Learning, Career Paths, and the Distribution of Wages

Santiago Caicedo  Robert E. Lucas Jr.  Esteban Rossi-Hansberg
University of Chicago  University of Chicago  Princeton University

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Abstract

We develop a theory of career paths and earnings in an economy in which agents organize in production hierarchies. Agents climb these organizational hierarchies as they learn stochastically from other individuals. We study the resulting career paths for agents with different schooling levels. Earnings grow over time as agents acquire knowledge and occupy positions with larger numbers of subordinates. The cross-sectional variance of earnings also increase with experience. We contrast these and other implications of the theory with U.S. census data for the period 1990 to 2010. The increase in wage inequality over this period, and other concurring phenomena, can be rationalized with a shift in the distribution of the complexity and profitability of technologies relative to the distribution of knowledge in the population.

1. Introduction

This paper develops a new model of an economy that generates sustained productivity growth. One distinctive feature of the model is that all knowledge in the economy is held by the individual people who comprise it: there is no abstract technology hovering above them in the ether. A second feature, necessarily involving heterogeneous labor, is a kind of complementarity in production involving people with different skill levels: the marginal product of any one person is contingent on the people he works with. A third feature, closely
related to the second, is that improvements over time in individual skill levels depend on imitation or stimulation or inspiration from other people in the economy. All growth is taken to arise from this force.

Mathematically we will study the behavior of a continuum of agents, each with different skill levels. Production at any date will depend on the way people are organized, on which tasks are assigned to which people at different skill levels. Production increases by any one person will depend on the knowledge of the people with whom he interacts. We add to these features a cohort structure with a stationary birth and death process and a role for schooling. The resulting model then has the familiar ingredients of human capital theory and so invites comparisons to census cross-section evidence and age-earnings profiles, to panel evidence on individual careers over time, and the effects on both of differences in schooling. After working out the logic of the model, then, we address some of these empirical challenges.

We begin in Section 2 with a static model built on the hierarchical structures pioneered by Garicano (2000) and Garicano and Rossi-Hansberg (2004, 2006). These models describe a very specific complementarity among agents of different productivity types. Agents can contribute to production as workers or else as managers to whom a worker can turn for help with a problem that is too hard for him to solve on his own. Each manager can review several unsolved problems that are passed up to him. Those problems that are within the manager’s ability are then solved by the worker with his advice. Unsolved problems at this higher layer can be passed up to managers with still higher abilities, and so on.

One can think of successive layers of managers. Caliendo, Monte, and Rossi-Hansberg (2015) identify different occupations within a data set of French firms with these theoretical layers, and show that changes in firms’ actual occupational structure are well correlated with theoretical changes. It seems natural to think of these complementarities as organized into firms, as in this example, but one can also think of these managers as independent consultants, and workers as buyers of consultant services. What matters for overall production is not the corporate structure in place but the assignment of people of diverse skill levels to different roles in the production process.

For our purposes, the census evidence covers the entire economy and we need a theory at
a general equilibrium level. Since our focus is on the labor market, we want to determine the prices—earnings or wages—of people at every skill level. We view every agent as endowed with a given type, which we identify as the goods he could produce on his own.\footnote{We refer to the type of the agent interchangeably as his skill or knowledge level.} In the hierarchical model we use here, given types are central too but until we know the occupational structure we can’t determine earnings. A general equilibrium must be solved to connect types and earnings.

The rest of the paper is structured as follows. We begin with the static problem of solving for equilibrium wages and productivity. In Section 2 we set out the notation for this model, work out the assortative matching linking workers and managers, and define the hierarchy that we work with. In Section 3 we formulate and study the problem of an idealized planner who wants to maximize total goods production. The planner assigns some agents to be workers, others to be managers, and defines the matching function connecting them. Then in Section 4 we decentralize this planning problem to obtain a competitive equilibrium in which the earnings of all managers and workers are determined. In this modeling of assigning agents to tasks, only agents’ skill levels matter for earnings. The time and effort that may have led to those levels—years of schooling, age, luck, or any other qualities—are immaterial.

The framework we propose has two key differences relative to the previous work by Garicano and Rossi-Hansberg (2004, 2006). First it features distributions of skills and problems with unbounded support. Second, and perhaps more important, we assume that problems that are harder to solve also yield higher output. These two features are essential to introduce dynamics and growth into our theory since they facilitate the incorporation of knowledge diffusion in a setup that features a balanced-growth path. We do this in Section 5 where we introduce some dynamics into this model. We introduce a fixed demography, schooling, learning, and a cohort structure. Then we interpret the static model developed in Sections 2-4 as cross-sections evolving along a balanced growth path. With these elaborations, we connect the distribution of types studied in Sections 3 and 4 to age-earnings profiles.
As in Lucas (2009), we interpret age-earnings profiles as outcomes of a balanced growth path with a constant growth rate driven by a process of learning from others. An agent is identified by his type and at any date there is a distribution of types. Agents learn—improve their types—by interacting with people some of whom have higher types than their own. The type distribution has a Pareto tail, ensuring that every agent will always find someone who knows more than he does. In the balanced growth path, an agent’s career path starts at the bottom of the hierarchy and evolves over time taking him to higher management positions, with more subordinates, and higher wages. These transitions depend on his learning, which is stochastic, and on the distribution of knowledge in the economy. The learning process we use implies that the distribution of knowledge shifts over time, but maintains its assumed Pareto form.

In this paper, however, the type distribution does not, by itself, define production in the economy or its age-earnings profiles. For this we need a second distribution, describing the difficulty of the problems that agents are asked to solve. If these were to change over time while agent’s skills kept improving, all agents would eventually be able to solve virtually all the problems that confront them and there would be no need for a hierarchy. In the same way, a problem distribution that moved too fast to the right would eventually eliminate production. Using the language of Goldin and Katz (2007), the race of skills and technology would be won by one side or the other. In order to maintain a balanced growth we need to rule out these possibilities. Throughout, though, we are silent about the source of the evolution of the problem distribution and just assume that it evolves in a manner that guarantees the existence of a balanced growth path.

In Section 6 we show how we calibrate the model to fit the fraction of managers and the distribution of earnings in 1990 and discuss several comparative statics exercises. In Section 7 we compare the balanced growth properties of the calibrated model to age-earnings profiles for different schooling groups, as well as the dispersion of the wage distribution across age classes. The model is able to fit these patterns well. In particular, it is able to match the increase in the dispersion of wages for older agents, a pattern that was hard to fit in models without a hierarchical structure, such as Lucas (2009).
We finish our analysis in Section 8 where we show that, in the calibrated model, shifts in the distribution of the complexity of problems relative to the distribution of knowledge can account well for the increase in wage inequality between 1990 and 2010. The results propose a cause for the evolution of wages during this period: New technologies that only the most knowledgeable experts can utilize but that also pay more than in the past. This technological change leads to relatively large changes in the wage distribution but, in our calibration, to modest increases in output. Section 9 offers some final remarks.

2. Planning Problems: Examples

We consider a closed economy in which people of different types are employed to produce a single consumption good. Everyone is endowed with one unit of work time. The labor force is defined by a cdf $F(z)$ (density $f$) on $(0, \infty)$, where $z$ indexes a person’s skill level. Call $F$ the population distribution. An idealized planner organizes these people so as to maximize total production, given a production technology. This technology is modeled closely on earlier work by Garicano and Rossi-Hansberg but some of the details are new and we will provide a self-contained description.

First consider production under autarky. Every agent $z$ uses his unit of time to generate a production possibility that involves taking a draw from a distribution of problems, defined by a cdf $G(z)$ (density $g$) which we call the problem distribution. If he draws $y \leq z$ then he produces $y$ units of the good, which is to say he solves the problem given to him. If he draws $y > z$ he produces nothing. We think of many people at each $z$ level, who produce the average $\int_0^z yg(y)dy$. Total production at all levels $z$ is then

$$\int_0^\infty \int_0^z yg(y)dyf(z)dz.$$ 

The remaining problems, $\int_0^\infty \int_z^\infty yg(y)dyf(z)dz$ are simply discarded. In this example, the planner does nothing except collect all the goods that are individually produced. Clearly, knowledge is not optimally employed; more knowledgeable agents solve the same set of problems than less knowledgeable ones.
Garicano and Rossi-Hansberg propose a second role for agents, which we adopt here. Call the agents who generate problems and produce on their own, as described above, *workers*. Other agents, whom we call *managers*, can be used as advisors, using their time to help workers to solve some of the problems that they themselves could not solve. We assume that each manager can review $\kappa \geq 1$ unsolved problems with his endowed unit of time. A problem $y$ that is reviewed by a manager $z$ will be solved if $y \leq z$ and otherwise will remain unsolved. In this more complicated situation, the planner must determine which agents are workers and which are managers and he needs to assign $\kappa$ unsolved problems to each manager. We emphasize that no one in this economy, worker, manager, or planner, knows how difficult an individual problem is unless he either generates the problem himself and can solve it or he reviews the problem himself and knows how to enable the worker who drew the problem to solve it. Understanding the difficulty of a problem is thus equivalent to knowing how to solve it.

