Resilience in the Labor Market

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Stylized Facts

- Lump-of-labor fallacy
- Nature of work is rapidly transforming
- Demands are placed on the labor force to adapt
- Policy issue is NOT that we are “running out of work” BUT that workers need to be able to adjust to changing skill demands

What We Do

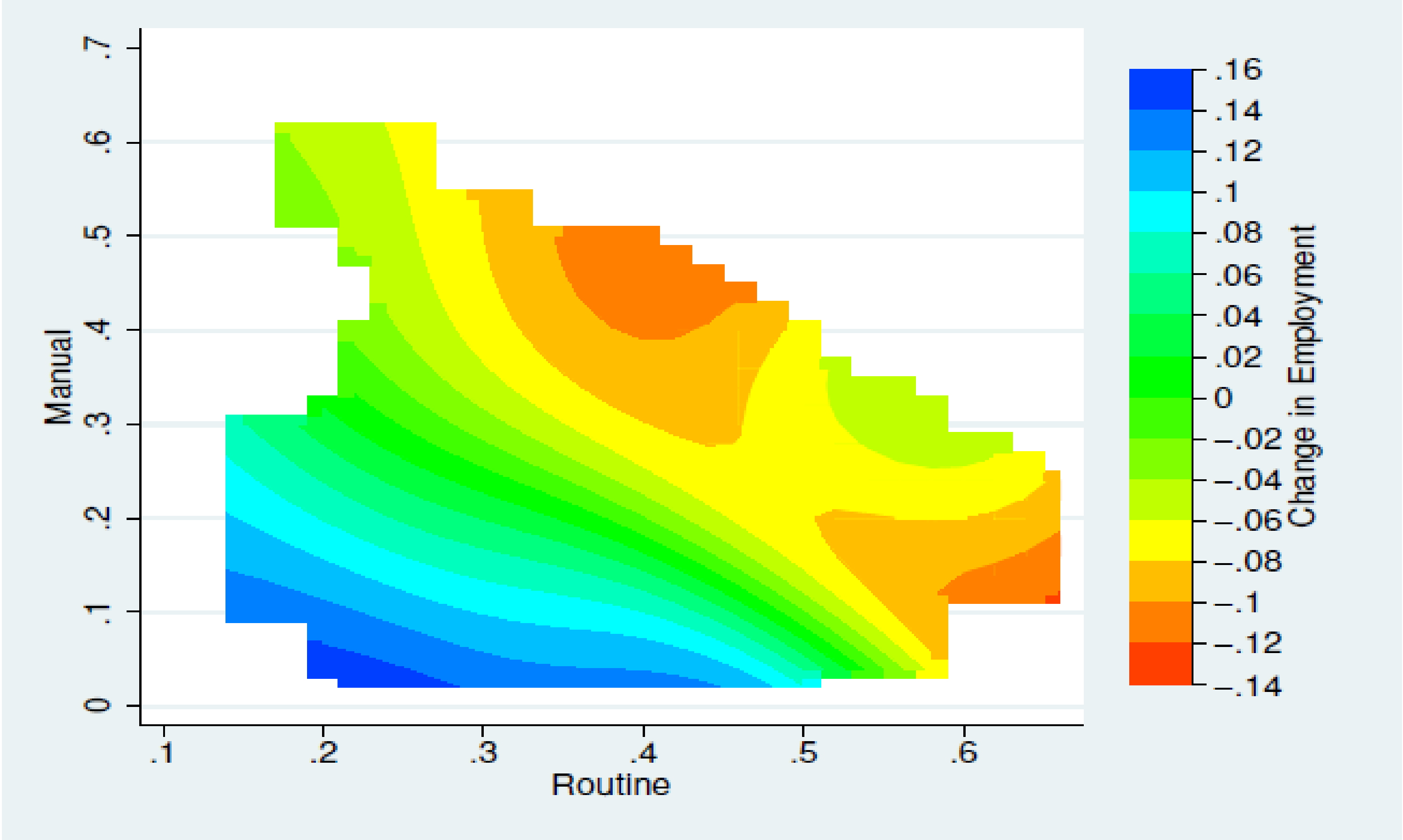
Provide anatomy of how workers adjust to changing skill demands brought about by recent technological changes, and how those adjustments relate to wage and employment outcomes

- Take a task-based approach
- Use high-quality individual-level panel data for West Germany (1990-2005)
- Data includes employment and wage history of workers together with individual level task measures that vary within and between occupations, and over time
- Investigate individual-level task changes owing to occupational mobility and task changes within occupations, taking differences in task-specific human capital and other forms of human capital into account

Task-Based Approach to Technological Change

Occupation	Nonroutine Cognitive Task Inputs	Manual Task Inputs	Routine Task Inputs
Roofer	25.7	60.4	**13.8**
Teacher	72.7	13.5	**13.9**
Painter, varnisher	24.4	56.3	**19.3**
Land surveyor	75.0	5.7	**19.4**
Construction/energy machinery operator	14.6	35.4	**50.0**
Quantity surveyor, accountants	48.3	1.7	**50.0**

Changes in Employment Shares by 1990 Task Inputs (1990-2005)



Main Findings

- Workers move away from routine tasks towards non-routine cognitive tasks
- Task adjustments occur within occupations and through occupational mobility
- Both sources of adjustment are important in terms of wages and employment
- Task-specific human capital important beyond general education effects
- Individual component important, not only average occupational task inputs

Lessons for AI and Labor

- Time period 1990-2005: computerization, information technology, automation relevant technologies (substitutes for routine tasks)

- AI potentially different effects on labor demand than robots and software

  – Affects different tasks/occupation (e.g. medical diagnosis, detecting fraud)

  – Affects very different people (e.g. laboratory personnel, doctors, lawyers)

- AI might potentially countervail current trends in wage inequality

Lessons for AI and Labor

- Assessment includes substantial uncertainty:
  - How will technology evolve in the future?
  - To which tasks is AI complementary?
  - Which new tasks/occupations will arise?
- Again: most likely we will not run out of work but workers need to be resilient, i.e. capable to cope with changes in skill demand

References

Own work with co-authors:

Sandra E. Black, Alexandra Fedorets, Bernd Fitzenberger

Literature (non-exhaustive list):

Task-Biased Technological Change and Polarization: Autor, Levy, Murnane (2003), Autor, Katz and Kearney (2006, 2008), Autor and Dorn (2009), Acemoglu and Autor (2011), Autor (2015), Goos and Manning (2007), Goos, Manning and Salomons (2014), Cortes (2016), Cortes, Jaimovich and Siu (2017), Cortes and Gallipoli (2018), Cortes and Salvatori (2019), Oesch and Menez (2011)

