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Essays in Directed Technical Change

Randy Cragun

Clemson University, rsragun@gmail.com

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ESSAYS IN DIRECTED TECHNICAL CHANGE

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Economics

by
Randy Cragun
May 2016

Accepted by:
Dr. Robert Tamura, Committee Co-Chair
Dr. Michal Jerzmanowski, Committee Co-Chair
Dr. Scott Baier
Dr. Curtis Simon

Abstract

This dissertation takes the position that a scientific theory ought to be general and parsimonious and apply this rule to Daron Acemoglu's theory of directed technical change to show that the theory provides useful structure for our knowledge of human capital and wages.

The first chapter estimates the shape of labor demand and the strength of technical bias by age group in the US while taking account of changes in directed technology that shift relative demand for worker age groups. The data are consistent with demand shifts produced from the theory of directed technical change when the elasticity of substitution between worker age groups in the United States is slightly above 2, the threshold for strong technical bias. Instrumenting for labor supplies with lagged populations gives similar results. The report illustrates how ignoring technical bias can produce higher estimates seen in past work.

The second chapter proposes a new macroeconomic mechanism for generating concavity in age-earnings profiles based on directed technical change. The mechanism does not depend on changes in the human capital of the individual as proposed by Ben-Porath and Mincer; rather changes in the relative human capital of age groups affect the profitability of age-specific technologies, biasing innovation toward improving the productivity of younger workers. Using new data, I estimate that on average a worker at the beginning of the career can expect a yearly wage increase of 6.2% while a worker at the end of a career with 40 years of experience can expect a yearly wage increase of 2.1%. The theory generates maximal earnings at a later age than observed by some past work with macroeconomic data but is consistent with some micro estimates. The theory should be taken as supplemental to—rather than replacing—human capital-based theories of age-earnings profiles.

Acknowledgments

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I thank also my classmates, whose feedback was essential to my research progress. I particularly thank Shan Jiang for discussing my work, recommending possible statistical strategies, and checking mathematical results, Mallika Garg for sharing her knowledge of the data, Jacob Burgdorf for providing feedback and reactions from outside the macro-labor economics world, and Tim Bersak for asking the best question in a seminar and with that question shaping the way I communicate these results.

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Chapter 1

The age structure of wages: On the importance of technical bias in estimates of the elasticity of substitution between worker age groups

1.1 Introduction

This chapter presents estimates for elasticities of substitution between workers by age group in the United States. I improve on past work by considering the role of directed technology in generating shocks to the relative demand for workers, by incorporating an instrument for labor supply by age group, and by reconciling multiple estimates.

1.1.1 Directed Technical Change

Daron Acemoglu's (1998; 2002; 2003; 2007) theory of directed technical change (DTC) posits an explanation for historically observed skill premia by showing that innovators have an incentive to direct their efforts toward technologies that complement inputs that are relatively abundant. "Technologies" here means ways of organizing inputs that expand the production set. This paper applies the theory to differences in wages between workers based on another characteristic of workers: age.

In the theory, technology is input-specific and the relative returns to development of new technologies for particular inputs depend positively on the prices of the products of that input and on the abundance of that input (because higher factor abundance allows the innovator to take advantage of low marginal costs of reproducing known technologies). Note that these two effects are negatively related along a given demand function for the input: if firms rent more of the input, its marginal product will fall. On the other hand, the mechanism of central importance for the directed technology literature is that innovation shifts the demand curve for the input; when an input is relatively more abundant, innovators have more incentive to develop technology for that input because the market for their innovations is larger, and when they do create new technologies this will improve the productivity of the input, which will increase demand for the input. Thus the story is that an increase in supply of an input first reduces wages and then induces innovation, which increases demand and wages. Figure 1.1 illustrates this theory.

To my knowledge, the extant research in this DTC field has focused solely on labor differentiated by skill level (college education, etc.). However, there is nothing in the theory that is inherently specific to explaining the wages of skilled and less-skilled workers rather than other classes of workers or even other productive inputs. I propose that if we are to take the theory seriously, it must be true that technical development follows productive input abundance for diverse classes of inputs. This observation follows the well-known standard for any good scientific theory: it ought to be general and parsimonious. I apply the theory to wage and labor supply data by age and skill group to provide estimates for elasticities of substitution between worker groups.

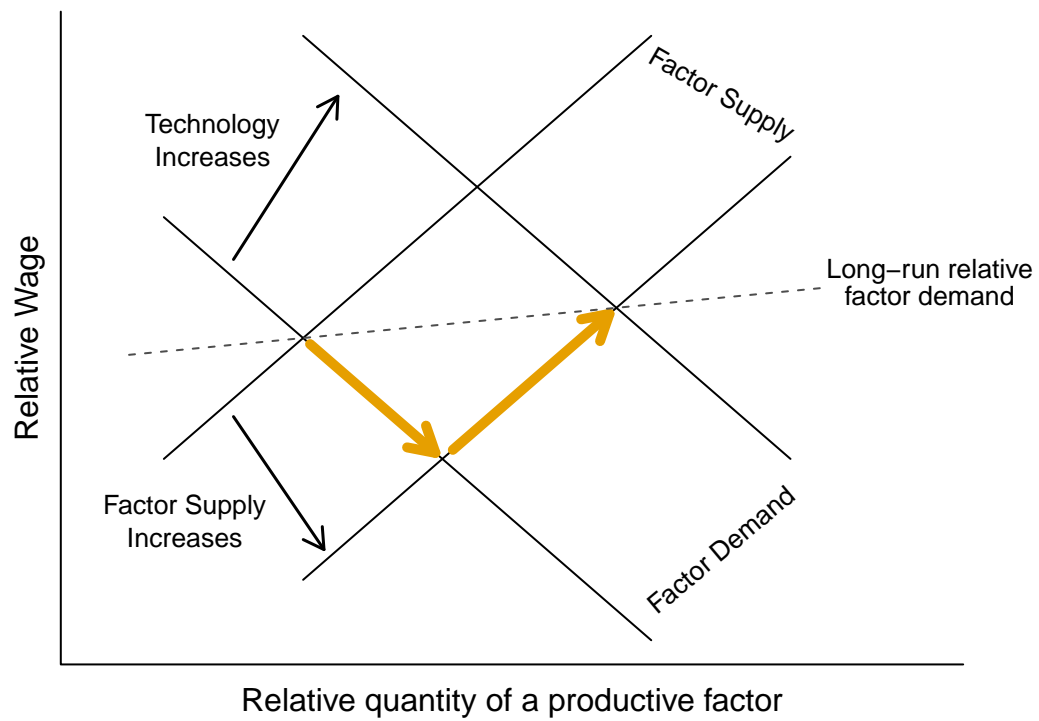


Figure 1.1: Illustration of directed technical change

Note: An increase in relative factor supply increases the market size for technologies that complement that factor. These new technologies increase demand for the factor, potentially increasing its wage.

1.1.2 The estimation problem

Estimates of the elasticity of substitution between worker groups are concerned with measuring the shape of the demand curve in Figure 1.1 by employing (hopefully) exogenous shifts in relative supply (usually they are assumed to be random). Unfortunately for these estimates, shifts in relative factor demand from increased relative technology will bias these results upward so long as wages do not increase from the new technology and could create a positive relationship between prices and quantities if the increase in technology is large, indicating to the casual statistician that the elasticity of substitution is negative.

1.1.3 Card and Lemieux's solution

This section presents a quick discussion of the methodology used by Card and Lemieux (2001), which is similar to the one used by Murphy and Welch (1992). They propose considering changes in the college wage premium partially as a result of imperfect substitutability between age groups of workers.

They suggest thinking of high-school-educated labor and college-educated labor supplied as CES aggregates of labor supplied by different age groups at those schooling levels:

$$H_t = \left[\sum_j \left(\alpha_j H_{jt}^{\frac{\sigma_a-1}{\sigma_1}} \right) \right]^{\frac{\sigma_1}{\sigma_a-1}} \quad (1.1)$$

$$C_t = \left[\sum_j \left(\beta_j C_{jt}^{\frac{\sigma_a-1}{\sigma_1}} \right) \right]^{\frac{\sigma_1}{\sigma_a-1}} \quad (1.2)$$

where H_{jt} is high-school-educated labor supplied by age group j in time t , C_{jt} is college-educated labor supplied by age group j in time t , α_j and β_j age-group-specific productivity (technology) parameters, and σ_a is the elasticity of substitution between age groups at the same education level.

They then use a standard approach (e.g. Murphy and Welch (1992)) and think of aggregate output as a CES aggregate of the high school and college labor indexes:

$$y_t = \left(\theta_{ht} H_t^{\frac{\sigma_e-1}{\sigma_c}} + \theta_{ct} C_t^{\frac{\sigma_e-1}{\sigma_c}} \right)^{\frac{\sigma_c}{\sigma_e-1}} \quad (1.3)$$

where θ_{ht} and θ_{ct} are productivity (technology) parameters and σ_e is the elasticity of substitution between workers by schooling group.

Optimization in these markets leads to relative demand wages that depend on the relative labor supplied and the productivity parameters:

$$\ln\left(\frac{w_{cjt}}{w_{hjt}}\right) = \ln\left(\frac{\theta_{ct}}{\theta_{ht}}\right) + \ln\left(\frac{\beta_j}{\alpha_j}\right) + \left[\frac{1}{\sigma_a} - \frac{1}{\sigma_e}\right] \ln\left(\frac{C_t}{H_t}\right) - \frac{1}{\sigma_a} \ln\left(\frac{C_{jt}}{H_{jt}}\right) + \epsilon_{jt} \quad (1.4)$$

They suggest that to estimate σ_a we can regress the college wage gaps (the left-hand-side of Equation 1.4) on relative college-educated labor of that age group with age group and year fixed effects to capture the productivity parameters and the relative aggregate college labor supplied term. This approach is reasonable given their model, but if there is age-group-specific technological innovation, then α_j and β_j should also change over time. In this case, the fixed effects will not capture the relevant variation, and the estimates of σ_a will be biased.

This paper will show that the directed technical change framework suggests that if workers of different ages are imperfect substitutes (the central claim of Card and Lemieux, 2001), then there will be age-group-specific innovation. I propose an alternative estimation method that accounts for this innovation.

1.2 Model of directed technical change using age groups and human capital

Here I set up a dynamic model of a macroeconomy that follows closely with Acemoglu (2002) except that I use the total human capital provided to the market by a given age group as a productive input rather than using the quantity of labor supplied by people of different levels of human capital. This would cause only negligible differences in solving the model (but not in applications to the data) if we were to simply exchange the two values wherever they occur (we could just stick an H wherever he has an L). However, because we cannot observe wages per unit of human capital, I solve the model for the wage per unit of labor. Thus the factor wages that concern us are not equivalent to those used by Acemoglu (in terms of their role in determining technology). This specification is almost the same as used in Chapter 2.

1.2.1 Final Goods

Aggregate output Y is produced competitively with intermediate goods Y_a specific to age groups indexed by a according to

$$Y = \left[\sum Y_a^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}} \quad (1.5)$$

1.2.2 Intermediate Goods

Intermediate goods are produced competitively using machines κ_a , labor L_a , and human capital h_a that are specific to the intermediate good:

$$Y_a = \frac{1}{1-\beta} (h_a L_a)^\beta \int_0^{X_a} \kappa_a(x)^{1-\beta} dx \quad (1.6)$$

In this particular application, the labor types are age groups, so readers can think of these intermediate goods industries indexed by a as composite sets of services offered to the market by workers of different ages. There is a continuum of length X_a of machine types indexed by x , representing the level of technology in age group (sector) a^1 , Y_a sells at price P_a , machines of type x can be rented at the price $p_a(x)$, and workers of age group a get paid wage w_a .

1.2.3 Demand for factors

The monopolist with the blueprint for a given line of machine produces and maintains each unit of the machine with a unit of capital² rented at price R . Thus the stock of capital is always equal to the stock of machines. Each monopolist has a competitor who can produce the same machine at cost vR , so the monopolist sets the limit price $p_a(x) = vR$. Assuming that first order conditions hold with equality, the profit maximization condition for demand for a machine line for age group a for a given capital rental rate is

$$\kappa_a(x) = \left(\frac{P_a}{vR} \right)^{\frac{1}{\beta}} h_a L_a \quad (1.7)$$

which is independent of the type x of machine.

¹This differs from the treatment of technology by Card and Lemieux (2001), who treat technology as independent schooling-group-specific and age-group-specific parameters. Their specification allows year and age group fixed effects to capture these technology differences. Here technology is complementary to a measure of total human capital by age groups.

²This is like assuming that one unit of capital can produce one unit of machine per unit of time and then machines depreciate fully but capital does not. The reader can think of machines as capital that has been temporarily repurposed for a specific method of production.

Profit maximization in machines and intermediate goods gives a specification for demand wages conditional on technology:

$$\frac{w_a}{w_b} = \left(\frac{X_a h_a}{X_b h_b} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{L_a}{L_b} \right)^{-\frac{1}{\sigma}} \quad (1.8)$$

where $\sigma = 1 + (\epsilon - 1)\beta$ is the elasticity of substitution between worker age groups conditional on fixed technology.

We could stop here if technology were observable, but one of the points of this paper is to discuss the impact on estimates of σ from not observing X and failing to understand that implicit in wage and labor supply data are changes in technology.

1.2.4 Technological innovation

I assume that a country builds its own stock of technology with $R\&D$ expenditures (foregone consumption) with the following innovation possibilities frontier:

$$\dot{X}_a = \eta_a R\&D_a \quad (1.9)$$

where $\sum_a R\&D_a = R\&D$ and η_a determines age-specific productivity of innovation. This follows the “lab equipment” model (Romer, 1987; Rivera-Batiz and Romer, 1991).

Along the balanced growth path (BGP), free entry into the innovation sector gives us the relative technologies:

$$\frac{X_a}{X_b} = \left(\frac{h_a L_a}{h_b L_b} \right)^{\sigma-1} \left(\frac{\eta_a}{\eta_b} \right)^{\sigma} \quad (1.10)$$

This gives us the endogenous technology values to put into Equation 1.8 to get the long-run relationship between wages and labor supplies:

$$\frac{w_a}{w_b} = \left(\frac{\eta_a}{\eta_b} \right)^{\sigma-1} \left(\frac{h_a}{h_b} \right)^{\sigma-1} \left(\frac{L_a}{L_b} \right)^{\sigma-2} \quad (1.11)$$

1.3 The trouble with ignoring age-specific technical change

Equations 1.11 and 1.8 highlight the difficulty of estimating the relevant demand elasticities. I have recreated them below to help illustrate the problem.

$$\frac{w_a}{w_b} = \left(\frac{X_a}{X_b}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{h_a}{h_b}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{L_a}{L_b}\right)^{-\frac{1}{\sigma}} \quad (1.8 \text{ revisited})$$

$$\frac{w_a}{w_b} = \left(\frac{\eta_a}{\eta_b}\right)^{\sigma-1} \left(\frac{h_a}{h_b}\right)^{\sigma-1} \left(\frac{L_a}{L_b}\right)^{\sigma-2} \quad (1.11 \text{ revisited})$$

Linear regressions of the logs of relative wages on the logs of relative labor supply, as in Card and Lemieux (2001), would produce coefficients whose meaning is ambiguous. Suppose the regression coefficient is γ . If the time frame for the data is so short that technology has not had a chance to adjust to a supply shock, then transforming γ into σ as in Equation 1.8 ($\sigma = -\frac{1}{\gamma}$) would be justified. However, if technology has been able to adjust close to the BGP, we would want to transform γ into σ as implied by Equation 1.11 ($\sigma = \gamma + 2$). This is not a minor difference. As illustrated in figure 1.1, the shift in relative factor demand from increased relative technology could create a positively-sloped relationship between prices and quantities, indicating to the casual statistician that the elasticity of substitution is negative.

Consider the results of misunderstanding the data in this way. Figure 1.2 plots point estimates for σ that we would get from various plausible regression coefficients using either the methodology from C&L or incorporating endogenous directed technology. The C&L estimates are unstable near the threshold for strong technical bias (where the coefficient is zero and my methodology gives $\sigma = 2$) even if the coefficient is estimated precisely. Estimates by Card and Lemieux (2001) fall within the highlighted box, corresponding to an actual elasticity of substitution slightly below 2 if they did not properly account for technology changes in their data. I will shortly produce similar estimates and demonstrate the volatility near $\sigma = 2$ by producing hugely negative and positive values from only slight changes in the sample years.

Card and Lemieux (2001) would possibly argue that their estimation method might capture changing technologies. They estimate models with time fixed effects to capture changes in relative productivities of worker groups (here called “technologies”). However, as they point out, “the relative supplies of different age groups are not all trending at the same rate”; this will necessarily induce technology changes that are not captured by the time trends that they use if the directed technology theory is applicable.

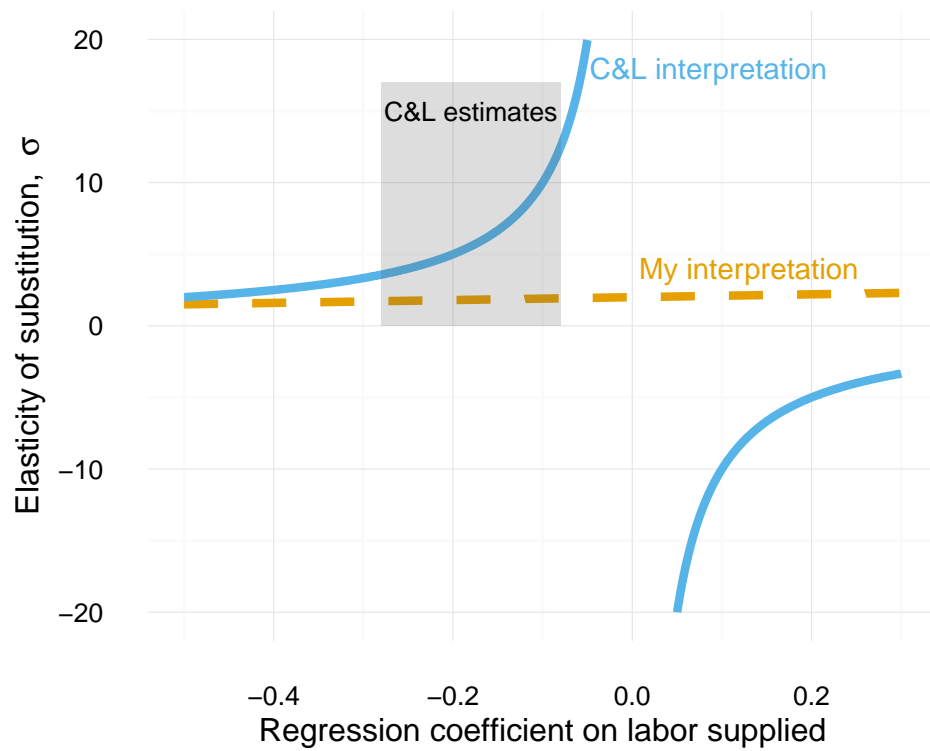


Figure 1.2: Estimates of σ derived by C&L's methodology and my methodology

Note: Estimates by Card and Lemieux (2001) lie within the highlighted box

1.4 Regression model and assumptions

To identify the regression models, I follow Murphy and Welch (1992), Card and Lemieux (2001), and Jerzmanowski and Tamura (2015) and think of the sector productivity of innovation parameters (η) as being captured by a full set of age group indicators and a full set of year indicators ³.

$$(\sigma - 1) \ln \frac{\eta_{at}}{\eta_{25t}} = \alpha_a + \delta_t + \xi_{at} \quad (1.12)$$

where ξ has conditional mean zero and I have indicated that the base category is age 20–24 with subscript 20. Taking the log of Equation 1.11 and adding time subscripts gives us the following regression equation:

$$\ln \left(\frac{w_{at}}{w_{25t}} \right) = (\sigma - 1) \ln \left(\frac{h_{at}}{h_{25t}} \right) + (\sigma - 2) \ln \left(\frac{L_{at}}{L_{25t}} \right) + \alpha_a + \delta_t + \xi_{a,t} \quad (1.13)$$

The reader should note the implied restriction on the coefficients on labor supplied and human capital.

1.5 Instrument for supply shifts

Estimating these demand models is problematic, because it requires assuming that fluctuations in the relative human capital and labor supplies are exogenous. Contrarily, they are likely sometimes responses to the relative wages. Because higher relative wages should drive up relative labor supply, a simple fit of these demand functions to the data will overestimate the relevant coefficients. In order to limit this endogeneity problem, I propose using relative age-group population sizes to instrument for supply shifts. It seems unlikely that population measures would respond much to wages. Potentially, populations could change because of

- Migration: this is probably the most serious threat to the validity of the instrument, and I will look at how much fluctuation there is in immigration and emigration by age group
- Death: poorer workers may be more likely to die

³Alternative specifications with linear and quadratic time trends produce almost identical results.

- Measurement error: work choices could influence the likelihood that a worker would be counted by population surveys

1.6 Data

1.6.1 US wages and labor supplies

I construct wages and labor supplied for individuals and age groups (25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, and 60–64) in the United States using wage micro data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) from the US Census from 1972 to 2015 (Ruggles et al., 2010)⁴. The CPS sample provides three useful measures for this purpose:

- The person’s wage and salary income earned over the previous year
- The number of weeks a person worked in the previous year (intervalled before 1976)
- The number of hours a person who worked in the previous year typically worked per week (only available from 1976 on)

I attempt to add up all hours of civilian labor supplied by people aged 25 to 64. I multiply the number of weeks worked last year by the usual hours worked per week to get the hours of labor supplied by each individual⁵. In calculating the totals by age group, I multiply the individual hours supplied by weights from the CPS that indicate how many people at the national level the sampled individual represents.

For wage estimates, I use only white, male workers in the labor force who were full time workers in the previous year⁶. I construct each worker’s weekly wage by dividing their income earned from wages and salaries over the last year by the number of weeks the person worked over the last year. I then construct an hourly wage by dividing this by the usual hours worked⁷ per week in the

⁴I use only the 5/8 sample for 2014

⁵Every year by age group cell contains more than 2000 non-institutionalized workers.

⁶With nine age groups per year, this gives a minimum cell size (in terms of number of non-institutionalized workers in the sample) of 241, while approximately 90% of the cells contain over 1000 workers and most cells contain more than 3000 workers.

⁷One problem with this method is that these “usual” values reported by the ASEC are likely not algebraic means. Hopefully this measurement error is common across individuals and age groups and does not impact *relative* hours.

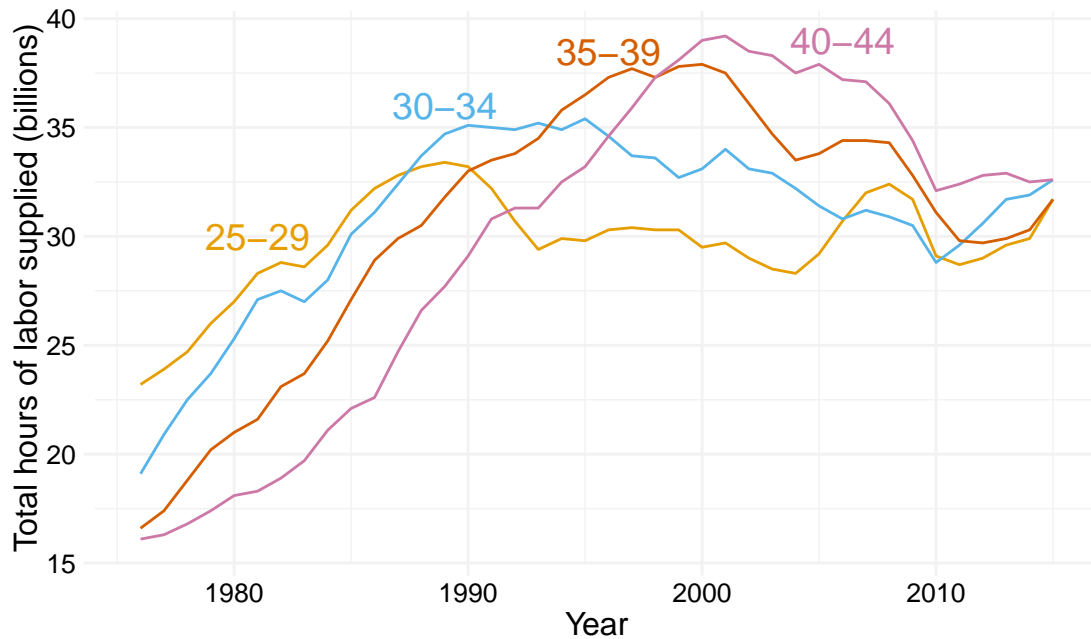


Figure 1.3: Total hours of labor supplied by each age group (younger workers)

last year. The mean values for wages within age groups are weighted means of these hourly wages, where the weights are provided by the CPS. Wages are deflated by the GDP deflator⁸.

The wage and salary data are top-coded, and the strategy for dealing with top-codes changed significantly over the sample period. I use a set of corrected wage and salary data distributed by the Census Bureau (acquired through IPUMS) that apply the 2012 rank proximity swap rule to top-coded incomes in all years from 1975 on.

Figures 1.3 and 1.4 show the total hours of labor supplied by age group (split up by the younger and older groups on separate graphs) and Figures 1.5 and 1.6 show the average hourly wage by age group. The baby boom is clearly visible in the labor supplied graphs, and as others have pointed out (again Murphy and Welch, 1992 and Card and Lemieux, 2001), this set of demographic changes had a big impact on “the structure of wages” (Murphy and Welch, 1992). The instrument for labor supply this report employs (lagged population) has the benefit of capturing changes due to these demographic shifts.

⁸Others (e.g. Murphy and Welch (1990), Murphy and Welch (1992), or Card and Lemieux (2001)) use the CPI, but since this report is interested primarily in the shape of the demand curve and the strength of incentives for firms to innovate rather than in explaining workers’ wages, the deflator seems more appropriate.

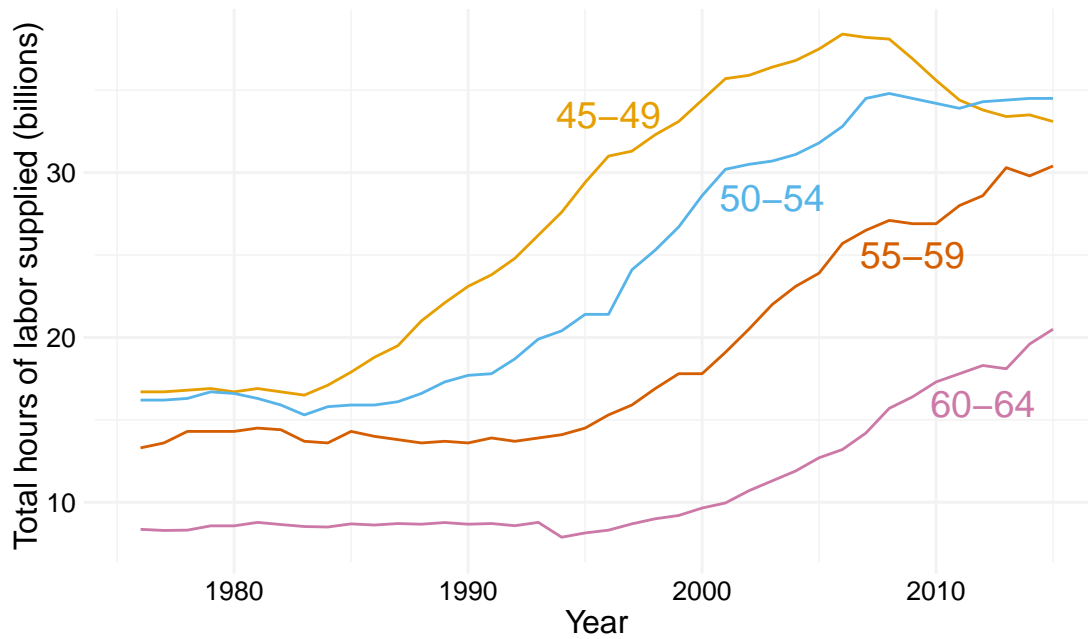


Figure 1.4: Total hours of labor supplied by each age group (older workers)

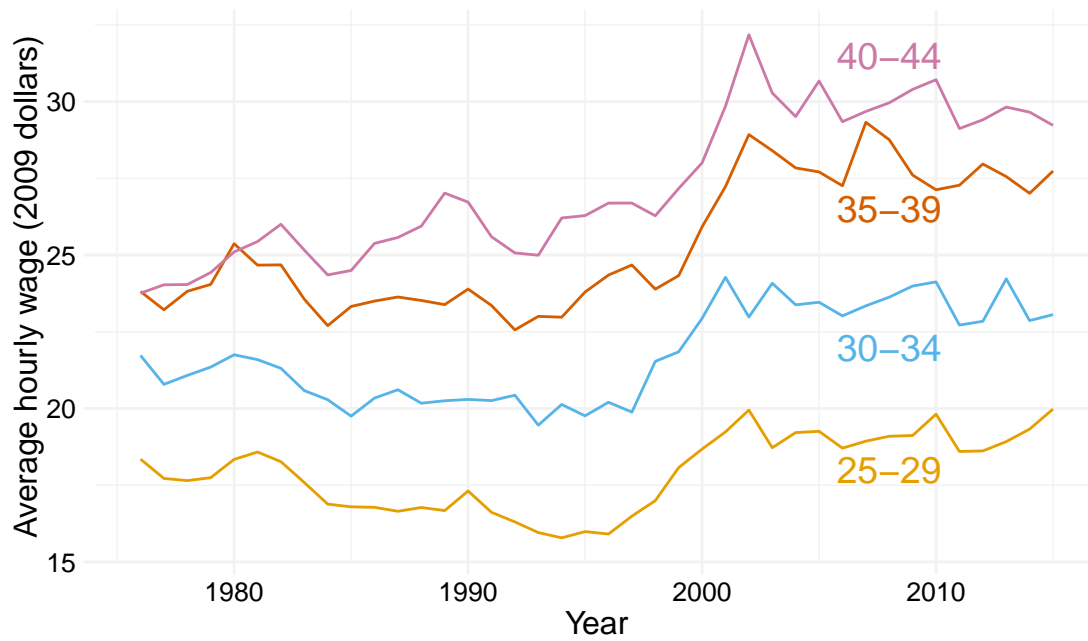


Figure 1.5: Average hourly wage of each age group (younger workers)

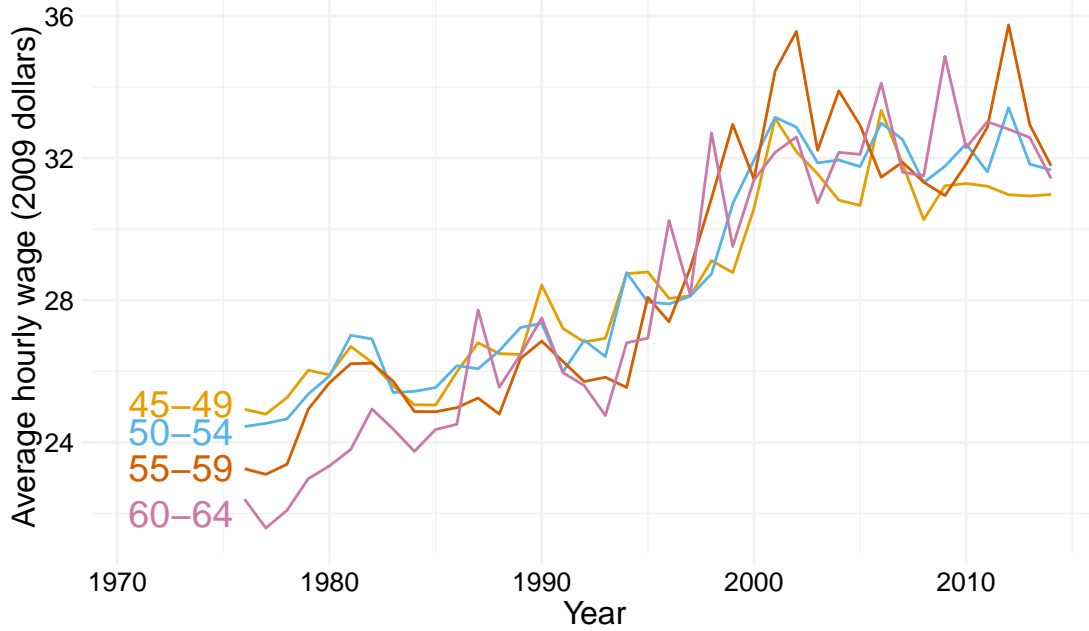


Figure 1.6: Average hourly wage of each age group (older workers)

1.6.2 Population

I construct the measures of population by age group from the CPS (ASEC) by adding up the weights for all non-institutionalized persons. The population values are lagged by one year. Thus the relative population measure for 35–39-year-olds would be the population aged 34–38 one year earlier divided by the population aged 25–29 one year earlier (since I take 25–29 as the base category in all regressions).

