right) & =N_{s}
\end{aligned}
$$

Both sectors are competitive so equilibrium prices are $p_{1}$ and $p_{2}$ where:

$$
\begin{aligned}
& c^{1}\left(w_{u}, w_{s}, r\right)=p_{1} \\
& c^{2}\left(w_{u}, w_{s}, r\right)=p_{2}
\end{aligned}
$$

Sector 2 is traded so $p_{2}$ is fixed. Sector 1 is local so with Cobb-Douglas demands from the local workers ${ }^{4}$ we require:

$$
y_{1}=\alpha_{u} w_{u} N_{u} / p_{1}+\alpha_{s} w_{s} N_{s} / p_{1}
$$

We have 5 equations in 5 unknowns $\left(w_{u}, w_{s}, y_{1}, y_{2}, p_{1}\right)$, with exogenous variables $N_{u}, N_{s}, p_{2}, r$. One nice feature of this model is "scale invariance": starting from an initial equilibrium, if the supplies of unskilled and skilled labor are both increased by $x$ percent, then a new equilibrium is established at the original wages and prices, with $y_{1}$ and $y_{2}$ both increased by $x$ percent. An implication of scale invariance is that relative wages and the relative size of the two sectors in the local economy are only affected by changes in the relative supplies of labor.

To analyze the effects of a shift in labor supply, begin by differentiating the labor market equilibrium conditions. After some manipulation, the resulting equations can be written as

$$
\begin{align*}
d \log N_{u} & =\lambda_{1 u} d \log y_{1}+\lambda_{2 u} d \log y_{2}+e_{u u} d \log w_{u}+e_{u s} d \log w_{s}  \tag{10a}\\
d \log N_{s} & =\lambda_{1 s} d \log y_{1}+\lambda_{2 s} d \log y_{2}+e_{s u} d \log w_{u}+e_{s s} d \log w_{s} \tag{10b}
\end{align*}
$$

where $d \log x=d x / x$ is the $\log$ differential of $x$, the coefficients $\lambda_{1 u}, \lambda_{2 u}, \lambda_{1 s}, \lambda_{2 s}$ represent the fractions of unskilled or skilled workers initially employed in sector 1 or 2 (with $\lambda_{1 u}+\lambda_{2 u}=1 ; \lambda_{1 s}+\lambda_{2 s}=1$ ), and the coefficients $e_{u u}, e_{u s}, e_{s u}, e_{s s}$ satisfy:

$$
\begin{aligned}
e_{u u} & =\lambda_{1 u} e_{u u}^{1}+\lambda_{2 u} e_{u u}^{2} \\
e_{u s} & =\lambda_{1 u} e_{u s}^{1}+\lambda_{2 u} e_{u s}^{2} \\
e_{s u} & =\lambda_{1 s} e_{s u}^{1}+\lambda_{2 s} e_{s u}^{2} \\
e_{s s} & =\lambda_{1 s} e_{s s}^{1}+\lambda_{2 s} e_{s s}^{2}
\end{aligned}
$$

where $e_{j g}^{i}$ represents the output-constant elasticity of demand for labor of skill group $j$ with respect to the wage of group $g$ in sector $i$. (Thus, $e_{u u}$ for example, is the effective elasticity of demand for unskilled labor w.r.t. its own wage - a weighted average of the elasticities in the 2 sectors).

These equations in turn can be solved for the proportional changes in output:

$$
\begin{align*}
d \log y_{1} & =\varphi_{1 u} d \log N_{u}+\varphi_{1 s} d \log N_{s}+\zeta_{1 u} d \log w_{u}+\zeta_{1 s} d \log w_{s}  \tag{11a}\\
d \log y_{2} & =\varphi_{2 u} d \log N_{u}+\varphi_{2 s} d \log N_{s}+\zeta_{2 u} d \log w_{u}+\zeta_{2 s} d \log w_{s} \tag{11b}
\end{align*}
$$

[^2]where
\[

$$
\begin{aligned}
\varphi_{1 u} & =\lambda_{2 s} /\left(\lambda_{1 u}-\lambda_{1 s}\right) \\
\varphi_{1 s} & =-\lambda_{2 u} /\left(\lambda_{1 u}-\lambda_{1 s}\right) \\
\zeta_{1 u} & =\left(-\lambda_{2 s} e_{u u}+\lambda_{2 u} e_{s u}\right) /\left(\lambda_{1 u}-\lambda_{1 s}\right) \\
\zeta_{1 s} & =\left(-\lambda_{2 s} e_{u s}+\lambda_{2 u} e_{s s}\right) /\left(\lambda_{1 u}-\lambda_{1 s}\right)
\end{aligned}
$$
\]