Automation: Acemoglu and Restrepo (2019a, 2019b, 2018), Autor and Salomons (2018), Caselli and Manning (2019), Dauth et al. (2019), Graetz and Michaels (2018)

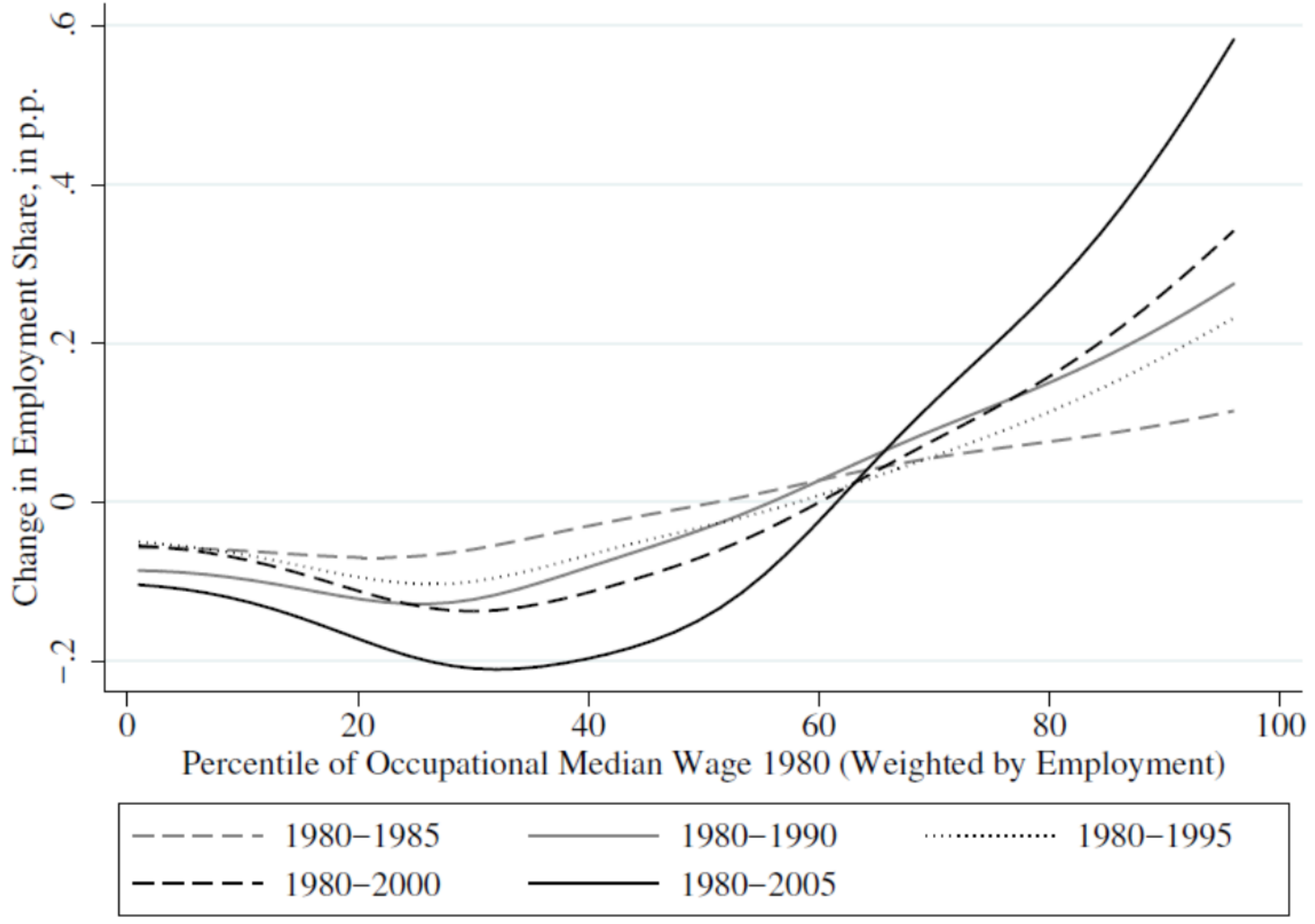
Task-specific Human Capital and Occupational Change: Gathmann and Schönberg (2010), Poletaev and Robinson (2008), Kamborouv and Manovskii (2008, 2009), Groes, Kircher and Manovskii (2014), Yamaguchi (2012)

AI and the Labor Market: Webb (2019)

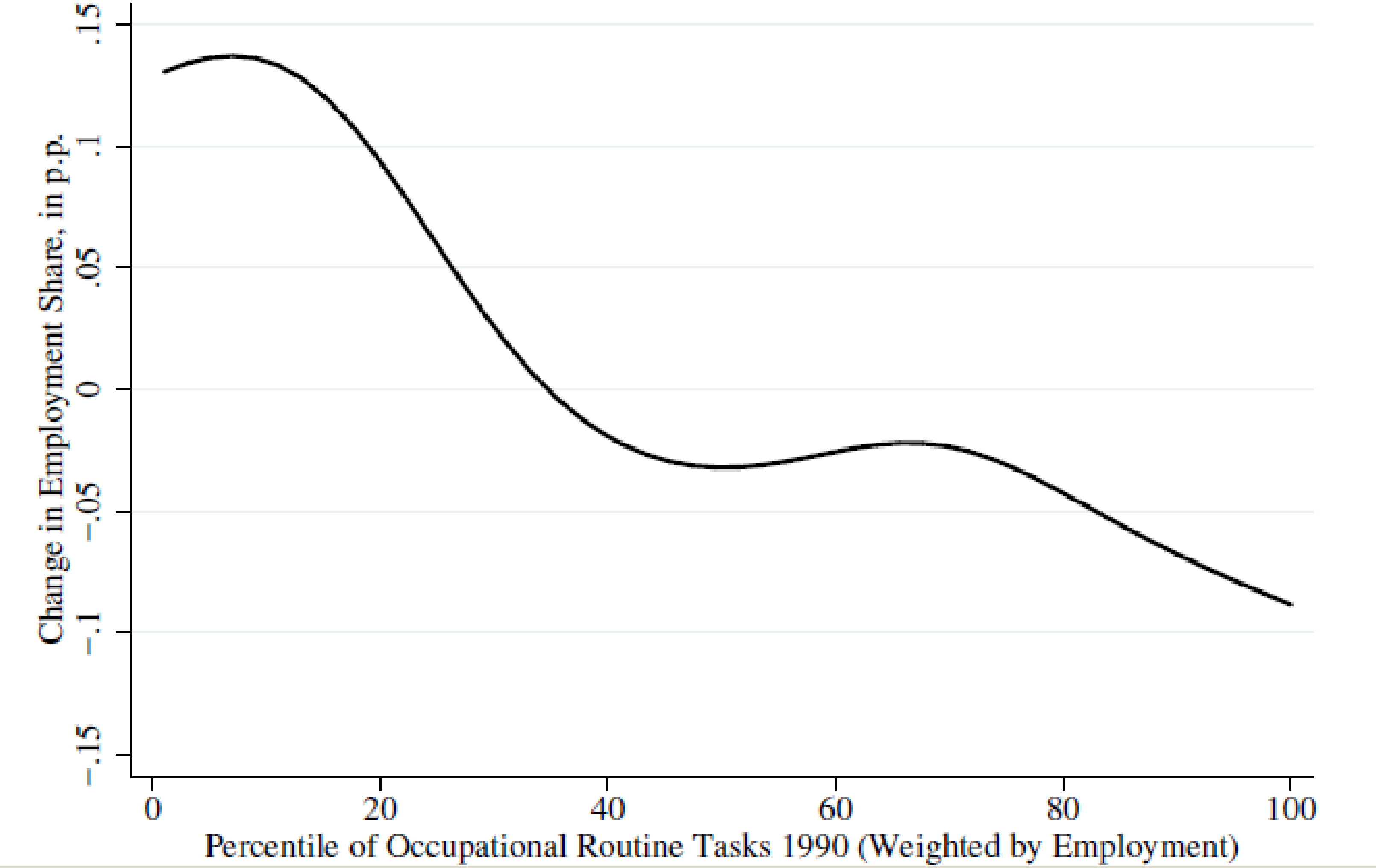
Thank You!

