# NBER Young Scholars Workshop on the Economics of AI – Skills, Tasks, and Technologies

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(Provisional draft)

# Agenda

1. **Motivation: The Canonical Model and Its Limitations**
2. **A Simplified Task Model with New Tasks**
   - Model setup
   - The displacement effect—Extensive margin tech Δ
   - Deepening of automation—Intensive margin tech Δ
   - Labor-Augmenting Technological Δ
   - New task creation
3. **A Task Model with Comparative Advantage Across Skill Groups [for self-study]**
   - Production
   - Three equilibrium conditions
   - Comparative statics
   - Factor Augmentation, Factor Displacement, Offshoring
4. **Tasks and Technologies: Some Applications**
   - Projecting the Labor Market Effects of Artificial Intelligence
   - The Skill Complementarity of Broadband Internet
5. **Where Does New Work Come From?**

# The Canonical Model

**Elegantly, powerfully operationalizes supply and demand for skills**

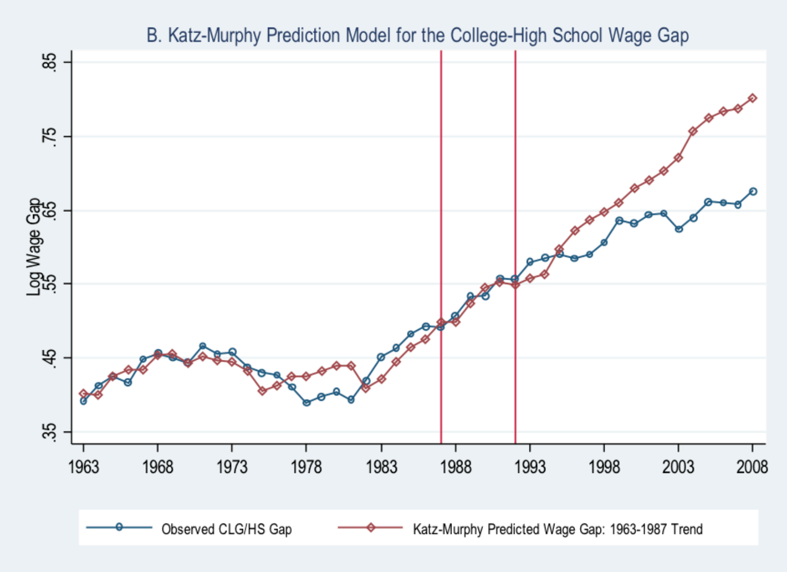
- A formalization of Tinbergen's "Education Race" analogy
- Two distinct skill groups that perform two different and imperfectly substitutable tasks

**Model is a theoretical and empirical success**

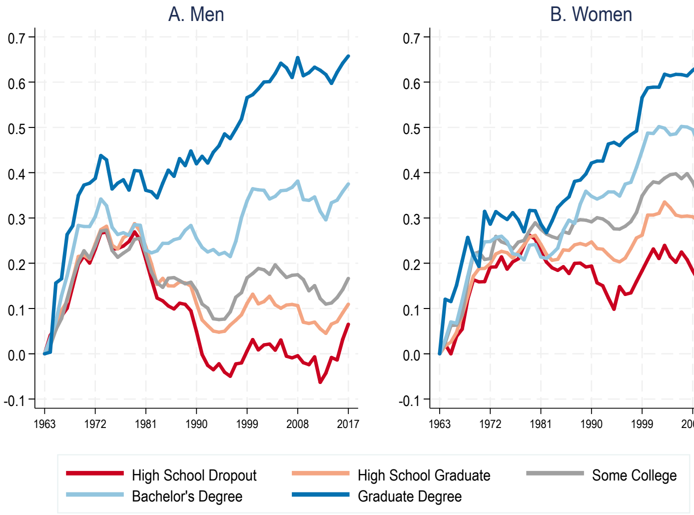
- Katz and Murphy '92
- Autor, Katz, Krueger '98
- Card and Lemieux '01
- Acemolgu, Autor and Lyle '04
- Goldin and Katz '08
- Carneiro and Lee '11

**But its limitations are also apparent**

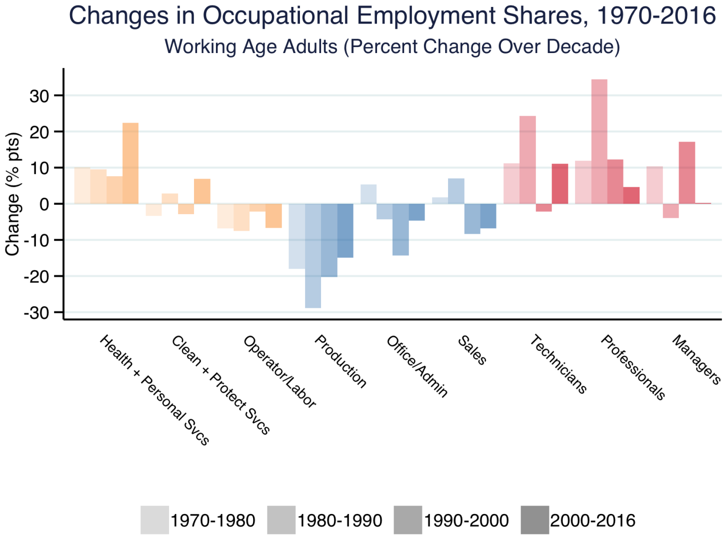
# Wage Inequality Rises Less than Predicted by the Canonical Model



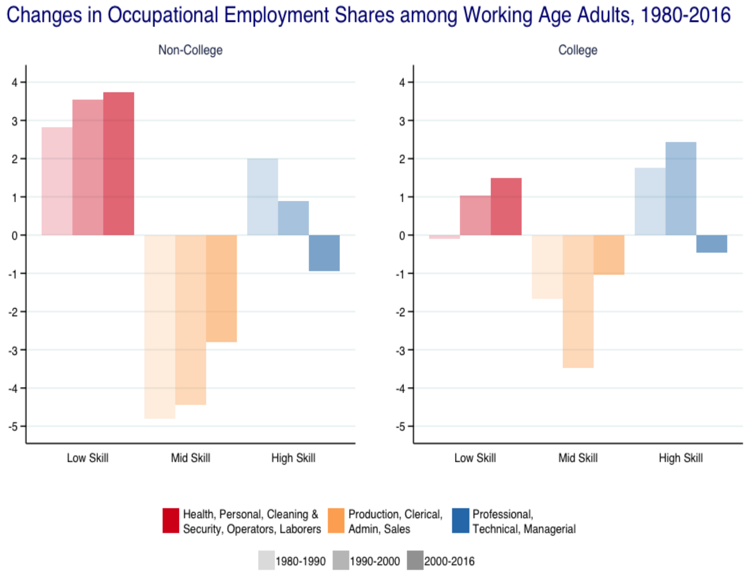
# Declining Log Real Wages Among Non-College Workers after 1980 – Despite Falling Relative Supply



# Occupational Polarization, 1970 – 2016: Percent Growth in Employment by Occupational Category



# Changes in Employment Shares 1970 – 2016 by Broad Occupational Category: Non-College and College Workers



# Occupational Polarization in Sixteen European Union Countries, 1993 - 2010


Goos, Manning and Salomons, 2014

# Labor's Falling Share of National Income

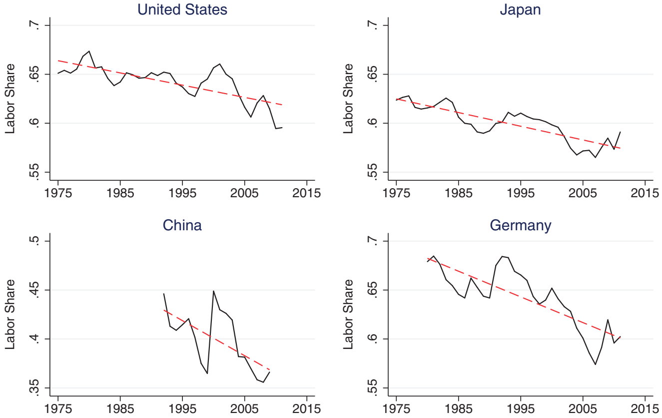


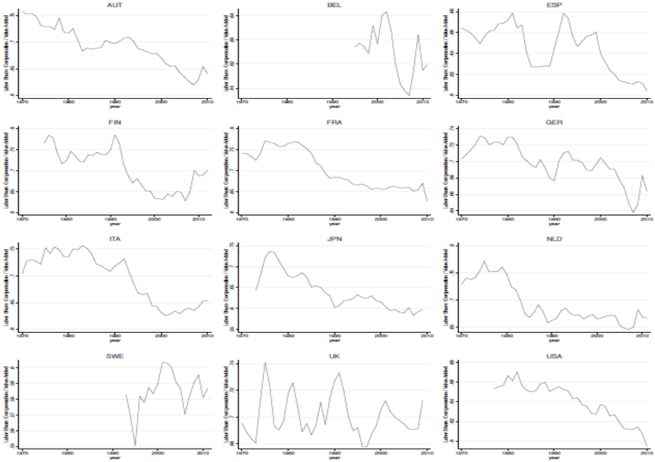

FIGURE II

Declining Labor Share for the Largest Countries

Karabarbounis and Neiman, 2014

# Labor's Falling Share of National Income

Figure 1: International Comparison: Labor Share by Country




Notes: Each panel plots the ratio of aggregate compensation over value-added for all industries in a country based on KLEMS data.

