Employment, Retirement, and Careers

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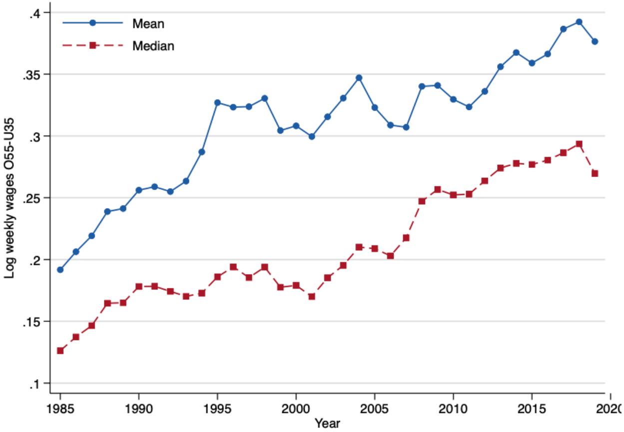
Roadmap

1. The effect of demographic change on labour markets (empirics)
2. Investigating “career spillovers”.
3. Age & skills: mapping the lifecycle to physical and cognitive skills.
4. Task-based lifecycle model

Large rises in old vs. young age gap (Italy)

Figure 1: Age Gap in Weekly Wages



Source: Bianchi and Paradisi (2025, working paper)

Large rises in old vs. young age gap

	Change in mean worker age		Level and change in age pay gap at the mean					
	last y. - first y.		first year	2007 - first y.	2013 - first y.	last year - first year		
	Δ years	Δ %	pay gap (log)	Δ pay gap (log)	Δ pay gap (log)	Δ pay gap (log)	Rank gap (%)	Distr. gap (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Employer-employee administrative data								
Italy (1985-2019)	6.87	19.21	0.192	0.115	0.164	0.185	78.32	17.52
Germany (1996-2017)	3.44	8.67	0.282	0.201	0.127	0.101	55.83	28.04
Panel B: Survey data from the Luxembourg Income Study (LIS) Database								
Australia (1995-2018)	5.66	16.22	0.039	0.166	0.183	0.177	80.01	7.23
Canada (1973-2018)	0.92	2.38	0.056	0.384	0.314	0.273	77.19	4.63
Denmark (1987-2018)	6.46	17.36	0.157	0.252	0.321	0.267	105.62	0.12
Finland (1987-2016)	6.81	19.00	0.153	0.088	0.116	0.111	106.59	2.12
France (2002-2018)	2.24	5.74	0.374	0.062	0.002	0.029	40.36	45.44
Germany (1994-2018)	3.77	9.82	0.448	0.162	0.175	0.084	48.40	48.98
Greece (1995-2016)	2.95	7.51	0.278	0.294	0.218	0.180	100.75	3.40
Israel (1979-2018)	-3.16	-7.77	0.046	0.393	0.756	0.700	58.30	8.81
Netherlands (1983-2018)	3.40	9.09	0.314	0.380	0.428	0.226	7.69	73.48
Norway (1986-2016)	4.17	10.68	0.123	0.095	0.139	0.159	77.78	16.86
Spain (1993-2018)	4.98	12.88	0.189	0.265	0.330	0.509	60.99	15.56
Switzerland (1982-2018)	2.44	6.20	0.131	0.727	0.621	0.481	49.61	7.03
United Kingdom (1979-2018)	3.21	8.66	0.103	0.044	0.134	0.042	15.24	51.81
United States (1979-2018)	4.51	11.91	0.222	0.144	0.176	0.136	89.00	19.93

Source: Bianchi and Paradisi (2025, working paper)

Puzzle: more older workers....but their work valued more...

- Older and younger workers are imperfect substitutes (Freeman (1979), Welch (1979), Berger (1985))
- Relative increase in **supply** of older workers should—all else equal—reduce their wage...but that has not happened.
- Explanations?