Additional Slides

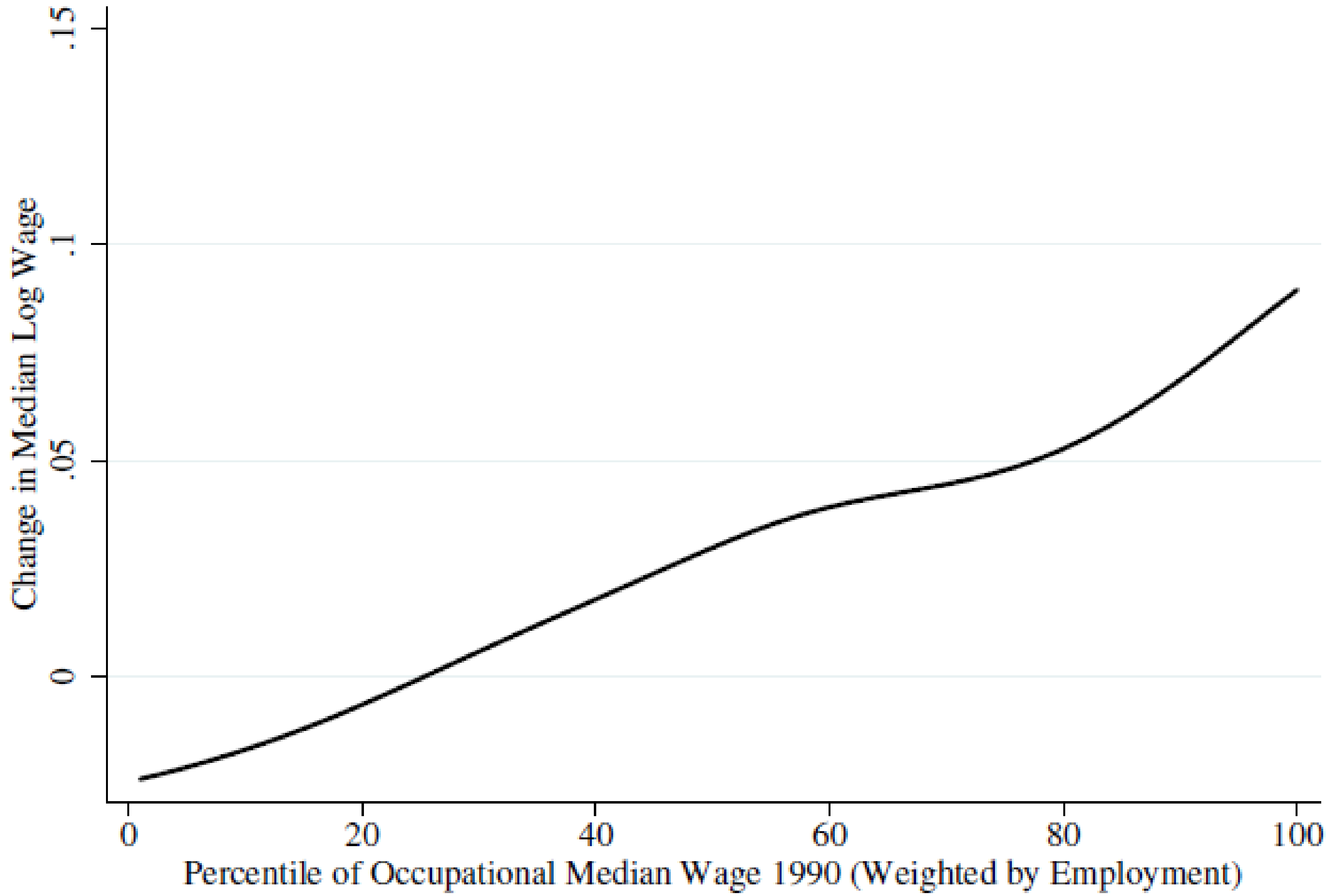
Changes in Employment by Occupational Skill Percentile, 1980-2005



Changes in Employment by Occupational Skill Percentile (1990-2005)

