The Allocation of and the Returns to Talent: An Empirical Model

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Introduction

Inequality has returned with a vengeance to center-stage of the economic debate.[1] Not least since the great success of Thomas Piketty's book "Capital in the Twenty-First Century" (Piketty, 2014) do we know that income and wealth inequality in developed countries have increased massively since the 1970s. To be more precise, research conducted over the last decade shows that wages in the upper third of the earnings distribution have risen handsomely while top shares of income have sky-rocketed (Machin and Van Reenen, 2008; Alvaredo, Atkinson, Piketty, and Saez, 2013). At the same time, there was hardly any real wage growth at the middle of the income distribution and a even a decrease of wages at the bottom of the income distribution in some countries and time periods, for example in the US during the 1980s (Acemoglu and Autor, 2011).

There exist several views why these developments occurred as they did, ranging from increased rent-extraction by the privileged (Bivens and Mishel, 2013)

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[1] This was already noted by Nico Pestel in the previous issue of this journal (Pestel, 2013). While Pestel focused on the role of household composition, marital sorting, and female labor supply for inequality in Germany, I will concentrate my article on a method for better understanding the changing returns' to skills role in increasing inequality.

to the relatively high returns on capital (Piketty, 2014) to "efficient" market forces governed by supply and demand. In fact, the prevailing view among many economists is still that rising inequality in the overall population as well as at the top reflect increasing returns to skill or talent (Kaplan and Rauh, 2013). That is, if new technologies and increasing market sizes due to globalization shift out the demand curve for skill, the rewards for the talented will rise compared to the rest of the population.

But what do we mean by talent? Just calling the high earners the most talented would not be helpful since changes in demand, supply and many other factors would be able to explain the rising inequality in this case. Therefore, researchers have long been using individuals' education as a proxy for skill or even talent.

However, there are some problems with equating education and talent. First, formal educational attainment has increased substantially over the decades. Since it is rather unlikely that "talent" in society has improved accordingly, educational attainment does not enable us to compare like with like over time. Second, educational attainment is a one-dimensional measure of skill while there is now ample evidence that individuals' productive attributes are multidimensional and that they include cognitive as well as non-cognitive dimensions (Heckman, Stixrud, and Urzua, 2006, for example)

Fortunately, much better data has recently become available that get us closer to observing multidimensional talents of workers. In particular, survey datasets such as the National Longitudinal Survey of Youth in the United States and the Socio-Economic Panel in Germany measure respondents in terms of several cognitive and non-cognitive attributes. Moreover, detailed social security data in the Nordic countries provide cognitive and non-cognitive scores from military enlistment tests together with workers' detailed employment histories in firms that they have worked for. Thus, we are now in a substantially better position than in the past to analyze the sorting of talents into occupations, industries, and firms as well as the returns that go in hand with it.

In this article, I will outline a theoretical framework that I developed in my Ph.D. dissertation and that can be used to examine such questions (Boehm, 2013). The framework is based on the Roy model (Roy, 1951) of occupational choice and it can readily be brought to the data, either via simple comparison of its comparative statics with the actual evidence or via direct estimation of key parameters.

Skill Demand

Suppose overall output in the economy is produced using inputs from different industries, firms, or occupations k.[2] For example, production could be determined by a CES function of the form

$$Y_t = A_t \left[\sum_{k=1}^{K} \alpha_{kt} \left(S_{kt} \right)^{\rho-1/\rho} \right]^{\rho/\rho-1}, \tag{1}$$

where S_{kit} is the amount of k*-specific* skill employed in job k, α_{kt} is the productivity of job k in contributing to final output, and ρ the elasticity of substitution between jobs.

Differentiating (1) gives the return to S_{kt} in a competitive economy

$$R_{kt} = MPS_{kt} = \alpha_{kt} A^{\rho/\rho-1} Y_t^{1/\rho} S_{kt}^{-1/\rho}. \tag{2}$$

The relative return

$$\frac{R_{kt}}{R_{\tilde{k}t}} = \frac{\alpha_{kt}}{\alpha_{\tilde{k}t}} \left(\frac{S_{kt}}{S_{\tilde{k}t}} \right)^{-1/\rho} \tag{3}$$

[2] For brevity, I refer to all of these as “jobs” from now on.

to two skills k and $\tilde{k}$ thus depends positively on the relative productivity $\frac{\alpha_{kt}}{\alpha_{\tilde{k}t}}$ of the jobs that they are employed in and negatively on the extent that they are employed in these jobs $\frac{S_{kt}}{S_{\tilde{k}t}}$.