Autor, Dorn, Katz, Patterson, & Van Reenen *Forthcoming*

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# A Model of Skills, Tasks and Technologies

1. **Explicit distinction between skills and tasks**
   - Tasks—Unit of work activity that produces output
   - Skill—Worker's endowment of capabilities for performing various tasks
2. **Allow for comparative advantage among workers and machines in accomplishing tasks**
   - Assignment of workers to tasks is endogenous (as in Roy, 1951)
3. **Allow for multiple sources of competing task 'supplies'**
   - Workers of different skill levels
   - Machines—Task can be routinized/automated
   - Trade/offshoring—Tasks can be performed elsewhere
4. **Trade and automation**
   - Substitution of machines or foreign workers for labor, can lead to the displacement of workers from some tasks

# Task Framework: Motivation

**Framework builds on**

- Autor, Levy, Murnane (2003)
- Grossman, Rossi-Hansberg (2008)
- Acemoglu and Autor (2011)
- Acemoglu and Restrepo (2016, 2017, 2018*a* - 2020$z^3$)

1. First model in this lecture: **Acemoglu and Restrepo (2018)**, "Artificial Intelligence, Automation, and Work"
2. Second model in this lecture: **Acemoglu-Autor** (2011), "Skills, Task and Technologies"

# Task Framework: Model

**Aggregate output** $Y$

- Produced by combining the services, $y(x)$, of a unit measure of tasks $x \in [N-1, N]$:

$$\ln Y = \int_{N-1}^{N} \ln y(x) dx,$$

- Tasks run between $N-1$ and $N$ allows for changes in *range* of tasks
- Notice that this is a Cobb-Douglas structure with identical factor shares for services of each task

# Task Framework: Model

**Tasks produced by human labor, $\ell(x)$, <u>or</u> by machines, $m(x)$**

- Tasks above $I$ are **not technologically automated** and must be produced by labor:

$$y(x) = \begin{cases} \gamma_L(x)\ell(x) + \gamma_M(x)m(x) & \text{if } x \in [N-1, I] \\ \gamma_L(x)\ell(x) & \text{if } x \in (I, N]. \end{cases}$$

- $\gamma_L(x)$ =productivity of labor in task $x$, increasing in $x$
- $\gamma_M(x)$ =productivity of machines in automated tasks
- **Comparative advantage**: $\gamma_L(x)/\gamma_M(x)$ is increasing in $x$
- $L$ workers and $K$ units of capital (machines) supplied inelastically

# Task Framework: Aggregate Output

**Simplifying assumption**

$$\frac{\gamma_L(N)}{\gamma_M(N-1)} > \frac{W}{R} > \frac{\gamma_L(I)}{\gamma_M(I)} \tag{A1}$$

- where $R$ is the capital rental rate
- Implies that tasks below $I$ are produced with machines/offshoring

**Assumption says that new tasks (rising $N$) raise output**

- Wage ratio not so high that new task creation lowers output
- Not so low so that technologically automated tasks are still performed by labor

# Task Framework: Aggregate Output

**Aggregate output takes the form**

$$Y = \Theta \left( \frac{K}{I - N + 1} \right)^{I-N+1} \left( \frac{L}{N - I} \right)^{N-I},$$

$$\Theta = \exp \left( \int_{N-1}^{I} \ln \gamma_M(x) dx + \int_{I}^{N} \ln \gamma_L(x) dx \right)$$

- Notice that this production function is **pure Cobb-Douglas with non-constant shares**
- $\Theta$ = Solow residual: *All* technological $\Delta$ generates Hicks-neutral TFP gain $\Delta\Theta$

# Task Framework: The Demand for Labor

**The demand for labor is given by**

$$W = (N - I)\frac{Y}{L} \tag{1}$$

- This expression is equal to labor share of total output, $(N - I)$, times output $Y$ divided by number of workers $L$
- The share of labor in national income is given by

$$s_L = \frac{WL}{Y} = N - I$$

**Factor-augmentation, automation and labor share**

- Factor-augmenting technical $\Delta$ *does not change labor share $S_L$ in this model* even though *automation* (task encroachment) does
- Even if underlying production f'n were CES with $\sigma < 1$, factor-augmenting tech $\Delta$ would have *indirect (generally small) effect* on $S_L$, automation would have *first-order* effect

# Task Framework: Four Forces at Play

1. **Automation at the extensive margin – displacement**
   - Expansion of the set of tasks that are technologically automated or trade-substituted, $I$
   - Not present in conventional models
2. **Automation at the intensive margin – deepening of automation**
   - Increases in the productivity of tasks that are already automated/offshored.
   - Corresponds to an increase in the $\gamma_M(x)$ function for tasks $x < I$
3. **Labor-augmenting technological advances**
   - Increases in the function $\gamma_L(x)$
   - This is the canonical factor-augmenting model
4. **Creation of new tasks**
   - An increase in $N$
   - A new idea due to Acemoglu-Restrepo '16 via Jeffrey Lin '11 *ReStat*

# Mechanism 1. Extensive Margin Tech $\Delta$: The Displacement Effect

**Automation or trade/offshoring (an increase in $I$) generates a displacement effect**

- From equation (1)

$$\frac{d \ln W}{dI} = \underbrace{\frac{d \ln(N - I)}{dI}}_{\substack{\text{Displacement} \\ \text{effect} < 0}} + \underbrace{\frac{d \ln(Y/L)}{dI}}_{\substack{\text{Productivity} \\ \text{effect} > 0}}$$

- The displacement effect implies that **wages—marginal product of labor—can decline**, despite the fact that output per worker rises
- **Wages necessarily grow by less than output per worker** $\rightarrow$ labor share falls

$$\frac{ds_L}{dI} = -1 < 0$$

# Displacement also Has a Productivity Effect

**By reducing the cost of producing a subset of tasks, automation/trade raises the demand for labor in remaining tasks**

- Formally

$$\frac{d\ln(Y/L)}{dI} = \ln\left(\frac{W}{\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right) > 0$$

- Note that $\ln\left[w/\gamma_L\left(I\right)\right] - \ln\left[R/\gamma_M\left(I\right)\right]$ is the cost difference btwn labor and capital/offshoring in the marginal task $I$

# Displacement also Has a Productivity Effect

**The overall impact on labor demand can be written as**

$$\frac{d\ln W}{dI} = \underbrace{-\frac{1}{N-I}}_{\substack{\text{Displacement} \\ \text{effect} < 0}} + \underbrace{\ln\left(\frac{W}{\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right)}_{\substack{\text{Productivity} \\ \text{effect} > 0}}$$

1. **Case 1: Productivity effect dominates displacement effect**: $\gamma_M(I)/R >> \gamma_L(I)/W$. Productivity jump big enough to overcome displacement effect
2. **Case 1: Displacement effect dominates productivity effect**: $\gamma_M(I)/R \approx \gamma_L(I)/W$. New technologies/trade are so-so

# Displacement also Has a Productivity Effect

**Two complementary manifestations of the productivity effect**

1. **Raising labor demand in non-automated tasks in adopting sectors**
   - **Uber effect:** People take a lot more 'cab rides' than they used to
   - ATMs raised demand for tellers (Bensen, 2016)
   - Automation in weaving increased the price of yarn and the demand for the complementary task of spinning (Mantoux, 1928)
2. **Raising demand for labor in other sectors (not in this model)**
   - **Network effects**: productivity improvements in one sector raise demand in supplier and customer sectors, e.g., rising productivity in steel production raises steel demand in autos, ore demand in mining
   - **Walmart effect:** Lower prices rise HH's purchasing power, increasing spending elsewhere. By reducing food prices, mechanization enriched consumers who then demanded more non-agricultural goods (Herrendorf, Rogerson and Valentinyi, 2013)