1.6.3 Human capital

I construct data on human capital following the methodology from Tamura, Dwyer, Devreux and Baier (2015) (TDDB), who borrow their measure of the returns to experience from macro estimates from Bils and Klenow (1996, 2000), Klenow and Rodríguez-Clare (1997), and Hall and Jones (1999a) and their measure of returns to schooling from Banerjee and Duflo (1995). The human capital of person i in age group a in year t is

$$h_{ait} = \exp\left(\frac{\text{SCHOOL}_{ait}}{10} + .0495\text{EXPERIENCE}_{ait} - \frac{.0495}{67}\text{EXPERIENCE}_{ait}^2\right) \quad (1.14)$$

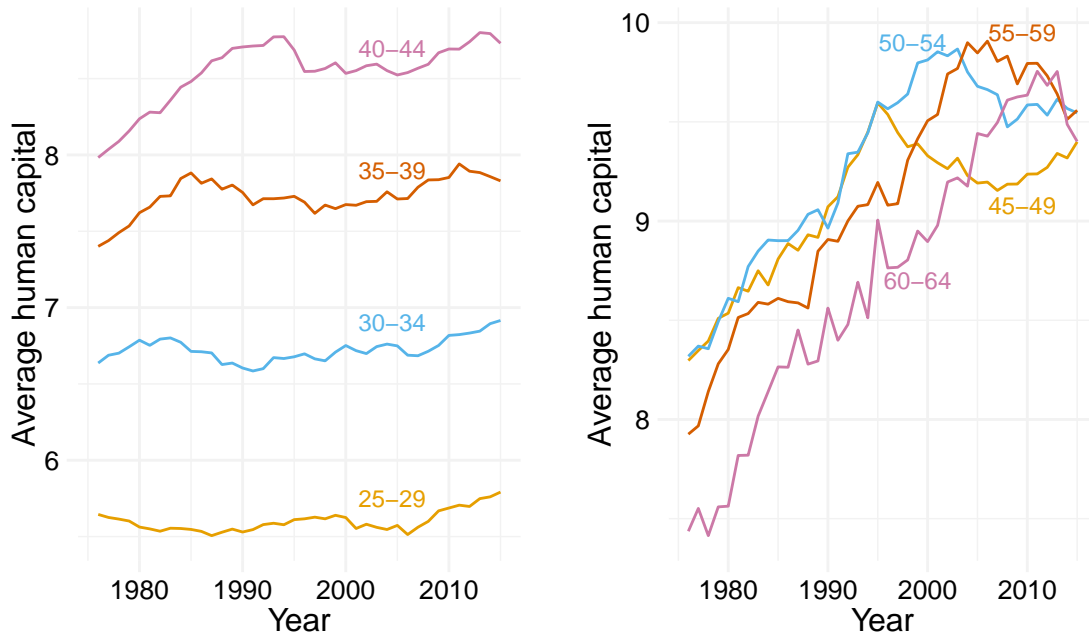


Figure 1.7: Average human capital of each age group

where $SCHOOL$ is the number of years of school the person completed and $EXPERIENCE$ is a measure of years of work experience, equal to $\max\{0, AGE_{ait} - SCHOOL_{ait} - 5\}$.

In order to calculate average human capital by age groups, I use the same sample of workers that were used for the average wage calculations: white, male workers in the labor force who were full time workers in the previous year. Figure 1.7 shows the average human capital of each age group over time. The differences between age groups (driven mainly by higher age producing higher implied experience) dominate the differences within age groups over time for younger workers. Older workers are further in their careers, so the negative quadratic term in experience has a greater influence on them and makes the relative human capital levels between age groups of older workers closer to 1. Figure 1.8 illustrates this wage plateau for the older workers by plotting human capital for each birth cohort throughout its life.

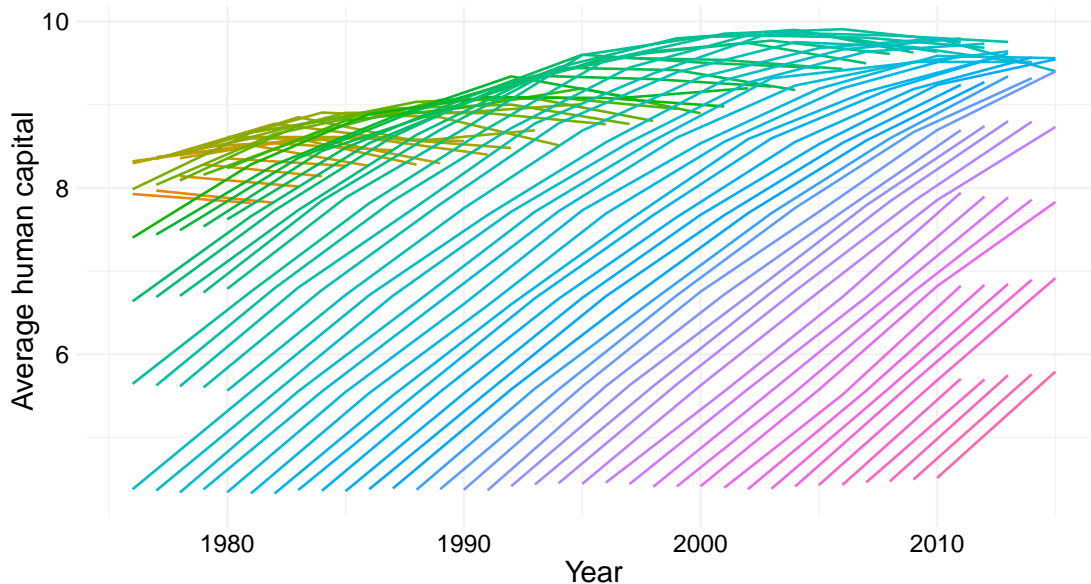


Figure 1.8: Average human capital. Each line is a birth cohort.

1.7 OLS estimates of σ

There are nine age groups for labor, so there will be eight separate age-specific intercepts and time trends. I take 20–24 as the base category in all regressions and indicate this group with the subscript “20”.

Table 1.1 presents estimates of the restricted model in 1.13. At the bottom of the table, I present the estimates for σ from transforming the coefficients. Column 1 presents OLS estimates of the restricted model and suggests an elasticity of substitution a little above 2. In this specification, unlike in Card and Lemieux (2001), increasing labor supply is associated with rising relative wages (true when the coefficient on relative human capital is greater than one or the coefficient on relative labor supplied is greater than zero). Although the coefficient estimate I get is close to theirs, the point estimate I calculate for *sigma* with their methodology (-36.60) is far from their estimates (typically less than 10 and greater than 4) and not even the expected sign. I remind the reader that this instability occurs because they transform the coefficient on labor supplied into the elasticity with the relationship $COEFFICIENT = -\frac{1}{\sigma}$.

In order to test the restriction on the coefficients on relative labor supply and relative average human capital, Column 2 of Table 1.1 presents the unrestricted regression estimates of 1.13.

Table 1.1: Least squares estimates of σ

Dependent Variable:	OLS		1 st Stage	IV	
	$\ln\left(\frac{w_{at}}{w_{20t}}\right)$		$\ln\left(\frac{L_{at}}{L_{20t}}\right)$	$\ln\left(\frac{w_{at}}{w_{20t}}\right)$	
	Restricted			Restricted	
	(1)	(2)	(3)	(4)	(5)
$\ln\left(\frac{pop_{at}}{pop_{20t}}\right)$			1.112 (0.0195)		
$\ln\left(\frac{h_{at}}{h_{20t}}\right)$	1.028 (0.0126)	1.142 (0.0701)	0.538 (0.1267)	1.034 (0.0120)	1.124 (0.0715)
$\ln\left(\frac{L_{at}}{L_{20t}}\right)$	0.028 (0.0126)	0.017 (0.0137)		0.034 (0.0120)	0.026 (0.0130)
Observations	360	360	360	360	360
Age group FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
R^2	0.858	0.859	0.972		
σ_h	2.028	2.142		2.034	2.124
σ_L	2.028	2.017		2.034	2.026
C&L σ_h	-35.97	-7.05		-29.57	-8.05
C&L σ_L	-35.97	-57.95		-29.57	-38.64
90% CI for diff btwn h and L coefs		(0.999, 1.241)			(0.972, 1.220)
95% CI for diff btwn h and L coefs		(0.973, 1.264)			(0.948, 1.241)
99% CI for diff btwn h and L coefs		(0.925, 1.308)			(0.890, 1.290)

– Standard errors are in parentheses and are bootstrap estimates from sampling data de-meanned by age group

– R^2 and standard errors calculated using data de-meanned by age group

– Confidence intervals are bootstrap estimates

The fit is essentially the same, and the point estimates of σ are not substantially different in terms of their implications for economic behavior. It is also true that in this case the two coefficients within the unrestricted models give us separate estimates of σ , and the coefficients on human capital consistently give slightly higher estimates for σ . The theoretical value $\nu_h - \nu_L = 1$ is at the left edge of the relevant confidence intervals (shown at the bottom of the table), so it is at least possible that the restriction holds.⁹

1.8 IV estimates of σ

I attempt to correct for potential endogeneity in labor supply in the CPS data by using relative population levels by age groups as an instrument for labor supply. A potential weakness of this instrument is that immigration could respond to wage differentials between age groups, so I use relative population values lagged by one year from the sample month, whereas the wage is calculated for work done in the year leading up to the sample month. The IV estimates in Columns 3 through 5 of Table 1.1 (with the first stage in column 3, the restricted second stage in column 4, and unrestricted estimates in Column 5) are comparable to the OLS estimates. Doing a search over years for the location of a

Again, we can test the coefficient restriction. The 90% confidence interval for the difference in the coefficients in Column 5 of Table 1.1 is consistent with the structural model's value of 1.

1.9 Further exploration of the wage-supply relationship in the data

It is valuable to graph the data to see what we might expect from the relationship between labor supplied and wages. Figure 1.9 splits up the data by age group and shows average wages (relative to 25–29-year-olds) against total hours of labor supplied (again relative to 20–24-year-olds) for each sample year. The sample year is represented with color intensity so that later years are lighter colors. If there is an overall relationship between the two variables, it is that there is a slight positive correlation, but we might wonder if the left and right sides of the older workers' data come

⁹Both because of concerns about heteroskedasticity and because of poor small-sample performance of IV estimators, the standard errors and confidence intervals are based on bootstrap estimates.

from different data generating processes.

(Acemoglu, 2007) discusses the dynamics of directed technology and shows that there was an early period of falling skill premiums as the relative supply of skilled workers rose that was followed by a period of positive correlation between the relative supply and relative wage. We may be seeing a similar pattern here. Early samples for some age groups seem to exhibit a negative relationship between relative quantities supplied and relative wages (consistent with movement along a labor demand curve), while later samples are inconsistent with movements along a demand curve. As pointed out by (Acemoglu, 2007), it could take some time before technology changes respond to supply shocks enough to shift out demand, creating an essentially null relationship in later years. These results may weaken the argument of this paper, which relies on the assumption that technology adjusts to its BGP every year. Alternatively, there could be something correlated with labor supplies by age group in later years (e.g. labor supplies by schooling group) that is driving the technical changes. This is a concern that warrants further investigation.

It is also important to note that because Card and Lemieux, 2001 (and Murphy and Welch, 1990, 1992) use pre-1976 data and do not use the later data that I use, that they will see a stronger negative relationships between wages and labor supplies. Hence C&L estimate a positive elasticity of substitution, whereas applying their methodology to the data used here produces negative estimates for the elasticity of substitution. I leave out the pre-1976 data, because using them requires making very strong assumptions about hours of work over the previous year, and attempts to model labor supplied based on the information observed in the pre-1976 samples (similar to in Murphy and Welch, 1990, 1992) produces very low-quality estimates. Cursory analysis suggests that including pre-1976 data would lower the estimated elasticities if the pre-1976 data followed a similar trend to the early data presented here.

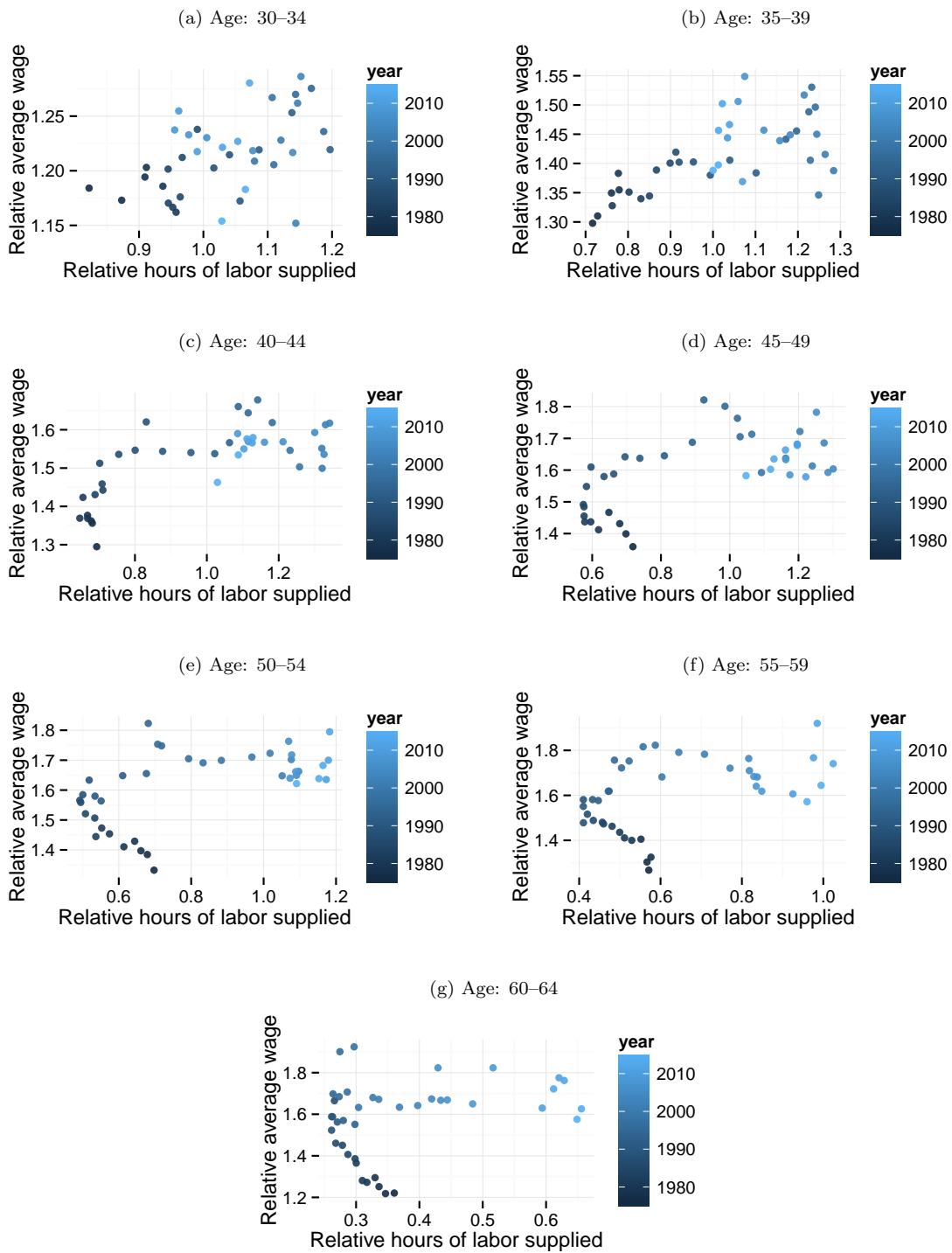


Figure 1.9: Labor supply and wage data relative to 25–29-year-olds

1.10 Estimates with a structural break

One potential interpretation of the evidence in Figure 1.9 is that there was structural break in the data generating process in the 1980s. This could be due to demographic shifts resulting from the baby boom or increased educational attainment for post-baby-boom cohorts. If we know the timing of the break, we can estimate (where I_{early} is an indicator for being before the break and I_{late} is an indicator for being after the break):¹⁰

$$\begin{aligned} \ln\left(\frac{w_{at}}{w_{25t}}\right) = & I_{early} \left[(\sigma_{early} - 1) \ln\left(\frac{h_{at}}{h_{25t}}\right) + (\sigma_{early} - 2) \ln\left(\frac{L_{at}}{L_{25t}}\right) \right] + \\ & I_{late} \left[(\sigma_{late} - 1) \ln\left(\frac{h_{at}}{h_{25t}}\right) + (\sigma_{late} - 2) \ln\left(\frac{L_{at}}{L_{25t}}\right) \right] + \\ & I_{early}\alpha_a + I_{late}\alpha_a + \delta_t + \xi_{a,t} \end{aligned} \quad (1.15)$$

Estimating this model by searching over years for the break indicates that if there is a break, it is around 1986, the year that maximizes the R^2 of the model estimates:

Estimates for the model with a break in 1986 are in Table 1.2. The restricted estimates in columns 1 and 4 suggest a negative relationship (“weak bias”) between relative hours worked and relative wages conditional on supply shocks and demand shifts due to directed technology. The unrestricted estimates in columns 2 and 5 might suggest strong bias as in the pooled regressions but only for the coefficients on human capital and only for the early period. However, the main purpose of the unrestricted regressions is to test the restriction on the coefficients on human capital and labor. There seems to be evidence against the restriction (an assumed difference of 1) in both the early and later periods, but the error is in opposite directions between these periods.

1.11 Be cautious in applying point estimates

The estimates of the elasticity of substitution between workers by age group in the report are consistently near 2. The higher values in the regressions with earlier and later data pooled imply “strong bias” under the directed technology framework. This means that as relative labor supply for a group increased, the increase in technology specific to that group was so great that relative demand shifted out enough to raise their wages (again in relative terms).

¹⁰The age group fixed effects differ in the early and late periods, because these are a function of both σ and the productivity of innovation for each age group (see Equation 1.12).

Table 1.2: Least squares estimates of σ with a structural break

Dependent Variable:	OLS		1 st Stage	IV	
	$\ln\left(\frac{w_{at}}{w_{20t}}\right)$		$\ln\left(\frac{L_{at}}{L_{20t}}\right)$	$\ln\left(\frac{w_{at}}{w_{20t}}\right)$	
	Restricted (1)	(2)	(3)	Restricted (4)	(5)
$\ln\left(\frac{pop_{at}}{pop_{20t}}\right)$ (Early)			0.994 (0.0432)		
$\ln\left(\frac{pop_{at}}{pop_{20t}}\right)$ (Late)			1.089 (0.0174)		
$\ln\left(\frac{h_{at}}{h_{20t}}\right)$ (Early)	0.885 (0.0228)	1.093 (0.0883)	-1.018 (0.2054)	0.920 (0.0254)	1.149 (0.0890)
$\ln\left(\frac{h_{at}}{h_{20t}}\right)$ (Late)	0.958 (0.0120)	0.627 (0.0951)	1.288 (0.1176)	0.964 (0.0119)	0.617 (0.0952)
$\ln\left(\frac{L_{at}}{L_{20t}}\right)$ (Early)	-0.115 (0.0228)	-0.102 (0.0238)		-0.080 (0.0254)	-0.076 (0.0250)
$\ln\left(\frac{L_{at}}{L_{20t}}\right)$ (Late)	-0.042 (0.0120)	-0.014 (0.0138)		-0.036 (0.0119)	-0.011 (0.0137)
Observations	360	360	360	360	360
Age group \times early/late FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
R^2	0.618	0.636	0.620		
σ_h (Early)	1.885	2.093		1.920	2.149
σ_L (Early)	1.885	1.898		1.920	1.924
C&L σ_h (Early)	8.72	-10.74		12.57	-6.69
C&L σ_L (Early)	8.72	9.83		12.57	13.09
σ_h (Late)	1.958	1.627		1.964	1.617
σ_L (Late)	1.958	1.986		1.964	1.989
C&L σ_h (Late)	23.91	2.68		27.75	2.61
C&L σ_L (Late)	23.91	71.69		27.75	87.80
95% CI for diff btwn h and L coeffs (Early)	(1.023, 1.338)			(1.058, 1.372)	
99% CI for diff btwn h and L coeffs (Early)	(0.975, 1.389)			(1.017, 1.431)	
99% CI for diff btwn h and L coeffs (Late)	(0.385, 0.877)			(0.372, 0.867)	

– Standard errors are in parentheses and are bootstrap estimates from sampling data de-meanned by age group
– R^2 and standard errors calculated using data de-meanned by age group
– Confidence intervals are bootstrap estimates

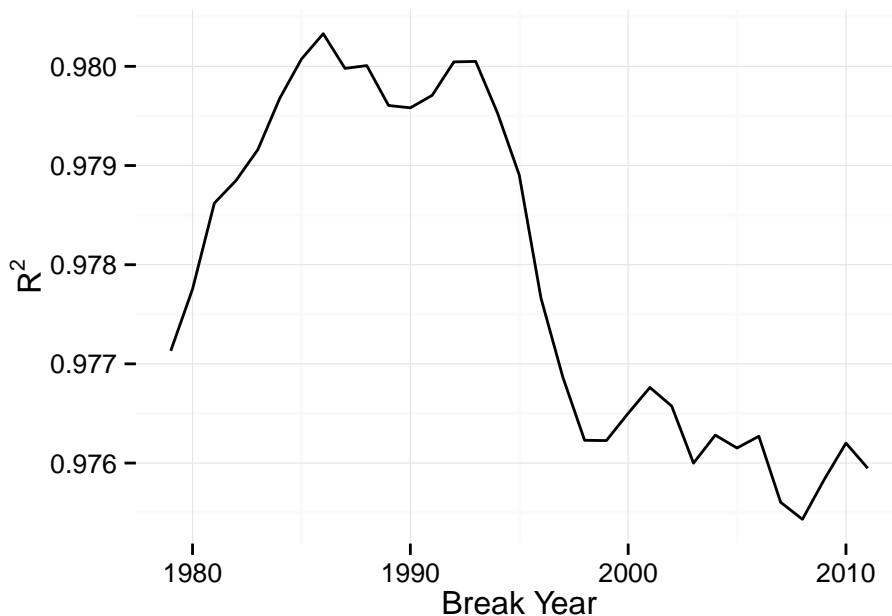


Figure 1.10: R^2 from estimating the model allowing σ to differ before and after the indicated year
Note: R^2 measures include variation within age groups, because changes in the fit of the model within age groups are an important component of the effect of changing the location of the break

My results suggest caution in applying the estimates by Card and Lemieux (2001), since their methodology led to unstable estimates for the elasticity even when the variance of the regression coefficients was small. An alternative interpretation, of course, is that their methodology is sound but that the elasticity of substitution varies greatly (and is sometimes negative) over time and with slight changes in specifications of worker groups.

Readers should also be cautious about applying the estimates here in the wrong context. The regression coefficients should be generally applicable, but how we should interpret those coefficients depends on what we know about the scenario at hand. Consider, for instance, that the innovation possibilities frontier I proposed may be too simplistic. No nation is totally insulated from the supply of technologies throughout the rest of the world. Suppose that we modified Equation 1.9 to account for international spillovers of technology:

$$\dot{X}_a = \eta_a \left(\frac{X_a^W}{X_a} \right)^\phi R\&D_a \quad (1.16)$$

where X_a^W is some function of world technology (possibly the maximum or some average of the

highest values for nearby countries). The ratio $\left(\frac{X_a^W}{X_a}\right)$ is included to account for the fact that it is easier for lower-income countries to catch up to the frontier (e.g. Caselli (2005); Caselli and Coleman (2006); Barro and Sala-i-Martin (1991, 1992, 2004); Chui et al. (2001)). In this case relative endogenous technologies will take a slightly different form:

$$\frac{X_a}{X_b} = \left(\frac{h_a L_a}{h_b L_b}\right)^{\frac{\sigma-1}{1+\sigma\phi}} \left(\frac{X_a^W}{X_b^W}\right)^{\frac{\sigma\phi}{1+\sigma\phi}} \left(\frac{\eta_a}{\eta_b}\right)^{\frac{\sigma}{1+\sigma\phi}} \quad (1.17)$$

Relative wages will similarly depend on the world technologies and the rate of international spillovers (ϕ):

$$\frac{w_a}{w_b} = \left(\frac{\eta_a}{\eta_b}\right)^{\frac{\sigma-1}{1+\sigma\phi}} \left(\frac{h_a}{h_b}\right)^{\frac{\sigma-\phi-2}{1+\sigma\phi}+1} \left(\frac{L_a}{L_b}\right)^{\frac{\sigma-\phi-2}{1+\sigma\phi}} \left(\frac{X_a^W}{X_b^W}\right)^{\frac{\phi(\sigma-1)}{1+\sigma\phi}} \quad (1.18)$$

This new form very clearly changes the way we would interpret regression coefficients, so that letting γ_L be the (log-log) regression coefficient on labor supply, the elasticity of substitution, σ , can be recovered as $\sigma = \frac{\gamma_L + \phi + 2}{1 - \gamma_L \phi}$, which is the same as the interpretation in the main body of this report only when $\phi = 0$.

This discussion might seem to imply that we cannot be confident about the elasticity of substitution, and to some degree that interpretation is correct. However, we can be confident in the conclusions we make based on the regression coefficient itself. For instance, the condition on σ that generates strong technical bias when there are no international technical spillovers is $\sigma > 2$. In the presence of international technical spillovers, this condition changes into $\sigma > 2 + \phi$. These inequalities correspond to exactly the same set of regression coefficients. Thus we can say (based on the regressions presented above) that there is evidence that within the US over the last four decades there has been strong technical bias between age groups.

Chapter 2

Directed Technical Change: a Macro Perspective on Life Cycle Earnings Profiles¹

2.1 Introduction

2.1.1 Experience-earnings profiles overview

One of the well-known trends in analyses of life-cycle earnings is that earnings are hill-shaped: they grow quickly early in the career and then slowly late in life² (as illustrated in Figure 2.1). Typically economists explain this by concluding that human capital accumulation is faster earlier in the career (Becker, 1964, 1967; Ben-Porath, 1967; Mincer, 1974, 1997). Human capital accumulation slows late in life both because the cost of investment—foregone wages—increases and because the benefit decreases (for two reasons: the amount of time over which new human capital can be used falls as people age and shifting income into the future reduces its present value). These effects lead to hill-shaped age-earnings or experience-earnings profiles. Because human capital depreciates,

¹This chapter is based on joint work with Professors Robert Tamura and Michal Jerzmanowski of Clemson University. I thank them for their contributions.

²The shape of this relationship is so accepted that empirical researchers studying the returns to education assume that they must have sufficient data to observe it in order to get valid comparisons of the lifetime earnings between different age groups (Psacharopoulos, 1994).

it is possible for low returns to human capital accumulation to actually produce late-life decreases in wages. A supplementary explanation is that human capital depreciation speeds up as workers age.

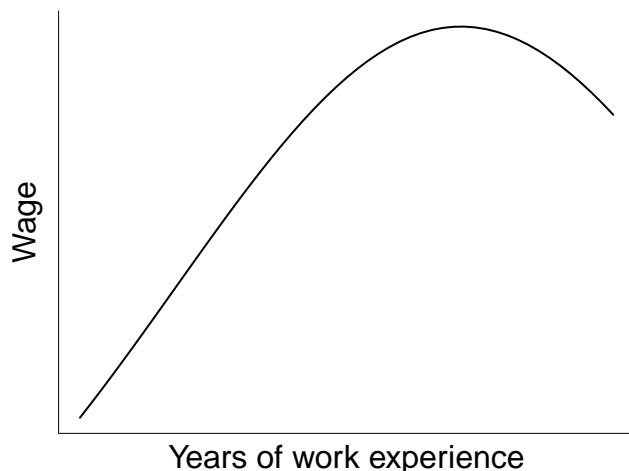


Figure 2.1: An example of the typical pattern of life cycle wage earnings observed in past research. This relationship is what we want to explain.

These theories are driven by changes in the human capital of the individual worker. However, I will show that the directed technology framework can produce hill-shaped wage-experience profiles like those in the actual data without even allowing human capital to vary over the person’s career. Instead macro-level technology is the main culprit. Before examining the details of the mechanism, we must look at the theory of directed technical change and work through a formalization of the model.

2.1.2 Directed Technical Change

Daron Acemoglu’s (1998; 2002; 2003; 2007) theory of directed technical change (DTC) posits an explanation for historically observed skill premia by showing that innovators have an incentive to direct their efforts toward technologies that complement inputs that are relatively abundant. “Technologies” here means ways of organizing inputs that expand the production set.

In the theory, technology is input-specific and the relative returns to development of new technologies for particular inputs depend positively on the price of the products of that input and on the abundance of that input (because higher factor abundance allows the innovator to take advantage of low marginal costs of reproducing known technologies). Note that these two effects are negatively related along a given demand function for the input: if firms rent more of the input,

its marginal product will fall. On the other hand, the mechanism of central importance for the directed technology literature is that innovation shifts the demand curve for the input; when an input is relatively more abundant, innovators have more incentive to develop technology for that input because the market for their innovations is larger, and when they do create new technologies this will improve the productivity of the input, which will increase demand for the input. Thus the story is that an increase in supply of an input first reduces wages and then induces innovation, which increases demand and wages. Figure 2.2 illustrates this theory, and the formal model below explains it more thoroughly.