Consider then a second example in which agents $z = (0, z_w)$ are assigned to be workers and the rest, $z = (z_w, \infty)$, are assigned to be managers in an economy. Suppose the planner chooses a cutoff $z_w$ and a continuous, increasing matching function $\varphi : (0, \infty) \rightarrow (z_w, \infty)$ that together satisfy

$$\kappa [F(\varphi(y)) - F(z_w)] = \int_0^y [1 - G(z)] f(z)dz, \quad \text{all } y \in (0, z_w]. \quad (2.1)$$

The right side is the number of problems that people in $(0, y)$ cannot solve on their own. The left side is the number of problems that the assigned managers in $(\varphi(0) = z_w, \varphi(y)]$ can review. That is, equation (2.1) guarantees that there are enough managers to deal with all the problems generated by workers: a sort of market clearing of problems. Clearly, generating problems that will not be reviewed, or allocating unemployed management time, is not optimal. An optimal allocation necessarily satisfies (2.1).

Now suppose that $z_w$ is chosen so that every unsolved problem in $(0, z_w)$ is reviewed by exactly one manager in $(z_w, \infty)$ and that all managers are so employed. Then equation (2.1) would imply

$$1 - F(z_w) = \frac{1}{\kappa} \int_0^{z_w} [1 - G(z)] f(z)dz. \quad (2.2)$$
In this case, total production would become

$$\int_{0}^{z} \int_{0}^{z} yg(y)dyf(z)dz + \int_{0}^{z} \int_{z}^{\varphi(z)} yg(y)dyf(z)dz$$

$$\int_{0}^{z} \int_{0}^{\varphi(z)} yg(y)dyf(z)dz$$

\[ (2.3) \]

This is a feasible plan, but is it optimal?

The reason this plan might not be optimal is that all problems above $\varphi(z)$ for $z \in (0, z_w]$ are discarded. Could it be the case that the planner prefers to have some of the more knowledgeable agents deal with the problems that the less knowledgeable managers discard? Maybe it is optimal to have managers solve other manager’s discarded problems.

To allow for this possibility, let $z_1 = \varphi(z_w)$ and impose the following condition for managers performing this role,

$$F(\varphi(y)) - F(z_1) = \int_{z_w}^{y} \frac{1 - G(z)}{1 - G(\varphi^{-1}(z))} f(z)dz,$$

for all $y \in (z_w, \varphi(z_w))$. The right side is the number of problems that managers in $(z_w, y)$ cannot solve (conditional on workers below them not being able to solve them either, $1 - G(\varphi^{-1}(z))$) and thus are passed up to managers in the second layer, $(z_1, y)$. Again, if this condition is not satisfied, a manager’s time is clearly not allocated efficiently.

In general, a matching function that includes agents that solve the problems discarded by $i + 1$ groups of agents will have to satisfy

$$F(\varphi(y)) - F(z_{i+1}) = \int_{z_i}^{y} \frac{1 - G(z)}{1 - G(\varphi^{-1}(z))} f(z)dz,$$

for all $y \in [z_i, z_{i+1}]$ \[ (2.4) \]

where

$$z_{i+1} = \varphi(z_i) \quad \text{for} \quad i = 1, 2, \ldots$$

\[ (2.5) \]

Following the practice of Garicano and Rossi-Hansberg we refer to the intervals $(z_i, z_{i+1})$ with $z_0 = z_w$ as managerial layers, denoted $L_1, L_2, \ldots$

All of these task assignments of the given labor force $F(z)$ are feasible, as are many other assignments not yet discussed. But which, if any, of these can maximize total production?

\[ ^2 \text{For example, in all the examples above we assumed that agents generating problems are the least knowledgeable ones and that the interval of workers is connected. Clearly, there exists other feasible allocations that do not satisfy these properties.} \]
This question is answered in Section 3.

3. Planning Problems: Optimality

To consider all possible assignments we need a better notation. Let \( Z_w \subset [0, \infty) \) denote the set of agents that the planner assigns to the role of generating problems (workers). Let \( Z_m \subset [0, \infty) \) denote the set of managers with subordinates and a manager above them. Let \( Z_e \subset [0, \infty) \) denote the set of top managers without a manager above them (whom we call entrepreneurs). Note that \( Z_w \cap Z_m = \emptyset \) and \( Z_m \cap Z_e = \emptyset \) but \( Z_w \cap Z_e \) could be non-empty since some workers might be self-employed. Furthermore, \( Z_w \cup Z_m \cup Z_e = [0, \infty) \): all agents belong to one of these sets.

As shown in Garicano and Rossi-Hansberg (2006), the production process described above implies a technology that is supermodular in the talent of an agent and its subordinates. This implies that the assignment function, \( \varphi : (Z_w \setminus Z_e) \cup Z_m \to Z_m \cup Z_e \), is monotone increasing. With some abuse of notation let \( \varphi(Z) \) denote the set of managers assigned to a set of agents \( Z \).

The problem of a planner is then given by

\[
\max_{\{\varphi(\cdot)\} (Z_w \setminus Z_e) \cup Z_m, Z_e} \int_{Z_w} \int_{0}^{\infty} yg(z) dyf(z)dz - \kappa \int_{Z_e} \int_{z}^{\infty} y \frac{g(y)}{1 - G(\varphi^{-1}(z))} dyf(z)dz, \quad (3.1)
\]

subject to

\[
\int_{\varphi(Y)} f(z)dz = \frac{1}{\kappa} \int_{Y} [1 - G(z)] f(z)dz, \quad \text{all } Y \subset Z_w \setminus Z_e, \quad (3.2)
\]

and

\[
\int_{\varphi(Y)} f(z)dz = \int_{Y} \frac{1 - G(z)}{1 - G(\varphi^{-1}(z))} f(z)dz, \quad \text{all } Y \subset Z_m. \quad (3.3)
\]

where the first term in the objective function (3.1) is the value of all the generated problems if all of them are solved, and the second term is the value of the discarded problems. The constraints just replicate the ones we introduced in equations (2.1), (2.4) and (2.5). Note that, given the sets \( Z_w, Z_m, \) and \( Z_e \), the two constraints (3.2) and (3.3) fully specify the assignment function \( \varphi \). Hence, the problem of the planner can be reduced to choosing the sets of agents that become workers, managers, and entrepreneurs.
In this section we report what we can establish about the solution to this planning problem. The next theorem shows that in the optimal allocation, the sets of workers, managers (if non-empty) and entrepreneurs are connected and ordered by their skill level, where workers are the least skilled agents and entrepreneurs the most skilled ones. The results allows us to eliminate many feasible allocations as solutions. All proofs are relegated to the Appendix.

**Theorem 1.** Suppose that \( F(\cdot) \) and \( G(\cdot) \) are differentiable. Then any solution to the planning problem is characterized by a matching function \( \varphi(\cdot) \), and a pair of thresholds \( z_w \) and \( z_e \) such that \( Z_w = [0, z_w], Z_m = [z_w, z_e], Z_e = [z_e, \infty) \). If \( Z_m \neq \emptyset \) then \( z_w < z_e \); otherwise, \( z_w = z_e \).

The proof of Theorem 1 relies on the next three lemmas.

**Lemma 1:** Let \( (\varphi(\cdot), Z_w, Z_m, Z_e) \) solve the planner’s problem. Then for \( \varepsilon \) sufficiently small \( 0, \varepsilon \not\in Z_w \cap Z_e \).

**Lemma 2:** Let \( (\varphi(\cdot), Z_w, Z_m, Z_e) \) solve the planner’s problem. Then if \( z_m \in Z_m \) and \( z_e \in Z_e \) we have \( z_m < z_e \).

**Lemma 3:** Let \( (\varphi(\cdot), Z_w, Z_m, Z_e) \) solve the planner’s problem. Then \( z \in Z_w \) implies that \( z \leq z' \) for all \( z' \in Z_m \cup Z_e \).

Together, these three lemmas imply that the optimal allocation is such that \( Z_w, Z_m, Z_e \) are ordered with \( Z_w \leq Z_m \leq Z_e \), where \( Z_m \) is potentially empty.\(^3\) This implies that in any optimal allocation with a maximum number of layers \( L \), the set of hierarchies active in the allocation has either \( L \) or \( L - 1 \) layers. For example, in an economy where the maximum number of layers is 3, there cannot be any self-employed agents working on their own, a feature also present in Garicano and Rossi-Hansberg (2006).