# Mechanism 2. Intensive Margin Technological $\Delta$: Deepening of Automation

**Initially, a task or process is automated/offshored $\rightarrow$ Displacement**

- Subsequent improvements or cost reductions in already-automated tasks may raise productivity without further displacement
- Consider an increase in the productivity of machines by $d \ln \gamma_M(x) = d \ln \gamma_M > 0$ for $x < I$, with no change in the extensive margin of automation, $I$
- Wage impact is

$$d \ln W = d \ln Y/L = (I - N + 1) d \ln \gamma_M > 0$$

- Intensive margin improvements tend to increase labor demand and wages, further counteracting the displacement effect
- This is a pure capital-skill complementarity

# Intensive margin technological change: Some examples

- Introduction of electric lighting increased operating hours, work precision, and safety in factories without changing task allocation
- Improvements in tractors make farm workers more efficient without changing task allocation
- Better auto-assembly robots improve the quality of welds on new cars (even though robots have been doing the welding for years)

# Intensive Margin Technological Change and Capital Supply

**If capital supply fixed, displacement effect on $W$ magnified**

- **With fixed supply of capital**
  - Automation at extensive margin increases the demand for capital
  - Raises the equilibrium rental rate, $R$
- **"Medium-run"**
  - Supply of machines expands as well (or more offshore supplies come online)
  - Capital accumulation bolsters the productivity effect by reducing the cost of machinery
- **If capital accumulation fixes $R$**
  - Productivity effect dominates the displacement effect—all gains go to inelastically supplied factor
  - See "Robotic Arithmetic" paper by Caselli and Manning in *AERi* in 2019

# Mechanism 3. Labor Augmenting Technological $\Delta$: The Canonical Mechanism

- Consider an increase in the productivity of workers by $d \ln \gamma_L(x) > 0$ for $x > I$, with no change in the extensive margin of automation, $I$
- Wage impact is

$$d \ln W = d \ln Y/L = (N + 1 - I) d \ln \gamma_L > 0$$

- This is a a pure factor-augmenting technological change, as in the Katz-Murphy/Tinbergen model
- This could come from rising education or better management practices

# Mechanism 4. New Task Creation

**Creation of new, labor-using tasks may be counterbalancing force**

1. In 19th-century Britain, rapid expansion of new industries and jobs—engineers, machinists, repairmen, and managers (Landes, 1969, Chandler, 1977, and Mokyr, 1990)
2. In early 20th-century America, agricultural mechanization coincided with a large increase in employment in new industry and factory jobs (Olmstead and Rhode, 2001, Rasmussen, 1982)
3. From 1980 to 2010, new tasks and job titles explain non-negligible share of employment growth (Acemoglu and Restrepo, 2016)
4. In general, new tasks tend to be more skill-intensive—which is both good and bad news

# New Tasks and the Demand for Labor

- **An increase in $N$—the creation of new tasks—raises productivity**

$$\frac{d \ln Y/L}{dN} = \ln\left(\frac{R}{\gamma_M(N-1)}\right) - \ln\left(\frac{W}{\gamma_L(N)}\right) > 0$$

  which is positive from Assumption A1

- Besides its effect on productivity, new tasks also increase labor demand and equilibrium wages by creating a *reinstatement effect*:

$$\frac{d \ln W}{dN} = \underbrace{\ln\left(\frac{R}{\gamma_M(N-1)}\right) - \ln\left(\frac{W}{\gamma_L(N)}\right)}_{\substack{\text{Productivity} \\ \text{effect} > 0}} + \underbrace{\frac{1}{N-I}}_{\substack{\text{Reinstatement} \\ \text{effect} > 0}}$$

- (Reinstatement effect *partially* an artifact of unit range of tasks)

# New Tasks and Automation

**Creation of new tasks generates additional labor demand, increases the share of labor in national income**

- Total wage effect equals

$$d \ln W = \left[ \ln \left( \frac{R}{\gamma_M(N-1)} \right) - \ln \left( \frac{W}{\gamma_L(N)} \right) \right] dN + \left[ \ln \left( \frac{W}{\gamma_L(I)} \right) - \ln \left( \frac{R}{\gamma_M(I)} \right) \right] dI + \frac{1}{N-I}(dN - dI),$$

  and also for the labor share, we get

$$ds_L = dN - dI.$$

- Labor share stable and wages increase 1:1 w/productivity **iff** new tasks, $N$, introduced at same rate as automation, $I$

# The Endogenous Evolution of New Tasks

**Some reasons why new tasks, $N$, may keep up with automation**

- Rapid automation may endogenously generate incentives for firms to introduce new labor-intensive tasks (Acemoglu and Restrepo, 2016)
- Some automation technology platforms, especially AI, may facilitate the creation of new tasks
- But it is also possible that we are heading to a future with a lower range of tasks done by human labor, $N - I$

# Summary: Four Forces at Play

1. **Automation at the extensive margin – displacement**
   - Expansion of the set of tasks that are technologically automated or trade-substituted, $I$
   - Not present in conventional models
2. **Automation at the intensive margin – deepening of automation**
   - Increases in the productivity of tasks that are already automated/offshored.
   - Corresponds to an increase in the $\gamma_M(x)$ function for tasks $x < I$
3. **Labor-augmenting technological advances**
   - Increases in the function $\gamma_L(x)$
   - This is the canonical factor-augmenting effect
4. **Creation of new tasks**

# Some Implications

1. **Welfare:** Technological change or trade/outsourcing only Pareto improving in restrictive special cases
2. **Task displacement**: Automation (or trade) can directly substitute for labor
3. **Disruptive:** Process is *disruptive* – displacement almost inevitable
4. **Comparative advantage**: Can forecast which tasks will be displaced by understanding comparative advantage of workers, machines, foreign suppliers, etc.
5. **Complementarity**: Automation (or trade) should boost *productivity and wages* in tasks not displaced: workers/tasks that are not not substituted should be *complemented*
6. **Speed of adjustment:** Gains are typically diffuse and possibly slow-moving—demand effects, income effects, capital deepening
7. **New task creation**: May 'reinstate' labor by creating new labor-using tasks. We know little about this process at present

# Agenda

# A Ricardian Model of Skills, Tasks and Technologies
## Production technology: Tasks into goods

- Static environment with a unique final good, $Y$
- $Y$ produced with continuum of *tasks* on the unit interval, $[0, 1]$
- Cobb-Douglas technology mapping tasks the final good:

$$\ln Y = \int_0^1 \ln y(i) di,$$

  where $y(i)$ is the "service" or production level of task $i$.
- Price of the final good, $Y$, is numeraire.

# A Ricardian Model of Skills, Tasks and Technologies
## Supply of skills to tasks

**Three types of labor: High, Medium and Low**

- Fixed, inelastic supply of the three types. Supplies are $L$, $M$ and $H$
- We later introduce capital or technology (embedded in machines)

**Each task on continuum has production function**

$$y(i) = A_L \alpha_L(i)\, l(i) + A_M \alpha_M(i)\, m(i) \\ + A_H \alpha_H(i)\, h(i) + A_K \alpha_K(i)\, k(i),$$

- $A$ terms are factor-augmenting technologies
- $\alpha_L(i)$, $\alpha_M(i)$ and $\alpha_H(i)$ are *task productivity schedules*
- For example, $A_L \alpha_L(i)$ is the productivity of low skill workers in task $i$, and $l(i)$ is the number of low skill workers allocated task $i$.