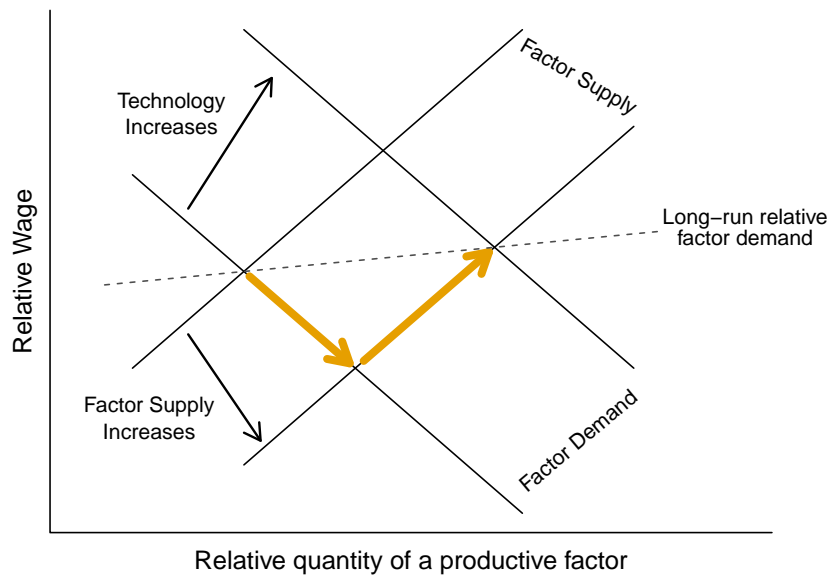


Figure 2.2: Illustration of directed technical change

Note: An increase in relative factor supply increases the market size for technologies that complement that factor. These new technologies increase demand for the factor, potentially increasing its wage.

To our knowledge the extant research in this DTC field has focused solely on labor differentiated by skill level (college education, etc.) with hints at applications to earnings of labor versus capital (e.g. the forthcoming Acemoglu (2014)). However, there is nothing in the theory that is inherently specific to explaining the wages of skilled and less-skilled workers rather than other classes of workers or even other productive inputs. We propose that if we are to take the theory seriously, it must be true that technical development follows productive input abundance for diverse classes of inputs. This observation follows the well-known standard for any good scientific theory: it ought to be general and parsimonious.

I apply the theory to international differences in age demographics with new data from Tamura, Dwyer, Devereux and Baier (2015) to provide estimates for labor wages for 148 countries over an average of 120 years that can be compared against observation. I then show that the directed technical change theory can match some of the curvature in observed age-earnings profiles without assumptions about on-the-job human capital accumulation that are typically needed to match the trend.

2.1.3 A new mechanism driving age-earnings profiles

To understand the mechanism, we must think about human capital shares or relative human capital. Although I have stated that I apply the directed technology framework to age groups, I technically apply it to a measure of effective labor units³ supplied by age groups. When an age group supplies a large share of the human capital in a country technology will heavily complement that age group. Thus different age groups essentially compete for wage-raising technologies.

My contribution is to show that it is not necessary for the individual's human capital to decline in order for her wage to grow slowly relative to others' wages. It is enough that the human capital possessed by her age group represent a smaller share of the total human capital in the market because this shrinks the relative profits for innovators producing technology for her age group. This occurs as people age for three main reasons:

- First, the size of a cohort declines over time as members die.
- Second, in many places new generations are larger than the previous generation because of high fertility (it takes very low fertility by historical standards for this to not be true).
- Third, younger generations usually have more average human capital than older generations: parents invest in growing the wealth of their dynasties.

If some of these conditions hold to a sufficient degree, then the market size for technologies directed at younger workers will be greater than the market size for technologies directed at older workers, and workers will see their wages stagnate as they age.

In order to get hill-shaped wage patterns over time, we need a little more than this, because these conditions only produce falling wages as workers age. There are four macro effects we can use

³The measure is a composite of workers' schooling, the schooling of their ancestors, and the maximum human capital in the world. See the data section for more details.

to explain rising wages early in the career:

1. Middle-aged workers have the greatest human capital share, leading to them receiving the bulk of productivity improvements.
2. Wages rise over time as technology and, hence, productivity improve.
3. The technical frontier for middle-aged or older workers is higher for some reason, lowering the cost of copying these frontier technologies.
4. There are systematic differences in the ease of innovating for different age groups (due, for instance, to the different industries or occupations they fill).

The first condition is likely an accurate representation of the world because of the microeconomic patterns described by Ben-Porath (1967) and Mincer (1997), but because we do not allow human capital to grow over lifetimes, we cannot observe it in this paper. Note that although it would be necessary to allow human capital to change over workers' lives to observe this condition, it would still produce a macro effect driving technology improvements for the middle-aged workers and would induce additional wage curvature on top of the micro effects described by Ben-Porath and Mincer.

The second condition is fairly obviously true, at least over the last two centuries in most countries. This condition can explain a positive relationship between age and wages in both cross-sectional and longitudinal research. In the longitudinal case, workers take advantage of improved technologies as they age. In the case of cross sections, the older workers likely invested less in human capital when they were young than the currently young workers did because the productivity of human capital that they would face over their lifetimes was lower, and, hence, the returns on the investment were lower. This report focuses on longitudinal assessments.

There is no particular reason to suspect the third condition of holding except to the extent that wage curvature is a characterization of the incentives of those in the frontier economies to invest in the productivity of middle-aged workers. It might seem silly to use wage curvature to explain itself, but the effect may be self-reinforcing as the higher middle-aged technologies from the frontier nations spill over into lower-productivity nations.

The fourth condition may seem the least intuitive, but it is what I observe to have the greatest impact on rising early-life wages in this paper. See Section 2.5.2 for more details.

This report produces wages for each age group in each country in each decade without allowing a cohort's human capital to change throughout its life. I show that for most cohorts the estimated wages rise and then plateau (and sometimes fall) over the working life.

2.2 Model of directed technical change using age groups and human capital

The model follows closely with Acemoglu (2002) with two major differences:

1. I use the total human capital provided to the market by a given age group as a productive input rather than using the quantity of labor supplied by people of different levels of human capital. This would cause only negligible differences in solving the model (but not in applications to the data) if we were to simply exchange the two values wherever they occur (we could just stick an H wherever he has an L). However, because we cannot observe wages per unit of human capital, I solve the model for the wage per unit of labor. Thus the factor wages that concern us are not equivalent to those used by Acemoglu (in terms of their role in determining technology).
2. Because I look at cross-country differences, I modify the technology accumulation function to limit scale effects and to incorporate country-level innovation productivities (as in Jerzmanowski and Tamura, 2015).

2.2.1 Final Goods

Aggregate output Y is produced competitively with intermediate goods Y_a according to ⁴

$$Y = \left[\sum Y_a^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}} \quad (2.1)$$

⁴A more general version of this production function would seem to be one that allows for different weights on the intermediate goods:

$$Y = \left[\sum \gamma_a Y_a^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}$$

However, these weights are not separately identified from the levels of production of the intermediate goods (which are not observed) and the technology levels that lead to that production. Thus we normalize $\gamma_a = 1$ and allow the production of intermediate goods to capture all aspects of the value of constituent markets in final good production.

Final good output is the numeraire, so

$$\sum P_a^{1-\epsilon} = 1 \quad (2.2)$$

The typical final good producer purchases intermediate goods at prices P_a and faces the problem

$$\begin{aligned} \max_{\{Y_a\}} \left\{ Y - \sum P_a Y_a \right\} \\ \Rightarrow \frac{P_a}{P_b} = \left(\frac{Y_a}{Y_b} \right)^{-\frac{1}{\epsilon}} \end{aligned} \quad (2.3)$$

where b indicates a second age group. If we combine Equation 2.3 with a zero profit condition, we get that

$$P_a = Y Y_a^{-\frac{1}{\epsilon}} \left(\sum_b Y_b^{\frac{\epsilon-1}{\epsilon}} \right)^{-1} \quad (2.4)$$

2.2.2 Intermediate Goods

Intermediate goods are produced competitively using machines κ_a , labor L_a , and human capital h_a that are specific to the intermediate good:

$$Y_a = \frac{1}{1-\beta} (h_a L_a)^\beta \int_0^{X_a} \kappa_a(x)^{1-\beta} dx \quad (2.5)$$

In this particular application, the labor types are age groups, so readers can think of these intermediate goods industries indexed by a as composite sets of services offered to the market by workers of different ages. There is a continuum of length X_a of machine types indexed by x , representing the level of technology in age group (sector) a , Y_a sells at price P_a , machines of type x can be rented at the price $p_a(x)$, and workers of age group a get paid wage w_a . Thus the problem for the intermediate good producer is

$$\max_{\kappa, L} \left[\frac{P_a}{1-\beta} (h_a L_a)^\beta \int_0^{X_a} \kappa_a(x)^{1-\beta} dx - \int_0^{X_a} p_a(x) \kappa_a(x) dx - w_a L_a \right]$$

2.2.3 Demand for machines

I assume that first order conditions hold with equality. Then profit maximization condition with respect to machines of for age group a is that

$$P_a (h_a L_a)^\beta \kappa_a(x)^{-\beta} = p_a(x)$$

The monopolist with the blueprint for a given line of machine produces and maintains each unit of the machine with a unit of capital⁵ rented at price R . Thus the stock of capital is always equal to the stock of machines. Each monopolist has a competitor who can produce the same machine at cost vR , so the monopolist sets the limit price $p_a(x) = vR$. The demand for a machine line for age group a for a given capital rental rate is then

$$\kappa_a(x) = \left(\frac{P_a}{vR} \right)^{\frac{1}{\beta}} h_a L_a \quad (2.6)$$

which is independent of the type x of machine. Production of intermediate goods then takes the form

$$Y_a = \frac{1}{1-\beta} \left(\frac{P_a}{vR} \right)^{\frac{1-\beta}{\beta}} X_a h_a L_a \quad (2.7)$$

Combined with equation 2.3, this means that

$$\frac{P_a}{P_b} = \left(\frac{X_a h_a L_a}{X_b h_b L_b} \right)^{-\frac{\beta}{\sigma}} \quad (2.8)$$

where $\sigma = 1 + (\epsilon - 1)\beta$ is the elasticity of substitution between worker age groups conditional on fixed technology.

2.2.4 Monopoly profits for machine blueprint owners

The stream of profits per unit of κ_a is $(v-1)R$, so the stream of profits per machine blueprint is

$$\pi_a = (v-1)R\kappa_a = \frac{v-1}{v} P_a^{\frac{1}{\beta}} h_a L_a (vR)^{\frac{\beta-1}{\beta}} \quad (2.9)$$

⁵This is like assuming that one unit of capital can produce one unit of machine per unit of time and then machines depreciate fully but capital does not. The reader can think of machines as capital that has been temporarily repurposed for a specific method of production.

2.2.5 Demand for labor

The profit maximization condition with respect to labor is that

$$w_a = \frac{\beta}{1-\beta} P_a (h_a L_a)^\beta L_a^{-1} \int_0^{X_a} \kappa_a(x)^{1-\beta} dx$$

Combined with the condition for machines, this gives us that

$$w_a = \frac{\beta}{1-\beta} P_a^{\frac{1}{\beta}} (vR)^{-\frac{1-\beta}{\beta}} X_a h_a \quad (2.10)$$

which means that the relative wages are

$$\frac{w_a}{w_b} = \frac{X_a}{X_b} \left(\frac{P_a}{P_b} \right)^{\frac{1}{\beta}} \frac{h_a}{h_b} \quad (2.11)$$

Combining 2.11 with 2.8 gives

$$\frac{w_a}{w_b} = \left(\frac{X_a h_a}{X_b h_b} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{L_a}{L_b} \right)^{-\frac{1}{\sigma}} \quad (2.12)$$

2.2.6 Allocation of capital

Because one unit of capital produces one machine and machine varieties are symmetric industries within age groups, $K_a(x) = \kappa_a(x)$, the total capital used in an intermediate good market is

$$K_a = \int_0^{X_a} \kappa_a(x) dx = X_a \kappa_a = X_a \left(\frac{P_a}{vR} \right)^{\frac{1}{\beta}} h_a L_a \quad (2.13)$$

Foregone consumption produces capital K , which is allocated between the intermediate goods markets to produce machines. The relative capital allocations (using the relative prices already derived) are

$$\frac{K_a}{K_b} = \left(\frac{X_a h_a L_a}{X_b h_b L_b} \right)^{\frac{\sigma-1}{\sigma}} \quad (2.14)$$

We can find the values of capital allocated to each age group by considering that

$$K_a = K \left[\sum_b \frac{K_b}{K_a} \right]^{-1} = K \left[\sum_b \left(\frac{X_b h_b L_b}{X_a h_a L_a} \right)^{\frac{\sigma-1}{\sigma}} \right]^{-1} \quad (2.15)$$

which we will need to determine the levels of technology for each age group.

2.2.7 Interest rates

In order to get the rental rate, write the intermediate good output as

$$Y_a = \frac{1}{1-\beta} K_a^{1-\beta} (X_a h_a L_a)^\beta \quad (2.16)$$

and note that the marginal product of capital in this market is

$$MPK_a = (1-\beta) P_a \frac{Y_a}{K_a} \quad (2.17)$$

Capital market equilibrium requires that $vR = MPK_a$, so

$$P_a Y_a = R K_a \frac{v}{1-\beta} \quad (2.18)$$

The intermediate goods markets adjust so that there are zero profits in the final good market, so the sum of the five age-group-specific versions of Equation 2.18 must equal Y , which requires that

$$R = \frac{1-\beta}{v} \frac{Y}{K} \quad (2.19)$$

The interest rate in this economy must be the rate that could be earned by producing capital:

$$r = (1-\tau) R - \delta = (1-\tau) \frac{1-\beta}{v} \frac{Y}{K} - \delta \quad (2.20)$$

where τ is the tax rate on capital income and δ is the rate of capital depreciation.

2.2.8 Consumption Demand

For simplicity, assume a continuum of measure⁶ 1 of infinitely-lived consumers with CRRA preferences over a single consumption good over time. Consumers can borrow and lend at the interest rate r . The representative consumer earns income equal to the aggregate output of final goods and spends it on consumption C , investment in capital I , and research and development efforts $R\&D$.

⁶The choice of size of the consumer base does not impact the results, because this analysis looks at income per worker rather than income per consumer. This normalization is simply convenient for talking about a representative consumer.

With preferences ordered by

$$U = \int_0^\infty e^{-\rho t} \frac{C_t^{1-\theta} - 1}{1-\theta} dt \quad (2.21)$$

consumption growth will be

$$\frac{\dot{C}}{C} = \frac{1}{\theta} (r - \rho) \quad (2.22)$$

Thus along the balanced growth path (BGP), r must be constant.

2.2.9 Technological innovation

There are multiple countries that build their own stock of technology with $R\&D$ expenditures (foregone consumption) with the following innovation possibilities frontier:

$$\dot{X}_a = \frac{\eta_a R\&D_a}{\zeta hL} \quad (2.23)$$

where $\sum_a R\&D_a = R\&D$, L is the size of the labor force, $h = \sum_a h_a \frac{L_a}{L}$ is the average human capital of the labor force, X_a^W is the world frontier technology, η_a determines age-specific productivity of innovation⁷, and ζ is a country-specific innovation entry barrier that tells us how many units of R&D expenditure are equivalent to one unit of R&D expenditure in the US (with the normalization that $\zeta_{USA} = 1$). $\frac{R\&D_a}{\zeta}$ should be thought of as the effective expenditure on R&D, with any losses due to poor institutions.

This form is different from that used by Acemoglu because $R\&D$ expenditures are scaled by the size of the labor force to reduce scale effects. I justify this by recognizing that people compete to produce new technologies by partially duplicating efforts. Additionally, the purpose of the innovation technology in this paper is to fit sectoral differences *within* countries. It is not within the scope of the work to explain international variation in outcomes with differences in average human capital, and this functional form allows us to abstract away from that issue.

Although the owners of machine blueprints produce their machines with some market power once they have the blueprint, there is free entry into innovation. One unit of R&D expenditure produces a stream of $\frac{\eta_a}{\zeta} \frac{1}{hL}$ new blueprints, each with a present value V_a , so free entry requires

$$1 = \frac{\eta_a V_a}{\zeta hL} \quad (2.24)$$

⁷I consider and reject a version without η . See Appendix C.

and

$$\frac{V_a}{V_b} = \left(\frac{\eta_a}{\eta_b} \right)^{-1} \quad (2.25)$$

2.2.10 Characterizing the balanced growth path

No arbitrage requires that

$$rV_a = \pi_a + \dot{V}_a \quad (2.26)$$

This application deals only with the balanced growth path⁸. Along the BGP, $\dot{V}_a = 0$. Using the value for instantaneous profits from Equation 2.9, the BGP values of machine blueprints must satisfy

$$V_a = \frac{\pi_a}{r} = \frac{v-1}{vr} P_a^{\frac{1}{\beta}} h_a L_a (vR)^{\frac{\beta-1}{\beta}} \quad (2.27)$$

and

$$\frac{V_a}{V_b} = \left(\frac{P_a}{P_b} \right)^{\frac{1}{\beta}} \frac{h_a L_a}{h_b L_b} = \left(\frac{X_a}{X_b} \right)^{-\frac{1}{\sigma}} \left(\frac{h_a L_a}{h_b L_b} \right)^{\frac{\sigma-1}{\sigma}}$$

using Equation 2.8 to give us the relative prices. Combining this with the equilibrium condition in 2.25 gives us a relationship between relative technology between age groups, relative frontier technology between age groups, and relative productivity of innovation between age groups:

$$\frac{X_a}{X_b} = \left(\frac{h_a L_a}{h_b L_b} \right)^{\sigma-1} \left(\frac{\eta_a}{\eta_b} \right)^{\sigma} \quad (2.28)$$

We can get this relationship in terms of relative wages, which are observable, rather than relative technologies, which are not, by using the labor market equilibrium condition in Equation 2.12:

$$\frac{w_a}{w_b} = \left(\frac{\eta_a}{\eta_b} \right)^{\sigma-1} \left(\frac{h_a}{h_b} \right)^{\sigma-1} \left(\frac{L_a}{L_b} \right)^{\sigma-2} \quad (2.29)$$

Knowing the relative technologies (Equation 2.28) will allow us to determine the actual levels of technology, which we will want in order to estimate the technical frontier. Using Equation

⁸Although Acemoglu (2007) showed that off-BGP trends may be needed to match historical changes in skill premia because the price effect dominates the short run and the market size effect often dominates in the long run, I do not expect this to be a substantial weakness of my work. The reason is that when workers age, they are simply moving to a different but established role in the economy rather than changing the expected distribution of workers across ages. If there were instead a sudden, unexpected age demographic shock, then this could cause problems for this analysis. The baby boom is one potential shock, but innovators had over an entire decade to prepare for this shock (average fertility rates are not private information). Other potential shocks are wars, which may differentially kill young, male workers) and diseases, which often differentially kill older workers).

2.16 and the final good production function,

$$Y = \frac{1}{1-\beta} \left(\sum_a \left[(h_a L_a X_a)^\beta K_a^{1-\beta} \right]^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}$$

$$\Rightarrow X_b = \left[\frac{Y(1-\beta)}{\left(\sum_a \left[\left(h_a L_a \frac{X_a}{X_b} \right)^\beta K_a^{1-\beta} \right]^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}} \right]^{\frac{1}{\beta}} \quad (2.30)$$

where the values of K_a above are those determined by Equation 2.15.

Combining the condition on relative technologies in Equation 2.28 with what we know about relative intermediate goods prices from Equation 2.8, we find that

$$\frac{P_a}{P_b} = \left(\frac{h_a L_a}{h_b L_b} \right)^{-\beta} \left(\frac{\eta_a}{\eta_b} \right)^{-\beta} \quad (2.31)$$

which depends only on observables (when we substitute the values for relative η from Equation 2.29). Using the price normalization from Equation 2.2 we find a form for the levels of intermediate goods prices that also depends only on observed values. They must satisfy

$$P_a = \left[\sum_b \left(\frac{P_b}{P_a} \right)^{1-\epsilon} \right]^{\frac{-1}{1-\epsilon}} \quad (2.32)$$

2.2.11 Bias and elasticities of substitution

“Weak bias” is defined to mean that when the relative supply of a factor increases its relative technology also increases. This is equivalent to saying that demand for the factor increases when its supply increases (see Figure 2.2). “Strong bias” occurs when an increase in the relative supply of a factor leads to an increase in its relative wage, which occurs when there is a large increase in demand for the factor due to increases in technology.

It is clear from Equation 2.28 that we have weak bias as long as $\sigma > 1$. That is: any increase in the relative total human capital of a particular age group induces a relative increase in the technology used by that age group. Note that an increase in human capital could occur either because the quantity of labor supplied increases or because the average human capital of workers

increases.

Strong bias requires more strict conditions on substitutability of workers. Using Equation 2.29 we can see that an increase in the relative average human capital of a particular age of workers will always increase their relative wage when $\sigma > 1$, but an increase in the labor share supplied by a particular age group will lead to an increase in its relative wage only when $\sigma > 2$ ⁹.

The wage used in Equation 2.29 is not the wage for the factor that really matters for production. Rather firms care about the total human capital provided to them. If we were to look at the typical story of technical bias using this model, we would ask how changes in the total human capital provided to a sector impact the wage earned (or technology used) by a unit of human capital in that sector. Although the question that interests us is not “how much does human capital earn?” but “how much do people earn?”, seeing if we have strong bias in the typical sense requires knowing the wage per unit of human capital:

$$\frac{w_a/h_a}{w_b/h_b} = \left(\frac{\eta_a}{\eta_b}\right)^{\sigma-1} \left(\frac{h_a L_a}{h_b L_b}\right)^{\sigma-2} \quad (2.33)$$

As expected (because we are taking average human capital as exogenous, and producers care only about the total human capital they hire), the relative wage per unit of human capital depends only on the relative total human capital between age groups. We have strong technical bias as long as $\sigma > 2$. It is not surprising that this condition is the same as the one for strong bias using just the relative supplies of labor. The reason is that the total human capital can be increased either by increasing the quantity of labor supplied or by increasing the average human capital. Thus the condition for strong bias from increasing total human capital will be the stronger of the conditions for getting strong bias from either of these. This result for bias in the relative wages paid to human capital is the same as for those paid to labor in Acemoglu (2002).

⁹Alternative forms for the innovation possibilities frontier might include international technical spillovers (see e.g. Jerzmanowski and Tamura, 2015), but they have only a minor impact for this analysis, so I leave them out for simplicity. The condition for strong bias in the case with international technical spillovers of stronger, but assuming these spillovers also can change estimates for the elasticity of substitution by the same magnitude as the change in the threshold for strong bias (see Section 1.11)

2.3 Data

2.3.1 Income, labor force, and physical capital

The data on income, physical capital, populations by age group, labor force size, and human capital are from Tamura, Dwyer, Devereux and Baier (2015) (TDDB), who get their income data mainly from the Maddison Project. The data include observations on 146 countries over the years 1790 to 2010.

Early in the sample, the number of countries represented is small relative to late in the sample (one country in 1790, 16 in 1800, and 54 in 1820 compared to 146 in 1990). I use only the data from 1820 on, because there are so few countries present before 1820. The data from TDDB are available at variable frequencies. I construct decadal data by interpolating¹⁰ the values for countries whose data are for years other than multiples of 10.

Because these data do not include explicit information on the amount of labor supplied from particular age groups, I assume that persons from every (working age) age group are equally likely to supply labor. Thus if L is the size of the labor force and s_{1524} is the proportion of the working aged population¹¹ that is aged 15–24, then the size of the labor force for ages 15–24 is taken to be $s_{1524}L$. I also assume that members of the labor force have the same average human capital as the population in their age group.

2.3.2 Human capital

The human capital estimates have with intergenerational transfers and between-country spillover effects as in TDDB. This form reflects the fact that parents with more human capital can invest more in their children’s human capital through efforts outside of the labor market and schooling. The international spillovers reflect the possibility that more investment in human capital in one place may improve the available technology for human capital production.

I do not allow experience to impact human capital because this effect may confound the technology effects discussed here. For instance, if people begin to earn lower wages late in life, this may be due either to the technology available to them or to changes in human capital. This

¹⁰Most data years are multiples of 10, so this only matters in a few cases.

¹¹Working age is 15–64 in this case. Some members of the labor force are outside of this age range, and the validity of this approach depends on the number of such workers being small.

specification allows us to address how changes in the technology used throughout life can account for observed age-earnings profiles.

The algorithm for calculating the human capital data is taken from TDDB. It includes three major components:

- Higher average schooling raises the cohort’s human capital.
- Intergenerational transfers raise the human capital of a cohort if the previous cohort in that nation had high human capital.
- There are positive externalities on human capital accumulation from the world supply of human capital.

For comparison, I also solve the model with human capital with an experience effect (again as in TDDB), where the size of the effect of experience is based on estimates from Klenow and Rodríguez-Clare (1997).

2.3.3 US wages

Relative wages for different age groups in the United States come from wage micro data for full-time workers¹² over 16 from the US Census from 1940 to 2010 (Ruggles et al., 2010), which reports the income each person earned from wages over the last year and the number of weeks the person worked over the last year. These data are censored, and every person who earned more than the top code is assumed to earn 150% of the top code.

Although one of the age groups in this paper is persons aged 15 to 24, the Census gives wage data only for persons older than 16, so I must assume that the average wages of persons aged 15 to 24 are similar to average wages of persons aged 16 to 24.

Because Tamura et al. (2015) use average schooling levels to construct their human capital estimates, in order to be consistent, I use only workers whose schooling attainment is within one year of the average they report.

Table 2.1 shows the average relative wage values (rounded) used in section 2.4 to find the age-specific research productivities. These are not real wages and are comparable only within time periods. Only their ratios for this analysis.

¹²Full time workers here are those for whom the WKSWORK2 variable—as defined by IPUMS—is 4, 5, or 6. From 1950 on, these are workers who worked at least 40 weeks for profit or pay in the previous calendar year. In 1940, these are workers who estimated that they worked an equivalent of 40 full-time weeks or more in the previous calendar year.

Table 2.1: Relative US wages by age group

Year	15-24	25-34	35-44	45-54	55-64
1940	1	1.531094	1.858733	2.000964	1.981202
1950	1	1.433281	1.565728	1.56728	1.605344
1960	1	1.503833	1.657948	1.640844	1.604354
1970	1	1.557603	1.556575	1.607562	1.507444
1980	1	1.476986	1.680514	1.603107	1.572386
1990	1	1.714991	2.062006	2.022685	1.735932
2000	1	1.601674	1.778192	1.907719	1.738758
2010	1	1.708349	2.088417	1.984855	1.912004

In any given year, the youngest people have the lowest wages. While younger people may have lower education because they have not yet finished their education, I selected only the workers whose education is similar to the lifetime average for their cohort. If there is a problem, it is not that I ignore education but that young people who finish their education early might be systematically different from those who finish their education later. This is unlikely to be an issue for older age groups, since the average education for a cohort in the US is never more than three years of college. While work experience almost certainly contributes to wage differences between ages, the point of this paper is to imagine a world in which this is not true so that we can put upper bounds on the strengths of other effects.

One important question for this analysis is what shape of age-earnings profile we should expect to reproduce. Although many macro estimates produce declining late-life wages (e.g. Bils and Klenow, 2000; Klenow and Rodríguez-Clare, 1997; Tamura et al., 2015), Murphy and Welch (1990) and Murphy and Welch (1992) found that these declines were small or non-existent and Casanova (2013) showed that individual wage per hour of work may not decline over the normal working life, whereas measured reductions are typically due to averaging over people who work different amounts. Even though this paper averages wages over workers with variable hours worked, all of these workers reported working more than 40 hours per week, which should limit reductions due to retirement and increased part-time work. After deflating the calculated wage levels by the Urban Wage Earners and Clerical Workers CPI, the wage data recreate the pattern of increasing wages over the entire (working) lifetime, as seen in Figure 2.3. If the US is typical, then a good fit by the directed technology model would produce increasing wages over the normal working lifetime with reductions in the rate of growth of wages (but not reductions in the levels of wages) later in life.

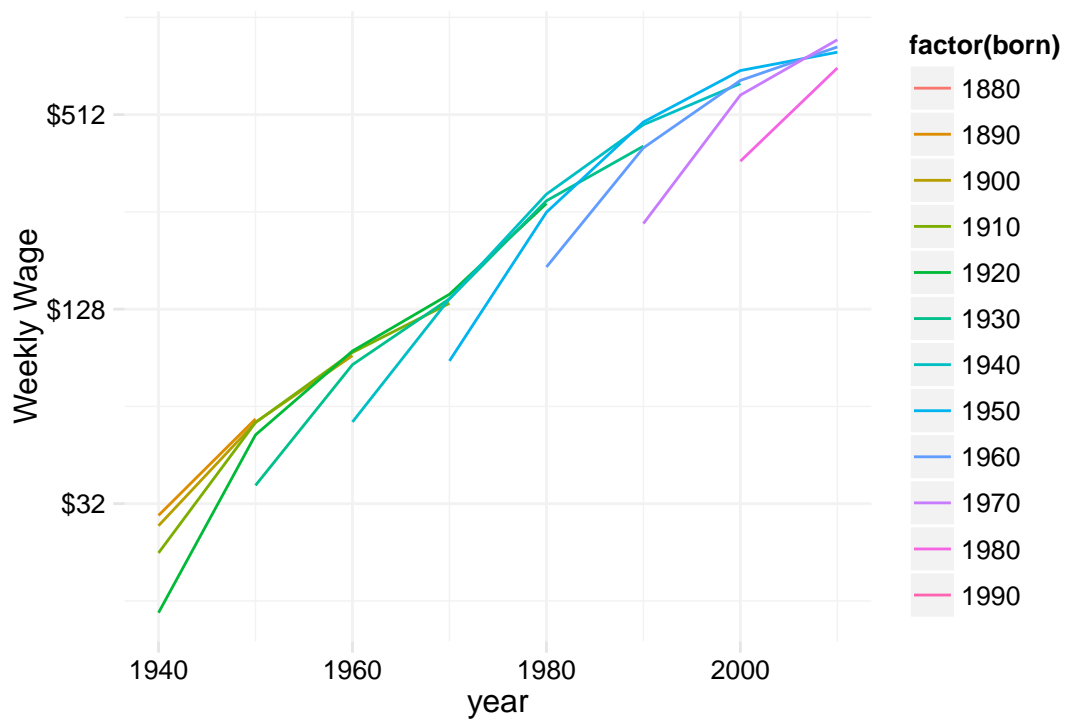


Figure 2.3: Each US cohort's wages rise throughout its life

2.4 Fitting the model

2.4.1 Solution algorithm

I assume that the data are observations from balanced growth paths (BGP). For each decade a new BGP for each country can be calculated using the following process:

1. Choose values for the parameters σ , β , v , ρ , θ , g and δ .
2. Use Equation 2.29 to calibrate the values of η (the age-specific innovation productivities) to the US wage data. Assign the 1940 values of $\frac{\eta_a}{\eta_b}$ to each of the years before 1940, because there are not appropriate wage data for those years.
3. Construct relative wages for each of the other countries with Equation 2.29.
4. Solve for $\frac{X_a}{X_b}$ using Equation 2.28.
5. Solve for $\frac{K_a}{K_b}$ using Equation 2.14.
6. Solve for levels of
 - (a) K_a using Equation 2.15,
 - (b) K_b using Equation 2.15,
 - (c) X_a using Equation 2.30,
 - (d) sectoral prices using Equation 2.4, and
 - (e) wages using Equation 2.10.

