Compensating differentials, Matching and Mobility

Álvaro A. Novo
ISEG

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Part I

Equalizing Differences in the Labor Market

1 Binary Model

- Workers are productively **homogeneous**
- **Two types of jobs:** $D = 0, 1$
  - This is a non-market consumption of job attributes, tied to a particular job. Call it **job disamenity**, a by-product of production.
- Worker and firm choices generate a supply and demand for each type of job
- Market consumption: C

$U = U(C, D)$, with partial derivatives $U_C > 0$ and $U_D \leq 0$

Assume that $U(C, 0) \geq U(C, 1)$.

Let C^* be consumption level required to achieve same utility with job $D = 1$ as in job $D = 0$. Formally,

$U(C^*, 1) = U(C_0, 0)$

Then $Z = C^* - C_0$ is defined as the **compensating variation**.

And $\Delta w = w_1 - w_0$ is the **market equalizing differential**; the additional income necessary to consume the additional Z.

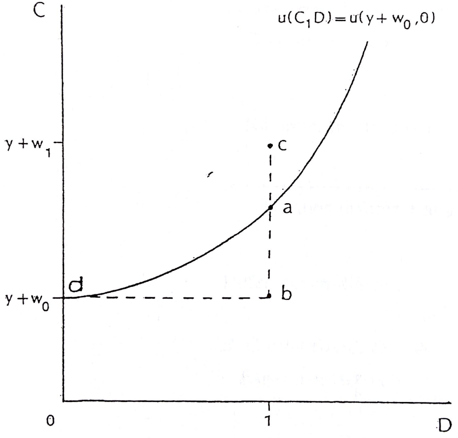

Figure 12.1

The worker chooses:

- $D = 1$ if $\Delta w > Z$
- $D = 0$ if $\Delta w < Z$
- Flips a coin if $\Delta w = Z$

Market supply

Workers **maximize utility** given Δw and their Z's.

$Z \sim G(Z)$; $g(Z)$ is **density** funtion of Z in population.

$L_1^S =$ fraction of workers applying to jobs with $D = 1$

$L_0^S =$ fraction of workers applying to jobs with $D = 0$

Then,

$L_1^S = \int_0^{\Delta w} g(z)dz = G(\Delta w)$

i.e. fraction of workers with $\Delta w > Z$.

And

$L_0^S = \int_{\Delta w}^{\infty} g(z)dz = 1 - G(\Delta w)$

i.e. fraction of workers with $\Delta w < Z$.

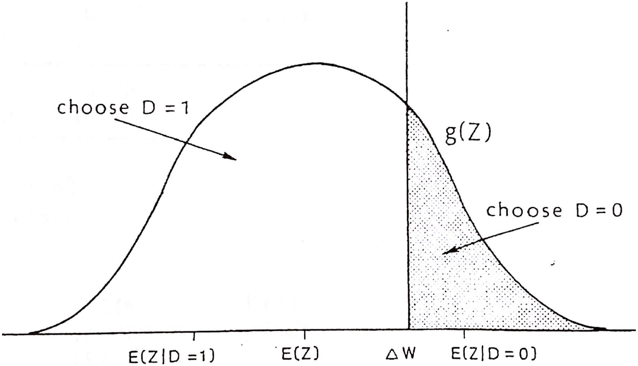

Figure 12.2

Market demand: technology and firm choice

Firms must **choose type of job** to offer.

Let $x =$ **market good** (output); normalize price to 1.

$D =$ **non-market good** (job disamenity); a by-product of production x.

- $x = a_1 L \quad$ if $D = 1$
- $x = a_0 L \quad$ if $D = 0$

$B = a_1 - a_0 =$ **marginal cost per worker of producing improved environment** expressed in terms of foregone output x;
$B > 0$ means $D = 1$ is productive.