Theorem 1 implies that the problem of the planner can then be rewritten as

\[
\max_{\{\varphi(\cdot)\}_{[0,z_e]}(z_w,z_e)} \int_0^{z_w} \int_0^\infty yg(y) df(z) dz - \kappa \int_{z_e}^\infty \int_z^\infty y \frac{g(y)}{1 - G(\varphi^{-1}(z))} df(z) dz, \tag{3.4}
\]

\(^3\)We use \( Z_w \leq Z_m \leq Z_e \) to mean that for any \( z_w \in Z_w \), any \( z_m \in Z_m \), and any \( z_e \in Z_e \), \( z_w \leq z_m \leq z_e \).
subject to

\[ F(\varphi(y)) - F(\min \{z_w, z_e\}) = \frac{1}{\kappa} \int_0^y [1 - G(z)] f(z) dz, \quad \text{all } y \in \left[0, \min \{z_w, z_e\}\right], \quad (3.5) \]

and

\[ F(\varphi(y)) - F(\varphi(\min \{z_w, z_e\})) = \int_{\min \{z_w, z_e\}}^y \frac{1 - G(z)}{1 - G(\varphi^{-1}(z))} f(z) dz, \quad \text{all } y \in \left[\min \{z_w, z_e\}, z_e\right]. \quad (3.6) \]

A solution to the planning problem is thus fully described by a matching function \( \varphi(\cdot) : [0, z_e] \to [z_w, \infty) \) and two cutoffs \((z_w, z_e)\).

As we mentioned above, for any pair of cutoffs we can construct the matching function \( \varphi \) using (3.5) and (3.6). That is, provided that \( F(\cdot) \) is strictly increasing, we have

\[ \varphi(y) = F^{-1} \left( F(z_w) + \frac{1}{\kappa} \int_0^y [1 - G(z)] f(z) dz \right), \quad \text{all } y \in \left[0, \min \{z_w, z_e\}\right] \]

and

\[ \varphi(y) = F^{-1} \left( F(\varphi(\min \{z_w, z_e\})) + \int_{\min \{z_w, z_e\}}^y \frac{1 - G(z)}{1 - G(\varphi^{-1}(z))} f(z) dz \right), \quad \text{all } y \in \left[\min \{z_w, z_e\}, z_e\right]. \]

Moreover, if we assume that \( F(\cdot) \) is differentiable then \( \varphi(\cdot) \) is continuous and differentiable except possibly at \( \min \{z_w, z_e\} \), where there is a kink in the matching function if \( \kappa \neq 1 \).

In light of these facts, our task is to find the cutoffs \((z_w, z_e)\) that solve the planning problem. We first consider the situation where there are no intermediate managers, or where \( Z_m = \emptyset \). In this case, \( z_w = z_e \) and only one cutoff needs to be determined. Note further than in this case \( \varphi(z_w) = \infty \) and so (3.5) implies, for \( y = z_w \), that equation (2.2) holds. That is,

\[ 1 - F(z_w) = \frac{1}{\kappa} \int_0^{z_w} [1 - G(z)] f(z) dz. \]

Clearly, violating this constraint is not optimal since it implies that either too many problems are generated, or there is excess managerial capacity to review problems. Lemma 4 in
the appendix makes this argument precise. Hence, when $z_w = z_e$, equation (2.2) determines the value of $z_w$ that maximizes output. In turn, $\varphi(\cdot)$, is determined by (3.5) for $y < z_w$.

Focus next on the case where $Z_m \neq \emptyset$ and so $z_w < z_e$. Then we can restate the problem of the planner as

$$
\max_{(z_w, z_e)} \int_0^{z_w} \int_0^\infty yg(y) \, dy \, f(z) \, dz - \kappa \int_{z_e}^\infty \int_z^\infty yg(y) \, dy \frac{f(z)}{1 - G(\varphi^{-1}(z, z_w))} \, dz \tag{3.7}
$$

subject to

$$
F(\varphi(y)) - F(z_w) = \frac{1}{\kappa} \int_0^{y} [1 - G(z)] \, f(z) \, dz, \quad \text{all } y \in [0, z_w] \tag{3.8}
$$

and

$$
F(\varphi(y)) - F(\varphi(z_w)) = \int_{z_w}^{y} \frac{1 - G(z)}{1 - G(\varphi^{-1}(z, z_w))} \, f(z) \, dz, \quad \text{all } y \in [z_w, z_e] \tag{3.9}
$$

We have shown in Lemmas 1-4 that an optimal plan must satisfy (3.7) - (3.9). We now add

**Theorem 2.** Suppose that $F(\cdot)$ and $G(\cdot)$ are differentiable. Then there is a pair $(z_w, z_e)$ that satisfies (3.6) - (3.8).

This argument is not constructive and does not address uniqueness, so in the Appendix we describe the numerical algorithm we use to calculate maxima. In particular, we compare solutions in which all problems are eventually solved and so $z_e = \infty$ and solutions in which $z_e$ is finite and so some problems are optimally discarded. We also solve the case with $z_w = z_e$. We can then compare total production in these allocations and easily compute the maximum.

4. Decentralized Equilibrium

The planning problem studied in Section 3 was a step toward obtaining a competitive equilibrium. To this end, we next describe a decentralization of the planner’s allocation $(\varphi(\cdot), z_w, z_e)$, given $F, G$ and $\kappa$. We are looking for a wage function that gives incentives to firms to build the same production teams as the planner. Given that agents are income maximizers, they just choose the job that is willing to pay more for their services, conditional on their skill.
We consider organizations defined by a single worker \( z \in [0, z_w] \) that hires managers at levels

\[
\varphi(z), \varphi(\varphi(z)) = \varphi_2(z), ..., \varphi_L(z)
\]

where \( L \) denotes the maximum number of layers. This organization generates one problem with an expected return of

\[
\int_0^{\varphi_L(z)} yg(y)dy
\]

where \( \varphi_L(z) \) is the top manager matched to worker \( z \). We need to price the labor time of these managers \( w(\varphi_i(z)), i = 1, ..., L \), and the residual value \( w(z) \) of worker \( z \). The units of manager-of-layer-\( i \)’s time that the firm of worker \( z \) hires, \( n_i(z) \), is equal to the fraction of problems that subordinates one layer below cannot solve, relative to the number of problems a manager can handle, \( \kappa \). That is,

\[
n_i(z) = \frac{1 - G(\varphi_{i-1}(z))}{\kappa}, \quad \text{all } i = 1, ..., L. \tag{4.1}
\]

Let \( L \) be the maximum number of managerial layers consistent with the planner’s solution \((\varphi(\cdot), z_w, z_e)\). Firms in such an economy can then have either \( L \) or \( L - 1 \) layers.

The profit of an organization with worker \( z \in [0, z_w] \) and \( L_z \) layers is given by

\[
\Pi(z) = \int_0^{\varphi_L(z)} yg(y)dy - \sum_{i=1}^{L_z} \frac{1 - G(\varphi_{i-1}(z))}{\kappa}w(\varphi_i(z)) - w(z).
\]

The problem of this organization is

\[
w(z) = \max_{\varphi(z), L_z} \Pi(z). \tag{4.2}
\]

The associated first order conditions are

\[
\begin{align*}
    w'(z) &= \frac{g(z)}{\kappa}w(\varphi(z)), \\
    w'(\varphi_i(z)) &= \frac{g(\varphi_i(z))}{1 - G(\varphi_{i-1}(z))}w(\varphi_{i+1}(z)) \quad \text{for } i = 1, ..., L_z - 1, \\
    w'(\varphi_{L_z}(z)) &= \frac{\kappa}{1 - G(\varphi_{L_z-1}(z))}\varphi_{L_z}(z)g(\varphi_{L_z}(z)).
\end{align*} \tag{4.3}
\]
The equilibrium wage schedule \( w(z) \) is therefore calculated by solving the following differential equations, starting from the last layer in the economy, \( L \),

\[
\begin{align*}
    w'(z) &= \frac{g(z)}{\kappa} w(\varphi(z)) & \text{for } & z \in [0, z_w], \\
    w'(z) &= \frac{g(z)}{1 - G(\varphi^{-1}(z))} w(\varphi(z)) & \text{for } & z \in [z_w, z_e], \\
    w'(z) &= \frac{\kappa g(z) z}{1 - G(\varphi^{-1}(z))} & \text{for } & z \in [z_e, \infty). 
\end{align*}
\]

The matching function and the cutoffs \((\varphi(\cdot), z_w, z_e)\) are given by the solution to the planner’s problem. The choice of \( L_z \) is a discrete choice problem that also coincides with the hierarchies present in the planner’s allocation, namely \( L - 1 \) or \( L \).

Workers with knowledge given by \( \varphi_i(0) \), \( i = 1, \ldots, L \), should be indifferent between working in layer \( i - 1 \) or layer \( i \), since otherwise some agents close to them would like to work for a different employer which would imply that \( \varphi(\cdot) \) cannot be continuous. Since the planner chooses a continuous matching function \( \varphi(\cdot) \), in equilibrium the wage function needs to be continuous as well. Hence,

\[
\lim_{z \uparrow \varphi_i(0)} w(z) = \lim_{z \downarrow \varphi_i(0)} w(z) \quad \text{all } \ i = 1, \ldots, L. \tag{4.5}
\]

Furthermore, the profits of the least productive worker/organization \( \Pi(0) \) have to be equal to zero since workers are the residual claimants of the firm. Namely,

\[
\int_{0}^{\varphi_L(0)} yg(y)dy = \sum_{i=1}^{L} \frac{1 - G(\varphi_{i-1}(0))}{\kappa} w(\varphi_i(0)) + w(0). \tag{4.6}
\]

The conditions in (4.5) and (4.6) provide the \( L \) initial conditions that we need to solve the system of first order differential equations in (4.4).