2.4.2 Parameters

2.4.2.1 β , v , ρ , g , and r

I choose $\beta = 2/3$ in line with a long tradition of estimates on the share of income going to capital (Mankiw et al., 1992; Klenow and Rodríguez-Clare, 1997; Hall and Jones, 1996, 1999b; and Caselli, 2005 among many others). I use a value of 1.4 for the markup v in line with the work of Basu (1996), Norbin (1993), Comín (2004), and Jerzmanowski and Tamura (2015). I follow Jerzmanowski and Tamura (2015) and choose the inter-temporal elasticity of substitution to be 1,

the time discount rate to be 0.04, the depreciation rate to be 6%, and the frontier productivity growth rate to be 1.2%. Together these choices produce an equilibrium world interest rate (in the absence of capital distortions) of 5.2%.

2.4.2.2 Elasticity of substitution, σ

Card and Lemieux (2001) estimate the elasticity of substitution between age groups of workers with the same education level in the US, UK, and Canada, with typical estimates ranging from 4 to 6. Although the interpretation of this elasticity differs slightly from σ , the elasticity of substitution between human capital from different age groups, if workers of different ages from the same education group have similar human capital, then the measures should be similar. In fact, the elasticity of substitution between labor provided by different age groups is the same in our model as the elasticity of substitution between human capital provided by different age groups (provided that average human capital is not permitted to respond to changes in labor supply). The comparability between their case and ours is helped by the fact that they use workers with exactly a high school degree or exactly a 4-year college degree. Their specification—like ours—imposes that the elasticity of substitution between age groups is the same within college-educated and high-school-educated groups. Hopefully future work will test this restriction.

Chapter 1 shows that the Card and Lemieux estimates may be inappropriate in the presence of directed technology and estimated σ with almost the same model setup used here with estimates at approximately 2 and a lower bound around 1.8.

$\sigma = 2$ is the boundary between strong and weak bias and is consistent with estimates from Chapter 1, so I report estimates with this value in the main body of this chapter. Because estimates by Card and Lemieux (2001) are well above the level needed for strong bias and estimates in Chapter 1 cluster near the boundary between strong and weak bias, I am fairly confident that performing the analyses with values of 6, 3, 2, and 1.7 (both lower than all estimates from Chapter 1 and a typical value for the elasticity of substitution between high and low-skilled workers) for σ will give a good idea of the possible solutions. Appendix B reports results with multiple values for σ , finding that the estimates change little when σ is allowed to vary over a reasonable range. This chapter reports only results with $\sigma = 2$ for brevity.

2.5 Sources of life-cycle wage profiles in detail

2.5.1 Why does wage growth fall late in life?

To understand why wages fall late in life in this framework, think about human capital shares or relative human capital. When an age group supplies a large share of the human capital in a country, technology will heavily complement that age group. Thus different age groups essentially compete for wage-raising technologies.

Directed technology works on input shares, and an increase in the human capital share for one age group will always increase its relative technology (for reasonable values of σ), but this report is interested in the impact on wages. Human capital shares are determined both by labor shares and by relative human capital per worker. Section 2.2.11 already showed that increasing relative human capital per worker always increases relative wages and that whether an increase in relative labor supply increases or decreases relative wages depends on σ .

There are three possible scenarios, depending on the value of σ :

Scenario 1: strong bias If σ is large enough for strong bias, then a decrease in the *share* of total human capital possessed by an age group is sufficient to put downward pressure¹³ on their wage.

Scenario 2: weak bias If σ is much smaller than the boundary between strong and weak bias (but still larger than 1—a constraint of little concern, given estimates from Chapter 1), then a decrease in the average human capital *per worker* in an age group relative to other workers' human capital¹⁴ is necessary but not sufficient for directed technology to exert downward pressure on their wages. A decrease in the human capital share is not sufficient in this case, because decreases in the share of the labor force made up by an age group will push their wages up, working against this effect.

Scenario 3: boundary If σ is on the boundary between weak and strong bias (as we estimated—see section 2.4.2.2), then changes in labor force shares will have negligible effects on wages, and any changes in average human capital will dominate. Thus in this case, a decrease in

¹³We say “downward pressure” because there are factors that contribute to a general upward trend in wages, and we will discuss these shortly.

¹⁴Note that this is not the same as their individual human capital falling, since relative human capital can fall simply by being in a world where others have more human capital

the average human capital possessed by workers of their age group relative to that possessed by other workers is sufficient to put downward pressure on wages.

Table 2.2 helps to organize this information.

		$\uparrow \frac{h_a}{h_b}$	$\uparrow \frac{L_a}{L_b}$	$\uparrow \frac{h_a L_a}{h_b L_b}$
Strong bias:	$\sigma > 2$	$\uparrow \frac{w_a}{w_b}$	$\uparrow \frac{w_a}{w_b}$	$\uparrow \frac{w_a}{w_b}$
Weak bias:	$\sigma < 2$	$\uparrow \frac{w_a}{w_b}$	$\downarrow \frac{w_a}{w_b}$	Ambiguous
No bias:	$\sigma = 2$	$\uparrow \frac{w_a}{w_b}$	No effect	Ambiguous

Table 2.2: Effect of changes in the relative human capital and labor shares on relative wages conditional on σ , the elasticity of substitution between worker age groups

Human capital shares fall as people age for three main reasons:

- First, the size of a cohort declines over time as members die.
- Second, in many places new generations are larger than the previous generation because of high fertility (it takes very low fertility by historical standards for this to not be true).
- Third, younger generations usually have more average human capital than older generations: parents invest in growing the wealth of their dynasties.

These facts increase the market size for technologies directed at younger workers, thereby raising the relative technology for young workers. The first and second facts will contribute to higher wages for young workers only in the first scenario (strong bias), whereas the third fact contributes to higher wages when young for any reasonable values of σ .

If the human capital effects dominate the population demographic effects or if the elasticity of substitution is high, then workers will see their wages stagnate as they age. Because Chapter 1 estimates the elasticity of substitution to be statistically indistinguishable from the cutoff between strong and weak bias, I assume that population share changes have a small effect on relative wages.

Figure 2.4 shows that human capital shares for younger age groups are indeed higher than for older age groups in the US. Other countries typically produce the same result. We also see this pattern even though the United States (like many other countries) is aging, as seen in Figure 2.5. This occurs because of increases in education over time and intergenerational transfers of skills.

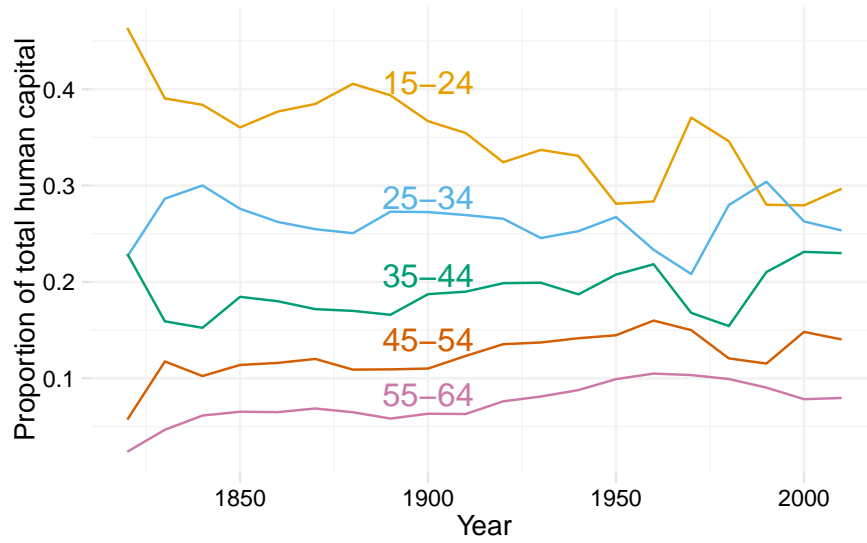


Figure 2.4: Age distribution of human capital in the US

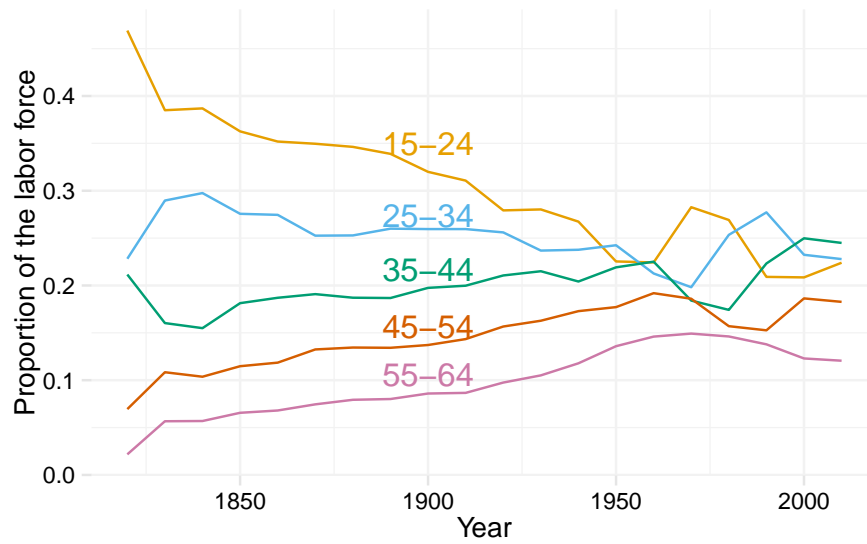


Figure 2.5: Age distribution of labor in the US

If we split these data up into time series for each cohort, the pattern becomes even more clear. Figure 2.6 does this with human capital for each cohort relative to the human capital of 15–24-year-olds in the given year. Every curve starts at 1, because each cohort consists of 15–24-year-olds when it is young. Because of increased schooling over time and inter-generational transfers, workers almost always lose relative human capital throughout their lives even though the actual level of human capital is constant for each cohort by construction. What matters here is that they have less human capital than the younger generations that follow them.

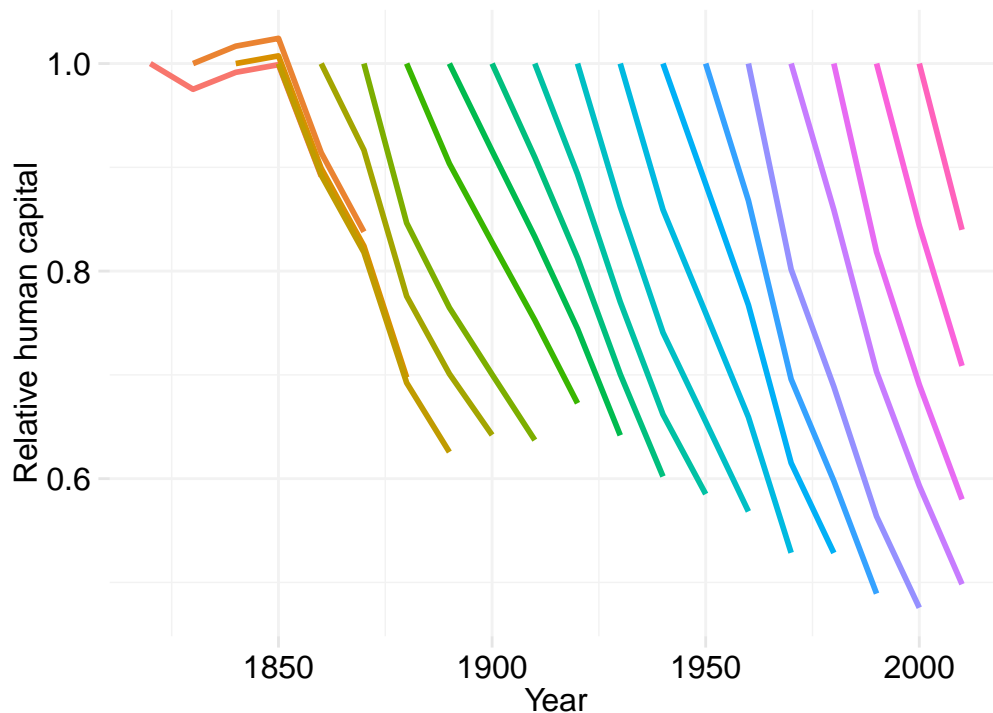


Figure 2.6: Cohort human capital per worker relative to 15–24-year-olds’ in the US

So far we have discussed relative wages between age groups *within* the same time period, so this analysis does not exactly tell us what will happen to people as they age. However, if age groups’ relative technologies are fairly constant over time and the levels of technologies are fairly constant, then moving into a different age group will produce wage gains that can be captured well by looking at the relative technologies for the two age groups involved.

2.5.2 Why do wages rise early in life?

We have explained why wages would fall over a worker's life, but why do they first rise? Equation 2.29 is shown again below to help with the exposition.

$$\frac{w_a}{w_b} = \left(\frac{\eta_a}{\eta_b}\right)^{\sigma-1} \left(\frac{h_a}{h_b}\right)^{\sigma-1} \left(\frac{L_a}{L_b}\right)^{\sigma-2} \quad (2.29 \text{ revisited})$$

We have already discussed the roles of human capital and labor. The other factor affecting relative wages is the relative productivity of innovation, which I estimate to rise over the lifetime, as seen in Figure 2.7. The reason why wages are highest in midlife is essentially that there are decreasing returns to η and to human capital, so wages are higher when each term is at a medium level than when one term is large and the other small. Middle age is the time when a cohort both possesses somewhat high relative human capital and easy innovation.

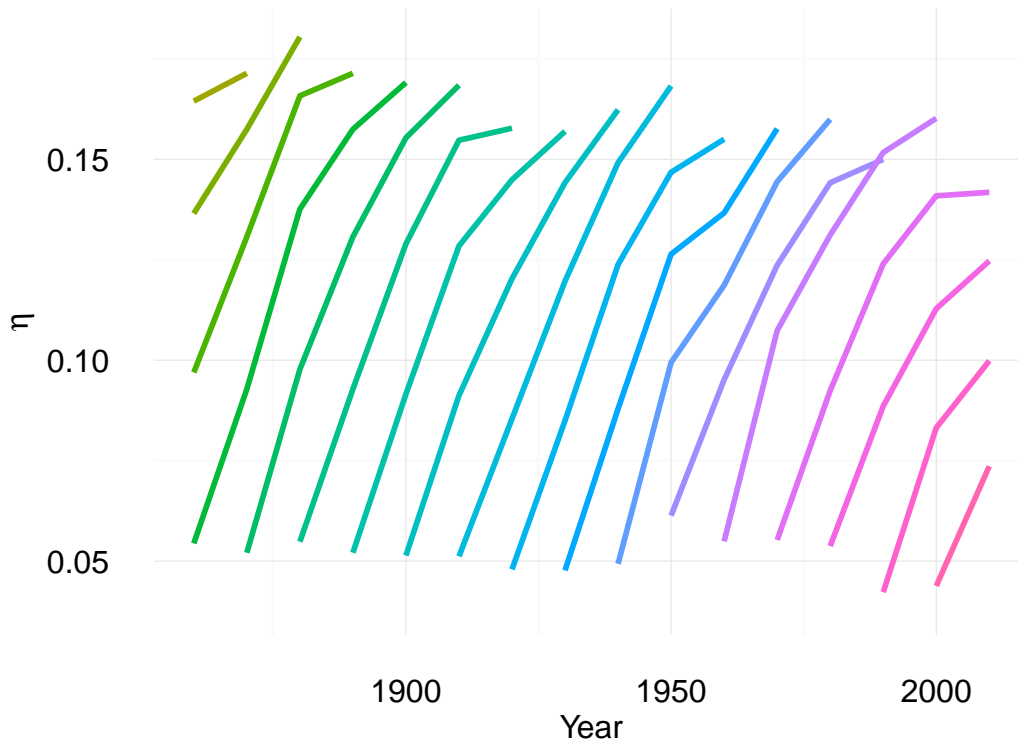


Figure 2.7: Fitted productivities of innovation, η , for each cohort throughout its life

In addition to η 's effect on *relative* wages, generic growth of technology over time raises the *levels* of wages, but this effect is small compared to the role played by movements into and out of

groups with higher or lower η s¹⁵.

2.6 Wage hills produced by the model

In fitting the model I produce wages for each age group in each country in each year without allowing a cohort's human capital to change throughout its life. I also construct work experience as the number of years that a cohort has been in the labor force on average, finding that for most cohorts wages rise and then plateau over the working life.

Figure 2.8 shows typical life-cycle wage trends for the United States, France, and China (see Appendix D for the same patterns for all countries). Each line is the life path of one birth cohort. For instance, the highest curve in the graph for France tells us how the wages constructed for French people born between 1946 and 1955 (with an average approximately in 1950) grow throughout their lives. 1950 is the last cohort that has completed its normal working age. Later cohorts are generally higher in the graph because incomes around the world grew over our sample period. Maximum experience falls for later cohorts because they spend more time in school on average. These graphs clearly show the point that in many cases the model's predicted wages rise and then plateau over the working life.

It is interesting to note that the analysis does not predict that this trend holds at all times in all countries. For instance, the 1950-born and 1930-born cohorts in China see rapid growth of predicted wage throughout their lives as they worked through a period when total factor productivity exploded. The reason for these exceptions is that the mechanisms described in the Section 2.5.1 are weak in these cases. There is nothing inherent in the theory that requires quadratic experience-earnings profiles; they are instead a product of the observed labor demographics. However, this does not mean that we should expect to see wages growing steadily throughout life in actual data in all of the exceptional cases, because the mechanism used here is not the only one that matters. These results do not undermine the extant theories that explain hill-shaped life cycle earnings trends. Micro effects as identified by Ben-Porath and Mincer almost certainly produce declining wage growth in many cases. However, these results suggest caution when talking about the causes of late-life wage reductions because the evidence is ambiguous and some of the trend could be explained by directed

¹⁵Eliminating the differences in η by setting $\eta_{at} = 1 \ \forall a, t$ eliminates much of the upward trend in wages for a cohort. This is not to say that long-run productivity growth is not important—it simply does not explain well the observed life-cycle patterns.

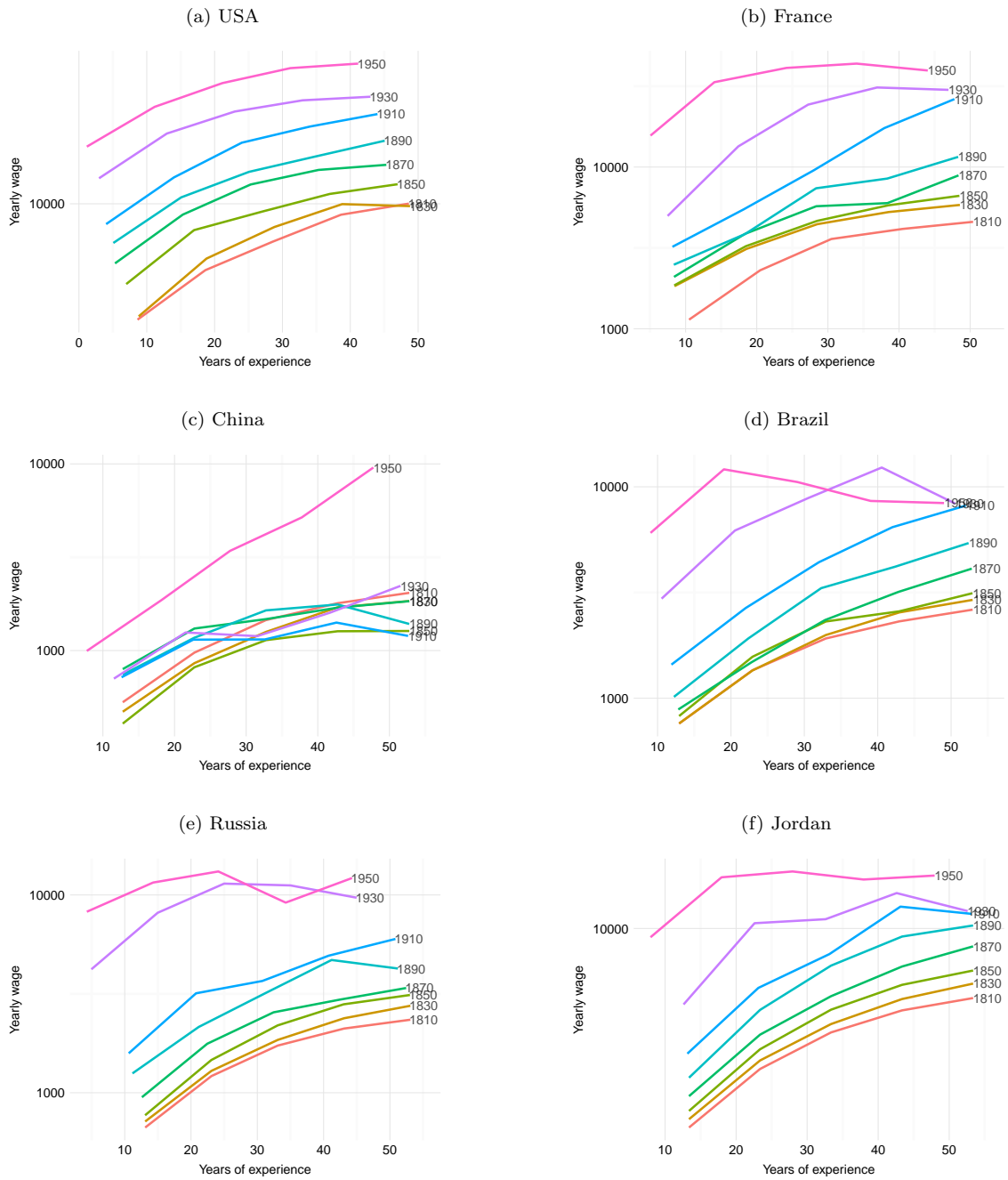


Figure 2.8: Predicted wage for each cohort throughout their lifetimes as they gain experience

Note: More recent cohorts are typically higher

technology.

The reader should recall that the model and data proscribe Mincerian returns to experience by construction. The slopes of the curves in Figure 2.8 are what they are because of generic productivity growth, (somewhat arbitrary) differences in costs of innovation, and directed technology, which *mimic* returns to experience.

To estimate the average size of the apparent Mincer returns to experience that the model produces, consider regressions of the form

$$\ln(w_{c,t-a,t}) = T_t + \alpha_{c,t-a} + \gamma_1 \text{XPR}_{c,t-a,t} + \gamma_2 \text{XPR}_{c,t-a,t}^2 + \chi \frac{K_{c,t-a,t}}{L_{c,t-a,t}} + \mu_{c,t-a,t} \quad (2.34)$$

where $t - a$ indexes a birth cohort (indicated by its approximate birth year) in country c in year t . I consider specifications both with and without year fixed effects (imposing $T_t = 0 \ \forall t$) and with and without physical capital (imposing $\chi = 0$).

The case with the year fixed effects does a better job of forcing experience to capture only the changes due specifically to directed technology (rather than generic income growth over time, for instance), but the purpose of this exercise is not to show how much curvature is induced by directed technology. If it were, it would be pointless to use experience as a proxy. Rather this report is interested in *the ability of the theory to reproduce data that are typically explained as being a result of experience*. Thus the main interest is in the case without year fixed effects (e.g. $T_t = 0 \ \forall t$), which allows experience to capture all of the (average quadratic) curvature in the lines in Figure 2.8 and is more in line with others' work.

Accumulation of technology affects capital allocations between age groups and the incentives to purchase more capital, but we may wish to know how much of the curvature in earnings is due only to technology without allowing for these secondary effects. Some specifications of the regression include physical capital per worker to help answer this question, but the main interest of this paper is in fitting the cohort-level curvature in Figure 2.8 to experience, so the main interest is in regressions that do not include physical capital. Human capital is not included in the regressions because that is picked up by the fixed effects.

Results from these regressions are in Table 2.3. The primary estimate of interest, Regression 1, shows that on average a decade increase in work experience is associated with a proportional increase in real wage of approximately $.600 - .049$ (Decades of Experience) or that a year

increase in work experience is associated with a proportional increase in real wage of approximately .0606 – .0005 (Years of Experience). These are similar to the estimates of .0512 and -.00071 of the actual wage structure using international macro data from Bils and Klenow (2000) and preliminary estimates from an early (1996) copy of that same paper of .0495 and .0007, which were used in Klenow and Rodríguez-Clare (1997), Hall and Jones (1999a), and TDDB (the analysis in this chapter does not depend on those values, since I did not include any experience effect on human capital). Thus workers early in their career can expect to earn approximately 6% more after a year, whereas after 40 years in the labor force they could expect approximately a mere 2.08% raise over the next year. For comparison, world GDP growth is around (and the model solutions assume exactly) 2%.

Table 2.3: Wage-experience regression results

	Log of Yearly Wage			
	(1)	(2)	(3)	(4)
Decades of Experience	0.600*** (0.010)	-0.786*** (0.281)	0.152*** (0.010)	-0.441** (0.213)
Decades of Experience ²	-0.049*** (0.001)	-0.066*** (0.001)	-0.009*** (0.001)	-0.026*** (0.001)
Log Capital per worker			0.665*** (0.009)	0.574*** (0.008)
Wage maximizing exp (dec.)	6.14	-5.99	8.27	-8.35
Year FE	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>
Cohort×Country FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	9,889	9,889	9,889	9,889
R ²	0.717	0.266	0.838	0.579
Adjusted R ²	0.525	0.194	0.613	0.423

Notes: ***Significant at the 1 percent level.
 **Significant at the 5 percent level.
 *Significant at the 10 percent level.

The negative coefficients on Experience in regressions 2 and 4 in the presence of year fixed effects show that generic growth of worker productivity over time and fitted values of η s account for the positive slopes of the curves in Figure 2.8. However, concavity of the experience-earnings profile remains despite controlling for years.

Regressions 3 and 4 in Table 2.3 show that much of the upward trend in wages is explained by capital growth and allocation. When accounting for capital growth and allocation, wage raises

fall more slowly, but the location of the peak is still at approximately 60 years.

Figure 2.9 shows estimates from column 1 (without year effects or capital as a regressor) beside Bils and Klenow's (2000) values of .0512 and -.00071. My coefficient on the linear term is slightly larger than theirs and my quadratic term is slightly smaller, making the curve from the estimates in this paper steeper with a later peak. Note that the heights of the curves are not significant here, since the heights depend on the values of the covariates observed in the data, which I have simply assumed to be values that place the curves close together in the 10–30 years of experience range in order to draw the figure. In line with findings by Murphy and Welch (1990), Murphy and Welch (1992), and Casanova (2013) that older workers do not experience wage decreases as long as they remain in full-time jobs, the estimates from regression 1 place the peak beyond the usual working life. I believe that this is a strength of my fit over previous macro estimates (e.g. Bils and Klenow, 1996, 2000).

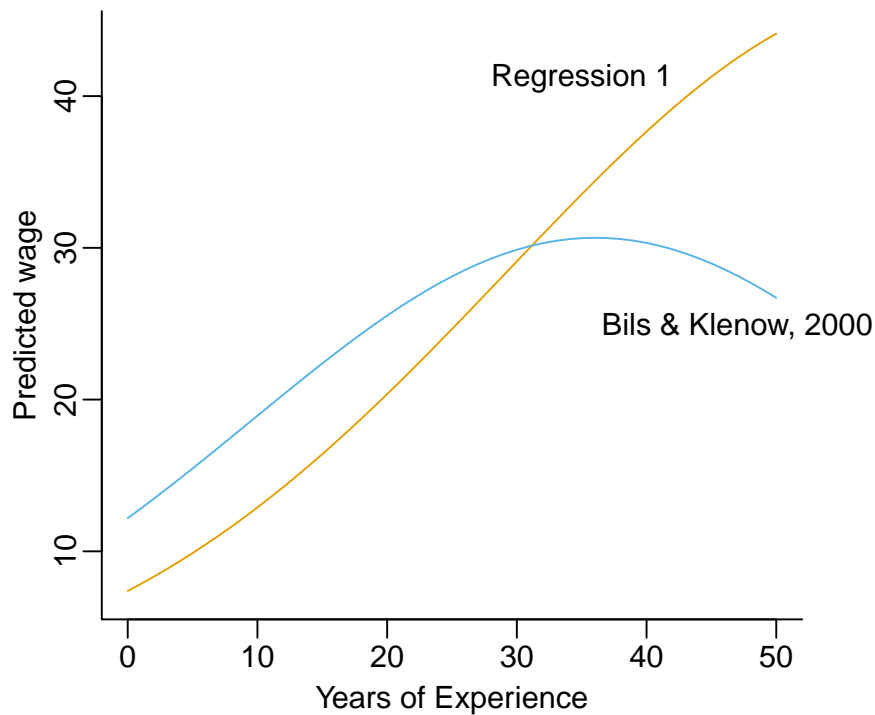


Figure 2.9: Predicted log wage from Regression (1) in table 2.4 and from Bils and Klenow (2000)

As an additional representation of this scenario, consider what would happen if we allowed work experience to impact human capital. In this case we would want to see if life cycle wage profiles have curvature that is not explained by TDDB's best estimate of the role of experience in producing

human capital. Thus we regress the wage per unit of human capital on experience:

$$\ln\left(\frac{w_{c,t-a,t}}{h_{c,t-a,t}}\right) = T_t + \alpha_{c,t-a} + \gamma_1 \text{XPR}_{c,t-a,t} + \gamma_2 \text{XPR}_{c,t-a,t}^2 + \chi \frac{K_{c,t-a,t}}{L_{c,t-a,t}} + \mu_{c,t-a,t} \quad (2.35)$$

Table 2.4 presents the estimates. We must reject the hypothesis that the quadratic term is negative, so these results do not show that directed technology explains wage curvature that is not explained by experience. However, there are two points to keep in mind with this result.

The first is that showing that DTC is necessary to explain wage hills is not the goal of this work. The point of this report is to show the ambiguity in the data: the theories that directed technical change causes wage curvature and that experience causes wage curvature are nearly observationally equivalent. Either or both could be the cause.

The second point is that the hypothesis test of a negative quadratic term is not very closely tied to the hypothesis that DTC induces curvature beyond that induced by experience effects. The reason is that experience effects on human capital are fit to observed age-earnings profiles. In fact the method of constructing human capital with experience effects presupposes that DTC does *not* induce wage curvature. Thus the test here is essentially the hypothesis that DTC could explain additional curvature that could not possibly be explained by a measure of experience constructed explicitly to match experience-earnings profiles. This test simply states that we cannot conclude that directed technology adds any explanatory power beyond the standard theories used to explain wage hills.

2.7 Discussion and conclusion

This work has attempted to show that directed technical change can account for some of the curvature in life cycle earnings without assumptions about on-the-job human capital accumulation that are typically needed to match the trend. This effect occurs because of the relative human capital of cohorts, supplementing other researchers' theories regarding the effects of individual human capital choices on life cycle earnings profiles. I should reiterate here that this chapter has not shown that directed technology replaces the other theories; what I have shown is that the framework can explain the same data. Some or all of the proposed theories could contribute to the observed effect. Future research should attempt to rule out theories based on more than just their ability to match this one

Table 2.4: Wage-Experience regression results with experience effect on human capital

	Log of Yearly Wage per unit of Human Capital			
	(1)	(2)	(3)	(4)
Decades of Experience	0.099*** (0.009)	0.041 (0.274)	-0.143*** (0.010)	0.303 (0.244)
Decades of Experience ²	0.006*** (0.001)	-0.003** (0.001)	0.034*** (0.001)	0.022*** (0.001)
Log Capital per worker			0.400*** (0.009)	0.339*** (0.008)
Wage maximizing exp (dec.)	-7.92	7.5	2.09	-6.8
Year FE	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>
Cohort×Country FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	8,814	8,814	8,814	8,814
R ²	0.402	0.001	0.535	0.205
Adjusted R ²	0.295	0.001	0.392	0.150

Notes:

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

effect.

