Exam Advanced Labor Economics

23 January 2025

1 Firm wage premia

1.1 Interpreting AKM estimates

Table III, taken from Card, Heinig and Kline (2013), summarizes estimates of AKM models for different time periods using German data. Discuss the AKM model as well as the estimates presented in Table III below.

1.2 Models of the labor market

Discuss which model(s) of the labor market would be consistent with the existence of firm wage premia and their increasing importance of time.

TABLE III

ESTIMATION RESULTS FOR AKM MODEL, FIT BY INTERVAL

	(1) Interval 1 1985–1991	(2) Interval 2 1990–1996	(3) Interval 3 1996–2002	(4) Interval 4 2002–2009
Person and establishment parameters				
Number person effects	16,295,106	17,223,290	16,384,815	15,834,602
Number establishment effects	1,221,098	1,357,824	1,476,705	1,504,095
Summary of parameter estimates				
Std. dev. of person effects (across person-year obs.)	0.289	0.304	0.327	0.357
Std. dev. of establ. Effects (across person-year obs.)	0.159	0.172	0.194	0.230
Std. dev. of Xb (across person-year obs.)	0.121	0.088	0.093	0.084
Correlation of person/establ. Effects (across person-year obs.)	0.034	0.097	0.169	0.249
Correlation of person effects/Xb (across person-year obs.)	−0.051	−0.102	−0.063	0.029
Correlation of establ. effects/Xb (across person-year obs.)	0.057	0.039	0.050	0.112
RMSE of AKM residual	0.119	0.121	0.130	0.135
Adjusted R-squared	0.896	0.901	0.909	0.927
Comparison match model				
RMSE of match model	0.103	0.105	0.108	0.112
Adjusted R^2	0.922	0.925	0.937	0.949
Std. dev. of match effect*	0.060	0.060	0.072	0.075
Addendum				
Std. dev. log wages	0.370	0.384	0.432	0.499
Sample size	84,185,730	88,662,398	83,699,582	90,615,841

Notes. Results from OLS estimation of equation (1). See notes to Table II for sample composition. Xb includes year dummies interacted with education dummies, and quadratic and cubic terms in age interacted with education dummies (total of 39 parameters in intervals 1–3, 44 in interval 4). Match model includes Xb and separate dummy for each job (person-establishment pair).

*Standard deviation of match effect estimated as square root of difference in mean squared errors between AKM model and match effect model.

2 The impact of automation on the labor market

2.1 Environment

Assume the following competitive economy:

- Aggregate production of a single final good, Y, is given by the following Cobb-Douglas production function:
$$Y = \exp\left[\int_0^1 \ln(y(z))dz\right] \tag{1}$$
with $y(z)$ the quantity of task z used in the production of Y. There is a continuum of tasks spread out over the unit-interval such that $z \in [0, 1]$.

- Each task is produced using a quantity of capital, $k(z)$, or of labor, $l(z)$, according to:
$$y(z) = \begin{cases} \gamma^K(z)k(z) \text{ if } z \in [0, I] \\ \gamma^L(z)l(z) \text{ if } z \in (I, 1] \end{cases} \tag{2}$$
with $\gamma^K(z)$ and $\gamma^L(z)$ the task-specific productivity of capital and labor, respectively. Task $z = I \in (0, 1)$ is an exogenous task threshold such that all tasks $z \leqslant I$ can only be produced by capital and all tasks $z > I$ can only be produced by labor.

- In equilibrium, clearing of capital and labor markets requires that:
$$\int_0^1 k(z)dz = K \text{ and } \int_0^1 l(z)dz = L \tag{3}$$
with K and L, respectively, a given aggregate quantity of capital and labor in the economy.

- Given the Cobb-Douglas production function in equation (1), the corresponding expression for the marginal cost of producing Y is given by:
$$MC = \exp\left[\int_0^1 \ln(p(z))dz\right] \tag{4}$$
with $p(z)$ the price or the unit-cost of task z.