Note that the zero profit condition together with (4.2) and (4.3) imply that the profits
for any organization $z \in [0, z_w]$ are zero, since for $i \geq 1$,
\[
\frac{\partial \Pi(z)}{\partial z} = \left( \varphi_L(z) g(\varphi_L(z)) - \frac{(1 - G(\varphi_{L-1}(z))) w'(\varphi_L(z))}{\kappa} \right) \frac{\partial \varphi_L(z)}{\partial z} \\
+ \ldots \\
+ \left( \frac{g(\varphi_i(z)) w(\varphi_{i+1}(z))}{\kappa} - \frac{(1 - G(\varphi_{i-1}(z))) w'(\varphi_i(z))}{\kappa} \right) \frac{\partial \varphi_i(z)}{\partial z} \\
+ \ldots \\
+ \left( \frac{g(z) w(\varphi(z))}{\kappa} - w'(z) \right) = 0.
\]

It should be clear that what we have called an “organization” in this section is only one of many possibilities. Our choice to consider organizations defined by a single worker $z \in [0, z_w]$ was adopted only as a convenience. This is a constant returns competitive equilibrium model in which profits are zero. We have developed a production technology involving a specific kind of complementarity about workers with different skill levels, not a theory of the firm. In equilibrium individual earnings depend jointly on an agent’s type and on the way he contributes to the productivity of others. This is all internalized—there are no external effects—but there are no distinctions between firms of different sizes or between employees and consultants.

5. Age-Earnings Profiles: Theory

We have developed a Garicano/Rossi-Hansberg type model that generates a model of individual earnings for the economy as a whole, $w(z)$. Now we merge these ideas with a model that admits stratification by age and other attributes. The knowledge distribution $F$ now evolves over time, so we write $F(z, t)$, and we introduce a family of cohort type distributions $H(z, s, t)$, interpreted as the probability that a person of age $s$ at date $t$ will have a type no larger than $z$. In the model we next develop, the distributions $F(z, t)$ and $H(z, s, t)$ will all be Fréchet, related by
\[
\log F(z, t) = \int_0^\infty \log H(z, s, t) \pi(s) ds, \tag{5.1}
\]
where $\pi(s)$ the density function of lifetimes, taken as a constant over time.
The addition of calendar time to the distributions \( F \) and \( H \) and, as we soon see, to a problem distribution \( G(z, t) \), will set the stage for a model of growth. In particular we assume a continuous arrival model of diffusion of ideas, in which agents have \( \alpha \) meetings per unit of time that take the form of draws of ideas from the entire population \( F(z, t) \). An agent \( z \) who engages with an agent of type \( z' \) emerges from the match with type \( \max(z, z') \).

If \( h \) is a time interval, then the probability that a person of age \( s + h \) who was born at \( t - s \) has productivity less than or equal to \( z \) is

\[
H(z, s + h, t) = H(z, s, t) \Pr\{\text{no draw at } t \text{ better than } z\} = H(z, s, t) F(z, t)^{\alpha h}.
\]

Taking the limit as \( h \to 0 \),

\[
\frac{\partial \log H(z, s, t)}{\partial s} = \alpha \log F(z, t).
\]

Assuming that at \( t - s \) the individual knew nothing and integrating this last expression from \( t - s \) to \( t \) we get

\[
\log H(z, s, t) = \alpha \int_{t-s}^{t} \log F(z, \tau) d\tau = \alpha \int_{0}^{s} \log F(z, t - s + \tau) d\tau. \tag{5.2}
\]

It is convenient for our purposes to assume that both \( F \) and \( H \) have Fréchet distributions, so

\[
\log F(z, t) = -\lambda(t) z^{-1/\theta}
\]

and

\[
\log H(z, s, t) = -\mu(s, t) z^{-1/\theta}.
\]

The Fréchet distributions have the property that they will be preserved under the operations we use. Only the location parameters \( \lambda(t) \) and \( \mu(s, t) \) will evolve. Then (5.1) and (5.2) imply

\[
\lambda(t) = \int_{0}^{\infty} \mu(s, t) \pi(s) ds \tag{5.3}
\]
and
\[ \mu(s, t) = \alpha \int_0^s \lambda(t - s + \tau) d\tau. \] (5.4)

We are interested in studying earnings along a balanced growth path. That is, we seek a path such that \( \lambda(t) = \lambda e^{\gamma t} \) for some \( \gamma > 0 \) to be determined. In this case, (5.4) becomes
\[ \mu(s, t) = \alpha \frac{\lambda}{\gamma} e^{\gamma t} (1 - e^{-\gamma s}). \] (5.5)

Combining (5.3) and (5.5) then implies
\[ \lambda e^{\gamma t} = \alpha \frac{\lambda}{\gamma} e^{\gamma t} \int_0^\infty (1 - e^{-\gamma s}) \pi(s) ds \]
and so
\[ \gamma = \alpha \int_0^\infty (1 - e^{-\gamma \tau}) \pi(\tau) d\tau. \] (5.6)

Equation (5.6) has two real solutions, one of which is always \( \gamma = 0 \). The other solution is positive if and only if
\[ \alpha \int_0^\infty s \pi(s) ds > 1. \]
Intuitively if the meeting rate \( \alpha \) is large enough and/or if people live long enough then the economy can have a positive growth rate. Otherwise the economy stagnates. In either case, as long as the parameter \( \theta \) is positive, individual careers will involve learning from others and on average older workers will have higher \( z \) values than younger ones.

The actual census data are stratified in many more dimensions than just age differences. For example, we will want to stratify by levels of schooling attainment, assuming that a person with schooling level \( S \) processes new ideas at a rate \( \alpha(S) \) where \( \alpha'(S) > 0 \). Schooling also postpones entry into the labor force. To incorporate these features into the model entails replacing (5.4) with
\[ \mu(s, S, t) = \alpha(S) \int_S^t \lambda(t - s + \tau) d\tau \]
for each \( S \) and replacing (5.6) with
\[ \gamma = \int_0^\infty \alpha(S) \int_S^\infty (1 - e^{-\gamma \tau}) \pi(\tau) d\tau \phi(S) dS \] (5.7)
where \( \phi \) indicates a fixed distribution of people by their schooling levels. In a balanced growth path it is easy to expand the number of cells one wants to consider.

For a given age \( s \), schooling level \( S \) and date \( t \) we know the entire distribution of types \( z \) and since we know the implied earnings levels \( w(z) \) we know the distribution of earnings for each \( (s, S, t) \) as well. Here we focus on two moments of these distributions: the mean and variance of log wages. Our model of the wage distribution in Section 3 to 5 did not include a schooling decision and so the implied \( w(z) \) does not depend on the schooling levels \( S \), directly. Clearly, on top of its effect on future learning ability, schooling increases the knowledge with which individuals start their working careers and perhaps changes them in other important ways that are valued in the labor market. Here, we simply model the effect of schooling on the wage distribution as a constant that shifts the mean of the distribution for each schooling level \( S, C(S) \).

Since we are on a Fréchet BGP the date \( t \) is immaterial and so we can write these two moments as

\[
W(s, S) = C(S) + \int_0^\infty \log w(z) \, d e^{-\mu(s, S)z^{-1/\theta}} \quad (5.8)
\]

and

\[
V(s, S) = \int_0^\infty (\log w(z) + C(S) - W(s, S))^2 \, d e^{-\mu(s, S)z^{-1/\theta}}, \quad (5.9)
\]

where \( S \) denotes the years of schooling (or more precisely the age at which an individual starts working).

6. Calibration and Comparative Statics

The implications of the decentralized model of Section 4 involve only types \( z \) and the implied earnings \( w(z) \). They do not depend on age, schooling levels, or other individual characteristics. Given information on the population \( F \), the problems \( G \) that agents must solve in order to produce, and the ability \( \kappa \) of managers to advise in solving harder problems, we can determine the occupations and earnings of everyone in the economy. It is instructive to choose specific parametric descriptions of \( F \) and \( G \) and to look at plots of \( z \) and \( w(z) \).
Here we assume Fréchet distributions for $F$ and $G$, with cdfs

$$ F(z, t) = \exp(-\lambda(t)z^{-1/\theta}) \quad \text{and} \quad G(z, t) = \exp(-K(t)z^{-1/\theta}). $$

That is, we assume that the shape parameter $\theta$ of both distributions is the same. This facilitates some of the intuition of the comparative statics and given that we are not addressing the economic underpinnings of the distribution of problems $G$, any other choice would have been arbitrary as well. We also assume an economy on a balanced growth path, with $\lambda(t) = \lambda e^{\gamma t}$ and $K(t) = K e^{\gamma t}$. In steady state the distribution of knowledge and problems grow at the same rate, $\gamma$. Thus, in a balanced growth path, the race between knowledge and technology is always tied.

