

The Demand for Older Workers: The Role Of Technology And Skill

John Abowd
John Haltiwanger
Julia Lane
Kevin McKinney
Kristin Sandusky

NBER Summer Institute 2004

Overview

- Rapid technological change characteristic of economy
- Documented impact on wage inequality and the relative demand for high skill and low-skill workers
- What is impact on older workers?
 - Retirement decisions
 - Income support
- Particularly important because of aging of baby boom generations
- What are policy implications?
 - Training?
 - Placement?

Contributions of Paper

- How do older workers differ from younger workers in terms of skills?
- What is the relationship between older workers' skill levels and the entry and exit of workers from the workforce?
- What is the relationship between technology at firm level and demand for skill?
- How do all these factors translate into outcomes for older workers (employment, retirement, wages)?

Why Contributions Are Possible

- New Measures of Workforce Skill
 - Measure human capital employed by the business
 - Exploit the linked employer-employee data
 - Exploit different dimensions (general skills vs. experience) of human capital
 - Differences by age group and by dimensions of skill
- New Dataset directly matching firm measures of technology and workforce composition
 - Can model and estimate demand for skills as function of technology
 - Universe measures of workforce composition at firm level
 - Measure technology changes and relate to changes in demand for human capital
 - Use joint distribution of skill and age and technology skill relationships to characterize impact of technology on demand for older workers.
- Use longitudinal nature of data to examine worker entry and exit

Firm-level Demand by Skill

- Production relationship at firm level as function of skill composition for firm j with technology Z :

$$y_{jt} = F(Z_{jt}, L_{1jt}, \dots, L_{Hjt})$$

where L_{sjt} is the quantity of type s workers

- Treating Z as quasi-fixed, cost minimization (Shepherd's lemma) yields for workers of type s (where S is share of type s workers:

$$S_{sjt} = S(Z_{jt}, y_{jt}, w_{1jt} / w_{Hjt}, \dots, w_{sjt} / w_{Hjt}, \dots)$$

Local Labor Supply by Skill

- County-level wage rate of workers of a given skill taken as fixed
- We measure the market relative wage rate as the ratio of the average wage for a particular skill group to the county-average wage rate for the given time period

Deriving the Demand for Age Groups from Skill Demand

- Aggregating across firms yields:

$$S_{st} = \sum_j (L_{jt} / L_t) S_{sjt}$$

- The accounting relationship between share of workers of age a (λ_{at}), the demand for type s workers, and the share of age a workers with type s skills (λ_{ast}), is given by:

$$\lambda_{at} = \sum_s \lambda_{ast} S_{st}$$

- We can characterize the firm level skill demand equations and use these accounting relationships to derive the demand for workers of a given age
- Supply conditions in the local labor market for given age groups complete the analysis

New Measures of Skill

- Skill measures are complex combination of variety of factors
 - Problem solving skills; people skills; ability; education; family background; experience
- Years of education are poor proxy for skill
 - particularly for older workers
- When using wage rates as a proxy for skill or human capital it is important to separate out firm effects

Theoretical Framework

- The general human capital of an employee is represented by h , which is estimated from the portable part of the individual's wage rate
- The firm-specific part of the wage rate is used to model compensation design issues
- The un-normalized distribution $f(h)$ measures the firm's human capital choices
- We estimate the normalized distribution of human capital, $g(h)$
- For details see Abowd, Lengermann and McKinney (2003) (lehd.dsd.census.gov)

Measuring Human Capital: Data

- State UI wage records and ES-202 employment data
- Universal for each state
- In this analysis, we focus on 3 states that have following properties
 - Data are available in 1992 and 1997 (Economic Census years so technology measures are available)
 - Among the seven states for which ALM estimate human capital

Measuring of Human Capital: Estimation

$$\ln w_{it} = \theta_i + x_{it}\beta + \psi_{J(i,t)} + \varepsilon_{it}$$

- We use a decomposition of the log real annualized full-time, full-year wage rate ($\ln w$) into person and firm effects.
- The person effect is θ .
- The firm effect is ψ , where $J(i,t)$ is the employer of i at t .
- Continuous, time-varying effects are in $x\beta$, where some of the x variables are human capital measures (labor force experience) and some correct for differential quality in our measure of full-time, full-year wage rate.