with parallel expressions for $\varphi_{1 u}, \varphi_{2 u}, \zeta_{1 u}, \zeta_{2 u} .{ }^{5}$ The coefficients $\left(\varphi_{1 u}, \varphi_{1 s}, \varphi_{2 u}, \varphi_{2 s}\right)$ represent the so-called "Rybcznski" effects of changes in factor endowments on sectoral outputs (for more on this, read Kuhn and Wooten). These are the effects that would be observed if wages were unaffected by shifts in labor supply - as would occur if both sectors were traded and we were inside the cone of diversification. If the export sector (sector 2 ) is relatively skill-intensive, for example, then $\lambda_{1 u}>\lambda_{1 s}$ and therefore $\varphi_{1 u}>0$ and $\varphi_{1 s}<0$. Ignoring wage adjustments, an increase in $N_{u}$ causes an increase in output in the sector that is more intensive in unskilled labor, whereas an increase in $N_{s}$ causes a reduction in output in that sector. Also, note that $\varphi_{1 s}=1-\varphi_{1 u}$, reflecting the scale invariance property of the model.

The next step is to differentiate the marginal cost equations, yielding the standard equations relating the share-weighted changes in input prices to the changes in output prices:

$$
\begin{align*}
& \theta_{1 u} d \log w_{u}+\theta_{1 s} d \log w_{s}=\log p_{1}  \tag{12a}\\
& \theta_{2 u} d \log w_{u}+\theta_{2 s} d \log w_{s}=0 \tag{12b}
\end{align*}
$$

where $\theta_{1 u}=w_{u} N_{1 u} / p_{1} y_{1}$ is unskilled labor's share in sector 1 , etc. Finally, differentiating the untraded good's equilibrium condition leads to:

$$
\begin{equation*}
d \log y_{1}=S_{1 u}\left[d \log N_{u}+d \log w_{u}\right]+S_{1 s}\left[d \log N_{s}+d \log w_{s}\right]-d \log p_{1} \tag{13}
\end{equation*}
$$

where $S_{1 u}$ is the share of output from sector 1 consumed by unskilled labor, and $S_{2 u}=1-S_{1 u}$ is the share consumed by skilled labor.

Combining (10a), (11a), (11b), and (12) leads to an equation that can be solved for the change in the unskilled wage as a function of the changes in the supplies of unskilled and skilled labor:

$$
d \log w_{u}=\pi_{u u} d \log N_{u}+\pi_{u s} d \log N_{s}
$$

where

$$
\begin{aligned}
\pi_{u u} & =\left(S_{1 u}-\varphi_{1 u}\right) / M \\
\pi_{u s} & =\left(S_{1 s}-\varphi_{1 s}\right) / M \\
M & =\left[\theta_{1 u}-S_{1 u}+\zeta_{1 u}\right]-\left(\theta_{2 u} / \theta_{2 s}\right) \times\left[\theta_{1 s}-S_{1 s}+\zeta_{1 s}\right]
\end{aligned}
$$

[^3]The effects of shifts in relative labor supply on the wages of skilled workers can be derived using equation (11b). Thus:

$$
d \log w_{s}=\pi_{s u} d \log N_{u}+\pi_{s s} d \log N_{s}
$$

where $\pi_{s u}=-\left(\theta_{2 u} / \theta_{2 s}\right) \pi_{u u}$ and $\pi_{s s}=-\left(\theta_{2 u} / \theta_{2 s}\right) \pi_{u s}$. These two can be substituted into the system to derive effects on output and employment in the two sectors. Table 1, at the end of the lecture, shows the simulated effect of an increase in unskilled labor supply under 2 simple choices for the technologies of the 2 sectors.

## 5. Labor share of nonfarm business sector output, first quarter 1947-third quarter 2010



NOTE: The shaded bars denote National Bureau of Economic Research (NBER)-designated recessions.

- Labor share is the portion of output that employers spend on labor costs (wages, salaries, and benefits) valued in each year's prices. Nonlabor share-the remaining portion of output-includes returns to capital, such as profits, net interest, depreciation, and indirect taxes.
- Labor share averaged 64.3 percent from 1947 to 2000. Labor share has declined over the past decade, falling to its lowest point in the third quarter of 2010, 57.8 percent. The change in labor share from one period to the next has become a major factor contributing to the compensation-productivity gap in the nonfarm business sector.


## The Long Run Trend in Capital per Unit of Labor



## A. United States



## B. United Kingdom


C. Canada


Estimated College-High School Wage Differentials for Younger and Older Men

## A. United States


B. United Kingdom



Figure II
Age Profiles of the College-High School Wage Gap
A. 26-30 Year Old Men

B. 46-50 Year Old Men


Kingdom before leveling off. The parallel movements in the United States and Canada are especially striking, and suggest that whatever forces led to the slowdown in the intercohort trend in educational attainment were common to the two nations. ${ }^{17}$

An important feature of Figure IV is that the timing of the
17. The 1945-1949 cohort in the United States seems to have slightly higher educational attainment than would be predicted given earlier and later cohorts and the pattern in Canada. This may be an effect of draft avoidance behavior by men in this cohort, who entered college to avoid service during the Vietnam war.

