NBER WORKING PAPER SERIES

SKILL PRICES, OCCUPATIONS, AND CHANGES IN THE WAGE STRUCTURE FOR LOW SKILLED MEN

Nicolas A. Roys
Christopher R. Taber

Working Paper 26453
http://www.nber.org/papers/w26453

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2019

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NBER Working Paper No. 26453
November 2019
JEL No. J21,J24,J3

ABSTRACT

This paper studies the effect of the change in occupational structure on wages for low skilled men. We develop a model of occupational choice in which workers have multi-dimensional skills that are exploited differently across different occupations. We allow for a rich specification of technological change which has heterogenous effects on different occupations and different parts of the skill distribution. We estimate the model combining four datasets: (1) O*NET, to measure skill intensity across occupations,(2) NLSY79, to identify life-cycle supply effects, (3) CPS (ORG), to estimate the evolution of skill prices and occupations over time, and (4) NLSY97 to see how the gain to specific skills has changed. We find that while changes in the occupational structure have affected wages of low skilled workers, the effect is not dramatic. First, the wages in traditional blue collar occupations have not fallen substantially relative to other occupations-a fact that we can not reconcile with a competitive model. Second, our decompositions show that changes in occupations explain only a small part of the patterns in wage levels over our time period. Price changes within occupation are far more important. Third, while we see an increase in the payoff to interpersonal skills, manual skills still remain the most important skill type for low educated males.

Nicolas A. Roys
Department of Economics
Royal Holloway
University of London
Egham, Surrey TW20 OEX
United Kingdom
nicolasroys@gmail.com

Christopher R. Taber
Department of Economics
University of Wisconsin -Madison
1180 Observatory Dr
Social Sciences Building #6448
Madison, WI 53706-1320
and NBER
ctaber@ssc.wisc.edu

1 Introduction

Compared to other demographic groups, low-skilled (no college) men have fared poorly in the last 40 years. This group has actually seen their median real wage decrease during this period. During the same time span, there has been a substantial shift in the type of work that this group performs as occupations have moved from more traditional blue collar occupations to service and clerical occupations. This paper tries to understand the relationship between these two trends by investigating the role of the change in occupational composition and the payments to multi-dimensional skills in explaining recent changes in the wage structure for low skilled men. From a policy perspective, if our goal is to invest in skills to help these men, the occupational trends have implications for which skills have increased most in value.

We develop a model in which individuals are endowed with a three dimensional vector of skills: cognitive, manual, and interpersonal. Each period they choose a "desired" occupation but may not be able to work in that occupation due to labor market frictions. Skills evolve on the job, but differently in different occupations.

The wage in an occupation is determined by a non-linear hedonic pricing equation that depends on the level of the three skills as well as occupational specific human capital. Both the hedonic prices and the frictions evolve over time. The nonlinearity in the hedonic pricing equation allows the wage difference between high skilled workers versus median workers within an occupation to evolve differently than the wage difference between low skilled workers versus median skilled workers in that occupation. This evolution could be due to technological change, labor market institutions, or changes in international trade-we do not model it explicitly.

One of the biggest challenges in this literature is separating wage changes within an occupation into the part due to changes in prices versus changes in composition. The age-cohort-time identification problem renders it impossible to perfectly separate these effects without assumptions. If cohort and age effects are completely unrestricted, there is always a distribution of skills that can reconcile any hedonic pricing equation. This is, of course, a feature of any analysis that follows different cohorts over time, not just a problem in our paper.

We address the age-cohort-time effect by assuming that the underlying initial skill level is identical across cohorts, conditional on the probability of going to college-cohorts look different ex-post only because the aggregate features of the economy have changed leading to different occupational patterns. We use our model of human capital accumulation to estimate the age effect. In doing this, we assume that this process does not vary across cohorts. Identification of the dynamic supply of skill comes from the NLSY79 in which we have a long panel of workers who face changing wages.

Identification of the prices come from three places. First, a crucial part of this uses O*NET to estimate the skill intensity of each occupation. Second we follow Deming (2017) by using the contrast between the NLSY79 and NLSY97 to measure the increasing importance of social skills. Third, once we know the supply of worker skill as a function of prices (identified from the NLSY79) we can use the CPS to recover the prices and also the aggregate supply of skill to the population. This part imposes some structure but due to the age-cohort-time problem the model is fundamentally unidentified without some type of structural assumption. We provide an identification argument of a stylized version of our model to show formally that the model is identified.

While we do need to make some strong assumptions to estimate our structural model, the advantage is that the resulting estimated model is rich and allows us to say a number of things about the wage structure for low skilled men.

First, we are able to estimate the changes in the hedonic pricing equation over time. We see skill prices falling for the median skilled worker in all occupations but rising for relatively high skilled workers in those occupations. Prices rise for the lowest workers in some professions, but fall in others.

We also find that many of the occupations that are expanding actually see relatively large declines in skill prices. We can not reconcile this trend with a frictionless model. Similarly even though the number of people doing blue collar jobs is falling, most of them remain relatively well paid. We also show occupational composition does little to explain changes in the wage structure. The changes in the different part of the wage distribution are primarily driven by skill prices that evolve within occupation.

We then explore the payoff to different skills and how that has changed over time. We find that the importance of interpersonal skills grows over time going from little value at the beginning of the period to substantial returns later. However, manual skills remain the most important skill. If we were able to boost these skills for low skilled men, we could substantially increase their lifetime earnings.

Section 2 discusses the related literature while Section 3 describes the data and presents some motivating facts. Section 4 presents the model that we use to explain them. Section 5 discusses identification while Section 6 describes the estimation strategy. Section 7 presents the results, Section 8 decomposes the changes in wages into different component, and Section 9 examines the change in the payoff to different skills. We conclude in Section 10.

2 Related Literature

This paper is related to large literatures on skill-biased technological change, human capital, and on structural models that try to address these issues. A full survey of all of these literatures is not possible, but we briefly name some major papers.

There is a very large literature on changes in the wage structure, a seminal paper is Katz and Murphy (1992) and surveys/overviews include Katz and Autor (1999), Dinardo and Card (2002), Goldin and Katz (2009), and Acemoglu and Autor (2011). Of particular relevance to us in this literature is the importance of occupations. There are two threads that focus on occupations.

The first is the polarization of the labor market: the simultaneous growth of the share of employment in high wage occupations and low wage occupations. This has been discussed in a large number of papers and a full survey is beyond our scope. Key ones are Autor et al. (2003), Autor et al. (2006), Acemoglu and Autor (2011), Autor and Dorn (2013), and Goos et al. (2014). Beaudry et al. (2016) highlight that this trend largely ends in 2000 after which we see a decrease in demand for cognitive skill. Michel et al. (2013) are critical of some aspects of this literature arguing that while it is an important feature of the occupational composition it does not explain most features of the wage distribution. Our results are broadly similar. Using a model-based approach, we estimate how these recent patterns are related to trends in different skill prices and we examine the consequences for the wage structure and we find that it is not a crucial determinant. We also differ from much of this literature in focusing on occupations directly and then using our three types of skills rather than focusing on routineness (or complexity which Caines et al., 2017 argue is important).

The second thread is papers that use decompositions to look at occupations. The fact that there is a lot of variation within occupations goes back at least to Slichter (1950). Using a variance decomposition, Juhn et al. (1993) show that much of the rise in wage inequality can be explain with an increased returns to unobserved ability. While Juhn et al. (1993) describes a method and says it could be used for occupations, they only show results for industries. Quite a few papers have used similar types of decompositions based on occupations or tasks since. Examples include Lemieux (2006), Alsalam et al. (2006), Kim and Sakamoto (2008), Mouw and Kalleberg (2010), Scotese (2013), and Burstein et al. (2019). The main findings of these papers is that within occupation variation tends to be most important in both levels and trends in inequality, but the relevant importance of occupations varies across the papers. Our counterfactual differ from these in quite a few ways. We focus on low skilled men, our main focus is on wage levels rather than inequality, we assess the role played by different skills, and we use our model to separate the "within variation" into components due to skill prices and components due to composition. This last part can not be done without some structure.

A few paper adopt various approaches to try to separate skill prices from composition effects. The major issue here is separating time, age and cohort effects. Antonczyk et al. (2018) address this problem by assuming separability between age and time effects following MaCurdy and Mroz (1995). They find that cohort effects are small in the U.S. Another approach is a "flat spot" method which assumes there is some point in the lifecycle for which age effects are flat allowing one to separate time effects from cohort effects. This approach was used by Heckman et al. (1998) and Bowlus and Robinson (2012). This approach is challenging here as we are trying to identify occupation specific prices and occupation switching is common even late in the life cycle so there is still a selection problem. Other papers use various panel approaches which at some level can be viewed as restrictions on age effects. These include Cortes (2016) and Lochner et al. (2018). Gottschalk et al. (2015) estimate return to different skills by focusing on entry level wages and using bounds to account for selection on unobserved variables. Bohm (2019) uses implications of a generalized Roy model and the envelope theorem to estimate skill differences between the different cohorts of the NLSY. Our approach uses various elements of these approaches in different ways. A key assumption is the cohorts are ex-ante identical (conditional on education levels) and as shown in Section 6 we require panel data (NLSY) and then combine it with O*NET and the CPS to obtain identification.

While it does not look specifically at occupations, Charles et al. (2019) is particularly relevant in that the main focus is really on high school men. They argue that a large part of the decrease in labor supply since 2000 was due to decrease in manufacturing, but before 2007 this was masked by the housing boom. They also find a large role for the decline in manufacturing to explain the decrease in wages for low skilled men. This does not contradict our finding of a relatively low role for occupations to explain falling wages because we are looking at different effects. They measure equilibrium effects by looking across regions. The decline in manufacturing could lead to a substantial decrease in wages for all jobs which is consistent with both their findings and ours.[1] This suggests that much of the decline that we find in wages within occupations could be due to declining manufacturing wages. It is also an important reminder that our analysis is partial equilibrium as we are not trying to

[1]Specifically Table 5 of their paper shows wage decline in other sectors of similar magnitude to the wage declines in manufacturing.

identify the source of decrease in demand.

Another key to identification for us is the contrast between NLSY79 and NLSY97 which we use to identify cohort effects and the returns to different type of skills. Comparing NLSY waves is also used by Altonji et al. (2012), Castex and Dechter (2014), and Deming (2017). Using pre-market measures of skills, Castex and Dechter (2014) find declining returns to cognitive skills while Deming (2017) documents the rising of social skills. We extend this literature by considering the role of manual skills. Using our structural model, we also find an increase in the payoff to interpersonal skills. However, we find that manual skills remain the most important skills for non-college educated men. We will return to Deming (2017) paper in greater details later on in Section 7 and Appendix D.

Closest to our approach are papers that estimate equilibrium models of the labor market to understand the skill premium (Heckman et al., 1998), the growth of the service sector (Lee and Wolpin, 2006), changes in the wage structure (Johnson and Keane, 2013), and the gains from trade (Dix-Carneiro, 2014, and Traiberman, 2019). These papers all assume log wages are additively separable in prices and skills, partly because this equation can be micro-founded with an aggregate production that features perfect substitutability across workers given observables (such as education, occupation or experience). We allow for a flexible non-linear relationship between wages and an index of unobserved skills. And we show that it is key for understanding changes in the wage structure. Our main question is also different from these other papers.

Our methodology is also closely related to structural papers that use the tasks approach to modeling specific human capital. Poletaev and Robinson (2008) and Gathmann and Schönberg (2010) show the importance of tasks as measures of human capital. Sanders and Taber (2012) provide a survey of the evidence. A number of papers use this approach in estimating models of the labor market including Sullivan (2010), Yamaguchi (2012), Sanders (2016), Lindenlaub (2017), Postel-Vinay and Lise (2019) and Guvenen et al. (2019). While they do not explicitly use the task approach, Keane and Wolpin (1997) predates the others and allows for two types of experience that differ by occupation. We differ from these papers in a number of ways. The most important one is our focus on understanding changes in the wage structure and labor market trends while they are more interested in the life-cycle.

In an attempt to directly measure the trends in returns to tasks, Atalay et al. (2019) use the text from job ads to construct a new data set of occupational content from 1960 to 2000. They find within-occupation task content shifts are at least as important as employment shifts across occupations. They however focus on the distinction between routine and nonroutine tasks.

3 Motivating Facts

We use four different datasets described in Appendix A. We need a consistent definition of occupations across these datasets and over time. We use a modified version of the occupation classification of Autor and Dorn (2013) reducing their 15 occupations down to the 8 listed in Table A1 (Appendix A1).[2]

First, we use the Outgoing Rotation Group data from the Current Population Survey (ORG CPS), to estimate the evolution of skill prices and occupations over time. Second, we use the National Longitudinal Survey of Youth, 1979 (NLSY79), to identify life-cycle supply effects.

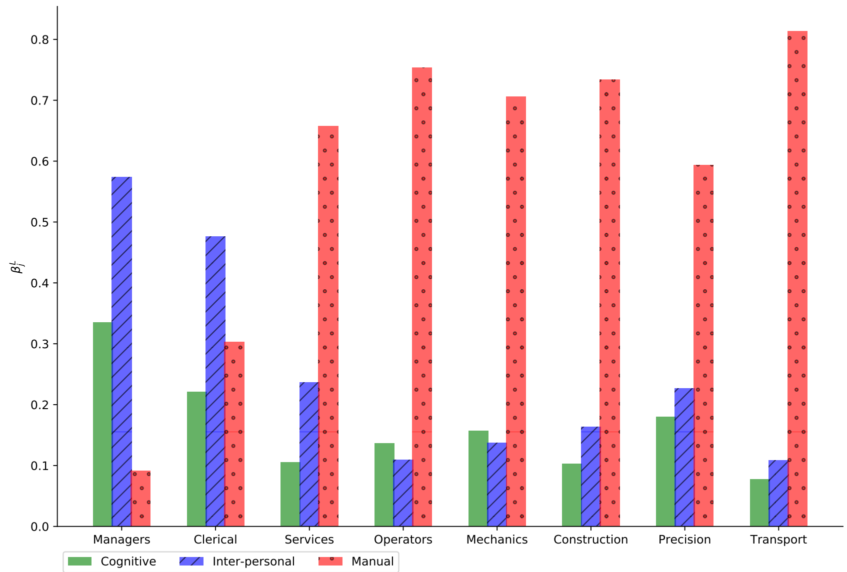
Third, we use O*NET, to measure skill intensity across occupations. We categorize skills into cognitive, interpersonal and manual. We use factor analysis to reduce these questions to a one dimensional factor for each combination of occupation and skill. Figure 1 reports the implied skill intensity of each occupation. We have renormalized so that the sum of the skills adds to one. Occupations can be characterized into three groups broadly defined. The first two occupations correspond to managerial and clerical occupations and are intensive in both cognitive and inter-personal skills. The service sector is intensive in inter-personal skills and manual skills. The remaining five occupations are intensive in manual skills which is expected since they are associated with blue-collar jobs. Overall, there is wide dispersion in the type of skills used by different occupations. Finally, we use the National Longitudinal Survey of Youth, 1997 NLSY97. O*NET measures the skill intensity of occupations at a point in time. To identify within occupation changes, we combine NLSY79 and NLSY97.

To motivate our analysis, we start by presenting data on changes in the distribution of log wages over time controlling for age. We examine 20-60 year old males with a high school degree or less. Figure 2 shows the familiar patterns. There are a few things to note. First, and most important, there has been a substantial decline in the median wage over this time period falling by around 0.12 log points.[3] The story for the 90^{th} quantile is quite different as wages for this group have risen during this time period. The 10^{th} quantile is somewhere

[2]Given the structural model that follows we need a sufficient number of people in an occupation in order to obtain reliable estimates of the occupation specific variables.

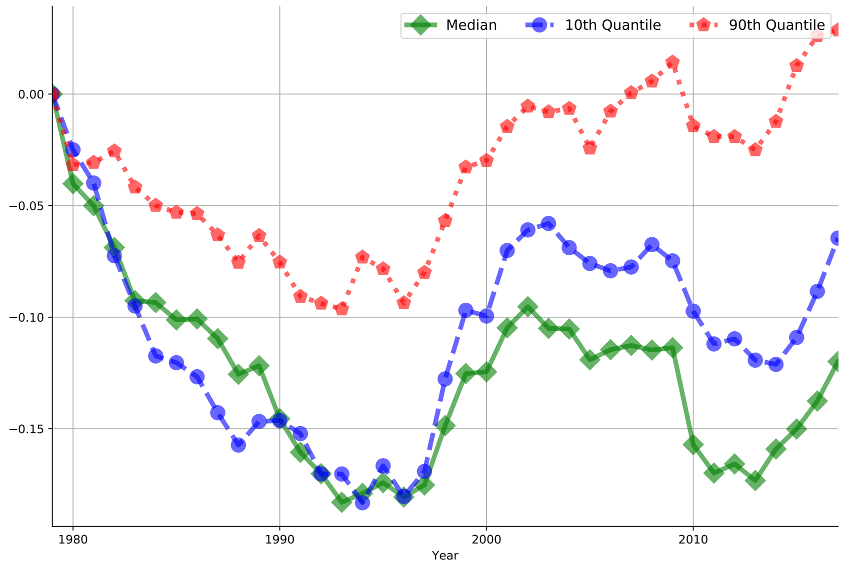
[3]This exact number depends substantially on how one accounts for inflation. The CPI yields a much larger decline than the PCE. However, even the PCE is not perfect as accounting for technological change and quality differences in constructing a measure is very difficult. The fact that median wages for low educated men has fallen relative to other demographic groups is very well established.

Figure 1: Skill intensity by occupations



in the middle. Wages have fallen, but not by as much as the median. Clearly the effects are not monotonic over the time period. The wages at every quantile fell through the eighties and early nineties, rose from the mid nineties to early 2000s. The patterns for the different quantiles are quite different during most of the 2000s, but then all three fall substantially during the great recession and have subsequently recovered.

Figure 2: Changes in Log Wage Quantiles over Time



Source: CPS. Schooling ≤ 12. Each quantile is normalized to 0 in 1979. age controls included.

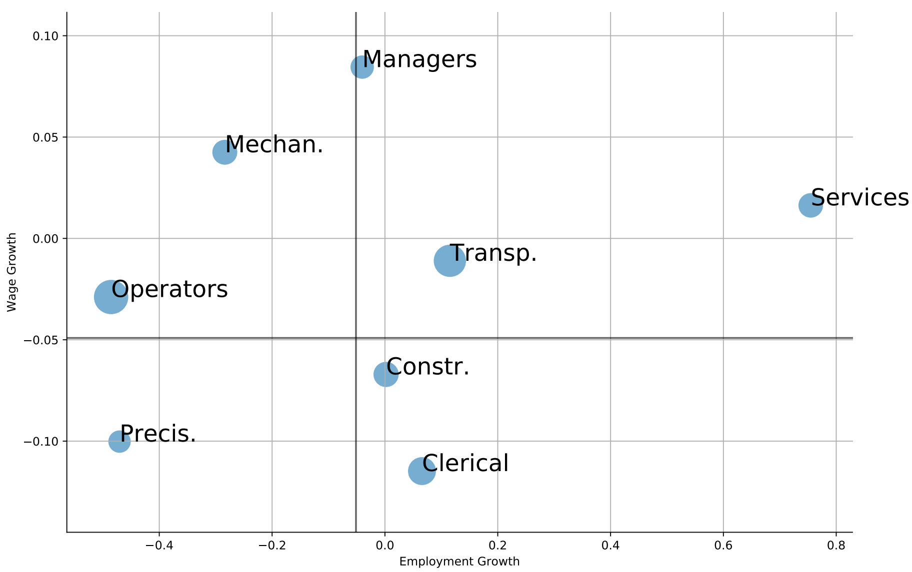
At the same time the occupation distribution has been changing considerably over time as can be seen in Table 1. The most notable changes are the decline in operators, the increase in services and the rise of not-working. It is also important to point out that the operator occupation is not representative of blue collar occupations. Construction and transportation have remained roughly constant and mechanics has had a relatively small fall. Precision production resembles operators and has almost been cut in half. Adding the five blue collar occupations together the decline has been from 56% of the workforce to 42%. This is a substantial change but not dramatic. Similarly the fraction of these workers doing service jobs has risen but not dramatically: only by about 6 percentage points. By comparison, the fraction of these men in the manufacturing sector has fallen much more substantially during this same period. It fell by more than half.

Table 1: Changes in Occupational Distribution over Time

Occupation	% in 1979	% in 2017	Difference
Managers	7.4	7.1	-0.3
Clerical	10.1	11.2	1.1
Services	8.3	14.0	5.7
Operators	17.3	8.0	-9.3
Mechanics	8.5	6.1	-2.3
Construction	8.5	8.9	0.4
Precision	6.8	3.5	-3.3
Transport	15.0	15.8	0.8
Not-working	18.2	25.4	7.3

Figure 3 presents the changes in mean wages across time for different occupations and the changes in occupation share.

Figure 3: Wages growth and employment growth



We see that most occupations experience decreases in wages. It is also clear that wage patterns are not that closely related to the changes in occupation share. For example, clerical workers see quite a large fall in their wages even though it is a growing occupation, and operators see a relatively modest fall in wages even though it is declining faster than any other occupation. This is surprising since we think that the change in occupations over time has primarily been driven by demand changes, one would expect this pattern to trace out a supply curve and be upward sloping.[4] Importantly, these wages patterns cannot directly be interpreted as technology shocks. Wages change for two reasons, because the composition of workers is changing and because skill prices are changing. A major goal of the empirical work is to sort out these differences.

4 Model

Overview

The only decision people make in each period is their desired occupation.

We use i subscript to denote an individual and t to index time. We let j_{it} denote the occupation in which individual i works at time t. Let $j = 1, .., J$ index occupations and $j = 0$ denotes not working.

The vector of state variables $\mathcal{S}_{it}$ at time t for individual i is,

$$\mathcal{S}_{it} \equiv \{\theta_{it}, a_{it}, \tau_{it}, j_{it-1}, t\}$$

where $\theta_{it} = (\theta^c_{it}, \theta^i_{it}, \theta^m_{it})$ is a vector of general skills composed of cognitive, interpersonal and manual skills. The other state variables are age a_{it}, consecutive tenure in the current occupation τ_{it} and last period occupation j_{it-1}. Time t is relevant as it indexes the current and future values of aggregate variables which vary across cohorts (conditional on age).

The workers are born with initial endowment of skills $\tilde{\theta}_i$. Skills then evolve over time depending on the occupation of choice. More generally the state variables evolve exogenously

[4] An illustrative example of the challenges ahead is the following. Consider an economy with two occupations indexed by j with wage rate w_j. Individuals are identical, indexed by i and derive utility from working in occupation $u_{ij} = \eta \log w_j + \epsilon_{ij}$, where ϵ_{ij} is an i.i.d. extreme-value distributed preference shock and $\eta > 0$ is a scale parameter. Relative labor supply to occupation 1 is $\left(\frac{w_1}{w_2}\right)^{\eta}$. The aggregate production function is $\left[(A_1 n_1)^{\frac{\sigma-1}{\sigma}} + (A_2 n_2)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$. Relative labor demand for occupation 1 is $\left(\frac{A_1}{A_2}\right)^{\sigma-1}\left(\frac{w_2}{w_1}\right)^{\sigma}$. Equilibrium relative wages satisfies $\left(\frac{w_1}{w_2}\right)^{\sigma+\eta} = \left(\frac{A_1}{A_2}\right)^{\sigma-1}$ and equilibrium relative occupation share is $\left(\frac{A_1}{A_2}\right)^{\frac{\eta(\sigma-1)}{\eta+\sigma}}$. Following a relative demand shock, relative wages changes and relative employment changes have the same sign if $\sigma > -\eta$. Only supply shifts, such as a change in η, can explain the lack of correlation.

and deterministically given the current occupation j_{it}

$$\mathcal{S}_{it+1} = F\left(j_{it}, \mathcal{S}_{it}\right).$$

An important feature of the model is labor market frictions which may prevent workers from working in their preferred occupation. These frictions, and more particularly their variation over time, will prove critical for fitting the evolution of occupational composition given the weak link between employment and wage evolution presented in Figure 3.

