# The "Task Approach" to Labor Economics and its Implications on the Impact of Technological Change

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August 17, 2023

## Contents

# 1. Comparison between Different Task-Based Models

The basic static model about task-based labor economics is Acemoglu and Autor (2011): The final good is produced by a continuum of tasks $i \in [0,1]$. For each task, it can possibly be produced by low-, medium-, high-skilled labor and capital. These four factors are substitutes in the sense that in equilibrium, each task $i$ is produced by one and only one factor based on their comparative advantage. Automation (see also Acemoglu and Restrepo (2018a) for a simplifed version) and offshoring are modelled as there is an interval of tasks originally produced by medium workers that can be produced by new technology or by foreign countries. It is used to account for the facts about job polarization, non-monotone changes in earnings levels, and etc.

One strand of extension is to introduce another exogenous layer ("occupation") to the production: A certain bundle of tasks must first be integrated as an "occupation" to put into production. Autor and Handel (2013); Gathmann and Schönberg (2010) regard an occupation as an exogenous and fixed vector of some base skill components. (Here, skills are classified as abstract, routine, and manual etc rather than different demographic groups as in Acemoglu and Autor (2011).) In particular, Autor and Handel (2013) studies the self-selection of workers with fixed skill vector endowments into different occupations, while Gathmann and Schönberg (2010) introduce a human capital accumulation process, that is, workers' skills will evolve with past occupations experience.

To further extend this strand, Ocampo (2022); Adenbaum (2023) endogenize the skill contents within each occupation. In their model, production is achieved by assigning a continnum of tasks (requiring the use of multidimentional skills) to finite number of workers endowed with some fixed skill vectors. Optimization is gained if the firm minimize the mismatch costs between tasks' and workers' skill composition. Ocampo (2022) aims to study how automation, training, and offshoring affect the skill composition of occupations. And Adenbaum (2023) introduces firm productivity heterogeneity and organizational costs to study the resulting occupations (or in his term, worker specilization) across different firms.

Another aspect of extension is to introduce industries, sectors and commuting zones into this static model and try to study the equilibrium effects of automation. These papers always start with a general equilibrium model and derive some comparative static results which motivate their measure of automation in the empirical part. The model guarantees that the measure can reflect the general equilibrium effects of automation on employment, wage, and inequality etc. Acemoglu and Restrepo (2020, 2022) are examples of this literature.

Finally, we can also dynamically model technological change. Acemoglu and Restrepo (2018b); Hémous and Olsen (2022) embed the task-framework into a dynamic environemnt by allowing both automation (replacement of workers using capital) and creation of new tasks (more complicated new tasks can only be done by labor) and study how autommation affects general employment, inequality, and etc. Acemoglu and Restrepo (2018b) has a good result regarding stability: if the rate of automation displacement effect and the rate of creation of new tasks are similar, the labor share won't decline.

# 2. Theory Papers about Task-Based Labor Economics

## 2.1. Acemoglu and Autor (2011)

**Paper**: Skills, Tasks and Technologies: Implications for Employment and Earnings, Handbook of Labor Economics

### 2.1.1. The Canonical Model

Most economic analyses of changes in wage structure and skill differentials build on the ideas proposed in Katz and Murphy (1992); Card and Lemieux (2001), among many others.

In this approach, *the college/high school log wage ratio* serves as a summary index of the premium that high skill workers command relative to low skill workers, and this premium is determined by the relative supply and relative demand for skills.

The relative demand for skills increases over time because changes in technology are assumed to be "skill biased," in the sense that new technologies have greater skill demands for or are more complementary to high skill workers. Since relative supply has also steadily increased over the last century and a half, both because of the greater public investments in schooling and because of greater willingness of families and individuals to acquire schooling, this leads to Tinbergen's famous race between technology and the supply of skills.

The effects of relative demand and supply on the earnings distribution is typically modelled in an environment with just *two types of workers (high and low skill)* and *competitive labor markets*. In addition, the substitution between the two types of workers is often captured using *a constant elasticity of substitution aggregate production function*. A framework with these features is referred to as the canonical model by the authors.

### 2.1.2. New Empirical Regularities

However, several empirical findings about American labor market trends cannot be explained by the canonical model:

- Low skill (particularly low skill male) workers have experienced significant real earnings declines over the last four decades.
- There have been notably non-monotone changes in earnings levels across the earnings distribution over the last two decades (sometimes referred to as wage "polarization"), even as the overall "return to skill" as measured by the college/high school earnings gap has monotonically increased.

- These changes in wage levels and the distribution of wages have been accompanied by systematic, non-monotone shifts in the composition of employment across occupations, with rapid simultaneous growth of both high education, high wage occupations and low education, low wage occupations in the United States and the European Union.
- This "polarization" of employment does not merely reflect a change in the composition of skills available in the labor market but also a change in the allocation of skill groups across occupations–and, in fact, the explanatory power of occupation in accounting for wage differences across workers has significantly increased over time.
- Recent technological developments and recent trends in offshoring and outsourcing appear to have directly replaced workers in certain occupations and tasks.

**Data**: the March Current Population Survey (March CPS), the combined Current Population Survey May and Outgoing Rotation Group samples (May/ORG CPS), the Census of Populations (Census), and the American Community Survey (ACS). [1]

#### 2.1.3. The Task-Based Model

Facing these new empirical regularities, the authors propose a tractable task-based model in which the assignment of skills to tasks is endogenous and technical change may involve the substitution of machines for certain tasks previously performed by labor.

More specifically, a *task* is a unit of work activity that produces output (goods and services). A *skill* is a worker's endowment of capabilities for performing various tasks. Workers apply their skill endowments to tasks in exchange for wages, and skills applied to tasks produce output. The distinction between skills and tasks becomes particularly relevant when *workers of a given skill level can perform a variety of tasks and change the set of tasks that they perform in response to changes in labor market conditions and technology*.

The model here is most relevant to Costinot and Vogel (2010); Acemoglu et al. (2001); Autor et al. (2003).

**A Brief Summary of the Model**:

The unique final good is produced by combining a continuum of tasks represented by the unit interval, $[0,1]$.

$$Y = \exp\left(\int_0^1 \ln\big(y(i)\big)di\right), \tag{2.1.1}$$

[1] The authors use the March files from 1964 to 2009 (covering earnings from 1963 to 2008) to form a sample of real weekly earnings for workers aged 16 to 64 who participate in the labor force on a full-time, full-year (FTFY) basis, defined as working 35-plus hours per week and 40-plus weeks per year. They also complement the March FTFY series with data on hourly wages of all current labor force participants using May CPS samples for 1973 through 1978 and CPS Outgoing Rotation Group samples for 1979 through 2009 (CPS May/ORG). To analyze levels and changes in occupational structure within and across detailed demographic groups, they exploit the 1960, 1970, 1980, 1990 and 2000 Census of Populations and the 2008 American Community Survey (ACS).

where $Y$ denotes the output of a unique final good and we will refer to $y(i)$ as the "service" or production level of task. [2]

Each task has the following production function

$$y(i) = A_L \alpha_L(i) l(i) + A_M \alpha_M(i) m(i) + A_H \alpha_H(i) h(i) + A_K \alpha_K(i) k(i), \tag{2.1.2}$$

where $A$ terms represent factor-augmenting technology, and $\alpha_L(i), \alpha_M(i), \alpha_H(i)$ are the task productivity schedules, designating the productivity of *low, medium and high skill* workers in different tasks. For example, $\alpha_L(i)$ is the productivity of low skill workers in task $i$, and $l(i)$ is the number of low skill workers allocated to task $i$. It is critical to observe that this production function for task services implies that each task can be performed by low, medium or high skill workers, but the comparative advantage of skill groups differ across tasks, as captured by the $\alpha$ terms. These differences in comparative advantage will play a central role in our model.

**Assumption 2.1.1.** $\frac{\alpha_L(i)}{\alpha_M(i)}$ and $\frac{\alpha_M(i)}{\alpha_H(i)}$ are continuously differentiable and strictly decreasing.

This assumption specifies the structure of comparative advantage in the model. It can be interpreted as stating that *higher indices correspond to "more complex" tasks in which high skill workers are better than medium skill workers and medium skill workers are better than low skill workers*. Though not very restrictive, this assumption ensures a particularly simple and tight characterization of equilibrium in this economy.

Factor market clearing requires

$$\int_0^1 l(i)di \leq L, \quad \int_0^1 m(i)di \leq M \quad \text{and} \quad \int_0^1 h(i)di \leq H. \tag{2.1.3}$$

In the following results, there is no labor supply decision on the part of the workers. Let us first ignore capital (equivalently, $\alpha_K(i) \equiv 0 \forall i$). This implies that initially there are no machines that can substitute for labor in the production of specific tasks.

Equilibrium is first characterized by Lemma 2.1.1.

**Lemma 2.1.1.** 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 $i > I_H, l(i) = m(i) = 0$.

This lemma shows that the set of tasks will be partitioned into three (convex) sets, one performed by low skill workers, one performed by medium skill workers and one performed by high skill workers.

[2] More generally, in Autor (2013), David Autor writes the production function as

$$Y = \left[ \int_0^1 y(i)^{\frac{\eta-1}{\eta}} di \right]^{\frac{\eta}{\eta-1}},$$

where $\eta$ is the elasticity of substitution between tasks.

Crucially, the boundaries of these sets, $I_L$ and $I_H$, are endogenous and will respond to changes in skill supplies and technology.

This introduces the first type of substitution that will play an important role in our model: *the substitution of skills across tasks*. Given the types of skills supplied in the market,firms (equivalently workers) will optimally choose which tasks will be performed by which skill groups.

After obtaining this result, the authors then derive the wage rate for different skill level workers using the simple "law of one price" that has to hold in any competitive equilibrium.

**Further Discussion and Extension**:

- Comparative statics
- Task replacing technologies: suppose that *there now exists a range of tasks* $[I', I''] \subset [I_L, I_H]$ *for which* $\alpha_K(i)$ *increases sufficiently (with fixed cost of capital* $r$ *) so that they are now more economically preformed by machines than middle skill workers*. For all the remaining tasks, we continue to assume that $\alpha_K(i) = 0$.
- Endogenous choice of skill supply: assume that each worker $j$ is endowed with some amount of "low skill", "medium skill", and "high skill", respectively $l^j, m^j$ and $h^j$.
- Offshoring: suppose that a set of tasks $[I', I''] \subset [I_L, I_H]$ can now be offshored to a foreign country.
- Directed technical change

## 2.2. Autor and Handel (2013)

**Paper**: Putting Tasks to the Test: Human Capital, Job Tasks, and Wages, Journal of Labor Economics

**Empirical Findings**: Using original, representative survey data, the authors document that *analytical*, *routine*, and *manual* job tasks can be measured with high validity, vary substantially *within and between occupations*, are significantly related to workers' characteristics, and are robustly predictive of wage differences between occupations and among workers in the same occupation.