We calibrate the model by setting $\lambda = 1$, $K = 0.6$, $\theta = 0.5$, and $\kappa = 1.2$. These parameters, together with $C(S)$ and $\alpha(S)$, are chosen to match the degree of inequality as measured by the U.S. Lorenz curve in 1990, the observed number of first layer managers in the data, as well as the mean of the wage distribution and the variance of wages across experience levels. We discuss these statistics and the earnings data in the next section.

Figures 1 to 6 show the resulting matching and wage functions for this parameter configuration, as well as the corresponding equilibria when we vary $\kappa$, $K$ and $\theta$. In Figures 1, 3, and 5 we show the relation of types $z$ (on the horizontal axis) to the managers assigned to them, $\varphi(z)$. The figure on the left shows $z$ and $\varphi(z)$ in common (though arbitrary) units. The figure on the right plots the cdfs for both of these, $F(z)$ and $F(\varphi(z))$. The small circles identify $\varphi(0), \varphi(\varphi(0))$, etc. Using our baseline parameters implies that 64% of individuals are workers ($F(\varphi(0)) = 0.64$) which is approximately consistent with the evidence in Caliendo, et al. (2015) in manufacturing for France, although somewhat larger than what we observe for the whole U.S. economy (about 50%). Figure 1 also shows that $F(\varphi(\varphi(0))) - F(\varphi(0)) = 0.92 - 0.64 = 0.28$ is the fraction of agents assigned as layer one managers, which matches relatively well with a share of 0.32 for the U.S.\footnote{We obtain the fraction of agents employed in different layers after converting the IPUMS-USA occupation data into the French PCS classification used in Caliendo et al. (2015). The Appendix explains these calculations in more detail.}
In Figures 2, 4, and 6 we show the relation of types to earnings. We plot \( w(z) \) against \( F(z) \), and the right panel is a vertical enlargement of the lowest types. One can see how the managerial complementarities reward the best managers, making the wage function extremely steep at the top.

An increase in \( \kappa \), which might be interpreted as an improvement in communication technology, allows managers to review a larger number of problems and so, in equilibrium, increases the number of workers. It also raises the earnings of all workers, and many managers, although not all of them. Overall, it increases output and reduces wage inequality since it makes managerial talent less scarce. The Gini coefficient of the wage distribution decreases monotonically with \( \kappa \). These results are presented in Figures 1, 2 and 7.

In Figures 3 and 4 we present comparative statics with respect to the level of the initial distribution of problems, \( K \), leaving the initial mean of distribution of knowledge, \( \lambda \), unchanged.\(^5\) Higher \( K \) implies that problems are more complicated to solve, relative to the

\(^5\)The means of the distribution of problems and knowledge are both growing at rate \( \gamma \). A change in \( K \),
available knowledge in the economy, and also pay more. The result is that the number of workers declines and the number of managers increases. Furthermore, the wages of workers decline since the relative value of generating versus solving problems declines. Inequality at the bottom of the distribution tends to decrease, but at the very top it increases since more problems require the skill of the very best experts. These experts are the ones that obtain the big gains from the more profitable and complicated problems.

The implications of a rise in $K$ are reminiscent of the evidence for the U.S. labor market during the last few decades, as documented by Acemoglu and Author (2013). An increase in $K$ leads to an increase in output only if there are enough talented agents in the population to take care of the problems, namely, if $K$ is relatively low or $\theta$ is high enough. Otherwise, it can lead to a decline in output since high-$z$ problems, although more profitable, cannot be solved by a large fraction of agents and so, on average, require more managerial time. Given $\lambda$, generates a one-time shift in the mean of the distribution of problems beyond the constant drift in the mean. Hence, with a rise in $K$, technology improves permanently relative to knowledge in the balance growth path.

Figure 3: Comparative Statics for $K$, Matching  
Figure 4: Comparative Statics for $K$, Wages
We return to changes in $K$ in the Section 8 where we argue that a change in $K$, on its own, can go a long way towards rationalizing the observed changes in cross-sectional wages in the U.S. economy between 1990 and 2010.

The last comparative static we analyze here is the one with respect to the shape parameter of the distribution of knowledge and the distribution of problems. An increase in $\theta$ increases the mass in the tail of these distributions and so increases the availability of hard and profitable problems as well as the availability of agents that can solve them. Because, by assumption, we are changing both distributions in the same manner, the matching across agents when measured in terms of their position in the distribution hardly changes (see the second panel in Figure 5). As is evident in Figure 6, an increase in $\theta$ increases all wages, and leads to higher wage inequality among workers but lower wage inequality among managers. Worker’s time used generating problems is more valuable since problems pay more on average. It also increases total output as it makes problems more profitable but not more difficult relative to the knowledge of the population.

Figure 5: Comparative Statics for $\theta$, Matching

Figure 6: Comparative Statics for $\theta$, Wages
Figures 7 and 8 present the Lorenz curves for the distribution of wages in the 1990 and 2010 U.S. data, as well as the model-based ones for different values of $\kappa$ and $K$, respectively.\footnote{We discuss in detail the earnings data we use in Section 7.}

We relegate to the Appendix a similar plot with comparative statics with respect to $\theta$, since the Lorenz curves change little with variations in this parameter. The figures plot $\int_0^x w(z) dF(z)$ versus $F(x)$ for $x \in [0, \infty)$. The effects discussed in the context of Figures 1 to 4 appear even more clearly. In Figure 7, raising $\kappa$ reduces wage inequality as opposed to the increase in wage inequality clearly evident during this period in the U.S. Figure 8 shows the Lorenz curves for 1990 and 2010 again, together with three alternative calibrations of our model when we let $K$ vary between 0.5 and 0.7. The figure illustrates that for $K = 0.6$ the model can match the overall inequality in the aggregate economy quite well. Furthermore, as we argued above, increases in $K$ can generate changes in the Lorenz curves similar to the ones observed in the data. Namely, it increases overall wage inequality, and it increases dispersion particularly for the very top managers. In Section 8 we return to
this comparative static when we measure the change in \( K \) that can rationalize the change in wage inequality during the 1990 - 2010 period.

7. Career Paths

The evidence on wages we use in this paper includes log means and log variances from the 1990 and 2010 IPUMS-USA.\(^7\) We used yearly nominal wages data for white males, heads of households, that worked more than 30 weeks and 30 hours per week the previous year, for three schooling categories: high-school graduates (12 years of schooling), some college (13-15 years of schooling) and college graduates (more than 15 years of schooling). We focus on full time workers only since we have not modeled the labor supply decision of agents. The 1990 census data correspond to a sample of 5\% of the US population, while the 2010 survey contains the compiled American Community Survey (ACS) 1\% sample for 5 years (2006-2010).\(^8\) Of course, good data are available for many decades prior to 1990 and there are many more categories of workers than those we use here.

In order to compare the implications of the model to the data of wages of a worker’s life-cycle, in this section we carry forward the function \( w(z) \) that maps types into earnings, as well as the parameters \( \lambda = 1, K = 0.6, \theta = 0.5, \) and \( \kappa = 1.2 \) that we used in Section 6. We treat schooling levels as constant fixed effects, as in types. To calibrate the moments (5.8) and (5.9) we use the parameters of (5.5), namely,

\[
\mu(s, S, t) = \alpha(S) \frac{\lambda}{\gamma} e^{\gamma t} (1 - e^{-\gamma t}).
\]

On a balanced path calendar time does not matter and \( \alpha(S) \) is treated as a level effect. The only parameter left to determine is \( \gamma \). One could think of using (5.7) to compute \( \gamma \) but this would require knowledge of all the \( S \) levels and the weights \( \phi(S) \) of each. We have not done this. Instead we use the implication that on a BGP the per capita growth rate is the product \( \theta \gamma \). In the U.S. this rate is about 0.02. We have already chosen \( \theta = 0.5 \). This implies an estimate of \( \gamma \) of \((0.02)/(0.5) = 0.04\).

\(^7\)We have also analyze the data for 2000 and found similar patterns.

\(^8\)In the survey nominal income is measured in 2010 dollars.
To calculate the parameters $C(S)$ in (5.8) we minimized the mean squared difference between the predicted value of the mean log wages in the model and the actual value of the data for experience years $\{N_l, \ldots, N_u\}$. We can compute $\hat{C}(S)$ explicitly as,

$$
\hat{C}(S) = \frac{1}{N_u - N_l} \sum_{s=N_l}^{N_u} \left( \omega(s, S) - \int_{0}^{\infty} \log w(z) \, de^{-u(S+s,S)z^{-\frac{1}{\gamma}}} \right),
$$

where $\omega(s, S)$ denotes the observed mean of log wage data for individuals with $s$ years of experience and schooling level $S$. In the simulations below, we use $N_l = 5$ years of experience and $N_u = 30$, which is to say that we are going to locate the curves that best fit the data for this range of years of experience.

Similarly we estimate $\alpha(S)$ minimizing the mean squared difference between the predicted value of the variance of log wages in the model and the data,

$$
\hat{\alpha}(S) = \arg\min_{\alpha(S)} \frac{1}{N_u - N_l} \sum_{s=N_l}^{N_u} \left( \sigma^2(s, S) - V(s, S) \right)^2,
$$

where $\sigma^2(s, S)$ denotes the observed variance of log wage data for individuals with $s$ years of experience and schooling level $S$.