A stylized framework of career spillovers (Bianchi and Paradisi (2025))

- **Labor:** Fixed supply of l_y (young) and l_o (old) workers.
- **Jobs:** Top (t) and Bottom (b).
- **Production:** $A \cdot Y(L_y, L_o)$
  - Young & old are complements: $Y_{L_y,L_o} > 0$.
- **Labor Inputs:** $L_a = \theta_{a,t} l_{a,t} + \theta_{a,b} l_{a,b}$
  - Top job is more productive: $\theta_{a,t} > \theta_{a,b}$.

The mechanism of career spillovers

Negative spillovers arise from two key features:

1. **Incumbent wage stickiness**
   - Older workers' wages and job allocations are stickier than those of new entrants.
   - **Reasons:** Firm-specific human capital, backloaded pay, layoff costs.
   - **In the model:** The firm inherits "legacy" older workers ($\rho_j l_{o,j}^{-1}$) with non-renegotiable wages from period -1.
2. **Changing the org structure**
   - The firm has K total slots at the top ($K = l_{o,t} + l_{y,t}$).
   - Incurs a quadratic administrative cost for top jobs: $\frac{c}{2}K^2$.
   - This cost ($c > 0$) represents the organizational cost of creating new, high-responsibility positions.
   - Disincentivizes the firm from creating top jobs for all qualified younger workers.

- **Wage Formation**
  - Top jobs pay an exogenous rent over bottom jobs.
  - $w_{a,t} = \mu_a w_{a,b}$, where the wedge $\mu_a > 1$.

- **Timing of the Game**
  1. Firm receives legacy older workers.
  2. Given wages, firm chooses $l_{y,t}$ and $l_{y,b}$ by equating marginal revenue product to marginal cost.

- **The Firm's Problem**
  - Choose $l_{y,b}$ and $l_{y,t}$ to maximize profits:

$$\max_{l_{y,b},l_{y,t}} \left(A \cdot Y(L_y, L_o) - \sum_{a,j} w_{a,j} l_{a,j} - \frac{c}{2} K^2 \right)$$

Proposition 1: Mechanism & Implications

- **Overall Effect on Mean Wage of Young Workers**

$$\frac{\partial \bar{w}_y}{\partial l_{o,t}^{-1}} = \frac{1}{l_y}(\mu_y - 1) w_{y,b} \frac{\partial l_{y,t}}{\partial l_{o,t}^{-1}} + \left[\frac{l_{y,t}}{l_y}(\mu_y - 1) + 1 \right] \frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}}$$

- **Force 1 (Negative): Career Spillovers**
  - More legacy workers restrict access for the young: $\frac{\partial l_{y,t}}{\partial l_{o,t}^{-1}} < 0$.
  - **Why?** When the cost c is high, the firm creates some new top slots (due to complementarity) but not enough to offset the new legacy workers.

- **Force 2 (Positive): Wage Level**
  - Base wage for young workers increases: $\frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}} > 0$.
  - **Why? (Two-fold)**
    1. More older workers → higher marginal product for young (complementarity).
    2. Young workers are pushed to bottom jobs → *further* increases marginal product of young labor.

Departing from L

- So far our notion of labour has been rather aggregate (i.e. L).
- But key questions pertain not to L but to more disaggregated notions of L, such as occupations (bundles of tasks).
- Cannot think about "careers" (i.e. changing task bundles) in models with L.
- Need a framework that models tasks explicitly. Can help organize thoughts about occupational sorting, differential impact of new tech across the age distribution, etc.

Why a task-based framework for demographics & labour markets?