Human Capital: Individual Measure

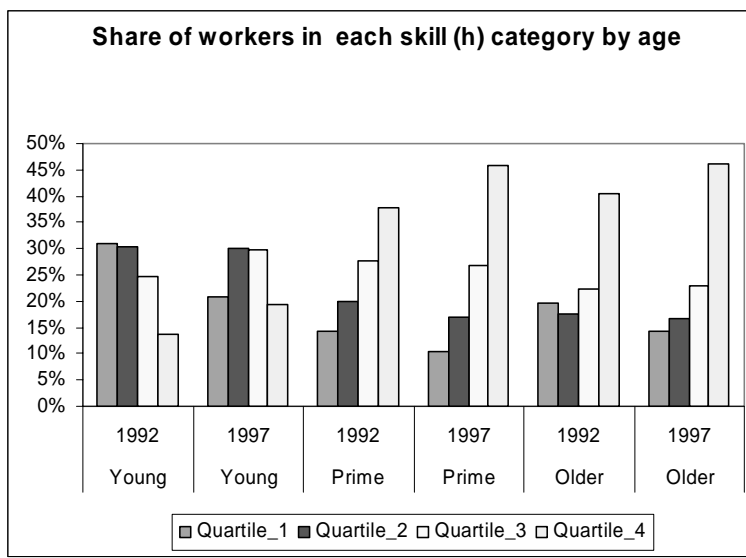
$$\hat{h}_{it} = \hat{\theta}_i + \text{labor force experience part of } x_{it}\hat{\beta}$$

- Individual human capital, h , is the part associated with the person effect and the measurable time-varying personal characteristics (labor force experience).
- Our human capital measure is not a simple ranking by wage rate because of the removal of the firm effect and residual.
- In what follows, we exploit overall h but also components.
- Firm human capital measures, H , are based on statistics computed from the distribution of $g(h)$.