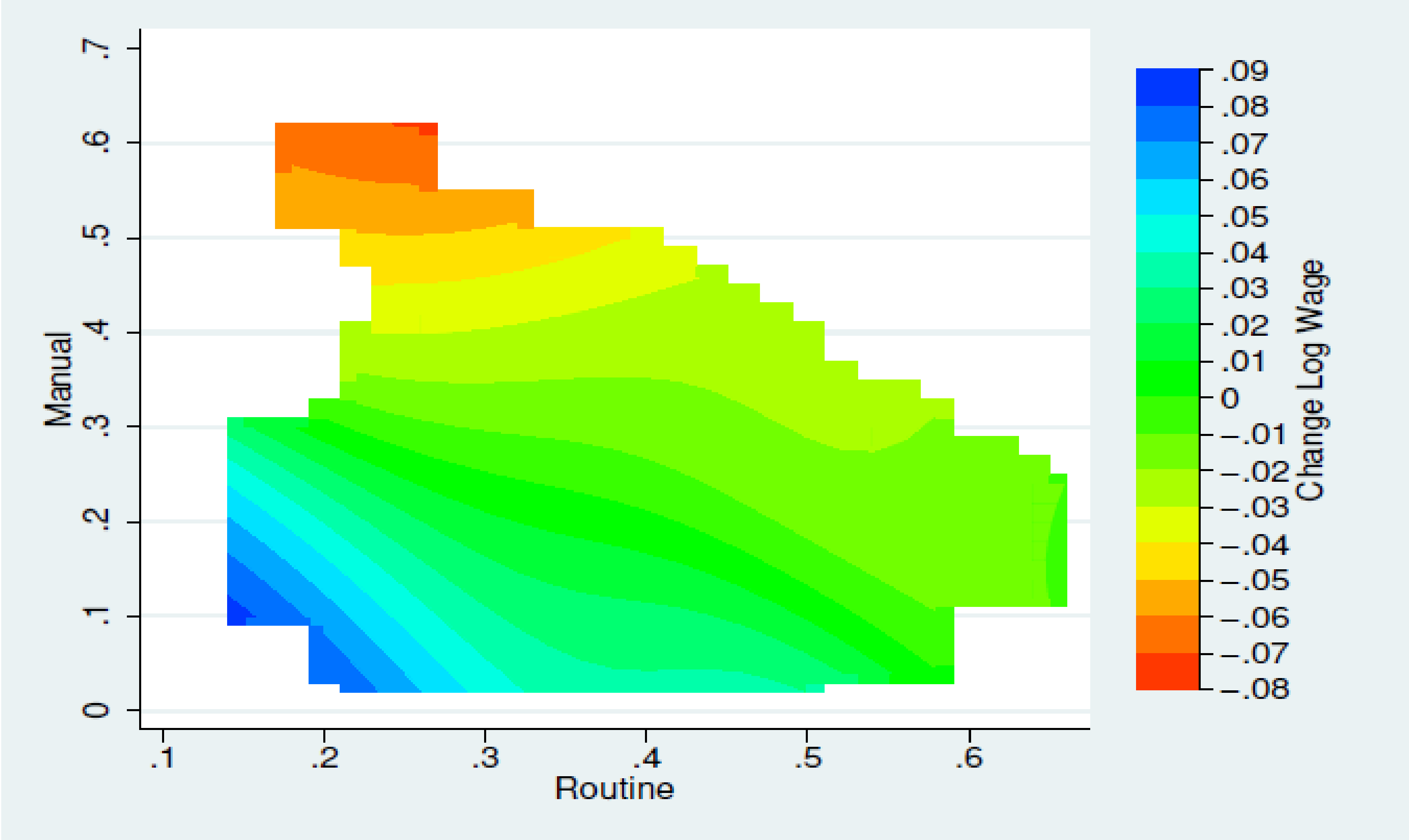


Changes in Wages by Occupational Skill Percentile (1990-2005)

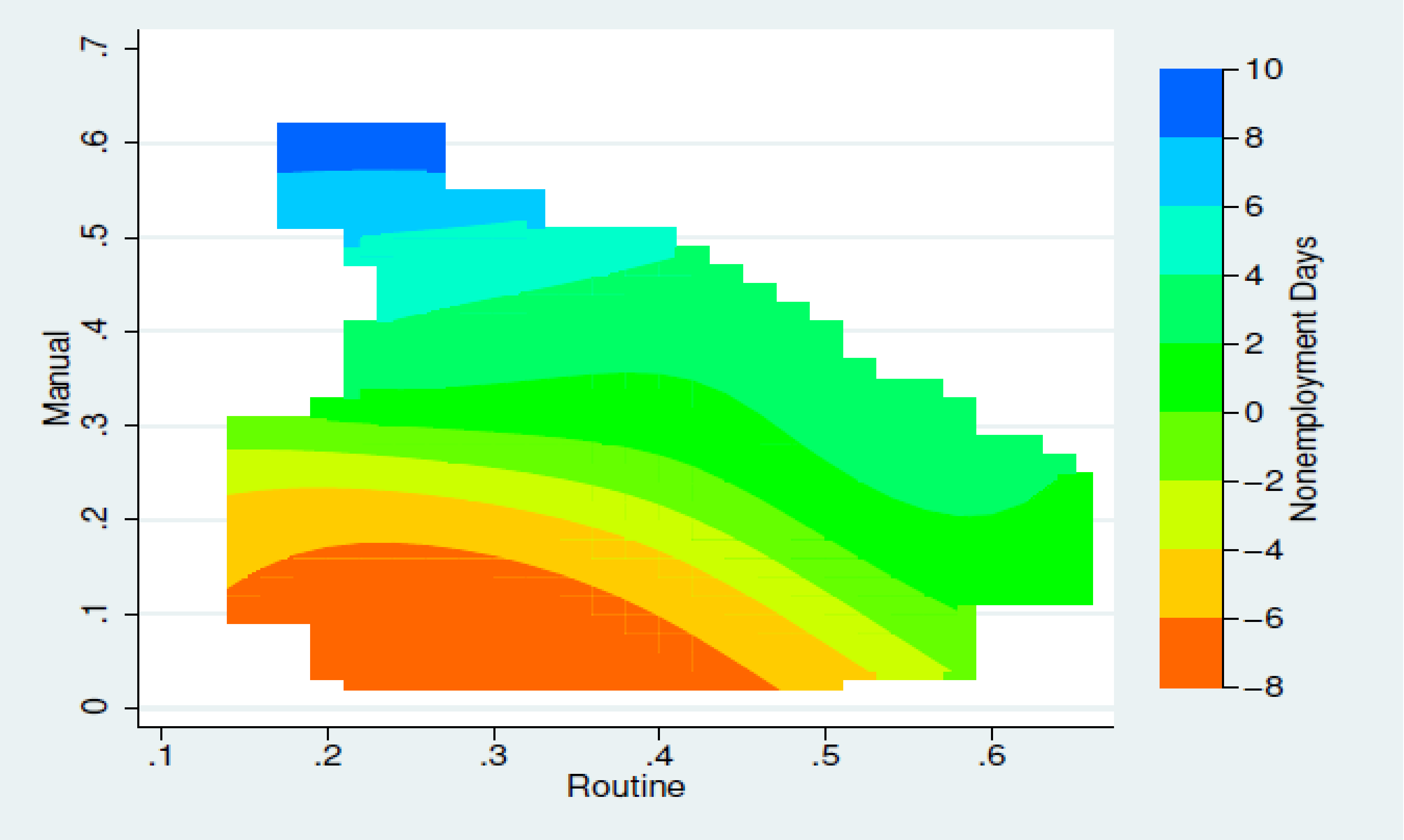


Changes in Wages by Occupational Skill Percentile (1990-2005)