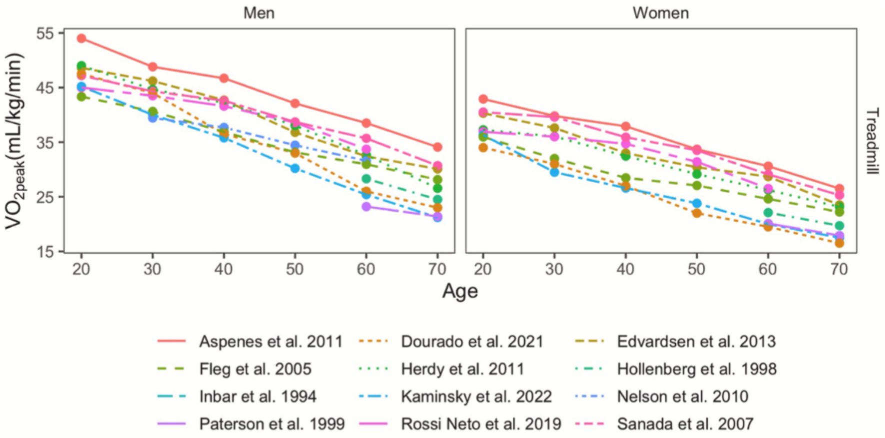
- **Skills → tasks → wages.**
  Demographic change shifts the *skill* composition of the workforce. A task framework can map these shifts into changes in task assignment (sorting), wages, etc.

- **Technology impacts**
  As some worker types become scarce (e.g. middle-aged or physically strong cohorts), the least-cost supplier of a task may switch between domestic labour and capital/automation.

- **Demographics reshape the *demand* for tasks.**
  An ageing population increases demand for specific task bundles (e.g. elderly care, health services, etc). Task-based framework can model how demographic shocks shift the composition of required tasks.

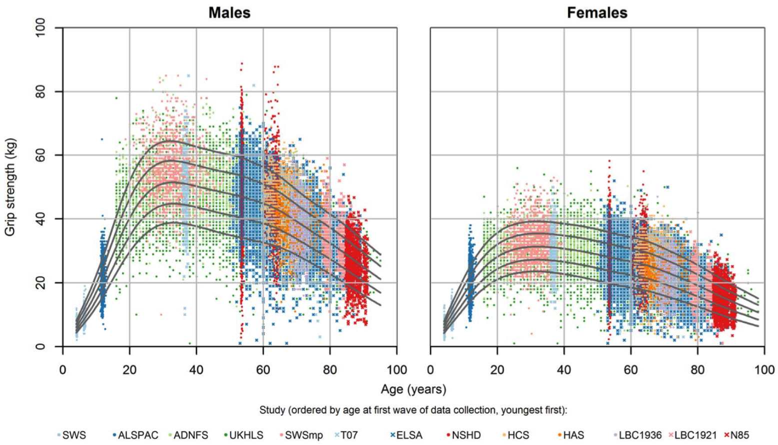
Some key ingredients: mapping age → skills & mapping skills ↔ to occupations

VO2 max declines with age



Source: Letnes et al. (2023, International Journal of Cardiology Cardiovascular Risk and Prevention)

Grip strength declines with age



Source: Dodds et al. (2014, PLOS ONE)

Fluid vs. Crystallized Cognition

- Standard task models bundle all "Non-Routine Cognitive" tasks.
- But important subcomponents of cognition evolve **differentially** with age.

Fluid Intelligence (G_f)

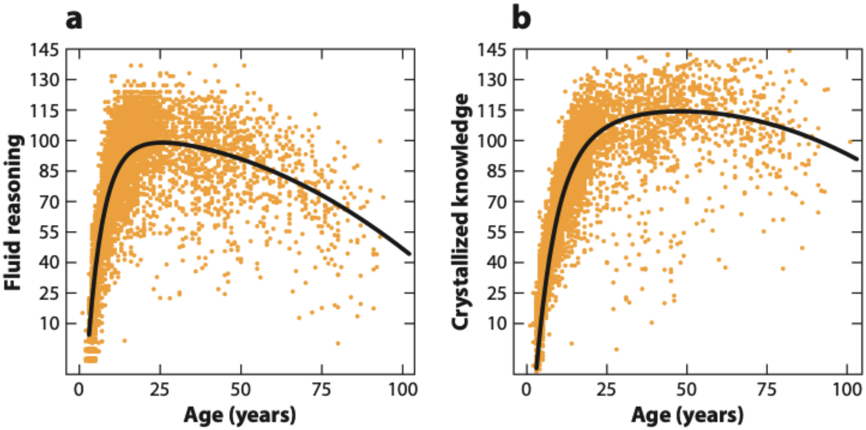
- Solving **novel** problems (processing speed, abstract reasoning).
- Peaks in young adulthood, then **declines**.