**Data**: The primary data source is a module of the Princeton Data Improvement Initiative survey (PDII) that collects data on the cognitive, interpersonal, and physical job tasks that workers regularly perform on their jobs.

### 2.2.1. The Model

The skill endowment of worker $i$ is written as $\mathbf{\Phi}_i = \{\phi_{i1}, \ldots, \phi_{iK}\}$. Each element of $\mathbf{\Phi}_i$ is a strictly positive number measuring the efficiency of worker $i$ at task $k$. $\mathbf{\Phi}_i$ is interpreted as representing a worker's stock of human capital, which may be a result of human capital investments, innate abilities, or some combination.

Occupations produce output using the vector of K tasks, where the productive value of tasks differs among occupation. Let the output of worker $i$ in occupation $j$ equal:

$$Y_{ij} = \exp\left(\alpha_j + \sum_k \lambda_{jk}\phi_{ik} + \mu_i\right), \tag{2.2.1}$$

where $\lambda_{jk} \geq 0 \ \forall j,k$ and $\mu_i$ is a worker-specific error term. Normalize the output price for each occupation at unity. The production structure of occupation $j$ is summarized using a vector $\mathbf{\Lambda}_j = \{\alpha_j, \lambda_{j1}, \ldots, \lambda_{jK}\}$.

If the workers are paid their marginal product, the log wage of worker $i$ in occupation $j$ is:

$$\omega_i = \alpha_j + \sum_k \lambda_{jk}\phi_{ik} + \mu_i. \tag{2.2.2}$$

Taking the production structure as given, each worker chooses the occupation $j$ that maximizes her output and hence earnings:

$$Y_i = \max_j \{Y_{i1}, \ldots, Y_{iK}\} = \max_j \left\{\alpha_j + \mathbf{\Phi}_i \mathbf{\Lambda}_j'\right\} \tag{2.2.3}$$

This economy is characterized by *self-selection of workers into occupations* based on comparative advantage. The equilibrium of the model ensures that workers are employed in the occupation that has the highest reward to their bundle of tasks. But this does not imply that workers necessarily receive the maximum market reward to each element in their task bundle or that each element is equally valuable in all occupations.

### 2.2.2. Empirical Implications

Estimating task returns ($\lambda$'s) using observational data is challenging when the rewards to clusters of tasks are correlated. However, this model does imply some testable restrictions on the relationships between tasks and wages that do not rely on these structural parameters. They are mainly summarized by Propositions 2.2.2 and 2.2.3.

**Proposition 2.2.1.** Let $\Gamma$ be the set of all occupations that have non-zero employment in equilibrium. For each occupation $j \in \Gamma$, it must be the case that $\mathbf{\Lambda}_j$ is not vector dominated by some other occupation $\mathbf{\Lambda}_{j'}$, where $j' \in \Gamma$.

**Proposition 2.2.2.** For all occupations $j \in \Gamma$, the cross-occupation variance among task returns cannot be uniformly positive across all task pairs $k, k'$. That is, either $\operatorname{cov}(\lambda_k, \lambda_{k'}) \leq 0$ for some $k, k'$, or $\operatorname{cov}(\alpha, \lambda_k) \leq 0$ for some $k$, or both.

**Proposition 2.2.3.** Consider a case with two occupations, $j$ and $j'$, and two distinct tasks, $k$ and $k'$. Let the population distribution of worker endowments of tasks 1 and 2 be given by the bivariate unit normal distribution:

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & . \\ \rho & 1 \end{bmatrix}\right) \tag{2.2.4}$$

A necessary condition for workers to be positively self-selected on task 1 capability into occupation $j$ and on task 2 capability into occupation $j'$ is that

$$\rho < \min\left(\frac{\lambda_1}{\lambda_2'}, \frac{\lambda_2'}{\lambda_1}\right). \tag{2.2.5}$$

A sufficient condition for this expression to hold is that $\rho \leq 0$: worker abilities in tasks 1 and 2 are either uncorrelated or negatively correlated.

Proposition 2.2.3 reflects an empirical implication of the Roy model: workers who have higher efficiency equivalently, ability–in a given task domain will generally self-select into occupations that have a higher return to that task.

The reminder of this article mainly tests the last two propositions using OLS regression.

## 2.3. Gathmann and Schönberg (2010)

**Paper**: How General Is Human Capital? A Task-Based Approach, Journal of Labor Economics

**Research Question**: How portable are skills accumulated in the labor market?

**Findings**: Their results on occupational mobility and wages show that labor market skills are more portable than previously considered. They find that individuals move to occupations with similar task requirements and that the distance of moves declines with experience. Task specific human capital is an important source of individual wage growth, accounting for up to 52% of overall wage growth.

### 2.3.1. The Model

Consider the case of two tasks, denoted by $j = A, M$ (*analytical tasks* and *manual tasks*). Worker $i$ has a productivity in each task, which is varied by occupations (denoted by $o$) and time in the labor market (denoted by $t$): $t_{iot}^{j}$. Occupations combine the two tasks in different ways. Let $\beta_0 (0 < \beta_o < 1)$ be the relative weight on the analytical task and $(1 - \beta_o)$ be the relative weight on the manual task. Worker $i$'s task productivity $S$ (measured in log units) in occupation $o$ at time $t$ is then

$$\ln(S_{iot}) = \beta_o t_{iot}^{A} + (1 - \beta_o)\, t_{iot}^{M} \tag{2.3.1}$$

By restricting the weights on the tasks to sum to one, the authors focus on the relative importance of each task in an occupation, not its task intensity. The weight $\beta_o$ can then be interpreted as the share of time a worker spends on average in the analytical task in occupation $o$.

Two occupations are $o$ and $o'$ are *similar* if they employ analytical and manual tasks in similar proportions, that is, $\beta_o$ is close to $\beta_{o'}$.

Worker productivity $t_{iot}^{j}$ is determined by a person's initial endowment in each task ("ability") and the human capital accumulated in the labor market. More specifically,

$$t_{iot}^{j} = t_i^j + \gamma_o H_{it}^j, \quad j = A, M, \tag{2.3.2}$$

where $t_i^j$ is worker $i$'s initial skill endowment in task $j$ and $H_{it}^j$ is the human capital accumulated in task $j$ until time period $t$. Human capital $H_{it}^j$ is accumulated as follows:

$$H_{it}^A = \beta_{o'} O_{io't}, \tag{2.3.3}$$

$$H_{it}^M = \left(1 - \beta_{o'}\right) O_{io't}, \tag{2.3.4}$$

where $O_{io't}$ denotes the tenure in each prior occupation. We then get

$$\ln S_{\text{iot}} = \underbrace{\gamma_o \left[\beta_o H_{it}^A + \left(1 - \beta_o\right) H_{it}^M\right]}_{T_{\text{iot}}} + \underbrace{\beta_o t_i^A + \left(1 - \beta_o\right) t_i^M}_{m_{io}}, \tag{2.3.5}$$

where $T_{iot}$ is our *observable measure of task-specific human capital* and $m_{io}$ is the *unobservable task match*, that is, how well an individual is matched to his occupation given his endowment. Our parameter of interest is $\gamma_o$, the return to task-specific human capital, which varies across occupations.

The assumptions from (2.3.2) to (2.3.4) allow us to collapse the accumulation of skills in multiple tasks into a one-dimensional observable measure of task-specific human capital.

Wages in occupation $o$ and time $t$ equal the worker $i$'s productivity multiplied with the occupation-specific skill price, $P_o$. Hence, log wages satisfy

$$\ln\left(w_{iot}\right) = p_o + \gamma_o T_{iot} + m_{io}, \tag{2.3.6}$$

where $p_o = \ln\left(P_o\right)$. We observe task-specific skills $\left(T_{iot}\right)$ but do not observe the quality of the match, $m_{io} = \beta_o t_i^A + \left(1 - \beta_o\right) t_i^M$.

Workers search over occupations to maximize earnings. The decision to switch occupations is determined by three factors: the transferability of task-specific human capital $\left(T_{iot}\right)$, the task match $\left(m_{io}\right)$, and the occupation-specific return to human capital $\left(\gamma_o\right)$.

### 2.3.2. Empirical Implications

**Three predictions from the Model**:

- Everything else equal, individuals are more likely to make distant moves earlier, rather than later, in their careers.
- Wages at the source occupation are a better predictor for wages at the target occupation if the two occupations require similar tasks.
- Tenure in the last occupation is valuable in a new occupation, and the value should be higher the more similar the two occupations are in their task requirements.

**Data**: Repeated cross-section German Qualification and Career Survey (1979, 1985, 1991/92, and 1998/99). Each wave contains information from 30,000 employees between the ages of 16 and 65. In the survey, individuals are asked whether they perform any of 19 different tasks in their job. Tasks vary from repairing and cleaning to buying and selling, teaching, and planning. For each respondent, we know whether he performs a certain task in his job and whether this is his main activity.

**Measuring the Distance between Occupations**:

$$\text{AngSep}_{oo'} = \frac{\sum_{j=1}^{J}\left(q_{jo} \times q_{jo'}\right)}{\left[\left(\sum_{j=1}^{J} q_{jo}^2\right) \times \left(\sum_{k=1}^{J} q_{ko'}^2\right)\right]^{1/2}},$$

where $q_{jo}$ ($q_{jo'}$) is the fraction of workers using task $j$ in occupation $o$ ($o'$).

$$\text{Dis}_{oo'} = 1 - \text{AngSep}_{oo'}. \tag{2.3.7}$$

It is zero for occupations that use identical skill sets and unity if two occupations use completely different skills sets.

**Measuring the Task-Specific Human Capital** $T_{iot}$:

The construction of this variable crucially depends on the weights occupations place on tasks $\beta_o$. The authors measure these occupation-specific weights as follows. First, they calculate the share of time workers spend in each of the 19 tasks, assuming that they spend the same amount of time in each task they perform. They then average over all workers in the occupation. This ensures that the occupation-specific weights add up to one.