# A Ricardian Model of Skills, Tasks and Technologies

**Role of comparative advantage**

- All tasks can be performed by low, medium or high skill workers

$$
\begin{aligned}
y(i) &= A_L \alpha_L(i)\, l(i) + A_M \alpha_M(i)\, m(i) \\
&\quad + A_H \alpha_H(i)\, h(i) + A_K \alpha_K(i)\, k(i)
\end{aligned}
$$

**But comparative advantage differs** $\{\alpha_L(i), \alpha_M(i), \alpha_H(i)\}$

- **Assumption:** $\alpha_L(i)/\alpha_M(i)$ *and* $\alpha_M(i)/\alpha_H(i)$ *are continuously differentiable and strictly decreasing*
- Higher indices correspond to "more complex" tasks
- In all tasks, $H$ has absolute advantage relative to $M$, $M$ has abs. adv. relative to $L$
- But *comparative advantage* determines task allocations

# A Ricardian Model of Skills, Tasks and Technologies

**Equilibrium objects: Task thresholds, $I_L$, $I_H$**

- In any equilibrium there exist $I_L$ and $I_H$ such that $0 < I_L < I_H < 1$ and for any $i < I_L$, $m(i) = h(i) = 0$, for any $i \in (I_L, I_H)$, $l(i) = h(i) = 0$, and for any $i > I_H$, $l(i) = m(i) = 0$

**Allocation of tasks to skill groups determined by $I_H$, $I_L$**

- Tasks $i > I_H$ will be performed by high skill workers (Abstract)
- Tasks $i < I_L$ will be performed by low skill workers (Manual)
- Middle tasks $I_L \leq i \leq I_H$ will be performed by medium skill workers (Routine)

**Boundaries of these sets are endogenous**

- Given skill supplies, firms (equivalently workers) decide which skills perform which tasks $\rightarrow$ *Substitution of skills across tasks*.

# Three equilibrium conditions

1. **Law of one price for skills**
2. **Equal division of labor among tasks within a skill group**
3. **No arbitrage between tasks**

# Three equilibrium conditions: Law of one price for skill

**1. Law of one price for skills**

- Let $p(i)$ denote the price of services of task $i$. In equilibrium all tasks employing $L$ workers must pay them the same wage, $w_L$, and similarly for $H$ and $L$:

$$W_L = p(i) A_L \alpha_L(i) \text{ for any } i < I_L.$$

$$W_M = p(i) A_M \alpha_M(i) \text{ for any } I_L < i < I_H.$$

$$W_H = p(i) A_H \alpha_H(i) \text{ for any } i > I_H.$$

# Three equilibrium conditions: Law of one price for skill

**1. Law of one price for skills**

- In equilibrium all tasks employing $L$ workers must pay them the same wage, $w_L$, and similarly for $H$ and $L$:

$$W_L = p(i)A_L\alpha_L(i) \text{ for any } i < I_L.$$

- This has a convenient implication:
  - $p(i)\alpha_L(i) = p(i')\alpha_L(i') \equiv P_L$ for any $i, i' < I_L$
  - $p(i)\alpha_M(i) = p(i')\alpha_M(i') \equiv P_M$ for any $I_H > i, i' > I_L$
  - $p(i)\alpha_H(i) = p(i')\alpha_H(i') \equiv P_H$ for any $i, i' > I_H$

# Three equilibrium conditions: Equal division of labor

**2. Equal division of labor among tasks within a skill group**

- The Cobb-Douglas technology implies:

$$p(i)y(i) \quad = \quad p(i')y(i')$$

- Noting that

$$\begin{aligned} y(i) &= A_L \alpha_L(i) \, l(i) \text{ for any } i < I_L \\ P_L &= p(i) \, \alpha_L(i) \text{ for any } i < I_L \\ \Rightarrow p(i) \, y(i) &= P_L A_L l(i) \end{aligned}$$

- Substituting

$$\begin{aligned} P_L A_L l(i) &= P_L A_L l(i') \\ \Rightarrow l(i) &= l(i') \text{ for any } i, i' < I_L \end{aligned}$$

# Three equilibrium conditions: Equal division of labor

**2. Equal division of labor among tasks within a skill group**

$$l(i) = l(i')$$

- which implies

$$l(i) = \frac{L}{I_L} \text{ for any } i < I_L,$$
$$m(i) = \frac{M}{I_H - I_L} \text{ for any } I_H > i > I_L,$$
$$h(i) = \frac{H}{1 - I_H} \text{ for any } i > I_H.$$

- Any two tasks performed exclusively by workers of one skill group use identical amounts of labor, equal to the group's total labor supply divided by the fraction of the task continuum performed by the group.

# Three equilibrium conditions: No arbitrage across skill groups

**3. No arbitrage between tasks**

- Start with observation that wages equal marginal products:

$$W_L = P_L A_L = A_L p(i)\,\alpha_L(i) \text{ for } i < I_L$$

$$W_M = P_M A_M = A_M p(i)\,\alpha_M(i) \text{ for } I_L < i < I_H$$

$$W_H = P_H A_H = A_H p(i)\,\alpha_H(i) \text{ for } i > I_H$$

# Three equilibrium conditions: No arbitrage across skill groups

**3. No arbitrage between tasks**

- The threshold task $I_H$ must be such that it can be profitably produced using either $H$ or $M$ workers, and similarly for the threshold task $I_L$:

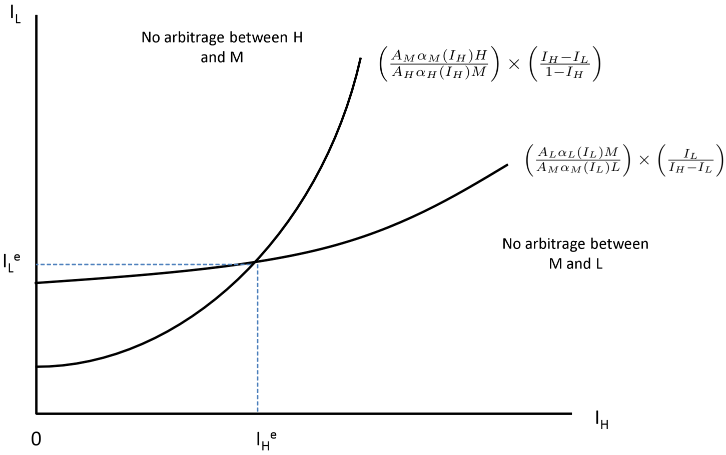
$$
\begin{aligned}
A_H \alpha_H (I_H) H / (1 - I_H) &= A_M \alpha_M (I_H) M / (I_H - I_L) \\
A_M \alpha_M (I_L) M / (I_H - I_L) &= A_L \alpha_L (I_L) L / I_L
\end{aligned}
$$

- Implies

$$
\begin{aligned}
P_H A_H H / (1 - H) &= P_M A_M M / (I_H - I_L) \\
P_M A_M M / (I_H - I_L) &= P_L A_L L / (I_L)
\end{aligned}
$$

# No Arbitrage Across Skill Groups: Relative Cost of Producing Marginal Task(s) Rising in Task Threshold(s)

Figure 22. Determination of Equilibrium Threshold Tasks



# Relative Supply and Demand for Skills Across Tasks

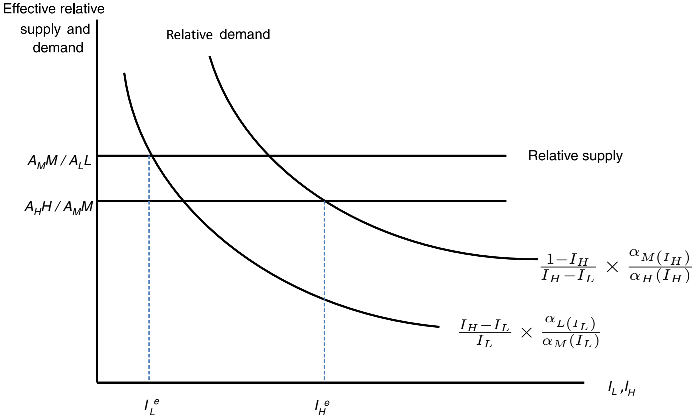



**Figure 23** ***Equilibrium allocation of skills to tasks.***

# Three equilibrium conditions

**3. No arbitrage between skill groups across tasks**

$$P_H A_H H / (1 - I_H) = P_M A_M M / (I_H - I_L)$$
$$P_M A_M M / (I_H - I_L) = P_L A_L L / (I_L)$$

- Substituting

$$W_H = P_H A_H, \; W_M = P_M A_M, \; W_L = P_L A_L$$

$$W_H H / (1 - H) = W_M M / (I_H - I_L)$$
$$W_M M / (I_H - I_L) = W_L L / (I_L)$$

$$\Rightarrow \frac{W_H}{W_M} = \left(\frac{1 - I_H}{I_H - I_L}\right) \frac{L}{H}, \; \frac{W_M}{W_L} = \left(\frac{I_H - I_L}{I_L}\right) \frac{L}{M}, \; \frac{W_H}{W_L} = \left(\frac{I_H}{I_L}\right) \frac{L}{H}$$

# A Ricardian Model of Skills, Tasks and Technologies

- These three conditions [law of one price, equal shares, no arbitrage] imply that relative wages are solely a function of labor supplies and task thresholds $w_J = w_J \left[ I_H, I_L | H, M, L, A_H, A_M, A_L, \alpha_H(\cdot), \alpha_M(\cdot), \alpha_L(\cdot) \right]$ for $J \in [H, M, L]$:

$$\begin{aligned} \frac{w_H}{w_M} &= \left( \frac{1 - I_H}{I_H - I_L} \right) \left( \frac{H}{M} \right)^{-1}, \\ \frac{w_M}{w_L} &= \left( \frac{I_H - I_L}{I_L} \right) \left( \frac{M}{L} \right)^{-1} \end{aligned}$$

- So, labor supplies $L$, $M$, $H$ plus compare adv. $\alpha(L)$, $\alpha(M)$, $\alpha(L)$ determine task allocation, $I_L$ and $I_H$, and hence wages.
- It's that simple!