Changes in Wages by 1990 Task Inputs (1990-2005)

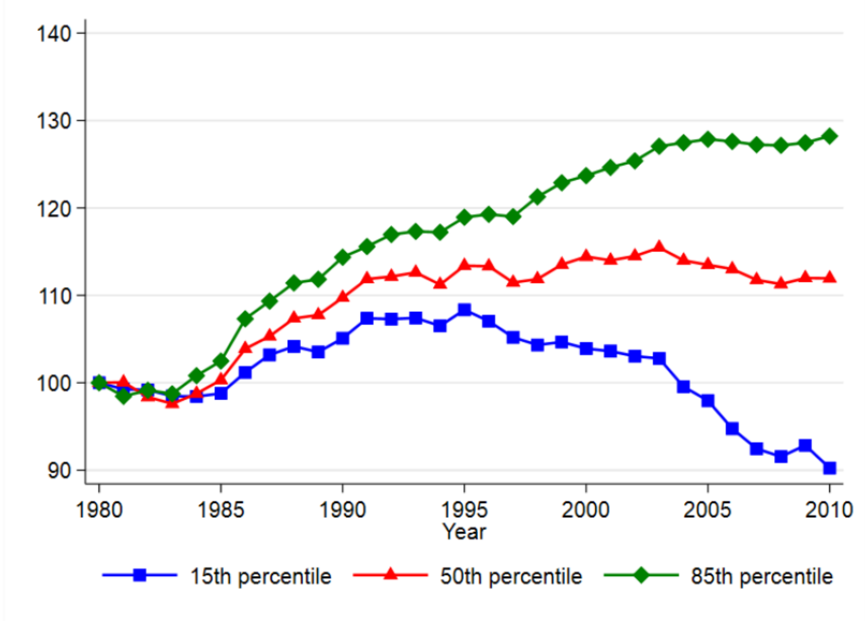


Non-Employment by 1990 Task Inputs (1990-2005)

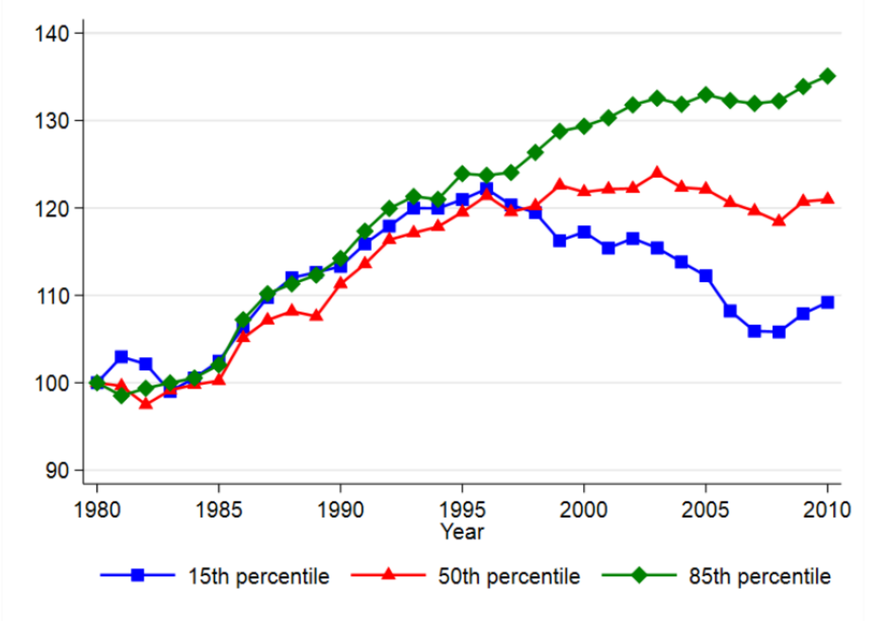


Broad Labor Market Trends: Indexed Wage Growth (1980-2010)

Men



Women



Data: IAB Sample-of-Integrated-Labor-Market-Biographies Regional-File, 1975-2010.

Is Germany an Interesting Country to Look at?

	Number Robots per Million Hours Worked	Changes from 1993-2007
GER	1.71	2.73
SWE	1.36	0.80
BEL	1.20	1.23
ITA	1.13	1.39
FRA	0.79	1.20
FIN	0.68	1.05
AUT	0.63	0.61
UK	0.50	0.34
DNK	0.42	1.57
US	0.41	0.97
ESP	0.36	1.21
KOR	0.28	1.31
NLD	0.25	0.54
AUS	0.07	0.12
HUN	0,05	0.08
GRC	0.00	0.03
IRL	0.00	0.10
Average	0.58	0.90

Source: International Federation of Robotics (IFR)--World Robotics database (2012). Country-level and overall means weighted by each industry's 1993 share of hours within a country (Graetz and Michaels, 2018).

Main Finding

- Resilient worker navigate the labor market by adjusting what they do using both adjustments within occupations and adjustments associated with occupational mobility.

- Both sources are important in terms of wages and employment.

- Task-specific human capital important, in addition to general human capital.

- Individual component important, not only average occupational task inputs.

Data I

SIAB (1990-2005)

- 2 percent random sample of employment subject to social security with employment and occupational mobility history of workers

Qualification and Career Survey (BIBB-IAB/BauA data)

- Independent cross-sections of West German employees (1979, 1986, 1992, 1999, 2006)
- Task information on individual level

->quality of data corroborated recently by Atalay et al. 2018.

Assignment of Activities

Task Category	Activity
Non-Routine Cognitive	**Human resources management**: recruiting, negotiating, prescribe rules, instructing. **Research and development**:researching, analyzing, evaluating, construction, designing, developing. **Public relations**: marketing, publishing, acquisition, presenting, consultation, lobbying. **Management and organisation**: purchasing, sales, coordinating, planning, legal interpretation. **Education**: teaching, training.
Routine Manual or Routine Cognitive	**Accounting and controlling**: calculating, bookkeeping, archiving, sorting, correction. **Quality management**: measuring, monitoring, quality checks. **Production**: producing, packaging, loading, transporting, sending, operate machines.
Non-Routine Manual	**Maintenance**: repairing, renovation, servicing machines, restoring. **Construction**: building, installing. **Hotel and restaurant**: serve, accommodating, catering. **Other Services**: cleaning, security, care.