After computing the $\beta_o$ for each occupation, the authors compute the task-specific human capital following equation (2.3.5) with one additional normalization process. [3]

[3] Because the goal is to compare the return to task-specific human capital with that to general experience and the less portable occupation-specific skills. To ensure this comparability, they normalize the accumulation of task-specific human capital for occupational stayers to be one in each occupation. They do this by dividing the task-specific human capital accumulated in the current period by the sum of squared weights in that occupation. This normalization also

**Test the Predictions**:

The results are all descriptive and correlational. Jointly, they directly confirm the three hypotheses presented in the previous section. The authors also spend one section on comparing the role of task-specific human capital and general experience in explaining individuals' wage growth using two methods: subsampling based on exogenously displaced workers from plant closure and control function approach.

### 2.4. Autor et al. (2003)

**Paper**: The Skill Content of Recent Technological Change: An Empirical Exploration, The Quarterly Journal of Economics

**Abstract**: We apply an understanding of what computers do to study how computerization alters job skill demands. We argue that computer capital (1) substitutes for workers in performing cognitive and manual tasks that can be accomplished by following explicit rules; and (2) complements workers in performing nonroutine problemsolving and complex communications tasks. Provided that these tasks are imperfect substitutes, our model implies measurable changes in the composition of job tasks, which we explore using representative data on task input for 1960 to 1998. We find that within industries, occupations, and education groups, computerization is associated with reduced labor input of routine manual and routine cognitive tasks and increased labor input of nonroutine cognitive tasks. Translating task shifts into education demand, the model can explain 60 percent of the estimated relative demand shift favoring college labor during 1970 to 1998. Task changes within nominally identical occupations account for almost half of this impact.

## 3. The Organization of Production: Endogenizing Occupations

### 3.1. Ocampo (2022)

**Paper**: A Task-Based Theory of Occupations with Multidimensional Heterogeneity, Working Paper

**Summary of the Model**: Occupations arise endogenously when firms optimally assign continuously distributed tasks to discretely distributed workers with a finite number of types. Since occupations are endogenous, this model can be used to study how automation, skill-biased technology change, offshoring, and worker training affects occupations.

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ensures that task-specific human capital always increases more for occupational stayers than for occupational movers.

### 3.1.1. The Task Assignment Model

**Workers**: Workers are characterized by a vector of skills $x \in S \subset \mathbb{R}^d$, where $S$ is the space of skills and $d \geq 1$ is the number of skills. There are $N$ types of workers in the economy: $\{x_1, \ldots, x_N\} \equiv X$ . There is a mass $p_n$ of workers of type $x_n$. Each worker is endowed with one unit of time and supplies their time inelastically so that workers of type n supply a total of $p_n$ units of time. The workers' outside option, if they are not assigned to any task, has a value of $\underline{w} \geq 0$.

**Tasks**: Production requires completing a set of tasks $Y \subset T \equiv S$. Tasks $y \in Y$ differ in the skills involved in performing them and how many times they must be performed. One unit of time is required to perform a task once. Tasks are continuously distributed on $Y$. The density of tasks used in production is denoted by $g : Y \to \mathbb{R}_+$ and it satisfies the following assumption throughout:

**Assumption 3.1.1.** The set and distribution of tasks satisfy the following properties:

1. $g : Y \to \mathbb{R}_+$ is an absolutely continuous probability density function with an associated absolutely continuous measure $G$ on $Y$;
2. there are enough workers to complete all tasks; i.e., $G(Y) = \int_Y g(y) dy \leq \sum_{n=1}^N p_n$;
3. and the set of tasks $Y$ is compact.

**Task Output**: Workers vary in their productivity across tasks depending on the degree of mismatch between the skills they possess $(x)$ and the skills involved in performing the task $(y)$. The function $q : X \times Y \to \mathbb{R}$ gives the worker-task-specific output generated by a worker with skills $x$ performing task $y$.

**Assumption 3.1.2.** The task output production function satisfies

$$q(x, y) = \exp\left(a_x' x + a_y' y - (x-y)' A (x-y)\right), \tag{3.1.1}$$

where $A$ is symmetric and positive definite.

Under (3.1.1), the mismatch between a worker and a task is measured by the weighted quadratic distance between the worker's and task's skills.

**Assignment**: The assignment of tasks to workers is described by a function $T : Y \to X$ so that task $y$ is performed by worker $T(y) \in X$ . The set of tasks performed by a type of worker forms that worker's occupation. The occupation of type $x_n$ workers is

$$Y_n \equiv T^{-1}(x_n) = \left\{ y \in Y \mid x_n = T(y) \right\}. \tag{3.1.2}$$

An assignment is feasible if workers can supply the time demanded by their occupation. The demand for workers $x_n$ corresponds to the time required to perform their assigned tasks:

$$D_n \equiv \int_{Y_n} dG. \tag{3.1.3}$$

**Definition 3.1.1.** An assignment $T$ is feasible if $D_n \leq p_n$ for all $n \in \{1, \ldots, N\}$.

**Production Technology**: Production at the plant aggregates the output from all worker/task pairs through a Cobb-Douglas technology given an assignment $T$:

$$F(T) = \exp\left(\int_Y \ln q(T(y), y)\, dG\right). \tag{3.1.4}$$

### 3.1.2. Characterizing the Optimal Assignment of Tasks to Workers: Occupations

The problem is finding a feasible assignment that maximizes output:

$$\max_T F(T) \quad \text{s.t. } \forall_n D_n \leq p_n \tag{3.1.5}$$

Then the Proposition 3.1.1 in the article states the existence and uniqueness of a solution by imposing conditions only on the production technology $q$.

**Proposition 3.1.1.** Proposition 1. Consider the optimal assignment problem in (3.1.5). If $q$ is such that

1. every worker/task pair is productive: $q(x, y) > 0$ for all pairs $(x, y) \in X \times Y$;
2. $q(x, \cdot)$ is upper-semicontinuous in y given $x \in X$; and
3. $q$ discriminates across workers: for all $x_n \neq x_\ell, q\left(x_n, y\right) \neq q\left(x_\ell, y\right)$ $G$-a.e.

Then, there exists a $(G-)$ unique solution $T^\star$ to the problem in (3.1.5). Moreover, there exists a unique $\lambda^\star \in \mathbb{R}^N$ with $\min \lambda_n^\star = 0$ such that $T^\star$ is characterized as

$$T^\star(y) = \underset{x \in X}{\operatorname{argmax}} \left\{\ln q(x, y) - \lambda_{n(x)}^\star\right\}, \tag{3.1.6}$$

where $n(x)$ gives the index of a type of worker $x \in X$.

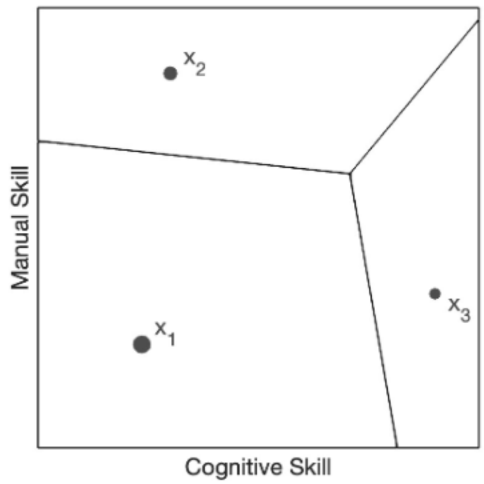
The characterization of the optimal assignment in (3.1.6) allows me to more explicitly characterize the occupations in terms of the production technology $q$:

$$Y_n = \left\{y \in Y \mid \forall_\ell \ln q\left(x_n, y\right) - \lambda_n^\star \geq \ln q\left(x_\ell, y\right) - \lambda_\ell^\star\right\}. \tag{3.1.7}$$

*Tasks are optimally assigned to workers who are more productive at performing them (lower skill mismatch), subject to the penalty captured by $\lambda^\star$ that balances the demand for that type of worker with the limited supply of workers ($p_n$).*

If we impose Assumption 3.1.2, then the graphical illustration of the endogenous occupations is the following:

Figure 3.1.1: Assignment Example (Quadratic Mismatch Loss)




**Properties of the Assignment**:

The author then talks about the property of the optimal assignment (occupations):

- Marginal products and worker ranks
- Worker compensation and the skill premia
- Substitutability across workers

**Impact of Technological Change on Division of Tasks into Occupations**:

Automation (worker-replacing technologies) is modelled as additional worker named *robot* with skills $r \in S$ and $p_r \geq 0$. Then, the impact of automation on occupations is to study the optimal assignment after introducing this new worker–robot to the original labor force.

Technical change can also complement workers' skills. The impact of this kind of skill-biased technical change is modelled by changing the $q$ function. Or more specifically, changing the $A$ matrix, which means that the introduction of new technology puts different weights on the productivity of different combinations of skills.

**Further Extension with Unassigned Tasks**:

In the last, the author extend the model to allow tasks to be left unassigned.

## 3.2. Adenbaum (2023)

**Paper**: Endogenous Firm Structure and Worker Specialization, Working Paper

**Summary of the Model**: The model in this paper is an extension to the previous paper (Ocampo, 2022). In addition to the task assignment problem raised there, it adds an occupation choice problem to the heterogeneous firms (differ in the aspect of productivity), in which firms face a trade-off between their degree of worker specialization and the organizational cost of hiring and managing more types of workers.

#### 3.2.1. The Model

**Aggregation of Output**:

Consider a continuum of firms, with a unit mass. Each firm, indexed by $j \in [0,1]$, produces a differentiated good by hiring labor to complete tasks.

Final output $Q$ is produced by a competitive firm using the output $q_j$ of the continuum of intermediate firms.

$$Q = \left[\int_0^1 q_j^\sigma \, dj\right]^{\frac{1}{\sigma}}. \tag{3.2.1}$$

The price index $P$ is given by

$$P = \left[\int_0^1 p_r\left(q_j\right)^{\frac{\sigma}{\sigma-1}} \, dj\right]^{\frac{\sigma-1}{\sigma}}, \tag{3.2.2}$$

and the inverse demand function for the output of each intermediate firm is given by

$$p_r\left(q_j\right) = P\left(\frac{q_j}{Q}\right)^{\sigma-1}. \tag{3.2.3}$$

Final goods producing firms aggregate the output of the intermediate goods producing firms, using a CES aggregation technology, to produce output to be sold to the household.