# Canonical skill-biased technical change case – rising $A_H$ (relative to $A_M, A_L$)

1. **A rise in $A_H$ (SBTC)**
2. **A rise in high-skilled labor supply**
3. **Analogous comparative statics for rise in $A_L$ or $A_H$**
4. **What about a rise in $A_M$ or $M$ on $W_H/W_L$?**

# The response of task location to technology and skill supplies

- **An increase in the supply of $H$ labor or an $H$-augmenting technical change $A_H$**
  1. Own task share $\frac{dI_H}{d\ln A_H} = \frac{dI_H}{d\ln H} < 0$
  2. $L$ task share: $\frac{dI_L}{d\ln A_H} = \frac{dI_L}{d\ln H} < 0$
  3. $M$ task share: $\frac{d(I_H - I_L)}{d\ln A_H} = \frac{d(I_H - I_L)}{d\ln H} < 0$
- **Analogously for $d\ln L$ or $d\ln A_L$**
  - $\frac{dI_H}{d\ln A_L} = \frac{dI_H}{d\ln L} > 0$, $\frac{dI_L}{d\ln A_L} = \frac{dI_L}{d\ln L} > 0$
  - and $\frac{d(I_H - I_L)}{d\ln A_L} = \frac{d(I_H - I_L)}{d\ln L} < 0$

# The response of wages to skill supplies

- **Impact of an increase in the supply of labor on relative wages**
  1. **High skill supply:** $\frac{d \ln(w_H/w_L)}{d \ln H} < 0, \ \frac{d \ln(w_H/w_M)}{d \ln H} < 0$
  2. **Medium skill supply:** $\frac{d \ln(w_H/w_M)}{d \ln M} > 0, \ \frac{d \ln(w_M/w_L)}{d \ln M} < 0$
  3. **Low skill supply:** $\frac{d \ln(w_M/w_L)}{d \ln L} > 0, \ \frac{d \ln(w_H/w_L)}{d \ln L} > 0$
- **What about** $\frac{d \ln(w_H/w_L)}{d \ln M}$ **...? (see below)**

# The response of wages to factor-augmenting technological changes

- **Impact of technological changes on relative wages**
  1. $H$ **augmenting:** $\frac{d\ln(w_H/w_L)}{d\ln A_H} > 0$, $\frac{d\ln(w_H/w_M)}{d\ln A_H} > 0$, $\frac{d\ln(w_M/w_L)}{d\ln A_H} < 0$;
  2. $M$ **augmenting:** $\frac{d\ln(w_H/w_M)}{d\ln A_M} < 0$, $\frac{d\ln(w_M/w_L)}{d\ln A_M} > 0$
  3. $L$ **augmenting:** $\frac{d\ln(w_H/w_L)}{d\ln A_L} < 0$, $\frac{d\ln(w_H/w_M)}{d\ln A_L} > 0$, $\frac{d\ln(w_M/w_L)}{d\ln A_L} < 0$;
- **What about** $\frac{d\ln(w_H/w_L)}{d\ln A_M}$ **...?**

# Change in productivity or supply of middle-skill workers

**What happens when either $M$ or $A_M$ rises?**

- Depends critically on this term

$$\beta_H(I) \equiv \ln \alpha_M(I) - \ln \alpha_H(I), \beta_L(I) \equiv \ln \alpha_L(I) - \ln \alpha_M(I)$$

- $\beta$ are comp. advantage of $L$ versus $H$ workers in $M$ tasks
- $\beta'_L(I_L) I_L = \partial \beta_L / \partial I_L$ and $\beta'_H(I_H) I_H$
- If $\beta'_L(I_L)$ is low relative to $\beta'_H(I_H)$, high skill workers have *strong comparative advantage* for tasks above $I_H$

**Hence, rise in $M$ displaces $L$ workers more than $H$ iff**

$$\frac{d \ln(w_H/w_L)}{d \ln M} > 0 \text{ iff } |\beta'_L(I_L) I_L| < |\beta'_H(I_H)(1 - I_H)|$$

*Implicitly this occurs because $I_L$ falls more than $I_H$ rises*

# How labor-replacing technology enters

**Easy to model a 'task replacing technology'**

- Both $K$ and Labor can supply tasks—all perfect substitutes
- $K$ supplies task if can perform more cheaply than $L$, $M$, or $H$.

**Example: Routine Task Replacing technology**

- Capital that out-competes $M$ in a subset of tasks $i'$ in the interval $I_L < i' < I_H$

**Own wage effects**

- Immediately lowers relative wage of $M$ by narrowing set of $M$ tasks

**Cross-price effects on $W_L$ and $W_H$?**

- Again depend on $|\beta_L'(I_L)\, I_L| \gtreqless |\beta_H'(I_H)\,(1 - I_H)|$
- If $M$ workers better suited to $L$ than $H$ tasks, then $W_H/W_L$ rises

# Routine task replacing technology

**Focal case**

- Task replacing technology concentrated in middle-skill/routine tasks
- Strong comparative advantage of $H$ relative to $L$ at respective margins with $M$

**Leads to wage and employment 'polarization'**

1. Wages:
    - Middle wages fall relative to top and bottom.
    - Top rises relative to bottom
2. Employment:
    - Middle-skill/routine tasks mechanized
    - Declining labor input in Routine tasks
    - Given comparative advantage, middle-skill workers move disproportionately downward in task distribution.

# Offshoring

**Offshoring works identically to capital that competes for tasks**

- In this sense, model is akin to Grossman and Rossi-Hansberg (2008)
- But the comparative advantage setup here is much more general

# Two further extensions

**Endogenous choice of skills**

- Workers can have a bundle of $l$, $m$, and $h$ skills
- When comparative advantage of one skill sufficiently eroded, may switch skills
- Example: Former manager, now driving delivery truck

**Endogenous technical change**

- Endogenous tech change favoring *skills* is well understood from Acemoglu (1998, 2007)
- We also consider endogenous technical change *favoring tasks* in this model

# Ricardian Model: Summary

**Model's inputs**

1. Explicit distinction between *skills* and *tasks*
2. *Comparative advantage* among workers in different tasks
3. Multiple sources of competing task 'supplies'

**What the model delivers**

- A natural concept of occupations (bundles of tasks)
- An endogenous mapping from skill to tasks via comparative advantage
- Technical change (offshoring) that can raise and *lower* wages
- Migration of skills across tasks as technology changes
- Polarization of wages and employment as *one possible outcome*

# Conclusions

**Canonical model has been a conceptual and empirical success**

- But silent on some key phenomena of interest
    - Falling real wages for some groups
    - Non-monotone wage changes
    - Polarization of employment
    - Reallocation of skill groups across occupations

**Additional insights gained by**

1. Distinguishing between *skills* and *tasks*
2. Allowing for *comparative advantage* among workers in different tasks
3. Allowing for multiple sources of competing task 'supplies'