This chapter has three major implications for estimations of human capital and returns to schooling:

- Changes in experience are negatively correlated with changes in cohort human capital relative to the workforce in late life and, therefore, with changes in age-specific productive technology.
- Individual investments in human capital are correlated with cohort investments in human capital and, therefore, with changes in productive technology. This correlation can create an illusory correlation with individual wages.
- Individual investments in human capital have external effects on other workers' productivity through the directed technology mechanism, and estimates of returns to education or other human capital investments should include this effect.

Consider estimates of human capital derived from fitting life cycle earnings trends. If the human capital estimates are required to account for the entire variation in wages, then the variance of human capital will be high. Allowing directed technical development to explain some of the variance

in wages will produce human capital estimates that change less over the life time (potentially more in the limited set of cases with empirical relationships with little curvature). This is a problem for the methodology as in TDDB and Klenow and Rodríguez-Clare (1997), but it is not a problem where entire age-earnings profiles of persons with the *same* age are compared (see Psacharopoulos 1994, for examples).

Another important aspect of this result is in what it says about estimates of the returns to investment in human capital. Past research (following specifications by Mincer, 1974) has attempted to measure the cost of investments at different periods of a worker's career and estimated the returns based on their increased earnings. The actual private returns to investment are the wage gains that would occur with the effects of directed technology (and general improvements in productivity) removed. Because the direction of technical bias is likely positively correlated with rates of human capital accumulation, the results in this report suggest that this past research underestimates the returns to investments in education or other skill acquisition late in life (and overestimates the value early in life). Research comparing the lifetime earnings paths of similar workers that do and do not invest does not face this problem (again see Psacharopoulos 1994, for examples) and could help to measure the size of the curvature due to technology effects.

This research suggests an additional measurement error in past estimates of returns to human capital investment. While researchers have rightly emphasized the importance of the social costs and benefits of education (Psacharopoulos, 1994), those estimates often will not sufficiently account for the external effect a worker has on the technology available to her cohort when she invests in human capital.

These results have implications for broader issues in development. Much of growth literature has focused on the necessity of properly measuring the inputs to production. Klenow and Rodríguez-Clare (1997), for instance, attempt to show that better measurements of factors can produce estimates of their roles in income growth and differences that are much higher than previous estimates. The results here show that proper accounting of post-schooling human capital investments may be less important than it seems immediately. Although Mincer (1974) lauded “the schooling model as a component of human capital analysis”, he claimed that “it is necessary to turn to the post-school phase of investment behavior in order to extend the analysis to the whole earnings distribution.” Here I have illustrated an alternative view: that schooling combined with technical changes can explain a great deal of observed earnings distributions.

This work also provides a guide for other researchers wishing to treat the theory of directed technical change as a viable representation of wages and factor productivity for broad classes of productive inputs, and I hope that I have inspired others to demand generality from this theory and others.

Appendices

Appendix A

Model of directed technical change using age groups and human capital for elasticity of substitution estimates

This section formalizes the solutions to the model presented in Chapter 1.

The model follows closely with Acemoglu (2002) except that I use the total human capital provided to the market by a given age group as a productive input rather than using the quantity of labor supplied by people of different levels of human capital. This would cause only negligible differences in solving the model (but not in applications to the data) if we were to simply exchange the two values wherever they occur (we could just stick an H wherever he has an L). However, because we cannot observe wages per unit of human capital, I solve the model for the wage per unit of labor. Thus the factor wages that concern us are not equivalent to those used by Acemoglu (in terms of their role in determining technology). This specification is similar to the one used in Chapter 2 with slight modifications to the innovation possibilities frontier (because here we do not need to fit data for multiple countries).

A.1 Final Goods

Aggregate output Y is produced competitively with intermediate goods Y_a specific to age groups indexed by a according to ¹

$$Y = \left[\sum Y_a^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}} \quad (\text{A.1})$$

Final good output is the numeraire, so

$$\sum P_a^{1-\epsilon} = 1 \quad (\text{A.2})$$

The typical final good producer purchases intermediate goods at prices P_a and faces the problem

$$\begin{aligned} \max_{\{Y_a\}} \{Y - \sum P_a Y_a\} \\ \Rightarrow \frac{P_a}{P_b} = \left(\frac{Y_a}{Y_b} \right)^{-\frac{1}{\epsilon}} \end{aligned} \quad (\text{A.3})$$

where I have indicated a second age group with the subscript b . If we combine Equation A.3 with a zero profit condition, we get that

$$P_a = Y Y_a^{-\frac{1}{\epsilon}} \left(\sum_b Y_b^{\frac{\epsilon-1}{\epsilon}} \right)^{-1} \quad (\text{A.4})$$

A.2 Intermediate Goods

Intermediate goods are produced competitively using machines κ_a , labor L_a , and human capital h_a that are specific to the intermediate good:

$$Y_a = \frac{1}{1-\beta} (h_a L_a)^\beta \int_0^{X_a} \kappa_a(x)^{1-\beta} dx \quad (\text{A.5})$$

¹A more general version of this production function would seem to be one that allows for different weights on the intermediate goods:

$$Y = \left[\sum \gamma_a Y_a^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}$$

However, these weights are not separately identified from the levels of production of the intermediate goods (which are not observed) and the technology levels that lead to that production. Thus I normalize $\gamma_a = 1$ and allow the production of intermediate goods to capture all aspects of the value of constituent markets in final good production.

In this particular application, the labor types are age groups, so readers can think of these intermediate goods industries indexed by a as composite sets of services offered to the market by workers of different ages. There is a continuum of length X_a of machine types indexed by x , representing the level of technology in age group (sector) a , Y_a sells at price P_a , machines of type x can be rented at the price $p_a(x)$, and workers of age group a get paid wage w_a . Thus the problem for the intermediate good producer is

$$\max_{\kappa, L} \left[\frac{P_a}{1-\beta} (h_a L_a)^\beta \int_0^{X_a} \kappa_a(x)^{1-\beta} dx - \int_0^{X_a} p_a(x) \kappa_a(x) dx - w_a L_a \right]$$

A.3 Demand for machines

Assuming that first order conditions hold with equality, the profit maximization condition with respect to machines of for age group a is that

$$P_a (h_a L_a)^\beta \kappa_a(x)^{-\beta} = p_a(x)$$

The monopolist with the blueprint for a given line of machine produces and maintains each unit of the machine with a unit of capital² rented at price R . Thus the stock of capital is always equal to the stock of machines. Each monopolist has a competitor who can produce the same machine at cost vR , so the monopolist sets the limit price $p_a(x) = vR$. The demand for a machine line for age group a for a given capital rental rate is then

$$\kappa_a(x) = \left(\frac{P_a}{vR} \right)^{\frac{1}{\beta}} h_a L_a \tag{A.6}$$

which is independent of the type x of machine. Production of intermediate goods then takes the form

$$Y_a = \frac{1}{1-\beta} \left(\frac{P_a}{vR} \right)^{\frac{1-\beta}{\beta}} X_a h_a L_a \tag{A.7}$$

²This is like assuming that one unit of capital can produce one unit of machine per unit of time and then machines depreciate fully but capital does not. The reader can think of machines as capital that has been temporarily repurposed for a specific method of production.

Combined with equation A.3, this means that

$$\frac{P_a}{P_b} = \left(\frac{X_a h_a L_a}{X_b h_b L_b} \right)^{-\frac{\beta}{\sigma}} \quad (\text{A.8})$$

where $\sigma = 1 + (\epsilon - 1)\beta$ is (as I will show) the elasticity of substitution between worker age groups conditional on fixed technology.

A.4 Monopoly profits for machine blueprint owners

The stream of profits per unit of κ_a is $(v - 1)R$, so the stream of profits per machine blueprint is

$$\pi_a = (v - 1)R\kappa_a = \frac{v - 1}{v} P_a^{\frac{1}{\beta}} h_a L_a (vR)^{\frac{\beta - 1}{\beta}} \quad (\text{A.9})$$

A.5 Demand for labor

The profit maximization condition with respect to labor is that

$$w_a = \frac{\beta}{1 - \beta} P_a (h_a L_a)^\beta L_a^{-1} \int_0^{X_a} \kappa_a(x)^{1 - \beta} dx$$

Combined with the condition for machines, this gives us that

$$w_a = \frac{\beta}{1 - \beta} P_a^{\frac{1}{\beta}} (vR)^{-\frac{1 - \beta}{\beta}} X_a h_a \quad (\text{A.10})$$

which means that the relative wages are

$$\frac{w_a}{w_b} = \frac{X_a}{X_b} \left(\frac{P_a}{P_b} \right)^{\frac{1}{\beta}} \frac{h_a}{h_b} \quad (\text{A.11})$$

Combining A.11 with A.8 gives a specification for demand wages conditional on technology that shows that the elasticity of substitution between worker age groups is σ :

$$\frac{w_a}{w_b} = \left(\frac{X_a h_a}{X_b h_b} \right)^{\frac{\sigma - 1}{\sigma}} \left(\frac{L_a}{L_b} \right)^{-\frac{1}{\sigma}} \quad (\text{A.12})$$

We could stop here if technology were observable, but one of the points of this paper is

discuss the impact on estimates of σ from not observing X and failing to understand that implicit in wage and labor supply data are changes in technology.

A.6 Allocation of capital

Because one unit of capital produces one machine and machine varieties are symmetric industries within age groups, $K_a(x) = \kappa_a(x)$, and the total capital used in an intermediate good market is

$$K_a = \int_0^{X_a} \kappa_a(x) dx = X_a \kappa_a = X_a \left(\frac{P_a}{vR} \right)^{\frac{1}{\beta}} h_a L_a \quad (\text{A.13})$$

Foregone consumption produces capital K , which is allocated between the intermediate goods markets to produce machines. The relative capital allocations (using the relative prices already derived) are

$$\frac{K_a}{K_b} = \left(\frac{X_a h_a L_a}{X_b h_b L_b} \right)^{\frac{\sigma-1}{\sigma}} \quad (\text{A.14})$$

and we can use this relationship to back out the levels of technology allocated to age groups from measures of the total capital.

A.7 Interest rates

In order to get the rental rate, we write the intermediate good output as

$$Y_a = \frac{1}{1-\beta} K_a^{1-\beta} (X_a h_a L_a)^\beta \quad (\text{A.15})$$

and note that the marginal product of capital in this market is

$$MPK_a = (1-\beta) P_a \frac{Y_a}{K_a} \quad (\text{A.16})$$

Capital market equilibrium requires that $vR = MPK_a$, so

$$P_a Y_a = R K_a \frac{v}{1-\beta} \quad (\text{A.17})$$

The intermediate goods markets adjust so that there are zero profits in the final good market,

so the sum of the five age-group-specific versions of Equation A.17 must equal Y , which requires that

$$R = \frac{1 - \beta}{v} \frac{Y}{K} \quad (\text{A.18})$$

The interest rate in this economy must be the rate that could be earned by producing capital:

$$r = (1 - \tau) R - \delta = (1 - \tau) \frac{1 - \beta}{v} \frac{Y}{K} - \delta \quad (\text{A.19})$$

where τ is the tax rate on capital income and δ is the rate of capital depreciation.

A.8 Consumption Demand

For simplicity, I assume a continuum of measure³ 1 of infinitely-lived consumers with CRRA preferences over a single consumption good over time. Consumers can borrow and lend at the interest rate r . The representative consumer earns income equal to the aggregate output of final goods and spends it on consumption C , investment in capital I , and research and development efforts $R\&D$.

A.9 Technological innovation

I assume that a country builds its own stock of technology with $R\&D$ expenditures (foregone consumption) with the following innovation possibilities frontier:

$$\dot{X}_a = \eta_a R\&D_a \quad (\text{A.20})$$

where $\sum_a R\&D_a = R\&D$ and η_a determines age-specific productivity of innovation. This follows the “lab equipment” model (Romer, 1987; Rivera-Batiz and Romer, 1991).

A.10 Characterizing the balanced growth path

Although the owners of machine blueprints produce their machines with some market power once they have the blueprint, there is free entry into innovation. One unit of $R\&D$ expenditure

³The choice of size of the consumer base does not impact the results, because I am not trying to explain income (or anything else) per consumer. This normalization is simply convenient for talking about a representative consumer.

produces a stream of $\frac{\eta_a}{hL}$ new blueprints, each with a present value V_a , so as long as there are positive $R\&D$ expenditures for every age group (as there would be along a BGP), free entry requires

$$1 = \eta_a V_a \tag{A.21}$$

and

$$\frac{V_a}{V_b} = \left(\frac{\eta_a}{\eta_b} \right)^{-1} \tag{A.22}$$

No arbitrage requires that

$$rV_a = \pi_a + \dot{V}_a \tag{A.23}$$

In my applications, I deal only with the balanced growth path⁴. Along the BGP, $\dot{V}_a = 0$. Using the value for instantaneous profits from Equation A.9, the BGP values of machine blueprints must satisfy

$$V_a = \frac{\pi_a}{r} = \frac{v-1}{vr} P_a^{\frac{1}{\beta}} h_a L_a (vR)^{\frac{\beta-1}{\beta}} \tag{A.24}$$

and

$$\frac{V_a}{V_b} = \left(\frac{P_a}{P_b} \right)^{\frac{1}{\beta}} \frac{h_a L_a}{h_b L_b} = \left(\frac{X_a}{X_b} \right)^{-\frac{1}{\sigma}} \left(\frac{h_a L_a}{h_b L_b} \right)^{\frac{\sigma-1}{\sigma}}$$

using Equation A.8 to get the relative prices. Combining this with the equilibrium condition in A.22 gives a relationship between relative technology between age groups, relative frontier technology between age groups, and relative productivity of innovation between age groups:

$$\frac{X_a}{X_b} = \left(\frac{h_a L_a}{h_b L_b} \right)^{\sigma-1} \left(\frac{\eta_a}{\eta_b} \right)^{\sigma} \tag{A.25}$$

This gives us the endogenous technology values to put into Equation A.12 to get the long-run relationship between wages and labor supplies:

$$\frac{w_a}{w_b} = \left(\frac{\eta_a}{\eta_b} \right)^{\sigma-1} \left(\frac{h_a}{h_b} \right)^{\sigma-1} \left(\frac{L_a}{L_b} \right)^{\sigma-2} \tag{A.26}$$

⁴Although Acemoglu (2007) showed that off-BGP trends may be needed to match historical changes in skill premia because the price effect dominates the short run and the market size effect often dominates in the long run, I do not expect this to be a substantial weakness of my work. The reason is that when workers age, they are simply moving to a different but established role in the economy rather than changing the expected distribution of workers across ages. If there were instead a sudden, unexpected age demographic shock, then this could cause problems for my analysis. The baby boom is one potential shock, but innovators had over an entire decade to prepare for this shock (average fertility rates are not private information). Other potential shocks are wars, which may differentially kill young, male workers) and diseases, which often differentially kill older workers).

Appendix B

Effect of σ on wage curvature

Past researchers have emphasized the importance of the elasticity of substitution between worker types in fitting the data. For instance, Jerzmanowski and Tamura (2015) find that low values of σ induce the United States to appear to be a high-barrier nation. However, TDDB's strategy for constructing human capital includes intergenerational transfers of skills—if one generation is skilled, then the next one can borrow from the skills of the older generation. This reduces the apparent importance of schooling in generating human capital and allows the US and other wealthy nations to possess relatively high levels of human capital and low barriers despite having similar levels of schooling to lower income countries. This fact means that the model reduces the importance of this robustness issue from past work.

As argued earlier, elasticities of substitution are essential for determining the strength of bias in technical development and thus the distribution of technologies. I estimate kernel density functions for technologies relative to the US for each input type in the year 2010, and Figure B.1 shows how changes in the value of σ affect the calculated distribution of technologies.

The first thing to notice is that within the reasonable range for σ (2–3) the densities do not change much. We do see some changes in specialization of technology. For instance, the US has an older population than much of the rest of the world, so technologies relative to the US for older workers fall as σ increases, whereas technologies relative to the US for the youngest workers rise as σ increases. However, only when going from very small values to very large values of σ do we easily see this effect.

The graphs suggest that the position of the US in the distribution does not change much in

response to the elasticity of substitution (except for with the younger workers, in which the US is not relatively abundant), in contradiction with past research. Table B.1 quantifies this fact by showing the technology percentiles for the US for each level of σ for the last 60 years. The framework fits intuition that the US is a high-productivity country (for middle-aged and older workers) without requiring dubious assumptions about the elasticity of substitution.

It is useful to note that the US may show up as a lower-productivity country than expected simply because of an omission from the production function: natural resources. The data sample includes countries that are primarily commodity exporters or otherwise have a very small set of industries that rely on very specific inputs. For instance, Jordan (an oil exporter) and The Bahamas (mainly a tourism and banking producer) both appear to be highly productive countries in this analysis. It seems silly to base results off of small economies with unusual circumstances. Removing countries whose economies are more than 20% oil production and some island countries with large tourism industries moves the US higher in the technology distribution and shrinks the changes from $\sigma = 2$ to $\sigma = 3$ in Table B.1 so that they are almost always less than 3%.

Tables B.2 through B.4 show estimates for the average wage curvature within cohorts for values of the elasticity of substitution (σ) of 1.7, 3, and 6. There is significant wage concavity even in the weak bias case in Table B.2 where $\sigma = 1.7$. The high elasticity case (where $\sigma = 6$ in Table B.4) produces a much smaller upward trend in wages in the early career, but the reader should recall that the main point of the paper is to look at wage concavity rather than to explain why wages rise over time.

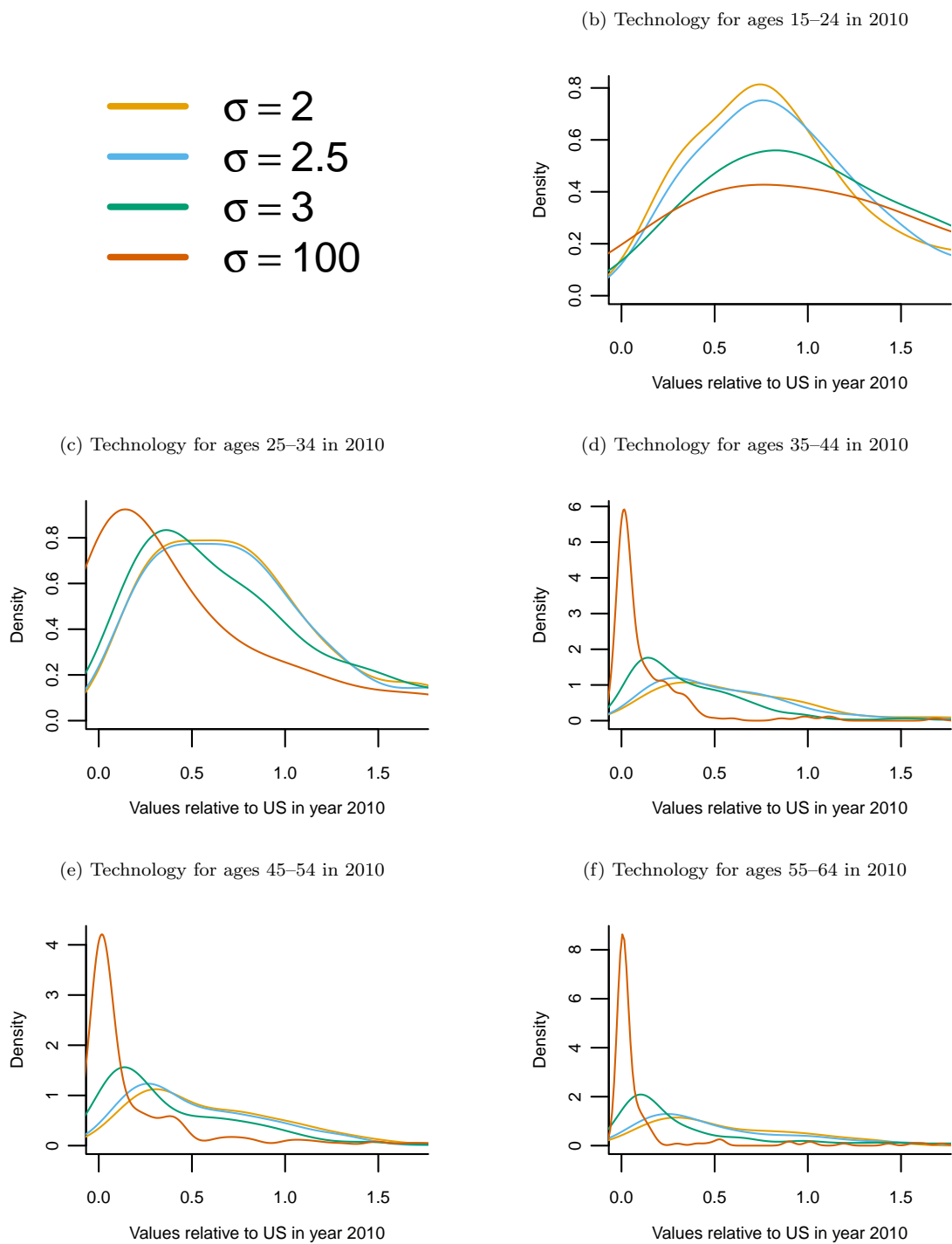


Figure B.1: How σ affects technologies relative to the US in 2010

	$\sigma = 1.7$	$\sigma = 2$	$\sigma = 3$	$\sigma = 6$
1950	0.785	0.765	0.698	0.544
1960	0.596	0.550	0.503	0.417
1970	0.576	0.558	0.564	0.612
1980	0.518	0.488	0.404	0.343
1990	0.470	0.429	0.274	0.149
2000	0.647	0.593	0.461	0.365
2010	0.629	0.587	0.443	0.431

(a) Ages 15–24

	$\sigma = 1.7$	$\sigma = 2$	$\sigma = 3$	$\sigma = 6$
1950	0.839	0.839	0.852	0.899
1960	0.689	0.702	0.728	0.795
1970	0.558	0.533	0.527	0.515
1980	0.608	0.627	0.735	0.898
1990	0.702	0.714	0.804	0.946
2000	0.707	0.695	0.725	0.790
2010	0.719	0.719	0.701	0.754

(b) Ages 25–34

	$\sigma = 1.7$	$\sigma = 2$	$\sigma = 3$	$\sigma = 6$
1950	0.866	0.886	0.919	0.966
1960	0.788	0.821	0.921	0.980
1970	0.655	0.673	0.733	0.848
1980	0.608	0.608	0.645	0.747
1990	0.750	0.780	0.899	0.970
2000	0.850	0.886	0.946	0.988
2010	0.850	0.886	0.946	0.976

(c) Ages 35–44

	$\sigma = 1.7$	$\sigma = 2$	$\sigma = 3$	$\sigma = 6$
1950	0.832	0.839	0.886	0.906
1960	0.715	0.768	0.848	0.927
1970	0.715	0.733	0.818	0.909
1980	0.693	0.723	0.801	0.886
1990	0.726	0.774	0.887	0.917
2000	0.850	0.892	0.964	0.982
2010	0.808	0.862	0.928	0.940

(d) Ages 45–54

	$\sigma = 1.7$	$\sigma = 2$	$\sigma = 3$	$\sigma = 6$
1950	0.846	0.846	0.832	0.832
1960	0.722	0.762	0.815	0.801
1970	0.721	0.764	0.842	0.873
1980	0.747	0.801	0.861	0.916
1990	0.857	0.905	0.923	0.940
2000	0.808	0.832	0.868	0.844
2010	0.826	0.850	0.880	0.862

(e) Ages 55–64

Table B.1: US' technology percentiles for various values of σ

Table B.2: Wage-experience regression results ($\sigma = 1.7$)

	Log of Yearly Wage			
	(1)	(2)	(3)	(4)
Decades of Experience	0.640*** (0.009)	-0.822*** (0.282)	0.188*** (0.010)	-0.454** (0.213)
Decades of Experience ²	-0.050*** (0.001)	-0.064*** (0.001)	-0.012*** (0.001)	-0.025*** (0.001)
Log Capital per worker			0.633*** (0.009)	0.576*** (0.008)
Wage maximizing exp (dec.)	6.36	-6.47	8.1	-8.95
Year FE	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>
Cohort×Country FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	9,889	9,889	9,889	9,889
R ²	0.768	0.252	0.861	0.573
Adjusted R ²	0.562	0.184	0.630	0.418
<i>Notes:</i>	***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.			

Table B.3: Wage-experience regression results ($\sigma = 3$)

	Log of Yearly Wage			
	(1)	(2)	(3)	(4)
Decades of Experience	0.464*** (0.016)	-0.798* (0.470)	-0.022*** (0.008)	-0.292 (0.237)
Decades of Experience ²	-0.044*** (0.002)	-0.074*** (0.002)	0.006*** (0.001)	-0.011*** (0.001)
Log Capital per worker			0.904*** (0.006)	0.822*** (0.006)
Wage maximizing exp (dec.)	5.25	-5.39	2.03	-13.44
Year FE	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>
Cohort×Country FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	9,889	9,889	9,889	9,889
R ²	0.287	0.141	0.826	0.782
Adjusted R ²	0.210	0.103	0.605	0.570
<i>Notes:</i>	***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.			

Table B.4: Wage-experience regression results ($\sigma = 6$)

	Log of Yearly Wage			
	(1)	(2)	(3)	(4)
Decades of Experience	0.021 (0.048)	-1.354 (1.502)	-0.075*** (0.008)	-0.202 (0.251)
Decades of Experience ²	-0.029*** (0.007)	-0.106*** (0.007)	0.011*** (0.001)	0.001 (0.001)
Log Capital per worker			1.004*** (0.002)	0.982*** (0.002)
Wage maximizing exp (dec.)	0.36	-6.37	3.4	124.98
Year FE	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>
Cohort×Country FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	9,889	9,889	9,889	9,889
R ²	0.032	0.032	0.973	0.973
Adjusted R ²	0.023	0.023	0.712	0.710

Notes: ***Significant at the 1 percent level.
 **Significant at the 5 percent level.
 *Significant at the 10 percent level.

Appendix C

An alternative measure of barriers

The functional form chosen for the barriers in Chapter 2 might seem unnecessarily complicated to some readers, because there are two separate parameters that both jointly determine the shape of the innovation frontier. Here I consider a simpler alternative and find that it does a poor job of matching observed wages, whereas the version used in the main paper precisely matches wages in the US by construction.

Although Jerzmanowski and Tamura (2015) need η to help fit observed skill premia, we might think that the cost of developing technologies for 25–34-year-olds is more similar to the cost of developing technologies for 35–44-year-olds than the cost of technology for low-skilled workers is to the cost of technology for highly-skilled workers. In other words, age groups may differentiate workers less than their education or other skills do. If this is true, including η in the analysis may obscure the results by inducing unnecessary uncertainty over other parameters.

This appendix considers the case where $\eta_a = \eta_b = 1$ for all age groups a and b . In the main analysis, η s were fit to wages in the United States and then used to produce wages elsewhere. Without including η , we can produce wage estimates and then see if they match those observed in the US.

The solution algorithm is essentially the same as before except that I omit step 3 because Equation 28 in the main paper already gives the relative technologies in terms of the frontier technologies.

Figure C.1 compares the relative wages produced with this methodology against the relative wages constructed from the US Census. In each case, there is a strong negative correlation between

the two series. This framework does not do a good job of reproducing actual wage patterns, so I abandon it.

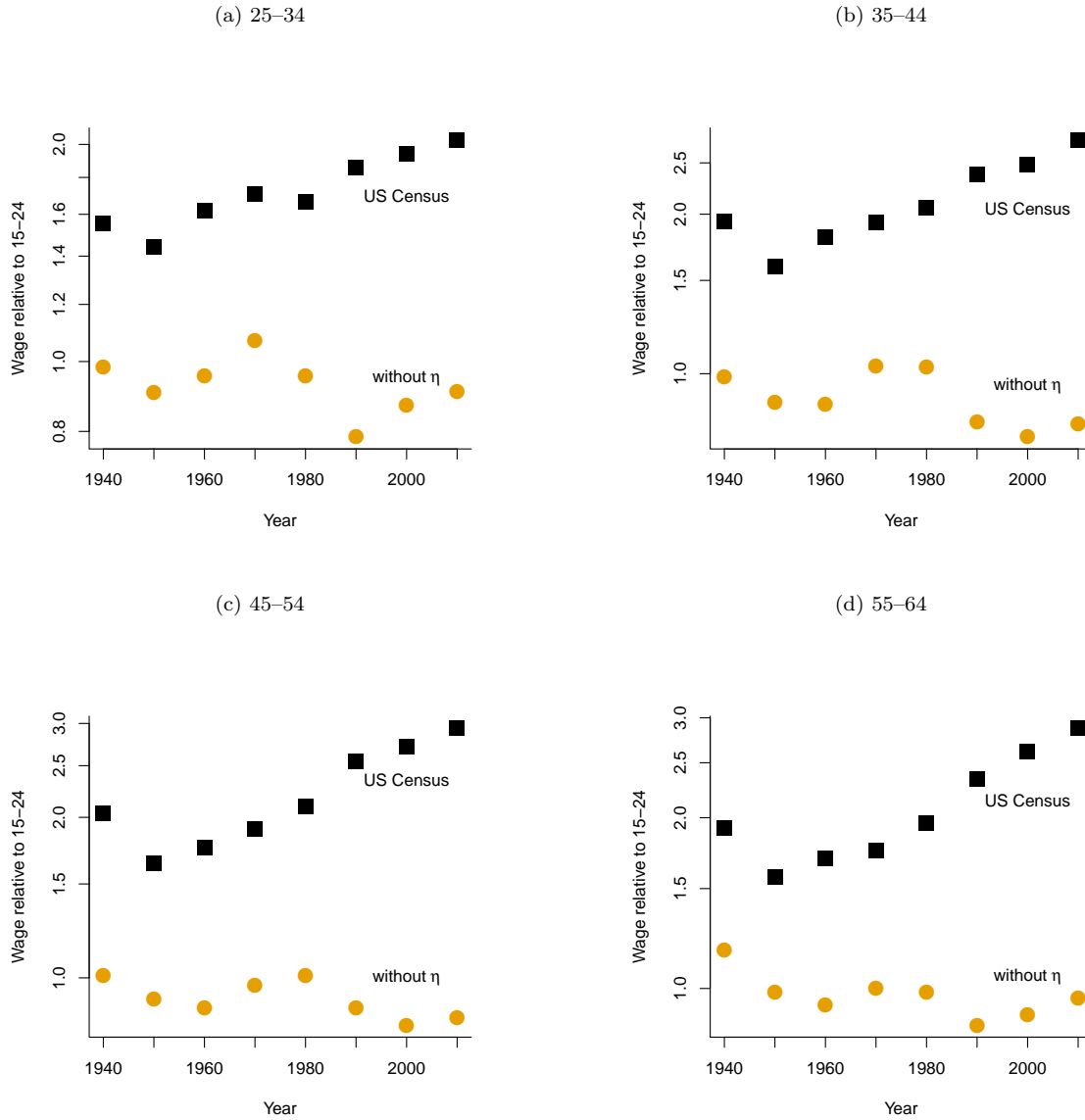


Figure C.1: Time series of wages from the US Census and constructed assuming $\eta = 1$.