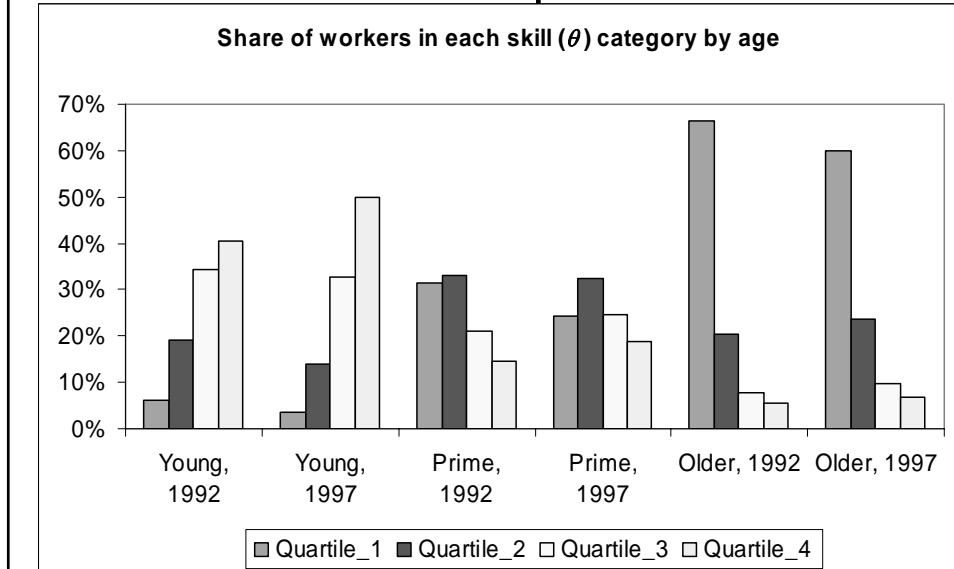
Gathering Information

Characterizing the Distribution of Human Capital by Age

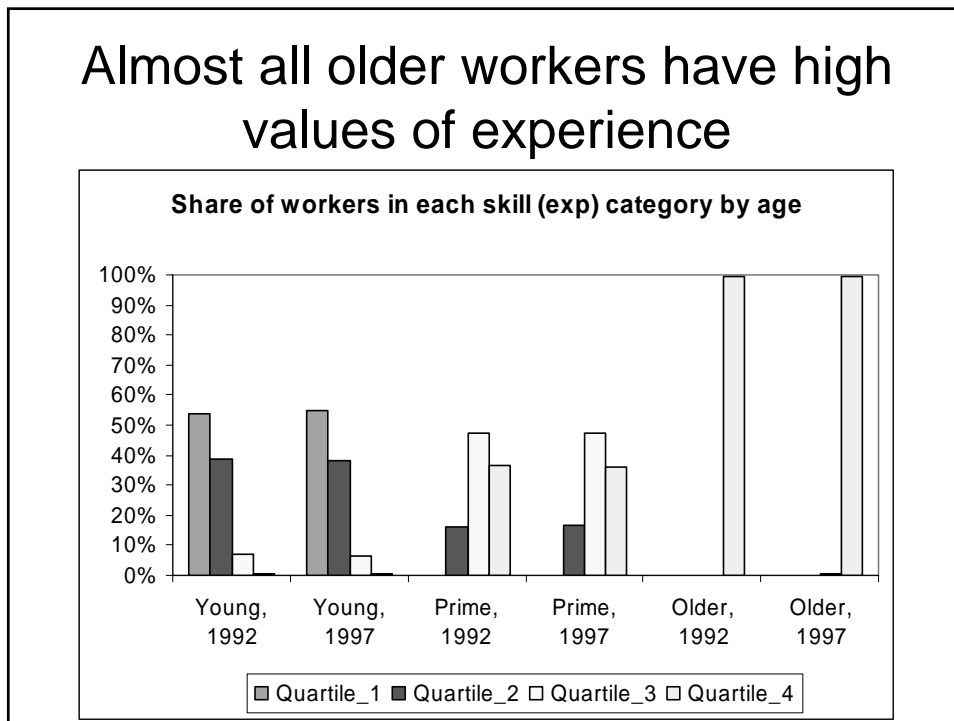
Older and prime age workers more skilled than younger workers