Task Shares

$$Task_{it}^{j} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in cross section } t}{\text{total number of activities performed by } i \text{ over all categories } j \text{ at time } t}$$

By construction, $\sum_{j=c,r,m} Task_{it}^{j} = 1$.

with c: non-routine cognitive tasks

r: routine cognitive or manual tasks

m: non-routine manual tasks

Sample

SIAB restricted to:

- Male prime-age workers (25-55)
  - who work full-time
  - have no more than 95 days of employment interruptions within two consecutive years
  - who had only one occupational change within this time window
- Time period: 1990-2005
- Number of observations: 1,443,269

Augmented with task information imputed on very small cell level

(~ individual- level) using the BIBB-IAB data

Evolution of Task Inputs in the Labor Market

	1990	1995	2000	2005
Nonroutine Cognitive Tasks	0.380	0.406	0.455	0.483
	(0.225)	(0.246)	(0.265)	(0.255)
Manual Tasks	0.259	0.255	0.236	0.252
	(0.202)	(0.181)	(0.136)	(0.162)
Routine Tasks	0.361	0.339	0.309	0.265
	(0.155)	(0.166)	(0.189)	(0.152)

Advantage of Data

Occupation	Nonroutine Cognitive Task Inputs	Manual Task Inputs	Routine Task Inputs
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Teacher	72.7	13.5	**13.9**
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Individual-Level Specification I

Main specification:

$$\Delta Y_{iots} = \beta_0 + \beta_1 \mathrm{RTI}^{1986}_{o_{i(t-1)}} + \beta_2 \text{Past task tenure}_{it} + \beta_3 \text{Controls}_{it}$$
$$+ \gamma_s + \gamma_t + \epsilon_{iot}$$

where i indicates individuals, o occupations, t calendar year and s sector.

Main outcome variables:

- Occupational mobility of individual i between t-1 and t
- Task changes by individual i between t-1 and t+1

Definition of Main Variables

Proxy for Automation:

$$\text{RTI}_o^{1986} = (1/N)\sum_{i=1}^{N} \text{Task}_{i,1986}^{r} \text{ if } i \in o$$

- Typical recent measure of potential technology shock (e.g. Acemoglu and Autor in various studies).
- Captures `automation' broadly defined, including its early developments, i.e. automation that substitutes individuals mostly in performing codifiable/programmable tasks.

Task-specific HK:

$$\text{Past task tenure}_{i_{(t-1)}}^{j} = \frac{\sum_{\tau=1}^{4} Task_{i_{(t-\tau)}}^{j}}{\sum_{\tau=1}^{4} Task_{i'_{(t-\tau)}}^{j}}$$

-> task shares of the past four years relative to the task shares of a person who worked all the time in the occupation

Endogeneity

Sources for potential bias:

- unobserved heterogeneity that affects the type of occupations in which individuals work, occupational mobility and task adjustments (for example, evidence that occupational employment declines driven by inflows falling short of outflows, with `incumbents' becoming increasingly selective).

Addressed as follows:

- IV approach that uses information on what robots do in combination with U.S. occupation information from the 1980 (Graetz and Michaels, 2018).
- Uncorrelated with ε_{iot} because robots capabilities and U.S. occupational content in 1980s uncorrelated with contemporaneous unobserved heterogeneity in German occupational employment.
- IV likely to be partially correlated with RTI_o^{1986} because of historical similarities in occupational content (before computer and information technology started to spread at the workplace).

Data II

International Federation of Robotics (IFR) Data

- Data used by Graetz and Michaels (2018), Acemoglu and Restrepo (2019b) and Dauth et al. (2019).

- Country-industry-time data on deliveries of robots and robot applications for 50 countries 1993-2007.

- IFR definition of robots: `manipulating industrial robots', i.e. automatically controlled, re-programmable, multi-purpose machines

  (International Standardization Organization, ISO Code 8373).

- We use the industry-level instrumental variable suggested by Graetz and Michaels (2018) on the occupation-level (i.e. before the variable is aggregated on the industry level).

Instrumental Variable: Replaceable Occupation

- IFR data include data on robot applications, classifying the tasks performed by robots.
- Match these data to U.S. occupations in 1980, before the spread of robots, and classify those occupations as `replaceable' if by 2012 the occupations tasks would have been replaced by robots.
- Graetz and Michaels (2018) use this variable aggregated to the industry level; we use the occupation-level variable before the aggregation to the industry-level and match these to our German occupation codes.
- Graetz and Michaels (2018) has finer occupational codes, so we use employment-weighted measures (weights from Graetz and Michaels).

Change in Occupation Between (t-1) and t
Linear Probability Models

	(1)	(2)	(3)	(4)	(5)
Proxy for Automation Technology ($RTI^{1986}_{o_{i(t-1)}}$)		0.007***	0.037***	0.037***	0.030***
		(0.002)	(0.002)	(0.002)	(0.002)
Past Task Tenure ($i_{(t-1)}$)				-0.017***	
				(0.001)	
Past Nonroutine Cognitive Tenure ($i_{(t-1)}$)					-0.019***
					(0.001)
Past Manual Tenure ($i_{(t-1)}$)					-0.023***
					(0.001)
Past Routine Tenure ($i_{(t-1)}$)					-0.016***
					(0.001)
Age/10	-0.054***	-0.054***	-0.061***	-0.138***	-0.138***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
$Age^2/100$	0.004***	0.004***	0.005***	0.014***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low level of education			-0.038***	-0.042***	-0.042***
			(0.001)	(0.001)	(0.001)
Medium level of education			-0.026***	-0.034***	-0.033***
			(0.001)	(0.001)	(0.001)
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Change in Occupation Between (t-1) and t
IV, Second Stage Results