## Figures

Figure 1: Alternative nesting models


Model B


Model C


Model D


## Tables

## Table 1:

Immigration and Changes in Native Wages: Education-Experience groups, 1990-2006

| Column 1: <br> Education | Column 2: <br> Experience | Column 3: <br> Percentage change in hours worked in the group due to new immigrants 1990-2006 | Column 4:  <br> Percentage  <br> change in <br> weekly wages, <br> Natives, $1990-$ <br> 2006  |
| :---: | :---: | :---: | :---: |
| No High School Degree (ND) | 1 to 5 years | 8.5\% | 0.7\% |
|  | 6 to 10 years | 21.0\% | -1.5\% |
|  | 11 to 15 years | 25.9\% | 0.6\% |
|  | 16 to 20 years | 31.0\% | 1.6\% |
|  | 21 to 25 years | 35.7\% | 1.3\% |
|  | 26 to 30 years | 28.9\% | -1.6\% |
|  | 31 to 35 years | 21.9\% | -8.8\% |
|  | 36 to 40 years | 14.3\% | -10.1\% |
|  | All Experience groups | 23.6\% | -3.1\% |
| High School Degree (HSD) | 1 to 5 years | 6.7\% | -5.3\% |
|  | 6 to 10 years | 7.7\% | -1.6\% |
|  | 11 to 15 years | 8.7\% | -1.4\% |
|  | 16 to 20 years | 12.1\% | 1.8\% |
|  | 21 to 25 years | 13.0\% | 0.6\% |
|  | 26 to 30 years | 11.8\% | -0.9\% |
|  | 31 to 35 years | 11.0\% | -2.0\% |
|  | 36 to 40 years | 9.3\% | -4.0\% |
|  | All Experience groups | 10.0\% | -1.2\% |
| Low Education (ND+HSD) | All Experience groups | 13.2\% | -1.5\% |
|  |  |  |  |
| Some College Education (SCO) | 1 to 5 years | 2.6\% | -5.4\% |
|  | 6 to 10 years | 2.6\% | -2.0\% |
|  | 11 to 15 years | 3.9\% | 0.1\% |
|  | 16 to 20 years | 6.2\% | 0.6\% |
|  | 21 to 25 years | 8.4\% | -2.5\% |
|  | 26 to 30 years | 12.0\% | -3.1\% |
|  | 31 to 35 years | 12.3\% | -3.8\% |
|  | 36 to 40 years | 12.7\% | -3.0\% |
|  | All Experience groups | 6.0\% | -1.9\% |
| College Degree (COD) | 1 to 5 years | 6.8\% | 0.4\% |
|  | 6 to 10 years | 12.2\% | 6.5\% |
|  | 11 to 15 years | 13.7\% | 14.2\% |
|  | 16 to 20 years | 12.2\% | 17.3\% |
|  | 21 to 25 years | 17.5\% | 9.1\% |
|  | 26 to 30 years | 24.4\% | 4.3\% |
|  | 31 to 35 years | 26.1\% | 1.7\% |
|  | 36 to 40 years <br> All Experience groups | 14.6\% | 9.3\% |
| High Education (SCO+COD) | All Experience groups | 10.0\% | 4.5\% |

## Table 2

Estimates of the coefficient ( $\mathbf{( 1 / \sigma _ { N } \text { ) }}$
National Census and ACS, U.S. data 1960-2006