# Agenda

# Michael Webb 2019 (JMP): Using Patent Text to Measure Automation Exposure

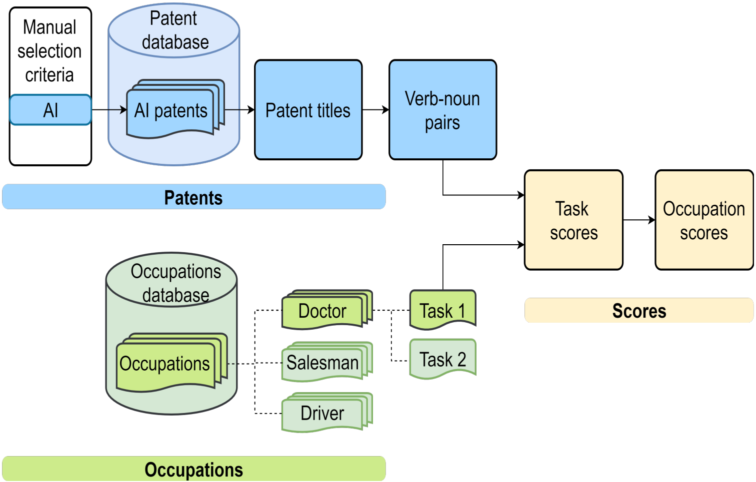



Figure 2: Illustration of process for constructing technology exposure measures

# Assessing Relative Employment and Wage Effects of Three Technologies

1. Software
2. Robots
3. Artificial Intelligence
    - Note: no outcome data yet available!

Table 6: **Top extracted verbs and characteristic nouns for software.**

| Verb | Example nouns | Verb | Example nouns |
|---|---|---|---|
| **record** | data, position, log, location, reservation, transaction | **detect** | defect, error, malware, fault, condition, movement |
| **store** | program, data, information, image, instruction, value | **generate** | data, image, file, report, map, key, password, animation, diagram |
| **control** | access, display, unit, image, device, power, motor | **measure** | rate, performance, time, distance, thickness |
| **reproduce** | data, picture, media, file, sequence, speech, item, document, selection | **receive** | signal, data, information, message, order, request, instruction, command |

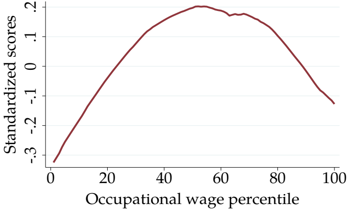
*Notes:* This table lists the top eight verbs by pair frequency extracted from the title text of patents corresponding to software, together with characteristic direct objects for each verb chosen manually to illustrate a range of applications. Patents corresponding to each technology are selected using a keyword search. A dependency parsing algorithm is used to extract verbs and their direct objects from patent titles.

# I. Software: Most/Least Exposed Occupations

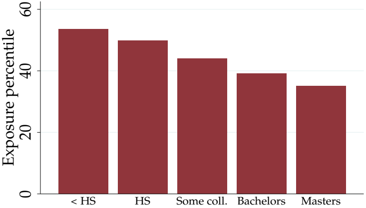
Table 7: **Occupations with highest and lowest exposure to software.**

| Most exposed occupations | Least exposed occupations |
|---|---|
| Broadcast equipment operators | Barbers |
| Water and sewage treatment plant operators | Podiatrists |
| Parking lot attendants | Subject instructors, college |
| Packers and packagers by hand | Art/entertainment performers |
| Locomotive operators: engineers and firemen | Mail carriers for postal service |

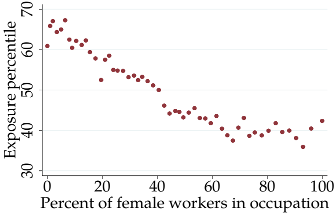
*Notes:* Table displays census occupation title for the five occupations with the highest exposure scores and with the lowest exposure scores above employment threshold of 150.



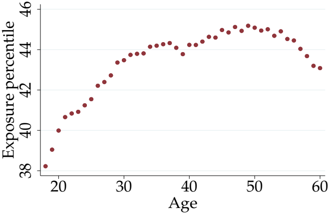

(a) Smoothed scores by occupational wage percentile




(b) Exposure by level of education




(c) Exposure by percent of female workers in occupation




(d) Exposure by age.

Figure 5: **Exposure to software by demographic group**

# I. Binscatter: Changes in Employment and Wages 1980 – 2010 by Exposure to Software

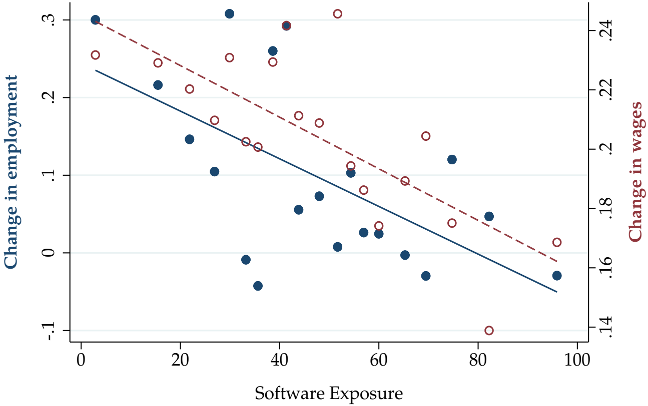



Figure 6: **Change in employment and wages 1980-2010 by exposure to software.**

*Notes:* Plot is a binscatter. Change in employment is measured as DHS change of an occupation-industry cell's share of overall employment between 1980 and 2010, winsorized at the top and bottom 1%. Change in wages is measured as log difference in a cell's mean FTFY weekly wage. Controls added for offshorability and industry fixed effects. Observations are weighted by cell's labor supply, averaged between 1980 and 2010.

# II. Robotics Patents: Keywords

Table 2: **Top extracted verbs and characteristic nouns for robots.**

| Verb | Example nouns | Verb | Example nouns |
|---|---|---|---|
| **clean** | surface, wafer, window, glass, floor, tool, casting, instrument | **walk** | robot, structure, base, stairs, circuit, trolley, platform, maze |
| **control** | robot, arm, motion, position, manipulator, motor, path, force | **carry** | substrate, wafer, tray, vehicle, workpiece, tool, object, pallet |
| **weld** | wire, part, tong, electrode, sensor, component, nozzle | **detect** | position, state, collision, obstacle, force, angle, leak, load, landmine |
| **move** | robot, body, object, arm, tool, part, substrate, workpiece | **drive** | unit, wheel, motor, belt, rotor, vehicle, automobile, actuator |

*Notes:* This table lists the top eight verbs by pair frequency extracted from the title text of patents corresponding to robots, together with characteristic direct objects for each verb chosen manually to illustrate a range of applications. Patents corresponding to each technology are selected using a keyword search. A dependency parsing algorithm is used to extract verbs and their direct objects from patent titles.

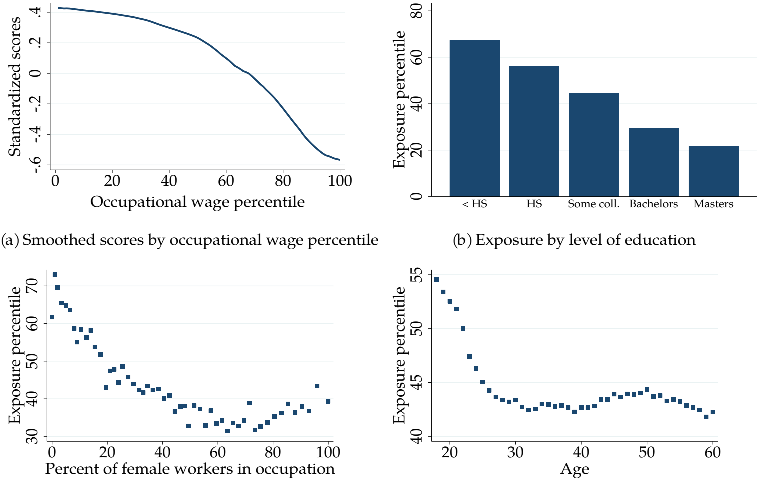
## II. Robots: Most/Least Exposed Occupations

Table 3: **Occupations with highest and lowest exposure to robots.**

| Most exposed occupations | Least exposed occupations |
|---|---|
| Forklift driver | Payroll and timekeeping clerks |
| Operating engineers of cranes, derricks, etc. | Art/entertainment performers |
| Elevator installers and repairers | Clergy |
| Janitors | Correspondence and order clerks |
| Locomotive operators: engineers and firemen | Eligibility clerks for government programs |

*Notes:* Table displays census occupation title for the five occupations with the highest exposure scores and with the lowest exposure scores above employment threshold of 150.

# II. Robotics: Who Performs Robot-Relevant Tasks?




(a) Smoothed scores by occupational wage percentile

(b) Exposure by level of education

(c) Exposure by percent of female workers in occupation

(d) Exposure by age.