It is widely believed that changes that the economy has experienced in recent decades constituted shifts in the productivity of occupations, industries, firms, or tasks. For example, skill-biased technical change (or globalization) in the production framework (1) would constitute a rise of α_{kt} in the more highly skilled occupations or industries such as professional services, finance, or IT. Alternatively, routine-biased technical change (or offshoring of production) would be the provision of routine jobs k, e.g. in manufacturing or clerical work, at a lower price than R_{kt} by computers or foreign workers.

The next section shows what will happen to employment in different jobs and the wages of workers with different skills and talents in such cases.

Skill Supply

Suppose each worker i takes the job $k \epsilon \{1, ...K\}$ that offers him the highest potential wage:

$$W_{it} = max\{W_{1it}, W_{2it}, ..., W_{Kit}\}. \tag{4}$$

These potential wages are composed of the product of i's skill to carry out work in job S_{Kit} and the wage rate that prevails for that work in point in time t (R_{Kt}).

The crucial point in this analysis is that workers are heterogeneous in terms of their skills. Some workers have more skill than the average person in almost all jobs (absolute advantage) while others may be particularly productive in some dimensions (relative advantage).

Where may such differences in workers' skills stem from? We could think of them as arising from differences in endowments of talents.[3] For example,

[3]There could also be investments that may depend on the endowments of talents and on the

workers differ in cognitive mathematical and verbal ability, in physical strength and agility, but also in non-cognitive traits such as persistence and motivation. All of these talents combine to make individuals more and less skilled in different jobs, that is $S_{kit} = f_k(math_{it}, strength_{it}, persistence_{it}, ...)$.

Thus, potential log wages (logged variables are denoted in lower-case letters) in job k may become:

$$w_{kit} = r_{kt} + s_{kit} = r_{kt} + \beta_k x_{it} + u_{kit}, \tag{5}$$

where the vector $x_{it} = [x_{1it}, ..., x_{jit}, ..., x_{Jit}]'$ contains the observed components of talents such as the cognitive, physical and non-cognitive abilities mentioned above and the β_{Kj}s are the corresponding linear projection coefficients. The regression error u_{kit} is the unobserved component of worker i's skill in firm k, i.e. talents that are unobserved by the econometrician and their corresponding β_ks.[4]

Supply's reaction to changing demand

What can we learn from this model about the allocation of and the returns to talents? Suppose for example that for technological reasons there is an increase in the productivity of high-skill sectors such as IT or professional services.[5] To keep it simple, consider only two sectors in the following with sector 2 being the high-skilled sector for which demand rises. The increase in the productivity of this sector implies that α_{2t} increases compared to α_{1t} in production function (1). From equation (3) this also implies that for given quantities of skill hired, the relative wage rate offered for working in the high-skill sector rises by

prevailing or expected returns to skills. I abstract from these here.

[4]I am writing this in logs because then it becomes additive and it corresponds to log wage regressions that are usually run in empirical work.

[5]As an alternative, we could a analyze a drop in the demand for routine occupations.

$$\triangle(r_{2t} - r_{1t}) > 0. \tag{6}$$

From a labor supply perspective, this triggers two interrelated changes. First, consider figure 1 which plots the indifference line between working in sector 1 and sector 2 into the skill space (s_{2it}, s_{1it}). With $\triangle(r_{2t} - r_{1t}) > 0$ this line shifts to the bottom right so that more workers (the area **C**) now prefer working in sector 2. Employment in the high-skill sector will thus rise.[6]

The second effect that (3) has is that it will raise the wages of those workers who have *relatively* high skills in the sector 2. By extension, this means that the returns to talents that are important for producing skill s_{2it} will also increase compared to talents that are important for producing s_{1it}.