Crystallized Intelligence (G_c)

- Accumulated knowledge & experience (expert judgement, vocabulary).
- Peaks later and declines less rapidly.

Relevance to Task Framework:

- Generates a **shifting comparative advantage**: younger workers $\rightarrow$ G_f tasks; older workers $\rightarrow$ G_c tasks.
- Helps explain **occupational sorting by age** and changes in skill supply.



Source: Tucker-Drob (2019, Annual Review of Developmental Psychology)

Production: the final good

A representative, competitive firm produces a final good, Y, using a CES aggregator over a **discrete** set of tasks $\mathcal{T}$.

The production function includes an exogenous **demand shifter**, D_j, for each task j:

$$Y = \left(\sum_{j \in \mathcal{T}} (D_j y_j)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

- y_j is the quantity of task j used in production.
- $\sigma > 0$ is the elasticity of substitution between tasks.
- D_j is the exogenous demand shifter for task j.
- Each task $j \in \mathcal{T}$ is defined by a vector of requirements $T_j = (\tau_P, \tau_F, \tau_C)$.

Firm optimization & task demand

The firm chooses y_j to maximize profits $\Pi = Y - \sum_j p_j y_j$, taking task prices p_j as given.

The first-order condition yields the (inverse) demand for each task j:

$$p_j = \frac{\partial Y}{\partial y_j} = Y^{\frac{1}{\sigma}} (D_j y_j)^{-\frac{1}{\sigma}} D_j \tag{2}$$

Inverting this gives the standard CES demand function, modified by the demand shifter D_j:

$$y_j = Y \cdot p_j^{-\sigma} \cdot D_j^{\sigma - 1} \tag{3}$$

- Task demand y_j^D increases with total output Y.
- It decreases with its own price p_j (elasticity σ).
- It is shifted by the exogenous term D_j.

Households: population & skill endowment

The economy is populated by a measure of workers, L_{pop}.

Each worker is defined by a **type** $i = (a, \textbf{type})$, where:

- $a \in [18, 80]$ is the worker's **age**.
- $\text{type} \in \{\text{Low Skill}, \text{High Skill}\}$ is their **cognitive type**.

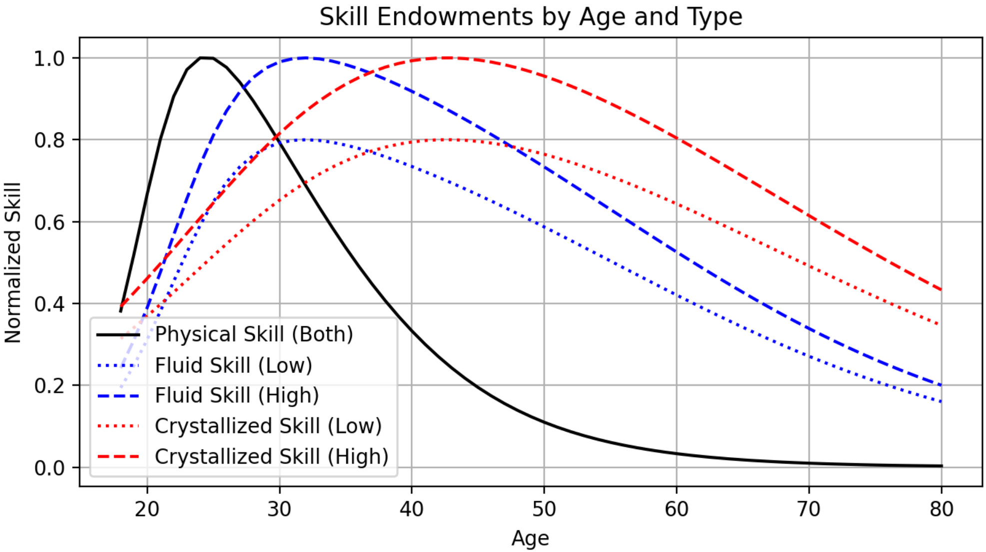
There is an exogenous population mass $L_{\text{pop}}(i)$ for each worker type.