Firm choice:

- $D = 1 \quad$ if $B > \Delta w$
- $D = 0 \quad$ if $B < \Delta w$

$B \sim F(B)$; $f(B)$ is density function of B in population of firms

Define
$L_1^D =$ fraction of firms/jobs offered with $D = 1$

and
$L_0^D =$ fraction of firms/jobs offered with $D = 0$

Then,

$L_1^D = \int_{\Delta w}^{\infty} f(B)dB = 1 - F(\Delta w)$

fraction of firms with $B > \Delta w$, market demand for workers in $D = 1$ jobs.

$L_0^D = \int_0^{\Delta w} f(B)dB = F(\Delta w)$

fraction of firms with $B < \Delta w$, market demand for workers in $D = 0$ jobs.

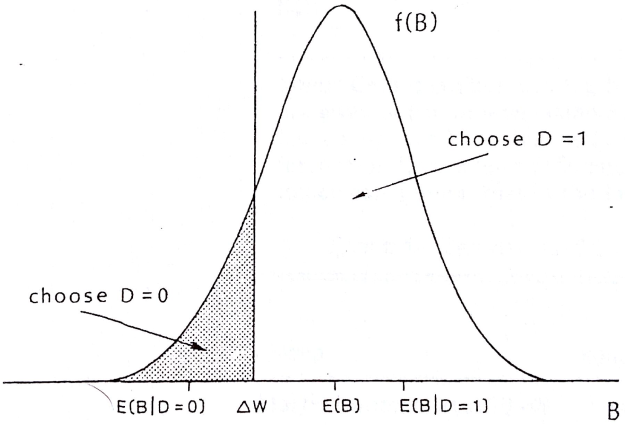

Figure 12.3

Market equilibrium:
equality of supply and demand for workers in each type of job.

Wages w_0 and w_1 must adjust so that the number of workers seeking positions in each job equals number of positions to be filled:

Δw adjusts to make $L_1^S = L_1^D$, equivalently $L_0^S = L_0^D$

Thus **equilibrium wage,** Δw^***, solves** $G(\Delta w^*) = 1 - F(\Delta w^*)$

Matching

Workers and firms are matched, **negative assortive mating**:
workers with greatest distaste for dirt (**high** Z) go to firms with least productivity benefit of dirt (**low** B).

Note that:

- $E(Z|D=0) > E(Z)$
- $E(Z|D=1) < E(Z)$
- $E(B|D=0) < E(B)$
- $E(B|D=1) > E(B)$

2 Continuous model: kissing equilibrium

Let $D =$ a **continuous disamenity** (pollution level, accident probability)

$U(C, D)$ the utility function with partial derivatives:

$\partial U(C, D)/\partial D < 0$

$\partial U(C, D)/\partial C > 0$

And $w(D) =$ **hedonic wage equation**.

Worker choice: $\max U(C, D) \quad$ s.t. $C = w(D)$.

The maximum is characterized by the marginal condition:

$-U_D/U_C = w'(D) = MRS$ between D and C

Firm choice: analogous.

Set MRT between D and $C = w'(D)$

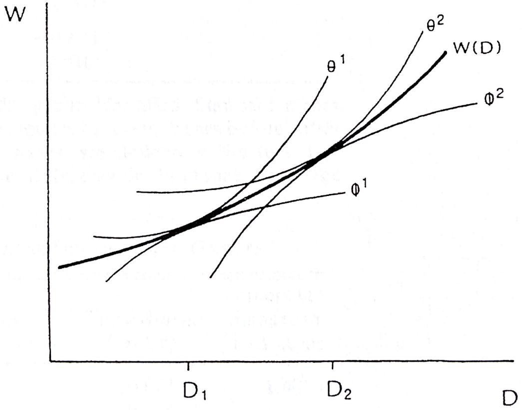

Figure 12.4

Kissing equilibrium

θ_1 and θ_2 are **indiference curves**;
worker 1 has greatest distaste for D

ϕ_1 and ϕ_2 are **iso-profit curves**;
firm 1 finds it easier to get rid of D

3 Application: Incidence of mandated benefits

$C =$ cost of **mandated benefit to employer**

$\alpha C =$ **value employees** place on the benefit

$L^d = L^d(w + C)$

$L^s = L^s(w + \alpha C)$

Equilibrium: $L^d(w + C) = L^s(w + \alpha C)$

Totally differentiate equilibrium conditions and rearrange terms

$dw/dC = -(\eta_d - \alpha\eta_s)/(\eta_d - \eta_s)$,

$dL/L = \eta_d(dw + dC)/w$,

where

$\eta_d =$ **labor demand elasticity** (< 0)

and

$\eta_s =$ **labor supply elasticity** (> 0)

Demand and supply curves both shift; new equilibrium lower wages, ambiguous employment effect.