Each period an individual chooses between three options:

1. Continue to work in current occupation ($j_{it} = j_{it-1}$)

2. Move to non-employment ($j_{it} = 0$)

3. Direct search to another occupation κ.

If an individual chooses the third option, he must pay a search cost that allows him to find a job in that occupation with probability λ_{jt}. If the search is unsuccessful, he chooses between the first two options. If the worker is currently non-employed, choices 1 and 2 coincide.

Preferences

Individual i with state variables $\mathcal{S}_{it}$ who searches for a job in occupation κ and works in occupation j has flow utility

$$w(j, \mathcal{S}_{it}) + \nu_{ijt} - \chi_{i\kappa t}$$

where $w(j, \mathcal{S}_{it})$ are wages, ν_{ijt} is a taste shifter for an occupation, and $\chi_{i\kappa t}$ is the cost of search.

We let $\kappa = 0$ denote no search. We can write

$$\chi_{i\kappa t} = \begin{cases} \widetilde{\chi}_{i0t} & \kappa = 0 \\ \bar{\chi} + \widetilde{\chi}_{i\kappa t} & \kappa = 1, ..., J \end{cases}$$

where $\widetilde{\chi}_{\kappa t}$ are i.i.d. and type I extreme value with scale parameter σ_{χ}. The ν_{ijt} are type I extreme value with scale parameter σ_{ν}.

Timing of the model

Each period can be broken into three sub-periods.

Sub-period 1: The $\widetilde{\chi}_{\kappa t}$ are revealed and then the agents decide whether to search for another occupation (only one at a time)

Sub-period 2: Nature reveals whether the search was successful or not. The probability of success is $\lambda_{\kappa t}$ if the agent searches in occupation κ. This determines the choice set $\mathcal{B}_{it}$ which will be available in sub-period 3. This is determined as

$$\mathcal{B}_{it} = \begin{cases} \{0, j_{it-1}, \kappa\} & \text{successful search} \\ \{0, j_{it-1}\} & \text{unsuccessful/no search.} \end{cases}$$

Note that the second element in the choice set is redundant when $j_{it-1} = 0$.

Sub-period 3: The ν_{jt} are revealed and the agent chooses an option from choice set $\mathcal{B}_{it}$.

All other state variables evolve between periods.

Wages

We think of our model as an approximation of a directed search model in which workers direct their search to a particular occupation, but wages contracts within those occupations are posted. In this subsection we describe our parameterization of those wage contracts.

Hedonic Pricing Equation

In order to allow the pricing of high, medium, and low skilled workers to vary differently within occupation, we model the wage function using a nonlinear hedonic pricing equation rather than a standard linear additive model.

We assume the wage of a worker in occupation j with state variables $\mathcal{S}_{it}$ is

$$w(j, \mathcal{S}_{it}) = \begin{cases} \exp\{f_{jt}(h(j, \mathcal{S}_{it}))\} & j = 1, \ldots, J \\ 0 & j = 0 \end{cases}$$

where f_{jt} is a hedonic pricing equation and h is a human capital index. In practice, we simplify and parameterize the hedonic pricing function f_{tj} as follows,

$$f_{jt}(h) = \begin{cases} \delta_{jt} + \alpha_{1jt} h & \text{if } h > h_j^* \\ \delta_{jt} + \alpha_{1jt} h_j^* + \alpha_{2jt}\left(h - h_j^*\right) & \text{otherwise} \end{cases} \tag{1}$$

which is a linear spline (in logs) with a kink point at h_j^*. That is, within each occupation, all individuals are affected equally by technology changes through the occupation specific constant δ. Depending on the level of his human capital index h, an individual sees his skills multiplied by either α_1 or α_2 depending on whether his index is below (or above) some threshold h_j^*.

A standard labor demand model in which workers are perfect substitutes within an occupation would yield special case of Equation (1) in which $\alpha_{1jt} = \alpha_{2jt} = 1, \forall j, t$.[5] We chose this more general parameterization for two main reasons. First, with the standard formulation, an increase in the within-variance can only be attributed to supply factors or occupational composition. Our more general formulation allows technology to favor some level of human capital more than other. And we will show it is key for understanding changes in the wage structure. Second, Figure 2 shows quite different patterns of the three different quantiles. We use a more flexible model in an attempt to capture these patterns.

Note that we are not trying to estimate the underlying production function, but just the hedonic pricing equations. Therefore our counterfactuals must be interpreted as partial equilibrium experiments that hold these pricing equations fixed.

Human capital index

We parameterize the human capital index h as

$$h(j, \mathcal{S}_{it}) \quad = \quad \theta_{it}' \beta_{jt} + \sigma(j, \tau) \, 1 (j = j_{it-1}),$$

where β_{jt} is a vector of skill weights and σ is occupation-specific human capital. In practice we estimate the β_{jt} using data from O*NET and from information from the two NSLY data sets. We provide details in section 6 below.

Evolution of State Variables

Initial human capital $\widetilde{\theta}_i$ is drawn from a multivariate normal distribution, $\widetilde{\theta}_i \sim N\left(\mu_c^\theta, \Sigma^\theta\right)$, where Σ^θ is the variance and μ_c^θ is a cohort specific mean which accounts for selection on

[5]Formally, write a time-varying aggregate production function $G_t(H_{1t,}, \ldots, H_{Jt})$, where the arguments are the human capital stocks H_{jt} provided by each J occupation at time t. When workers within an occupation are perfect substitutes, we can write $H_{jt} = \int e^h d\Psi_{jt}(h)$ where Ψ_{jt} is the distribution of human capital indexes supplied to occupation j at time t. With competitive labor markets, the equilibrium wage function f_{jt} is such that $\delta_{jt} = \log \frac{\partial}{\partial H_{jt}} G_t(H_{1t,}, \ldots, H_{Jt})$ and $\alpha_{jt}^1 = \alpha_{jt}^2 = 1$.

schooling. For each cohort c and for each skill l

$$\mu_{cl}^{\theta} \equiv b_l \times (P_c\,(\text{College}) - P_{1979}\,(\text{College}))\,, \tag{2}$$

where b_l is a parameter to be estimated and $P_c\,(\text{College})$ is the share of low-skilled men that attended college in cohort c. We estimate $P_c\,(\text{College})$ using the Census and ACS. Appendix C gives more details.

The general human capital variables transition takes the form,

$$\theta_{it+1}^{l} = d_{0j_{it}} d_{1l} \exp\left[-d_2\left(a_{it} - 18\right)\right] + \theta_{it}^{l}\left(1 - d_{3l}\right).$$

The individual accumulates general skills at different speed depending on an occupation fixed effect d_{0j}, a skill fixed effect d_{1l} and potential experience $a_{it}-18$ according to $\exp\left[-d_2\left(a_{it} - 18\right)\right]$. Skills depreciates at rate d_{3l}.[6]

Occupation specific human capital and occupation specific tenure are determined, respectively, by

$$\sigma\left(j,\tau\right) = \begin{cases} 0 & \tau = 0 \\ \sigma\left(j,\tau - 1\right) + \gamma_{0j}\exp\left(-\gamma_1\tau\right) & \tau > 0 \end{cases}$$
$$\tau_{it+1} = \left(\tau_{it} + 1\right) 1\left(j_{it} = j_{it-1}\right),$$

with $\tau_{it} = 0$ at labor market entry. Occupation specific human capital σ is a deterministic function of τ. Occupation tenure is reset to zero after a switch to keep the dimension of the state space tractable-otherwise we would need to keep track each individual entire work history. Stayers get additional occupation-specific tenure through $\gamma_{0j}\exp\left(-\gamma_1\tau\right)$ where the specific human capital profile is concave in τ,$\gamma_1 > 0$.

The intensity of skill utilization and the relative weights of different skills also contributes to wage growth as individuals switch occupations, due to changes in α, δ and β across occupations. A wage growth decomposition is presented in Appendix G.

[6]We settle on this parametrization of the accumulation equation because more general versions lead to large standard errors. We will however present identification results for a very general accumulation process in the next section.

Solving the Model

Every period t, the agent chooses an occupation to maximize their discounted present value of income.[7] The discount rate is R. Since the terminal period is simpler than prior periods, we show this expression for periods prior to the terminal period. Let $V^1(\mathcal{S}_{it})$ and $V^3(\mathcal{S}_{it}, \mathcal{B}_{it})$ be the expected value functions at the beginning of sub-periods 1 and 3 respectively where $\mathcal{B}_{it}$ is the choice set defined above. We can write the value functions as

$$\begin{aligned}
V^3(\mathcal{S}_{it}, \mathcal{B}_{it}) &= E_\nu \max_{j \in \mathcal{B}_{it}} \left\{ w(j, \mathcal{S}_{it}) + \nu_j + \frac{1}{1+R} V^1(F(j, \mathcal{S}_{it})) \right\} \\
V^1(\mathcal{S}_{it}) &= E_\chi \max \Bigg\{ -\chi_0 + V^3(\mathcal{S}_{it}, \{0, j_{it-1}\}), \\
&\quad \max_{\kappa \in \{1,\dots,J\} \setminus \{j_{it-1}\}} \left\{ -\chi_\kappa + \lambda_{\kappa t} V^3(\mathcal{S}_{it}, \{0, j_{it-1}, \kappa\}) + (1 - \lambda_{\kappa t}) V^3(\mathcal{S}_{it}, \{0, j_{it-1}\}) \right\} \Bigg\}.
\end{aligned}$$

5 Identification of Stylized Model

In this section we consider identification of a stylized version of the model. To focus on the main ideas, we make this model more general than our baseline model in some ways but simpler in others. It is more general in that we put no structure on occupational choice but show we can non-parametrically estimate the supply of individuals to occupations as a function of the lifetime prices that they face. We are also more general in the way we allow human capital to accumulate. We simplify in three important ways. First, we assume that people live for 4 periods. We do not view this as a strong assumption as it seems clear that the results will generalize to more periods. Second, we restrict the hedonic wage equation to be linear. We do this in large part because it simplifies the expressions substantially. Since the model is linear-identification of most of the parameters depends on first and second moments only. Allowing for non-linearity makes the problem more difficult but also means that higher order moments can help identify the model. Further, much of the identification problem we are worried about has to do with distinguishing age from experience from cohort effects. This problem shows up in the linear model and is perhaps easiest to see there. We have not shown explicitly that these results would generalize to a non-linear case, but we see no reason to expect that they would not. The third restriction is that we abstract from the labor supply decision by assuming people work in all periods. This allows us to avoid the

[7] We do not allow for non-pecuniary benefits because identifying them separately from frictions proved difficult in practice.

selection issue of who works. Since the key data set is the NLSY79, and almost all men work for multiple periods this does not seem important but simplifies the analysis considerably.

We use different notation from the previous section. We index experience by $e \in \{0, 1, 2, 3\}$ and let h_{ie} be the human capital of individual i at experience level e in the occupation in which they work at that time. We let e_{it} be the experience of individual i at time t. The key data is the log of measured wages $\widetilde{w}_{it}$ which we write as,

$$\widetilde{w}_{it} = \delta_{j_{it}t} + \alpha_{j_{it}t} h_{ie_{it}} + u_{it},$$

where u_{it} is i.i.d. measurement error across both individuals and time.

We generalize the human capital production function relative to Section 4. Let $\tau(i, e)$ be the (calendar) year in which individual i has experience level e. Let $j_i^* = \left[j_{i\tau(i,0)}, j_{i\tau(i,1)}, j_{i\tau(i,2)}, j_{i\tau(i,3)}\right]$ denote the labor market history of individual i.

In the year of labor market entry, human capital is

$$h_{i0} = \theta_i' \beta_{j_{i\tau(i,0)}}.$$

As mentioned above, we allow human capital with experience e to be more general than in the model section. It can be written as

$$h_{ie} = \theta_i' D^e \beta_{j_{i\tau(i,e)}} + \psi_{j_i^*, e},$$

where ψ_{j^*e} is the tenure from history j^* at experience level e.[8] It depends flexibly on the exact labor market history. For example, ψ_{j^*e} incorporates both returns to tenure σ and changes in θ_i other than depreciation. D picks up depreciation and is a diagonal matrix where each element is $1 - d_{3\ell}$ defined in the human capital production function above.

We take a simplified version of our model in which β is fixed and known from O*NET.[9]

We consider identification from two different types of data sets

- Panel data for which we observe the full lifecycle for some cohorts. This is like the NLSY79.
- Cross section data for additional years in which we don't observe the panel. This is like the CPS.

[8] In practice the experience level at e should only depend on the history up to that point. We do not need this for identification though so we do not impose it.

[9] In practice we allow this to change using the contrast between the two NLSY data sets following Deming (2017). Since identification of this is obvious, we focus on the more subtle parts.

As is standard in these types of models, time effects, cohort effects, and age effects are not separately identified and some assumption is needed. We assume that all cohorts are ex-ante identical. In practice this means that the ex-ante distribution of θ_i and the supply function to occupations does not vary by cohort. To see this more formally, let p_τ be the set of lifetime prices facing a cohort that enters the market during period τ. The per capita lifetime supply of skills is $S(p_\tau)$ which is cohort invariant. Cohorts will differ ex-post because they face different prices, but ex-ante they will be identical. Both p_τ and $S(\cdot)$ are defined formally in Appendix D. In practice in our estimation we relax this by allowing the distribution to depend on the probability of college attendance and assume that cohorts are ex-ante identical conditional on the probability of attending college. We can then think of the identification argument as conditional on college.[10] Note that since the college attendance rate of men changes little since the late 1960s, in practice the difference between these is not important.

We need two types of exclusion restrictions for identification.[11] For each occupation at experience e we need variables that influence the selection equation but not wages directly. We also need variables that affect wages but have no separate effect on the selection equation. We use skill prices for both. In particular for occupation j, the prices in all other occupations operate as exclusion restrictions in the selection equation. The skill prices in occupation j work as the second type of exclusion restriction-they affect wages in occupation j directly, but only affect occupational choice through their effect on wages. Dealing with this is non-standard because we do not observe prices directly. We must first identify them. As is standard in non-parametric identification of selection models,[12] we need very strong support conditions as well which allow us to condition on very unlikely events.

The identification results comes in the following 5 steps.

Step 1: From the panel data using the prices as exclusion restrictions we identify the variance of the measurement error σ_u^2, depreciation D, and the unconditional variance of θ_i from conditional second moments.

Step 2: Using the same type of argument but with first moments we identify $\psi_{j_i^*(e)}$.

Step 3: Given multiple cohorts and exclusion restrictions we identify δ_{jt} and α_{jt} for the relevant panel data sample from first and second moments.

[10] And in practice the college fraction does not increase monotonically so it is not difficult to separate this effect from the time effect in general.

[11] See e.g. Willis and Rosen (1979), Heckman and Honoré (1990), or French and Taber (2011).

[12] See e.g. Heckman (1990).

Step 4: Given that we have estimated prices, we show how to identify $S(p_\tau)$.

Step 5: Given the supply function, we show that we can identify the prices δ_{jt} and α_{jt} from the cross section data.

We go through these five steps in Appendix D.

6 Estimation

Let Λ be the vector of structural parameters. We estimate our model using indirect inference. Indirect inference works by selection of a set of statistics of interest $\hat{\Psi}$ which the model is asked to reproduce.[13] For an arbitrary value of the vector of parameters to be estimated Λ, we use the model to generate the target moments $\Psi(\Lambda)$. The parameter estimate $\hat{\Lambda}$ is then derived by searching over the parameter space to find the parameter vector that minimizes the criterion function,

$$\hat{\Lambda} = \arg\min_{\Lambda} \left(\hat{\Psi} - \Psi(\Lambda)\right)' W \left(\hat{\Psi} - \Psi(\Lambda)\right) \tag{3}$$

where W is a weighting matrix. This procedure generates a consistent estimate of Λ. Before discussing the estimation approach we fill in some details about the econometric specification.

Pre-set parameters

- We set h_j^* threshold from Equation (1) to the median wage in each occupation in 1979.
- α_1 is normalized to one in clerical occupation in 1979.
- The real interest rate R is set to 5%.

Measurement/Classification Error

We allow reported wages and occupations to be contaminated by measurement errors. In the simulation, we multiply true wages by u where $\log(u) \sim N(0, \sigma_u^2)$ before calculating target moments. Occupations can be misclassified but not-working is always correctly reported. Let $\pi_t(j_0, j_1)$ be the probability that occupation j_0 is reported given that the true occupation is

[13] See Gourieroux et al. (1993) for a general discussion of indirect inference.

j_1 at time t. Formally,

$$\pi_t(j_0, j_1) = \Pr\left(j_{it}^* = j_0 \left| j_{it} = j_1\right.\right), \qquad j_0, j_1 = 1, \ldots, J.$$

In principle that is $J(J-1)$ additional parameters to be estimated for any given set of control variables. We follow Keane and Wolpin (2001) and assume classification errors are unbiased, e.g. the probability that a person is observed in an occupation is equal to the true probability that he/she chooses that occupation. Formally,

$$\Pr\left(j_{it}^* = j\right) = \Pr\left(j_{it} = j\right), \qquad j = 1, \ldots, J.$$

Under that assumption, the π_t are known up to an unknown parameter E,

$$\pi_t(j_0, j_1) \quad = \quad \begin{cases} (1-E)\Pr(j_{it} = j_0), & j_1 \neq j_0 \\ E + (1-E)\Pr(j_{it} = j_0) & j_1 = j_0. \end{cases}$$

Test scores are noisy measure of skills before labor market entry. AFQT is a noisy measure of cognitive skills $\tilde{\theta}_1$. The measure of social skills constructed by Deming (2017) is a noisy measure of inter-personal skill $\tilde{\theta}_2$. The variance of these two measures is denoted by $\tilde{\sigma}_l, l = 1, 2$.

Specification and Estimation of factor prices β

Figure 1 presented our estimates of skill weights from O*NET. Unfortunately O*NET is not a proper panel so we can not use it alone to estimate changes in skills weights. We augment the O*NET by using information from the comparison between the NLSY79 and the NLSY97. Specifically we let $\overline{\beta_j^l}$ be the time-invariant loading factor we estimated from O*NET. We assume it represents the (constant) skill intensity from 2008 and on. We allow for time trends prior to that year.

To reduce the dimension of the problem, we allow for a trend common to all occupations a_l but that differs across skills. And we allow for a trend that is a function of the observed change in the skill composition of an occupation. If individuals with a high skill level are more represented in an occupation across NLSY waves, it suggests that this occupation became more intense in that skill, ceteris paribus. Formally, let x_{jl} denotes the difference in difference in proportions for each occupation j and test score l. It is a difference between above/below median in skill l and a difference across NLSY waves. For $l = 1, 2$,

$$\beta_{jt}^{l} = \begin{cases} \overline{\beta_j^l} - (a_{0l} + a_{1l}x_{jl}) \times 29 & t \leq 1979 \\ \overline{\beta_j^l} - (a_{0l} + a_{1l}x_{jl}) \times (2008 - t) & 1979 < t \leq 2008 \\ \overline{\beta_j^l} & t > 2008 \end{cases} \tag{4}$$

Finally, $l = 3$ is calculated as a residual $\beta_{jt}^3 = 1 - \left(\beta_{jt}^1 + \beta_{jt}^2\right)$. We then estimate these parameters along with the rest of the structural parameters. To identify these parameters, we use the combination of NLSY waves. We give more details when we present the auxiliary parameters below.

Algorithm Details

It is in principle possible to estimate the full vector of parameters Λ at once starting from scratch but we found that to be computationally prohibitive. Small variations in some parameters can lead some individuals to switch occupations creating discontinuities in the objective function. We also have a large number of parameters. Instead, we develop a sequential algorithm. We first divide both the structural parameters $\Lambda = (\Lambda_1, \Lambda_2, \Lambda_3, \Lambda_4)$ and auxiliary parameters $m = (m_1, m_2, m_3, m_4)$ into four groups. We obtain starting values by dividing the estimation algorithm into four iterative steps which we repeat until convergence. Each step selects a subset of the structural parameters to fit a subset of the auxiliary parameters. Let $\mathcal{J}(\Lambda)$ be individual optimal decisions given a sequence of shocks and parameters Λ. Given Λ^{-1} from a previous iteration.

1. Choose Λ_1 to fit $m_1\left(\Lambda_1, \Lambda_2^{-1}, \Lambda_3^{-1}, \Lambda_4^{-1} \left| \mathcal{J}\left(\Lambda_1, \Lambda_2^{-1}, \Lambda_3^{-1}, \Lambda_4^{-1}\right)\right.\right)$
2. Choose Λ_2 to fit $m_2\left(\Lambda_1, \Lambda_2, \Lambda_3^{-1}, \Lambda_4^{-1} \left| \mathcal{J}\left(\Lambda_1, \Lambda_2^{-1}, \Lambda_3^{-1}, \Lambda_4^{-1}\right)\right.\right)$
3. Choose Λ_3 to fit $m_3\left(\Lambda_1, \Lambda_2, \Lambda_3^{-1}, \Lambda_4^{-1} \left| \mathcal{J}\left(\Lambda_1, \Lambda_2, \Lambda_3^{-1}, \Lambda_4^{-1}\right)\right.\right)$
4. Choose Λ_4 to fit $m_4\left(\Lambda_1, \Lambda_2, \Lambda_3, \Lambda_4 \left| \mathcal{J}\left(\Lambda_1, \Lambda_2, \Lambda_3, \Lambda_4\right)\right.\right)$

Using NLSY79 moments m_1, Step 1 estimates the preference and time invariant technology parameters $\Lambda_1 = \left(\Sigma, \left\{\delta_j^0, \alpha_j^0, \lambda_j^0\right\}_{j=1}^{J}, \overline{\chi}, \sigma_\nu, \sigma_\chi, \sigma_u, \tilde{\sigma}_1, \tilde{\sigma}_2, E\right)$ where δ_j^0, α_j^0 are initial hedonic prices and λ_j^0 are initial occupation offer rate.

Step 2 estimates life-cycle wage growth parameters $\Lambda_2 = \left(\left\{d_{0j}, \gamma_{0j}\right\}_{j=1}^{J}, \left\{d_{1l}, d_{3l}\right\}_{l=1}^{L}, \gamma_1, d_2\right)$, holding fixed individual choice, to fit m_2. The advantage is that we only need to solve the model at the beginning of this step.

We apply a similar procedure to estimate the trend in prices, skill intensity and the cohort trend parameters $\Lambda_3 = \left(\left\{\delta_{jt}, \alpha^1_{jt}, \alpha^2_{jt}, \beta_{jt}\right\}_{j=1}^{J}, \mu^\theta_c\right)$ using m_3 in Step 3. Because occupation' choices by year m_4 are, by definition, discrete, we re-solve the model at each new parameters guess $\Lambda_4 = \left(\{\lambda_{jt}\}_{j=1}^{J}\right)$ which contains the trend in frictions parameters.