Figure 3: **Exposure to robots by demographic group**

# II. Binscatter: Changes in Employment and Wages 1980 – 2010 by Exposure to Robots

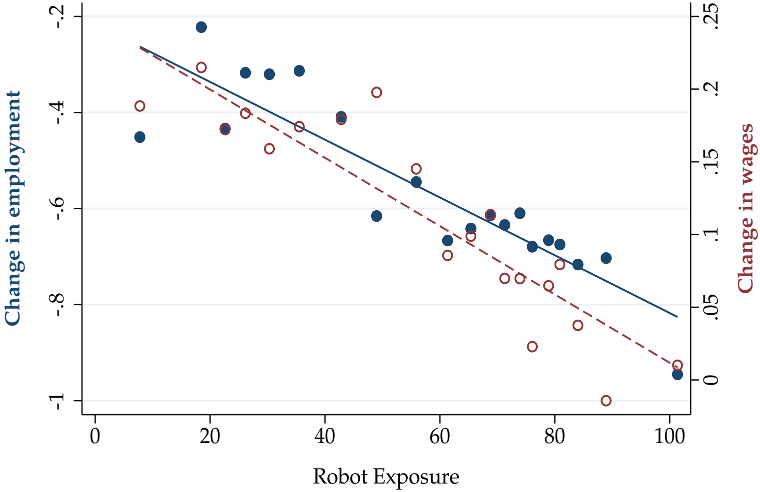



Figure 4: **Change in employment and wages 1980-2010 by exposure to robots.**

# III. Artificial Intelligence Patents: Keywords

Table 10: **Top extracted verbs and characteristic nouns for AI.**

| Verb | Example nouns | Verb | Example nouns |
|---|---|---|---|
| **recognize** | pattern, image, speech, face, voice, automobile, emotion, gesture, disease | **determine** | state, similarity, relevance, importance, characteristic, strategy, risk |
| **predict** | quality, performance, fault, behavior, traffic, prognosis | **control** | process, emission, traffic, engine, robot, turbine, plant |
| **detect** | signal, abnormality, defect, object, fraud, event, spammer, human, cancer | **generate** | image, rating, lexicon, warning, description, recommendation |
| **identify** | object, type, damage, illegality, classification, relationship, importance | **classify** | data, object, image, pattern, signal, text, electrogram, speech, motion |

*Notes:* This table lists the top eight verbs by pair frequency extracted from the title text of patents corresponding to AI, together with characteristic direct objects for each verb chosen manually to illustrate a range of applications. Patents corresponding to each technology are selected using a keyword search. A dependency parsing algorithm is used to extract verbs and their direct objects from patent titles.

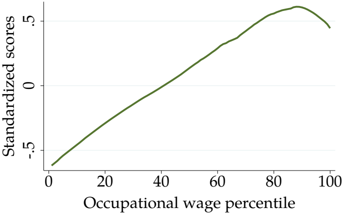
# III. Artificial Intelligence: Most/Least Exposed Occupations

Table 11: **Occupations with highest and lowest exposure to artificial intelligence.**

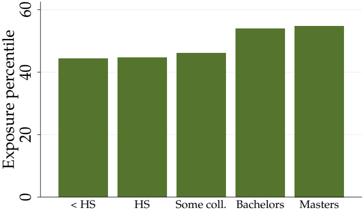
| Most exposed occupations | Least exposed occupations |
|---|---|
| Clinical laboratory technicians | Animal caretakers, except farm |
| Chemical engineers | Food preparation workers |
| Optometrists | Mail carriers for postal service |
| Power plant operators | Subject instructors, college |
| Dispatchers | Art/entertainment performers |

*Notes:* Table displays census occupation title for the five occupations with the highest exposure scores and with the lowest exposure scores above employment threshold of 150.

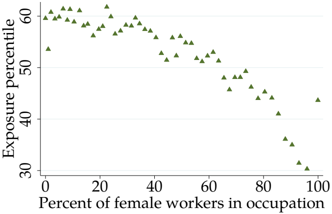
# III. Artificial Intelligence: Who Performs AI-Relevant Tasks?



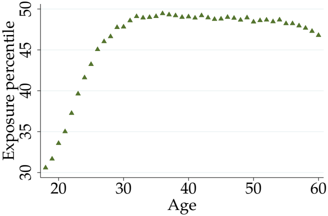

(a) Smoothed scores by occupational wage percentile




(b) Exposure by level of education




(c) Exposure by percent of female workers in occupation




(d) Exposure by age.

Figure 7: **Exposure to AI by demographic group**

# Summary of Webb 2019

- A general methodology for identifying 'task content' of new technologies, linking them to occupations
- Remarkably clear results on relationship between software and robot exposure and changes in employment and wages by industry-occupation
- Definitely possible but *far from certain* that AI exposure will have similar relationship (like software, robots) to employment/earnings in exposed occupations group

# Summary

**What is potentially missing here?**

1. Cannot say where complementarity happens: Is it all substitution?

2. Complementarity *is* actually operating in background
   - Overall employment and wage growth largely absorbed by including industry fixed effects
   - We know that high skill employment and wages *rose* in *non-substitutable* activities
   - Importance of *relative complements*

3. Naïve read: Asymptotic task encroachment
   - But is that right? Studying 'new tasks'
   - Do they exist? Where to they come from? How important are they for skill demands?

# The Skill Complementarity of Broadband Internet: Rollout of Broadband Internet in Norway, 2001 – 2005

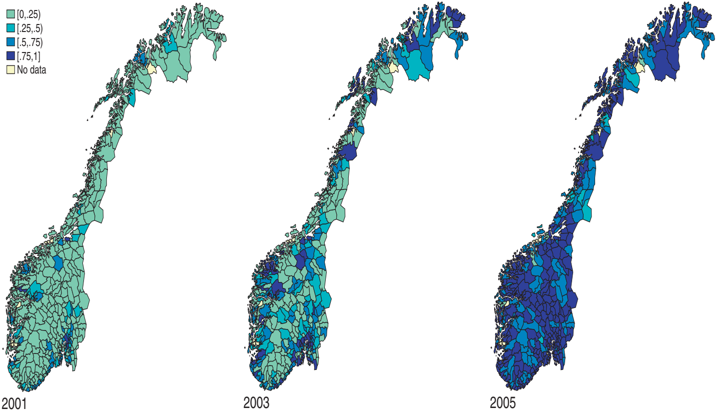



FIGURE I

Geographical Distribution of Broadband Availability Rates

The graphs show the geographical distribution of broadband availability rates of households in 2001, 2003, and 2005.

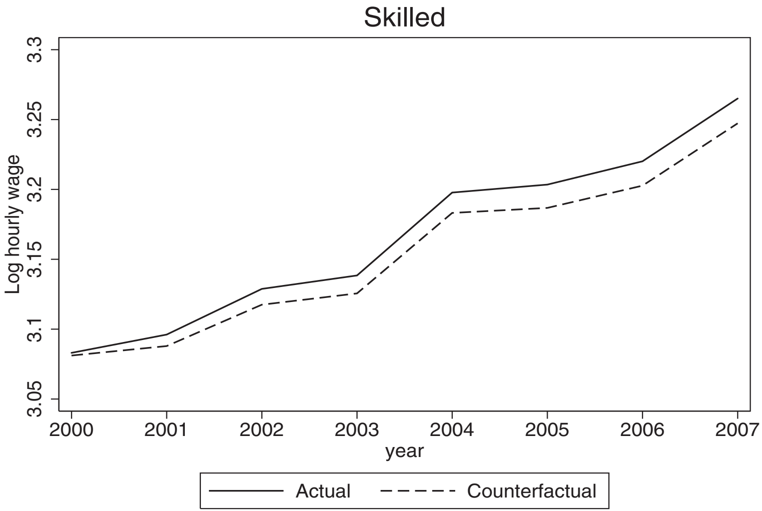
# Estimated Effect of Broadband Availability on Wages and Employment by Skill Level