Very high proportions of older workers have low person effects

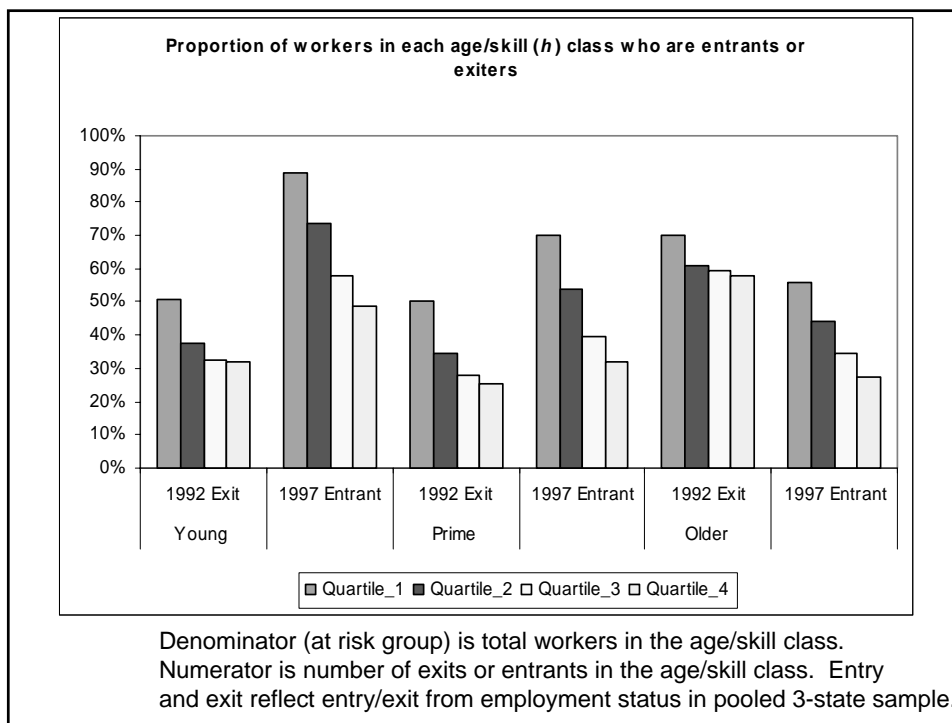


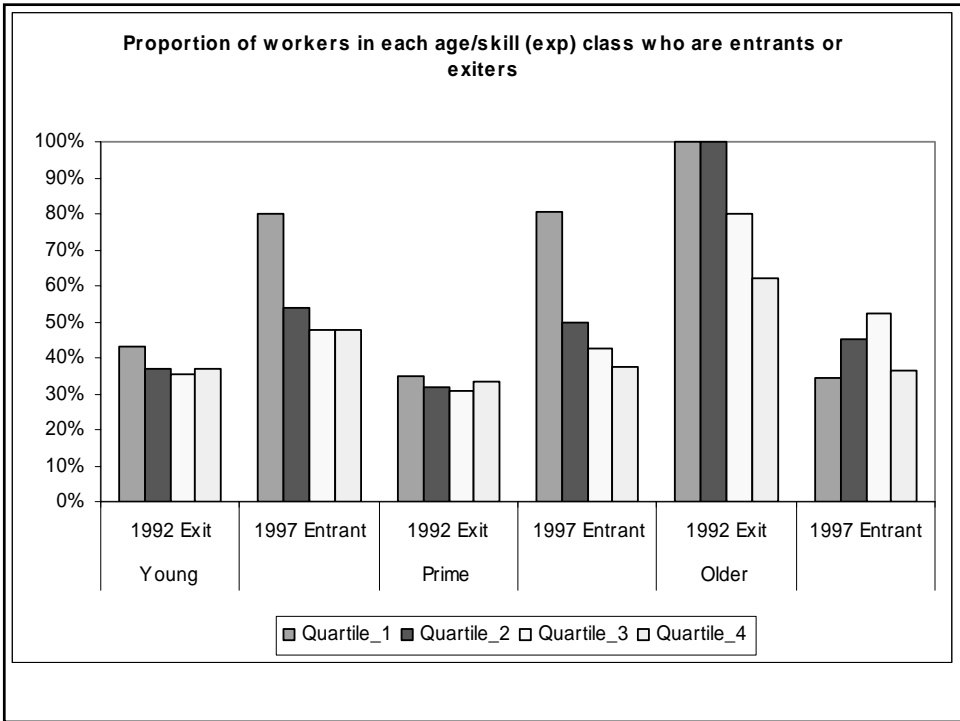
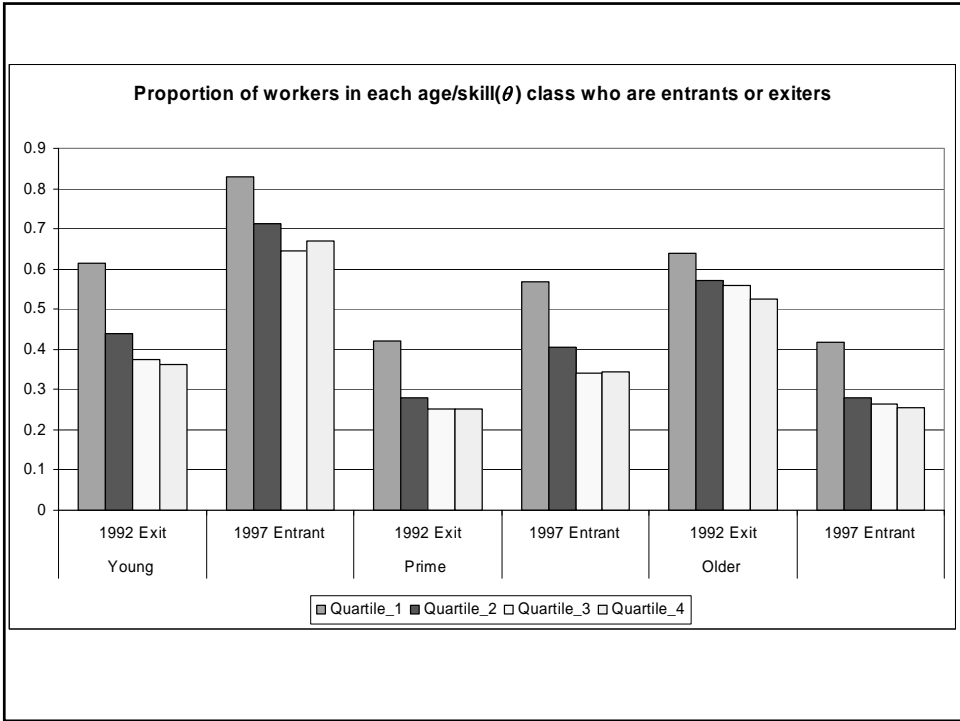
Almost all older workers have high values of experience