Each worker type i is endowed with a skill vector $S(i)$:

$$S(i) = (s_P(i), s_F(i), s_C(i)) \tag{4}$$

- $s_P(i)$: Physical skill (depends only on age).
- $s_F(i)$: Fluid skill (depends on age and type).
- $s_C(i)$: Crystallized skill (depends on age and type).

Skill endowment evolves with age



Household: worker productivity

Productivity $\Gamma(i,j)$ in task j depends on the match between worker i's skills $S(i)$ and task j's requirements T_j.

Productivity is defined as **absolute productivity**, $G(i)$, minus a **mismatch cost**, $M(i,j)$:

$$G(i) = G_{\text{base}} + w_P s_P(i) + w_F s_F(i) + w_C s_C(i) \tag{5}$$

$$M(i,j) = \sum_{k \in \{P,F,C\}} \frac{\theta_k}{2} (s_k(i) - \tau_k(j))^2 \tag{6}$$

The final productivity is the non-negative part of this difference:

$$\Gamma(i,j) = \max\left(0, G(i) - M(i,j)\right) \tag{7}$$

Workers are **price-takers** but **wage-makers** through their choice of task. The **wage** for worker i in task j is the **price** of the task multiplied by their productivity in it:

$$w(i,j) = p_j \cdot \Gamma(i,j)$$

Workers do not perfectly sort. Instead, they choose tasks probabilistically based on potential wages, following a **logit (smooth max)** model.

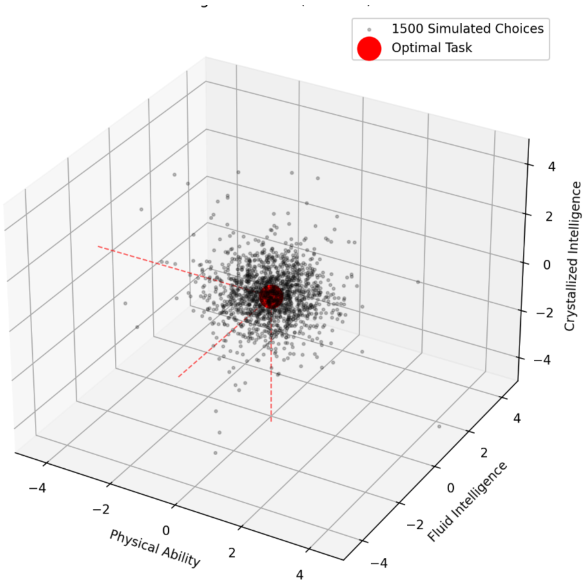
The probability that worker i chooses task j is:

$$\pi(i,j) = \frac{\exp(\lambda \cdot w(i,j))}{\sum_{j' \in \mathcal{T}} \exp(\lambda \cdot w(i,j'))} \tag{8}$$

- $\lambda \geq 0$ is the "smoothness" parameter, governing the sensitivity of sorting to wage differences.
- As $\lambda \to \infty$, this model approaches the "perfect sorting" $\arg\max$ case.

What does this actually mean and why do we do it?!

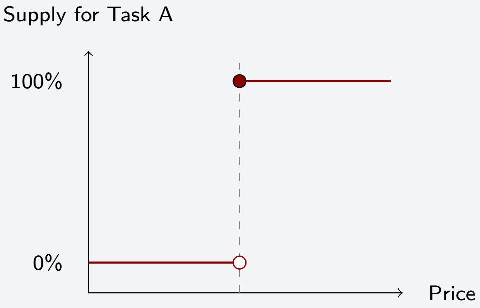
Workers of type $\{a, \text{skill}\}$ do not all pick same task bundke



"Smooth model" also helps with computational stability

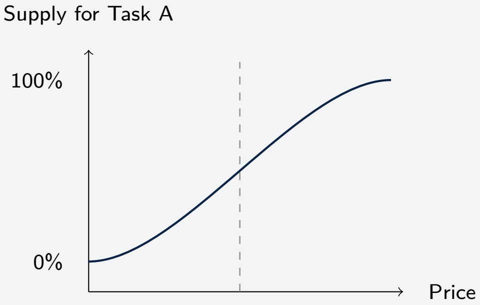
1. The 'Hard' `argmax` Problem

- A tiny change in its guess causes a massive, chaotic jump in labor supply.