| Specification | (1) <br> No Fixed Effects | $\begin{gathered} (2) \\ \text { With } F E \end{gathered}$ | (3) <br> Not weighted with FE | (4) <br> No Fixed Effects | (5) <br> With FE | $\begin{gathered} \text { (6) } \\ \text { Not weighted } \\ \text { with FE } \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Wage Sample: | All workers, weighted by hours |  |  | Full time workers only |  |  |
| Estimates of (-1/ $\mathbf{\sigma}_{\mathrm{N}}$ ) |  |  |  |  |  |  |
| Men | $\begin{gathered} -0.053^{* * *} \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.033^{* *} \\ (0.013) \end{gathered}$ | $\begin{gathered} -0.045^{* * *} \\ (0.013) \end{gathered}$ | $\begin{gathered} -0.063^{* *} \\ (0.005) \end{gathered}$ | $\begin{gathered} -0.048^{* * *} \\ (0.010) \end{gathered}$ | $\begin{gathered} -0.059 * * * \\ (0.012) \end{gathered}$ |
| Women | $\begin{gathered} -0.037^{* * *} \\ (0.009) \end{gathered}$ | $\begin{gathered} -0.058 * * * \\ (0.017) \end{gathered}$ | $\begin{gathered} -0.067^{* * *} \\ (0.016) \end{gathered}$ | $\begin{gathered} -0.050 * * * \\ (0.007) \end{gathered}$ | $\begin{gathered} -0.066^{* * *} \\ (0.014) \end{gathered}$ | $\begin{gathered} -0.071^{* * *} \\ (0.012) \end{gathered}$ |
| Pooled Men and Women | $\begin{gathered} -0.032 * * * \\ (0.008) \end{gathered}$ | $\begin{aligned} & -0.024^{*} \\ & (0.015) \end{aligned}$ | $\begin{gathered} -0.026^{* *} \\ (0.15) \end{gathered}$ | $\begin{gathered} -0.044^{* * *} \\ (0.006) \end{gathered}$ | $\begin{gathered} -0.037 * * * \\ (0.012) \end{gathered}$ | $\begin{gathered} -0.038^{* *} \\ (0.013) \end{gathered}$ |
| Men, Labor supply measured as employment | $\begin{gathered} -0.057^{* *} \\ (0.007) \\ \hline \end{gathered}$ | $\begin{aligned} & 0.027^{* *} \\ & (0.014) \end{aligned}$ | $\begin{aligned} & 0.030^{* *} \\ & (0.015) \end{aligned}$ | $\begin{gathered} -0.066^{* * *} \\ (0.006) \\ \hline \end{gathered}$ | $\begin{gathered} -0.040^{* *} \\ (0.012) \\ \hline \end{gathered}$ | $\begin{gathered} -0.041^{* *} \\ (0.014) \\ \hline \end{gathered}$ |
| Separate estimates of ( $-1 / \sigma_{\mathrm{N}}$ ) by Education Group |  |  |  |  |  |  |
| Men, No degree | $\begin{gathered} -0.073^{* * *} \\ (0.007) \end{gathered}$ | $\begin{gathered} -0.070^{* * *} \\ (0.010) \end{gathered}$ | $\begin{gathered} -0.070^{* * *} \\ (0.009) \end{gathered}$ | $\begin{gathered} -0.085^{* * *} \\ (0.004) \end{gathered}$ | $\begin{gathered} -0.084^{* *} \\ (0.006) \end{gathered}$ | $\begin{gathered} -0.081^{* *} \\ (0.007) \end{gathered}$ |
| Men, High School Graduates | $\begin{gathered} -0.089 * * * \\ (0.016) \end{gathered}$ | $\begin{gathered} -0.090^{* * *} \\ (0.020) \end{gathered}$ | $\begin{gathered} -0.093^{* * *} \\ (0.018) \end{gathered}$ | $\begin{gathered} -0.097 * * * \\ (0.013) \end{gathered}$ | $\begin{gathered} -0.099 * * * \\ (0.015) \end{gathered}$ | $\begin{gathered} -0.100^{* * *} \\ (0.015) \end{gathered}$ |
| Men, Some College education | $\begin{gathered} -0.071^{* *} \\ (0.024) \end{gathered}$ | $\begin{gathered} -0.060 \\ (0.035) \end{gathered}$ | $\begin{aligned} & -0.070^{*} \\ & (0.034) \end{aligned}$ | $\begin{gathered} -0.077^{* *} \\ (0.023) \end{gathered}$ | $\begin{aligned} & -0.068^{*} \\ & (0.033) \end{aligned}$ | $\begin{gathered} -0.075^{* *} \\ (0.034) \end{gathered}$ |
| Men; College Graduates | $\begin{array}{r} -0.017 \\ (0.026) \\ \hline \end{array}$ | $\begin{array}{r} 0.006 \\ (0.042) \\ \hline \end{array}$ | $\begin{array}{r} 0.019 \\ (0.030) \\ \hline \end{array}$ | $\begin{array}{r} -0.024 \\ (0.027) \\ \hline \end{array}$ | $\begin{array}{r} -0.009 \\ (0.041) \\ \hline \end{array}$ | $\begin{aligned} & -0.0150 \\ & (0.029) \\ & \hline \end{aligned}$ |
| Separate estimates of ( $-1 / \sigma_{\mathrm{N}}$ ) by Experience Group |  |  |  |  |  |  |
| Men, 0-10 years of experience | $\begin{aligned} & \hline-0.012 \\ & (0.018) \end{aligned}$ | $\begin{gathered} \hline-0.14^{* * *} \\ (0.028) \end{gathered}$ | $\begin{aligned} & -0.15^{* *} \\ & (0.030) \end{aligned}$ | $\begin{gathered} \hline-0.037^{* *} \\ (0.014) \end{gathered}$ | $\begin{gathered} -0.151^{* * *} \\ (0.020) \end{gathered}$ | $\begin{gathered} \hline-0.157 * * * \\ (0.031) \end{gathered}$ |
| Men, 11-20 years of experience | $\begin{gathered} -0.044^{* *} \\ (0.011) \end{gathered}$ | $\begin{gathered} -0.061^{* * *} \\ (0.014) \end{gathered}$ | $\begin{gathered} -0.066^{* *} \\ (0.013) \end{gathered}$ | $\begin{gathered} -0.050^{* * *} \\ (0.011) \end{gathered}$ | $\begin{gathered} -0.068^{* * *} \\ (0.014) \end{gathered}$ | $\begin{gathered} -0.073 * * * \\ (0.014) \end{gathered}$ |
| Men, 21-30 years of experience | $\begin{gathered} -0.073^{* *} \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.052^{* *} \\ (0.022) \end{gathered}$ | $\begin{gathered} -0.058^{* *} \\ (0.017) \end{gathered}$ | $\begin{gathered} -0.077 * * * \\ (0.007) \end{gathered}$ | $\begin{gathered} -0.059^{* *} \\ (0.022) \end{gathered}$ | $\begin{gathered} -0.066 * * * \\ (0.018) \end{gathered}$ |
| Men, 31-40 years of experience | $\begin{gathered} -0.094^{* *} \\ (0.013) \\ \hline \end{gathered}$ | $\begin{gathered} -0.065^{* *} \\ (0.014) \\ \hline \end{gathered}$ | $\begin{gathered} -0.063^{* *} \\ (0.016) \\ \hline \end{gathered}$ | $\begin{gathered} -0.096^{* * *} \\ (0.013) \\ \hline \end{gathered}$ | $\begin{gathered} -0.064^{* * *} \\ (0.015) \\ \hline \end{gathered}$ | $\begin{aligned} & 0.060 * * \\ & (0.018) \\ & \hline \end{aligned}$ |