Basic Facts

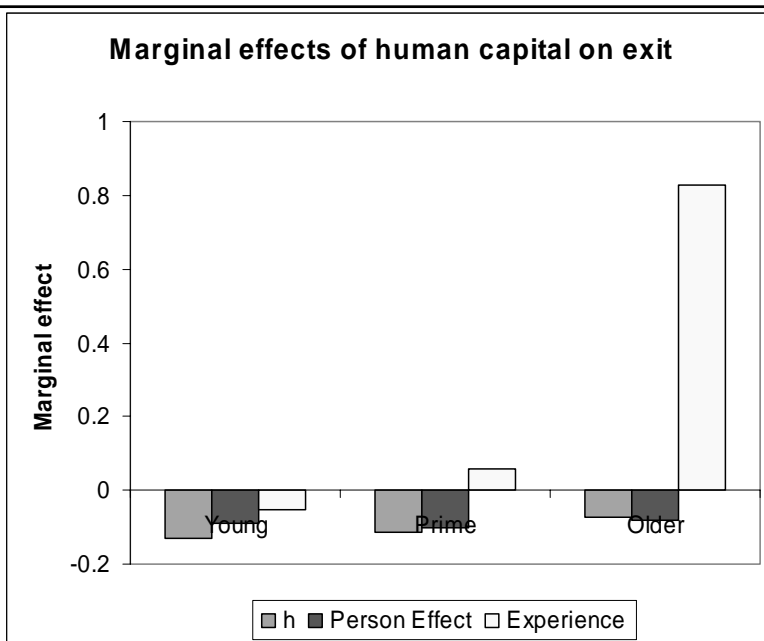
- Up-skilling for all age groups
- Prime and older workers with a large share of high h workers
 - But older workers high h is mostly high experience
 - In terms of general experience, a much smaller share with high general skills (person effect)