**Firms**:

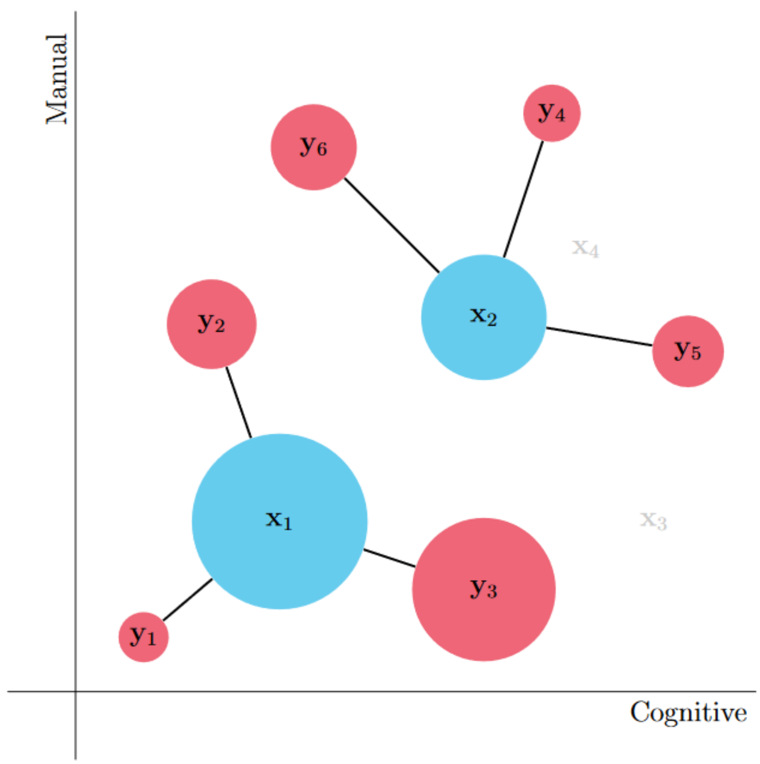
Each intermediate firm has a set of $K$ discrete tasks $\boldsymbol{y}_k \in Y = [0,1]^d$ which they must complete in order to produce output, and which are defined by their relative difficulty along $d$ different dimensions of skill. The tasks occur in fixed proportions, and are distributed according to a probability mass function $\boldsymbol{G} \in \Delta^K \subset \mathbb{R}^K$. While the firm can scale the total measure of tasks they want to complete up or down by a factor of $s$, the relative shares of each task must remain fixed.

Firms hire workers with a set of skills $\boldsymbol{x} \in X = [0,1]^d$ which are a bundle of skills in the same $d$ dimensions, i.e., tasks and skills live in the same space. Workers are endowed with their bundle of skills $\boldsymbol{x} \in X$, an idiosyncratic productivity v, and a unit endowment of time. Their output scales linearly with their idiosyncratic productivity, and so workers can be thought of as supplying $v$ units of effective labor.

Each firm has a productivity $z_j \in \mathbb{R}$ that are distributed with cdf $F : \mathbb{R} \to \mathbb{R}$. Firms produce output by completing tasks. When a task $\boldsymbol{y}$ is paired with a worker $\boldsymbol{x}$, the worker produces $f(\boldsymbol{x},\boldsymbol{y})$ units of output. Firms pay workers a wage $w(\boldsymbol{x})$, where $w: X \to \mathbb{R}$ is a competitive wage function that depends on the worker's skill. Firms must pay an organizational cost $\kappa$ for every discrete worker type that they employ (which captures the additional organizational cost and complexity of managing many different types of workers). As a result, they will choose to hire only a finite number of distinct worker types $N$ in production.

Firms decide how to produce by choosing a time allocation $\pi : X \times Y \to \mathbb{R}_+$. This function takes pairs of workers $\boldsymbol{x}$ and tasks $\boldsymbol{y}$, and maps them to the amount of time that workers of type $\boldsymbol{x}$ will spend working on task $\boldsymbol{y}$. Since both $X$ and $Y$ are finite sets, with size $N$ and $K$, respectively, it is natural to think about $\pi$ as a vector in $\mathbb{R}^{NK}$, and I will write $\pi_{nk} = \pi(\boldsymbol{x}_n, \boldsymbol{y}_k)$. That is, $\pi_{nk}$ denotes the amount of time that a worker of type $n$ is assigned to work on task $k$. The graphical illustration of this task assignment problem is as follows:

Figure 3.2.1: An example worker allocation for a firm




The time allocation that the firm chooses must respect two physical constraints. First, the total amount of time that the firm allocates to workers of type $n$ cannot exceed that amount of labor $\boldsymbol{L}_n$ that the firm has hired from workers of that type. In other words, they must respect the time constraints of the workers that they choose to hire.

$$\sum_{k=1}^{K} \pi_{nk} \leq \boldsymbol{L}_n \quad n = 1, \ldots, N \tag{3.2.4}$$

Second, the total amount of time that the firm allocates to tasks of type $n$ must be equal to the amount $\boldsymbol{G}_k s$ of task $k$ which they have chosen to do:

$$\sum_{n=1}^{N} \pi_{nk} = \boldsymbol{G}_k s \quad k = 1, \ldots, K \tag{3.2.5}$$

By requiring that this constraint hold with equality, I insist that every task must be done in the given proportions. Although the firm can choose to scale the entire distribution of tasks up or down by a factor $s$, the relative shares of the tasks must always remain the same.

Firm aggregate the individual units of output from each worker-task pairing using a CES production technology:

$$q_j = z_j \left[ \sum_{n=1}^{N} \sum_{k=1}^{K} f\left(\boldsymbol{x}_n, \boldsymbol{y}_k\right)^{\eta} \pi_{nk} \right]^{\frac{1}{\eta}} \tag{3.2.6}$$

where $\eta$ controls the degree to which output from different worker-task pairings are substitutes or complements.

The firm problem is then to choose:

1. how much output $q$ to produce,
2. how many distinct worker types $N$ to employ in production,
3. the bundle of worker skill vectors $\{x_n : n = 1, \ldots, N\}$,
4. the measure of each worker type's labor $\boldsymbol{L}_n$ to hire,
5. the scale of production $s$, and
6. the time allocations $\pi_{nk}$

in order to maximize profits.

That is, firms choose their total production, and the number of worker types to satisfy

$$\max_q p(q) q - c^N\left(q, z_j\right) - \kappa \times N \tag{3.2.7}$$

where $c^N(q, z)$ is the cost of producing $q$ units of output. The firm's choice of the number of workers to hire depends on their scale of production. It is key to observe here that the organizational cost $\kappa \times N$ does not scale with the firms output $q$; it functions as a fixed cost for producing at that organizational scale. A firm with relatively low productivity will choose a lower level of organizational complexity, whereas a firm with a higher productivity may be able to support the additional fixed costs of hiring more types of workers, in order to achieve the commensurate gains in worker productivity (and therefore lower per-unit costs of production) due to specialization.

Firms then choose $\{x_n : n = 1, \ldots, N\}$, $\boldsymbol{L}$, $s$, and $\pi$ to minimize total costs subject to an output constraint,

$$
\begin{array}{rll}
c^N(q,z) = \min_{\mathbf{x}_n,\mathbf{L}_n,\pi,s} & \sum_{n=1}^N w_n \mathbf{L}_n & \text{Total costs} \\
\text{s.t.} & \sum_{k=1}^K \pi_{nk} = \mathbf{L}_n \quad \forall n & \text{Every worker is fully utilized} \\
& \sum_{n=1}^N \pi_{nk} = s \times \mathbf{G}_k \quad \forall k & \text{Every task is fully assigned} \\
& z\left[\sum_{n=1}^N \sum_{k=1}^K f\left(\mathbf{x}_n,\mathbf{y}_k\right)^\eta \pi_{nk}\right]^{\frac{1}{\eta}} \geq q & \text{Output constraint}
\end{array}
\tag{3.2.8}
$$

**Identification**:

After describing the model, the author then uses Theorem 1 in this paper to claim that we can identify the distribution of tasks $\boldsymbol{G}$.

### 3.2.2. Estimation and Counterfactual Analysis

There are four crucial objects in the model that must be estimated: the distribution of tasks $\boldsymbol{G}(\boldsymbol{y})$, the worker task production function $f(\boldsymbol{x},\boldsymbol{y})$, the distribution of firm productivities $F(z)$, and the fixed costs of hiring an additional occupation $\kappa$. To estimate them, I proceed in three stages:

1. I assume a parametric functional form for both $\boldsymbol{G}(\boldsymbol{y})$ and $f(\boldsymbol{x},\boldsymbol{y})$, and estimate these parameters and the elasticity of substitution $\eta$ using nonlinear GMM on the moment conditions implied by the firm's problem Equation (3.2.8).

2. Given these estimates from stage 1, I recover firm level estimates of both output $q$ and productivity $z$ by choosing the ratio $q/z$ to match the firm's observed wage bill, and backing out $q$ and $z$ from the first order conditions for the firm's choice of $q$ in Equation (3.2.7).

3. I then estimate $\kappa$ using simulated method of moments to match the observed relationship in the data between the firm's wage bill and the total number of occupations hired.

In the last, to quantify the contribution of endogenous worker specialization within the firm to aggregate productivity and output, I will consider two counterfactual exercises. First, I consider reducing the fixed costs $\kappa$ faced by the firms to zero. Second, to quantify the productivity gains from the specialization already occurring in the economy, I consider a scenario where $\kappa$ is set sufficiently large that no firm chooses to hire more than a single occupation.

# 4. The Impact of Technological Change

## 4.1. Acemoglu and Restrepo (2018b)

**Paper**: The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment, American Economic Review

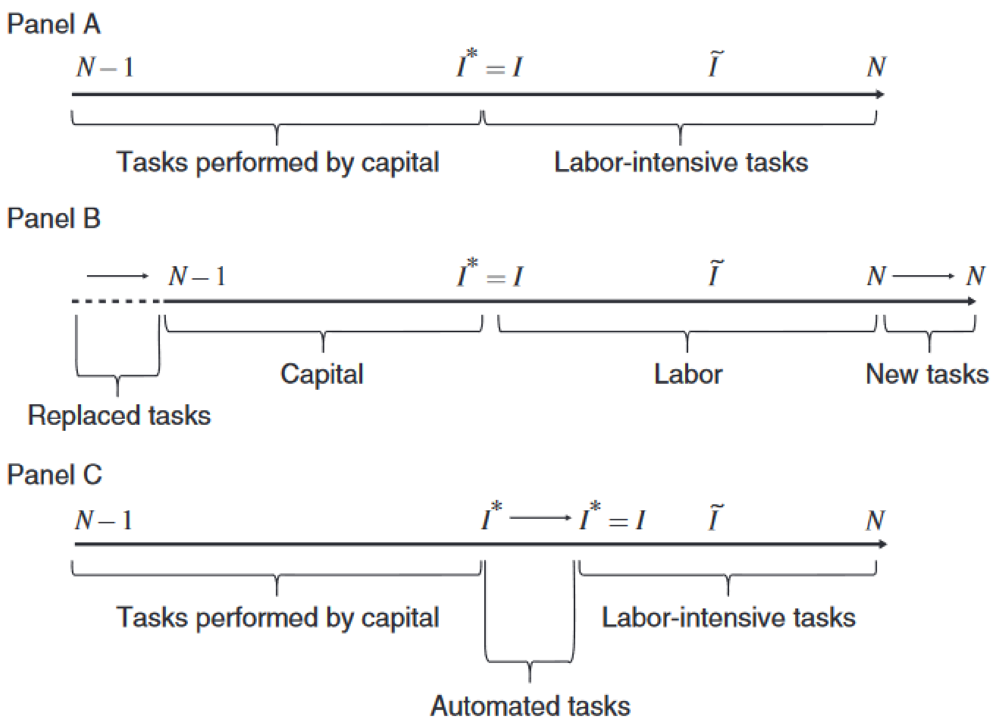
**Research Question**:

Theoretically, how will automation affect employment and wage? What are the implications in a static model? What are the implications if capital deepening, automation and creation of new tasks are all endogenized in a dynamic model?