Note: Each cell reports the estimate of the parameter $-1 / \sigma_{\mathrm{N}}$. from specification (12) in the text. Method of estimation is Least Squares. In parenthesis we report the heteroskedasticity-robust standard errors, clustered over the 32 education-experience groups. In specification 1, 2, 4 and 5 we weight each cell by its employment. FE (fixed Effects) include Education by Experience plus time effects in Rows one to four, Experience fixed effects are included in rows 5 to 8 and Education fixed Effects are in rows 9$12 . . * * *=$ significant at $1 \%$ level; **=significant at $5 \%$ level; *= significant at $10 \%$ level.

## Table 3

## Estimates of (-1/ $\left.\sigma_{E X P}\right)$

(National Census and ACS U.S. data 1960-2006)

| Structure of the nest | Model A and B | Model C |  | Model D |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) |
| Estimated coefficient: | $\left(-1 / \sigma_{\text {EXP }}\right)$ | (-1/ $\sigma_{\text {EXP }}$ ) | (-1/ $\sigma_{\mathrm{Y}-\mathrm{O}}$ ) | (-1/ $\sigma_{\text {EXP }}$ ) |
| Men | -0.16*** | -0.19** | -0.31* | -0.30*** |
| Labor Supply is Hours worked | (0.05) | (0.08) | (0.15) | (0.06) |
| Women | -0.05 | 0.08* | -0.14 | -0.01 |
| Labor Supply is Hours worked | (0.05) | (0.045) | (0.12) | (0.06) |
| Pooled Men and Women | -0.14*** | -0.17** | -0.28** | -0.23*** |
| Labor Supply is Hours worked | (0.04) | (0.06) | (0.12) | (0.05) |
| Men | -0.13*** | -0.18** | -0.26* | $-0.22 * * *$ |
| Labor Supply is Employment | (0.05) | (0.08) | (0.12) | (0.06) |
| Cells: | Education-experience- year | Education-experience-year | Education-Young/Old- year | Experience-year |
| Effects Included | Education by Year and Education by Experience | Education-Young-Year, Education-Old-Year and Education by Experience | Education- Year and Education-Young/Old | Experience effects and year effects |
| Observations | 192 | 192 | 96 | 48 |

Note: Each cell reports the estimates from a different regression that implements equation (7) in the text for the appropriate characteristics and using the appropriate aggregate and fixed effects. The method of estimation is 2SLS using immigrant workers' hours as instrument for total workers' hours. Cells are weighted by their employment. Standard errors are heteroskedasticity robust and clustered at the education-experience level for columns 1 and 2, at the education-young/old level for column 3 and at the experience level for column 4. *, **, ${ }^{* * *}=$ significant at the 10,5 and $1 \%$ level.