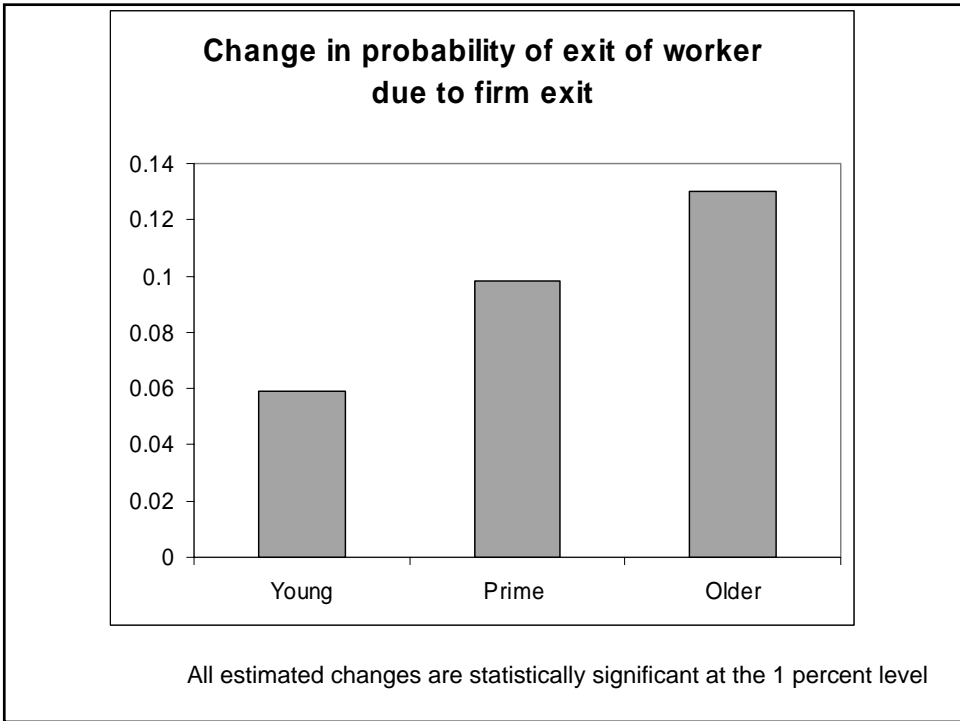
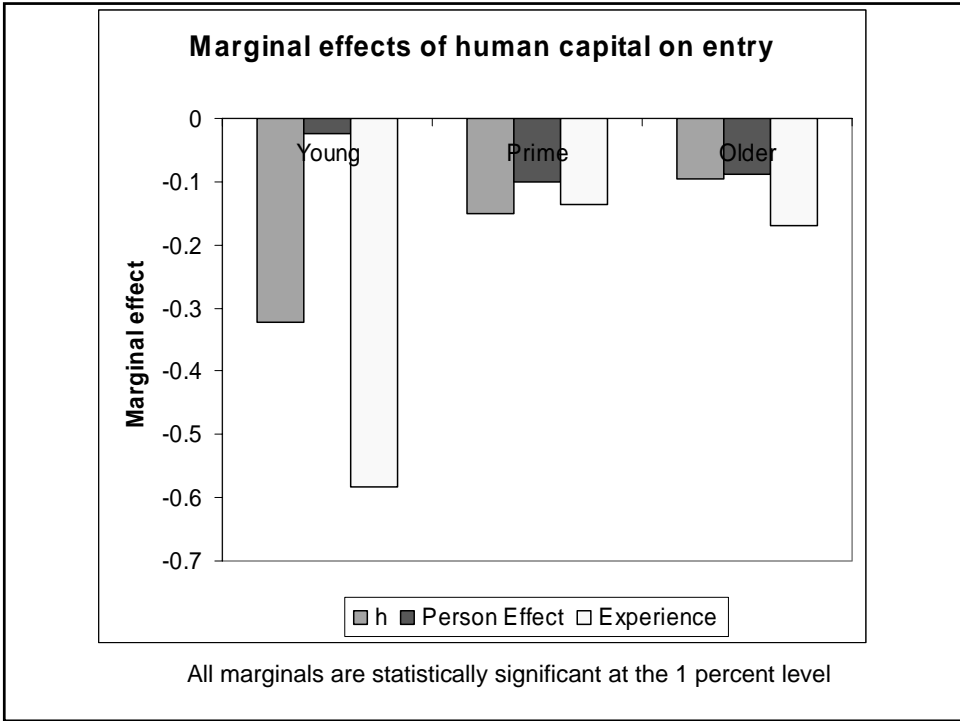


Basic Facts

- Higher entry/exit rates for:
 - Younger and Older
 - Low skill conditional on age
- Entry rates especially high for:
 - Young workers
 - Low skill workers conditional on age
 - Pattern driven by person effects
 - For older workers, high experience workers at least as likely to enter
- Exit rates especially high for:
 - Older workers
 - Low skill workers conditional on age
 - Pattern driven by person effects
 - Prime age workers, not much difference in exit rates by experience.
- Recall that high proportion of older workers are low person effect workers:
 - Large positive gap between exit rate and entry rate for older, low person effect workers
 - Suggests up-skilling of older workers partly driven by high exit rate of low person effect older workers.
- Simple probits of exit and entry confirm and reinforce differences in exit and entry patterns by skill



All marginals are statistically significant at the 1 percent level



Demand for Human Capital and Technology

- Specify demand equations at the firm level
- Merge in technology measures from surveys in 1992 and 1997 (Economic census years)
- Estimate these equations for entire labor force
- Extract demand for older workers from these demand equations

Empirical Specification at Establishment-Level

Model 1: Levels

$$S_{sjt} = \alpha_0 + \sum_{\ell} \alpha_{1\ell} Z_{\ell jt} + \sum_{\ell} \alpha_{2\ell} (w_{\ell jt} / w_{Hjt}) + \alpha_3 Y_{jt} + \varepsilon_{sjt}$$