2. The 'Smooth' Logit Solution

- As Task A's price increases, its *probability* of being chosen increases smoothly.



Household: labour supply choice

Workers make a static labor supply decision $L(i) \in [0,1]$ to maximize expected utility.

The worker's problem is:

$$\max_{L(i)\in[0,1]} \quad \mathbb{E}[U(i)] = \underbrace{E[C(i)]}_{\text{Expected consumption}} + \underbrace{\phi \cdot \log(1 - L(i))}_{\text{Utility from Leisure}} \tag{9}$$

$$\text{s.t. } C(i) = w(i) \cdot L(i)$$

Solving yields the optimal labor supply function:

$$L(i) = \max\left(0, 1 - \frac{\phi}{\bar{w}(i)}\right) \tag{10}$$

- ϕ is the reservation wage (or value of leisure).
- If the expected wage $\bar{w}(i)$ is below ϕ, the worker "retires" (supplies 0 labor).

Equilibrium

An equilibrium is a set of task prices $\{p_j\}_{j \in \mathcal{T}}$ and total output Y such that all task markets clear.

Market Clearing

For all tasks $j \in \mathcal{T}$, supply must equal demand ($y_j^S = y_j^D$):

$$\underbrace{\sum_i \underbrace{L_{\text{pop}}(i)}_{\text{Pop.}} \cdot \underbrace{L(i)}_{\text{Labor Supply}} \cdot \underbrace{\pi(i,j)}_{\text{Sorting}} \cdot \underbrace{\Gamma(i,j)}_{\text{Productivity}}}_{\text{Total Task Supply } (y_j^S)} = \underbrace{Y \cdot p_j^{-\sigma} D_j^{\sigma-1}}_{\text{Total Task Demand } (y_j^D)}$$

Where total output Y is the sum of all worker income:

$$Y = \sum_i L_{\text{pop}}(i) \cdot L(i) \cdot \bar{w}(i)$$

Think of workers having a target task bundle (the one that pays the highest income). This target task bundle is:

$$T^*(a) = \arg\max_{T \in \mathcal{T}} \{ \underbrace{p(T)}_{\text{Task Price}} \cdot \underbrace{\Gamma(a, T)}_{\text{Productivity}} \} \tag{11}$$

Optimal choice of job does not just on how "good" I am at that job; it also depends on how much I get paid to do that job.

Household FOC: The core tradeoff

$$\underbrace{\frac{\partial p(T)}{\partial \tau_k}\Gamma(i,T)}_{\text{Marginal Benefit}} = \underbrace{-p(T)\frac{\partial \Gamma(i,T)}{\partial \tau_k}}_{\text{Marginal Cost}}$$

Marginal Benefit (Price-Chasing)

- **What it is:** The wage *gain* from the market's "skill premium" ($\frac{\partial p}{\partial \tau_k}$), scaled by your productivity (Γ).
- **Intuition:** "If I choose a task with a higher requirement, how much more money does the market pay me?"

Marginal Cost (Mismatch-Cost)

- **What it is:** The wage *loss* from lower productivity ($\frac{\partial \Gamma}{\partial \tau_k}$), scaled by the task's price (p).
- **Intuition:** "If I choose a task that's a worse fit for my skills, how much productivity (and thus income) do I lose?"