**Summary of the Model**:

This model is a dynamic extension to Autor and Handel (2013) by adding directed technological change to automation technologies and creation of new tasks. The basic idea of the model is best illustrated by the following graph:

Figure 4.1.1: The Task Space and a Representation of the Effect of Introducing New Tasks (Panel B) and Automating Existing Tasks (Panel C)




### 4.1.1. The Static Model

**Environment in the Production Side**:

The economy produces a unique final good $Y$ by combining a unit measure of tasks, $y(i)$, with an elasticity of substitution $\sigma \in (0, \infty)$:

$$Y = \widetilde{B}\left(\int_{N-1}^{N} y(i)^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}} \tag{4.1.1}$$

where $\widetilde{B} > 0$. An increase in $N$ represents the upgrading of the quality (productivity) of the unit measure of tasks.

Each task is produced by combining labor or capital with a task-specific intermediate $q(i)$, which embodies the technology used either for automation or for production with labor. We start by assuming that these intermediates are supplied competitively, and that they can be produced using $\psi$ units of the final good. Hence, they are also priced at $\psi$.

All tasks can be produced with labor. We model the technological constraints on automation by assuming that there exists $I \in [N-1, N]$ such that tasks $i \le I$ are *technologically automated* in the sense that it is feasible to produce them with capital. Although tasks $i \le I$ are technologically automated, whether they will be produced with capital or not depends on relative factor prices. Conversely, tasks $i > I$ are not technologically automated, and must be produced with labor.

The production function for tasks $i > I$ takes the form

$$y(i) = \overline{B}(\zeta)\left[\eta\frac{1}{\zeta}q(i)^{\frac{\zeta-1}{\zeta}} + (1-\eta)\frac{1}{\zeta}(\gamma(i)l(i))^{\frac{\zeta-1}{\zeta}}\right]^{\frac{\zeta}{\zeta-1}}, \tag{4.1.2}$$

where $\gamma(i)$ denote the productivity of labor in task $i$, $\zeta \in (0,\infty)$ is the elasticity of substitution between intermediates and labor, $\eta \in (0,1)$ is the share parameter of this CES production function, and $\overline{B}(\zeta)$ is a constant, $\overline{B}(\zeta) = \psi^{\eta}(1-\eta)^{\eta-1}\eta^{-\eta}$ when $\zeta = 1$, and $\overline{B}(\zeta) = 1$ otherwise.

Tasks $i \le I$ can be produced using labor or capital, and their production function is identical to (4.1.2) expect for the presence of capital and labor as perfectly substitutable factors of production:

$$y(i) = \overline{B}(\zeta)\left[\eta\frac{1}{\zeta}q(i)^{\frac{\zeta-1}{\zeta}} + (1-\eta)\frac{1}{\zeta}(k(i)+\gamma(i)l(i))^{\frac{\zeta-1}{\zeta}}\right]^{\frac{\zeta}{\zeta-1}} \tag{4.1.3}$$

Throughout, we impose the following assumption.

**Assumption 4.1.1.** $\gamma(i)$ is strictly increasing.

It implies that labor has strict comparative advantage in tasks with a higher index and will guarantee that, in equilibrium, tasks with lower indices will be automated, while those with higher indices will be produced with labor.

**Household Side**:

The demand side of the economy is a representative household with preferences given by

$$u(C,L) = \frac{\left(Ce^{-\nu(L)}\right)^{1-\theta} - 1}{1-\theta}, \tag{4.1.4}$$

where $\nu(L)$ designates the utility cost of labor supply with some standard assumptions.

Finally, in the static model, the capital stock, $K$, is taken as given.

**Implications of the Static Model**:

In this static version where capital is fixed and technology is exogenous, automation reduces employment and the labor share, and may even reduce wages, while the creation of new tasks has the opposite effects.

#### 4.1.2. Implications from the Extended Dynamic Model

The authors then extend the previous static model to endogenize capital accumulation and the direction of research toward automation and the creation of new tasks.

If the long-run rental rate of capital relative to the wage is sufficiently low, the long-run equilibrium involves automation of all tasks.

Otherwise, there exists a *stable balanced growth path* in which the two types of innovations go hand-in-hand. *Stability* means that periods in which automation runs ahead of the creation of new tasks tend to trigger self-correcting forces, and as a result, the labor share and employment stabilize and could return to their initial levels. This property is a consequence of the fact that automation reduces the cost of producing using labor, and thus discourages further automation and encourages the creation of new tasks.

### 4.2. Acemoglu and Restrepo (2019)

**Paper**: Artificial Intelligence, Automation, and Work (Chapter 8 in book "The Economics of Artificial Intelligence: An Agenda")

**Summary**:

This chapter is basically a justification, description, and summary of Acemoglu and Restrepo (2018b). First, it provides a lot of examples from history to justify the ingredients and implications of the model. Second, it provides a nontechnical description of the model elements and predictions. Specifically, it is a conceptual framework about how automation in general, and AI and robotics in particular, impact the labor market and productivity.

- "Key effect":Automation and thus AI and robotics replace workers in tasks that they previously performed, and via this channel, create a powerful *displacement effect*.
- "Traditional countervailing forces that push against the displacement effect":
  - First, the substitution of cheap machines for human labor creates a *productivity effect*: as the cost of producing automated tasks declines, the economy will expand and increase the demand for labor in nonautomated tasks.
  - Second, *capital accumulation* triggered by increased automation (which raises the de-

mand for capital) will also raise the demand for labor.

  – Third, automation also operates at the intensive margin as well, increasing the productivity of machines in tasks that were previously automated. This phenomenon, which is referred to as *deepening of automation*, creates a productivity effect but no displacement, and thus increases labor demand.

- "Key countervailing force": Though these countervailing effects are important, they are generally insufficient to engender a "balanced growth path," meaning that even if these effects were powerful, ongoing automation would still reduce the share of labor in national income (and possibly employment). There is a more powerful countervailing force that increases the demand for labor as well as the share of labor in national income: the creation of new tasks, functions and activities in which labor has a comparative advantage relative to machines. *The creation of new tasks* generates a reinstatement effect directly counterbalancing the displacement effect.

- "Other factors that affect the adjustment of an economy to the rapid rollout of automation technologies":

  – A potential *mismatch between technology and skills* – between the requirements of new technologies and tasks and the skills of the workforce.

  – The possibility of *excessive automation* – a variety of factors (ranging from a bias in favor of capital in the tax code to labor market imperfections create a wedge between the wage and the opportunity cost of labor) will push toward socially excessive automation, which not only generates a direct inefficiency, but also acts as a drag on productivity growth. Excessive automation could potentially explain why, despite the enthusiastic adoption of new robotics and AI technologies, productivity growth has been disappointing over the last several decades.

### 4.3. Acemoglu and Restrepo (2020)

**Paper**: Robots and Jobs: Evidence from US Labor Markets, Journal of Political Economy

**Research Question**: How do industrial robots affect employment and wage across commuting zones in equilibrium?

**Findings**: In equilibrium, one more robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42%.

**Summary of the Model**: This model is an extension to Autor and Handel (2013) by adding commuting zones and industries. The production in each industry takes the form of the static version model in Acemoglu and Restrepo (2018b) where on the spectrum of tasks $[0,1]$, the tasks in the interval $[0,\theta]$ can be automated by industrial robots. The model itself is used to motivate a measure on *US exposure to robots*. The measure is of the Bartik-style but with adjustments implied by the model.

**Identification Strategy**: Use other countries exposure to industrial robots as an IV for US exposure to robots.

### 4.3.1. Motivating the Identification Strategy: A Model

The economy consists of $|\mathscr{C}|$ commuting zones. Each commuting zone $c \in \mathscr{C}$ has preferences defined over an aggregate of the output of $|\mathscr{I}|$ industries, given by

$$Y_c = \left( \sum_{i \in \mathscr{I}} \nu_i^{1/\sigma} Y_{ci}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}, \tag{4.3.1}$$

where $\sigma > 0$ denotes the elasticity of substitution across goods produced by different industries and the $\nu_i$'s are share parameters that designate the importance of industry $i$ in the consumption aggregate (with $\sum_{i \in \mathscr{I}} \nu_i = 1$).

Denote the price of the output of industry $i$ in commuting zone $c$ by $P_{ci}^X$.

Each industry produces output by combining capital with a continuum of tasks indexed by $s \in [0,1]$, each of which can be produced using industrial robots or human labor. We use $x_{ci}(s)$ to denote the quantity of task $s$ utilized in the production of $X_{ci}$ ($= Y_{ci}$ in the autarky version without trade between commuting zones). These tasks must be combined in fixed proportions so that

$$X_{ci} = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)} A_{ci} \left[ \min_{s \in [0,1]} \{x_{ci}(s)\} \right]^{\alpha} K_{ci}^{1-\alpha}, \tag{4.3.2}$$

where $K_{ci}$ denotes the nonrobot capital used in industry $i$, $1-\alpha$ represents its share in the production process, $A_{ci}$ represents the productivity of industry $i$, and the term $\alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}$ is a convenient normalization. Differences in the $A_{ci}$'s will translate into different industrial compositions of employment across commuting zones.