Once this procedure is done, we use these estimates as an initial guess and then estimate the structural parameters using Equation (3). We find this works very well in practice as the procedure provides excellent starting points so the final stage is relatively quick.

This leaves us with a total of 216 parameters divided into groups of 58, 23, 103 and 32.

Auxiliary Parameters

As mentioned above, we partition the vector of auxiliary parameters m into four vectors defined as follows.

m_1 contains all the auxiliary parameters that are used to identify the preference and time invariant technology parameters. The data moments are

- (CPS for NLSY79 cohorts) Quantiles of the wage distribution by occupation and by age.
- (CPS for NLSY79 cohorts) The proportion of individuals choosing each of the $J + 1$ occupations by age
- (NLSY79) Occupation Mobility
  - The proportion of occupation-stayers between t and $t+1$ and between t and $t+2$ for each of the $J+1$ occupations in the population and for two different age group.
  - The proportion of occupation-switchers moving into each $J+1$ occupation between t and $t + 1$ and between t and $t + 2$ in the population and for two different age group.
  - The transition between each of the $J + 1$ occupation between t and $t + 1$ and between t and $t + 2$ in the population for two different age group.
  - The median occupation-specific tenure and the median experience in each of the $J + 1$ occupations
  - The auto-correlation of wages by age

m_2 contains all the auxiliary parameters that are used to identify the human capital accumulation parameters. Using NLSY79 cohorts, the moments are

- (CPS) The median wage by occupation and age.
- (NLSY79) The median wage by years of general work experience for each of the J occupations. The median wage by years of occupation-specific experience for each of the J occupations.
- (NLSY79) The auto-correlations of wages in level between t and $t+1$ separately for occupation stayers and occupation switchers.
- (NLSY79) The mean 1-year difference in wages by current occupation, past occupation, and for two different experience group and for two different occupation-specific tenure group.

m_3 contains all the auxiliary parameters used to identify movement in prices.

- (CPS) Quantiles of the wage distribution for each year and for each of the J occupation.
- (NLSY79 and NLSY97) The test scores coefficients in log-wage linear regressions across NLSY waves and controlling for age and year fixed effects. See Appendix E for details.
- (NLSY79 and NLSY97) The proportion of individuals choosing each of the $J+1$ occupations by test scores and across NLSY waves.

m_4 are the proportions of individuals choosing each of the $J+1$ occupations by year in the CPS used to identify trends in search frictions.

7 Changes in the Wage Structure

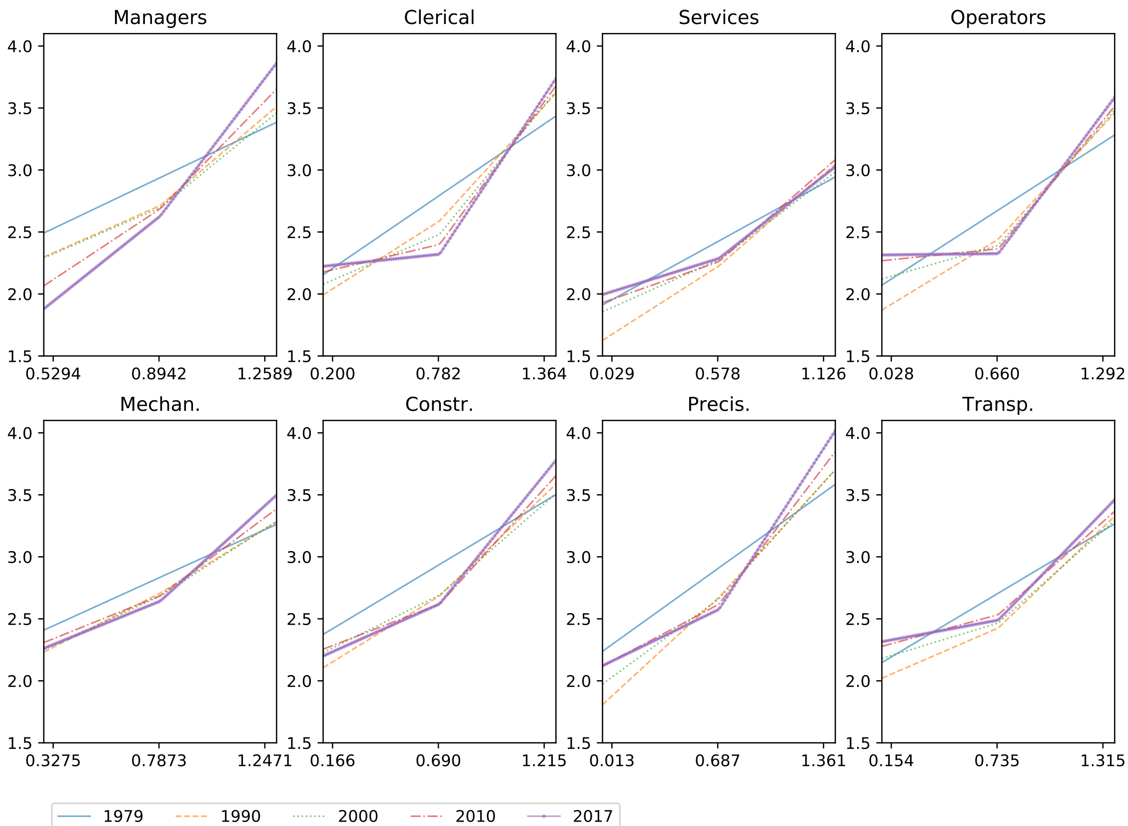
This section discusses the estimates of our model. We have a lot of parameters and can not discuss all in detail. The structural parameters related to the life-cycle are relegated to Appendix F. In this section we examine the estimated time trends which are our main focus.

Price Series

Figure 4 summarises the estimated price series. For each occupation, we graph our estimate of the hedonic pricing equation $f_{jt}(h)$ function at five different points in time.[14] The het-

[14]Standard errors are reported in Table I3 (Appendix I). Using a Wald test, we can reject that the parameters of the function f_{jt} are equal to each other for any distinct pair of decades, given any occupation j. We cannot reject equality of the slopes for some occupations between 1990 and 2000, a decade with little changes in the pricing equations.

Figure 4: Price series by decades



erogenous effects of technological changes are apparent. None of the occupations has been positively affected by technological change (or other drivers of the wage structure) throughout their distribution. The 1980s led to a large a decline in the price for all but the best workers in most occupations. This is precisely the period of acceleration of technological change documented by the literature dating back to at least Katz and Murphy (1992). An example are operators who saw price increase larger than 10% at the top while the median and the bottom saw decline of close to 10% during the same time period. We conjecture that these values reflect the evolution of the manufacturing sector where many low skilled workers have been replaced by machines. Yet, some workers, the most talented one, are now in charge of operating these machines and whose skills became much more important than in the past. This is an example that leads to a rise in wages for high skill workers but a decline for the median worker.

The pricing function has been more stable since 1990. Yet, prices at the bottom have increased relative to prices in the middle within all occupations except managers and mechanics. Further, the last decade saw another wave of decrease in prices for all but those at the top of the distribution within most occupations.

Skill Weights

Table 2 reports time-trends for skill weights and cohort effects.

Table 2: Skill weights by occupations and cohort effects

	Cognitive		Inter-personal		Manual	
a_{0l}	-0.0042	(0.0001)	0.0083	(0.0001)		
a_{1l}	0.0040	(0.0001)	0.0064	(0.0012)		
cohort effects (b_l)	-0.4823	(0.0581)	0.0413	(0.1111)	0.1612	(0.0404)

a_{0l} and a_{1l} are defined in Equation (4). The weight on inter-personal skills rose significantly over time $a_{02} > 0$. It was zero in all occupations except for management and clerical occupations at the beginning of the period. This is driven by the coefficients on inter-personal skills in linear wages regressions across NLSY waves (reported in Table E1 in Appendix E). The inter-personal skills coefficients lack statistical significance for both wages and the probability of working in NLSY79. Following the same logic, we find that the loading factor on cognitive skills declined in all occupations. The weight on manual skills is overall stable but displays heterogeneous trends by occupations. It remained fairly stable or rose in manual occupations but declined in management, clerical and services occupations.

Cohort Effects

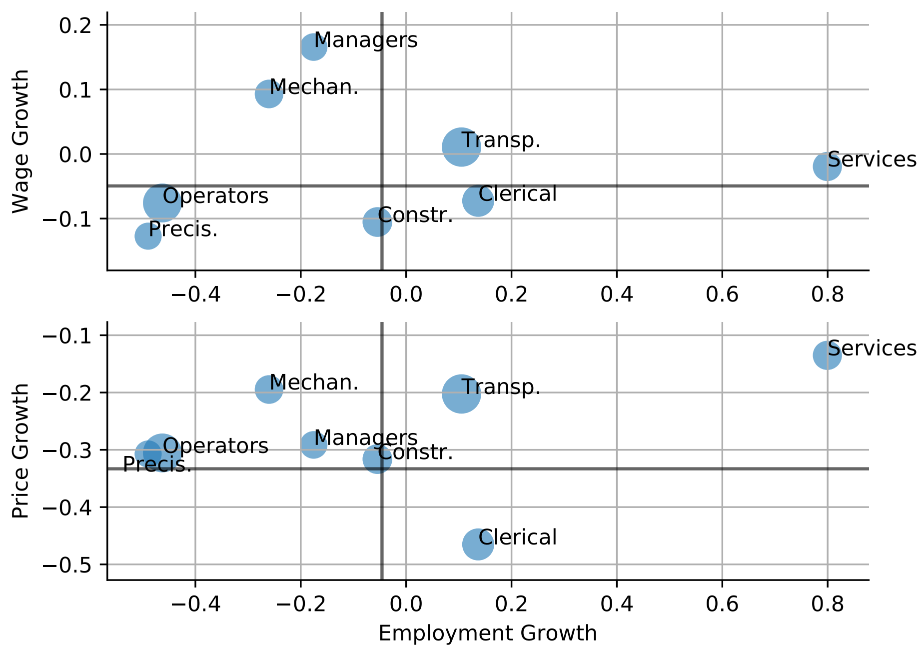
Turning to cohort effects, we present b_l which is defined in Equation (2) in Table 2. As one would expect, we find a positive selection on cognitive skills. As more people went to college, the endowment in cognitive skills declined for low-skilled men. Interestingly, there is negative selection for manual skills which suggests that more manually able men are less likely to go to college so the increasing college attendance rate actually leads to a more positively selected group. This is important as manual skills turn out to be the most important for low skilled men as we will discuss below. Finally, there have been little change for inter-personal skills.

Evolution of Occupational Composition

We saw in Section 3 that employment and wages evolutions are only weakly related. There are two reasons why this could be the case within our model. Either selection effects are strong and wages evolutions are not in line with price changes or the reallocation of labor cannot be attributed to the evolution of relative productivity. We can now assess these explanations.

In Figure 5, we assess within the model the extent controlling for selection improves on this dimension. The top panel of Figure 5 reports the model analog of Figure 3, wage growth and employment growth for each J occupation. The right panel controls for selection as follows. We calculate the distribution of the human index supplied in each occupation at the beginning of the period, 1979. We then estimate the evolution of the wage associated with this fixed human capital index. The top panel shows as in Section 3 the low correlation between employment and wages evolution. The bottom panel shows that controlling for selection allows us to make some progress understanding the data patterns. There are three main things to notice. First, there is a positive (but low) correlation between average price growth and employment growth while the correlation is close to zero for wages. Second, looking at prices as opposed to wages solves some of the puzzle of the apparent lack of convergence of wages between shrinking operators and expanding services. Indeed, the average price in services fell relatively less than for operators. Last, average prices mask considerable heterogeneity within occupations. For instance, the price of the average human index decline substantially for clerical occupation but it declines much less for human capital index

Figure 5: Changes in Employment, Wages and Prices

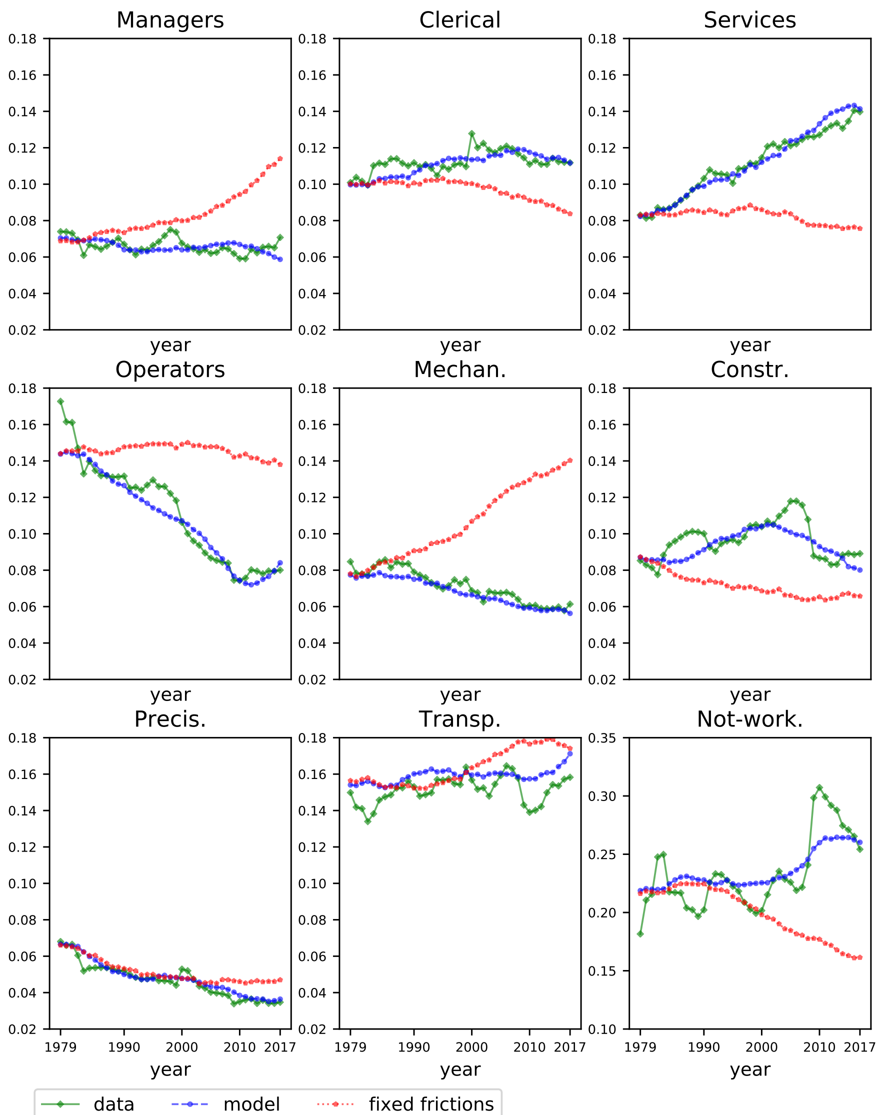


at the bottom or at the top of the distribution, as reported in Figure 4. Another illustration are managerial occupations that saw a large influx of high skilled individuals. As a result, average wages grew faster than the price of an average manager skills.

While we do find some evidence of selection in Figure 5, it turns out that selection alone can not reconcile the results. Figure 6 reports the evolution of employment share by occupation. The dot markers are from the baseline simulated model and the diamond markers are from the CPS data. One can see that we fit the data very well. To show the importance of increasing search frictions we impose that the job finding rates are fixed over time, $\lambda_{jt} = \lambda_{j1979}$ for all t. The pentagon markers represents the implied occupational composition.[15] While the baseline model fits the evolution of employment share in each occupation well, the restricted model can not match the decline of operators nor the rise of services. In other words, we attribute the decline of manual occupations to a decline in the number of manual jobs opportunities rather than a decline in prices. The wages in traditional blue collar occupations have not fallen substantially relative to other occupations. This suggests, non-competitive forces drove individuals away from manual occupations while

[15]We also estimated a restricted version of the model where we impose that frictions are fixed over time. It could not fit the evolution of occupation composition.

Figure 6: Evolution of occupation share by year



keeping wages high. Table I2 in Appendix I reports the estimates of the trends in frictions.

The rise of not-working cannot be attributed to price changes either. The evolution of the price series alone cannot match the growing share of low skilled men not-working. We attribute the rise of not-working to an increase in frictions in all occupations but it could as well be explained with a rise of the value of not working (Aguiar et al., 2018), nonphysical aspects of some jobs (Kaplan and Schulhofer-Wohl, 2018) or health considerations (Borella et al., 2019). In practice we cannot separately identify these factors from search frictions.

8 Decomposition of Wage Trends

Given our estimates we can decompose the simulated wages into various components. The simplest case is average wages. In our model there are three forces that determine average wages: skill prices, occupational composition, and selection into occupations. The differences between mean log wages between any two periods can be decomposed into these three components as:

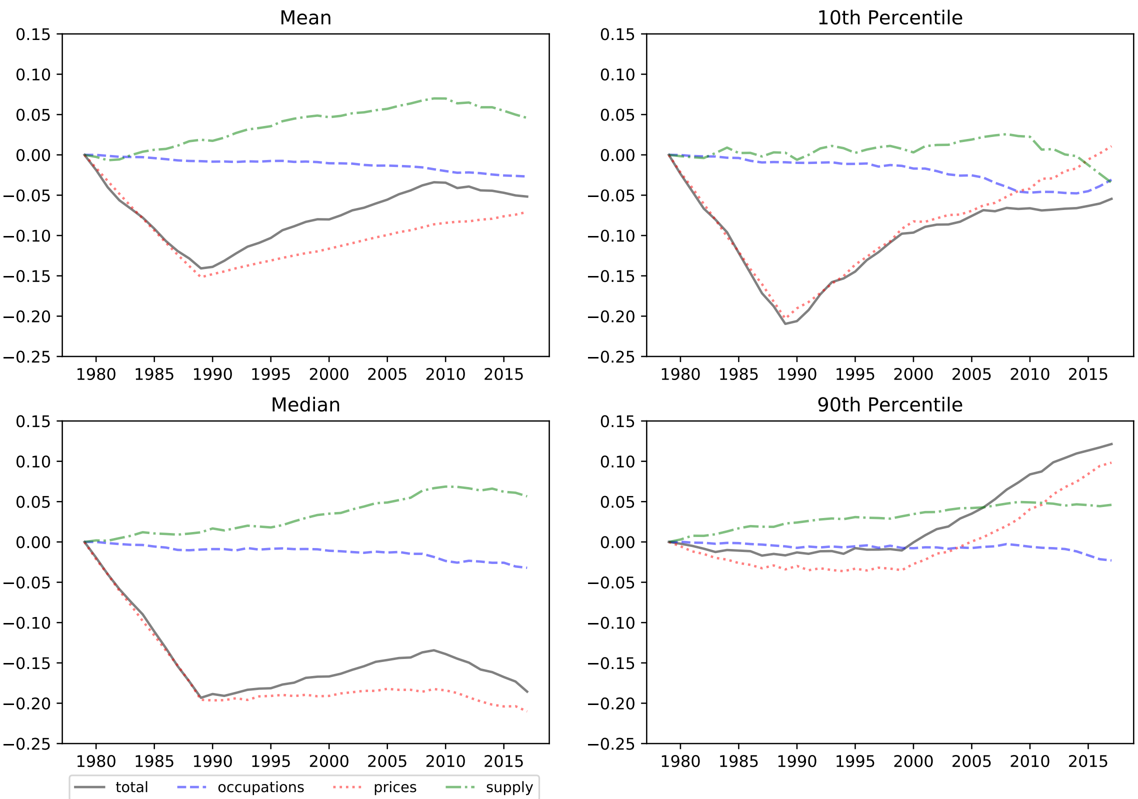
$$
\begin{aligned}
& E_t\left(w_i\right) - E_\tau\left(w_i\right) \\
= & \sum_j \left[p_{jt} E_{jt}\left(f_{jt}\left(h\left(j, \mathcal{S}_{it}; \beta_{jt}\right)\right)\right) - p_{j\tau} E_{j\tau}\left(f_{j\tau}\left(h\left(j, \mathcal{S}_{it}; \beta_{j\tau}\right)\right)\right)\right] \\
= & \sum_j \left[p_{jt} - p_{j\tau}\right] E_{jt}\left(f_{jt}\left(h\left(j, \mathcal{S}_{it}; \beta_{jt}\right)\right)\right) \\
& + \sum_j p_{j\tau}\left[E_{jt}\left(f_{jt}\left(h\left(j, \mathcal{S}_{it}; \beta_{jt}\right)\right)\right) - E_{jt}\left(f_{j\tau}\left(h\left(j, \mathcal{S}_{it}; \beta_{j\tau}\right)\right)\right)\right] \\
& + \sum_j p_{j\tau}\left[E_{jt}\left(f_{j\tau}\left(h\left(j, \mathcal{S}_{it}; \beta_{j\tau}\right)\right)\right) - E_{j\tau}\left(f_{j\tau}\left(h\left(j, \mathcal{S}_{it}; \beta_{j\tau}\right)\right)\right)\right], \qquad (5)
\end{aligned}
$$

where we have defined p_{jt} as the proportion of individuals working in occupation j in year t and

$$h\left(j, \mathcal{S}_{it}; \beta_{j\tau}\right) \equiv \theta_{it}' \beta_{j\tau} + \sigma\left(j, \tau\right) 1\left(j = j_{it-1}\right).$$

The first term represents the role of occupational occupation. The second term reflects prices and the last term captures supply. Note that from the raw data we could directly identify the first component, but separating prices from skill composition requires the structural model. The top left panel of Figure 7 reports each three components and the total change in the mean. The main thing to take away from the picture is that the prices track the mean closely so the primary determinant of the pattern is prices. These changes would

Figure 7: Mean and Quantiles Decomposition



have lowered average wages by about 15 percentage points in the 1980s and then increased average wages since. This was expected from the prices series where the constant of the wage function dropped in the 1980s and slowly recovered.

While the results on the mean are interesting they miss an important part of the wage distribution. We know from Figure 2 that the patterns at the high and low end are quite different. The other three panels of Figure 7 show the analogous pattern for the median level, the 10^{th} quantile, and the 90^{th} quantile.[16]

In all cases one sees that the primary determinant is the price change. Note that price changes are due in part to the hedonic pricing equation (f_{jt}) and in part to the factor loading terms (β_{jt}). In practice this is virtually all due to the former.

Remarkably, occupational composition is relatively unimportant for understanding these patterns. The changing composition does lead to a roughly 5 percentage point decrease in wages in all four panels in the picture. Since mean changes were small, this is similar to the overall mean change throughout the period-though clearly it can not explain the fall in the eighties and subsequent increase. It also contributes little to understanding median wages which have fallen considerably more than the mean-or the 90^{th} quantile which has risen.

Table 3 provides much more details. Looking at the formula in the decomposition equation (5), one can see that each of the three pieces is really a summation of pieces across occupations. Table 3 reveals all 24 pieces over the full period and between 1979 and 1990-the period in which we see the large decrease. We modify the formula above slightly when doing this, since $\sum_j [p_{jt} - p_{j\tau}] = 0$ we can rewrite the first term as $\sum_j [p_{jt} - p_{j\tau}] [E_{jt} (f_{jt} (h (j, \mathcal{S}_{it}; \beta_{jt}))) - E_t (w_i)]$ The first row of each table provides a 3 part decomposition, and the next part provides all 24 components.