Optimal task choice

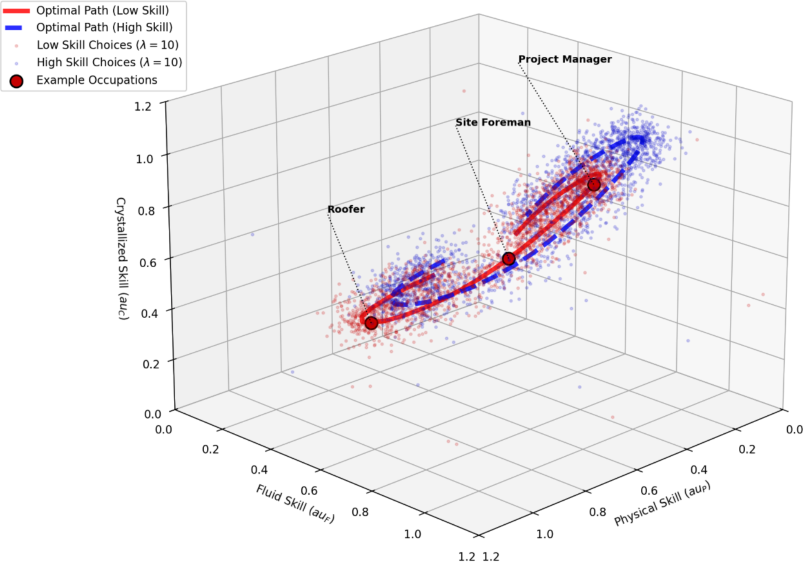
The first-order condition for the optimal choice of a characteristic τ_k^* is:

$$\underbrace{\tau_k^*}_{\text{Optimal Task}} = \underbrace{s_k(a)}_{\text{Worker Skill}} + \underbrace{\left[\frac{1}{\theta_k}\right] \cdot \left[\frac{\Gamma(a, T^*)}{p(T^*)}\right] \cdot \left[\frac{\partial p(T)}{\partial \tau_k}\right]}_{\text{Optimal Deviation from Perfect Match}} \tag{12}$$

Intuition for the Optimal Deviation:

- $\frac{\partial p(T)}{\partial \tau_k}$ (**The Skill Premium**): The market "price" for a higher skill requirement. A high premium provides an incentive to "reach" for a task with a higher τ_k.
- $\frac{1}{\theta_k}$ (**Mismatch Cost**): A high cost θ_k makes mismatch painful. This term shrinks the deviation, pushing $\tau_k^* \to s_k(a)$.
- $\frac{\Gamma(a,T^*)}{p(T^*)}$ (**Productivity-Price Ratio**): Magnifies the incentive. A highly productive worker (Γ) gains more from chasing a price premium.

Occupational sorting along the lifecycle path through task space



Introduction of “age-friendly” labour technology

Example: warehouse worker moving boxes

Intervention: Firm invests in a powered lift-assist tool or exoskeleton.

Before (High τ_P)

- Task: Manually lift and carry boxes
- Mismatch: High mismatch cost for older workers with lower $s_P(i)$.

After (Low τ_P)

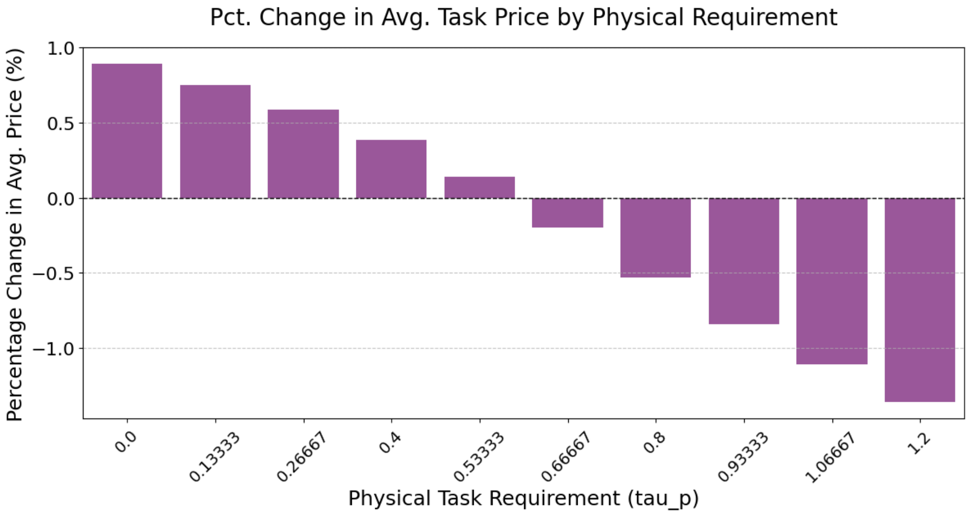
- Task: Operate the tool to move boxes.
- Mismatch: Low mismatch cost for older workers with lower $s_P(i)$.