Model 2: First Differences

$$\Delta S_{sjt} = \sum_{\ell} \alpha_{1\ell} \Delta Z_{\ell jt} + \sum_{\ell} \alpha_{2\ell} \Delta (w_{\ell jt} / w_{Hjt}) + \alpha_3 \Delta Y_{jt} + \Delta \varepsilon_{sjt}$$

Construction of Linked Data

- Human capital file containing worker and firm identifiers, detailed worker characteristics
- Business file containing firm identifiers and detailed business characteristics.
- These two files linked by employer identifiers to form a business-level file.
- Unit of business observation is the most detailed disaggregation available of EIN, State, 2-digit SIC, and county (pseudo-establishment)

Construction of Technology Measures

- Data for the manufacturing sector for the 1992 and 1997 Annual Survey of Manufacturers (ASM).
- For services, wholesale trade and retail trade we use data from the Business Expenditure Survey (BES).
- In the majority of ASM cases, we are able to link the two files by EIN, State, 2-digit SIC (SIC2), and county.
- In the BES, there is no state county level detail and the survey is conducted using more aggregated business units (EIN, 2-digit SIC or Enterprise, 2-digit SIC)
- In all cases, unit of observation is EIN, SIC2, County
 - If technology measures are available only at more aggregated level for firm, we make a uniformity assumption.

Establishment Human Capital Measures

- Using $g_{jt}(h)$ measure
 - Proportion of employment above median percentile (1992 basis)
 - Proportion above the 75th percentile
 - Proportion below the 25th percentile

Technology Measures

- Technology Measures
 - Computer Investment/Total Investment (ASM, BES, 1992 only)
 - Spending on Computer Software and Data Processing Services/Sales (ASM, BES, 1992 and 1997)
 - Inventory/Sales (higher inventories indirect indicator of lack of technology; ASM, BES, 1992 and 1997)
- Traditional Technology Measures
 - Equipment Investment/Total Investment (ASM, BES, 1992)
 - Average Beginning and Ending Assets/Employment (ASM 1992 and 1997, BES 1992)
- Firm Effect from Wage Equation
 - Potential proxy for “unmeasured” technology and other things

Technology Measures across Sectors (Median Business)

- Computer investment/investment much higher in non-manufacturing (0.000 v. 0.005)
- Equipment investment/total investment much higher in manufacturing (0.97 v. 0.82)
- Non-manufacturing more capital intensive (3.8 v. 9.8)
- Inventory holdings higher for manufacturing (0.09 v. 0.04)
- Firm effect lower in non-manufacturing and dispersion greater (0.14 v. -0.10)

Regression Results

- All specifications include controls for scale (output)
 - Results show non-homotheticity (larger businesses demand more skilled workers).
- All specifications include relative wage measures by skill type at county level
 - Results show that businesses in counties with high wages for skilled workers substitute away from skilled workers.
- Focus on details of results to follow show impact of technology:
 - Results labeled Sep. are for specifications single “technology” measure as designated.
 - Results labeled Comb. Are for specifications with all “technology” measures.
- Results are estimated using both level and first difference specifications:
 - Measures of technology consistently available in 1992 and 1997 are not as rich.
- Only results available to date are for overall human capital “h”.
 - Results for different components of “h” (experience and person effect) are in process and are critical for this analysis of the demand for older workers

Computer Investment to Total Investment (Level)

		<i>ASM</i>	<i>BES</i>
Proportion of workers at business above median	Sep.	0.057 (0.011)	0.117 (0.014)
	Comb.	0.091 (0.010)	0.087 (0.014)
Proportion of workers at business above 75th percentile	Sep.	0.070 (0.008)	0.097 (0.012)
	Comb.	0.089 (0.008)	0.080 (0.012)
Proportion of workers at business below 25th percentile	Sep.	-0.022 (0.009)	-0.088 (0.012)
	Comb.	-0.049 (0.008)	-0.055 (0.012)

Software and Data Processing Expenditures to Sales (Level)