[16] To see this let $M_0(t)$ be the median wage in time t. Then for year t we calculate the conditional distribution of wages conditional on occupation at time t. Then to simulate the counterfactual unconditional distribution we weight the occupations by their importance in 1979 rather than t. We calculate the median distribution of that distribution, call that $M_1(t)$. The dashed line plots $M_1(t) - M_0(t)$. To calculate $M_2(t)$ we simulate the counterfactual conditional distribution of wages in time t by using the actual skill distribution but the 1979 prices. We then weight by the 1979 occupation distribution and take the median to get $M_2(t)$. The dotted line plots $M_2(t) - M_1(t)$. The dash-dot line plots $M_2(t)$. Note that the three lines add up to the median, $M_0(t)$. The 10th and 90th quantile are calculated analogously.

Table 3: Mean decomposition: contribution of each occupation

Years: 1979 - 2017. Mean Change: -0.0517

	Occupational Composition	Prices	Skills
Total	-0.0268	-0.0708	0.0458
Managers	-0.0041	-0.0001	0.0151
Clerical	0.0005	-0.0165	0.0074
Services	-0.0244	-0.0027	0.0004
Operators	0.0101	-0.0142	-0.0011
Mechan.	-0.0040	-0.0023	0.0101
Constr.	-0.0003	-0.0161	0.0035
Precis.	-0.0048	-0.0131	0.0024
Transp.	0.0002	-0.0058	0.0080

Years: 1979 - 1990. Mean Change: -0.1389

	Occupational Composition	Prices	Skills
Total	-0.0084	-0.1479	0.0174
Managers	-0.0019	-0.0079	0.0063
Clerical	0.0008	-0.0147	0.0022
Services	-0.0075	-0.0154	0.0019
Operators	0.0023	-0.0284	0.0060
Mechan.	0.0003	-0.0102	0.0014
Constr.	0.0014	-0.0201	0.0004
Precis.	-0.0030	-0.0181	0.0002
Transp.	-0.0008	-0.0331	-0.0010

A surpring result (to us) is that supply acted as a countervailing force to changes in technology even though college enrollment is increasing. There are several forces at play. First, there has been an increased sorting between individuals and occupations. With the increased slope of the price series, individuals have more incentives to work in the occupation that best fit their skills. To assess the contribution of each skill and each occupation to these supply effects, we use an approximation to decompose the log of the sum and we use the

Table 4: Contribution of each occupation to the supply component

Years: 1979 - 2017. Mean Change: 0.0223				
	Cognitive	Interpersonal	Manual	Specific
Total	0.0037	0.0035	0.0121	0.0029
Managers	0.0034	0.0022	0.0012	0.0010
Clerical	0.0008	0.0012	0.0011	0.0006
Services	-0.0005	0.0000	0.0004	0.0003
Operators	-0.0006	0.0000	0.0001	0.0000
Mechan.	0.0011	0.0000	0.0033	0.0002
Constr.	-0.0003	0.0000	0.0016	0.0002
Precis.	0.0000	0.0000	0.0009	0.0001
Transp.	-0.0002	0.0000	0.0034	0.0006

fact $\log f_{j\tau}$ is linear up to 1979. It gives:

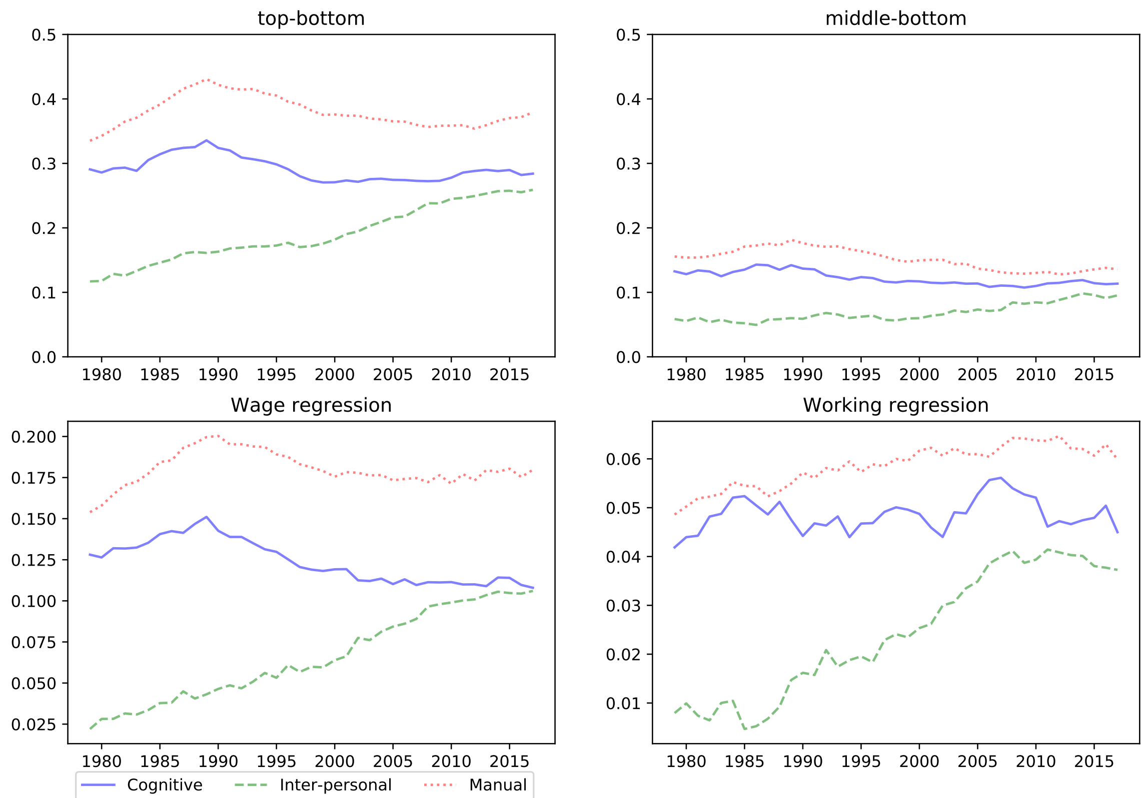
$$E_{jt}\left(w_{ijt}^{\tau}\right) - E_{j\tau}\left(w_{ij\tau}\right) \approx \frac{\alpha_{j\tau}^{1}}{\delta_{j\tau}}\left(\sum_{l=1}^{L}\beta_{lj\tau}\left[E_{jt}\left(\theta_{lit}\right) - E_{j\tau}\left(\theta_{li\tau}\right)\right] + \left[E_{jt}\left(\sigma_{jt}\right) - E_{j\tau}\left(\sigma_{j\tau}\right)\right]\right).$$

Table 4 gives a decomposition of the contribution of each occupation and each skill. Manual skills are the dominant forces behind the positive supply effect. High manual skills individuals have increasingly sorted into transport and mechanics. And high cognitive or high inter-personal skills individuals have increasingly moved to management occupations. The remaining factors that contributed to a positive supply effects are the following. First, and as discussed in Section 7, different cohorts enter with different labor market skills. Selection on manual skills is positive and it is the skill they use the most. And while selection is negative on cognitive skills, the returns to these skills has declined over time. Second, low skill men have gotten older. The average age rose from 38.5 years olds in 1979 to 40 years old in 2017. And, older workers have more human capital than younger worker. Last, the skill gap between working people and not-working has increased over time.

9 Skill Premium

In this section we examine how the relationship between skills and wages has changed over time.

Figure 8: Skill Premium



Preliminary Evidence

We begin with a simple exercise in which we classify the individuals from our estimated simulated model based on their endowment in each of the three skills at labor market entry. Precisely, for each skill we look at whether their endowment is in the top third, bottom third, or in the middle of the distribution. We then compare the mean wage of these different groups of individuals as we simulate the model. Note that if initial skills were observable in the CPS, this is something we could produce from the raw data without a model. Figure 8 reports the results. The top-left panel reports the difference between the top and bottom mean wages while the top-right panel reports the difference between the middle group and the bottom group. The bottom-left panel reports the skills coefficients in the following regressions. For each year, we regress log-wage on a measure of each skills at labor market entry, controlling for age fixed effects. We normalize each skill to have mean 0 and standard deviation 1.

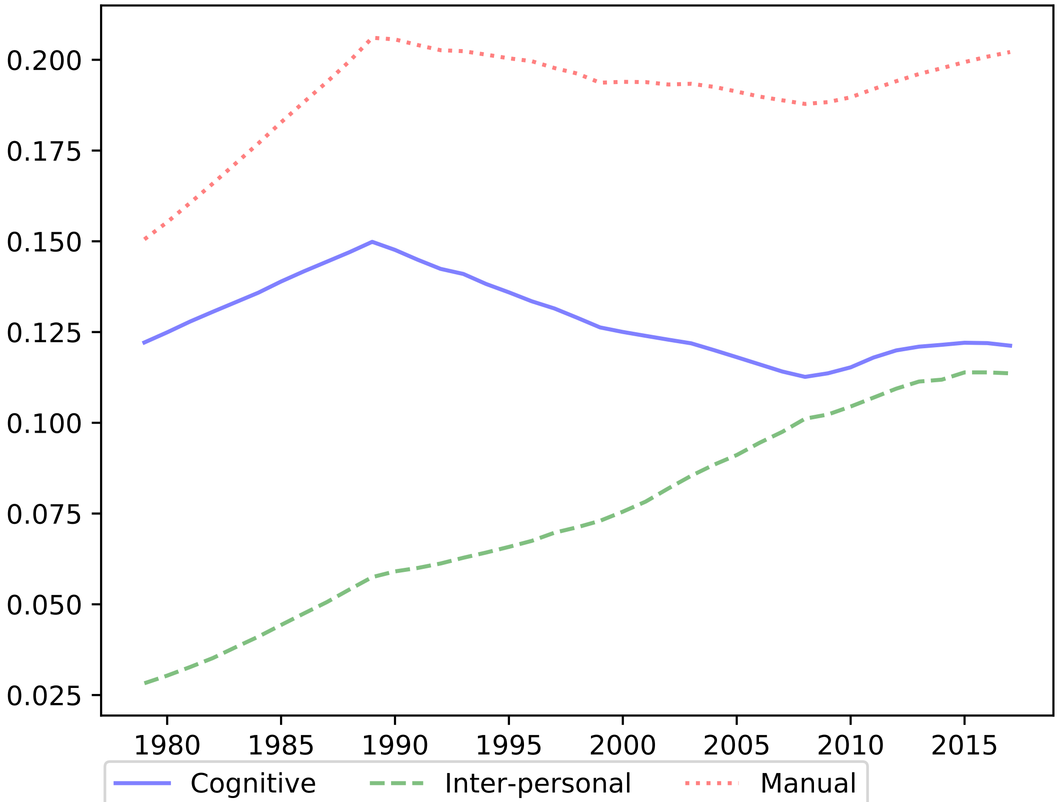
The bottom-right panel reports the same regression where the left-hand side variable takes the value of one if the individual is working and zero otherwise. At the beginning of the period, manual skills have the most predictive power on wages followed by cognitive skills. Individuals in the top third in manual skills earn more than 30% more than individuals in the bottom third (at labor market entry) in 1979. The corresponding number is close to 30% for cognitive skills. On the hand, the pay gap associated with inter-personal skills is only 12% in 1979. The regression coefficients have the same ordering. A one standard deviation increases in manual, cognitive and inter-personal skills, increases log wages by, respectively, 15%, 12% and 2%. The pay premium associated with each three skills increased in the 1980s. The top mean wages increases by 10% compared to the bottom in manual skills and the increase is around 5% for both cognitive skills and interpersonal skills. In the 1990s, the premium fell for both manual and cognitive skills and they remain fairly stable since 2000. By contrast, the premium for inter-personal skills kept rising in the 1990s and it is about 25% today which is about the same as the premium for cognitive skills. The premium for manual skills is about 35% and therefore remains the highest. The regression coefficients show the same ordering when either the wage or a dummy for working are on the left hand side. The large increase in all the premiums in the 1980s was expected from the increase of the slope in the price series for each occupation, that we saw in Figure 4. Since 1990 individuals at the bottom in either cognitive or manual skills did relatively better that individuals in the middle due to the flattening of the price series at the bottom. This is not the case for inter-personal skills however.

Counterfactual Skill Investment

Should we conclude that we should invest in individuals inter-personal skills before they enter the labor market? We next do an exercise to help answer this question. Since we don't know the relative costs of investing in the three different skills nor exactly how one might do it, we consider a simpler case. Suppose that it were equally costly to increase skill by a standard deviation, in which skill would we prefer to invest? We investigate this question by increasing the endowment of each individual at labor market entry by one-standard deviation for each skill. These are partial equilibrium experiments because the hedonic pricing function is fixed.

Figure 9 reports the average wage gain of each policy.

Figure 9: Skill improvement program



Improving low-skilled men manual skills before labor market entry has the highest rewards. This is true throughout the period of observations. This reflects the fact that this group predominantly uses manual skills. The returns to improving either cognitive or manual skills has increased during the 1980s and fell since. Improving interpersonal skills had little returns at the beginning of the period. It increased throughout the period of analysis and it is now only slightly lower than the returns to improving cognitive skills.

To isolate the role of occupations, we again increase each individual skills but we force individuals to work in the same occupations as before the policy was implemented. Table 5 reports the average gain for each policy. Occupation composition only explains 31% of the returns to improving manual skills while it explains almost 40% of the returns to improving inter-personal skills and up to 45% for cognitive skills. This is intuitive as improving the last two skills leads some individuals to move away from declining manual occupations.

These policies also improve the probability of working as reported in Table 6. Increasing

Table 5: Skill improvement program: Decomposition

Table 6: Skill improvement program: probability of working

cognitive skills or manual skills by one standard deviation raises the probability of working by more than 4.5 percentage points in 1979. It remains fairly stable over time for cognitive skills while it increased by more than 2 percentage points for manual skills. On the other hand, improving inter-personal skills had little impact, less than 1.5 percentage points, at the beginning of the period while it boosts the probability of working by 3.5 percentage points at the end of the period.

Heterogeneity

Are the returns to these policies heterogenous? To answer this question, we again classify people depending on whether their endowment in a particular skill is in the top third, bottom third, or in the middle of the distribution. Table 7 reports the returns for each subgroup at the beginning of the period (column t_0) and at the end of the period (column t_1). The last three columns report respectively, the policy that the highest returns at the beginning of the period, at the end of the period, and the policy that saw the highest increase in its return. The analysis by group confirms that investing in manual group has the highest return for most groups throughout the period of analysis. There is a high return to specializing in manual skills for individual that are in the top group in manual skills at labor market entry. This is the policy that has the highest return for any endowment in the remaining skills. It is true both at the end and the beginning of the period of analysis. The only exception is for people that are in the top group in each three skills in which case cognitive skills have

Table 7: Counterfactual: heterogeneity and interactions

the highest returns and improving their inter-personal skills sees a very large increase in its returns. This is driven by management occupations which attracts the highest skilled workers. This is interesting as it happens simultaneously as the premium for cognitive skills declined overall.

The returns to improving interpersonal skills has increased more than the returns to improving manual skills for more than two-thirds of the population. This not true however for individuals that are in the top group in manual skills but not in the top group for either of the remaining two skills. For these individuals, the reward to specializing further in manual skills has increased the most.

By the end of the period, improving interpersonal skills has the highest reward only for individuals that are in the bottom in manual skills and that are at least in the middle in the other two skills. Only about 10% of individuals fall in that category.Lifetime inequality by cohort

We examine the impact of the policies on lifetime earnings following Huggett et al. (2011). We ask how much compensation is equivalent to entering the labor market with a one standard deviation increase in any initial skill. We express this compensation in terms of the percentage change in earnings in all periods that would leave an agent with the same expected lifetime earnings as an agent with a one standard deviation change in the relevant initial skill. Table 8 also reports these results for different cohorts.

Table 8: Lifetime Inequality

For the cohort that enters the labor market at the end of the 1970s, a one standard deviation increase in cognitive skills is equivalent to an increase of 12.5% of wages on average. This number drops to close to 5% for the cohort that enters the labor market towards the end of the period of analysis. The compensating variation for manual skills increased from 26% to 28%. It goes up for inter-personal skills from 3.2% to 4.4%. Consistent with the analysis above, inter-personal skills saw an increase in their returns but manual skills remain the most valuable skills.

10 Conclusions

We propose and estimate a model to understand the evolution of the wage structure of low skilled men since 1979. We allow for a rich specification of change in the demand for workers which has heterogenous effects on different occupations and different parts of the skill distribution. We document the relative role of demand-side factors and supply-side factors.

Our first main finding is that while there was noticeable change in the occupational composition of workers, the implications of this on wages is not dramatic. We find that the main driver of the decline in median wages (as well as the rise at the 90^{th}) is driven by skill price changes not the occupational distribution. Our second main finding is that we see that skill prices in shrinking occupations have not been falling noticeably slower than those in growing occupations-so much so that we can not reconcile the data with a competitive model. Our third main finding is that while the importance of interpersonal skills has grown for this group, manual skills still remain the most important.

In going forward, this paper has only shed light on a small part of the picture. The policy response to these results is that if we want to increase wages of low skilled workers we should invest in their skills. The results suggest that interpersonal skills have become much more important for this group than they were before and that manual skills remain the most important. While intuitively education seems like the clear way to raise cognitive skills, it is not at all clear how we improve manual or interpersonal skills. Further progress on these problems would focus on how to invest in skills, incorporation of this model into a general equilibrium framework, and inclusion of other demographic groups.

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Appendix

A Datasets description

ORG CPS Wages are calculated using Outgoing Rotation Group data from the Current Population Survey for earnings years 1979-2017 for all male workers aged 20-60 with 12 years of education or less who are not in the military, institutionalized or self-employed. We do the same data trimming as Acemoglu and Autor (2011). Wages are weighted by CPS sample weights. Hourly wages are equal to the logarithm of reported hourly earnings for those paid by the hour and the logarithm of usual weekly earnings divided by hours worked last week for non-hourly workers. Top-coded earnings observations are multiplied by 1.5. Hourly earners of below $1.675/hour in 1982 dollars are dropped, as are hourly wages exceeding 1/35th the top-coded value of weekly earnings. All earnings are deflated by the chain-weighted (implicit) price deflator for personal consumption expenditures (PCE). Allocated earnings observations are excluded in all years, except where allocation flags are unavailable. We start from the cohort that left or graduated from high school no latter than 1915 and we end with cohorts that left or graduated from high school no earlier than 2017.

NLSY79 We use the 1979-2015 survey years of the National Longitudinal Survey of Youth, 1979 (NLSY79). The NLSY79 is a representative sample of US households that was administered yearly from 1979-1994 by the Bureau of Labor Statistics, and once every two years since. We use both the core sample and the supplemental sample that over-represents economically disadvantaged respondents and minorities. We reweight observations to have a representative sample. In any given year, we only consider earnings observations for individuals who work 30 or more total hours in a week and who work full time at least 20 of the past 24 weeks. We construct measures of labor market experience using the work history file. We define work experience and occupation-specific experience as, respectively, the sum of weeks worked since labor market entry and the sum of weeks worked in a particular occupation since labor market entry.[17]

O*NET We use O*NET to obtain data on the skill intensity of different occupations. It is a representative survey of occupations developed by the U.S. Department of Labor.

[17] This definition of occupation-specific tenure is different from its model counterpart presented below which we simplify for computational purposes. It is also less affected by misclassification errors.

Individuals were asked to complete a survey asking about the tasks and activities workers perform in those occupations.

NLSY97 We follow Deming (2017) and combine NLSY79 and NLSY97. We restrict the sample to ages 25–33 to exploit the overlap in ages across surveys. This means comparing the returns to different skills for individuals of similar ages during the late 1980s and early 1990s, compared to the more recent 2004–2015 period. We use respondents' standardized scores on the Armed Forces Qualifying Test (AFQT) to proxy for cognitive skill as in Altonji et al. (2012). And following Deming (2017), we construct a measure of social skills to maximize the comparability of the two measures of social skills across NLSY waves. All test scores are normalized to have mean 0 and standard deviation 1.

Table A1: Occupation Categories Low Educated Men

	Occupations	Label
1	Executive, Administrative, and Managerial Professional Specialty	Managers
2	Technicians Sales Administrative Support	Clerical
3	Housekeeping and Cleaning Protective Service Other Services	Services
4	Farming, Forestry, and Fishing Machine Operators, Assemblers, Inspectors	Operators
5	Mechanics and Repairers	Mechanics
6	Construction Trades, Extractive	Construction
7	Precision Production	Production
8	Transportation and Material Moving	Transportation

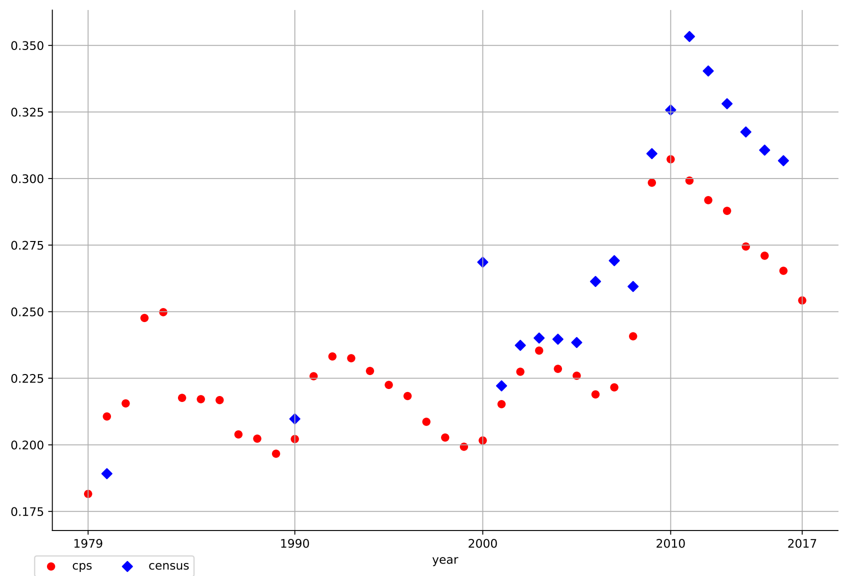
B Occupation share in the Census/ACS

We use the Census to assess the robustness of our results on the evolution of occupation composition and the share of men not-working that we reported in the main text using CPS data.

We use data from the 1980 , 1990, 2000 Census and the 2001-2016 American Community Survey (ACS). We include all males with at most 12 years of education between the ages of 20 and 60. We exclude individuals in the military. The number of observations range between 284,400 in 2002 and 3,816,849 in 2000.

Figure B1 reports the share not-working in the Census and in the CPS.