Table C.1 estimates Equation 2.34 based on wages calculated assuming that $\eta_a = \eta_b = 1$ for all age groups a and b . Removing these age-specific productivity measures eliminates most of the upward trend in wages (other than whatever is captured by year fixed effects).

Table C.1: Wage-experience regression results ($\eta = 1$)

	Log of Yearly Wage			
	(1)	(2)	(3)	(4)
Decades of Experience	0.062*** (0.009)	-1.605*** (0.274)	-0.016** (0.007)	-0.815*** (0.210)
Decades of Experience ²	0.025*** (0.001)	0.018*** (0.001)	0.017*** (0.001)	0.010*** (0.001)
Log Capital per worker			0.570*** (0.009)	0.556*** (0.008)
Wage maximizing exp (dec.)	-1.24	43.8	0.47	42.07
Year FE	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>
Cohort×Country FE	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	9,889	9,889	9,889	9,889
R ²	0.626	0.032	0.762	0.433
Adjusted R ²	0.458	0.023	0.557	0.316

Notes:

***Significant at the 1 percent level.

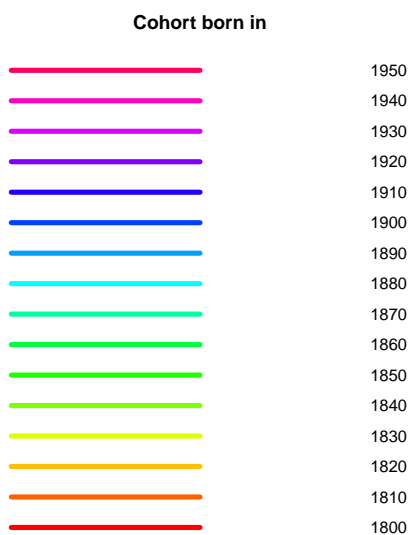
**Significant at the 5 percent level.

*Significant at the 10 percent level.

Appendix D

Life-cycle wage patterns for all countries

This section presents results for solutions for wages for every cohort born before 1990 in every country. The legend below indicates the approximate birth year for each cohort. There is a lot of information to communicate in a small space, so it can be difficult to pair the lines with birth years. The cohorts born later are typically in the upper left of each plot.



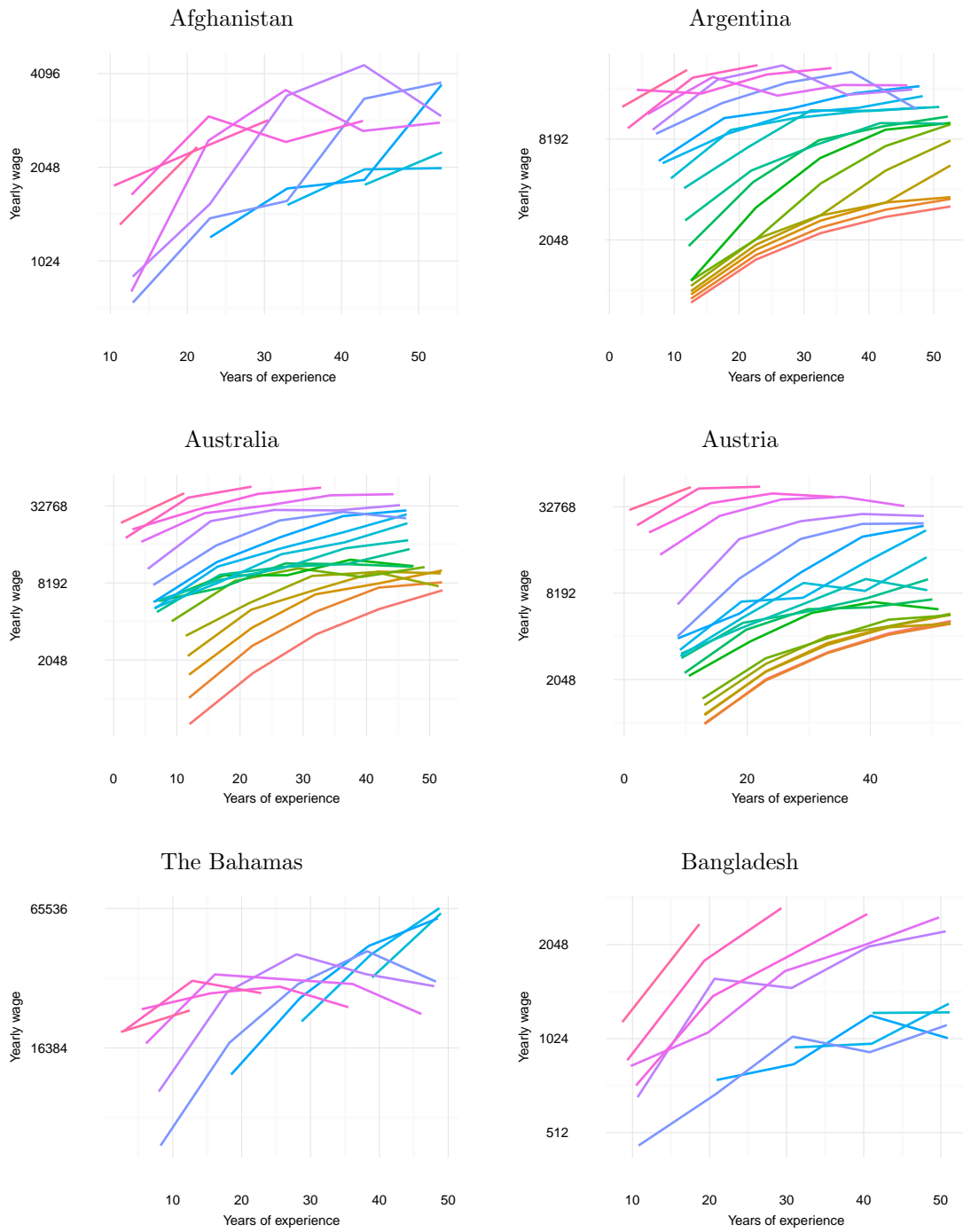


Figure D.1: Predicted wage for each cohort throughout their lifetimes as they gain experience (every country)

Note: More recent cohorts are typically higher and to the left

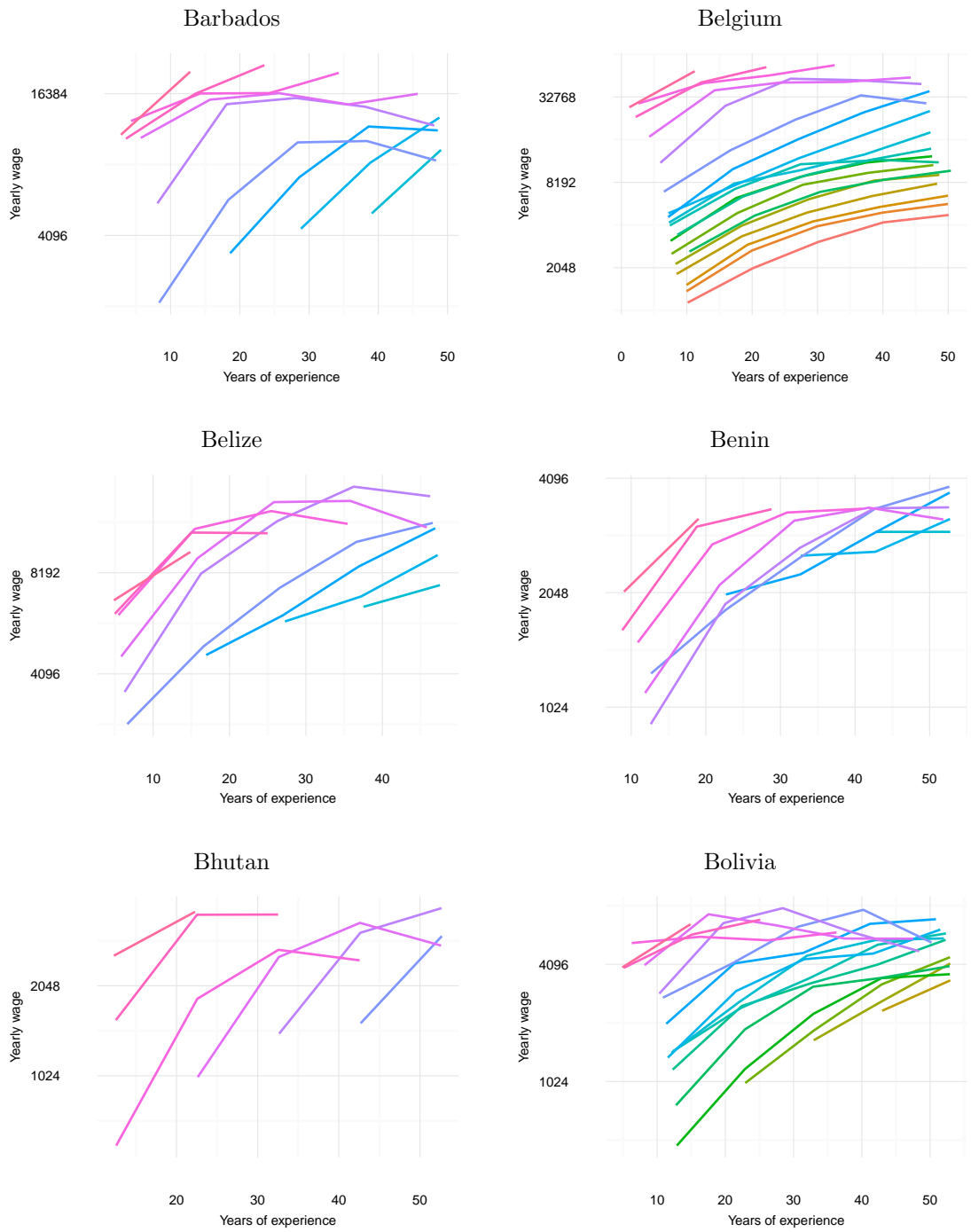


Figure D.1: Predicted wage for each cohort throughout their lifetimes as they gain experience (every country)

Note: More recent cohorts are typically higher and to the left

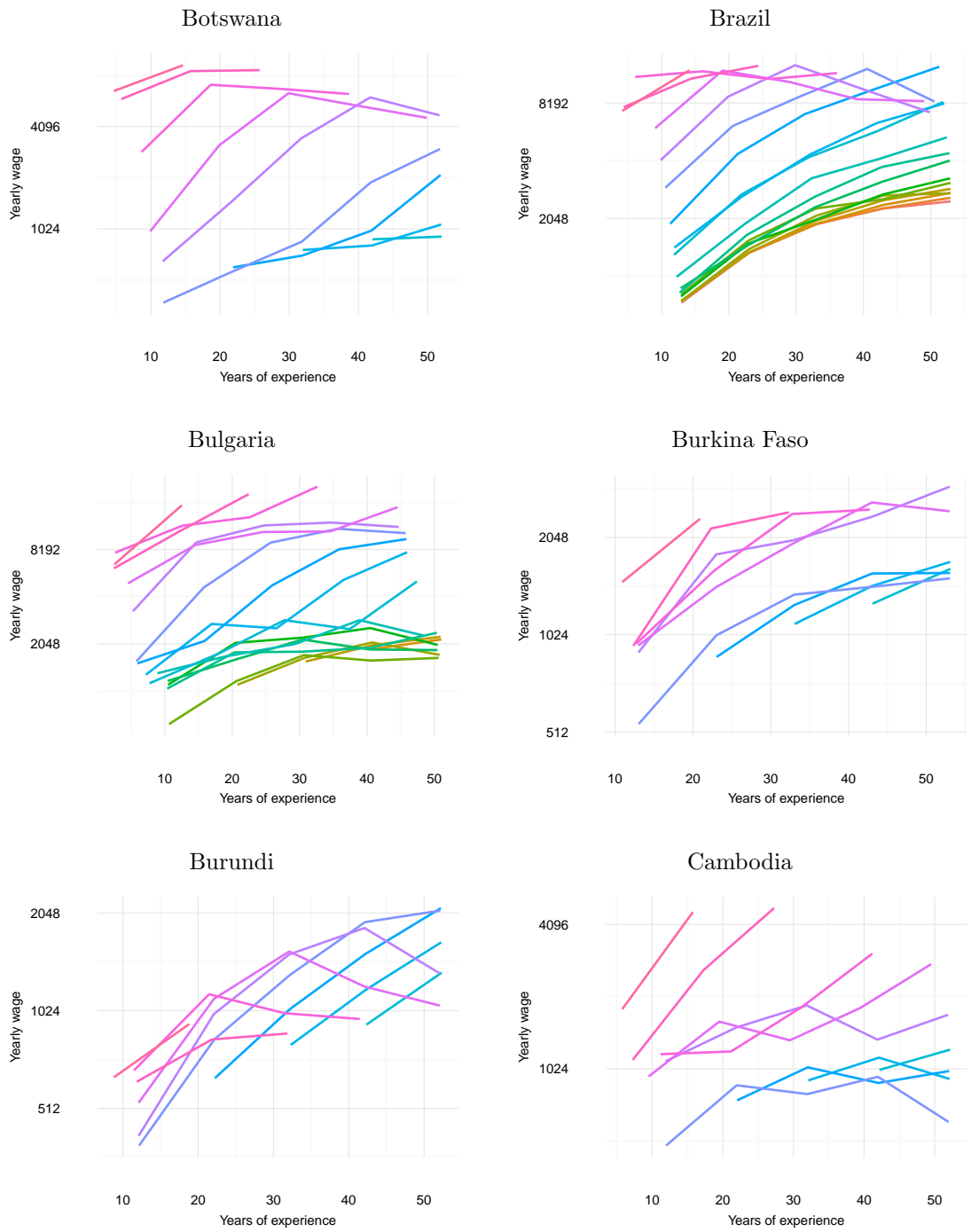


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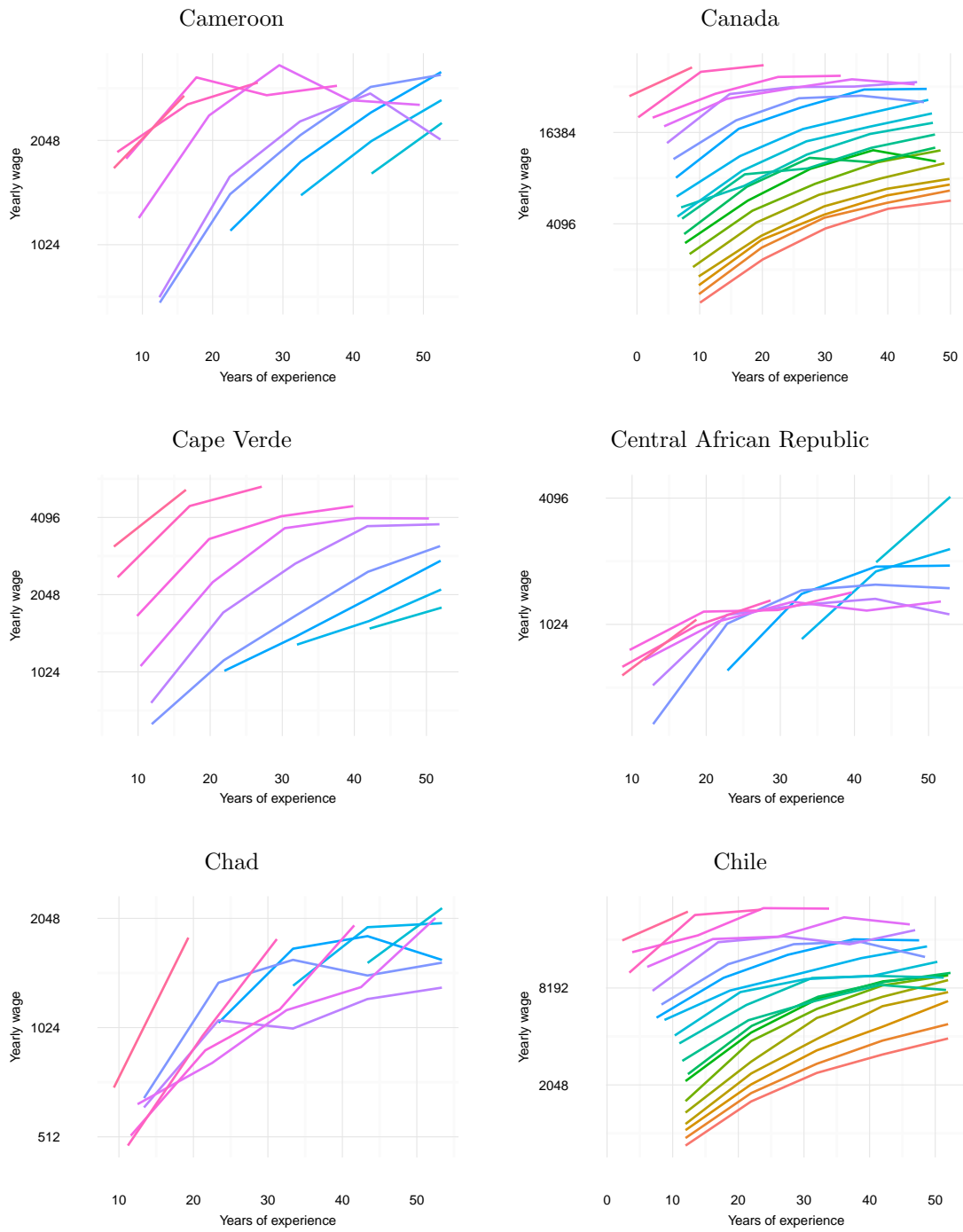


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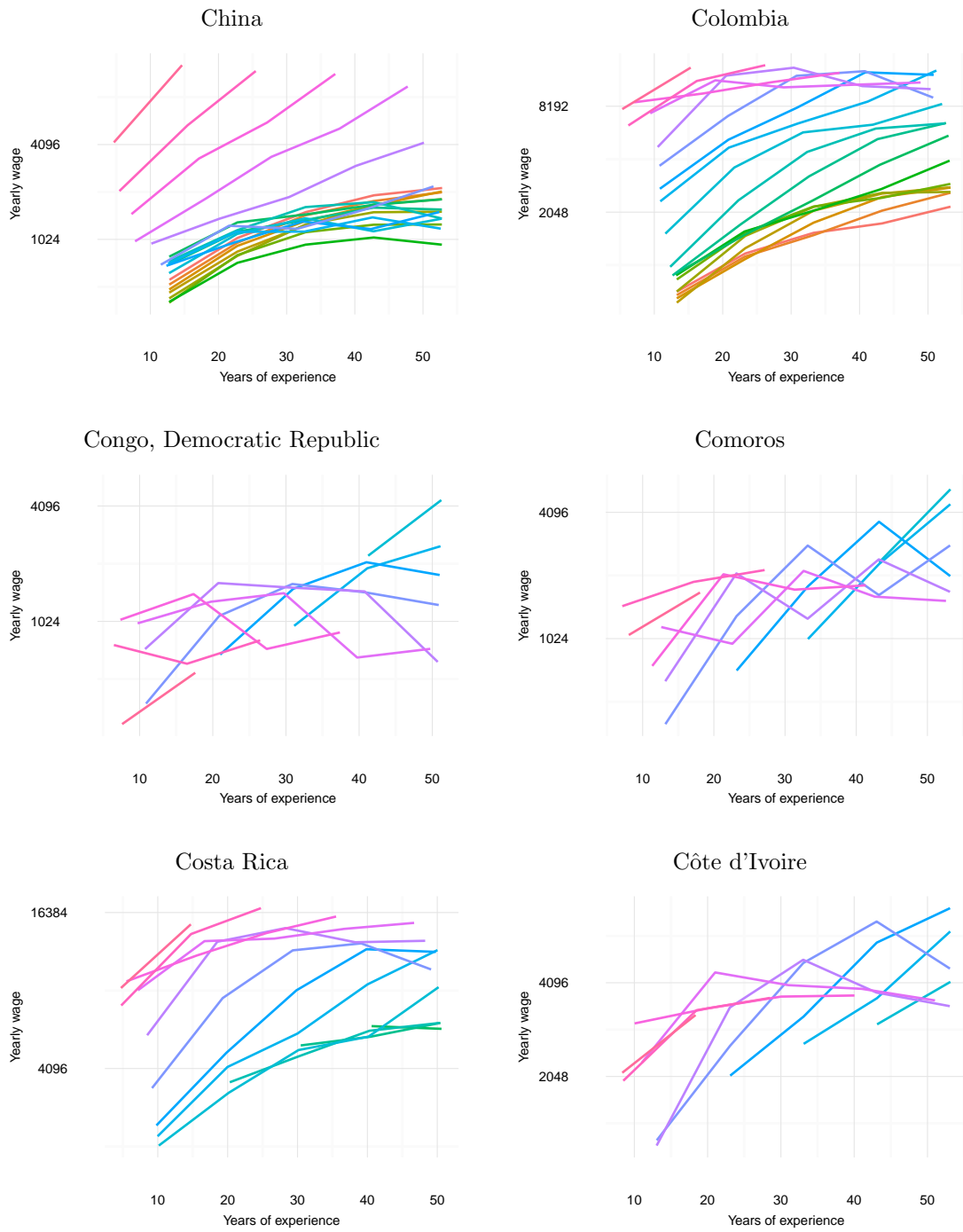


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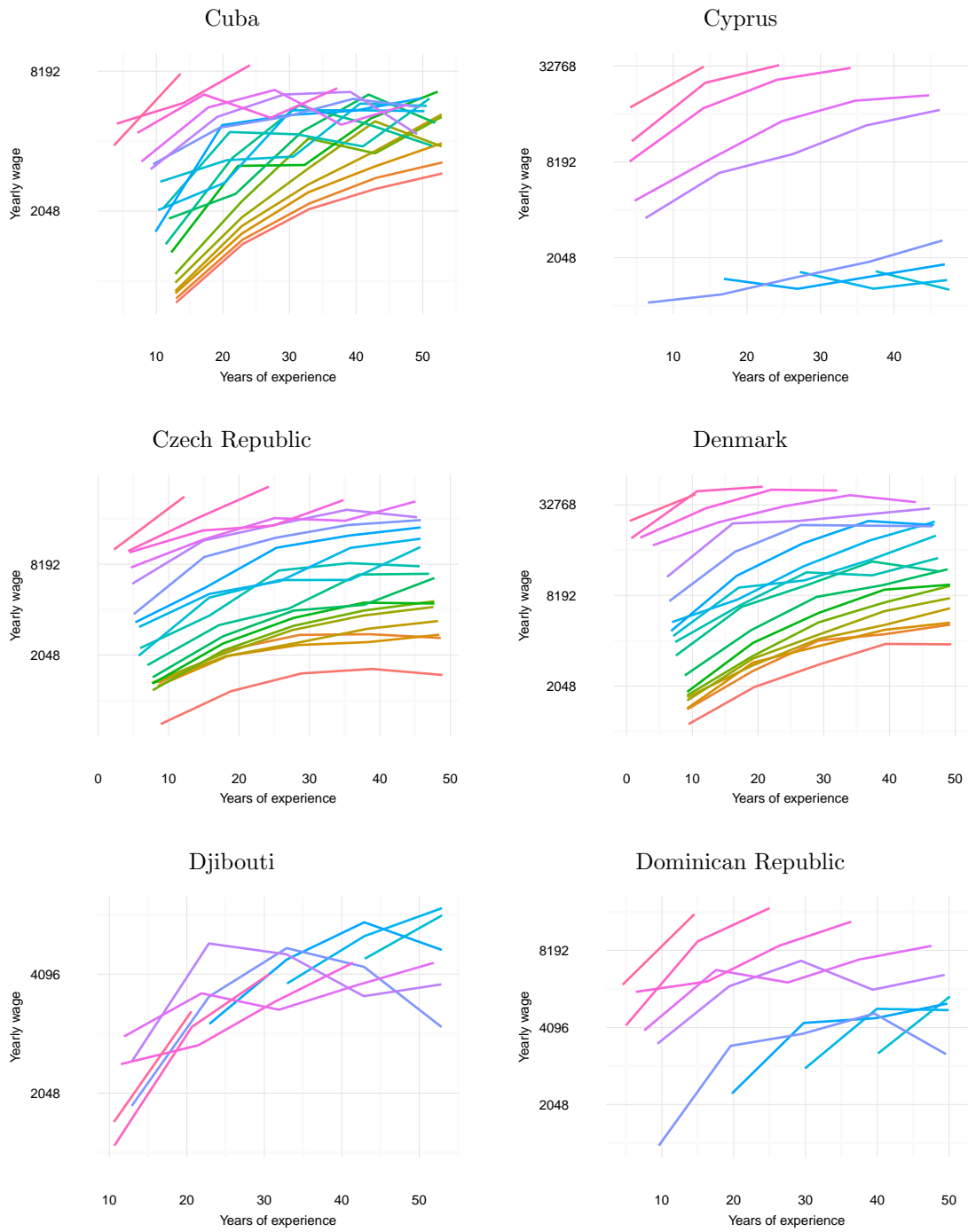


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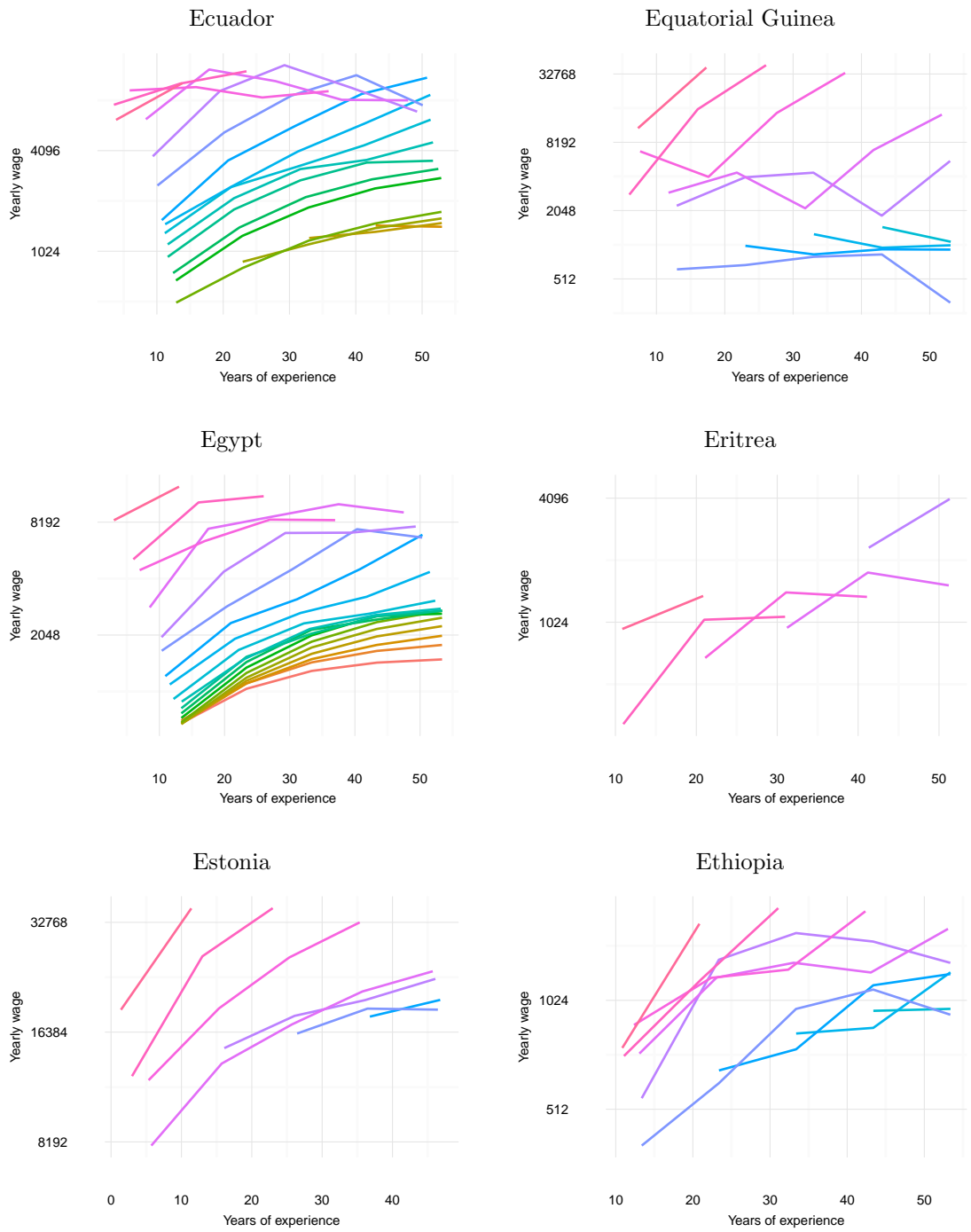


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Note: More recent cohorts are typically higher and to the left

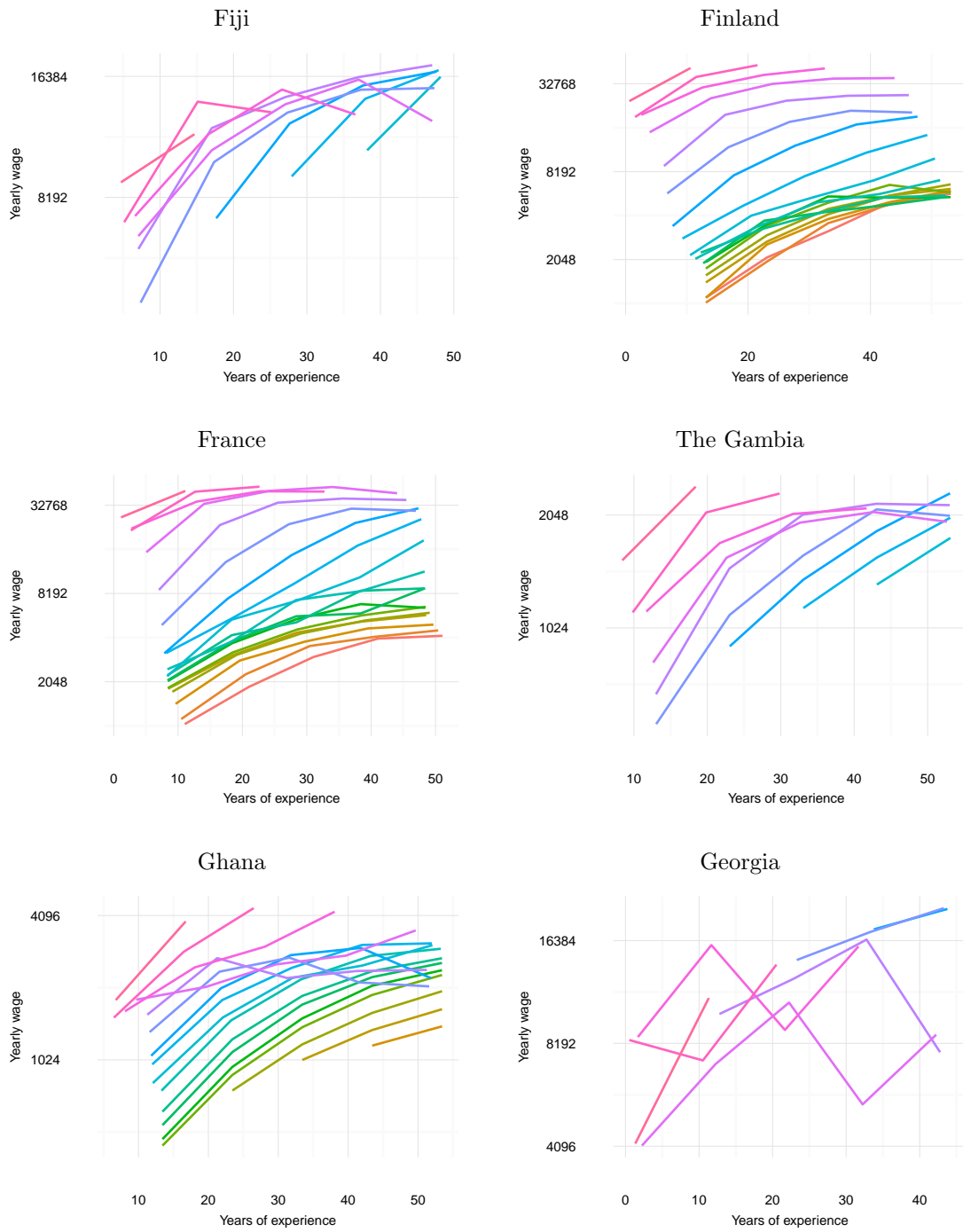


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Note: More recent cohorts are typically higher and to the left