Industrial robots replace workers in some of the tasks that they were previously performing. Specifically, in industry $i$, tasks $[0, \theta_i]$ are technologically automated and can be performed by robots. We assume that all commuting zones have access to the same technology–that is, the same $\theta_i$ in industry $i$. Denoting the productivity of labor by $\gamma_L$ and the productivity of robots by $\gamma_M > 0$, we have

$$x_{ci}(s) = \begin{cases} \gamma_M M_{ci}(s) + \gamma_L L_{ci}(s) & \text{if } s \le \theta_i, \\ \gamma_L L_{ci}(s) & \text{if } s > \theta_i, \end{cases} \tag{4.3.3}$$

where $L_{ci}(s)$ and $M_{ci}(s)$ represent, respectively, the numbers of workers and robots used in task $s$.

In each commuting zone $c$, labor is supplied by a representative household with preferences

$$\frac{C_c^{1-\psi} - 1}{1-\psi} - \frac{B}{1+\varepsilon} L_c^{1+\varepsilon}, \tag{4.3.4}$$

where $C_c$ denotes this household's consumption and $L_c$ represents its labor supply. Its budget constraint is $C_c \leq W_c L_c + \Pi_c$, where $\Pi_c$ is nonlabor (capital and profit) income.

Robots are produced using investment (in units of the final good), denoted by $I_c$, with the production function $M_c = D(1+\eta)I_c^{1/(1+\eta)}$ and have a rental price of $R_c^M$. This formulation, with $\eta > 0$, allows the supply of robot services to a commuting zone to be upward sloping. Finally, in the autarky model, we take the supply of capital in commuting zone $c$ to be fixed at $K_c$ and denote its price by $R_c^K$.

An equilibrium is a tuple of prices $\{W_c, R_c^M, R_c^K\}_{c\in\mathscr{C}}$ and quantities $\{C_c, Y_c, I_c, L_c, M_c\}_{c\in\mathscr{C}}$, such that in all commuting zones, firms maximize profits, households maximize their utility, and the markets for capital, labor, robots, and final goods clear.

To analyze the equilibrium impact of robots, let's define cost savings from using robots in commuting zone $c$ as

$$\pi_c = 1 - \frac{\gamma_L R_c^M}{\gamma_M W_c}.$$

Robots will not be adopted when $\pi_c < 0$.

**Proposition 4.3.1.** Suppose that $\pi_c > 0$. Then

$$d\ln L_{ci} = -\frac{d\theta_i}{1-\theta_i} + \frac{1}{\alpha} d\ln Y_c - \left(\sigma + \frac{1}{\alpha} - 1\right) d\ln P_{ci}^X, \tag{4.3.5}$$

where $L_{ci}$ denotes the employment in industry $i$ in commuting zone $c$.

There are three different forces shaping labor demand of industry $i$.

- There is a *negative displacement effect*: an increase in $\theta_i$ leads to the use of robots in tasks otherwise performed by labor, displacing workers employed in these tasks.
- There is a *positive productivity effect* represented by the second term. Intuitively, automation lowers the cost of production (thus increasing productivity) and via this channel raises the demand for labor in nonautomated tasks in all industries.
- There is a *composition effect*, represented by the their term: industries undergoing automation expand at the expense of others, and this raises the demand for labor coming from their nonautomated tasks.

We can aggregate the industry-level implications of Proposition 4.3.1 to derive the effects of robots on local labor demand as follows:

$$d\ln L_c = -\sum_{i\in\mathscr{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i} + \frac{1}{\alpha} d\ln Y_c - \left(\sigma + \frac{1}{\alpha} - 1\right) \sum_{i\in\mathscr{I}} (\ell_{ci} - \chi_{ci})\, d\ln P_{ci}^X \tag{4.3.6}$$

where $\ell_{ci}$ represents industry $i$'s share in total employment in commuting zone $c$, while $\chi_{ci}$ represents this industry's share of value added in the local economy. The third term shows that the impact of the composition effect for labor demand depends on whether automation is reallocating output toward sectors that are more labor intensive than average (those for which $\ell_{ci} > \chi_{ci}$). This composition effect disappears when all industries have the same labor share.

Equation (4.3.6) provides a partial equilibrium characterization of how the demand for labor changes following automation.

**Extension**:

The authors then extend current autarky model by allowing commuting zones to trade with each other. And finally, they get the general equilibrium characterization of how demand for labor and wage change following automation. This result is summarized by Proposition 4.3.2 as follows:

**Proposition 4.3.2.**

$$d\ln L_c = \left[-\bar{\zeta}^{disp}\phi + \bar{\zeta}^{\text{prod}}\,\phi\pi_0 - \bar{\zeta}_L^{inc}\psi\right]\sum_{i\in\mathscr{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M} + \bar{\zeta}_L^{Y}d\ln Y + \bar{\zeta}_L^{\Pi}d\ln\Pi + \bar{\zeta}_{cL}^{\text{price}} \tag{4.3.7}$$

$$d\ln W_c = \left[-\bar{\zeta}^{\text{disp}}\,\varepsilon + \bar{\zeta}^{\text{prod}}\,\varepsilon\pi_0 + \bar{\zeta}_W^{inc}\psi\right]\sum_{i\in\mathscr{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M} + \bar{\zeta}_W^{Y}d\ln Y + \bar{\zeta}_W^{\Pi}d\ln\Pi + \bar{\zeta}_{cW}^{\text{price}} \tag{4.3.8}$$

### 4.3.2. Empirical Implications

The key equation, (4.3.7) and (4.3.8), show that the equilibrium impact of robots depends on the same object, which we will call a commuting zone's US exposure to robots,

$$\text{US exposure to robots}_c = \sum_{i\in\mathscr{I}}\ell_{ci}\cdot APR_i \tag{4.3.9}$$

where

$$APR_i = \frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M} = \frac{dM_i}{L_i} - \frac{dY_i}{Y_i}\frac{M_i}{L_i}, \tag{4.3.10}$$

is the US adjusted penetration of robots in industry $i$. Exposure to robots is thus a Bartik-style measure combining industry-level variation in the usage of robots and baseline employment shares.

With this measure of exposure to robots, the authors then estimate

$$\begin{aligned} d\ln L_c &= \beta_L\cdot\ \text{US exposure to robots}_c + \epsilon_c^L \\ d\ln W_c &= \beta_W\cdot\ \text{US exposure to robots}_c + \epsilon_c^W \end{aligned} \tag{4.3.11}$$

Ideally, we want to use changes in robot penetration only driven by exogenous improvements in technology, $d\theta_i$. To identify the component of robot penetration driven by changes in technology, we instrument the US exposure to robots using an analogous measure constructed from the penetration of robots in European countries that are ahead of the United States in robotics technology.

$$\text{Exposure to robots }_c = \sum_{i \in \mathscr{I}} \ell_{ii} \cdot \overline{APR}_i, \tag{4.3.12}$$

where $\overline{APR}$ represents the adjusted penetration of robots computed from European countries.

### 4.4. Acemoglu and Restrepo (2022)

**Paper**: Tasks, Automation, and the Rise in U.S. Wage Inequality, Econometrica

**Research Question**: Can automation explain changes in the US wage structures (relative wages across different demographic groups)?

**Summary of the Model**:

The model is an extension to Autor and Handel (2013) by adding multiple sectors (industries) to the economy. There are some other subtle differences. For instance, these two papers have similar interpretation with regard to the production factor of tasks (low, medium, or high-skilled workers in Autor and Handel (2013) versue different demographic groups defined by education in Acemoglu and Restrepo (2022)). The equilibrium is also very similar: tasks are assigned to single labor group or capital based on their productivity. And they use the same way to model automation in the model. The only differnce is that, in Acemoglu and Restrepo (2022), the focus has become task shares and inequality between different labor groups. And similar to Acemoglu and Restrepo (2020), the model is used to motivate a measure the task displacement across different labor groups and industries.

**Findings**: Between 50% and 70% of changes in the U.S. wage structure over the last four decades are accounted for by relative wage declines of worker groups specialized in routine tasks in industries experiencing rapid automation.

### 4.5. Acemoglu et al. (2022)

**Paper**: Artificial Intelligence and Jobs: Evidence from Online Vacancies, Journal of Labor Economics

**Research Question**: How does AI exposure (defined as how the applicability of AI to a task in an establishment) affect establishments' AI and non-AI related job hiring?

**Findings**: There is rapid growth in AI-related vacancies over 2010-18 that is driven by establishments whose workers engage in tasks compatible with AI's current capabilities. As these AI-exposed establishments adopt AI, they simultaneously reduce hiring in non-AI positions and change the skill requirements of remaining postings. While visible at the establishment level, the aggregate impacts of AI-labor substitution on employment and wage growth in more exposed occupations and industries is currently too small to be detectable.

**Data**:

Burning Glass Data collects roughly 40,000 company websites and online job boards, with no more than 5% of vacancies from any one source. The coverage is the near universe of online vacancies from 2010 onward in the United States, with somewhat more limited coverage in 2007. The primary sample comprises data from the start of 2010 until October 2018. Vacancies in BG data contain information on skill requirements, scraped from the text of the vacancy. Drop the AI production sectors and focus on AI-using sectors.

**Variable Definition**:

Classify each firm as belonging to the *industry* in which it posts the most vacancies over our sample period. Define an *establishment* of a firm as the collection of vacancies pertaining to a firm and commuting zone (CZ). Construct two measures of *AI vacancies*: The narrow category includes a selection of skills relating to AI.13 The broad measure of AI includes skills belonging to the broader skill clusters of machine learning, AI, natural language processing, and data science.

Three measures of AI exposure:

- Felten et al. (2019). It is based on data from the AI Progress Measurement project, from the Electronic Frontier Foundation. The Electronic Frontier data identify a set of nine application areas in which AI has made progress since 2010, such as image recognition or language modelling. Felten et al. use Amazon MTurk to collect crowdsourced assessments of the relevance of each of these application areas to the 52 O*NET ability scales (e.g., depth perception, number facility, and written comprehension). The authors then construct the AI occupational impact for each O*NET occupation as the weighted sum of the 52 AI application-ability scores, where weights are equal to the O*NET-reported prevalence and importance of each ability in the occupation.

- Webb (2020). It seeks to measure what tasks AI can perform by identifying overlaps between claims about capabilities in AI patents and job descriptions in O*NET.

- Brynjolfsson et al. (2019). They develop a 23-item rubric that enables the scoring of the suitability of any task for machine learning. They derive the SML scores by applying this rubric to the textual description of the full set of O*NET occupations using CrowdFlower, a crowdsourcing platform.

The measures differ in the way they capture the applicability of AI to a task. Felten et al. and Webb focus on identifying tasks that fall within existing capabilities, either by relying on the reports from the AI Progress Measurement project or based on the text of patents. The Brynjolfsson et al. SML index is more forward looking and identifies tasks that could be performed by machine learning/AI in the near term, even if outside the reach of existing capabilities.