Figure B1: Share not-working by year: Census and CPS

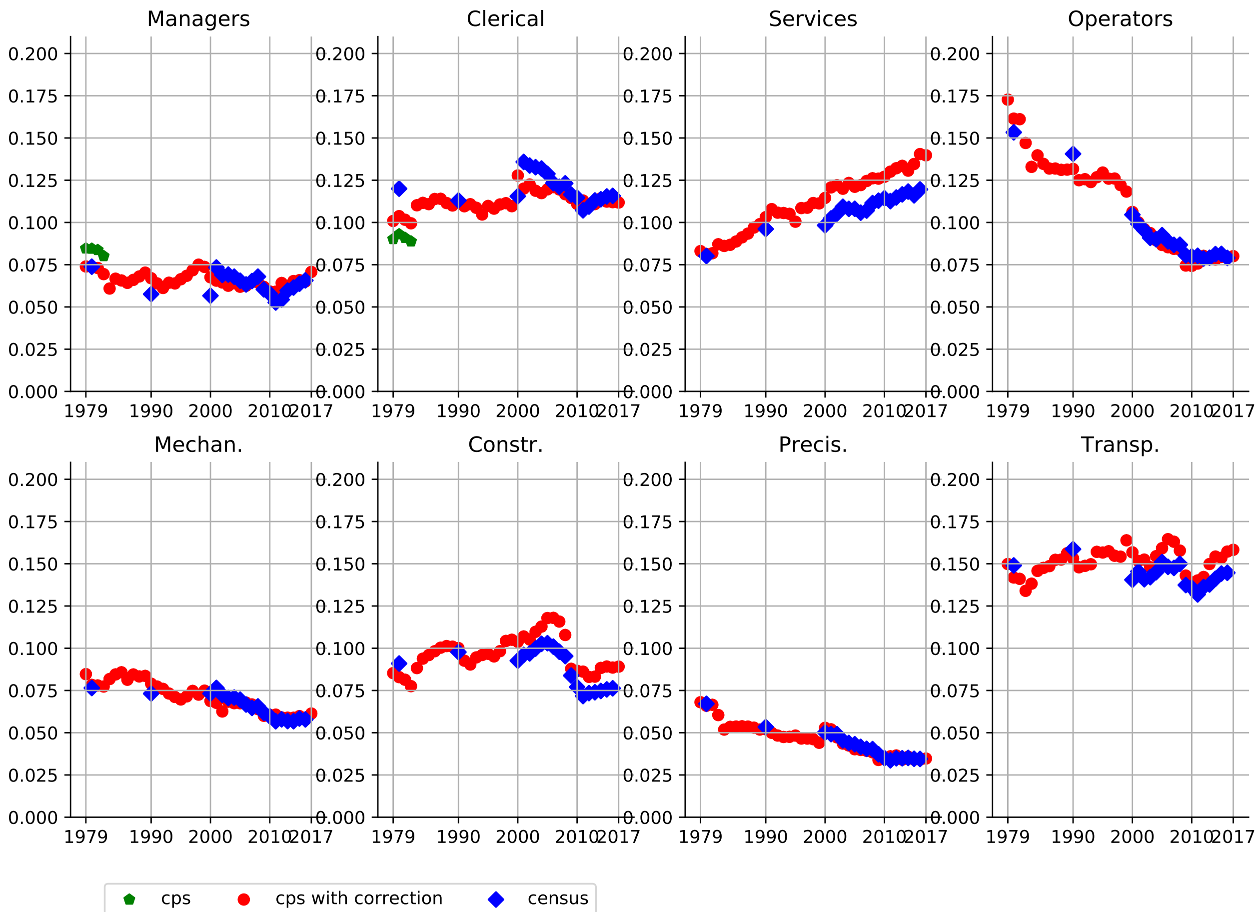


The trend is about similar in both sample with a rise until 2010 and a decrease since. However, the level is about 3 percentage point higher in the Census since 2010.

Figure B2 reports the occupational composition in the CPS and in the Census for all relevant years. Overall, the numbers are reassuringly close to each other. Between 1982 and 1983, there is an apparent discontinuity in the proportions of managers and the proportions of clerical in the CPS data. It can be attributed to the change in the occupational classification scheme. Up to 1982, occupations were coded using the 1970 Census classification scheme. In 1983 (and up to 1991), occupations were coded using the 1980 Census classification scheme.

To smooth out the discontinuity, we assume the CPS data have a constant share of manager misclassified as clerical worker for the year between 1979 and 1982. To recover the bias in the CPS data, we assume the proportion of managers in 1980 is measured without error in the Census. The line "CPS-corrected" reports the corrected occupational share.

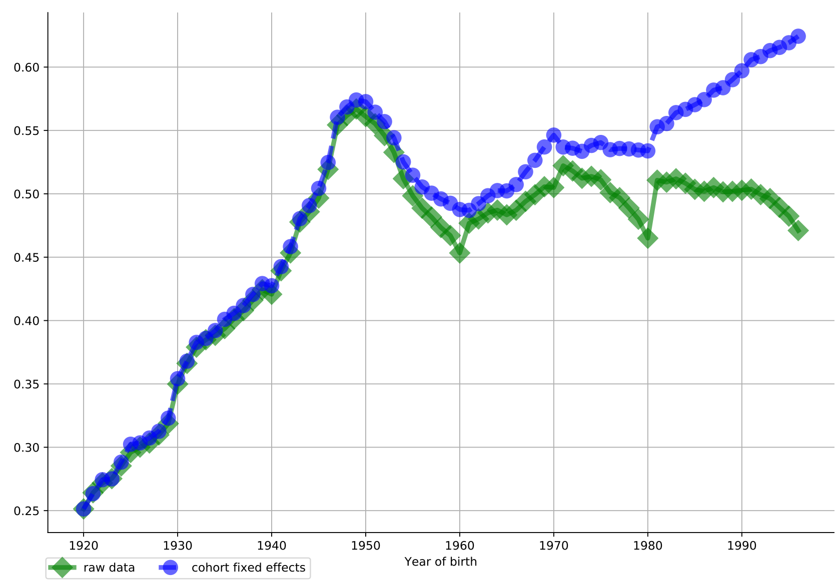
Figure B2: Occupational composition: Census and CPS



C Probability of going to college by cohort

We allow labor market endowments to differ across cohorts. Figure C1 reports the probability of going to college by year-of-birth in the Census and ACS. We report two different measures. The first measure simply calculates the fraction of the sample that goes to college in the census data for all men aged between 20 and 60. To calculate the second measure, we first regress a dummy variable taking the value one for individuals that went to college and zero otherwise. The regressors are a set of dummies for each age and for each cohort. We then report the cohort fixed effects.

Figure C1: Probability of going to college by cohort



D Identification

Here we show formally the identification results described in Section 5 of the paper. We begin by enhancing the notation introduced in the text. We define

- C_τ to be the set of people (indexed by i) who enter the market in year t
- $\mathcal{J}$ to be the the set of the 4^J different labor market histories
- j^* to generically denote ahistory in $\mathcal{J}$
- $j^*(e)$ the eth element of j^*
- Σ to be the unconditional variance covariance matrix of θ_i.
- $P_\tau \equiv \{(\alpha_{jt}, \delta_{jt}), j = 1, ..., J, t = \tau, ..., \tau + 4\}$ to be the set of prices faced by a cohort that enters at time τ. We normalize $\alpha_{\overline{j}\overline{t}} = 1$ for one fixed occupation $\overline{j}$ in one given year $\overline{t}$.
- p_τ to be a generic realization of P_τ

For the following 3 the notation already incorporates the assumption that there are no cohort effects.

- $\rho_{j^*}(p_\tau)$ to be the probability of choosing sequence j^* given prices p_τ.
- $G_{j^*}(\theta_i; p_\tau)$ to be the c.d.f. of θ_i conditional on choosing sequence j^* when faced with prices p_τ.
- $S(p_\tau) \equiv \{(\rho_{j^*}(p_\tau), G_{j^*}(\cdot; p_\tau)), j^* \in \mathcal{J}\}$ to be the supply function which is identical across cohorts

We make the following additional assumptions

- J is at least 5
- as in the paper the dimension of θ_i is three
- Normalize location: $E(\theta_i) = 0$
- Normalize scale: $\Sigma_{1,1} = 1$ (note that this is a different normalization than we use in the body of the paper-but is useful here)

We want to identify the following components of the model:

- Prices δ_{jt} and α_{jt} for both the panel and cross section data
- Skill depreciation D
- Unconditional distribution of θ_i and u_{ie} (which includes σ_w^2 and Σ)
- Returns to experience ψ_{j^*}
- Supply of skill θ_i as a function of prices $S(p_\tau)$

We do this in the 5 steps listed in Section 5. Prices are identified in steps 3 and 5, depreciation in step 1, the unconditional distributions in 1 and 4, return to experience in 2, and the supply of skills in 4.

We show that the model is generically identified, one might be able to construct very special cases of parameter combinations that are not identified.

Step 1: σ_u^2, D, and Σ

In this subsection we will identify σ_u^2, D, and Σ. This part of identification uses the panel data. We will also identify $\alpha_{j\tau}^2\beta_j'\Sigma\beta_j$, $\alpha_{j\tau}^2\beta_j'D\Sigma D\beta_j$, and $\alpha_{j\tau}^2\beta_j'DD\Sigma DD\beta_j$ for each j which are used used in intermediate steps.

Here we use identification at infinity in a strong way. We assume there is a three-year period $\tau, \tau+1$, and $\tau+2$ for which

- the cohort that enters in period τ all work in occupation j for the first three years.
- the cohort that enters in $\tau+1$ all workin in j there for two years.
- the cohort that enters in $\tau+2$ all work in occupation j for that year.

This is produced by extreme versions of the prices, but we do not need to observe the prices themselves to see when the selection is extreme.

We get the following relationships:

$$
\begin{aligned}
var\left(\widetilde{w}_{i\tau} \mid i \in C_{\tau}\right) =& \alpha_{j\tau}^{2}\beta_{j}^{\prime}\Sigma\beta_{j}+\sigma_{u}^{2} \\
var\left(\widetilde{w}_{i\tau+1} \mid i \in C_{\tau}\right) =& \alpha_{j\tau+1}^{2}\beta_{j}^{\prime}D\Sigma D\beta_{j}+\sigma_{u}^{2} \\
var\left(\widetilde{w}_{igt+2} \mid i \in C_{\tau}\right) =& \alpha_{j\tau+2}^{2}\beta_{j}^{\prime}DD\Sigma DD\beta_{j}+\sigma_{u}^{2} \\
var\left(\widetilde{w}_{i\tau+1} \mid i \in C_{\tau+1}\right) =& \alpha_{j\tau+1}^{2}\beta_{j}^{\prime}\Sigma\beta_{j}+\sigma_{u}^{2} \\
var\left(\widetilde{w}_{i\tau+2} \mid i \in C_{\tau+1}\right) =& \alpha_{j\tau+2}^{2}\beta_{j}^{\prime}D\Sigma D\beta_{j}+\sigma_{u}^{2} \\
var\left(\widetilde{w}_{i\tau+2} \mid i \in C_{\tau+2}\right) =& \alpha_{j\tau+2}^{2}\beta_{j}^{\prime}\Sigma\beta_{j}+\sigma_{u}^{2}
\end{aligned}
$$

Solving algebra it is straightforward to show

$$
\begin{aligned}
&\alpha_{j\tau}^{2}\beta_{j}^{\prime}\Sigma\beta_{j} \\
=&\frac{\left[var\left(\widetilde{w}_{i\tau+2} \mid i \in C_{\tau+2}\right)-var\left(\widetilde{w}_{i\tau} \mid i \in C_{\tau}\right)\right]\left[var\left(\widetilde{w}_{i\tau+1} \mid i \in C_{\tau}\right)-var\left(\widetilde{w}_{i\tau} \mid i \in C_{\tau}\right)\right]}{var\left(\widetilde{w}_{i\tau+1} \mid i \in C_{\tau+1}\right)+var\left(\widetilde{w}_{i\tau+2} \mid i \in C_{\tau+1}\right)-var\left(\widetilde{w}_{i\tau+2} \mid i \in C_{\tau+2}\right)-var\left(\widetilde{w}_{i\tau+1} \mid i \in C_{\tau}\right)} \\
&-\frac{\left[var\left(\widetilde{w}_{i\tau+1} \mid i \in C_{\tau+1}\right)-var\left(\widetilde{w}_{i\tau} \mid i \in C_{\tau}\right)\right]\left[var\left(\widetilde{w}_{i\tau+1} \mid i \in C_{\tau+1}\right)-var\left(\widetilde{w}_{i\tau} \mid i \in C_{\tau}\right)\right]}{var\left(\widetilde{w}_{i\tau+1} \mid i \in C_{\tau+1}\right)+var\left(\widetilde{w}_{i\tau+2} \mid i \in C_{\tau+1}\right)-var\left(\widetilde{w}_{i\tau+2} \mid i \in C_{\tau+2}\right)-var\left(\widetilde{w}_{i\tau+2} \mid i \in C_{\tau}\right)}
\end{aligned}
$$

$$
\begin{aligned}
\sigma_{u}^{2} =& var\left(\widetilde{w}_{i\tau} \mid i \in C_{\tau}\right)-\alpha_{j\tau}^{2}\beta_{j}^{\prime}\Sigma\beta_{j} \\
\frac{\alpha_{j\tau+1}^{2}}{\alpha_{j\tau}^{2}} =& \frac{\left[var\left(\widetilde{w}_{i\tau+1} \mid i \in C_{\tau+1}\right)-var\left(\widetilde{w}_{i\tau} \mid i \in C_{\tau}\right)\right]+\alpha_{j\tau}^{2}\beta_{j}^{\prime}\Sigma\beta_{j}}{\alpha_{j\tau}^{2}\beta_{j}^{\prime}\Sigma\beta_{j}} \\
\frac{\alpha_{j\tau+2}^{2}}{\alpha_{j\tau}^{2}} =& \frac{\left[var\left(\widetilde{w}_{i\tau+2} \mid i \in C_{\tau+2}\right)-var\left(\widetilde{w}_{i\tau} \mid i \in C_{\tau}\right)\right]+\alpha_{j\tau}^{2}\beta_{j}^{\prime}\Sigma\beta_{j}}{\alpha_{j\tau}^{2}\beta_{j}^{\prime}\Sigma\beta_{j}} \\
\alpha_{j\tau}^{2}\beta_{j}^{\prime}D\Sigma D\beta_{j} =& \frac{\alpha_{j\tau}^{2}}{\alpha_{j\tau+1}^{2}}\left(var\left(\widetilde{w}_{i\tau+1} \mid i \in C_{\tau}\right)-\sigma_{u}^{2}\right) \\
\alpha_{j\tau}^{2}\beta_{j}^{\prime}DD\Sigma DD\beta_{j} =& \frac{\alpha_{j\tau}^{2}}{\alpha_{j\tau+2}^{2}}\left(var\left(\widetilde{w}_{i\tau+2} \mid i \in C_{\tau}\right)-\sigma_{u}^{2}\right)
\end{aligned}
$$

Note that the second expression shows that σ_u^2 is identified. We can do this for each occupation $j = 1, ..., J$.

From this step, we identify $\alpha_{j\tau}^2\beta_j'\Sigma\beta_j$, $\alpha_{j\tau}^2\beta_j'D\Sigma D\beta_j$, and $\alpha_{j\tau}^2\beta_j'DD\Sigma DD\beta_j$ for each occupation. If we have J occupations this gives us $3J$ equations in $J + 5 + 3$ unknowns: J $\alpha_{j\tau}^2$ parameters, 5 elements of Σ (since there is a scale normalization) and 3 elements of D. As long as $J \geq 5$ we have more equations than parameters and the parameters are generically identified.

Step 2: ψ_{j^*}

There are a total of 4^J different histories through the first three periods leading to different Ψ_{j^*}. Using the full support condition, for any j^* we find a τ^* such that

- Cohort C_{τ^*} chooses history j^* with probability one
- Cohort C_{τ^*+1} chooses job j_1 in period τ^*+1 with probability one
- C_{τ^*+2} chooses job j_2 in period τ^*+2 with probability one
- C_{τ^*+3} chooses job j_3 in period τ^*+3 with probability one

First, note that for each $\tau = \tau^*, \tau^*+1, \tau^*+2$,and τ^*+2,

$$Var\left(\widetilde{w}_{i\tau} \mid i \in C_\tau\right) = \alpha^2_{j^*(e)\tau}\beta'_{j^*(e)}\Sigma\beta_{j^*(e)} + \sigma^2_u$$

We have identified everything else in this expression other than $\alpha^2_{j^*(e)\tau}$ so that is identified (we are assuming it is non-negative).

Then notice that for each $e = 1, 2, 3$

$$\Psi_{j^*e} = \frac{E\left(\widetilde{w}_{i\tau^*+e} \mid i \in C_{\tau^*}\right) - E\left(\widetilde{w}_{i\tau^*+e} \mid i \in C_{\tau^*+e}\right)}{\alpha^2_{j^*(e)\tau}}$$

We can do this for any history $j^* \in \mathcal{J}$.

Step 3: α and δ for any panel data cohort

Now choose any arbitrary cohort C_τ with the only restriction that all potential histories $j^* \in \mathcal{J}$ can be observed for this cohort. Even though we haven't yet identified p_τ we can identify the population probability of choosing each history $\rho_{j^*}(p_\tau)$. While we have not yet shown the function is identified, we can directly identify the population probability of each sequence which is $\rho_{j^*}(p_\tau)$ evaluated at the true (but still unknown) value of p_τ. We condition on cohorts for which $\rho_{j^*}(p_\tau) > 0$ for all $j^* \in \mathcal{J}$.

In this section we will use first and second moments to identify the parameters. Let

$$\mu_{\tau j^*} \equiv E\left(\theta_i \mid i \in C_\tau, j^*_i = j^*\right)$$
$$\Sigma_{\tau j^*} \equiv Var\left(\theta_i \mid i \in C_\tau, j^*_i = j^*\right)$$

For each cohort×history we have 4 first moments:

$$E\left(\widetilde{w}_{i\tau+e} \mid i \in C_\tau, j_i^* = j^*\right) = \delta_{j^*(e)\tau+e} + \alpha_{j^*(e)\tau+e}\mu'_{\tau j^*}\, D^e \beta_{j^*(e)} + \psi_{j^* e}$$

for $e = 0, ..., 3$ where $\psi_{j^* e}$ is the relevant experience profile.

We have 4 different variances

$$Var\left(\widetilde{w}_{i\tau+e} \mid i \in C_\tau, j_i^* = j^*\right) = \alpha^2_{j^*(e)\tau+e}\beta'_{j^*(e)}D^e\Sigma_{\tau j^*}D^e\beta_{j^*(e)} + \sigma_u^2$$

for $e = 0, ..., 3$ and 6 covariances

$$Cov\left(\widetilde{w}_{i\tau+e}, \widetilde{w}_{i\tau+\epsilon} \mid i \in C_\tau, j_i^* = j^*\right) = \alpha_{j^*(e)\tau+e}\alpha_{j^*(\epsilon)\tau+\epsilon}\beta'_{j^*(e)}D^e\Sigma_{\tau j^*}D^\epsilon\beta_{j^*(\epsilon)}$$

for $(e, \epsilon) = (0, 1), (0, 2), (0, 3), (1, 2), (1, 3)$, and $(2, 3)$.

This gives a total of $14J^4$ equations and $(3 + 6)J^4 + 4J + 4J$ unknowns. Each history $\mu_{\tau h}$ has 3 parameters and $\Sigma_{\tau h}$ has 6. Furthermore we have $4J$ $\delta's$ and $4J$ $\alpha's$.

To fix scale and location we need to fit the population values that is we know

$$\sum_{j^{d*} \in \mathcal{J}} \rho_{j^*}(p_\tau)\mu_{\tau j^*} = 0$$
$$\sum_{j^* \in \mathcal{J}} \rho_{j^*}(p_\tau)\left[\Sigma_{\tau j^*} + \mu_{\tau j^*}\mu'_{\tau j^*}\right] = \Sigma$$

As long as $J \geq 2$ the parameters are generically identified.

Stage 4 Supply of skill $S(\cdot)$

The goal of this section is identification of the supply function for a cohort-that is for a given vector of prices $(\delta_{j\tau+e}, \alpha_{j\tau+e})$ for $e = 0, .., 3$ we show that we can identify the probability of each job history, and the distribution of θ_i conditional on choosing that history.

From the previous section we know that we can identify all of the relevant δ and α for any cohort (except extreme cases in which some profiles are not observed). We invert that argument, given the support conditions, for any set of prices we can find a cohort that faces those prices. Let that cohort be C_τ. We condition on data from that cohort and show that we can non-parametrically identify the supply of skill.

For each history we can directly identify the probability of choosing that history, $\rho_{j^*}(p_\tau)$ as well as the joint distribution of wages over the four periods conditional on that history.

Thus we need to show that from the conditional distribution of lifetime wages we can identify the conditional distribution of θ_i for each history j^*.

Let φ_u be the characteristic function of the measurement error and let $\phi^w_{\tau j^*}(s)$ be the characteristic function of

$$\left(\frac{\widetilde{w}_{i\tau}-\delta_{j^*(0)\tau}}{\alpha_{j^*(0)\tau}},\frac{\widetilde{w}_{i\tau+e}-\delta_{j^*(1)\tau+1}-\alpha_{j^*(1)\tau+e}\psi_{j^*1e}}{\alpha_{j^*(1)\tau+1}},\frac{\widetilde{w}_{i\tau+2}-\delta_{j^*(2)\tau+2}-\alpha_{j^*(2)\tau+2}\psi_{j^*2}}{\alpha_{j^*(2)\tau+2}},\frac{\widetilde{w}_{i\tau+3}-\delta_{j^*(3)\tau+3}-\alpha_{j^*(3)}}{\alpha_{j^*(3)\tau+3}}\right.$$

Note that all of these terms are identified so the characteristic function can be identified as well. Since we use i to index individuals we use ι to be the imaginary number so

$$\begin{aligned}
\phi^w_{\tau j^*}(s) \equiv & E\left(exp\left(\iota\sum_{e=0}^{3}s_e\left(\frac{\widetilde{w}_{i\tau+e}-\delta_{j^*(e)\tau+e}-\alpha_{j^*(e)\tau+e}\psi_{j^*e}}{\alpha_{j^*(e)\tau+e}}\right)\right)\mid i\in C_\tau, j_i^*=j^*\right)\\
=&E\left(exp\left(\iota\sum_{e=0}^{3}s_e\left(\beta'_{j^*(e)}D^e\theta_i+\frac{u_{it+e}}{\alpha_{j^*(e)\tau+e}}\right)\right)\mid i\in C_\tau, j_i^*=j^*\right)\\
=&E\left(exp\left(\iota\left(\sum_{e=0}^{3}s_e\beta'_{j^*(e)}D^e\right)\theta_i\right)\mid i\in C_\tau, j_i^*=j^*\right)\prod_{e=0}^{3}\varphi_u\left(\frac{s_e}{\alpha_{j^*(e)\tau+e}}\right)
\end{aligned}$$

Note that this first expression is directly identified from the data and is the characteristic function of the vector of four wages adjusted for prices levels and ψ as described below conditional on history j^* and cohort C_τ.

Our goal now is to manipulate this to get the characteristic function of θ_i by rewriting this to make it similar to the Kotlarski (1967) case.

We will focus on the random variable from the first period, h_{i0}.

The variable σ which has support $\Re$ will play the role of the second index in Kotlarski. We will manipulate the model into that form by choosing $(s_1(\sigma), s_2(\sigma), s_3(\sigma))$ so that

$$\sum_{e=1}^{3}s_e(\sigma)D^e\beta_{j^*(e)}=\sigma\beta_{j^*(0)}.$$

Next let $\eta_{\tau j^*}$ be the characteristic function of h_{i0} conditional on $i\in C_\tau$ and $j_i^*=j^*$. Let

$$\widetilde{\phi}(\sigma)\equiv\prod_{e=1}^{3}\varphi_u\left(\frac{s_e(\sigma)}{\alpha_{j^*(e)\tau+e}}\right).$$

Then, for any s_0 and σ we can identify

$$\begin{aligned}
&\phi^w_{\tau j^*}(s_0, s_1(\sigma), s_2(\sigma), s_3(\sigma)) \\
=&E\left(exp\left(\iota\left(s_0\beta'_{j_0} + \sum_{e=1}^{3} s_e(\sigma)\beta'_{j^*(e)}D^e\right)\theta_i\right) \mid i \in C_\tau, j_i^* = j^*\right)\widetilde{\phi}(\sigma) \\
=&E\left(exp\left(\iota\left(s_0 + \sigma\right)\nu_i\right) \mid i \in C_\tau, j_i^* = j^*\right)\varphi_u\left(s_0\right)\widetilde{\phi}(\sigma) \\
=&\eta_{\tau j^*\nu}(s_0 + \sigma)\varphi_u\left(s_0\right)\widetilde{\phi}(\sigma)
\end{aligned}$$

This expression is analogous to the characteristic for Kotlarski's lemma from which we know that we can identify φ_u.