Differences-in-Differences-in-Differences Estimation
Gruber (1994)“Efficiency of Group-Specific Mandated Benefit”

In the United States, before 1978, health insurance benefits for maternity were generally limited. During 1975-1979, 23 states passed laws that outlawed treating pregancy differently from comparable illnesses.

Differences-in-Differences-in-Differences (DDD) estimates are used in order to purge estimates of bias due to **omitted variables**.

For instance, DDD estimates are often used to study the effect of a country law change.

In such cases, the identifying assumption is that there is no shock **contemporaneous** with the law that affects the **relative** outcomes of the treatment group **in the same country-year**.

Estimates are purged of omitted variable bias due to:

- country effects that are constant over time
- time effects that are the same across countries
- selection into the country that is the same across treatment and control populations

TABLE 3—DDD ESTIMATES OF THE IMPACT OF STATE MANDATES ON HOURLY WAGES

Location/year	Before law change	After law change	Time difference for location
A. *Treatment Individuals: Married Women, 20–40 Years Old:*			
Experimental states	1.547 (0.012) [1,400]	1.513 (0.012) [1,496]	−0.034 (0.017)
Nonexperimental states	1.369 (0.010) [1,480]	1.397 (0.010) [1,640]	0.028 (0.014)
Location difference at a point in time:	0.178 (0.016)	0.116 (0.015)	
Difference-in-difference:	−0.062 (0.022)		
B. *Control Group: Over 40 and Single Males 20–40:*			
Experimental states	1.759 (0.007) [5,624]	1.748 (0.007) [5,407]	−0.011 (0.010)
Nonexperimental states	1.630 (0.007) [4,959]	1.627 (0.007) [4,928]	−0.003 (0.010)
Location difference at a point in time:	0.129 (0.010)	0.121 (0.010)	
Difference-in-difference:	−0.008: (0.014)		
DDD:	**−0.054** **(0.026)**		

Notes: Cells contain mean log hourly wage for the group identified. Standard errors are given in parentheses; sample sizes are given in square brackets. Years before/after law change, and experimental/nonexperimental states, are defined in the text. Difference-in-difference-in-difference (DDD) is the difference-in-difference from the upper panel minus that in the lower panel.

DDD estimates - Regression

$$w_{ijt} = \alpha + \beta_1 X_{ijt} + \beta_2 \delta_j + \beta_3 \tau_t + \beta_4 Treat_i + \beta_5 \delta_j * \tau_t$$
$$+ \beta_6 \delta_j * Treat_i + \beta_7 \tau_t * Treat_i + \beta_8 \delta_j * \tau_t * Treat_i$$

where:

- i indexes individuals
- j indexes states (1 if exeperimental, 0 if non-experimental)
- t indexes years (1 if after the law, 0 if before)
- w is the log real hourly wage
- X is a vector of observable characteristics
- δ_j is a fixed state effect
- τ_t is a fixed year effect
- $Treat$ is a dummy: 1 if treatment, 0 is control

TABLE 4—TREATMENT-DUMMY RESULTS ACROSS DEMOGRAPHIC GROUPS

Group	Log hourly wage	Log hours/week	Employment (probit)	Percentage changes in labor input
Married women, ages 20–40	−0.043 (0.023)	0.049 (0.022)	−0.047 (0.048) [−0.016]	1.40
Single women, ages 20–40	−0.042 (0.026)	−0.014 (0.024)	−0.095 (0.064) [−0.030]	−5.95
Married men, ages 20–40	−0.009 (0.018)	0.030 (0.015)	−0.139 (0.072) [−0.038]	−1.08
All treatments	−0.023 (0.015)	0.027 (0.014)	−0.079 (0.039) [−0.024]	−0.88

