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How Acid are Lemons?

Signaling and Adverse Selection
at the Second Labour Market Barrier
for Apprenticeship Graduates





1. Introduction
2. Data and Sample Restrictions
3. Estimation Strategy
4. First Results
5. Identification in the Data



Motivation

Issues:

- 2009: 468,852 appr. graduates
- Around 100,000 graduates change firm and/or occupation
- Qualification function of DS
- Outcome quality of DS
- Labour market success of firm changers?

- Adverse Selection vs. Signaling at second labour market barrier
- Theory 1: Changers are a negative selection and receive wages below their productivity
- Theory 2: Graduation creates signal to the labour market and signals differ between graduates

Which signals improve the labour market success / outcome quality of apprenticeship training?

(BIBB, 2010; Ebbinghaus, 2007; Wachter, 2008; Akerlof, 1970; Spence, 1973; Greenwald, 1986; Salop & Salop, 1976, Katz & Zideman, 1990, Acemoglu & Pischke, 1998; Weiss, 1995)



Motivation

Take-over decision of the training firm – an illustrative example:

Assumption: 10 apprentices with different ability levels (Rank order)

Firm decides that 7 out of 10 graduates have the required ability level
Retention rate: 70%
3 graduates leave firm as “negative selection”

1
2
3
4
5
6
7
8
9
10

Firm decides that 3 out of 10 graduates have the required ability level
Retention rate: 30%
7 graduates leave firm as “negative selection”

- ▶ According to this take-over rule, changers should be a negatively selected group



Motivation

Hiring decision at second labour market barrier – an illustrative example:

3 firm changes from a **firm with a high retention rate and good reputation** and 7 from a **firm with a low retention rate and bad reputation**:

High retention
rate and good
reputation

Low retention
rate and bad
reputation

8
9
10
4
5
6
7
8
9
10

- Firm has to hire from inferior group (= lemons)
 - Adverse selection problem
- Signal 1: Average ability of Red-Group higher than average ability of Green-Group => Red-Group should receive higher wages than Green-Group
- Signal 2: Green-Group from firm with good training reputation, Red-Group from firm with bad training reputation => Red-Group should receive lower wages than Green-Group
- Signal 3: Training firm evaluates individual ability level by assessing IHK / HWK grades

What signal is credible for the wage determination of the hiring firm?



Prior Evidence

Evidence on entry wages at second labour market barrier:

Firm Changers

- Evidence not conclusive – wage losses and gains

Occupation Changers

- Wage gains when changing to a close occupation
- Wage losses if changing to a distant occupation

Further Effects

- Positive post-apprenticeship wage effects found for age, education, firm size, IHK-Grade

Training Intensity & Occupational groups

- Training wage and duration / crafts & construction, manufacturing, commercial & trade

Our contribution:

Assess importance of individual and training firm factors for entry wages of apprenticeship graduates

(Werwatz, 1997; Harhoff & Kane, 1997; Acemoglu & Pischke, 1998; Wydra-Somaggio et al., 2010; Clark & Fahr, 2001; Fitzenberger & Spitz, 2003; Bougeas & Georgellis, 2004; Euwals & Winkelmann, 2004; Geel & Backes-Gellner, 2009; Goeggel & Zwick, 2010; Mohrenweiser & Zwick, 2009)



Research Question and Hypotheses

Research question:

Which apprenticeship signals influence entry wages of skilled employees?

Hypotheses:

1. Firm changers have on average a lower productivity rank in their training firm than stayers
2. The higher the retention rate in the training firm, the lower entry wages in the first skilled job for firm changers
3. The better the training reputation of the training firm, the higher entry wages in the first skilled job for firm changers
4. The higher the productivity rank of a graduate in the training firm, the higher entry wages in the first skilled job



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Overview

Data:

- Linked employer-employee data provided by the IAB (LIAB)
- Waves from 1993 to 2007 – used as pooled data set
- Sample definition: one apprenticeship training, age < 25, full-time position after apprenticeship training, no university degree

Sample restrictions:

- Hypothesis 1: Restrict sample to apprentices in last training spell
 - Enables us to create rank order within each training firm
- Other hypotheses: Restrict sample to those who do not change occupational at 2-digit level and use entry wage of the first skilled job
 - Excludes learning effects of hiring firm



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Overview

Hypothesis 1:

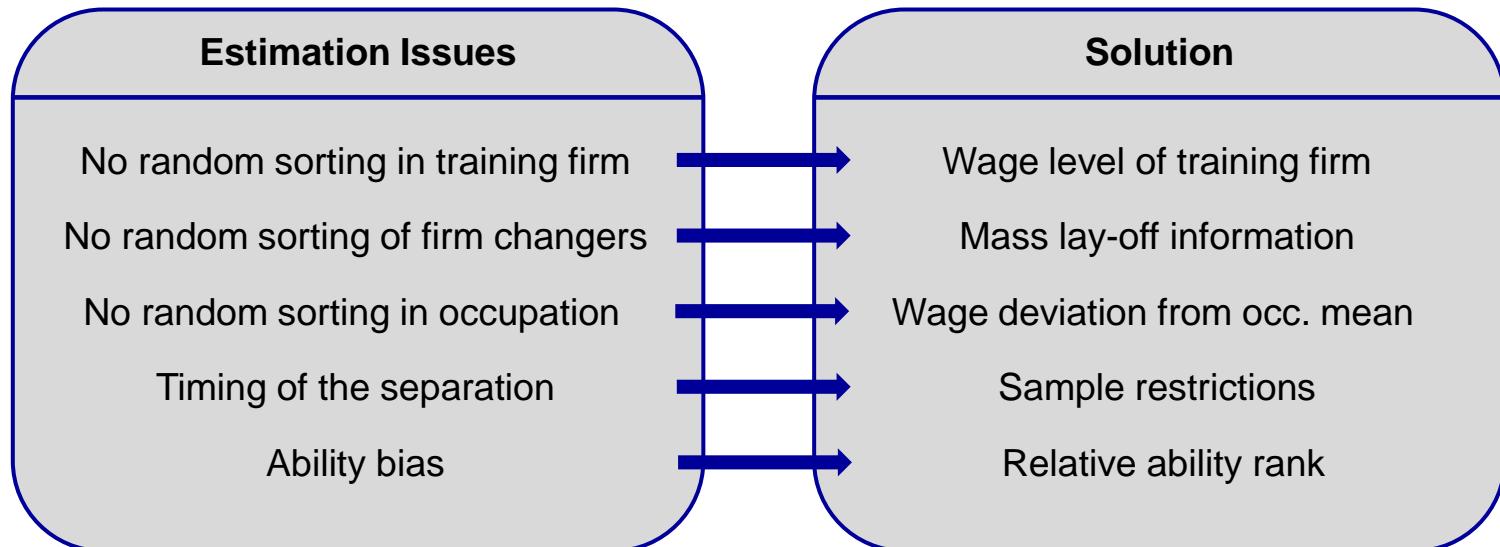
- Calculate relative wage rank of apprentices in their last apprenticeship spell as a proxy for relative productivity / ability level (RR = rank/N+1)
- Compare average RR for movers and stayers at different retention rates

Other Hypotheses:

- $y_{it} = \alpha' + \beta'X_{it} + \gamma'W_{it-1} + \delta'Z_{it} + \varepsilon_{it}$
- y = individual wage deviation from occupational mean in first skilled job
- X = individual characteristics (age, sex, education)
- W = training characteristics (retention rate, wage level, individual ability / productivity level at training firm)
- Z = covariates (training firm characteristics (sector, size), works council, union)



Estimation Issues



(Gibbons & Katz, 1991; von Wachter & Bender, 2006; Goeggel & Zwick, 2010)



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Hypothesis 1

	Stayer	Mover
Retention rate		
RR ≤ 40%	0.52 (0.25)	0.50 (0.23)
40% < RR ≤ 60%	0.52 (0.23)	0.47 (0.23)
60% < RR ≤ 80%	0.52 (0.25)	0.46 (0.28)
80% < RR ≤ 90%	0.51 (0.26)	0.43 (0.31)
RR > 90%	0.50 (0.24)	0.44 (0.29)



Mover-stayer differential seems to increase with retention rate – supports H1



Hypothesis 2-4 (Basic models)

	All	Firm Change	No Change
RR Occupation	-0.297 (0.008)***	-0.207 (0.029)***	-0.232 (0.031)***
RR-Ref-Cat ≤ 40%			
40% < RR ≤ 60%	-0.002 (0.004)	-0.017 (0.007) **	0.006 (0.005)
60% < RR ≤ 80%	0.011 (0.003)***	0.004 (0.007)	0.003 (0.004)
80% < RR ≤ 90%	0.030 (0.004) ***	0.012 (0.010)	0.029 (0.004)***
RR > 90%	0.035 (0.004)***	0.004 (0.023)	0.035 (0.004)***
Wage Rank	0.018 (0.003)***	-0.000 (0.009)	0.020 (0.003)***
Wage Level	0.007 (0.000)***	0.001 (0.000)***	0.011 (0.000)***
R-squared	0.25	0.15	0.29



Hypothesis 2-4 (Interactions with mass-layoff)

	Model with Interactions	
RR Occupation	-0.232 (0.031)***	0.178 (0.129)
RR-Ref-Cat ≤ 40%		
40% < RR ≤ 60%	-0.016 (0.008)**	-0.122 (0.051)**
60% < RR ≤ 80%	0.005 (0.008)	-0.126 (0.056)**
80% < RR ≤ 90%	0.015 (0.011)	-0.064 (0.092)
RR > 90%	-0.011 (0.027)	-
Wage Rank	0.002 (0.010)	0.013 (0.072)
Wage Level	0.001 (0.000)***	0.001 (0.001)
Mass-layoff	-0.030 (0.093)	
R-squared	0.16	