To get the supply of skills from this we let r be a three dimensional vector that will index the conditional characteristic function of the three dimensional vector θ_i. We then use $s(r)$ to map the three dimensional distribution of θ_i into the four dimensional distribution of wages. We do that by defining $s(r)$ so that $s_3(r) = 0$ and the other three satisfy

$$r = \sum_{e=0}^{2} s_e\left(r\right)D^e\beta_{j^*(e)}.$$

Then we can identify

$$\begin{aligned}
&\frac{\phi^w_{\tau j^*}(s(r))}{\prod_{e=0}^{3}\varphi_u\left(\frac{s_e(r)}{\alpha_{j_e\tau+e}}\right)} \\
=&E\left(exp\left(\iota\left(\sum_{e=0}^{2} s_e\left(r\right)\beta'_{j_e}D^e\right)\theta_i\right) \mid i \in C_\tau, j_i^* = j^*\right) \\
=&E\left(exp\left(\iota r'\theta_i\right) \mid i \in C_\tau, j_i^* = j^*\right)
\end{aligned}$$

which is the conditional characteristic function of θ_i. Since the conditional characteristic function is identified, the conditional distribution $G_{j^*}(\cdot; p_\tau)$ is as well.

Stage 5: Prices from Cross Section

Once we have non-parametrically estimated the supply function it is straight forward to see how prices can be identified. We have $8J$ different parameters but J^4 different histories. That gives us J^4 different conditional probabilities of choosing each option and J^4 different full 4 dimensional joint distribution of wages. It is clear that the prices are generically identified.

E Auxiliary parameters based on Deming (2017)

Combining NLSY79 and NLSY97, Deming (2017) finds that social skills are a significantly more important predictor of full-time employment and wages in the NLSY97 cohort. We reproduce this result for our sample of low skilled men. We estimate the following equations with either the log hourly wage (conditional on employment) or an indicator for full-time employment as the dependent variable y_{it}:

$$y_{it} = \alpha + \beta_1 \text{COG}_i + \beta_2 \text{SS}_i + \beta_3 \text{COG}_i \times \text{NLSY97}_i + \beta_4 \text{SS}_i \times \text{NLSY97}_i + \zeta X_{it} + \epsilon_{it}.$$

The regressors includes cognitive skills COG_i and social skills SS_i, To test the hypothesis that the returns to skills have changed over time, we include the interaction between skills and an indicator for being in the NLSY97 sample NLSY97_i. The X_{it} vector includes age and year fixed effects and the dummy variable NLSY97_i.

The results are in Table E1. A one standard deviation increase in cognitive skills increases

Table E1: Reproduction of Table 4 for low skilled men in Deming (2017)

	Employment	Wage
	(1)	(2)
Cognitive	0.074***	0.126***
	(0.004)	(0.008)
Social	0.005	0.010
	(0.004)	(0.008)
Cognitive*NLSY97	0.010	-0.057***
	(0.009)	(0.014)
Social*NLSY97	0.041***	0.030*
	(0.008)	(0.014)
age FE	Yes	Yes
year FE	Yes	Yes
NLSY97	Yes	Yes
N	40,227	32,106
R^2	0.065	0.108

the probability of employment by 7.5% and we cannot reject that the effect is the same in NLSY79 and NLSY97. It increases wages by 12.6% but the effect has decreased over time by

6 percentage points. We cannot reject that social skills have no effect on either the probability of working or log wages in NLSY79. In NLSY97, a one standard deviation increase in social skills increases the probability of employment by 4.1%. And it increases wages by 3%.

F Parameter Estimates: Life Cycle

F.1 Workers

Table F1 reports heterogeneity across individuals in terms of preferences, endowment and luck.

Table F1: Heterogeneity

Skill Endowment			Measurement			Shocks		
σ_1	0.4194	(0.0844)	E	0.8414	(0.0007)	σ_ν	28.3825	(2.2565)
σ_2	0.4061	(0.0388)				σ_χ	95.682	(1.9503)
σ_3	0.3898	(0.0286)	σ_u	0.2384	(0.0685)			
σ_{12}	0.0812	(0.0262)				search cost (deterministic)		
σ_{13}	0.0036	(0.0047)	$\tilde{\sigma}_1$	0.0397	(0.0184)	$\overline{\chi}$	251.4717	(0.2972)
σ_{21}	0.0069	(0.0053)	$\tilde{\sigma}_2$	0.8149	(0.0325)			

The actual magnitude of the skill depends on its value in different occupations, so the levels are not directly comparable. However, the levels would be directly comparable in an occupation that weighted them equally so we proceed to make these comparisons. Cognitive skills are the most unequally distributed at labor market entry, followed by manual skills and finally inter-personal skills.

Occupation-specific shocks are more predictable than search costs. There are large costs of attempting to switch occupations, though they are weighted against the variance of idiosyncratic shocks which is also large.

We find large measurement error in wages and it is on the higher side of estimates in related papers. Much of this is likely due to earnings shocks that we abstracted from. The interactions between human capital shocks and technological change is an important avenue for future research.

Each year, we estimate about 10% of individuals misreport their occupations. This number is reassuringly similar to estimates in the literature even though they are identified using different approaches. In Neal (1999) and Kambourov and Manovskii (2009), E is set using "spurious" transitions in the NLSY. These are all the within-firm occupational transitions where an individual works in occupation j_0 at both time t and $t+2$, and works in $j_1 \neq j_0$ at time t even though he remained in these three consecutive periods with the same employer. About 10% of occupational shifts are "spurious" transitions according to

Table F2: Offer arrival rate, constant and slope of the wage function (until 1979)

Occupation	Offer proba.		Wage cons.		Wage slope	
Managers	0.34	(0.01)	1.94	(0.12)	1.11	(0.1)
Clerical	0.57	(0.14)	2.01	(0.07)	1*	(0)
Services	0.84	(0.02)	1.93	(0.04)	0.86	(0.18)
Operators	1.0	(0.11)	2.1	(0.08)	0.87	(0.1)
Mechanics	0.4	(0.03)	2.17	(0.27)	0.84	(0.18)
Construction	0.51	(0.01)	2.26	(0.03)	0.98	(0.15)
Precision	0.37	(0.02)	2.28	(0.07)	0.91	(0.17)
Transport	1.0	(0.04)	2.06	(0.04)	0.88	(0.14)

Note: The asterisk (*) indicates normalized parameters.

this metric.

F.2 Occupations

Table F2 reports occupation specific parameters that are identified using the NLSY79. There exists a wide dispersion in the availability of jobs and the wage schedule across occupations. Applicants to become operators, work in service or in transport occupations have a high chance of being successful.[18] On the other hand, the probability of being successful after applying to become a manager or precision worker is only around 0.3. The slope with respect to skills is the highest in management.

F.3 Sources of Wage Growth

To understand the role of each skills in wage growth, we decompose additively log wage growth by simulating career decisions. This take into account occupation transitions and more generally people' choices. In simulating this we ignore technological change and assume that the δ, α and β do not change over time so we suppress t subscripts on these variables. To illustrate the decomposition, for simplicity consider the case in which a $\alpha_{1j} = \alpha_{2j}$ for each occupation. Letting w_{it} be the log wage of individual i at time t we can write

$$w_{it} = \delta_{j_{it}} + \alpha_{j_{it}} \left(\beta'_{j_{it}} \theta_{it} + \sigma_{it} \right),$$

[18] Though, it became harder for operators over time as we discussed in the body of the paper.

where we use the shorthand notation $\sigma_{it} = \sigma(j_{it}, \tau_{it})$. Then

$$
\begin{aligned}
w_{it} - w_{it-1} = & \delta_{j_{it}} - \delta_{j_{it-1}} + \left(\alpha_{j_{it}}\beta'_{j_{it}} - \alpha_{j_{it-1}}\beta'_{j_{it-1}}\right)\theta_{it} \\
& + \alpha_{j_{it-1}}\beta^c_{j_{it-1}}\left[\theta^c_{it} - \theta^c_{it-1}\right] \\
& + \alpha_{j_{it-1}}\beta^i_{j_{it-1}}\left[\theta^i_{it} - \theta^i_{it-1}\right] \\
& + \alpha_{j_{it-1}}\beta^m_{j_{it-1}}\left[\theta^m_{it} - \theta^m_{it-1}\right] \\
& + 1\left(j_{it} = j_{it-1}\right)\alpha_{j_{it-1}}\left[\sigma_{it} - \sigma_{it-1}\right] \\
& + 1\left(j_{it} \neq j_{it-1}\right)\left[-\alpha_{j_{it-1}}\sigma_{it-1}\right].
\end{aligned}
$$

The restrictions on α and δ mean that for stayers, the first term disappears and wage growth exclusively comes from skill variations: general $\Delta\theta_t$ or occupation-specific $\Delta\sigma_t$. For switchers, the first term in which δ, α, and β change will be a component. Also switchers will lose the value of their occupation specific human capital ($\alpha_{j_{it-1}}\sigma_{it-1}$).

In practice we can not use the simple formula above because $\alpha_{1j} \neq \alpha_{2j}$ but rather use a linear approximation to these equations.

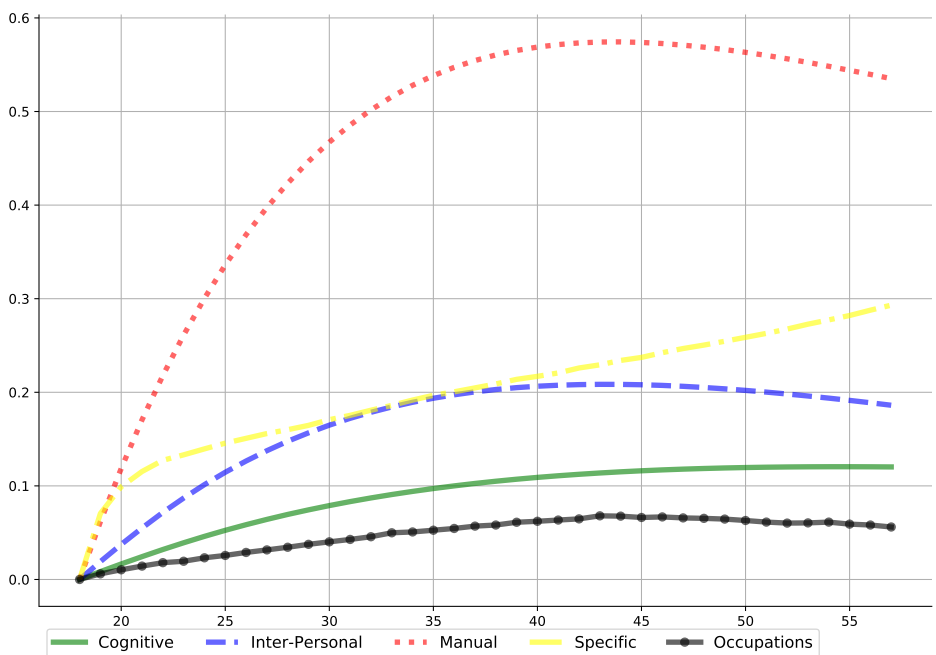
$$
\begin{aligned}
w_{it} - w_{it-1} = & f_{j_{it}}\left(\beta'_{j_{it}}\theta_{it} + \sigma_{it}\right) - f_{j_{it-1}}\left(\beta'_{j_{it}}\theta_{it} + \sigma_{it}\right) \\
& + \alpha^*\beta^c_{j_{it-1}}\left[\theta^c_{it} - \theta^c_{it-1}\right] \\
& + \alpha^*\beta^i_{j_{it-1}}\left[\theta^i_{it} - \theta^i_{it-1}\right] \\
& + \alpha^*\beta^m_{j_{it-1}}\left[\theta^m_{it} - \theta^m_{it-1}\right] \\
& + 1\left(j_{it} = j_{it-1}\right)\alpha^*\left[\sigma_{it} - \sigma_{it-1}\right] \\
& + 1\left(j_{it} \neq j_{it-1}\right)\left[-\alpha^*\sigma_{it-1}\right]
\end{aligned}
$$

where

$$
\alpha^* = \frac{f_{j_{it-1}}\left(\beta'_{j_{it}}\theta_{it} + \sigma_{it}\right) - f_{j_{it-1}}\left(\beta'_{j_{it-1}}\theta_{it-1} + \sigma_{it-1}\right)}{\left(\beta'_{j_{it}}\theta_{it} + \sigma_{it}\right) - \left(\beta'_{j_{it-1}}\theta_{it-1} + \sigma_{it-1}\right)}
$$

Details of this can be found in the following section. The results of the decomposition of the five terms above is presented in Figure F1.

Figure F1: Sources of wage growth: decomposition



G Wage Growth Decomposition

We use the steady-state values of the δ, α and β and therefore omit the t subscript on these variables. The wage function is:

$$\begin{aligned} w_{it} &= \delta_{j_{it}} + \alpha_{1j_{it}} \left(\theta'_{it}\beta_{j_{it}} + \sigma_{it}\right) \times \left\{\theta'_{it}\beta_{j_{it}} + \sigma_{it} \leq h^*_{j_{it}}\right\} \\ &+ \left(\alpha_{2j_{it}} \left[\theta'_{it}\beta_{j_{it}} + \sigma_{it} - h^*_{j_{it}}\right] + \alpha_{1j_{it}} h^*_{j_{it}}\right) \times \left\{\theta'_{it}\beta_{j_{it}} + \sigma_{it} > h^*_{j_{it}}\right\}. \end{aligned}$$

Stayers There are three different cases to consider:

1. $\left\{\theta'_{it}\beta_{j_{it}} + \sigma_{it} \leq h^*_{j_{it}}\right\} \times \left\{\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1} \leq h^*_{j_{it-1}}\right\} + \left\{\theta'_{it}\beta_{j_{it}} + \sigma_{it} > h^*_{j_{it}}\right\} \times \left\{\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1} > h^*_{j_{it-1}}\right\} > 0$.

$$\begin{aligned} \Delta w_{it} = \Bigg(& \alpha_{1j_{it}} \left\{\theta'_{it}\beta_{j_{it}} + \sigma_{it} \leq h^*_{j_{it}}\right\} \times \left\{\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1} \leq h^*_{j_{it-1}}\right\} \\ & + \alpha_{2j_{it}} \left\{\theta'_{it}\beta_{j_{it}} + \sigma_{it} > h^*_{j_{it}}\right\} \times \left\{\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1} > h^*_{j_{it-1}}\right\}\Bigg) \\ & \times \left(\beta_{j_{it}}\Delta\theta_{it} + \Delta\sigma_{it}\right) \end{aligned}$$

2. $\left\{\theta'_{it}\beta_{j_{it}} + \sigma_{it} > h^*_{j_{it}}\right\} \times \left\{\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1} \leq h^*_{j_{it-1}}\right\} = 1$.

$$\begin{aligned} \Delta w_{it} &= \alpha_{2j_{it}} \left(\theta'_{it}\beta_{j_{it}} + \sigma_{it} - h^*_{j_{it}}\right) + \alpha_{1j_{it}} \left(h^*_{j_{it-1}} - \left(\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1}\right)\right) \\ &= \alpha^*_{j_{it}} \left(\Delta\theta'_{it}\beta_{j_{it}} + \sigma_{it} - \sigma_{it-1}\right) \end{aligned}$$

where α^* is a linear approximation of the two slopes.

3. $\left\{\theta'_{it}\beta_{j_{it}} + \sigma_{it} \leq h^*_{j_{it}}\right\} \times \left\{\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1} > h^*_{j_{it-1}}\right\} = 1$.

$$\Delta w_{it} = \alpha_{2j_{it}} \left(h^*_{j_{it-1}} - \left(\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1}\right)\right) + \alpha_{1j_{it}} \left(\theta'_{it}\beta_{j_{it}} + \sigma_{it} - h^*_{j_{it}}\right)$$

we use as in case 2 a linear approximation of the two slopes.

Switchers There are four different cases to consider. Let $\Delta\delta_{it} = \delta_{j_{it}} - \delta_{j_{it-1}}$.

1. $\left\{\theta'_{it}\beta_{j_{it}} \leq h^*_{j_{it}}\right\} \times \left\{\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1} \leq h^*_{j_{it-1}}\right\} = 1.$

$$\begin{aligned}\Delta w_{it} =& \Delta\delta_{it} + \left(\alpha_{1j_{it}}\beta'_{j_{it}} - \alpha_{1j_{it-1}}\beta'_{j_{it-1}}\right)\theta_{it} \\ &+ \alpha_{1j_{it-1}}\beta_{j_{it-1}}\Delta\theta_{it} - \alpha_{1j_{it-1}}\sigma_{it-1}\end{aligned}$$

2. $\left\{\theta'_{it}\beta_{j_{it}} > h^*_{j_{it}}\right\} \times \left\{\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1} > h^*_{j_{it-1}}\right\} = 1.$

$$\begin{aligned}\Delta w_{it} =& \Delta\delta_{it} + \left(\left(\alpha_{1j_{it}} - \alpha_{2j_{it}}\right)h^*_{j_{it}} - \left(\alpha_{1j_{it-1}} - \alpha_{2j_{it-1}}\right)h^*_{j_{it-1}}\right) \\ &+ \left(\alpha_{2j_{it}}\beta'_{j_{it}} - \alpha_{2j_{it-1}}\beta'_{j_{it-1}}\right)\theta_{it} \\ &+ \alpha_{2j_{it-1}}\beta'_{j_{it-1}}\Delta\theta_{it} - \alpha_{2j_{it-1}}\sigma_{it-1}\end{aligned}$$

3. $\left\{\theta'_{it}\beta_{j_{it}} > h^*_{j_{it}}\right\} \times \left\{\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1} \leq h^*_{j_{it-1}}\right\} = 1.$

$$\begin{aligned}\Delta w_{it} =& \Delta\delta_{it} + \left(\alpha_{1j_{it}} - \alpha_{2j_{it}}\right)h^*_{j_{it}} \\ &+ \left(\alpha_{2j_{it}}\beta'_{j_{it}} - \alpha_{1j_{it-1}}\beta'_{j_{it-1}}\right)\theta_{it} \\ &+ \alpha_{1j_{it-1}}\beta'_{j_{it-1}}\Delta\theta_{it} - \alpha_{1j_{it-1}}\sigma_{it-1}\end{aligned}$$

4. $\left\{\theta'_{it}\beta_{j_{it}} \leq h^*_{j_{it}}\right\} \times \left\{\theta'_{it-1}\beta_{j_{it-1}} + \sigma_{it-1} > h^*_{j_{it-1}}\right\} = 1.$

$$\begin{aligned}\Delta w_{it} =& \Delta\delta_{it} - \left(\alpha_{1j_{it-1}} - \alpha_{2j_{it-1}}\right)h^*_{j_{it-1}} \\ &+ \left(\alpha_{1j_{it}}\beta'_{j_{it}} - \alpha_{2j_{it-1}}\beta'_{j_{it-1}}\right)\theta_{it} \\ &+ \alpha_{2j_{it-1}}\beta'_{j_{it-1}}\Delta\theta_{it} - \alpha_{2j_{it-1}}\sigma_{it-1}\end{aligned}$$

H Auxiliary Parameters not reported in the main text

This Section presents the auxiliary parameters calculated in the NLSY79, CPS and data simulated from the model at the estimated parameters values.

Figure H1 and Figure H2 report, respectively, occupation share in the population and occupation share by age. We use the CPS data but restricts to NLSY79 cohorts.

Figure H1: Occupation Share - CPS data, NLSY cohorts

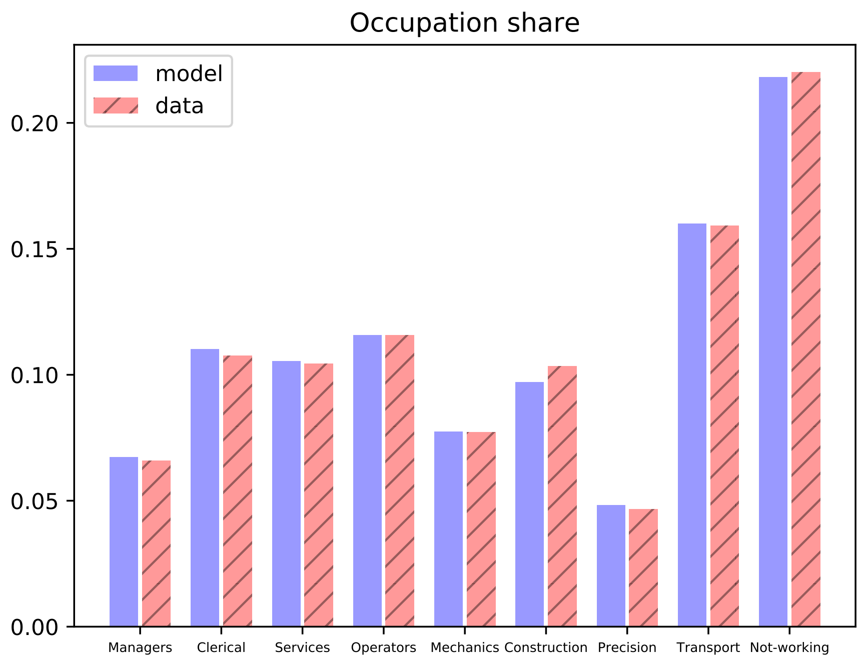


Figure H2: Occupation Share by Age - CPS data, NLSY cohorts

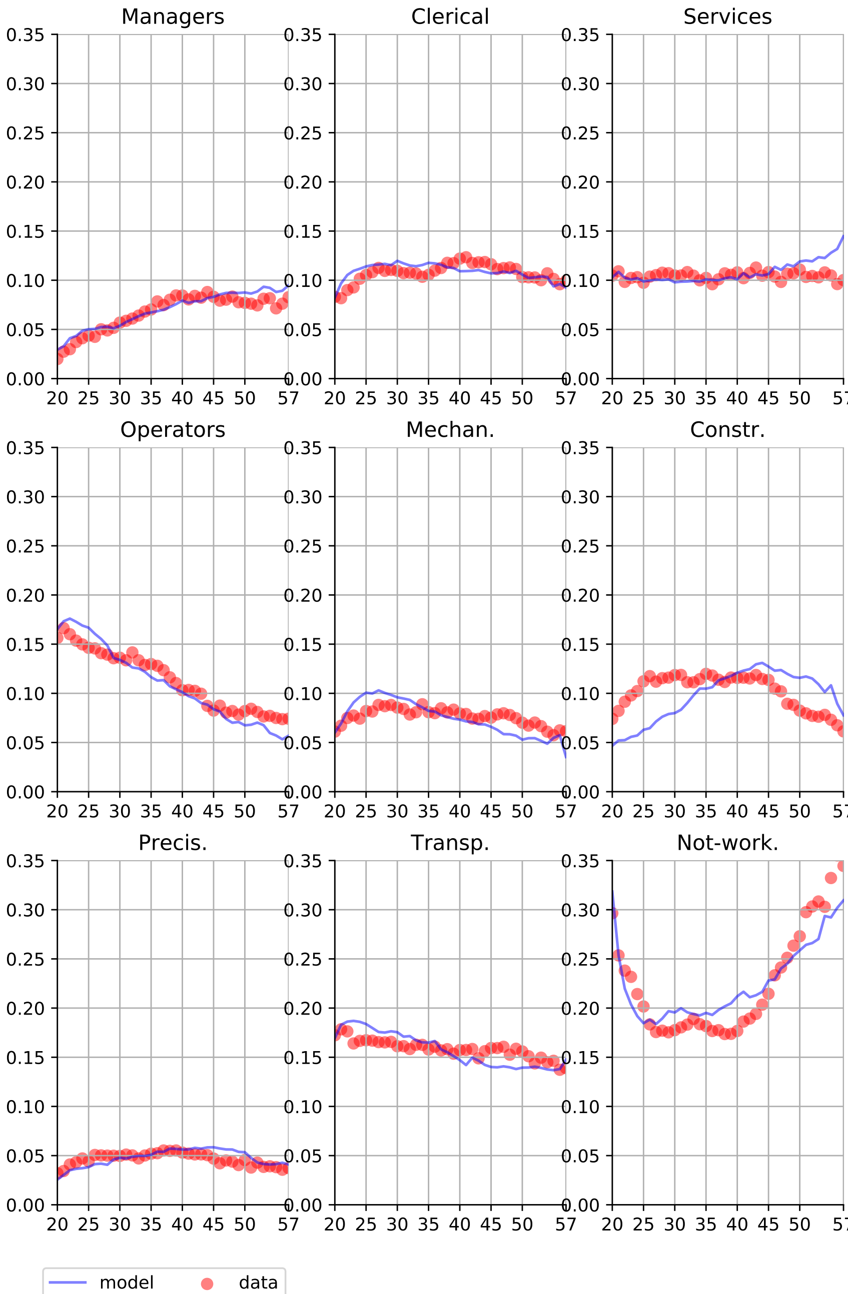


Figure H3 reports different quantiles of the wage distribution by occupation in the NLSY79 cohorts using CPS data.