**Empirical Strategy**:

$$\Delta y_{e,t-t_0} = \beta \mathrm{AI}_{e,t_0} + \mathbf{x}'_{e,t_0}\gamma + \varepsilon_{e,t-t_0},$$

where $\Delta y_{e,t-t_0}$ denotes the change in one of our establishment-level outcomes between 2010-12 and 2016-18. $\text{AI}_{e,t_0} = \sum_o \text{share postings}_{oe,t_0} \cdot \text{AI score}_o$ is one of our three measures of establishment AI exposure calculated using establishment data for 2010-12.

### 4.6. Acemoglu and Restrepo (2018a)

**Paper**: Modeling Automation, AEA Papers and Proceedings

**Summary of the Paper**:

It is a very short paper discussing about how to model automation in task-based production function. It is a simplified version of other papers in this section.

### 4.7. Graetz and Michaels (2018)

**Paper**: Robots at Work, Review of Economics and Statistics

**Research Question**: How does robot use affect labor productivity, total factor productivity, output prices, and the employment of workers with different skills across the developed world?

**Findings**: increased robot use contributed approximately 0.37 percentage points to annual labor productivity growth, while at the same time raising total factor productivity and lowering output prices. Robots did not significantly reduce total employment, although they did reduce low-skilled workers' employment share.

**Data**:

The main source of data on robots is the International Federation of Robotics (2012), which compiles data on industrial robots from national federations of robot manufacturers. The IFR provides data on the number of robots delivered to each industry, in each country and year. The authors construct the stock of robots based on deliveries using the perpetual inventory method, assuming a depreciation rate of ten percent.

The second major source of data for this paper is EUKLEMS. These data include information on inputs (including breakdowns of capital and labor aggregates), outputs, and prices at the industry-country-year level.

**Empirical Strategy**: Use the measures of replaceable hours as well as reaching & handling as instruments for the changes in robot density over time.

## 4.8. Hémous and Olsen (2022)

**Paper**: The Rise of the Machines: Automation, Horizontal Innovation, and Income Inequality, American Economic Journal: Macroeconomics

**Abstract**: We build an endogenous growth model with automation (the replacement of low-skill workers with machines) and horizontal innovation (the creation of new products). Over time, the share of automation innovations endogenously increases through an increase in low-skill wages, leading to an increase in the skill premium and a decline in the labor share. We calibrate the model to the US economy and show that it quantitatively replicates the paths of the skill premium, the labor share and labor productivity. Our model offers a new perspective on recent trends in the income distribution by showing that they can be explained endogenously.

**Notes**: It is closely related to Acemoglu and Restrepo (2018b).

## 4.9. Ales et al. (2023)

**Paper**: How It's Made: A General Theory of the Labor Implications of Technology Change, Working Paper

**Abstract**: We develop a general theory relating technology change and skill demand. Performers (human or machine) face stochastic issues that must be solved in order to complete tasks. Firms choose how production tasks are divided into steps, the rate at which steps need to be completed, and the type of performer assigned to a step. Longer steps are more complex. Performers face a tradeoff between the complexity of their step and the rate at which they can perform. Human performers tend to have an advantage in complex steps while machine performers have an advantage in high rates. The cost of fragmenting tasks into steps and the cost of allocating performers to multiple steps are both central to the theory. We derive the optimal division of tasks, the level of automation, and the demand for workers of different skill levels. The theory predicts that technology change that reduces fragmentation costs and increases process complexity (such as interchangeable parts) increases the dispersion of skill demand; that automation is skill polarizing at lower production volumes and upskilling at higher volumes; and that technology change that raises the cost of fragmenting tasks (such as parts consolidation) reduces the dispersion of skill demand. We find counterparts to the theory across a range of contexts and time periods, including the Hand-Machine Labor Study covering mechanization and process improvement at the end of the 19th century and in contemporary automotive body assembly and optoelectronic semiconductor manufacturing.

# 5. The Organization of Production: Knowledge Hierarchies

## 5.1. Garicano and Rossi-Hansberg (2006)

**Paper**: Organization and Inequality in a Knowledge Economy, The Quarterly Journal of Economics

**Summary of the Model**:

The model explicitly model four elements: production requires knowledge; individuals are heterogeneous in cognitive skill; communication is possible; and organization is hierarchical. In equilibrium, these elements allow for the formation of organizations in which agents specialize in either production or problem solving.

Properties of the equilibrium: First, it displays positive sorting, in the sense that higher ability agents share their knowledge with higher ability subordinates (production workers or lower level managers). Second, regardless of the distribution of skills, individuals are segmented by cognitive skill. The less skilled agents are production workers, the following agents by cognitive skill are first level problem solvers, the next are second level problem solvers, and so forth. Finally, the resulting earnings structure compensates agents for increases in talent more than proportionally.

Two types of comparative statics: decreasing the cost of communication among agents and decreasing the cost of accessing knowledge (e.g., the cost of information processing). Decreases in the cost of communication lead teams to rely more on problem solvers, increasing the centralization of the economy—more problems are solved at the top of the hierarchy. Reductions in the cost of accessing knowledge increase the number of problems solved by agents at all organizational layers.

### 5.1.1. The Model

**Production and Knowledge**:

Production requires labor and knowledge. Agents spend time in production and must solve the problems they confront in order to produce. Agents draw one problem per unit of time spent in production. Output is 1 if the problem is solved, and 0 otherwise. Problems are ranked by the likelihood that they will be confronted, so that problem $Z$ is associated with a continuous density $f(Z)$ and cdf $F(Z)$, where $f'(Z) < 0$.

Solving problems requires knowledge. The knowledge of an agent is characterized by a number $\tilde{z} \in \mathbb{R}_+$, signifying that an agent can solve all problems $Z \in [0, \tilde{z}]$. We define the proportion of problems a worker can solve as $q = F(\tilde{z})$. Then $\tilde{z} = z(q)$, where $z(\cdot) = F^{-1}(\cdot)$, and so $z' > 0, z'' > 0$. Thus, $z(q)$ denotes the knowledge required to solve a proportion $q$ of problems.

Agents differ in their cognitive ability so that higher ability agents incur lower learning costs. The distribution of ability in the population can be described by a continuous density function, $\alpha \sim \phi(\alpha)$, with support in $[0,1]$. In particular, we define ability so that the cost of learning to solve an interval of problems of length 1 is given by

$$c(\alpha;t) = t - \alpha. \tag{5.1.13}$$

A decrease in t represents an improvement in information technology that decreases the cost of learning.

**Communication and Organization**:

Agents can communicate their knowledge to others, and thus help them solve problems. The possibility of offering help to others allows agents to form organizations in which several individuals combine their time and knowledge to produce together. These organizations take the form of *knowledge hierarchies*.

Production proceeds as follows. *Workers* draw a problem per unit of time. If they can solve it, they produce; otherwise, they ask for help to the *managers* in the layer immediately above them, in which case these managers incur a communication cost of $h < 1$ units of time. If these managers know how to solve the problem they solve it; otherwise, they pass it on to the layer immediately above them, and so on, until the problem is solved or it reaches the highest layer in the organization, $L$. Teams have a pyramidal structure: each higher layer has a smaller number of agents than the previous one, since only a fraction of problems is passed on.

Consider an organization with $n_0$ production workers with knowledge $q_0 = F(z_0)$; and $n_l$ problems solving managers in layers $l = 1,\ldots,L$, with knowledge $q_l$. Workers in production draw one problem each, and solve in expectation a fraction $q_0$ of them. Hence they pass on a fraction, $1-q_0$, of all problems. Managers in layer 1 are thus asked to solve $n_0(1-q_0)$ problems, which they can address in $n_0(1-q_0)h$ units of time. Since all agents have one unit of time available, the number of managers in layer 1 is $n_0 h(1-q_0) = n_1$.

Managers in layer 1 can only solve a fraction $q_1$ of problems, and so pass up to the next layer $n_0(1-q_1)$ problems. Thus, the number of managers in layer 2 is given by $n_0 h(1-q_1) = n_2$. In general, the number of managers in layer $l$ satisfies $n_0 h(1-q_{l-1}) = n_l$.

Note that the organization is pyramidal, $n_0 > n_1 > \ldots > n_L$. Expected total output produced by the organization is then given by $y = q_L n_0$.

**Firms' Problem**:

The problem of a hierarchy of $L$ layers that faces a wage schedule, $w(\alpha)$, is to choose the ability, knowledge, and number of agents in each layer of the team. The expected profits of the hierarchy are

$$\Pi(L) = q_L n_0 - \sum_{l=0}^{L} n_l \left[ c(\alpha_l;t) z\big(q_l\big) + w(\alpha_l) \right] \tag{5.1.14}$$

subject to time constraints for the different layers of managers,

$$\begin{aligned} hn_0\left(1-q_{L-1}\right) &= n_L \equiv 1, \\ hn_0\left(1-q_{L-2}\right) &= n_{L-1} \\ &\vdots \\ hn_0\left(1-q_0\right) &= n_1. \end{aligned} \tag{5.1.15}$$

That is, profits are given by output minus wages, $w(\alpha)$, and learning costs, $n_l c_l z\big(q_l\big)$. We call the manager in the highest layer an *entrepreneur*, and normalize their number, $n_L$, to 1. The choice of the ability of subordinates implies that

$$w'(\alpha) = -c'(\alpha;t)z\big(q\big). \tag{5.1.16}$$

**Agents' Problem**:

Agents are income maximizers. Their problem is to choose their occupation to maximize income, given the available job opportunities. Available jobs are indexed by $\alpha'$. A job $\alpha'$ pays a wage, $w\big(\alpha'\big)$, plus learning costs given by $c\big(\alpha';t\big)z\big(q\big(\alpha'\big)\big)$, and requires agents to learn how to solve a proportion $q\big(\alpha'\big)$ of problems. The problem of an agent with ability $\alpha$ is to choose a job $\alpha'$ that maximizes her wage minus the difference between the learning costs paid by the firm and her actual learning costs, $c\big(\alpha';t\big)z\big(q\big(\alpha'\big)\big) - c(\alpha;t)z\big(q\big(\alpha'\big)\big)$, so

$$U(\alpha) = \max_{\alpha'} w\big(\alpha'\big) + \big(c\big(\alpha';t\big)z\big(q\big(\alpha'\big)\big) - c(\alpha;t)z\big(q\big(\alpha'\big)\big)\big). \tag{5.1.17}$$

Therefore, agents can either work for jobs designed for their ability $\alpha$ or for jobs designed for different abilities $\alpha'$. The FOC yields

$$w'\left(\alpha^*\right) = -c'\left(\alpha^*;t\right)z\left(q\left(\alpha^*\right)\right) - z'\left(q\left(\alpha^*\right)\right)q'\left(\alpha^*\right)\left[c\left(\alpha^*;t\right) - c(\alpha;t)\right].$$

Note that from (5.1.16), $w'(\alpha^*) = -c'(\alpha^*;t)z\big(q(\alpha^*)\big)$ and so $\alpha^* = \alpha$. Thus, in equilibrium agents have incentives to choose the job designed for their own ability. Hence, the slope of the wage function in equilibrium will be equal to the decrease in learning costs as ability increases and $U(\alpha) = w(\alpha)$.