2.2 Equilibrium

1. Define R as the price of capital and W as the price of labor. That is, R is the price of one unit of $k(z)$ and W is the price of one unit of $l(z)$. For given values of R and W, use that marginal revenue products of capital and labor must equal their marginal costs in equilibrium to replace the question marks in the following expression for the unit-cost of task z, $p(z)$:
$$p(z) = \begin{cases} \textbf{?} \text{ if } z \in [0, I] \\ \textbf{?} \text{ if } z \in (I, 1] \end{cases} \tag{5}$$

2. Given that equation (1) is a Cobb-Douglas production function using a continuum of tasks, cost shares must be constant and equal across all tasks in equilibrium. In particular, given that tasks are spread out over the unit-interval, we must have that $\forall z : p(z)y(z) = Y$. Using that $y(z) = Y/p(z)$ together with equations (2) and (5), show that:
$$k(z) = \begin{cases} \frac{Y}{R} \text{ if } z \in [0, I] \\ 0 \text{ if } z \in (I, 1] \end{cases} \tag{6}$$

and

$$l(z) = \begin{cases} 0 \text{ if } z \in [0, I] \\ \frac{Y}{W} \text{ if } z \in (I, 1] \end{cases} \tag{7}$$

which gives the demand for capital and labor for each task z, respectively.

3. Use equations (3), (6) and (7) to solve for equilibrium expressions for R and W.

4. In equilibrium, the marginal cost of Y, given by equation (4), must equal the price of Y which we denote by P. Choosing Y as the numeraire, we must therefore have that $P = MC = 1$ in equilibrium. Taking logarithms such that $\ln(P) = \ln(MC) = 0$ and using equations (4) and (5) together with the equilibrium expressions for R and W, re-write Y as an aggregate Cobb-Douglas production function and interprete its parameters.

2.3 The impact of automation

1. Assume that tasks are ranked on the unit-interval such that $\gamma^K(z)/\gamma^L(z)$ is decreasing in z. That is, capital has a comparative advantage in the production of lower-indexed tasks, and labor has a comparative advantage in the production of higher-indexed tasks. Now assume that technological progress consists of the automation by capital of labor tasks. As examples, think of the automation by industrial robots of car assembly lines or of software automating tasks done by office clerks. In our model, assume that automation is captured by an increase in the task threshold I.

   Taking the logarithm of the expression for W and differentiating, show that the impact of automation on (the logarithm of) W consists of two effects. The first is a negative *direct displacement effect* because the range of tasks done by workers decreases. The second is a *productivity effect* that captures a change in (the logarithm of) average labor productivity. A priori, the productivity effect can be positive or negative.

2. Proof that the productivity effect will be strictly positive if and only if:

$$\frac{R}{\gamma^K(I)} < \frac{W}{\gamma^L(I)}$$

   and interpret this inequality in terms of the unit-cost to produce the task threshold I.

3. Show that automation always decreases the aggregate labor share in the economy, defined by $s \equiv WL/Y$.

3 Local Labor Market Effects of Import Competition

This question will walk through some basic SSIV analyses using data from Autor, Dorn, and Hanson (ADH, 2013). As discussed in the lectures, ADH use a shift-share instrument aggregating economy-wide Chinese import shocks across 397 manufacturing industries with exposure weights calculated as the share of local industry employment.

Use three cleaned datasets from their setup that are available here:

1. *adh _shocks*: an industry-by-year dataset of the shocks
2. *adh _shares*: a location-by-industry-by-year dataset of the shares
3. *adh _noIV*: a location-by-year dataset of the main outcome (manufacturing employment growth, y), treatment (local growth of China import exposure, x), and other useful variables – excluding the ADH instrument

Answer the following questions:

1. Construct the ADH (location-by-year) instrument by appropriately combining the data on shocks and shares. Merge this into the *adh _noIV* dataset, and estimate an IV regression of the outcome onto the treatment which controls for year (i.e. the post variable) and weights by baseline total employment (the weight variable), clustering by state. Then estimate the exact same IV regression replacing the outcome y with the lagged outcome y _lag, capturing growth in manufacturing employment that took place before the ADH "China Shock" quasi-experiment. How does the latter IV regression help build support for the former IV regression?