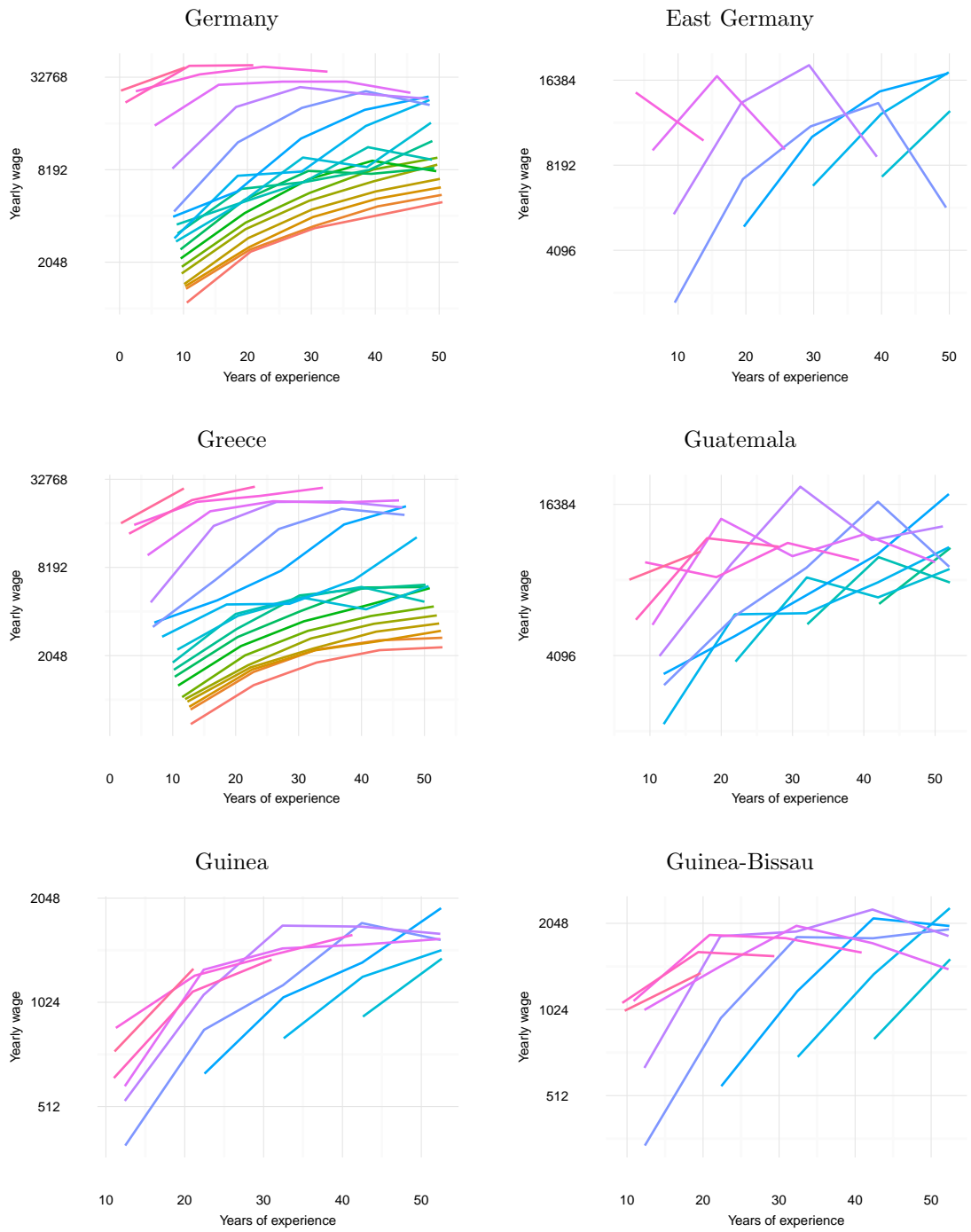


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Note: More recent cohorts are typically higher and to the left

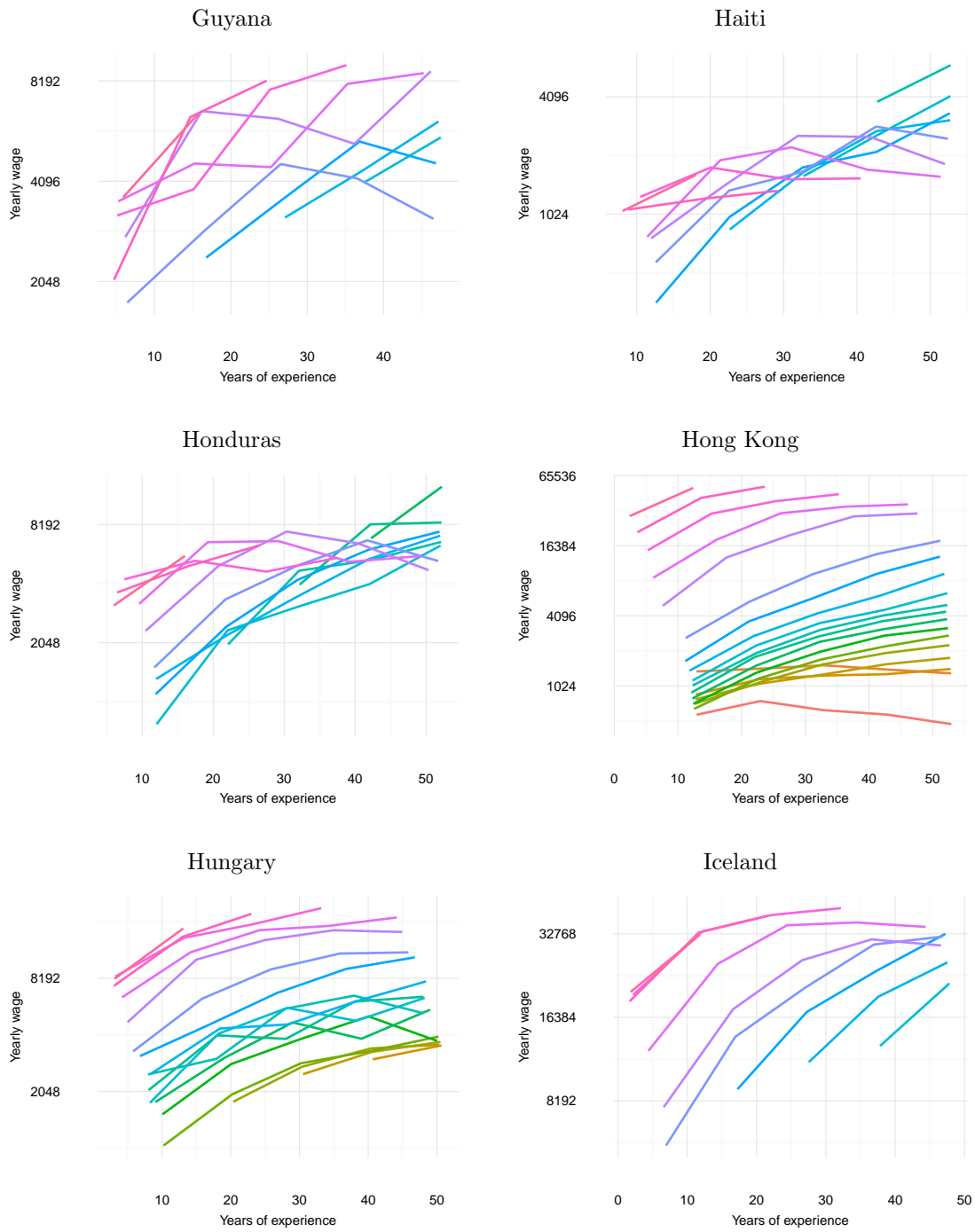


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Note: More recent cohorts are typically higher and to the left

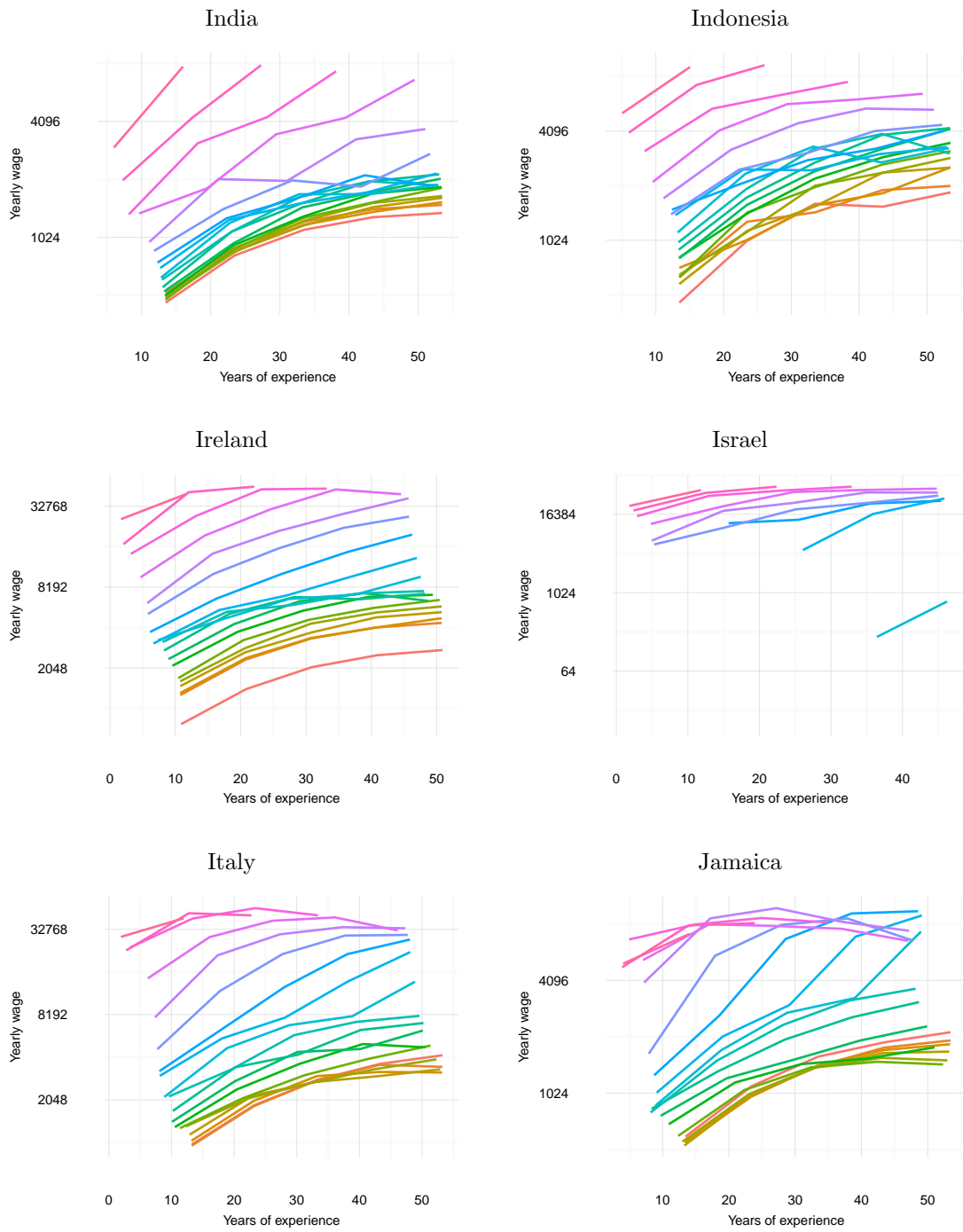


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Note: More recent cohorts are typically higher and to the left

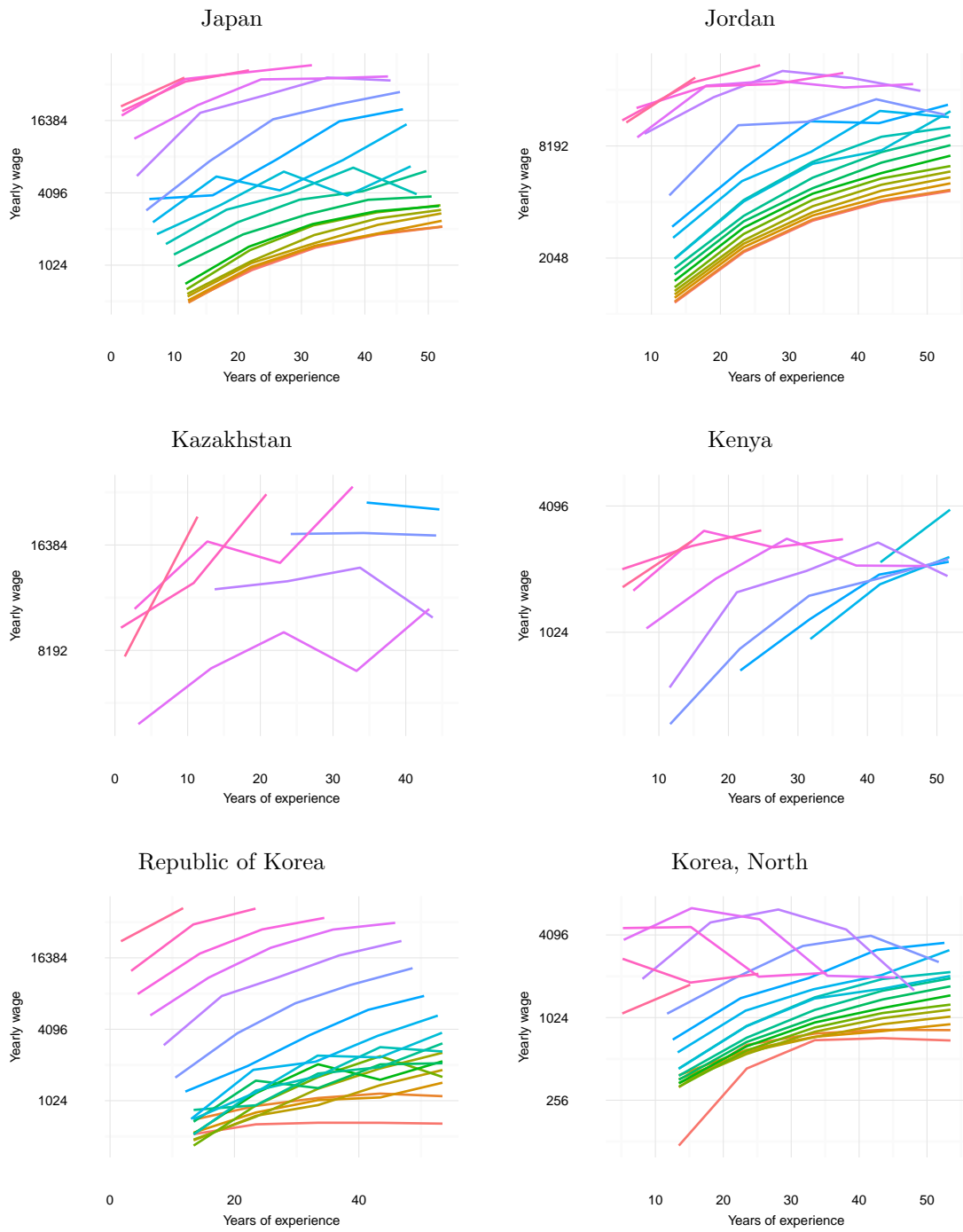


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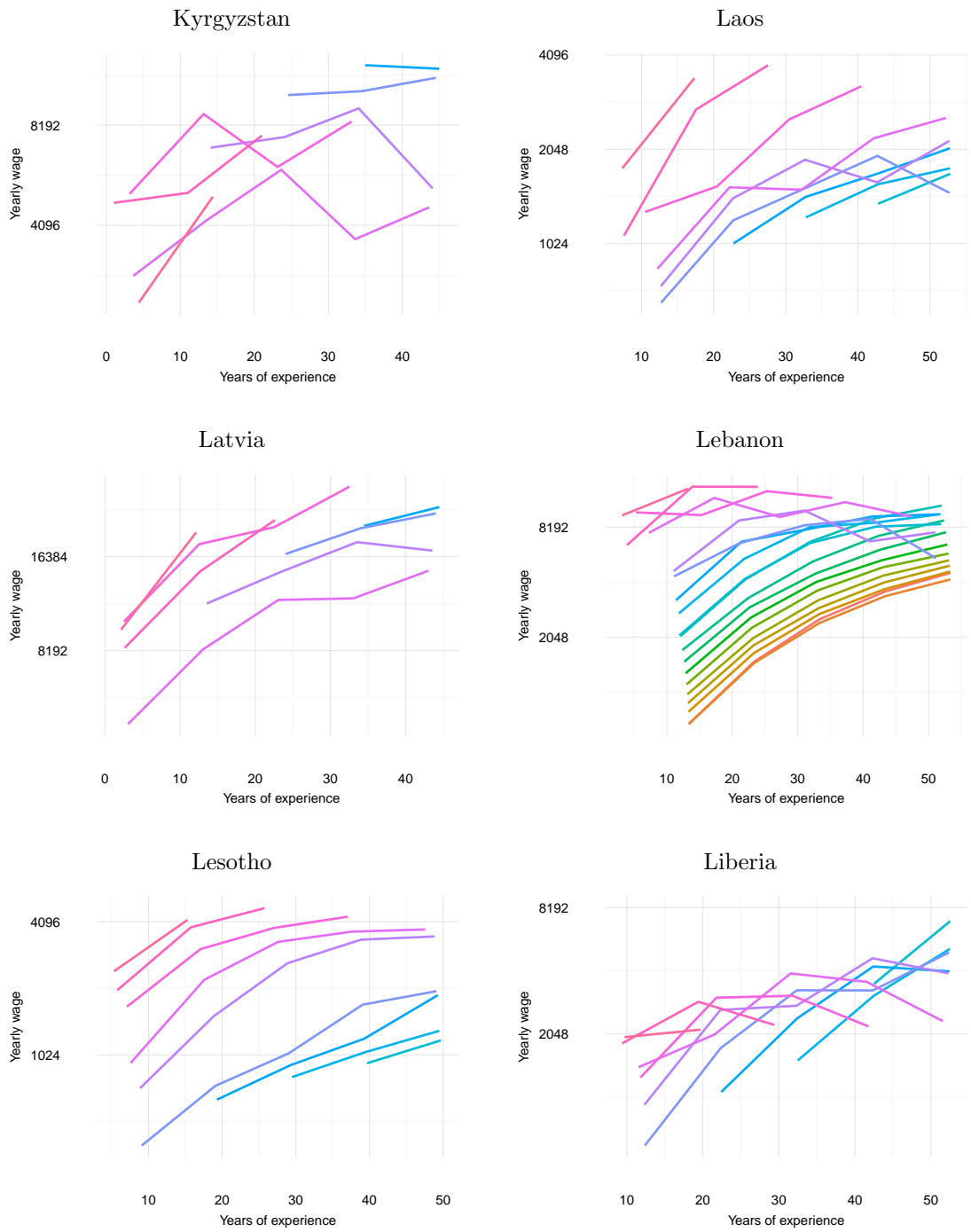


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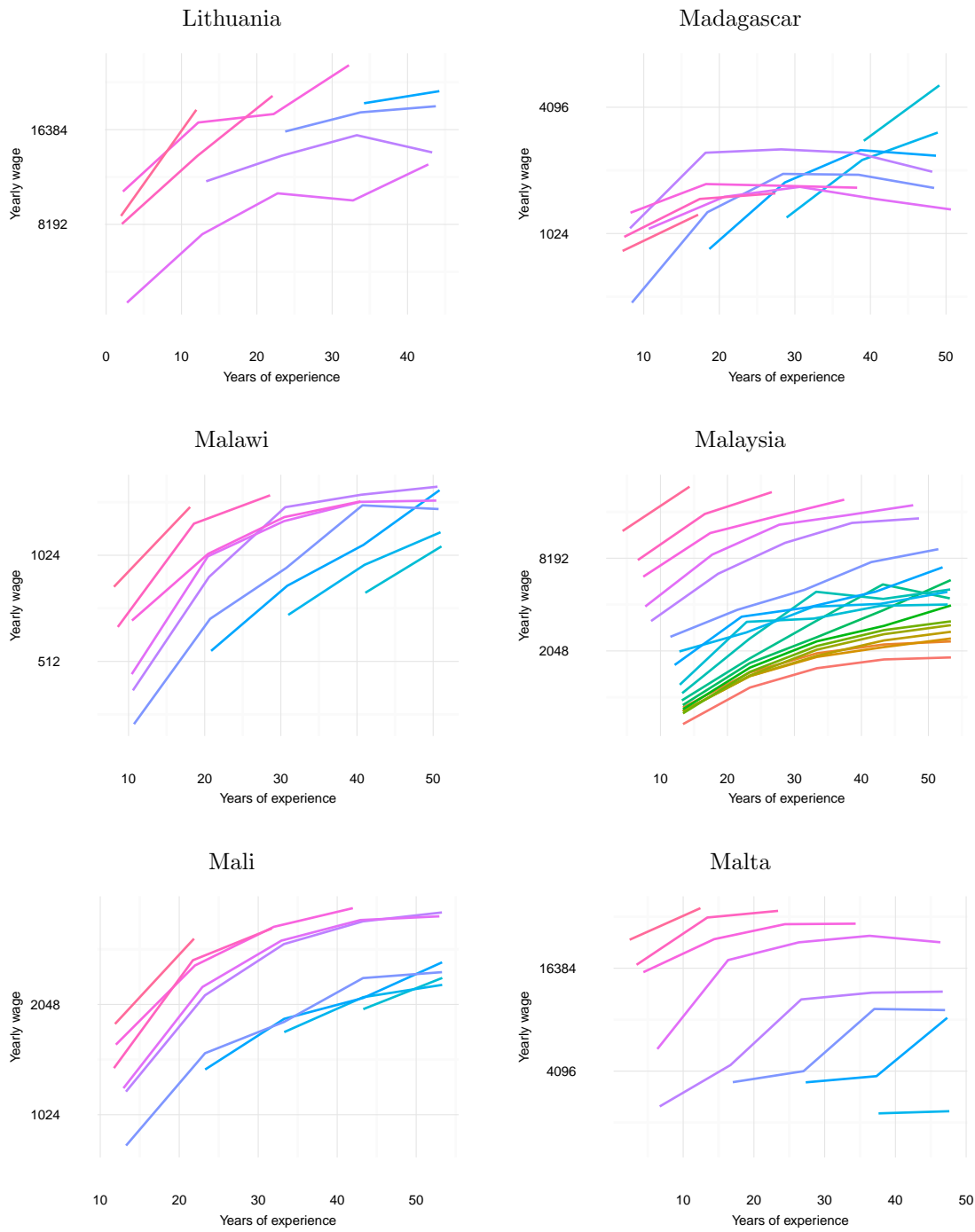


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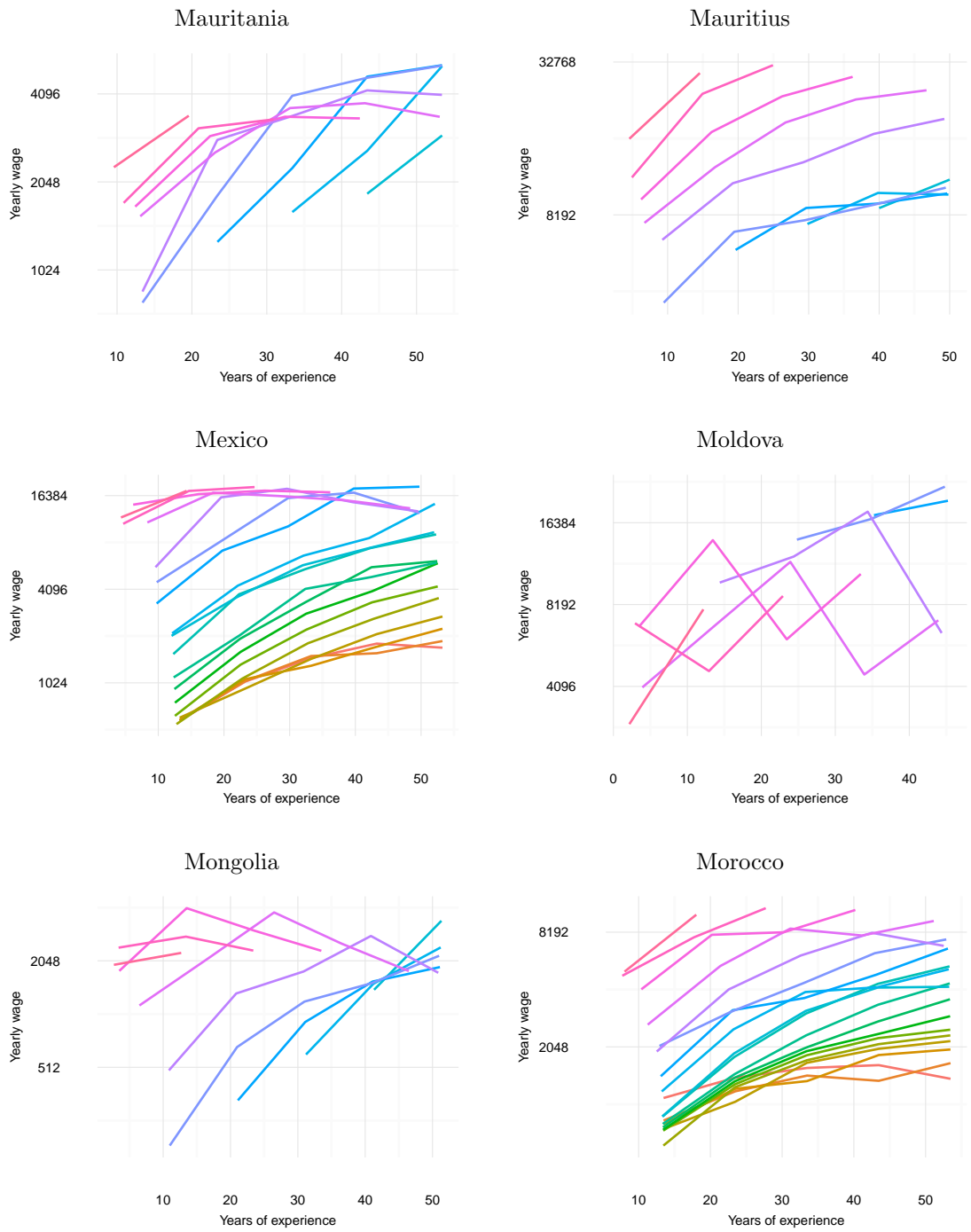


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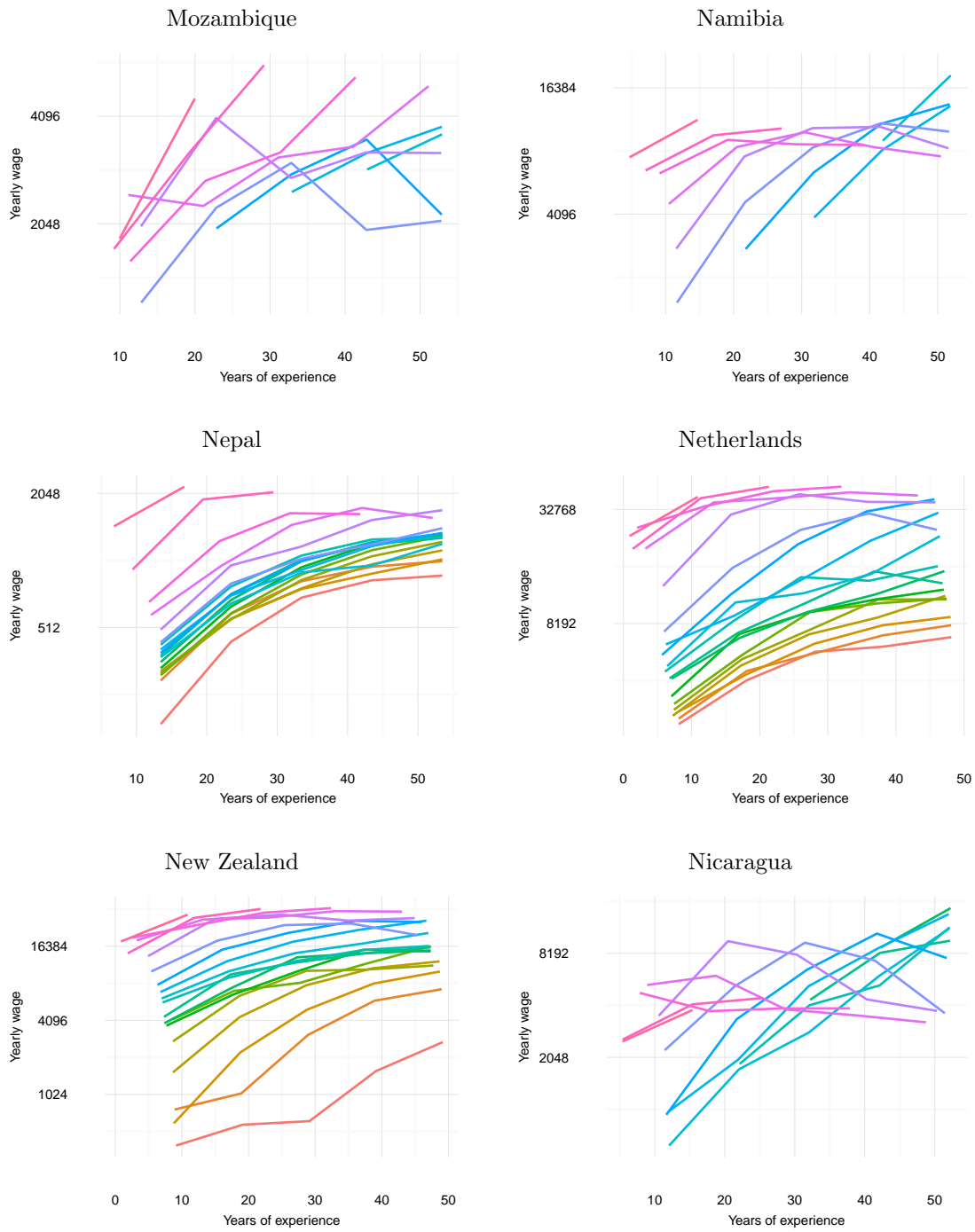