Table 4
Estimates of ( $\mathbf{- 1 / \sigma _ { \text { EDU } } )}$
(National Census and ACS, U.S. data 1960-2006)

|  | Model A |  | Model D |  |
| :---: | :---: | :---: | :---: | :---: |
| Specification: | (1) <br> With educationspecific FE and trends | (2) <br> With educationspecific trends only | (3) <br> With experienceyear FE | (4) With experienceyear, educationexperience and education-year FE |
| Men | -0.16 | -0.28** | -0.22* | -0.04 |
| Labor Supply is Hours worked | (0.12) | (0.10) | (0.12) | (0.03) |
| Women | -0.16 | -0.34** | -0.25** | -0.02 |
| Labor Supply is Hours worked | (0.15) | (0.14) | (0.11) | (0.04) |
| Pooled Men and Women | -0.15 | -0.30** | -0.23** | -0.02 |
| Labor Supply is Hours worked | (0.10) | (0.11) | (0.11) | (0.03) |
| Men | -0.17 | -0.43** | -0.28** | -0.03 |
| Labor Supply is employment | (0.10) | (0.16) | (0.09) | (0.03) |
| Cells | Education-Year | Education-Year | Education-Experience-years | Education-Experience-years |
| Fixed Effects Included: | Education-specific effects, Educationspecific trends and Year effects | Education-specific trends and Year effects | Experience by year only | Experience by year, Education by year and education by Experience |
| Number of observations | 24 | 24 | 192 | 192 |

Note: Each cell reports the estimates from a different regression that implements (7) in the text using the appropriate wage as dependent variable and labor aggregate as explanatory variable and the appropriate fixed effects. The method of estimation is 2SLS using immigrant workers as instrument for total workers in the relative skill group. Cells are weighted by their employment. Standard errors are heteroskedasticity robust and clustered at the education level for columns 1 and (2), and at the education-experience level for column 3 and 4.
$*, * *, * * *=$ significant at the 10,5 and $1 \%$ level.

Table 5
Elasticity of substitution between Broad and Narrow Education groups
CPS data 1962-2006, Pooled Men and Women

| Model B |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) |  | Observations |
|  | $-1 / \sigma_{\mathrm{H}-\mathrm{L}}$ | $-1 / \sigma_{\text {EDU,L }}$ | -1/GEDU,H |  |
| "Some College" split between $\mathrm{L}_{\text {High }}$ and $\mathrm{L}_{\text {Low }}$ | $\begin{aligned} & \hline-0.54^{* * *} \\ & (0.06) \\ & {[0.07]} \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline-0.029 \\ & (0.018) \\ & {[0.021]} \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline-0.16^{*} \\ & (0.08) \\ & {[0.10]} \\ & \hline \end{aligned}$ | 44 |
| "Some College" in L $\mathrm{L}_{\text {High }}$ | $-0.32^{* * *}$ <br> $(0.06)$ <br> $[0.08]$ | $\begin{aligned} & \hline-0.029 \\ & (0.018) \\ & {[0.021]} \\ & \hline \end{aligned}$ | $\begin{aligned} & -0.16^{*} \\ & (0.08) \\ & {[0.10]} \\ & \hline \end{aligned}$ | 44 |
| Employment as a Measure of Labor Supply | $\begin{aligned} & \hline-0.66^{* * *} \\ & (0.07) \\ & {[0.09]} \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline-0.039 \\ & (0.020) \\ & {[0.024]} \\ & \hline \end{aligned}$ | $\begin{aligned} & -0.08 \\ & (0.09) \\ & {[0.11]} \\ & \hline \end{aligned}$ | 44 |
| 1970-2006 | $\begin{aligned} & -0.52^{* * *} \\ & (0.06) \\ & {[0.08]} \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.021 \\ & (0.028) \\ & {[0.025]} \\ & \hline \end{aligned}$ | $\begin{aligned} & -0.13 \\ & (0.08) \\ & {[0.09]} \\ & \hline \end{aligned}$ | 36 |

Note: Each cell is the estimate from a separate regression on yearly CPS data. In the first column we estimate the relative wage elasticity of the group of workers with a high school degree or less relative to those with some college or more. Method and construction of the relative supply (hours worked) and relative average weekly wages are described in the text in Section 4.2.2. In the first row we split workers with some college education between H and L . In the second row we include them in group H , following the CES nesting in our model. In the second column we consider only the groups of workers with no degree and those with a high school degree (the dependent variable is relative wages and the explanatory is relative hours worked). In the third column we consider only workers with some college education and workers with a college degree or more (the dependent variable is relative wages and the explanatory is relative hours worked). In brackets are the standard errors and in square brackets the Newey-West autocorrelation-robust standard errors.
***= significant at $1 \%$ level; ${ }^{* *=}$ significant at $5 \%$ level; *= significant at $10 \%$ level.