		<i>ASM</i>	<i>BES</i>
Proportion of workers at business above median	Sep.	1.640 (0.421)	0.062 (0.036)
	Comb.	1.062 (0.376)	0.036 (0.033)
Proportion of workers at business above 75th percentile	Sep.	1.261 (0.315)	0.053 (0.030)
	Comb.	0.803 (0.302)	0.034 (0.028)
Proportion of workers at business below 25th percentile	Sep.	-0.898 (0.354)	-0.041 (0.031)
	Comb.	-0.514 (0.315)	-0.019 (0.029)

Log Capital Intensity (Level)

		<i>ASM</i>	<i>BES</i>
Proportion of workers at business above median	Sep.	0.075 (0.002)	0.017 (0.003)
	Comb.	0.067 (0.002)	0.016 (0.003)
Proportion of workers at business above 75th percentile	Sep.	0.037 (0.002)	0.011 (0.003)
	Comb.	0.036 (0.002)	0.012 (0.003)
Proportion of workers at business below 25th percentile	Sep.	-0.062 (0.002)	-0.012 (0.003)
	Comb.	-0.053 (0.002)	-0.012 (0.003)

Firm Effect (Level)

		<i>ASM</i>	<i>BES</i>
Proportion of workers at business above median	Sep.	0.276 (0.011)	0.205 (0.015)
	Comb.	0.172 (0.010)	0.173 (0.015)
Proportion of workers at business above 75th percentile	Sep.	0.113 (0.008)	0.132 (0.012)
	Comb.	0.056 (0.008)	0.105 (0.013)
Proportion of workers at business below 25th percentile	Sep.	-0.261 (0.009)	-0.191 (0.013)
	Comb.	-0.179 (0.009)	-0.169 (0.013)

Change in Software and Data Processing Expenditure to Sales (First Difference)

		<i>ASM</i>	<i>BES</i>
Proportion of workers at business above median (first difference)	Sep.	-0.312 (0.526)	0.007 (0.003)
	Comb.	-0.288 (0.524)	0.014 (0.004)
Proportion of workers at business above 75th percentile (first difference)	Sep.	0.317 (0.470)	0.005 (0.003)
	Comb.	0.322 (0.470)	0.011 (0.004)
Proportion of workers at business below 25th percentile (first difference)	Sep.	-0.125 (0.433)	0.001 (0.003)
	Comb.	-0.145 (0.429)	-0.003 (0.004)

Summary of Findings

- Computer Investment
 - In cross-section, positive correspondence between computer investment and the level of human capital at a business
- Capital Intensity
 - Consistently find positive relationship in all specifications (level and first difference)
- Other Computer-Related Expenditures
 - Consistently find positive relationship in level specifications. Change specification only significant for non-manufacturing
- Model Performance
 - Findings at firm level with these new measures of skill and technology support general finding in literature that high tech businesses demand high skilled workers
- Much to be done:
 - Sample selection corrections
 - Analysis for components of skill
 - Interesting in its own right but essential for this analysis of demand for older workers as workers of different ages have different bundles of skills

Implications for Older Workers?

- Without results on components of skill, difficult to draw inferences:
 - Older workers are high h workers on average but mostly via experience
 - Older workers are low person effect workers on average.
 - Open question:
 - While high tech businesses demand higher skills, which component of skill is demanded more?

Interesting Related Factors We Need to Consider...

- Distribution of older workers across firms is highly uneven:
 - Only ten percent of jobs are held by workers between the ages of 55 and 70
 - Less than half of all businesses employ even one older worker.
 - Less than 15% (of SEINs) employ 5 or more older workers.
 - This varies substantially by industry and size class
- Open question: Can we account for these differences across firms and industries with technology?

Putting Pieces Together...

- New measures of skill
- Age/skill distribution shows young, prime and older workers have very different dimensions of skill:
 - Not surprisingly, older workers are more experienced
 - Interestingly, older workers have lower person effects
- Age/skill distribution changing:
 - Upskilling for all age groups
 - Older workers upskilling driven in part by high exit rate of low person effect older workers
- Technology and skill closely linked at micro level
 - Substantial “to-do” list here especially with respect to impact of technology on different dimensions of skill
- Overall to-do list is to combine findings on technology/skill and joint age-skill distribution
 - Two separate effects – one on older worker earnings; the other on exit.