2. Construct the "sum-of-shares" control from the *adh _shares* dataset and add this control to both of the previous IV regressions. How does the main IV estimate change? Why, intuitively, is this control important to include?

3. Interact the "sum-of-shares" control with year and add this control to both of the previous IV regressions. How do both IV estimates change? Can you see why, intuitively, the interaction control shifts the main IV estimate so much?

4. Use the ssaggregate command to run both of the previous IV regressions at the shock level. You should control for year fixed effects in the shock-level IV regressions. The coefficients should be identical to the previous estimates, but the standard errors will be different. Comment on the change.

4 Monopsony and firm effects in wages

4.1 Worker preferences over non-pecuniary amenities

- Assume that workers have different preferences over the same workplace amenities. In particular, assume that utility of worker i from working in firm j is given by:

$$u_{ij} = \epsilon \ln(w_j) + \eta_{ij} \tag{1}$$

where η_{ij} captures idiosyncratic preferences for working at firm j, arising, for example, from non-pecuniary match factors such as distance to work or interactions with co-workers and supervisors. If $\{\eta_{ij}\}$ are independent draws from a type-I Extreme Value distribution, the total number of workers that will be employed at firm j is given by:

$$l_j = \frac{\exp\left(\epsilon \ln(w_j)\right)}{\sum_{k=1}^{J} \exp\left(\epsilon \ln(w_k)\right)} L \tag{2}$$

with L the total labor force.

- To simplify the analyses and abstract from strategic interactions in wage setting, assume that the number of firms J is very large such that we can write:

$$\ln(l_j) = \epsilon \ln(w_j) + \ln(\lambda L) \tag{3}$$

where λ is a constant common across all firms.

- Interpret equation (3). What does it mean if $\epsilon \to 0$?

4.2 Firm optimization

- Assume that firms have the following production functions:

$$q_j = \psi_j \ln(l_j) \tag{4}$$

where ψ_j is a firm-specific productivity shifter and the marginal product of labor is decreasing in employment. Both turn out to play an important role in our comparative statics later. Firms maximize profits by posting a wage that minimizes labor costs given equation (3):

$$\max_{w_j} \left[\psi_j \ln(l_j) - w_j l_j\right] \quad \text{s.t.} \quad l_j = l_j(w_j) \tag{5}$$

Note that we assume employers do not observe the idiosyncratic taste for amenities of any given worker given by equation (1). This information asymmetry implies employers cannot price discriminate between workers. Instead, if a firm wants to hire more workers it needs to offer higher wages to all workers.

- Using the first-order conditions, derive the following expression:

$$\ln(w_j) = \ln\left(\psi_j \frac{\epsilon}{1+\epsilon}\right) - \ln(l_j) \tag{6}$$

4.3 Equilibrium

- Given equations (3) and (6), derive expressions for firm-level wages and employment in equilibrium by replacing the question marks in the following expressions:

$$\ln(w_j) = \textbf{?} - \frac{1}{1+\epsilon} \ln(\lambda L) \tag{7}$$

where the right-hand side only depends on the model's parameters. Equilibrium firm-level employment is given by:

$$\ln(l_j) = \textbf{?} + \frac{1}{1+\epsilon} \ln(\lambda L) \tag{8}$$

4.4 Firm effects in wages

- Equations (7) and (8) show that relatively more productive firms (i.e. firms with higher ψ_j) pay higher wages and employ more workers. Briefly explain how you could use matched employer-employee data to estimate the importance of firm effects in wage inequality.
- Could an increased difference in firm-level productivity over time explain the rising importance of firm effects and the increased sorting of workers into high-wage firms?