Table 6

## Calculated Long-Run Wage Effects of Immigration, 1990-2006

| Nesting Structures: | Model A/C |  |  | Model D |  | Model B |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Specifications: | $\begin{gathered} \text { (1) } \\ \sigma_{\mathrm{N}}=\infty \end{gathered}$ | (2) <br> Estimated <br> $\sigma_{\mathrm{N}}$ | (3) <br> Education specific $\sigma_{N}$ | (4) <br> Estimated $\sigma_{\mathrm{N}}$ | (5) <br> Education specific $\sigma_{\mathrm{N}}$ | (6) <br> Estimated $\sigma_{\mathrm{N}}$ | (7) <br> Education specific $\sigma_{N}$ | (8) <br> Katz- <br> Murphy | $\begin{gathered} (9) \\ \sigma_{\mathrm{EXP}}=10 \end{gathered}$ |
| Parameters: | 2.5 | 2.5 | 2.5 | 2.5 | 2.5 | 2 | 2 | $\begin{gathered} \sigma_{\text {HIGH-Low }} \\ \hline 1.41 \end{gathered}$ | 2 |
| $\sigma_{\text {EDU,HIGH }}$ | 2.5 | 2.5 | 2.5 | 2.5 | 2.5 | 10 | 10 | 10 | 10 |
| $\sigma_{\text {Edu,Low }}$ | 2.5 | 2.5 | 2.5 | 2.5 | 2.5 | 10 | 10 | 10 | 10 |
| $\sigma_{\text {EXP }}$ | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 10 |
| $\left(\sigma_{\mathrm{N}}\right)_{\mathrm{H}}$ | $\infty$ | 20 | 33 | 20 | 33 | 20 | 33 | 33 | 33 |
| $\left(\sigma_{\mathrm{N}}\right)_{\mathrm{L}}$ | $\infty$ | 20 | 12.5 | 20 | 12.5 | 20 | 12.5 | 12.5 | 12.5 |

\% Real Wage Change of US-Born Workers Due to Immigration, 1990-2006

|  |  |  |  |  |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :--- |
| Less than HS | $-4.1 \%$ | $-3.1 \%$ | $-2.3 \%$ | $-2.6 \%$ | $-1.9 \%$ | $-0.1 \%$ | $0.6 \%$ | $0.5 \%$ | $0.6 \%$ |
| HS graduates | $0.9 \%$ | $1.4 \%$ | $1.6 \%$ | $1.4 \%$ | $1.7 \%$ | $0.5 \%$ | $0.8 \%$ | $0.7 \%$ | $0.8 \%$ |
| Some CO | $2.2 \%$ | $2.5 \%$ | $2.4 \%$ | $2.4 \%$ | $2.3 \%$ | $1.0 \%$ | $0.8 \%$ | $0.9 \%$ | $0.8 \%$ |
| CO graduates | $-1.4 \%$ | $-0.6 \%$ | $-1.0 \%$ | $-0.7 \%$ | $-1.0 \%$ | $0.5 \%$ | $0.2 \%$ | $0.2 \%$ | $0.2 \%$ |
| Average US-born | $\mathbf{0 . 0 \%}$ | $\mathbf{0 . 7 \%}$ | $\mathbf{0 . 6 \%}$ | $\mathbf{0 . 7 \%}$ | $\mathbf{0 . 6 \%}$ | $\mathbf{0 . 6 \%}$ | $\mathbf{0 . 6 \%}$ | $\mathbf{0 . 6 \%}$ | $\mathbf{0 . 6 \%}$ |

\% Real Wage Change of Foreign-Born Workers Due to Immigration, 1990-2006

| Less than HS | -4.1\% | -8.4\% | -11.0\% | -8.5\% | -11.0\% | -5.5\% | -8.0\% | -8.1\% | -8.0\% |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| HS graduates | 0.9\% | -6.1\% | -10.2\% | -6.0\% | -10.1\% | -6.9\% | -11.0\% | -11.1\% | -11.0\% |
| Some CO | 2.2\% | -2.4\% | -0.6\% | -2.5\% | -1.0\% | -4.0\% | -2.2\% | -2.1\% | -2.2\% |
| CO graduates | -1.4\% | -9.2\% | -6.3\% | -9.3\% | -6.7\% | -8.1\% | -5.0\% | -5.0\% | -5.0\% |
| Average Foreign-born | 0.0\% | -7.0\% | -6.6\% | -7.0\% | -6.9\% | -6.5\% | -6.1\% | -6.1\% | -6.1\% |
| Overall average | 0.0\% | 0.0\% | 0.0\% | 0.0\% | 0.0\% | 0.0\% | 0.0\% | 0.0\% | 0.0\% |

Note: The percentage wage changes for each education group are obtained averaging the wage change of each education-experience group (calculated using the formulas for the appropriate nesting structure and the coefficient listed in the first 6 rows). Those percentage changes are weighted by the wage share in the education group. The US-born and Foreign-born average changes are obtained weighting changes of each education group by its share in the 1990 wage bill of the group. The overall average wage change adds the change of US- and foreign-born weighted for the relative wage shares in 1990 and it is always equal to 0 due to the long-run assumption that the capital-labor ratio adjusts to maintain constant returns to capital.