We can see this effect more directly by exploiting the information about the allocation of talents. Consider a worker i's change in wage under a marginal shift in wage rates

$$dw_{it} = dr_{1t} + H_{it}\, d(r_{2t} - r_{1t}), \tag{7}$$

where $H_{it} = \mathbf{1}\left(s_{2it} - s_{1it} > -(r_{2t} - r_{1t})\right)$ is an indicator for i prefering to work in the high-skill sector.[7] Thus, workers who have high relative skill in sector 2 $(s_{2it} - s_{1it})$ benefit from a marginal increase of the relative wage rate $(r_{2t} - r_{1t})$ in that sector.

This result also persists for discrete changes in the wage rates. Integrating (7) gives

[6] While they have *relatively* lower skills in the high-skill sector, it is not obvious that the new entrants **C** into sector 2 are on average less skilled for that sector. It depends on the exact distribution of skills for *both* sectors in the population and can thus not generally be answered. Therefore, it can also not unambiguously be answered whether relative average wages in sector 2 will rise. In fact, the conditions under which the distribution of skill improves or deteriorates across sectors receives a lot of attention in textbook treatments of the Roy (1951) model.

[7] Note that by the optimality of the initial sector choices and the envelope theorem, H_{it} doesn't change for marginal shifts in wage rates.

$$\triangle w_{it} = \triangle r_{1t} + \int_{\widetilde{r_0}}^{\widetilde{r_1}} H_{it} d\widetilde{r}_t, \tag{8}$$

where $\widetilde{r}_t \equiv r_{2t} - r_{1t}$. We see in equation (8) that workers who start out in sector 2 or, to a lesser extent, who switch from sector 1 to sector 2 early have higher wage increases than workers who stay in sector 1. This is because the former benefit (more) from the positive additional wage rate increase in sector 2 via the integral in equation (8).

The workers in sector 2 or who switch into sector 2 early are also the ones who possess talents to which the returns rise. For example, math ability is probably important for producing in the high-skill sector, that is β_{2math} is high. Thus, workers who are more talented in math will have a higher relative skill in sector 2 ($s_{2it} - s_{1it}$) and their relative wages will rise. Moreover, the returns to math talent will rise when productivity in the high-skill sector increases.[8]

Estimation

Having shown theoretically how wages, the allocation of talents, and the returns to talents are related, we can also estimate key parameters of this model. First, given the fact that we often have data in the form of repeated cross-sections and thus don't observe the exact same worker in different points in time, let us consider the same "type" of workers according to their observable talents. Conditioning on observable talents x_{it} and taking expectations on both sides of equation (8) we get

$$E(\triangle w_{it}|x_i) = \triangle r_{1t} + \int_{\widetilde{r_0}}^{\widetilde{r_1}} p_H(x_{it}, \widetilde{r}_t) d\widetilde{r}_t, \tag{9}$$

where $p_H(x_{it}, \widetilde{r}_t) = Pr\left(s_2(x_{it}, u_{it}) - s_1(x_{it}, u_{it}) > -(r_{2t} - r_{1t})\right)$ is the prob-

[8] My CEP discussion paper (Boehm, 2013) shows more formally that the returns to talents in a linear wage regression change according to the sector they are productive in.

ability to enter the high-skill sector as a function of the observable talents x_{it}, unobservables u_{it}, and relative wage rates $\widetilde{r}_t$. Linearly approximating the integral in equation (9) between points in time $t = 0$ and $t = 1$ by

$$p_H(x_{it}, \widetilde{r}_t) \approx p_H(x_{it}, \widetilde{r}_t) + \frac{p_H(x_{it}, \widetilde{r}_1) - p_H(x_{it}, \widetilde{r}_0)}{\widetilde{r}_1 - \widetilde{r}_0}(\widetilde{r}_t - \widetilde{r}_0), \tag{10}$$

directly yields an estimable equation:

$$E(\triangle w_{it}|x_i) = \triangle r_{1t} + \frac{p_H(x_{it}, \widetilde{r}_1) + p_H(x_{it}, \widetilde{r}_0)}{2}\triangle(r_{2t} - r_{1t}). \tag{11}$$