Policy aim: Address **mismatch cost** $M(i, j)$ for older workers in high τ_p jobs

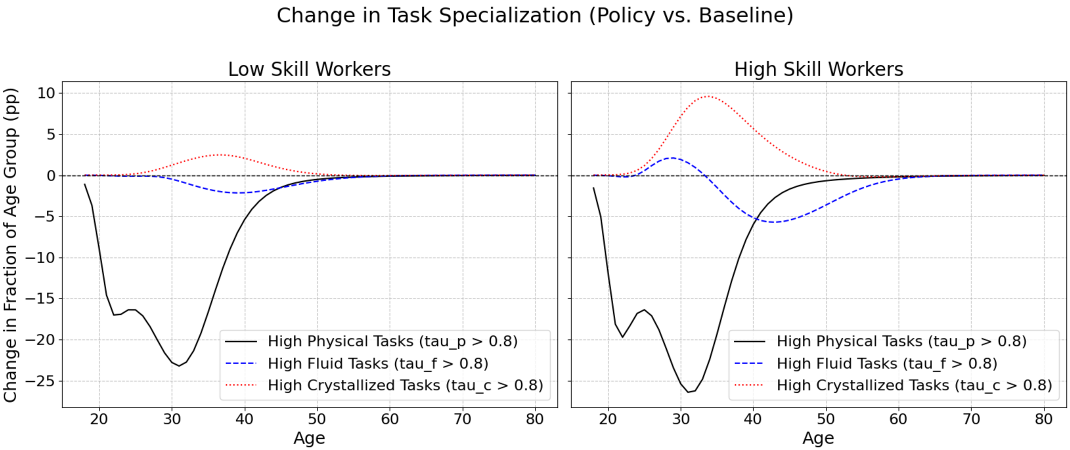
General Equilibrium Effect:

- The relative price p_j for these newly-popular low-τ_P tasks will **increase** which kicks off a round of re-sorting.
- This re-sorting of workers will, in turn, affect the prices and wages for *all other tasks and workers* in the economy.

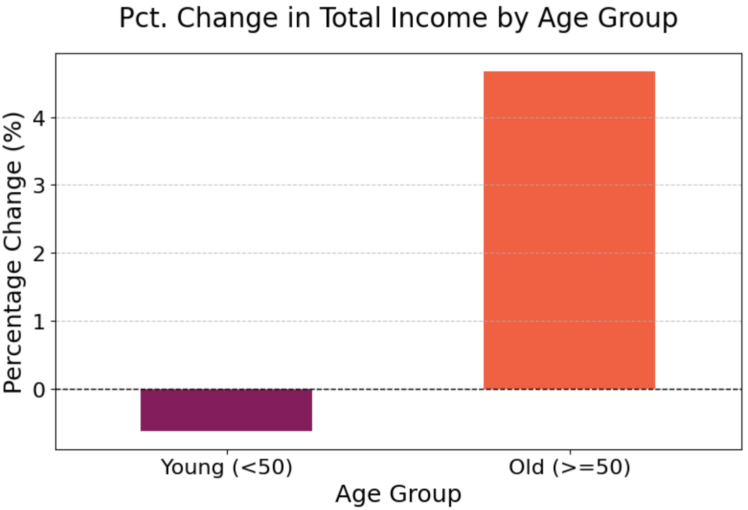
Firms pay higher price for low-physical tasks



Workers re-sort away from low-demand physical tasks



Older workers take larger share of total income



“Age friendly” jobs accrue to the young