Table 1: Simulated Effects of Increase in the Supply of Unskilled Labor

|  | Baseline Scenario | Baseline Settings Except: |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | $\sigma(\mathrm{u}, \mathrm{s})=3$ | $\sigma(u, s)=6$ | $\begin{aligned} & \theta(2, u)=.30 \\ & \theta(2, s)=.35 \end{aligned}$ | $\begin{aligned} & \theta(2, u)=.50 \\ & \theta(2, s)=.20 \end{aligned}$ |
| 1. Own-elasticity of demand for unskilled labor (average of two sectors) | -0.70 | -1.54 | -2.80 | -0.66 | -0.53 |
| 2. Elasticity of unskilled wage w.r.t. increase in unskilled labor $\pi(u, u)$ | -0.69 | -0.29 | -0.15 | -0.54 | -0.28 |
| 3. Elasticity of relative wage w.r.t. increase in unskilled labor $\pi(\mathrm{u}, \mathrm{u})-\pi(\mathrm{s}, \mathrm{u})$ | -1.00 | -0.42 | -0.22 | -1.00 | -1.00 |
| 4. Elasticity of output of local sector w.r.t. increase in unskilled labor | 0.46 | 0.41 | 0.40 | 0.49 | 0.54 |
| 5. Elasticity of output of export sector w.r.t. increase in unskilled labor | 0.31 | 0.35 | 0.37 | 0.46 | 0.71 |
| 6. Derivative of unskilled employment share in local sector w.r.t. increase in unskilled labor | 0.24 | 0.26 | 0.26 | 0.25 | 0.25 |
| 7. Derivative of unskilled employment share in export sector w.r.t. increase in unskilled labor | 0.24 | 0.23 | 0.23 | 0.25 | 0.19 |

Note: see text. Baseline scenario has Cobb-Douglas technologies in both sectors (all cross substitution elasticities=1) expenditure shares on local good equal to 0.5 , unskilled share in local sector=0.4, skilled share in local sector $=0.4$, unskilled share in export sector $=0.2$, and skilled share in export sector=0.45.


[^0]:    ${ }^{1}$ There is another (generally older) literature which works with general 3-factor production functions $y=f\left(K, L ‘, L_{2}\right)$. In this setting you can also impose the assumption that the marginal product of capital is set to some exogenous $r$.
    ${ }^{2}$ Sometimes people write the CES as $h\left(L_{1}, L_{2}\right)=\left(\theta_{1} L_{1}^{\rho}+\theta_{2} L_{1}^{\rho}\right)^{\frac{1}{\rho}}$, which is the same as the expression in the text with $\rho=\frac{\sigma-1}{\sigma}$. This implies that $\sigma=\frac{1}{1-\rho}$. Note that $\rho<1 \Longleftrightarrow \sigma>0$. The limiting case $\rho \rightarrow-\infty \quad(\sigma=0)$ is Leontief. The limiting case $\rho \rightarrow 1(\sigma \rightarrow \infty)$ is linear. The case $\rho=0(\sigma=1)$ is Cobb Douglas.

[^1]:    ${ }^{3}$ Recall $\sigma_{i, j}^{\text {Allen }} \equiv \frac{C_{i j} C}{C_{i} C_{j}}$. For a regular CES the Allen elasticity for two different inputs is just the elasticity of substitution.

[^2]:    ${ }^{4}$ Note that we are ignoring any other forms of income (in particular capital income)

[^3]:    ${ }^{5}$ These expressions are derived by writing equations (12) in matrix form:
    $d \log N=\Lambda d \log y+E d \log w$, and solving dlogy $=\Lambda^{-1} d \log N-\Lambda^{-1} E d \log w$, where $\Lambda$ is the matrix of $\lambda_{i j}$ terms $(i=1,2 ; j=u, s)$ and $E$ is the matrix of $e_{j g}$ terms $(j=u, s ; g=u, s)$. The determinant of $\Lambda$ is $\lambda_{1 u} \lambda_{2 s}-\lambda_{2 u} \lambda_{1 s}=\lambda_{1 u}-\lambda_{1 s}$.