Using these parameters we fit the model to the mean and variance of the 1990 IPUMS-USA data, limited to the males at three schooling levels as described above. Table 1 shows the estimated $\hat{\alpha}(S)$ for different census years and schooling levels. It implies that agents with a college degree meet agents from whom they can potentially learn three times faster than high-school graduates.

<table>
<thead>
<tr>
<th>Census Year</th>
<th>High school graduate</th>
<th>Some College</th>
<th>College graduate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>0.0052</td>
<td>0.0076</td>
<td>0.0137</td>
</tr>
</tbody>
</table>

Table 1: Calibration of $\hat{\alpha}(S)$

Figure 9 plots mean log wages for the 1990 census and three schooling levels. Figure 10 plots the corresponding variances of log wages for the same year. On both plots, the straight lines are theoretical, calibrated as described above. The dots are data. These are all displayed as experience-earnings profiles (as opposed to age-earnings profiles). The
levels of all these curves are set to match up to observed levels between 5 and 30 years of experience. Schooling increases the wages of individuals by increasing the level of their experience earnings profile according to $C(S)$. We have started all careers at levels of zero productivity, assuming that schooling enhances one’s ability to learn but does not teach how to produce anything of value initially. It would be easy to “fix up” this feature of Figure 9.

Consistent with the data, experience-earnings profiles increase over the career of individuals. In fact, the model is able to capture the rate of the increase quite well, although it does poorly on the curvature. At the other end, one can see that beyond 30 years of experience earnings decline in the data but not in the model. This may be a Ben Porath effect, or an early semi-retirement effect. These are earnings per year, but the same downturn appears in the hourly earnings data provided by IPUMs. These issues require adding labor supply,
schooling, and retirement decisions that are not present in the model described here.\footnote{Our model could readily be modified to add Ben Porath-like properties as in Lucas and Moll (2014).}

The variances shown on Figure 10 show that the dispersion of wages also increases with the years of experience. Everyone starts with similar prospects (particularly given their schooling level) but over time some are lucky, learn and get promoted, while others meet less interesting people, learn less, and do not climb as high in the organizational latter. Over time, these differences become much more pronounced and so the cross-sectional dispersion of wages increases. The model captures, by construction, the level of the variances by education group, since we are choosing the number of meetings per unit of time for each level of $S$ (see Table 1). In addition, the model is fairly successful in replicating the increase in the variance of earnings for agents with more experience, particularly after the first few years of their career. Neither the slope of the earning-experience profile nor the slope of the variance-experience profile are features of the data that we try to match with our calibration. In fact, if we use the same calibration and compare with data in 2010 the model would under-estimate the increase in the variance of log wages for colleague graduates over their carrier. Could a change in $K$ over this period explain this discrepancy? We now proceed to explore this possibility.

8. Matching Observed Changes in Wage Inequality

During the period 1990 to 2010, and perhaps starting a couple of decades before, the U.S. economy has experienced large changes in the distribution of earnings. These changes have been documented in a variety of studies including, for example, Katz and Murphy (1997), Goldin and Katz (2007) and Acemoglu and Autor (2013). These authors have pointed to the increase in overall inequality evident in the Lorenz curves portrayed in Figures 7 and 8, as well as to several other facts, such as the increase in the skill premium and wage polarization among skill groups. Polarization refers to the declines in the wages of agents in the middle part of the distribution relative to the ones at the top and the bottom, or, in other words, a decline in earnings inequality at the lower-half of the distribution, together
with an increase at the upper-half.

We have already alluded to the fact that these changes can be replicated, at least qualitatively, as a result of an increase in $K$. As the distribution of problems shifts to the right relative to the distribution of knowledge, problems become more difficult but also provide a larger return if successfully solved. The result is an increase in inequality generated by an increase in the skill premium. High-skilled agents are more useful since their knowledge is relatively more scarce and the problems they can solve more valuable. Furthermore, inequality among workers tends to decrease since they solve fewer problems, so their value relies more on the problems they generate (which is common to all workers) rather than the ones they solve. In contrast, inequality among managers increases since the new distribution favors the superstars.

Quantitatively we can use our baseline calibration for 1990, which uses a value of $K = 0.6$, and simply increase $K$ to 0.65 in order to fit the 2010 Lorenz curve. (Technically we describe
a one-time permanent shift in the problem distribution, resulting in a new BGP.) Figure
11 shows the Lorenz curves for 1990 and 2010 together with the model generated curves.
The fit for 2010 is quite good. The larger $K$ also generates an increase in the number of all
types of managers; a feature consistent with the data during this period. Figure 12 shows
the fraction of workers and managers in each layer for both calibrations, as well as the ones
we compute in the data.

The rise in $K$ also has implications on the mean experience-earnings profiles and the
variance of earnings across experience levels. Figures 13 and 14 present the mean and
variance of wages as a function of experience for 1990 and 2010, as well as the ones implied
by our calibrations for these years. The dashed lines correspond to $K = 0.6$, should be
compared to the data in 1990 and replicate Figures 9 and 10. The solid lines correspond
to $K = 0.65$ and should be compared to the data in 2010. Both in the data and in the
model, a change in $K$ has little impact on the mean experience-earnings profiles. In fact,
in Figure 13 it is hard to distinguish between the curves generated by each calibration.$^{10}$
In contrast, in Figure 14 the difference in variance is quite marked. Particularly for college
graduates with many years of experience. In 2010 the variance of log earnings increased
faster with experience both in the model and in the data (although the model underestimates
the change). The importance of this effect points to the need of studying inequality using
models that can replicate the increase in the variance of earnings as a function of experience
and not just its mean.

As emphasized above, we have not developed a model of the individual actions that
might generate the problem distribution or its evolution over time. The results above are
simply a thought-experiment involving the single parameter $K$, one that seems to provide a
good fit to changes observed in the labor market. An increase in $K$ reflects a technological
change that favors extreme outcomes, in the form of superstar ideas that are extremely well
compensated. This shift can in principle increase or decrease output. The change in $K$

$^{10}$In order to improve visibility, in Figure 13 we have normalize the curves corresponding to $K = 0.65$
and year 2010 so that the mean level for 5 years of experience is the same as for $K = 0.6$ and year 1990,
respectively.
that we measure during this period leaves de-trended output essentially unchanged.\textsuperscript{11} We underscore that we do not emphasize the source of this change, we only identify it as a likely cause relative to other potential phenomena during this period. Take, for example, an improvement in communication technology as measured by an increase in the parameter $\kappa$. Such a technological change has the opposite effect on overall inequality and so does not allow us to match the 2010 Lorenz curve. Another possibility is a technological change that increases the thickness of the tail of the distribution of problems and knowledge (an increase in $\theta$). Such a change does increase overall inequality slightly but, counterfactually, it tends to increase inequality at the bottom of the distribution relative to the top, as we showed in Figure 6.

\textsuperscript{11}In the Appendix we show that for our calibration total output is increasing in $K$ for small values of $K$ and decreasing for large values (inverted U-shaped pattern). The location of the maximum depends on other parameters, including $\theta$, as we pointed out in Section 6.
9. Final Remarks

Individual’s earnings are determined by their skill and schooling, but also by the characteristics of the agents they interact with. As individuals age, acquire more experience, and learn, their career paths take them progressively to jobs with more subordinates; they climb the organizational hierarchy. Some agents climb fast because they are highly educated or because they are lucky and manage to learn quickly from people they encounter during their careers. Others learn and climb the hierarchy slowly, if at all, since they meet the wrong people from whom they learn little. In this paper we build a model of an economy in which agents go through these career paths. Formally we have combined a model of the hierarchical organization of production similar to the one in Garicano and Rossi-Hansberg (2004, 2006) with a model of learning based on Lucas (2009). The outcome is a theory where, on the balanced growth path, individuals progress through the hierarchy according to the random set of people they encounter during their lives.

The model we propose is successful in replicating a variety of features of the U.S. data. In particular, adding a hierarchical structure allows the model to generate the increase in the variance of earnings for agents with more experience. Furthermore, the model identifies a shift in the distribution of problems relative to the distribution of knowledge as a potential source of the changes in wage inequality observed during the two decades between 1990 and 2010. Our theory suggests that, during this period, production became more difficult but also resulted in higher rewards than in the past. A technology more geared toward superstars, as suggested by Rosen (1981) and more recently by Gabaix, Lasry, and Moll (2015). Can these changes be traced to the general-purpose technologies associated with computers and the internet?12 Studying the source of this technological change is, we believe, essential to make progress in assessing the observed evolution of wage inequality and its consequences.

12See Jovanovic and Rousseau (2005).
References


Appendix

Proofs.—

Theorem 1. Suppose that \( F(\cdot) \) and \( G(\cdot) \) are differentiable, then any solution to the planning problem is characterized by a matching function \( \varphi(\cdot) \), and a pair of thresholds \( z_w \) and \( z_e \) such that \( Z_w = [0, z_w] \), \( Z_m = [z_w, z_e] \), \( Z_e = [z_e, \infty) \). If \( Z_m \neq \emptyset \) then \( z_w < z_e \); otherwise, \( z_w = z_e \).