Now run first-stage regressions that measure the allocation of talents in each period, i.e. that estimate $p_H(x_{it}, \widetilde{r}_t)$ as a function of x_{it} in $t = 0$ and $t = 1$. For example, this could be done using probit or logit type sorting regressions. From these regressions we learn which talents are associated with relatively more skill in sector 2 compared to sector 1 and vice versa. In the second stage we can then estimate the shifting wage rates $(\triangle r_{1t}, \triangle r_{2t})$ across sectors by regressing the changes in wages on the predicted probabilities $\hat{p}_H(x_{it}, \widetilde{r}_t)$ from the first stage as in equation (11).

Thus, the procedure outlined in this section demonstrates that the allocation of talents $(p_H(x_{it}, \widetilde{r}_t))$ is inherently linked to changing wages $(E(\triangle w_{it}|x_i))$ when demand in the economy evolves. At the same time this changes the returns to talents themselves. Moreover, the quantities discussed here are empirically measurable. Hence, we can estimate the shifts in wage rates that are offered across jobs, the sorting of talents, and the returns to talents that are due to these shifts.[9]

[9] We can also test restrictions of the model such as the hypothesis that all changes in returns to talents are due to shifts in wage rates across jobs (Boehm, 2013).

Conclusion

In my Ph.D. dissertation I have applied a framework similar to the one outlined above in order to estimate the wage effects of job polarization and routine-biased technical change. I found that job polarization plays an important role in holding down middle-skill workers' wages since the 1980s and that it may have generated a substantial part of the change in the overall wage distribution that we observe during this period.

As already mentioned, the framework can also be used to examine other hypothesized changes of the demand for skill in the economy, such as a rise in IT- or finance-related services. Of course there are several alternative frameworks with which one can approach the important questions about talent, skill, productivity, and inequality facing economics today. What seems certain, however, is that the improved data from surveys and administrative sources that have recently become available offer very promising new avenues to answering such questions.

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Appendix

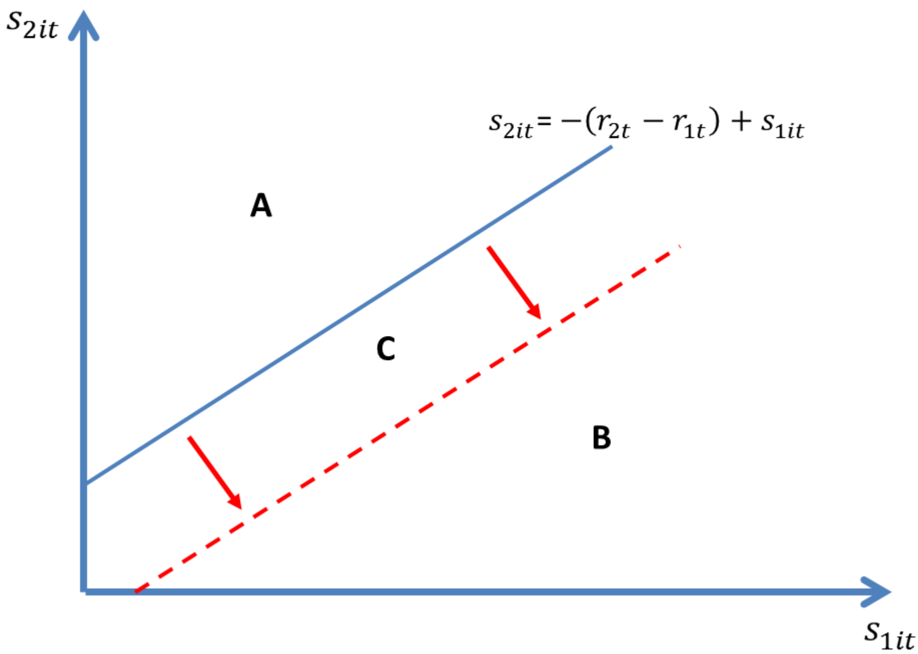

Figure 1: Skill selection into the two sectors.