	(1)	(2)	(3)	(4)
Proxy for Automation Technology ($RTI^{1986}_{o_{i(t-1)}}$)	0.067***	0.069***	0.090***	0.091***
	(0.007)	(0.007)	(0.008)	(0.012)
Past Task Tenure ($i_{(t-1)}$)			-0.016***	
			(0.001)	
Past Nonroutine Cognitive Tenure ($i_{(t-1)}$)				-0.017***
				(0.001)
Past Manual Tenure ($i_{(t-1)}$)				-0.021***
				(0.001)
Past Routine Tenure ($i_{(t-1)}$)				-0.024***
				(0.002)
Age/10	-0.053***	-0.061***	-0.142***	-0.144***
	(0.003)	(0.003)	(0.004)	(0.004)
$Age^2/100$	0.004***	0.005***	0.014***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)
Low level of education		-0.040***	-0.047***	-0.041***
		(0.001)	(0.002)	(0.001)
Medium level of education		-0.026***	-0.036***	-0.034***
		(0.001)	(0.001)	(0.001)
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

First Stage Results
Dep. Var.: Proxy for Automation

	(1)	(2)	(3)	(4)
Replaceable Occupation (US-RO$^{1980}_{o_{i(t-1)}}$)	0.277***	0.275***	0.248***	0.178***
	(0.001)	(0.001)	(0.001)	(0.001)
Past Task Tenure ($i_{(t-1)}$)			0.051***	
			(0.000)	
Past Nonroutine Cognitive Tenure ($i_{(t-1)}$)				0.034***
				(0.000)
Past Manual Tenure ($i_{(t-1)}$)				0.002***
				(0.001)
Past Routine Tenure ($i_{(t-1)}$)				0.151***
				(0.000)
Age/10	-0.026***	0.003**	-0.001	0.022***
	(0.001)	(0.001)	(0.002)	(0.002)
Age^2/100	0.003***	-0.001***	-0.001***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Low level of education		0.127***	0.145***	0.061***
		(0.000)	(0.000)	(0.001)
Medium level of education		0.098***	0.126***	0.090***
		(0.000)	(0.000)	(0.000)
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
P-Value (F-test excluded instrument)	0.000	0.000	0.000	0.000

Task Changes Between (t-1) and (t+1)
OLS

	Routine Tasks		Non-routine Cognitive		Manual Tasks	
	(1)	(2)	(3)	(4)	(5)	(6)
Proxy for Automation Technology ($RTI^{1986}_{o_{i(t-1)}}$)		-0.008***		-0.003***		0.011***
		(0.001)		(0.001)		(0.001)
Occupational Change (i_t)	-0.021***	-0.022***	0.036***	0.040***	-0.015***	-0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Nonroutine Cognitive Tenure ($i_{(t-1)}$)		0.005***		0.009***		-0.015***
		(0.000)		(0.000)		(0.000)
Past Manual Tenure ($i_{(t-1)}$)		0.076***		0.027***		-0.103***
		(0.000)		(0.000)		(0.000)
Past Routine Tenure ($i_{(t-1)}$)		-0.048***		0.041***		0.008***
		(0.000)		(0.000)		(0.000)
Age/10	0.015***	0.013***	-0.044***	-0.034***	0.029***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Age^2/100$	-0.001***	-0.001***	0.004***	0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low level of education	-0.012***	0.003***	0.006***	-0.014***	0.006***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Medium level of education	-0.006***	-0.006***	0.010***	0.004***	-0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Task Changes Between (t-1) and (t+1)
IV, Second Stage Results

	Routine Tasks		Non-routine Cognitive		Manual Tasks	
	(1)	(2)	(3)	(4)	(5)	(6)
Proxy for Automation Technology ($RTI^{1986}_{o_{i(t-1)}}$)	-0.435***	-0.324***	0.145***	0.252***	0.290***	0.073***
	(0.003)	(0.004)	(0.002)	(0.004)	(0.002)	(0.003)
Occupational Change (i_t)	-0.014***	-0.017***	0.033***	0.037***	-0.020***	-0.020***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Past Nonroutine Cognitive Tenure ($i_{(t-1)}$)		0.015***		0.001**		-0.016***
		(0.000)		(0.000)		(0.000)
Past Manual Tenure ($i_{(t-1)}$)		0.069***		0.031***		-0.100***
		(0.000)		(0.000)		(0.000)
Past Routine Tenure ($i_{(t-1)}$)		-0.001		0.003***		-0.002***
		(0.001)		(0.001)		(0.001)
Age/10	0.020***	0.023***	-0.047***	-0.041***	0.027***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Age^2/100$	-0.002***	-0.003***	0.004***	0.004***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low level of education	0.046***	0.023***	-0.011***	-0.030***	-0.035***	0.006***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Medium level of education	0.039***	0.025***	-0.006***	-0.022***	-0.033***	-0.003***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Sector effects	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Implications for Wages and Employment

	Changes in Log Wages$_{(i_{t-1},i_{t+1})}$			Nonemployment$_{(i_{t+2})}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Occupational Change (OC) (i_t)	0.012***	0.011***	0.009***	-0.010***	-0.011***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δ Non-routine Cognitive Tasks (NRCT) (i_{t-1}, i_{t+1})		0.063***	0.035***		0.051***	0.052***
		(0.003)	(0.003)		(0.004)	(0.005)
Δ Routine Tasks (RT) (i_{t-1}, i_{t+1})		-0.001	-0.016***		0.022***	0.038***
		(0.002)	(0.003)		(0.003)	(0.004)
Δ NRCT (i_{t-1}, i_{t+1})*OC(i_t)			0.076***			-0.074***
			(0.005)			(0.007)
Δ RT (i_{t-1}, i_{t+1})*OC(i_t)			0.052***			-0.057***
			(0.006)			(0.008)
Age/10	-0.118***	-0.113***	-0.113***	-0.889***	-0.886***	-0.885***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Age^2/100	0.011***	0.011***	0.011***	0.118***	0.117***	0.117***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Low level of education	-0.094***	-0.053***	-0.052***	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Medium level of education	-0.084***	-0.050***	-0.050***	-0.013***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Source Occupation FE	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Additional Results

Task-Specific Human Capital (Accounting for Individual Specific Tasks)

Wage of worker i in occupation o and year t:

$$\log(w_{iot}) = p_{ot} + q(\tilde{x}_{iot}, s_{iot}) \tag{1}$$

where
- p_{ot}: log output price
- $q(\tilde{x}_{iot}, s_{iot})$: log labor productivity
- $\tilde{x}_{iot}$: effective task inputs
- s_{iot}: task specific human capital (skills)
- $\tilde{x}_{iot}$, s_{iot}: 3×1 vectors (manual, routine, and nonroutine cognitive tasks)

Note: Occupations are perceived as a bundle of tasks, workers make use of their task specific human capital as demanded in the occupation.
Actual task inputs x_{iot} differ from effective task inputs $\tilde{x}_{iot}$.