The proof is given in the next three lemmas.

Lemma 1: Let \((\varphi(\cdot), Z_w, Z_m, Z_e)\) solve the planner’s problem. Then for \( \varepsilon \) sufficiently small \([0, \varepsilon) \notin Z_w \cap Z_e\).

Proof: Toward a contradiction, suppose \([0, x_0] \subset Z_w \cap Z_e\). We will show that this allocation can always be improved by building a hierarchy that includes workers with \( z \) close to zero and managers with \( z \) close to \( x_0 \). Note first that the expected payoff of the worst agent is given by

\[
\lim_{\varepsilon \to 0} \int_0^\varepsilon yg(y) \, dy = 0
\]
and for agent \( x_0 \) is

\[
\lim_{\delta \to 0} = \int_0^{x_0-\delta} yg(y) \, dy > 0.
\]

A manager with ability \( x_0 - \delta \) can manage \( \kappa / (1 - G(\varepsilon)) \) workers of ability \( \varepsilon \) and

\[
\lim_{\varepsilon \to 0} \kappa / (1 - G(\varepsilon)) = \kappa > 1.
\]

The total production of this team if they are all self-employed is

\[
\int_0^{x_0-\delta} yg(y) \, dy + \kappa \int_0^\varepsilon yg(y) \, dy.
\]

In contrast, if they form a team they produce

\[
\frac{\kappa}{1 - G(\varepsilon)} \int_0^{x_0-\delta} yg(y) \, dy > \int_0^{x_0-\delta} yg(y) \, dy + \kappa \int_0^\varepsilon yg(y) \, dy
\]
for \( \delta \geq 0 \) and \( \varepsilon \geq 0 \) small enough. The inequality follows since at the limit when \( \delta = \varepsilon = 0 \), \( \kappa > 1 \) implies that

\[
\kappa \int_0^{x_0} yg(y) \, dy > \int_0^{x_0} yg(y) \, dy.
\]
Hence, the planner would always prefer to form these hierarchies for a non-zero measure of agents than to have all of them as self-employed, which contradicts \((\varphi(\cdot), Z_w, Z_m, Z_e)\) being a solution to the planner’s problem. \(\blacksquare\)

**Lemma 2:** Let \((\varphi(\cdot), Z_w, Z_m, Z_e)\) solve the planner’s problem. Then if \(z_m \in Z_m\) and \(z_e \in Z_e\) we have \(z_m < z_e\).

**Proof:** Toward a contradiction, suppose \((\varphi(\cdot), Z_w, Z_m, Z_e)\) solves the planner’s problem above but that \(z_e < z_m\) for some \(z_e \in Z_e\) and a \(z_m \in Z_m\). In this case, note that since \(z_e \in Z_e\) the planner fails to solve all problems that require knowledge \(z > z_e\). These problems have total value
\[
(1 - G(z_e)) \int_{z_e}^{z_m} y \frac{g(y)}{1 - G(z_e)} dy = \int_{z_e}^{z_m} yg(y) dy
\]
if an agent with ability \(\bar{z}\) tries to solve them. In contrast, agent \(z_m\) passes along the problems he cannot solve to agent \(\varphi(z_m)\). These problems have total value
\[
(1 - G(z_m)) \int_{z_m}^{\varphi(z_m)} y \frac{g(y)}{1 - G(z_m)} dy = \int_{z_m}^{\varphi(z_m)} yg(y) dy
\]
if agent \(\varphi(z_m)\) tries to solve them. But, letting \(\bar{z} = \varphi(z_m)\), given \(z_e < z_m\), we have
\[
\int_{z_e}^{\varphi(z_m)} yg(y) dy > \int_{z_m}^{\varphi(z_m)} yg(y) dy.
\]
The value of the problems discarded by agent \(z_e\) exceed the value that would have been discarded if agent \(z_m\) had been assigned to agent \(\varphi(z_m)\) instead. A contradiction. \(\blacksquare\)

**Lemma 3:** Let \((\varphi(\cdot), Z_w, Z_m, Z_e)\) solve the planner’s problem. Then, \(z \in Z_w\) implies that \(z \leq z'\) for all \(z' \in Z_m \cup Z_e\).

**Proof:** Toward a contradiction, suppose \((\varphi(\cdot), Z_w, Z_m, Z_e)\) solves the planner’s problem above but does not satisfy this property. Then there exists a \(z_w \in Z_w\) and a \(z_m \in Z_m\) such that \(z_w > z_m\). Note first that the value of a problem passed up to a manager \(\bar{z}\) by any agent is given by \(\int_0^{\bar{z}} yg(y) dy\), independent of the ability of the worker who generated it. (It only depends on the best agent that tries to solve it, \(\bar{z}\).) In contrast, the value of a manager for the planner’s objective is given by
\[
k \int_{\varphi^{-1}(z_m)}^{z_m} y \frac{g(y)}{1 - G(\varphi^{-1}(z_m))} dy - \int_0^{z_m} yg(y) dy.
\]
Suppose the planner switches the role of $z_w$ and $z_m$ and makes $z_m$ the worker and $z_w$ the manager, holding fixed their supervisors and subordinates. Then the gain for the planner is given by
\[
\left( \kappa \int_{\varphi^{-1}(z_m)}^{z_w} y \frac{g(y)}{1 - G(\varphi^{-1}(z_m))} dy - \int_0^{z_w} yg(y) dy \right) - \left( \kappa \int_{\varphi^{-1}(z_m)}^{z_m} y \frac{g(y)}{1 - G(\varphi^{-1}(z_m))} dy - \int_0^{z_m} yg(y) dy \right) = \frac{\kappa}{1 - G(\varphi^{-1}(z_m))} \int_{z_m}^{z_w} yg(y) dy - \int_{z_m}^{z_w} yg(y) dy > 0
\]
since $\kappa > 1 - G(\varphi^{-1}(z_m))$. Hence a planner would gain with the switch: a contradiction.

**Theorem 2.** Suppose that $F(\cdot)$ and $G(\cdot)$ are differentiable, then there is a pair $(z_w, z_e)$ that satisfies (3.6) - (3.8).

**Proof:** Let $z_w^*$ be the highest cutoff $z_w$ that such that all problems are solved, the unique solution to
\[
1 - F(z_w) = \frac{1}{\kappa} \int_0^{z_w} [1 - G(z)] f(z) dz + \int_{z_w}^{\infty} \frac{1 - G(z)}{1 - G(\varphi^{-1}(z))} f(z) dz.
\]
Total production in this case will be
\[
\int_0^{z_w^*} \int_0^{\infty} yg(y) dy f(z) dz = F(z_w^*) \int_0^{\infty} yg(y) dy.
\]
Also note that as $z_w \to \infty$ total production converges to the autarchy level
\[
\int_0^{\infty} \int_0^{z} yg(y) dy f(z) dz.
\]
Then continuity ensures that for some $(z_w, z_e)$ with $z_w^* \leq z_w \leq z_e$
\[
\int_0^{z_w} \int_0^{\infty} yg(y) dy f(z) dz - \kappa \int_{z_e}^{\infty} \int_{z}^{\infty} yg(y) dy \frac{f(z)}{1 - G(\varphi^{-1}(z, z_w))} dz
\]
\[
\geq \max \left[ F(z_w^*) \int_0^{\infty} yg(y) dy, \int_0^{\infty} \int_0^{z} yg(y) dy f(z) dz \right].
\]

**Lemma 4:** Let $(\varphi(\cdot), z_w, z_m, z_e)$ solve the planner’s problem. Then if $z_w = z_e$, $z_w$ must satisfy
\[
\kappa \left[ 1 - F(z_w) \right] = \int_0^{z_w} f(z) \int_{z}^{\infty} g(y) dy dz.
\]
**Proof:** Toward a contradiction, suppose that $(\varphi(\cdot), Z_w, Z_m, Z_e)$ solves the planner’s problem and that

$$
\kappa [1 - F(z_w)] < \int_0^{z_w} f(z) \int_z^\infty g(y) dy dz.
$$

Then there are too few entrepreneurs to review all the problems unsolved by workers. Replacing $z_w$ with $z_w - h < z_w$, in this case will increase the left side by $\kappa [1 - F(z_w - h)] - \kappa [1 - F(z_w)] \simeq \kappa hf(z_w)$ and this will allow the new managers to solve $\kappa hf(z_w)$ problems worth on average $\int_0^{z_w} yg(y) dy$ each (since they do not know how to solve the more difficult problems). This replacement thus adds $\kappa hf(z_w) \int_0^{z_w} yg(y) dy$ to production. It also reduces the right side by

$$
\int_{z_w - h}^{z_w} f(z) \int_z^\infty g(y) dy dz \simeq hf(z_w) \int_{z_w}^\infty g(y) dy = hf(z_w) [1 - G(z_w)],
$$

workers. Since all the problems harder than $z_w$ where thrown away, the planner valued these problems only at

$$
hf(z_w) [1 - G(z_w)] \int_0^{z_w} yg(y) dy.
$$

Since $\kappa > [1 - G(z_w)]$, the planner will not choose to do this: a contradiction.