Notes: Standard errors are given in parentheses. The coefficient is that on the third-level interaction in equation (1). The treatment group is the group indicated for each row. The control group is the same as that for Table 3 (all those older than 40 and single men younger than 40). The number in brackets in the employment column is the marginal probability (see text). The change in total labor input is the change in hours at the average-employment/population ratio plus the change in employment in terms of average hours per employed person. This is then divided by the ratio of employment to population to get per-worker figures and then divided by average hours per week for the treatment group to get a percentage change.

The third level interaction, β_8, captures variation wages specific to:

people in treatment **within state** relative to people in control within state;

people in **treatment states** relative to people in **control states**;

people in the years **before** the law relative to people in the years **after** the law

Part II
Matching, mobility and earnings

4 Matching, mobility and earnings

- The **typical job** in modern economies is **brief**, lasts less than a year; but most workers hold **stable jobs** that will last a relatively long time (**more than 7 years**).

- Typical career: young males in the U.S. go through **several brief jobs** early in career (median=7) until finding "good" job which becomes **career jobs** (Hall, 1982; Topel and Ward, 1992; Farber, 2012). **Job shopping** important part of career development and **earnings growth** for young workers.

Topel and Ward (1992)

Following an initial period of **weak attachment** to employers and the labor force, careers tend to **stabilize** with strong labor force attachment and increasing durability of jobs.

The importance of **job-to-job transitions** as a source of turnover **increases with experience**. During first 10 years in the labor market, the typical young worker works for seven employers (2/3 of career jobs).

The evolution of **wages** plays a key role **in transition** to stable employment: **more than 1/3 of early career wage growth** appears to be accounted for by **job changes** (the location of better matches or "good jobs").

For women, less gains from job changes but then, similar rapid within job wage growth early in career (Loprest, 1992).

Some key empirical regularities

1. Earnings rise with labor market experience

2. Earnings positively related to years of job tenure even after controlling for experience in cross-section.

   For example, the basic cross-section regression from Mincer and Jovanovic (1981) using PSID 75-76:

   $$\ln w = \underset{(10.7)}{0.037}X - \underset{(8.08)}{0.0006}X^2 + \underset{(6.6)}{0.305}T - \underset{(4.3)}{0.007}T^2 + \underset{(17.6)}{0.073}ED + 0.2351$$

   $$R^2 = 0.295$$

   Concave cross-section earnings profiles in experience and tenure.

3. Turnover falls with tenure

4. Turnover falls with experience but largely explained by higher tenure (i.e. finding a good match)

4.1 Jovanovic, 1979 "Job matching and the theory of turnover"

Simple two-period model

Ilustrate key concept of **option value** in worker mobility (quit) decisions.

The worker is risk neutral, no discounting, two-period career.

If worker is **self-employed**, he gets q each period.

The **first period** job opportunity pays w_1.

The **second period** of job pays $\tilde{w}_2$, where $E(\tilde{w}_2|w_1) = w_1$ (this is a random walk).

If the worker takes the job in the first period, he gets to **observe** $\tilde{w}_2$ and choose whether to **stay** in the job or **move** to self-employment and earn q in the second period.

Thus **if keep** job at w_1, you have the possibility of getting a **high wage** in period 2, but can always quit, **fail to exercise the option** if gets a lousy wage draw.

So the worker chooses between $2q$ and $w_1 + E[\max(\tilde{w}_2, q)|w_1]$

Claim:

There exists a $w_1^* < q$ such that:

- It is optimal to take the job in period 1 if $w_1 > w_1^*$
- $q - w_1^*$ decreases to 0 as variance in the wages random walk falls.

  $w_1^* < q$ because of option value; **option value declines as variance declines.**

Thanks