Figure H3: Quantiles of the Wage Distribution by Occupation - CPS data, NLSY cohorts

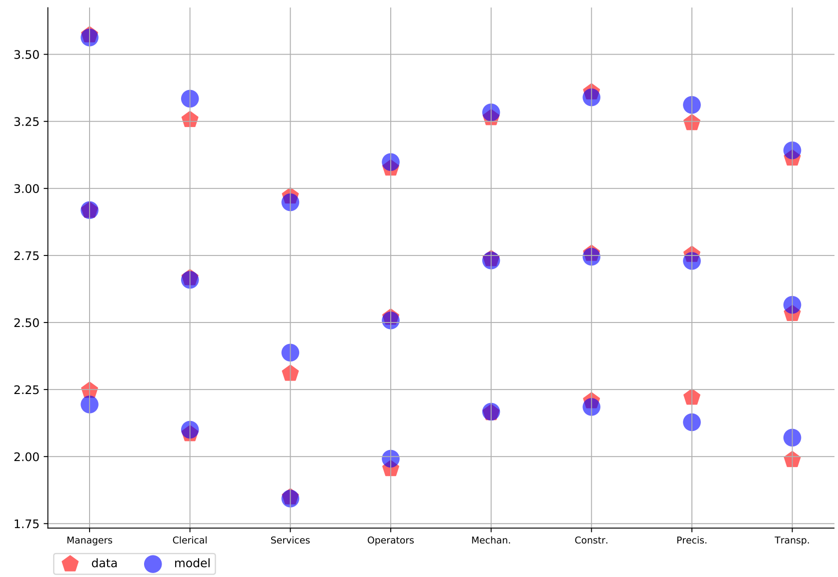


Figure H4 plots auto-correlations of wages by age. The horizontal lines represent autocorrelations without controlling for age. Figure H5 plots auto-correlations of wages by occupation. The upper-panel restricts the sample to stayers. The lower-panel restricts the sample to switchers. Table H1 reports age-earnings profile by occupation in the NLSY79 cohorts using the CPS data. Figure H6 reports different quantiles of the wage distribution by year and occupation in the CPS. These auxiliary parameters identify prices once we control for selection using the previous moments. Table H2 and Table H3 report the percentage of stayers by age and occupation, respectively, annually and bi-annually. Table H4 reports the mean difference in the log wages by current and lagged occupation. Table H5 and Table H6 report the same statistics separately for individuals with, respectively, experience and tenure, above and below median. Finally, Table H7 reports the same statistics separately for above median experience individuals with tenure above or below median. Table H8 and Table H9 report mean wages by, respectively, experience and tenure for each occupation. Table H10 reports the regression coefficients from Deming's regression. Table H11 and Table H12 report the occupation distribution by, respectively, cognitive skills and social skills.

Figure H4: Auto-correlations wages levels by age - NLSY79

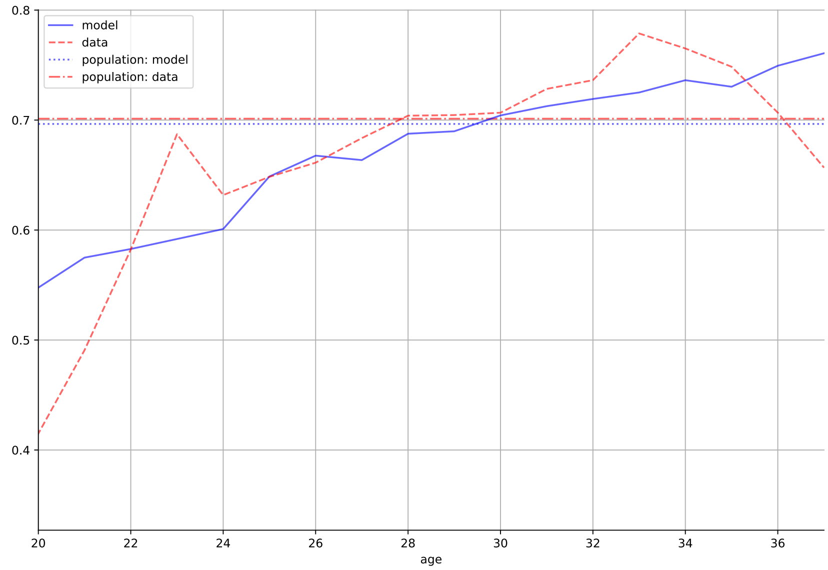


Figure H5: Auto-correlations wages levels by occupation - NLSY79

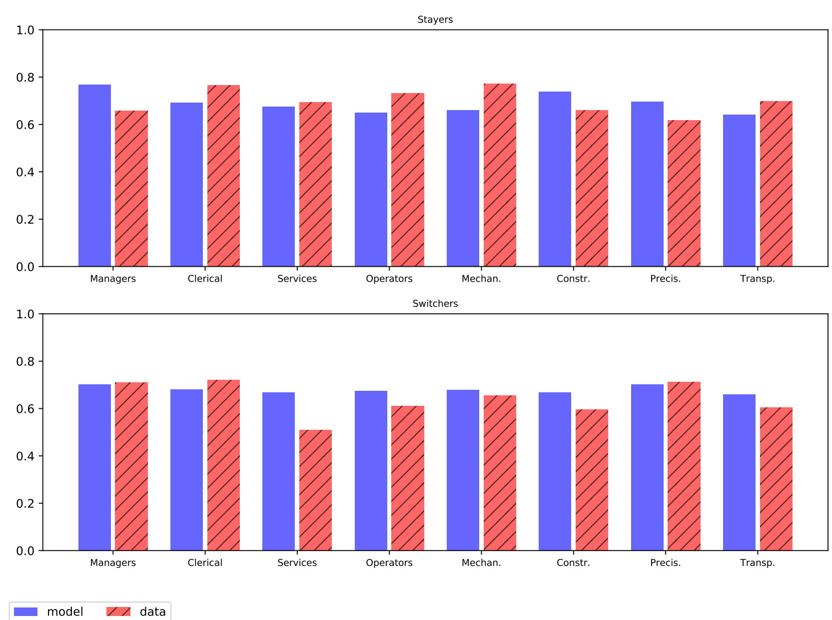


Table H1: Age earnings profile by occupation - CPS data, NLSY cohorts

Age	Managers		Clerical		Services		Operators		Mechan.		Constr.		Precis.		Transp.	
20	2.25	2.17	2.24	2.22	2.05	2.08	2.27	2.26	2.31	2.29	2.44	2.35	2.39	2.35	2.21	2.25
21	2.35	2.24	2.28	2.32	2.08	2.08	2.35	2.25	2.43	2.36	2.51	2.43	2.51	2.38	2.29	2.3
22	2.44	2.35	2.36	2.38	2.11	2.14	2.37	2.3	2.43	2.44	2.53	2.41	2.53	2.37	2.33	2.38
23	2.48	2.42	2.43	2.42	2.15	2.15	2.41	2.34	2.51	2.46	2.6	2.41	2.57	2.38	2.35	2.39
24	2.57	2.43	2.46	2.46	2.18	2.14	2.4	2.38	2.55	2.48	2.63	2.42	2.59	2.43	2.36	2.39
25	2.58	2.53	2.49	2.52	2.19	2.2	2.4	2.41	2.56	2.56	2.63	2.47	2.64	2.48	2.39	2.43
26	2.65	2.59	2.56	2.53	2.2	2.22	2.43	2.43	2.56	2.59	2.65	2.5	2.66	2.52	2.44	2.44
27	2.74	2.55	2.56	2.59	2.23	2.2	2.49	2.45	2.62	2.6	2.72	2.52	2.66	2.52	2.46	2.45
28	2.73	2.6	2.58	2.6	2.23	2.29	2.5	2.47	2.65	2.63	2.74	2.61	2.68	2.58	2.48	2.47
29	2.67	2.63	2.61	2.65	2.28	2.32	2.49	2.52	2.66	2.7	2.71	2.57	2.73	2.56	2.45	2.51
30	2.78	2.73	2.62	2.66	2.31	2.33	2.5	2.52	2.71	2.73	2.68	2.65	2.73	2.67	2.52	2.53
31	2.78	2.78	2.67	2.71	2.32	2.28	2.55	2.55	2.68	2.75	2.74	2.63	2.73	2.65	2.53	2.53
32	2.85	2.84	2.66	2.71	2.31	2.36	2.52	2.56	2.71	2.79	2.76	2.7	2.74	2.73	2.53	2.57
33	2.8	2.86	2.69	2.76	2.31	2.35	2.53	2.59	2.71	2.78	2.75	2.74	2.72	2.74	2.5	2.59
34	2.91	2.99	2.69	2.74	2.35	2.41	2.52	2.57	2.72	2.85	2.78	2.77	2.76	2.78	2.51	2.59
35	2.87	2.94	2.73	2.79	2.33	2.48	2.57	2.59	2.8	2.82	2.77	2.78	2.79	2.76	2.57	2.66
36	2.93	2.97	2.78	2.79	2.35	2.48	2.57	2.62	2.81	2.85	2.82	2.82	2.79	2.76	2.57	2.64
37	2.99	3.0	2.75	2.82	2.37	2.5	2.59	2.62	2.83	2.86	2.82	2.83	2.8	2.8	2.57	2.66
38	2.96	2.99	2.77	2.78	2.38	2.48	2.65	2.62	2.84	2.89	2.86	2.86	2.86	2.85	2.64	2.67
39	3.01	3.03	2.77	2.83	2.35	2.5	2.65	2.63	2.86	2.89	2.84	2.83	2.88	2.85	2.65	2.68
40	3.1	3.09	2.83	2.84	2.41	2.49	2.63	2.66	2.88	2.85	2.87	2.86	2.82	2.87	2.66	2.69
41	3.05	3.1	2.83	2.81	2.44	2.54	2.66	2.64	2.89	2.91	2.88	2.86	2.87	2.92	2.65	2.71
42	3.09	3.06	2.89	2.83	2.51	2.49	2.65	2.67	2.88	2.92	2.86	2.86	2.84	2.85	2.66	2.67
43	3.14	3.09	2.82	2.85	2.51	2.52	2.7	2.67	2.97	2.85	2.89	2.88	2.91	2.83	2.69	2.71
44	3.14	3.11	2.89	2.86	2.48	2.53	2.67	2.65	2.92	2.95	2.97	2.87	2.91	2.93	2.72	2.71
45	3.18	3.16	2.85	2.8	2.44	2.51	2.74	2.63	2.92	2.9	2.95	2.87	2.84	2.88	2.71	2.66
46	3.17	3.11	2.83	2.8	2.44	2.54	2.65	2.67	2.94	2.87	2.91	2.84	2.87	2.89	2.69	2.72
47	3.14	3.11	2.84	2.81	2.48	2.51	2.68	2.63	2.97	2.86	2.89	2.84	2.88	2.89	2.67	2.68
48	3.22	3.12	2.83	2.75	2.48	2.49	2.69	2.65	2.94	2.94	2.94	2.8	2.89	2.86	2.7	2.71
49	3.18	3.18	2.86	2.78	2.45	2.5	2.69	2.6	3.0	2.89	2.95	2.8	2.93	2.82	2.74	2.67
50	3.18	3.1	2.85	2.76	2.51	2.45	2.7	2.56	2.92	2.8	2.91	2.8	2.87	2.9	2.7	2.68
51	3.18	3.1	2.84	2.67	2.48	2.49	2.69	2.59	3.0	2.84	2.91	2.81	2.92	2.83	2.69	2.65
52	3.22	3.08	2.86	2.7	2.52	2.48	2.7	2.57	2.91	2.79	3.01	2.79	2.85	2.8	2.71	2.63
53	3.18	3.09	2.82	2.65	2.5	2.45	2.68	2.62	2.95	2.82	2.98	2.71	2.82	2.83	2.74	2.64
54	3.22	3.09	2.87	2.63	2.54	2.45	2.73	2.59	2.92	2.73	2.95	2.73	2.91	2.84	2.7	2.6
55	3.17	3.07	2.76	2.48	2.44	2.42	2.7	2.47	3.0	2.81	2.94	2.77	2.94	2.81	2.73	2.63
56	3.24	3.02	2.83	2.6	2.52	2.4	2.64	2.43	2.92	2.77	2.93	2.78	2.99	2.86	2.74	2.57
57	3.24	2.91	2.83	2.48	2.5	2.41	2.69	2.39	2.95	2.72	3.04	2.65	2.95	2.62	2.74	2.61

Table H2: Share of Stayers by Age and Occupation (Annual)

Age	Managers		Clerical		Services		Operators		Mechan.		Constr.		Precis.		Transp.		Not-work.	
20	0.35	0.3	0.34	0.58	0.36	0.54	0.46	0.64	0.28	0.57	0.33	0.38	0.11	0.45	0.37	0.59	0.48	0.65
21	0.44	0.48	0.43	0.64	0.49	0.5	0.5	0.67	0.46	0.63	0.48	0.51	0.33	0.5	0.38	0.63	0.46	0.66
22	0.36	0.52	0.38	0.64	0.48	0.57	0.5	0.62	0.49	0.67	0.54	0.55	0.27	0.53	0.39	0.65	0.46	0.68
23	0.43	0.65	0.48	0.67	0.54	0.61	0.45	0.68	0.6	0.62	0.46	0.6	0.36	0.63	0.47	0.65	0.49	0.7
24	0.38	0.61	0.41	0.65	0.52	0.58	0.57	0.64	0.51	0.66	0.49	0.64	0.46	0.62	0.41	0.68	0.48	0.71
25	0.56	0.63	0.54	0.69	0.54	0.66	0.49	0.62	0.55	0.69	0.53	0.62	0.42	0.61	0.44	0.63	0.46	0.76
26	0.56	0.64	0.51	0.67	0.59	0.6	0.5	0.64	0.57	0.74	0.59	0.61	0.36	0.66	0.5	0.66	0.57	0.72
27	0.52	0.61	0.51	0.64	0.51	0.6	0.55	0.65	0.58	0.7	0.56	0.63	0.42	0.58	0.51	0.66	0.49	0.74
28	0.56	0.64	0.51	0.64	0.57	0.6	0.55	0.61	0.57	0.68	0.5	0.55	0.41	0.62	0.56	0.69	0.54	0.76
29	0.53	0.65	0.5	0.64	0.6	0.58	0.56	0.64	0.6	0.65	0.59	0.62	0.45	0.65	0.5	0.65	0.56	0.74
30	0.59	0.65	0.59	0.65	0.59	0.62	0.57	0.65	0.59	0.69	0.52	0.63	0.36	0.59	0.57	0.63	0.54	0.77
31	0.57	0.7	0.61	0.65	0.61	0.58	0.57	0.64	0.67	0.68	0.5	0.66	0.43	0.61	0.52	0.65	0.6	0.75
32	0.56	0.7	0.56	0.66	0.67	0.61	0.62	0.63	0.65	0.65	0.61	0.62	0.47	0.57	0.55	0.66	0.59	0.77
33	0.6	0.68	0.6	0.64	0.74	0.6	0.65	0.61	0.61	0.68	0.59	0.67	0.42	0.62	0.68	0.65	0.6	0.75
34	0.68	0.72	0.54	0.64	0.71	0.62	0.56	0.65	0.73	0.72	0.55	0.64	0.61	0.65	0.66	0.66	0.62	0.79
35	0.73	0.72	0.73	0.72	0.71	0.6	0.59	0.63	0.72	0.65	0.67	0.7	0.5	0.76	0.64	0.65	0.71	0.76
36	0.78	0.72	0.49	0.65	0.72	0.61	0.69	0.67	0.84	0.69	0.64	0.63	0.66	0.62	0.62	0.71	0.65	0.79
37	0.72	0.76	0.75	0.64	0.8	0.62	0.96	0.6	0.79	0.67	0.72	0.66	0.66	0.67	0.84	0.68	0.78	0.8

Table H3: Share of Stayers by Age and Occupation (Bi-annual)

Age	Managers		Clerical		Services		Operators		Mechan.		Constr.		Precis.		Transp.		Not-work.	
21	0.24	0.26	0.28	0.49	0.34	0.36	0.33	0.54	0.25	0.48	0.4	0.32	0.31	0.32	0.28	0.5	0.4	0.47
22	0.27	0.31	0.28	0.54	0.4	0.38	0.5	0.54	0.36	0.57	0.43	0.39	0.2	0.31	0.33	0.53	0.41	0.48
23	0.28	0.47	0.4	0.54	0.42	0.46	0.35	0.55	0.43	0.57	0.43	0.41	0.22	0.39	0.35	0.56	0.4	0.51
24	0.45	0.59	0.39	0.59	0.44	0.48	0.43	0.59	0.42	0.58	0.44	0.51	0.27	0.51	0.34	0.59	0.41	0.54
25	0.44	0.57	0.42	0.59	0.44	0.5	0.47	0.53	0.51	0.62	0.48	0.49	0.46	0.5	0.38	0.55	0.37	0.57
26	0.46	0.56	0.42	0.59	0.5	0.51	0.4	0.55	0.52	0.65	0.48	0.53	0.29	0.55	0.41	0.54	0.37	0.56
27	0.43	0.61	0.35	0.59	0.45	0.49	0.45	0.53	0.58	0.66	0.51	0.52	0.37	0.5	0.44	0.57	0.46	0.58
28	0.48	0.57	0.44	0.55	0.44	0.49	0.48	0.5	0.52	0.61	0.48	0.52	0.42	0.51	0.5	0.6	0.43	0.62
29	0.47	0.58	0.45	0.6	0.54	0.5	0.49	0.52	0.55	0.62	0.52	0.5	0.36	0.54	0.44	0.57	0.49	0.6
30	0.5	0.59	0.42	0.61	0.52	0.48	0.52	0.55	0.5	0.64	0.51	0.52	0.31	0.55	0.47	0.54	0.48	0.6
31	0.53	0.62	0.57	0.57	0.57	0.46	0.47	0.54	0.54	0.59	0.42	0.56	0.36	0.52	0.51	0.54	0.5	0.59
32	0.53	0.67	0.42	0.58	0.6	0.48	0.5	0.53	0.63	0.59	0.52	0.52	0.37	0.49	0.47	0.54	0.58	0.59
33	0.57	0.65	0.44	0.59	0.61	0.46	0.52	0.52	0.46	0.59	0.54	0.6	0.42	0.54	0.49	0.55	0.55	0.6
34	0.53	0.63	0.46	0.58	0.62	0.49	0.54	0.54	0.72	0.61	0.6	0.55	0.48	0.51	0.57	0.59	0.52	0.62
35	0.61	0.67	0.5	0.62	0.57	0.51	0.5	0.54	0.52	0.59	0.53	0.55	0.5	0.65	0.57	0.57	0.55	0.65
36	0.61	0.71	0.49	0.54	0.64	0.52	0.57	0.57	0.79	0.6	0.62	0.59	0.48	0.64	0.56	0.62	0.52	0.64
37	0.63	0.65	0.55	0.56	0.68	0.53	0.58	0.62	0.64	0.6	0.68	0.61	0.49	0.58	0.59	0.6	0.66	0.69
38	0.62	0.68	0.47	0.61	0.74	0.55	0.67	0.51	0.59	0.59	0.66	0.57	0.53	0.51	0.68	0.63	0.55	0.66
39	0.62	0.7	0.71	0.57	0.73	0.57	0.69	0.58	0.59	0.64	0.52	0.65	0.56	0.61	0.63	0.56	0.58	0.67
40	0.67	0.64	0.62	0.56	0.67	0.54	0.72	0.54	0.71	0.59	0.7	0.63	0.65	0.58	0.67	0.62	0.63	0.73
41	0.61	0.68	0.78	0.61	0.72	0.48	0.68	0.58	0.73	0.58	0.68	0.59	0.65	0.55	0.75	0.57	0.64	0.69
42	0.73	0.72	0.77	0.65	0.67	0.57	0.71	0.55	0.87	0.62	0.68	0.64	0.58	0.7	0.8	0.63	0.71	0.69
43	0.68	0.66	0.73	0.6	0.84	0.46	0.75	0.53	0.83	0.57	0.8	0.66	0.76	0.65	0.76	0.59	0.67	0.69
44	0.73	0.74	0.78	0.59	0.76	0.53	0.72	0.52	0.83	0.55	0.77	0.63	0.56	0.57	0.7	0.61	0.66	0.72
45	0.7	0.72	0.76	0.56	0.84	0.55	0.8	0.49	0.79	0.59	0.81	0.6	0.65	0.66	0.74	0.63	0.7	0.73
46	0.87	0.69	0.83	0.65	0.8	0.51	0.68	0.5	0.81	0.62	0.8	0.6	0.76	0.63	0.83	0.64	0.8	0.74
47	0.78	0.73	0.7	0.62	0.86	0.55	0.82	0.57	0.81	0.56	0.85	0.68	0.83	0.6	0.72	0.57	0.78	0.74
48	0.75	0.66	0.83	0.59	0.72	0.54	0.79	0.67	0.74	0.59	0.77	0.63	0.87	0.67	0.72	0.6	0.78	0.76
49	0.83	0.73	0.88	0.6	0.81	0.55	0.73	0.6	0.84	0.63	0.79	0.62	0.79	0.64	0.71	0.6	0.79	0.72
50	0.93	0.69	0.83	0.62	0.87	0.58	0.71	0.56	0.79	0.61	0.77	0.61	0.78	0.6	0.69	0.63	0.81	0.73
51	0.85	0.75	0.78	0.68	0.74	0.55	0.65	0.55	0.8	0.51	0.89	0.66	0.73	0.59	0.8	0.66	0.82	0.72
52	0.82	0.69	0.94	0.56	0.75	0.59	0.81	0.48	0.92	0.48	0.71	0.63	0.8	0.49	0.71	0.63	0.8	0.71
53	0.75	0.73	0.82	0.54	0.93	0.53	0.8	0.5	0.9	0.6	1.0	0.57	0.7	0.57	0.78	0.58	0.78	0.73
54	0.92	0.59	0.86	0.65	0.86	0.64	0.94	0.52	0.79	0.63	0.91	0.59	0.71	0.53	0.8	0.6	0.93	0.79
55	0.82	0.69	0.75	0.53	0.74	0.59	1.0	0.41	1.0	0.49	0.71	0.53	0.18	0.55	0.62	0.69	0.78	0.77
56	0.0	0.72	1.0	0.6	0.5	0.56	0.0	0.44	1.0	0.59	1.0	0.69	1.0	0.57	0.84	0.6	0.61	0.75
57	1.0	0.78	0.0	0.5	1.0	0.64	0.5	0.48	1.0	0.48	0.0	0.59	0.0	0.43	0.66	0.57	1.0	0.69