If on the other hand the left side of (3.5) exceeds the right, there must be entrepreneurs who advise no one. They might choose to be workers, but this would violate Lemma 3: also a contradiction.

---

**Plots.**

Figure A1 shows the Lorenz curves for the distribution of wages in the 1990 and 2010 U.S. data, as well as the model-based ones for different values of $\theta$. As highlighted in Section 6, an increase in the tail parameter $\theta$, simultaneously increases the availability of complex and profitable problems and also the agents’ ability to solve them. Since the matching across agents stays relatively constant according to their ranking, the Lorenz curves indicate a small rise in inequality as $\theta$ increases.
Figure A1: Data and Theory Based Lorenz Curves for Different Values of $\theta$

Figure A2: Output as a Function of $K$, Baseline Calibration

Figure A2 shows that for our calibration total output is increasing in $K$ for small values of $K$ and decreasing for higher values. For a given skill distribution, if the problems are easy to solve, people would produce more output if they could draw from a distribution of more complex and profitable problems. However if the problems are too difficult, increasing their difficulty would reduce output as a smaller portion of the population would be able to solve them.

Occupational Codes

To obtain the fraction of agents employed in each layer, we convert the IPUMS-USA classification into the French PCS classification used in Caliendo et al. (2015).

The occupation data in the IPUMS-USA (OCC2010) is based on the occupation coding used by the Bureau of Labor Statistics (BLS) for the American Community Survey (ACS) in 2010. We use three different crosswalks to translate the coding to the French PCS data to define the layers of our economy. First we match the OCC2010 codes to the International...
Standard Classification of Occupations ISCO-08, then then to the ISCO-88 and finally to the PCS codes.

After doing this process there are some unmatched codes. Out of the 539 different ACS codes in our sample, 43 were unmatched (7.98%). In term of the weighted observations of our sample, Table A1 shows the percentage of unmatched weighted observations for 1990 and 2010.

<table>
<thead>
<tr>
<th>Unmatched 1990</th>
<th>Unmatched 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>21.9%</td>
<td>16.3%</td>
</tr>
</tbody>
</table>

Table A1: Unmatched Codes as a Fraction of the Weighted Observation of the Sample

In Section 8 we computed the fraction of individuals in each layer using only the codes that we matched directly. The results are similar if we impute to the missing codes the value of the top (or bottom) layer implied by the immediate neighboring codes.

**Computations.**

Here we provide a constructive method for finding a solution to the planner’s problem. To do so it is useful to describe the economy by the number of layers it has. Let $L$ denote the number of layers, where $L = 0$ means all the individuals in the economy are workers, $L = 1$ that there are workers and one level managers, and so on. We know from Lemma 1 that if $\kappa > 1$ it is never optimal to only have workers in the economy ($L = 0$) as it is always preferable to have managers for the lowest productivity workers. In general, we want to characterize the solution in terms of the number of layers the economy will optimally have.

The idea is to solve the planner’s problem iteratively. In each iteration we assume there are exactly $L$ layers in the economy and choose the matching function and cutoffs $(z_w^L, z_e^L, \varphi(z_w^L))$ that maximize total output. If total output is always increasing in

---

the number of layers, then the solution implies an infinite number of layers and all problems in the economy would be solved \((z_{e} = \infty)\). Otherwise, there exists an optimal finite number of layers \(L\) that solves the planner’s problem, with cutoffs and matching function \((z_{w}^{L}, z_{e}^{L}, \varphi(z, z_{w}^{L}))\).

First let’s introduce some useful notation. In an economy with \(L\) layers, each worker can be linked to \(L\) or \(L - 1\) managers. Specifically, suppose that workers below some productivity level \(x\) have \(L\) managers, while workers with productivity \(z \in [x, z_{w}]\) have \(L - 1\) managers. Let \(\varphi_{l}(z)\) denote the \(l\)'th manager matched with worker \(z \in [0, z_{w}]\). We define this mapping by applying the matching function \(l\) times, i.e. \(\varphi_{l}(z) := \varphi(\varphi(...\varphi(z)))\). Similarly we define the inverse matching function that maps managers to their subordinates. The function \(\varphi_{l}^{-1}(z)\), denotes the \(l\)'th subordinate of manager \(z\), and it is defined by applying the inverse of the matching function \(l\) times, \(\varphi_{l}^{-1}(z) := \varphi_{l}^{-1}(\varphi_{l}^{-1}(\varphi_{l}^{-1}(...\varphi_{l}^{-1}(z))))\).

To illustrate these definitions consider the case where

\begin{itemize}
  \item \((0, z_{w})\) are workers of all kinds,
  \item \((0, x)\) workers with access to \(L\) managers,
  \item \((x, z_{w})\) workers with access to \(L - 1\) managers,
  \item \((z_{w}, z_{e})\) are managers with access to other managers and
  \item \((z_{e}, \infty)\) are the top managers (entrepreneurs).
\end{itemize}

Figure A3 depicts this case,

```
Figure A3: Partition of Workers
```

Given this new notation we can describe an algorithm in which the output maximizing cutoffs are found layer by layer. As mentioned above, note that for a given set of cutoffs
(z_w, z_e) we can find a function \( \varphi(\cdot; z_w) \) that satisfies equations (3.7) and (3.8). Moreover as the planner’s objective function (total production) is increasing in both \( z_w \) and \( z_e \), the idea is to find the largest feasible cutoffs such that these equations are satisfied.

The algorithm will consist of three steps. In step 1 and 2, we take as given the number of layers \( L \) and compute the output maximizing cutoffs and matching function, \((z_w^L, z_e^L, \varphi(\cdot; z_w^L))\). In step 1, we assume that all workers have exactly \( L \) managers, and in step 2 we allow some of them to have \( L - 1 \) managers. In step 3, we repeat step 1 and 2 for \( L = 2, 3, \ldots \), until the value of the maximum output given the number of layers \( Y_L^* := Y(z_w^L, z_e^L) \) converges, i.e. \(|Y_L^* - Y_{L+1}^*| < \varepsilon \) for some small \( \varepsilon > 0 \).

The Algorithm.—

**Step 1:** Compute \( \hat{z}_w \) such that (3.9) is satisfied with \( z_e = \varphi_{L-1}(\hat{z}_w) \).

1. Start with some guess of \( z_w \).
2. Compute \( \varphi_k(y; z_w) \) for \( k \leq L \).
3. Calculate \( s_L(z_w) := F(z_w) + \frac{1}{\kappa} \int_0^{z_w} (1 - G(z)) f(z)dz + \int_{z_w}^{\varphi_{L-1}(\hat{z}_w)} \frac{1-G(z)}{1-G(\varphi^{-1}(y))} f(z)dz. \)
4. For small \( \varepsilon_1 > 0 \), if \( |1 - s_L(z_w)| > \varepsilon_1 \), choose \( z_w' < s_w \).

5. Repeat from 2 until \(|1 - s_L(z_w)| \leq \varepsilon_1 \).

**Step 2:** Choose \( z_e \in [\varphi_{L-2}(\hat{z}_w), \varphi_{L-1}(\hat{z}_w)] \) that maximizes the total output.

1. For \( z_e \in [\varphi_{L-2}(\hat{z}_w), \varphi_{L-1}(\hat{z}_w)] \), consider \( z_w \) such that satisfies,

\[
1 - F(z_w) = \frac{1}{\kappa} \int_0^{z_w} (1 - G(y)) f(y)dy + \int_{z_w}^{z_e} \frac{1 - G(y)}{1 - G(\varphi^{-1}(y))} f(y)dy.
\]

2. Let \( x = \varphi_{L-1}^{-1}(z_e) \) and compute total output as \( Y(z_w, z_e) = \int_0^x \int_0^{\varphi_{L-1}(y)} yg(y)dyf(z)dz + \int_{x}^{z_w} \int_0^{\varphi_{L-2}(z)} yg(y)dyf(z)dz. \)
3. Let \((z^*_w, z^*_e) := \arg \max_{z_w, z_e} Y(z_w, z_e)\).

**Step 3:** Calculate optimal number of layers, \(\hat{L}\).

Given that we have calculated the optimal cutoffs \((z^*_w, z^*_e)\) for an economy with \(L = 2, 3, ..\) number of layers, we can solve the planner’s problem as follows:

1. Let \(\varepsilon > 0\) be a sufficiently small number and compute step 1 and 2 for \(L = 2, 3, ....,\) calculate \((z^*_w, z^*_e)\) and the total production of an \(L\) layer economy, \(Y^*_L = Y(z^*_w, z^*_e)\).

2. Stop when \(|Y^*_L - Y^*_{L-1}| < \varepsilon\).

3. If there exists \(\hat{L} = \arg \max_{l=2, ..., L} Y^*_l\) then the solution to the planner problem is \(\delta(\varepsilon_1, \varepsilon) > 0\) close to

\[
\left( \varphi(\cdot; z^*_w), z^*_w, z^*_e \right).
\]