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Note: More recent cohorts are typically higher and to the left

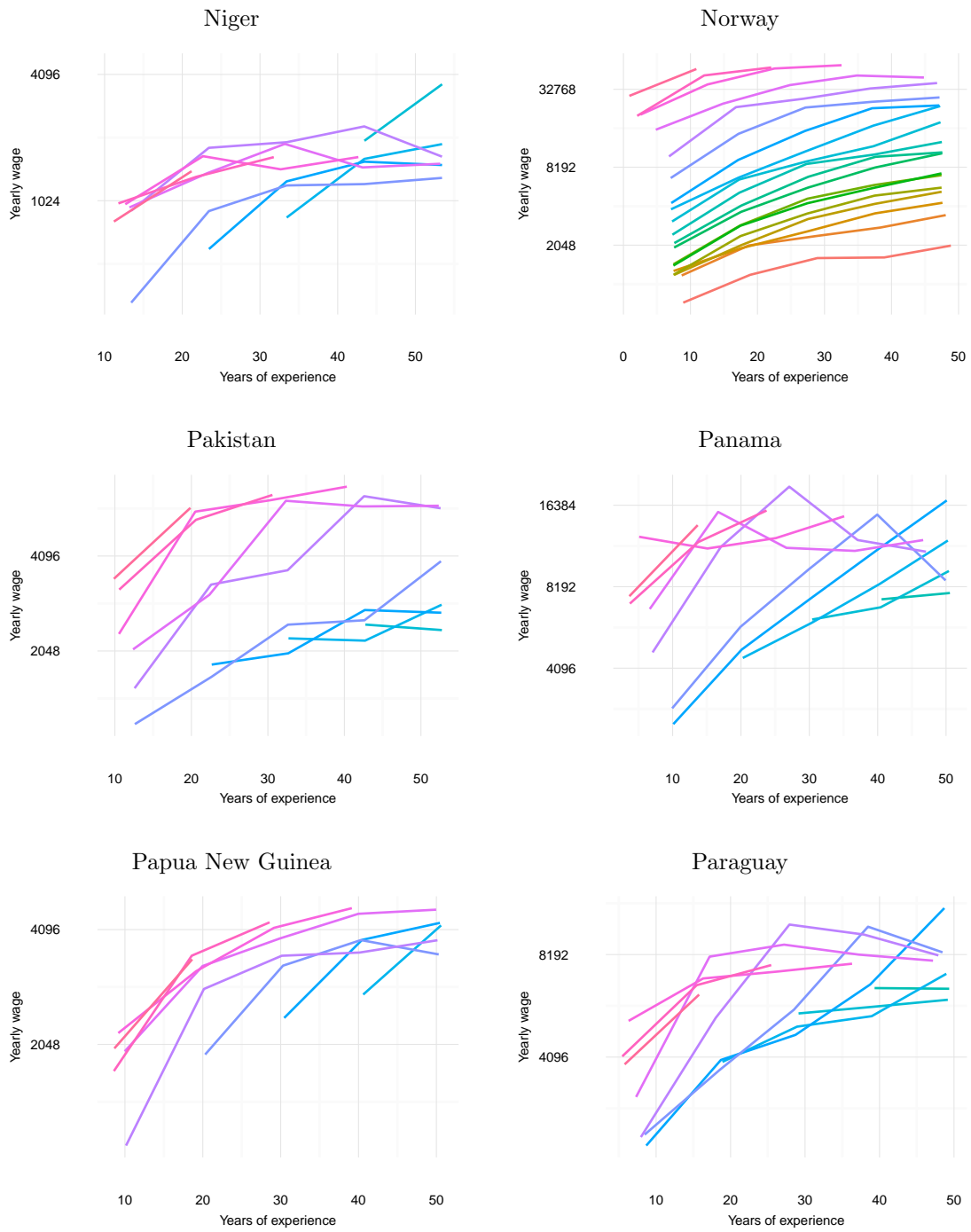


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Note: More recent cohorts are typically higher and to the left

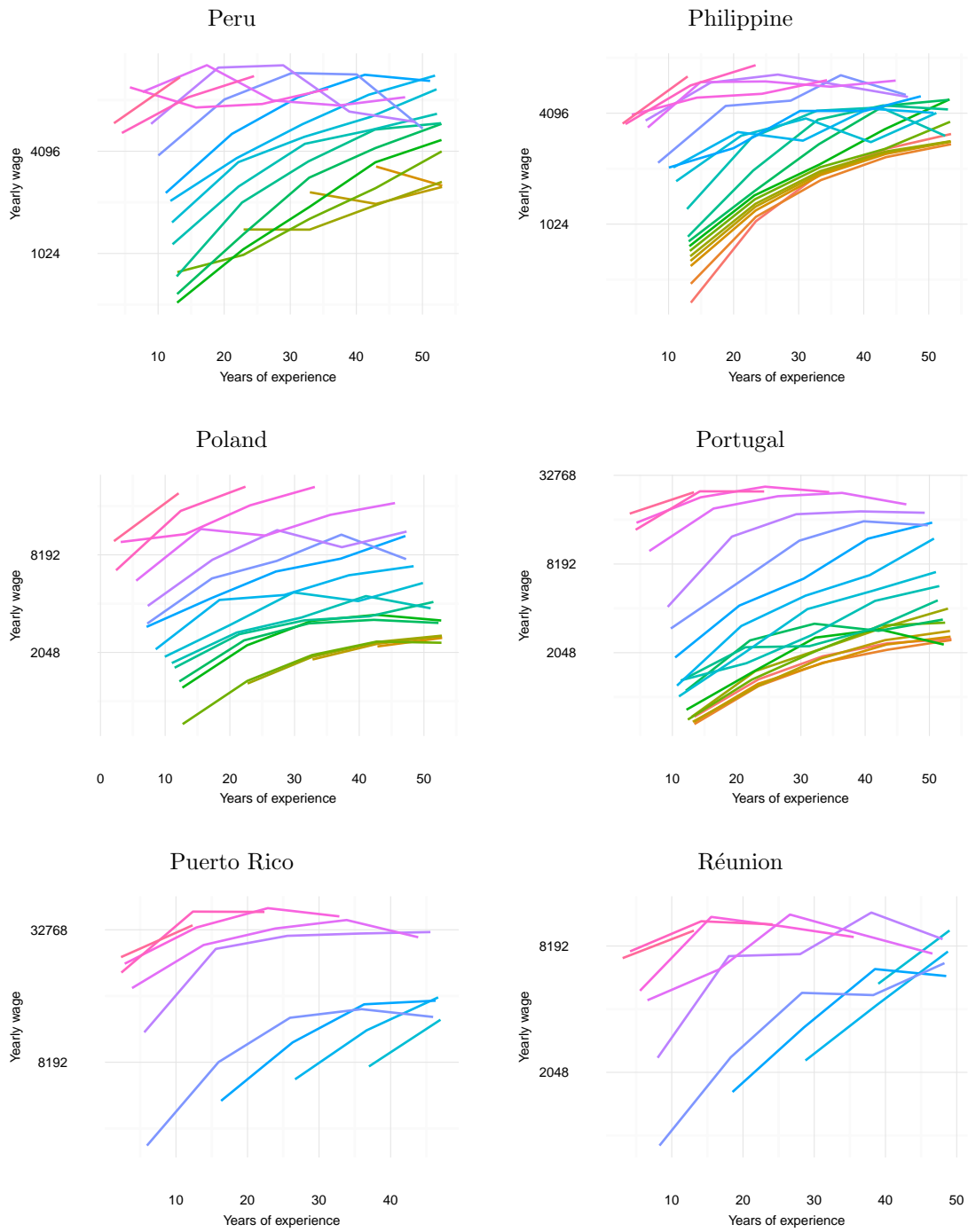


Figure D.1: Predicted wage for each cohort throughout their lifetimes as they gain experience (every country)

Note: More recent cohorts are typically higher and to the left

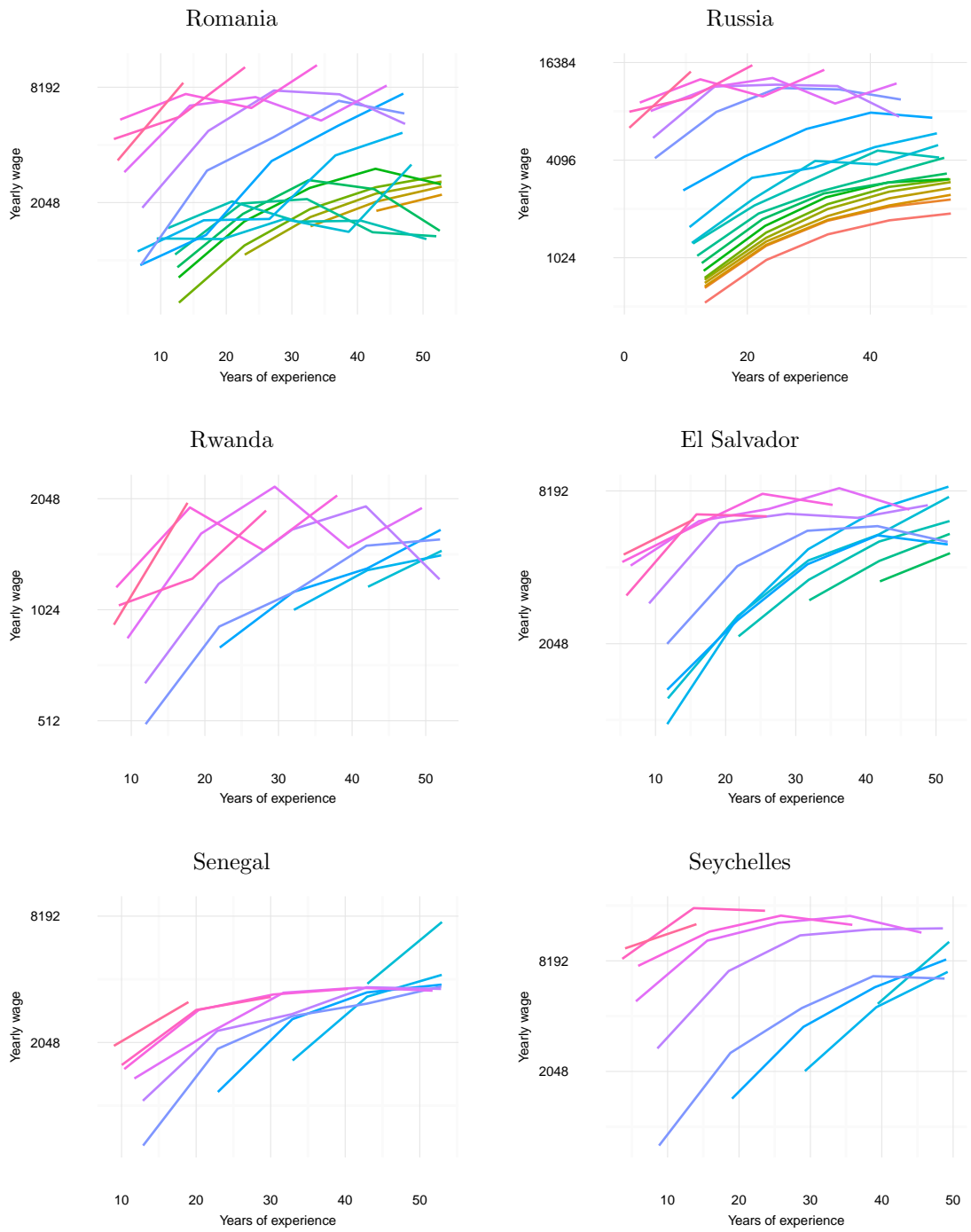


Figure D.1: Predicted wage for each cohort throughout their lifetimes as they gain experience (every country)

Note: More recent cohorts are typically higher and to the left

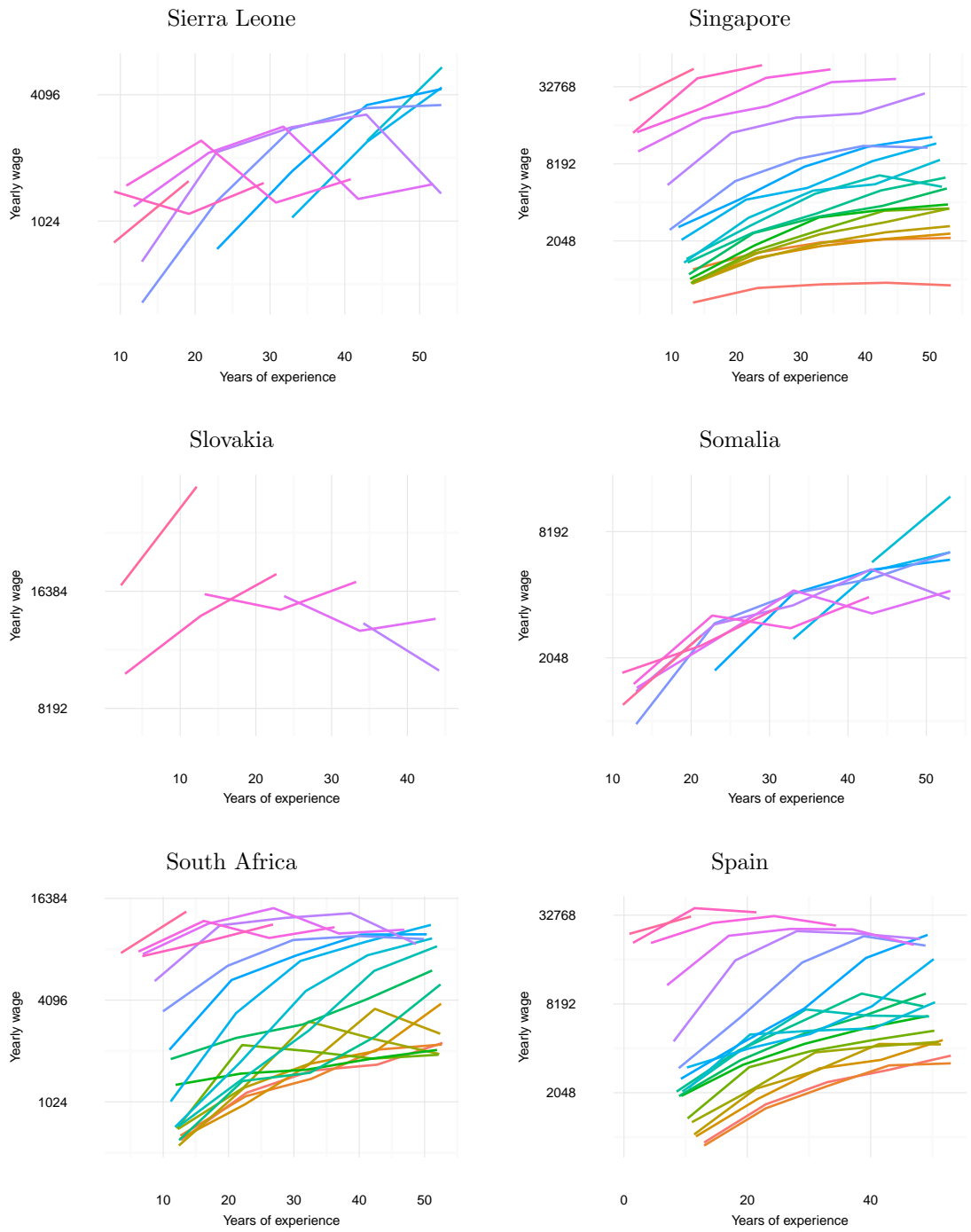


Figure D.1: Predicted wage for each cohort throughout their lifetimes as they gain experience (every country)

Note: More recent cohorts are typically higher and to the left

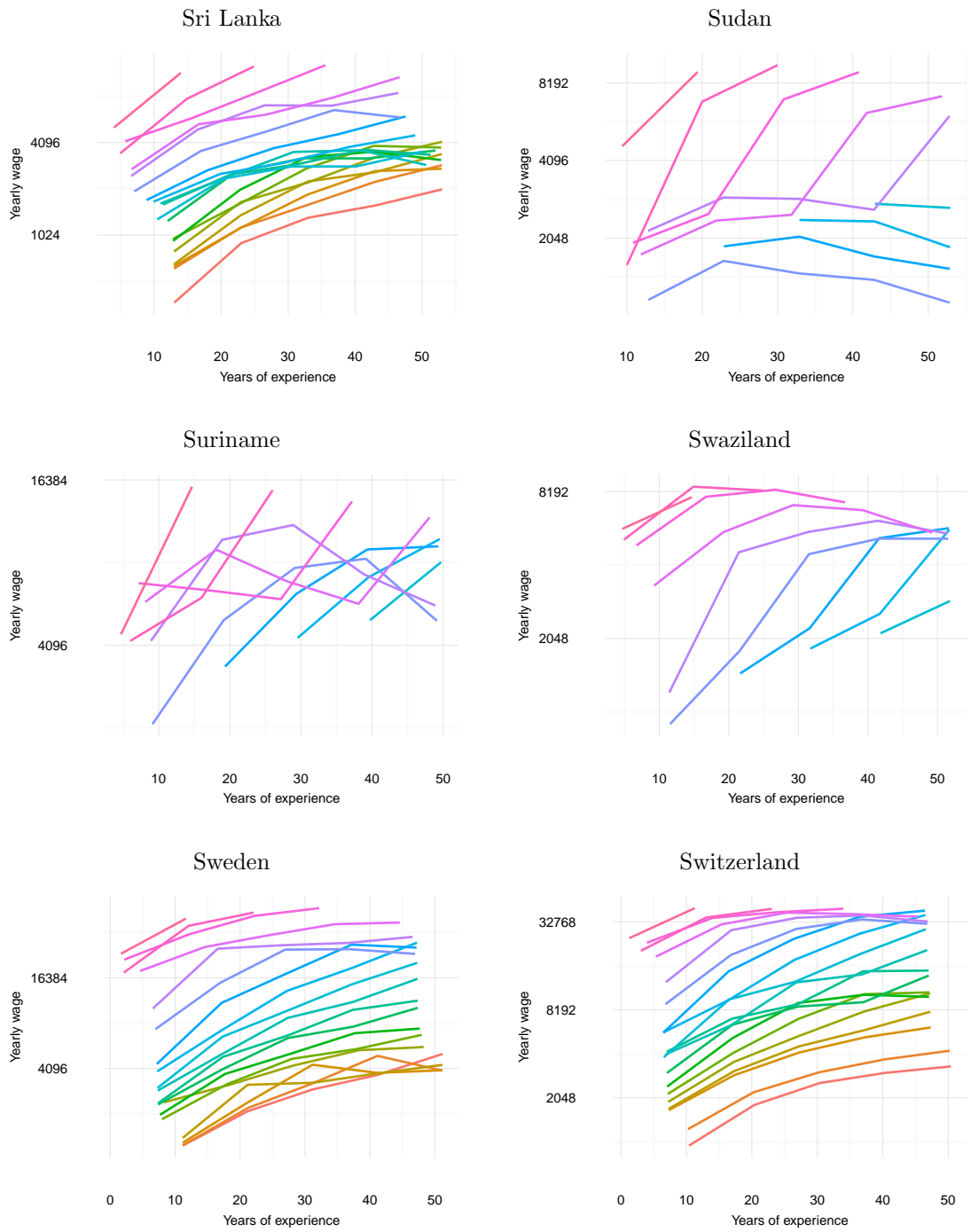


Figure D.1: Predicted wage for each cohort throughout their lifetimes as they gain experience (every country)

Note: More recent cohorts are typically higher and to the left

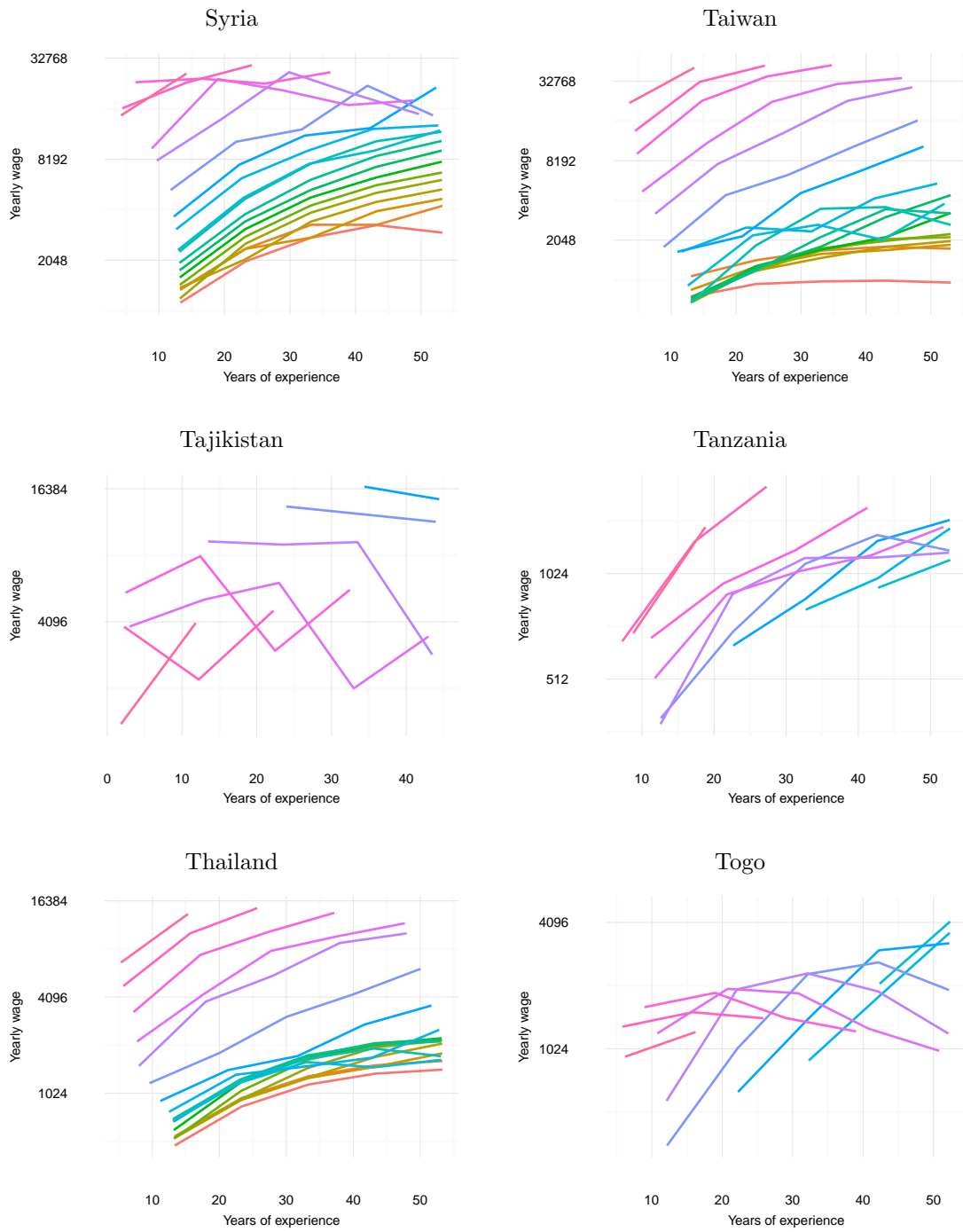


Figure D.1: Predicted wage for each cohort throughout their lifetimes as they gain experience (every country)

Note: More recent cohorts are typically higher and to the left

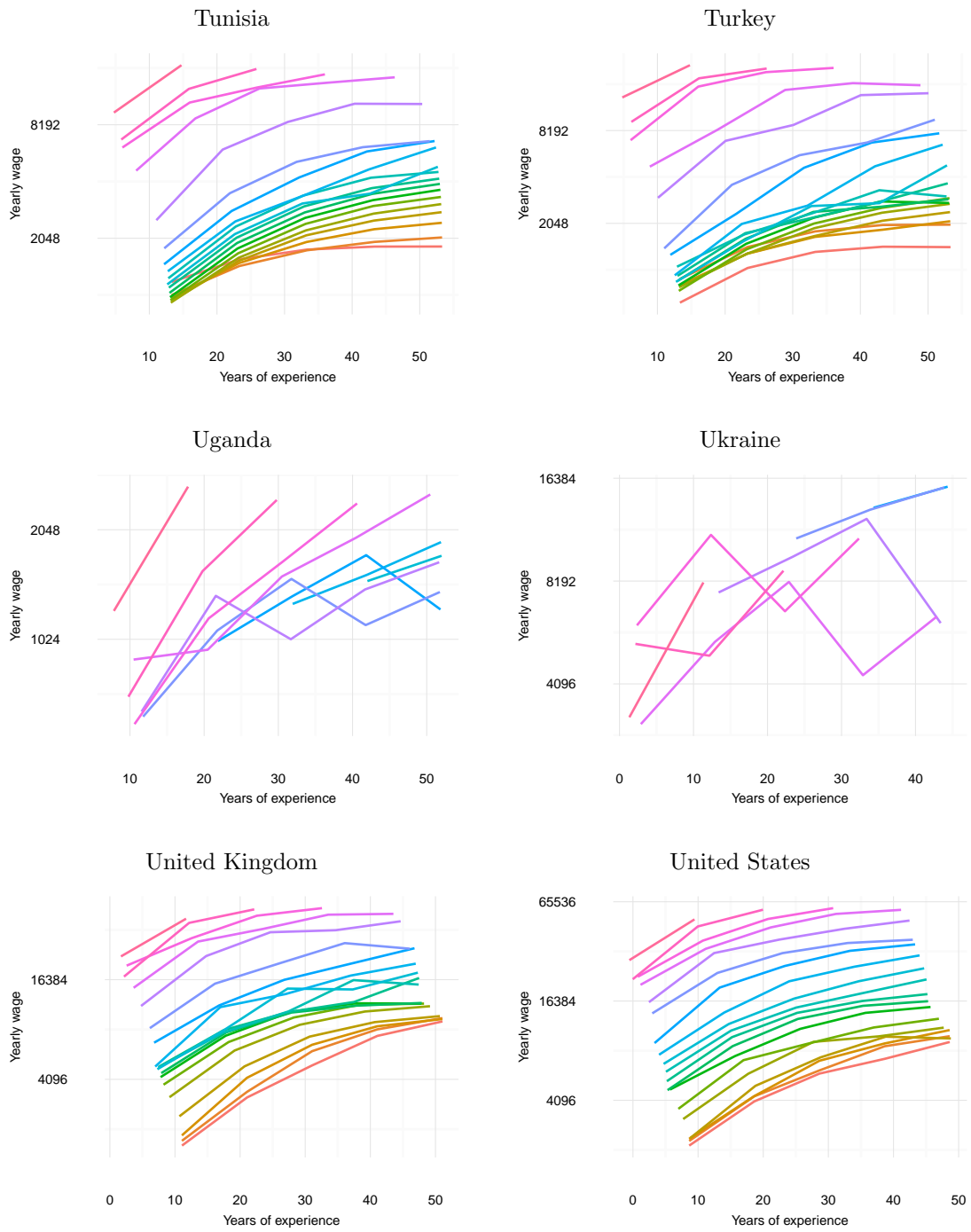


Figure D.1: Predicted wage for each cohort throughout their lifetimes as they gain experience (every country)

Note: More recent cohorts are typically higher and to the left

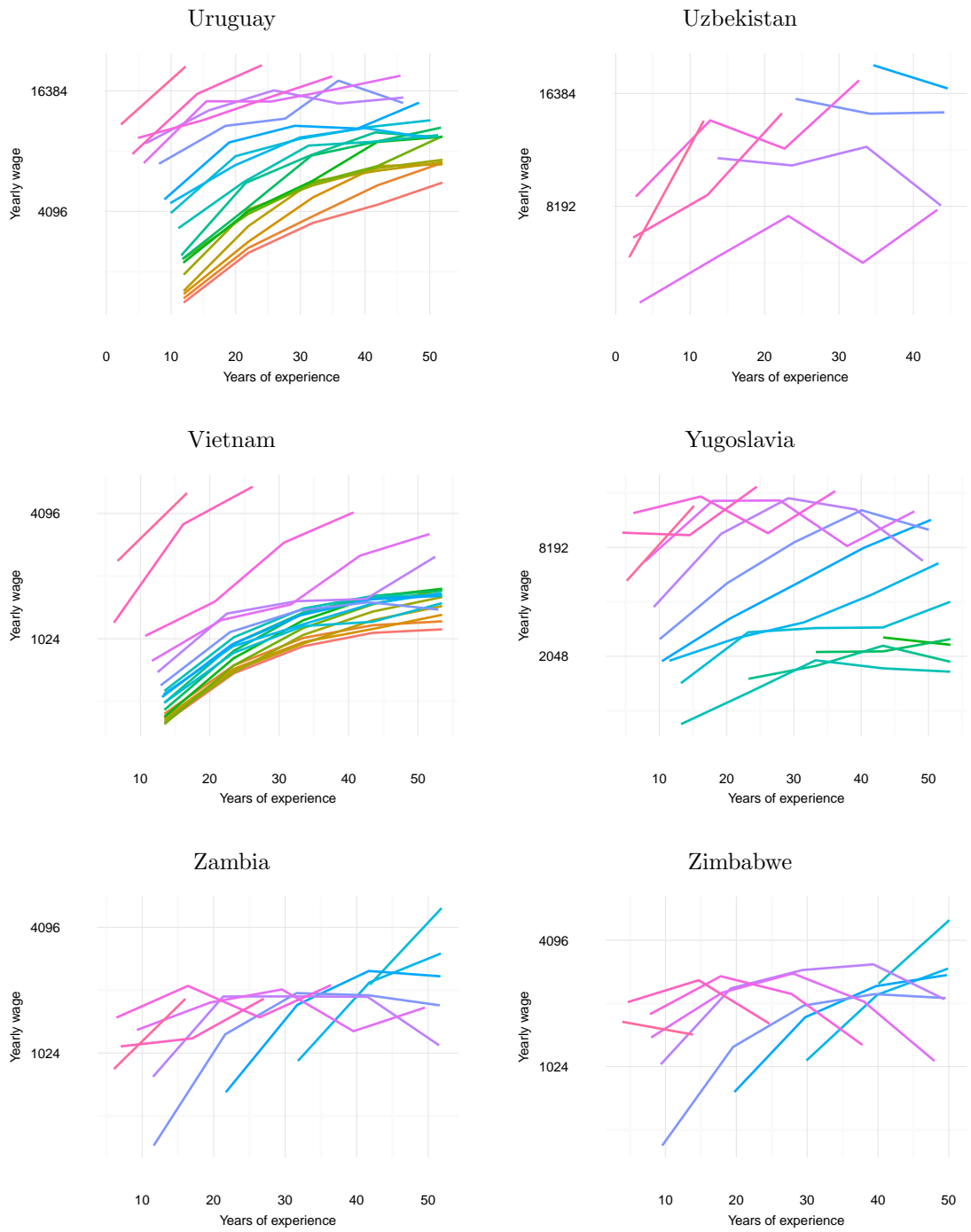


Figure D.1: Predicted wage for each cohort throughout their lifetimes as they gain experience (every country)

Note: More recent cohorts are typically higher and to the left

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