Intention-to-Treat Effects on Wages and Employment

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable | Log hourly wage | | Employment | |
| | 2 skills | 3 skills | 2 skills | 3 skills |
| Unskilled | 2.939*** | | 0.691*** | |
| | (0.00455) | | (0.00262) | |
| Low skilled | | 2.905*** | | 0.664*** |
| | | (0.00431) | | (0.00231) |
| Medium skilled | | 2.977*** | | 0.731*** |
| | | (0.00454) | | (0.00288) |
| Skilled | 3.169*** | 3.171*** | 0.734*** | 0.737*** |
| | (0.00420) | (0.00407) | (0.00480) | (0.00477) |
| Availability × | | | | |
| Unskilled | −0.00622 | | 0.000794 | |
| | (0.00455) | | (0.00252) | |
| Low skilled | | −0.0108*** | | −0.00392 |
| | | (0.00325) | | (0.00244) |
| Medium skilled | | −0.00793 | | 0.00388 |
| | | (0.00600) | | (0.00281) |
| Skilled | 0.0178** | 0.0202*** | 0.0208** | 0.0225** |
| | (0.00720) | (0.00692) | (0.00920) | (0.00892) |
| Worker-year observations | 8,759,388 | 8,759,388 | 20,327,515 | 20,327,515 |
| | | *p*-values | | |
| Test for no skill bias | .000 | .000 | .012 | .001 |

# Estimated Effect of Broadband Availability on Evolution of High-Skill Wages

(a) Log hourly wages



# Estimated Effect of Broadband Availability on Evolution of Low-Skill Wages

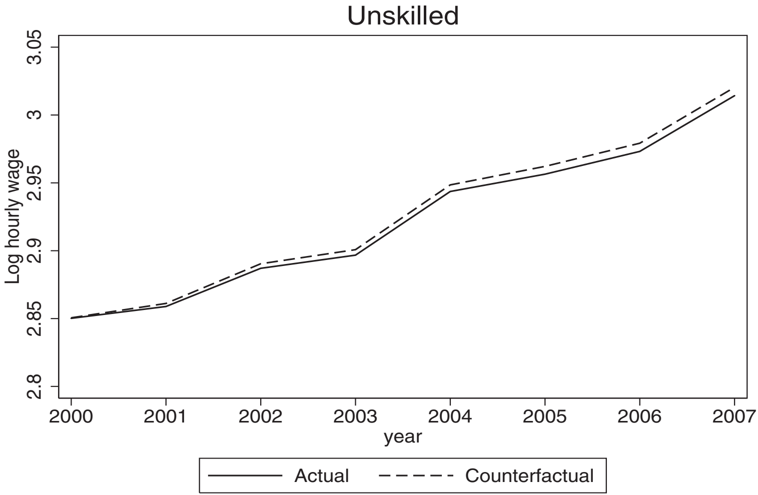



FIGURE III

Actual and Counterfactual Trends in Labor Market Outcomes

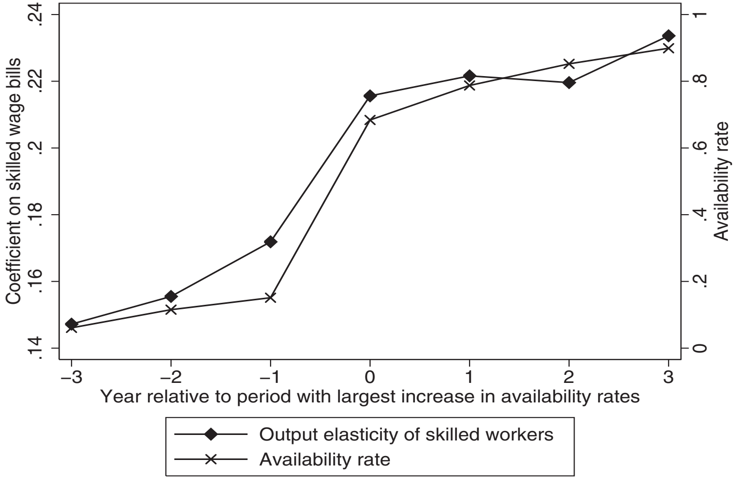
# Estimated Effect of Broadband Availability on Log Value-Added by Skill Group

Intention-to-Treat Effects on Output Elasticities

| | (1) | (2) |
|---|---|---|
| Dependent variable | Log value added | |
| | 2 skills | 3 skills |
| Intercept | 3.880*** | 4.537*** |
| | (0.0965) | (0.0791) |
| Log capital | 0.100*** | 0.0981*** |
| | (0.00495) | (0.00490) |
| Log unskilled | 0.576*** | |
| | (0.0116) | |
| Log low skilled | | 0.298*** |
| | | (0.00804) |
| Log medium skilled | | 0.265*** |
| | | (0.00684) |
| Log skilled | 0.136*** | 0.134*** |
| | (0.00678) | (0.00636) |
| Availability × | | |
| Intercept | −0.500*** | −0.561*** |
| | (0.111) | (0.0976) |
| Log capital | −0.00169 | 0.000188 |
| | (0.00750) | (0.00661) |
| Log unskilled | −0.0226 | |
| | (0.0234) | |
| Log low skilled | | −0.0274*** |
| | | (0.00934) |
| Log medium skilled | | 0.0179* |
| | | (0.00967) |
| Log skilled | 0.0755*** | 0.0645*** |
| | (0.0166) | (0.0137) |
| Firm-year observations | 149,676 | 137,498 |
| | $p$-values | |
| Test for no skill bias | .012 | .000 |

# Estimated Effect of Broadband on Output Elasticity of High-Skill Labor

(a) Output elasticity: Skilled labor



# Estimated Effect of Broadband on Output Elasticity of Low-Skill Labor

(b) Output elasticity: Unskilled labor

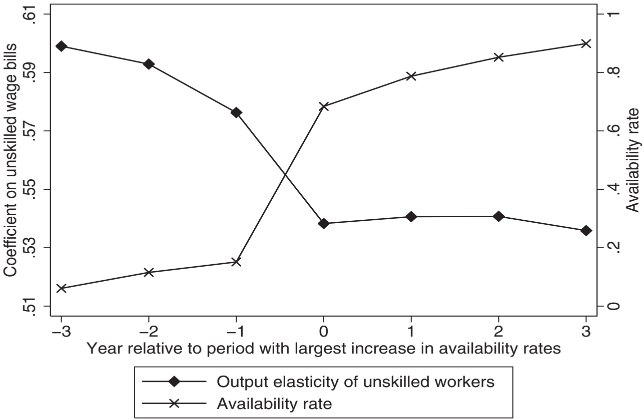



FIGURE II

Output Elasticities and Skill Premiums, Before and After the Largest Increase in Availability Rates (Period 0)

# Estimated Effect of Broadband Availability on Task-Wage Premiums

Wage Regressions with Interactions between Tasks and Broadband Availability

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable | Log hourly wage | | |
| | | Skill categories | |
| | | 2 skill levels | 3 skill levels |
| Abstract | 0.371*** | 0.283*** | 0.272*** |
| | (0.0142) | (0.0139) | (0.0140) |
| Routine | −0.0641*** | −0.0664*** | −0.0700*** |
| | (0.00653) | (0.00573) | (0.00577) |
| Manual | 0.0248*** | 0.0156** | 0.0138* |
| | (0.00791) | (0.00769) | (0.00740) |
| Availability × Abstract | 0.173*** | 0.157*** | 0.157*** |
| | (0.0320) | (0.0298) | (0.0297) |
| Availability × Routine | −0.0357*** | −0.0344*** | −0.0338*** |
| | (0.00798) | (0.00766) | (0.00791) |
| Availability × Manual | 0.00200 | 0.00145 | 0.00273 |
| | (0.0115) | (0.0107) | (0.0104) |
| Worker-year observations | 4,586,333 | 4,586,333 | 4,586,333 |
| Controlling for educational attainment: | | | |
| Skill levels | No | Yes | Yes |
| Availability × Skill levels | No | Yes | Yes |
| Tests for no task bias: | | *p*-values | |
| Equality of abstract and routine | .000 | .000 | .000 |
| Equality of abstract and manual | .000 | .000 | .000 |
| Equality of manual and routine | .041 | .040 | .036 |

# Agenda

1. **Motivation: The Canonical Model and Its Limitations**
2. **A Simplified Task Model with New Tasks**
   - Model setup
   - The displacement effect—Extensive margin tech $\Delta$
   - Deepening of automation—Intensive margin tech $\Delta$
   - Labor-Augmenting Technological $\Delta$
   - New task creation
3. **A Task Model with Comparative Advantage Across Skill Groups [for self-study]**
   - Production
   - Three equilibrium conditions
   - Comparative statics
   - Factor Augmentation, Factor Displacement, Offshoring
4. **Tasks and Technologies: Some Applications**
   - Projecting the Labor Market Effects of Artificial Intelligence
   - The Skill Complementarity of Broadband Internet
5. **Where Does New Work Come From?**

## Where Does New Work Come From?

Slides TBA at Young Scholars Workshop