Productivity function of effective task inputs ($\tilde{x}_{iot,j}$) and task specific skills ($s_{iot,j}$)

$$q(\tilde{x}_{iot}, s_{iot}) = \sum_{j \in \{m,r,c\}} \tilde{x}_{iot,j} s_{iot,j} \tag{2}$$

Three task inputs: manual $j = m$, routine $j = r$, nonroutine cognitive $j = c$.

As in Yamaguchi (2012):
Three dimensional vector of task specific skills $(s_{iot,j})_{j \in \{m,r,c\}}$.

Individual Deviation in Task Inputs from Occupation Average

Effective task input for task j

$$(3) \qquad \tilde{x}_{iot,j} = \bar{x}_{ot,j} + b_{io,j}(x_{iot,j} - \bar{x}_{ot,j}) - 0.5c_j(x_{iot,j} - \bar{x}_{ot,j})^2$$

where

$x_{iot,j}$:	actual task input
$b_{io,j}$:	individual specific return to deviate from average
c_j:	general organizational costs which are not specific to the job or to the individual

Assume a random individual specific return $b_{io,j}$ with $E(b_{io,j}) = 0$
$\rightarrow$ occupation characterizes task input on average and large deviations are costly due to convex costs

Deviations from occupation average are 'small': Assume $|b_{io,j}| < 1$

Optimal actual task input to maximize wage:

(4) $$x_{iot,j} = \bar{x}_{ot,j} + \frac{b_{io,j}}{c_j}$$

Actual productivity as a function of effective task input:

(5) $$q(\tilde{x}_{iot}, s_{iot}) = \sum_{j \in \{m,r,c\}} \left(\bar{x}_{ot,j} + \frac{b_{io,j}^2}{2c_j} \right) s_{iot,j}$$

Task-Specific Skill Accumulation

Task specific human capital while staying in occupation o:

(6) $$s_{io(t+1),j} = a_{0,j} + \delta_j s_{iot,j} + a_{1,j}\bar{x}_{ot,j} + a_{2,j} v_{it} \; .$$

where	δ_j:	depreciation within the same occupation $(0 < \delta_j < 1)$
	$a_{1,j}$:	task specific experience while working in occupation o
	v_{it}:	individual specific characteristics

Skill change for task j associated with occupational mobility in period t from source occupation o to target occupation o':

(7) $$s_{io't,j} = (d_{0,j} - d_{l,j}|\bar{x}_{o't,j} - \bar{x}_{ot,j}|)s_{iot,j}$$

Depreciation parameters: $0 < d_{0,j} < 1$ and $d_l > 0$

Decomposition of Wage Changes (1)

Wage change within occupation o:

(8)
$$\log(w_{io(t+1)}) - \log(w_{iot}) =$$

$$\underbrace{\log(p_{o(t+1)}) - \log(p_{ot})}_{\text{change in output price}} + \underbrace{\sum_{j\in\{m,r,c\}} \left(\bar{x}_{o(t+1),j} - \bar{x}_{ot,j}\right) s_{iot,j}}_{\text{change in average task inputs}}$$

$$+ \underbrace{\sum_{j\in\{m,r,c\}} \left(\bar{x}_{o(t+1),j} + \frac{b_{io,j}^2}{2c_j}\right)\left(s_{io(t+1),j} - s_{iot,j}\right)}_{\text{change in task specific human capital}}$$

Allows to account for task bias within occupations

Decomposition of Wage Changes (2)

Wage change associated with an occupational switch from source occupation o to target occupation o':

(9)
$$\log(w_{io't}) - \log(w_{iot}) =$$

$$\underbrace{\log(p_{o't}) - \log(p_{ot})}_{\text{change in output price}} + \underbrace{\sum_{j\in\{m,r,c\}} \left(\bar{x}_{o't,j} - \bar{x}_{ot,j}\right) s_{iot,j}}_{\text{change in average task inputs}}$$

$$+ \underbrace{\sum_{j\in\{m,r,c\}} \left(\bar{x}_{o't,j} + \frac{b^2_{io',j}}{2c_j}\right) \left(s_{io't,j} - s_{iot,j}\right)}_{\text{change in task specific human capital}} + \underbrace{\sum_{j\in\{m,r,c\}} \left(\frac{b^2_{io',j}}{2c_j} - \frac{b^2_{io,j}}{2c_j}\right) s_{iot,j}}_{\text{change in specific task inputs}}$$

Interpretation

- Output price for routine intensive occupations falling over time, and for nonroutine cognitive occupations rising.
- Individual may switch occupation voluntarily if wages increase because of higher output prices or because of higher individual return to task-specific human capital
- Involuntary occupation changes may be associated with wage declines because changes in average task inputs may render accumulated skills less productive or lead to depreciation of task-specific human capital (Gathmann and Schönberg, 2010; Kamborouv and Manovskii, 2008, 2009; Groes, Kircher and Manovskii, 2014)
- Decomposition rationalizes occupational churning (movements in and out of the same occupation) owing to individual/match specific effects

Additional Slides

Task Share Regressions

- Task shares for categories j∈ {non-routine cognitive, routine cognitive and routine manual, non-routine manual} based on Antonczyk, Fitzenberger, Schulze (2009):

$$Task_{ijt} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in cross section } t}{\text{total number of activities performed by } i \text{ over all categories at time } t}$$

- Regress task measures on occupations, age, skill groups, wage and interactions (e.g. wage x occupations, age x occupations)
- Impute fitted task share values for survey years of BIBB-IAB data in SIAB
- SIAB: Interpolate imputed values for years between BIBB-IAB survey years

Quality of Imputation: Standard Deviation of Observed and Fitted Task Shares

	Nonroutine Cognitive Tasks	Manual Tasks	Routine Tasks
Survey year		1986	
SD: Observed QCS info	.139	.076	.083
SD: Fitted by Occ & X	.135	.065	.08
SD: Fitted by Occ	.105	.044	.069
Survey year		1992	
SD: Observed QCS info	.17	.096	.101
SD: Fitted by Occ & X	.168	.092	.099
SD: Fitted by Occ	.142	.078	.09
Survey year		1999	
SD: Observed QCS info	.146	.085	.067
SD: Fitted by Occ & X	.143	.082	.064
SD: Fitted by Occ	.12	.072	.051
Survey year		2006	
SD: Observed QCS info	.154	.069	.094
SD: Fitted by Occ & X	.151	.066	.089
SD: Fitted by Occ	.127	.057	.073