Core Findings (Summary)

Hypothesis 1:

- Increasing difference between movers and stayers with retention rates
- Differences significant at the 1%-level

Other Hypotheses:

- No effect for individual signal (Rank in training wage distribution) for movers
- Positive wage effect of retention rate for stayers – not for movers
- Negative effect for occupational retention rate
- Training firm reputation might be important – further specifications and robustness checks necessary
- No wage penalty for changers from mass-layoff firm

Outlook:

- Further Instrument: Variation in retention rates
- Compare wages three years after entering the labour market



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Last Apprenticeship Spell

sort id spell_nr

*** Transition at second labour market barrier

```
gen Aus = 1 if (berstell[_n+1]>=1 & berstell[_n+1]<=4 | berstell[_n+1]==8 | berstell[_n+1]==9) &  
berstell==0 & id==id[_n+1] & leistart[_n+1]==. & leistart==. & pers_gr==102
```

*** Transition with unemployment spell

```
replace Aus = 2 if (berstell[_n+2]>=1 & berstell[_n+2]<=4 | berstell[_n+2]==8 | berstell[_n+2]==9) &  
leistart[_n+1]<3 & berstell==0 & id==id[_n+1] & id==id[_n+2] & pers_gr==102
```

*** Identify cases with two training programs

```
gen aus2 = 1 if Aus==1 | Aus==2  
egen ausx = sum(aus2), by (id)  
drop aus2
```

*** Date for last spell in apprenticeship period

```
gen date = .  
replace date = endepi if (Aus==1 | Aus==2) & ausx==1  
egen date_b = sum(date), by(id)  
replace date_b = . if date_b==0
```



First Employment Spell

sort id spell_nr

*** Direct transition in first job

```
gen Besch = 1 if (berstell>=1 & berstell<=4 | berstell==8 | berstell==9) & berstell[_n-1]==0 &  
id==id[_n-1] & leistart[_n-1]==. & leistart==. & pers_gr[_n-1]==102
```

*** Transition with unemployment detour

```
replace Besch = 2 if (berstell>=1 & berstell<=4 | berstell==8 | berstell==9) & leistart[_n-1]<3 &  
berstell[_n-2]<3 & id==id[_n-1] & id==id[_n-2] & pers_gr[_n-2]==102
```

*** Identify cases with only one first job

```
gen besch = 1 if Besch==1 | Besch==2  
egen beschx = sum(besch), by (id)  
drop besch
```

*** Generate date for first full time employment spell

```
gen date = .  
replace date = begepi if (Besch==1 | Besch==2) & beschx==1  
egen date_a = sum(date), by(id)  
replace date_a = . if date_a==0
```



Firm Changer

sort id spell_nr

gen agw=.

replace agw = 1 if Aus[_n-1]==1 & idnum!=idnum[_n-1] & id == id[_n-1] & Besch==1

replace agw = 1 if Aus[_n-2]==2 & leistart[_n-1]<3 & idnum!=idnum[_n-2] & id==id[_n-1] & id==id[_n-2] & Besch==2

replace agw = 0 if agw!=1

egen agwechsel = sum(agw), by(id)



Wages

*** Wage in the last apprenticeship spell

```
gen wage = .
replace wage = lohn if date_b == endepi
egen w_ausende = max(wage), by(id)
drop wage
```

*** Wage in first full time job

```
gen wage = .
replace wage = lohn if date_a == begepi
egen w_beschbeg = max(wage), by(id)
drop wage
```



Retention Rate

sort id spell_nr

```
gen anz_azu_ende = 1 if date_b==endepi & pers_gr==102 & leistart==. & berstell==0
replace anz_azu_ende = 0 if anz_azu_ende==.
egen anz_azu_firm = sum(anz_azu_ende), by(idnum jahr)
```

```
gen uebernahme = 1 if id==id[_n-1] & idnum==idnum[_n-1] & anz_azu_ende[_n-1]==1
replace uebernahme = 0 if uebernahme==.
egen uebernahme_firm = sum(uebernahme), by(idnum jahr)
drop uebernahme
drop anz_azu_ende
```

gen u_quote_ind=uebernahme_firm/anz_azu_firm

replace u_quote_ind=. if u_quote_ind>1



Relative Wage Rank

```
sort idnum jahr beruf2 w_ausende
```

```
by idnum jahr beruf2: egen rank = rank(w_ausende) if (Aus==1 | Aus==2) & ausx==1
```

```
by idnum jahr beruf2: egen n = count(w_ausende) if (Aus==1 | Aus==2) & ausx==1
```

```
replace n = n+1
```

```
gen gg = rank/n
```

```
egen rel_rank_b = max(gg), by(id)
```

```
by idnum jahr berufg: egen nr_rank = sum(rank)
```



Thank you for your attention!

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