Table H4: Mean wage growth by current and lagged occupation

	Managers		Clerical		Services		Operators		Mechan.		Constr.		Precis.		Transp.	
Managers	0.04	0.08	0.09	0.06	0.05	0.08	0.07	0.12	0.02	0.06	-0.03	0.07	-0.01	-0.02	0.08	0.07
Clerical	-0.01	0.06	0.05	0.08	0.04	0.11	-0.05	0.05	0.17	-0.02	-0.25	-0.06	-0.06	0.11	-0.0	0.06
Services	0.05	0.04	0.08	-0.03	0.04	0.07	0.0	-0.03	0.05	-0.02	-0.15	-0.04	-0.01	-0.16	0.03	-0.02
Operators	-0.02	0.03	0.13	0.06	0.11	0.11	0.05	0.05	0.04	0.01	-0.02	0.03	0.06	-0.01	0.06	0.01
Mechanics	0.07	0.04	0.09	0.08	0.14	0.09	0.09	0.09	0.05	0.07	0.05	-0.05	0.01	0.01	0.01	0.06
Construction	0.04	0.03	0.18	0.07	0.24	0.14	0.11	0.09	0.16	0.04	0.05	0.04	0.09	0.07	0.11	0.09
Precision	0.04	0.08	0.07	0.08	0.1	0.13	0.08	0.05	-0.0	0.03	0.07	0.03	0.06	0.05	0.13	0.04
Transport	-0.01	0.02	0.02	0.06	0.13	0.06	0.04	0.07	0.1	0.03	-0.0	-0.01	-0.05	-0.06	0.04	0.06

Table H5: Mean wage growth by current, lagged occupation and experience

	Managers		Clerical		Services		Operators		Mechan.		Constr.		Precis.		Transp.	
High Experience																
Managers	0.07	0.07	0.11	0.08	0.04	0.05	0.06	0.1	-0.01	0.11	-0.09	0.15	0.06	-0.05	0.15	0.1
Clerical	0.05	0.1	0.08	0.1	-0.01	0.12	-0.03	0.04	0.21	-0.06	-0.32	-0.07	0.01	0.11	0.0	0.09
Services	0.06	0.1	0.11	-0.04	0.04	0.07	0.07	-0.01	0.16	-0.03	-0.14	-0.01	0.02	-0.2	0.04	-0.02
Operators	0.01	0.06	0.16	0.07	0.18	0.13	0.07	0.05	0.12	0.02	0.01	0.03	0.08	-0.02	0.08	0.05
Mechanics	0.07	0.03	0.19	0.08	0.13	0.11	-0.01	0.09	0.08	0.07	0.09	-0.07	0.11	0.07	0.03	0.07
Construction	0.16	0.08	0.3	0.11	0.37	0.16	0.08	0.07	0.2	0.06	0.06	0.05	0.16	0.12	0.18	0.07
Precision	0.08	0.11	0.08	0.05	0.15	0.17	0.07	0.07	0.03	-0.08	0.07	-0.02	0.09	0.05	0.14	0.08
Transport	-0.1	0.0	0.02	0.09	0.17	0.09	0.03	0.06	0.12	0.02	0.01	0.02	-0.03	-0.02	0.06	0.07
Low Experience																
Managers	0.02	0.08	0.08	0.04	0.05	0.1	0.07	0.14	0.04	0.03	0.0	0.01	-0.07	0.01	0.03	0.04
Clerical	-0.09	0.02	0.02	0.07	0.11	0.1	-0.07	0.05	0.12	0.02	-0.19	-0.06	-0.14	0.11	-0.01	0.04
Services	0.02	-0.02	-0.01	-0.03	0.04	0.06	-0.09	-0.05	-0.21	-0.01	-0.15	-0.08	-0.1	-0.11	0.02	-0.02
Operators	-0.08	-0.02	0.08	0.05	0.02	0.08	0.03	0.04	-0.06	0.0	-0.06	0.03	0.02	0.01	0.03	-0.04
Mechanics	0.06	0.04	-0.02	0.08	0.14	0.06	0.16	0.1	0.02	0.06	0.01	-0.02	-0.09	-0.05	-0.01	0.06
Construction	-0.09	-0.03	0.05	0.02	0.09	0.12	0.14	0.1	0.1	0.01	0.03	0.03	-0.0	0.01	0.03	0.1
Precision	0.0	0.04	0.05	0.1	0.04	0.09	0.1	0.04	-0.02	0.1	0.06	0.08	0.03	0.05	0.12	0.0
Transport	0.11	0.04	0.02	0.03	0.05	0.03	0.05	0.08	0.06	0.05	-0.01	-0.04	-0.07	-0.12	0.03	0.06

Table H6: Mean wage growth by current, lagged occupation and tenure

	Managers		Clerical		Services		Operators		Mechan.		Constr.		Precis.		Transp.	
								High Tenure								
Managers	0.03	0.08	0.11	0.08	0.08	0.05	0.09	0.11	-0.07	0.08	-0.09	0.14	0.04	-0.03	0.12	0.09
Clerical	0.04	0.1	0.08	0.1	0.03	0.1	-0.05	0.04	0.22	-0.03	-0.25	-0.04	-0.02	0.11	-0.01	0.09
Services	0.04	0.08	0.08	-0.01	0.04	0.07	0.0	-0.01	0.09	-0.02	-0.13	0.03	0.06	-0.14	0.04	-0.03
Operators	-0.02	0.06	0.2	0.09	0.18	0.11	0.08	0.05	0.09	0.02	-0.02	0.04	0.1	-0.03	0.06	0.05
Mechanics	0.04	0.02	0.14	0.09	0.15	0.1	0.1	0.09	0.08	0.07	0.08	0.01	-0.01	0.08	0.01	0.06
Construction	-0.03	0.05	0.24	0.12	0.24	0.18	0.11	0.06	0.24	0.06	0.07	0.06	0.1	0.11	0.14	0.11
Precision	0.04	0.11	0.15	0.06	0.15	0.2	0.08	0.08	0.04	-0.04	0.07	-0.01	0.09	0.05	0.12	0.07
Transport	-0.04	0.01	0.03	0.1	0.13	0.07	0.03	0.06	0.08	0.03	-0.01	0.02	-0.03	0.01	0.06	0.07
								Low Tenure								
Managers	0.05	0.08	0.08	0.04	-0.0	0.11	0.05	0.12	0.11	0.03	0.0	-0.0	-0.06	-0.0	0.03	0.04
Clerical	-0.08	0.01	0.03	0.07	0.07	0.12	-0.05	0.05	0.08	-0.0	-0.26	-0.08	-0.11	0.12	0.0	0.03
Services	0.06	0.0	0.07	-0.07	0.03	0.06	0.01	-0.05	-0.04	-0.02	-0.2	-0.14	-0.37	-0.18	0.03	-0.0
Operators	-0.02	-0.02	-0.04	0.01	0.01	0.1	0.02	0.04	-0.1	-0.01	-0.02	0.02	-0.0	0.02	0.05	-0.05
Mechanics	0.13	0.06	-0.0	0.06	0.12	0.06	0.07	0.1	0.03	0.06	-0.03	-0.1	0.05	-0.08	0.01	0.07
Construction	0.2	0.0	0.08	0.01	0.25	0.09	0.09	0.12	-0.06	-0.0	0.03	0.02	0.02	0.03	0.07	0.07
Precision	0.04	0.02	-0.08	0.1	0.05	0.06	0.08	0.02	-0.06	0.09	0.06	0.07	0.04	0.05	0.15	0.0
Transport	0.07	0.04	-0.0	0.01	0.12	0.04	0.06	0.08	0.13	0.03	0.01	-0.06	-0.13	-0.18	0.02	0.05

Table H7: Mean wage growth by current, lagged occupation and tenure for high experience individuals

	Managers		Clerical		Services		Operators		Mechan.		Constr.		Precis.		Transp.	
High Tenure																
Managers	-0.05	0.11	0.14	0.08	0.04	-0.01	0.09	0.19	-0.05	0.11	-0.25	0.1	-0.02	0.4	0.08	-0.0
Clerical	-0.06	0.13	0.04	0.06	0.17	0.12	-0.07	0.05	0.24	-0.0	-0.11	-0.02	-0.11	0.04	0.01	0.07
Services	-0.24	0.02	-0.07	0.14	0.04	0.06	-0.29	-0.02	-0.23	-0.02	-0.09	0.23	0.2	0.33	-0.01	-0.06
Operators	-0.07	-0.07	0.15	0.15	0.09	0.05	0.08	0.06	-0.03	0.09	0.02	0.02	0.07	-0.0	0.01	-0.06
Mechanics	-0.1	-0.14	0.04	0.11	0.09	0.11	0.22	0.15	0.07	0.05	-0.01	0.12	-0.15	0.04	-0.09	0.07
Construction	-0.15	-0.24	0.11	0.1	0.09	0.2	0.17	0.05	0.25	-0.01	0.05	0.06	0.01	-0.17	-0.02	0.13
Precision	-0.01	0.15	0.12	0.12	0.22	0.2	0.1	0.06	0.0	0.26	0.05	0.18	0.04	0.08	0.12	0.05
Transport	0.12	0.13	0.04	0.2	-0.01	0.0	0.08	-0.03	-0.01	0.05	-0.03	0.01	-0.07	0.01	0.01	0.06
Low Tenure																
Managers	0.03	0.08	0.07	0.04	0.07	0.13	0.07	0.12	0.09	0.0	0.06	-0.0	-0.09	-0.04	0.01	0.05
Clerical	-0.11	0.01	0.02	0.07	0.05	0.1	-0.07	0.05	0.07	0.02	-0.24	-0.06	-0.15	0.13	-0.02	0.03
Services	0.06	-0.03	0.04	-0.07	0.03	0.06	0.05	-0.06	-0.2	-0.01	-0.2	-0.13	-0.41	-0.13	0.04	-0.01
Operators	-0.09	-0.02	-0.01	0.02	-0.05	0.09	0.02	0.04	-0.08	-0.02	-0.12	0.03	-0.0	0.01	0.03	-0.04
Mechanics	0.09	0.05	-0.06	0.06	0.21	0.04	0.1	0.08	0.01	0.06	0.04	-0.03	-0.04	-0.08	0.02	0.05
Construction	0.04	0.0	-0.0	-0.0	0.1	0.09	0.13	0.11	-0.02	0.01	0.03	0.02	-0.04	0.05	0.06	0.09
Precision	0.04	0.02	-0.02	0.1	-0.09	0.08	0.1	0.03	-0.04	0.09	0.07	0.06	0.02	0.05	0.12	-0.01
Transport	0.1	0.04	0.0	-0.02	0.09	0.03	0.04	0.1	0.11	0.05	-0.0	-0.05	-0.07	-0.15	0.03	0.06

Figure H6: Wage quantiles by year and by occupation. CPS

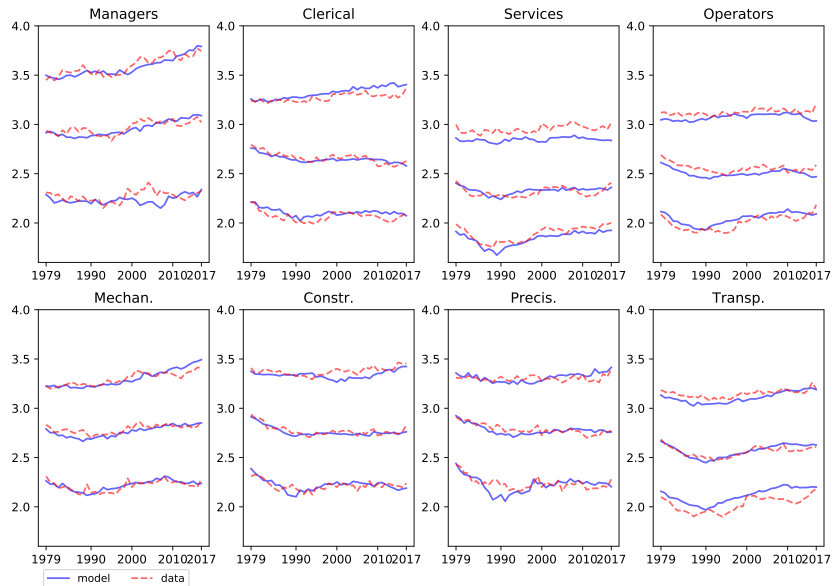


Table H8: Mean wages by experience and occupation

	1		2		3		4		5	
Managers	0.23	0.19	0.3	0.24	0.34	0.28	0.45	0.37	0.41	0.35
Clerical	0.09	0.12	0.13	0.22	0.24	0.25	0.31	0.3	0.29	0.35
Services	0.08	0.06	0.11	0.16	0.17	0.2	0.25	0.24	0.26	0.28
Operators	0.08	0.05	0.13	0.11	0.17	0.15	0.19	0.17	0.23	0.23
Mechanics	0.07	0.09	0.16	0.12	0.22	0.19	0.2	0.23	0.31	0.25
Construction	0.06	0.07	0.17	0.11	0.19	0.15	0.21	0.23	0.27	0.27
Precision	0.1	0.19	0.11	0.17	0.13	0.18	0.23	0.23	0.28	0.26
Transport	0.07	0.11	0.11	0.16	0.18	0.18	0.23	0.24	0.26	0.26

Table H9: Mean wages by tenure and occupation

	1		2		3		4		5	
Managers	0.34	0.09	0.43	0.15	0.41	0.17	0.47	0.23	0.52	0.24
Clerical	0.14	0.06	0.28	0.13	0.3	0.16	0.32	0.21	0.36	0.21
Services	0.05	0.03	0.09	0.07	0.1	0.12	0.09	0.16	0.06	0.21
Operators	0.12	0.06	0.2	0.07	0.23	0.1	0.27	0.13	0.31	0.17
Mechanics	0.17	0.01	0.22	0.05	0.25	0.08	0.34	0.1	0.4	0.15
Construction	0.1	0.1	0.23	0.12	0.21	0.17	0.25	0.2	0.26	0.2
Precision	0.13	0.12	0.22	0.11	0.26	0.13	0.31	0.19	0.33	0.21
Transport	0.14	0.09	0.2	0.12	0.26	0.14	0.26	0.2	0.3	0.23

Table H10: Deming's regressions

	Employment		Wages	
Cognitive	0.0742	0.0582	0.126	0.1248
Social	0.0053	0.0059	0.0103	0.0154
Cognitive*NLSY97	0.0097	-0.0049	-0.0575	-0.047
Social*NLSY97	0.0409	0.0154	0.03	0.0186

Table H11: Occupation distribution by cognitive skills

	NLSY79				NLSY97			
	High		Low		High		Low	
Managers	0.03	0.03	0.1	0.07	0.03	0.03	0.06	0.05
Clerical	0.06	0.09	0.11	0.13	0.09	0.09	0.17	0.14
Services	0.14	0.1	0.09	0.1	0.18	0.14	0.16	0.15
Operators	0.14	0.14	0.15	0.17	0.08	0.1	0.08	0.09
Mechanics	0.05	0.09	0.09	0.09	0.05	0.05	0.08	0.06
Construction	0.08	0.07	0.1	0.06	0.09	0.07	0.12	0.07
Precision	0.03	0.04	0.07	0.04	0.03	0.02	0.03	0.03
Transport	0.19	0.18	0.17	0.18	0.2	0.19	0.18	0.19
Not-working	0.26	0.25	0.12	0.16	0.26	0.31	0.12	0.21

Table H12: Occupation distribution by social skills

	NLSY79				NLSY97			
	High		Low		High		Low	
Managers	0.05	0.04	0.07	0.05	0.03	0.03	0.05	0.05
Clerical	0.07	0.1	0.09	0.12	0.11	0.11	0.15	0.13
Services	0.12	0.1	0.12	0.1	0.16	0.15	0.17	0.15
Operators	0.15	0.15	0.14	0.15	0.09	0.1	0.07	0.09
Mechanics	0.07	0.09	0.07	0.09	0.06	0.06	0.07	0.06
Construction	0.09	0.07	0.09	0.07	0.08	0.07	0.13	0.07
Precision	0.05	0.04	0.04	0.04	0.03	0.03	0.03	0.03
Transport	0.19	0.18	0.18	0.17	0.19	0.19	0.19	0.19
Not-working	0.2	0.22	0.21	0.2	0.24	0.28	0.14	0.24

I Structural Parameters not reported in the main text

Table I1: Learning-by-doing parameters

Occupation Specific		
γ_{01}	1.8773	(0.5229)
γ_{02}	1.5315	(0.369)
γ_{03}	0.7802	(0.3288)
γ_{04}	0.4606	(0.5357)
γ_{05}	0.8064	(0.7447)
γ_{06}	0.6501	(0.5852)
γ_{07}	1.203	(0.4771)
γ_{08}	1.5157	(0.6615)
$\overline{\gamma}_1$	2.4443	(0.206)

General Skills					
d_{01}	0.812	(0.0325)	d_{11}	0.0777	(0.0006)
d_{02}	1^*	(0)	d_{12}	0.1186	(0.0006)
d_{03}	0.8876	(0.0239)	d_{13}	0.1168	(0.0002)
d_{04}	0.9163	(0.0206)	d_2	0.054	(0.0)
d_{05}	1.1389	(0.0231)	d_{31}	0.0121	(0.0001)
d_{06}	0.6462	(0.0766)	d_{32}	0.0325	(0.0003)
d_{07}	0.6903	(0.1065)	d_{33}	0.034	(0.0001)
d_{08}	0.9211	(0.003)			

Table I2: Job offer arrival rates by decades

Occupation	1979		1990		2000		2010		2017	
Managers	0.3428	(0.0093)	0.2029	(0.0093)	0.1446	(0.0093)	0.0981	(0.0094)	0.0557	(0.0094)
Clerical	0.5696	(0.1404)	0.5699	(0.1404)	0.4730	(0.1404)	0.4192	(0.1404)	0.4464	(0.1405)
Services	0.8353	(0.0228)	0.9563	(0.0228)	0.8307	(0.0228)	0.8475	(0.0229)	0.9274	(0.0237)
Operators	1.0000	(0.1122)	0.7872	(0.1122)	0.5416	(0.1122)	0.3220	(0.1122)	0.5945	(0.1124)
Mechanics	0.4037	(0.0261)	0.3087	(0.0261)	0.1964	(0.0263)	0.1506	(0.0266)	0.1574	(0.0321)
Construct.	0.5082	(0.0097)	0.5794	(0.0098)	0.4842	(0.0101)	0.3004	(0.0102)	0.2727	(0.2514)
Precision	0.3718	(0.0167)	0.2968	(0.0168)	0.2228	(0.0169)	0.1123	(0.0177)	0.1674	(0.2783)
Transport	1.0000	(0.0395)	1.0000	(0.0395)	0.7090	(0.0396)	0.5461	(0.0398)	0.7584	(0.0453)

Table I3: Hedonic function's time trends

δ_{jt}: Time Trends								
Occupation	1980		1990		2000		2010	
Managers	-0.0155	(0.0)	0.0005	(0.0001)	-0.0493	(0.0002)	-0.049	(0.0031)
Clerical	-0.0153	(0.0001)	0.0132	(0.0001)	0.0138	(0.0002)	0.0108	(0.0009)
Services	-0.0283	(0.0001)	0.0226	(0.0002)	0.007	(0.0005)	0.0092	(0.0006)
Operators	-0.0202	(0.0)	0.0238	(0.0005)	0.014	(0.0005)	0.0062	(0.0014)
Mechanics	-0.0205	(0.0008)	0.0044	(0.0007)	0.0088	(0.0008)	-0.0069	(0.0026)
Construction	-0.0272	(0.0002)	0.0145	(0.0003)	0.0049	(0.0005)	-0.0095	(0.002)
Precision	-0.0419	(0.0001)	0.0156	(0.0008)	0.0133	(0.0011)	0.0	(0.0016)
Transport	-0.0101	(0.0001)	0.0179	(0.0002)	0.0102	(0.0002)	0.0072	(0.0015)

α_{1jt}: Time Trends								
Occupation	1980		1990		2000		2010	
Managers	-0.0079	(0.0)	-0.0024	(0.0002)	0.0539	(0.0004)	0.0452	(0.0031)
Clerical	-0.0068	(0.0001)	-0.0305	(0.0001)	-0.0278	(0.0004)	-0.0281	(0.0038)
Services	0.014	(0.0004)	-0.0303	(0.0004)	-0.0145	(0.0001)	-0.0095	(0.0001)
Operators	-0.005	(0.0003)	-0.0431	(0.0011)	-0.0252	(0.0011)	-0.0175	(0.0025)
Mechanics	0.0097	(0.0009)	-0.0085	(0.0004)	-0.0109	(0.0004)	0.0008	(0.0127)
Construction	0.0026	(0.0003)	-0.0199	(0.0003)	-0.0175	(0.0013)	0.0138	(0.0028)
Precision	0.026	(0.0002)	-0.0242	(0.0007)	-0.0254	(0.0011)	-0.0086	(0.0102)
Transport	-0.0242	(0.0002)	-0.0187	(0.0004)	-0.0047	(0.0006)	-0.0182	(0.0016)

α_{2jt}: Time Trends								
Occupation	1980		1990		2000		2010	
Managers	0.0877	(0.0004)	-0.0088	(0.0006)	0.0502	(0.001)	0.096	(0.0022)
Clerical	0.0609	(0.0001)	0.0195	(0.0006)	0.019	(0.0014)	0.0313	(0.006)
Services	0.0503	(0.001)	-0.0182	(0.0009)	0.0187	(0.0004)	-0.0197	(0.0132)
Operators	0.0595	(0.0001)	0.0101	(0.0009)	0.0087	(0.0018)	0.0227	(0.0172)
Mechanics	0.0294	(0.0021)	0.0051	(0.0025)	0.0196	(0.0055)	0.0438	(0.0318)
Construction	0.0586	(0.0001)	-0.0147	(0.0011)	0.0378	(0.0027)	0.0306	(0.0078)
Precision	0.048	(0.0014)	0.0016	(0.0019)	0.0256	(0.002)	0.0407	(0.0354)
Transport	0.0535	(0.0002)	-0.0117	(0.0005)	0.001	(0.0021)	0.0308	(0.0042)