### 5.1.2. Equilibrium

The firm's and agent's problem discussed earlier determine, for a given hierarchy, the proportion of tasks each agent should learn to perform, as well as team sizes, given wages. An equilibrium allocation specifies the sets of agents in different occupations, the assignment of agents to supervisors, and the wage schedule that supports this assignment.

Let $n(\alpha)$ denote the total number of workers or managers hired as direct subordinates of managers or entrepreneurs with ability $\alpha$ in equilibrium. Let $a(\alpha)$ denote the ability of the managers assigned to an employee of ability $\alpha$ in equilibrium. In order for $a(\alpha)$ to be defined over the whole set of abilities, $(0,1)$, we set $a(\alpha) = 1$ for all entrepreneurs. Since hierarchies have only one entrepreneur at the top, $n(a(\alpha)) = 1$ when agents with ability $\alpha$ are entrepreneurs. Let $A_S$ be the set of agents with subordinates and let $A_M$ denote the set of agents who are not at the top of the hierarchy (all agents who have a manager r entrepreneur above them). Then, labor markets clear if for every $\alpha \in A_M$,

$$\int_{[0,\alpha]\cap A_M} \phi\left(\alpha'\right) d\alpha' = \int_{[a(0),a(\alpha)]\cap A_S} \frac{n\left(\alpha'\right)}{n\left(a\left(\alpha'\right)\right)} \phi\left(\alpha'\right) d\alpha'. \tag{5.1.18}$$

The left-hand side is the supply of employees in the interval $(0,\alpha)$. The right-hand side is the demand for employees by managers and entrepreneurs in the interval $(a(0), a(\alpha))$: managers and entrepreneurs of ability $\alpha$ hire $n(\alpha)$ employees, and there are $n(a(\alpha))$ of them.

## 5.2. Garicano (2000)

**Paper**: Hierarchies and the Organization of Knowledge in Production, Journal of Political Economy

**Research Question**: Why is production in firms hierarchically organized? What is the impact of changes in information and communication technology on organizational design?

**Summary of the Model**:

The starting point is the observation that production requires physical resources and knowledge about how to combine them. If communication is available, workers do not need to acquire all the knowledge necessary to produce. Instead, they may acquire only the most relevant knowledge and, when confronted with a problem they cannot solve, ask someone else. Knowing if someone knows the solution to a problem inevitably involves asking that person. The author shows that, in this case, it is natural to organize the acquisition of knowledge as a "knowledge-based hierarchy." In such a structure, knowledge of solutions to the most common or easiest problems is located in the production floor, whereas knowledge about more exceptional or harder problems is located in higher layers of the hierarchy.

The key trade-off the organization confronts occurs between communication and knowledge acquisition costs. By adding layers of problem solvers, the organization increases the utilization rate of knowledge, thus economizing on knowledge acquisition, at the cost of increasing the communication required.

The model shows that decreases in the cost of both communicating and acquiring knowledge reduce the need for specialized problem solvers in the organization.

## 5.3. Garicano and Hubbard (2005)

**Paper**: Hierarchical Sorting and Learning Costs: Theory and Evidence from the Law, Journal of Economic Behavior & Organization

**Summary of the Model**:

It is an extension of Garicano and Rossi-Hansberg (2006) by adding on-the-job training to the model (while in Garicano and Rossi-Hansberg (2006), only pre-market investments are studied). The authors find that the existence of on-the-job training strengthens positive sorting between workers and managers, that is, managers with the lowest cost of acquiring knowledge or "learning cost" work with workers with the lowest learning cost.

Reason for the positive sorting: When managers are matched with workers, they must incur two costs that depend on the characteristics of the workers: they must help workers whenever they cannot deal with the problems on their own, and they must allow workers time to train on the job. Lower learning cost workers are more valuable to more skilled managers for two reasons related to these two costs. First, as in the pre-market training set-up analyzed by Garicano and Rossi-Hansberg (2006), more knowledgeable workers allow a more talented manager to leverage his knowledge adequately rather than distracting him with questions any other manager could have answered. Second, and this is the new effect we uncover, the opportunity cost of the time spent training increases the more knowledgeable the manager; thus, a more knowledgeable manager benefits more from a worker with lower learning cost.

**Test the Model**:

The authors then conduct an empirical analysis that investigates the existence and nature of positive sorting within law firms. They find evidence of positive sorting between associates and partners associated with law school quality, but not experience.

## 5.4. Caroli and Van Reenen (2001)

**Paper**: Skill-Biased Organizational Change? Evidence from A Panel of British and French Establishments, The Quarterly Journal of Economics

**Research Question**: Whether organizational changes (the decentralization of authority, delayering of managerial functions, and increased multitasking) are skill-biased?

**Implications of Skill-Biased Organizational Changes**: (i) organizational change should be followed by a declining demand for less skilled labor; (ii) falls in the relative cost of skills should increase the probability of organizational change; and (iii) organizational changes should have a larger impact on productivity in workplaces with higher levels of skills.

**Findings**: First, organizational changes reduce the demand for unskilled workers in both countries. Second, OC is negatively associated with increases in regional skill price differentials (a measure of the relative supply of skill). Third, OC leads to greater productivity increases in establishments with larger initial skill endowments.

## 5.5. Acemoglu et al. (2007)

**Paper**: Technology, Information, and the Decentralization of the Firm, The Quarterly Journal of Economics

**Research Question**: How do the adoption of new technology and the information structure between principles and managers affect the decentralization decisions of firms?

**Key Trade-offs and Implications of the Model**:

Decentralized control delegates authority to a manager, who potentially possesses more information than is available in the public history. Nevertheless, because the interests of the principal and the manager are not perfectly aligned, the manager can use his informational advantage to make choices that are not in the best interest of the principal. This tradeoff between the superior knowledge of the manager and the agency costs of managerial delegation determines the optimal degree of decentralization.

Three sets of empirical predictions:

- Firms closer to the technological frontier are more likely to choose decentralization, because they are dealing with new technologies about which there is only limited information in the public history.
- Firms in more heterogeneous environments are more likely to be decentralized, because greater heterogeneity makes learning from the experiences of others more difficult.
- Young firms, which have had a limited history in which to learn about their own specific needs, are also more likely to be decentralized than older firms.

**Definition of Decentralization**: Whether different units of the firm are organized into "profit centers."The main results are robust to proxying decentralization by the extent of delayering or measures of managerial autonomy over investment and/or employment decisions.

## 5.6. Caliendo and Rossi-Hansberg (2012)

**Paper**: The Impact of Trade on Organization and Productivity, The Quarterly Journal of Economics

**Summary of the Model**: This is an extension to Garicano and Rossi-Hansberg (2006) by allowing different firms to have different demand levels (heterogenous firms). As in Garicano and Rossi-Hansberg (2006), firms use labor and knowledge to produce. Entrepreneurs decide the number of layers of management and the knowledge and span of control of each agent. As a result, in the theory, heterogeneity in demand leads to heterogeneity in productivity and other firms' outcomes.

**Findings**: The authors use the theory to analyze the impact of international trade on organization and calibrate the model to the U.S. economy. As a result of a bilateral trade liberalization, firms that export will increase the number of layers of management. The new organization of the average exporter results in higher productivity, although the responses of productivity are heterogeneous across these firms. Liberalizing trade from autarky to the level of openness in 2002 results in a 1% increase in productivity for the marginal exporter and a 1.8% increase in its revenue productivity. Endogenous organization increases the gains from trade by 41% relative to standard models.

### 5.7. Antras et al. (2006)

**Paper**: Offshoring in a Knowledge Economy, The Quarterly Journal of Economics

**Abstract**: How does the formation of cross-country teams affect the organization of work and the structure of wages? To study this question, we propose a theory of the assignment of heterogeneous agents into hierarchical teams, where less skilled agents specialize in production and more skilled agents specialize in problem solving. We first analyze the properties of the competitive equilibrium of the model in a closed economy, and show that the model has a unique and efficient solution. We then study the equilibrium of a two-country model (North and South), where countries differ in their distributions of ability, and in which agents in different countries can join together in teams. We refer to this type of integration as globalization. Globalization leads to better matches for all southern workers but only for the best northern workers. As a result, we show that globalization increases wage inequality among nonmanagers in the South, but not necessarily in the North. We also study how globalization affects the size distribution of firms and the patterns of consumption and trade in the global economy.

### 5.8. Caliendo et al. (2015)

**Paper**: The Anatomy of French Production Hierarchies, Journal of Political Economy

**Summary**: This paper considers the same model as in Caliendo and Rossi-Hansberg (2012) and tries to use French data to test the implications of the model.

**Abstract**: We study the internal organization of French manufacturing firms. We divide the employees of each firm into "layers" using occupational categories. Layers are hierarchical in that the typical worker in a higher layer earns more, and the typical firm occupies less of them. The probability of adding/dropping a layer is positively/negatively correlated with value added. Reorganization, through changes in layers, is essential to understanding how firms grow. Firms that expand substantially add layers and pay lower average wages in all preexisting layers. In contrast, firms that expand little and do not reorganize pay higher average wages in all preexisting layers.

### 5.9. Sandvik et al. (2020)

**Paper**: Workplace Knowledge Flows, Working Paper

**Abstract**: We conducted a field experiment in a sales firm to test whether improving knowledge flows between coworkers affects productivity. Our design allows us to compare different management practices and isolate whether frictions to knowledge transmission primarily reside with knowledge seekers, knowledge providers, or both. We find large productivity gains from treatments that reduced frictions for knowledge seekers. Workers who were encouraged to seek advice from a randomly chosen partner during structured meetings had average sales gains exceeding 15%. These effects lasted at least 20 weeks after the experiment ended. Treatments intended to change knowledge providers' willingness to share information, in the form of incentives tied to partners' joint output, led to positive—but transitory sales gains. Directing coworkers to share knowledge raised average productivity and reduced output dispersion between workers, highlighting the role that management practices play in generating spillovers inside the firm.

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