Skills Prices, Occupations and Changes in the Wage Structure for Low Skilled Men

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Abstract

This paper proposes and estimates a model of occupational choice with multi-dimensional skills, time-varying skill prices and labor market frictions to understand the evolution of the wage structure since 1979 for low skilled men. A worker's multi-dimensional skills 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 three datasets: (1) O*NET, to measure skill intensity across occupations, (2) NLSY, to identify life-cycle supply effects, and (3) CPS, to estimate the evolution of skill prices and occupations over time. We find that a) reallocation of labor across occupations is hard to understand with a competitive model, b) occupational composition is substantially less important than within-occupation skill prices in explaining both the evolution of both medan wages and inequality, c) lifecycle wage growth depends on a combination of different skills, d) the premium to interpersonal skills has gone up most sharply for these workers.

PRELIMINARY AND INCOMPLETE

1 Introduction

A vast literature documents a pronounced rise in wage inequality in the United States and numerous other advanced nations commencing in the 1970s. Along virtually every dimension earnings inequality has gone up. The demographic group that has been hit the hardest is low-skilled (no college) men. This group has seen a large decrease in their median wage, accompanied by large increases in inequality like the other groups. During this time period, 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. If our goal is to invest in skills to counteract these patterns, the occupational trends have implications for which skills have increased most in value. This paper tries to understand 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.

In our model, 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. For example cognitive skills are allowed to grow more quickly in occupations that heavily use cognitive skill.

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 to evolve differently than the wage difference between low skilled workers versus median skilled workers. 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 essentially address the age-cohort-time effect by using our model of human capital accumulation to estimate the age effect. In doing this, we assume that this fundamental process does not vary across cohorts. We also assume that for a range of recent cohorts

the underlying initial skill level is identical-cohorts look different ex-post only because the aggregate features of the economy have changed leading to different occupational patterns. Identification of the dynamic supply of skill comes from the NLSY79 in which we have a long panel of workers who face a changing wages. One can think of identifying this in the NSLY79 taking prices as given and using these to estimate the supply of skill.

Identification of the prices come from two places. First, a crucial part of this use O*NET to estimate the skill intensity of each occupation measured by β. If we knew the supply of workers as a function of skills (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.

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. In general we see skill prices falling in all occupations but falling relatively less slowly (and sometimes rising) for relatively high skilled workers in those occupations. Second, we could not reconcile the data with a frictionless model. Many of the occupations that are expanding actually see relatively large declines in skill prices. While in theory, several features of our model could reconcile these patterns, in practice they could not. Third, all four skills are important in explaining wage growth over the lifecycle. Interpersonal skills are the least important. Manual skills are important at the very beginning. Cognitive skills are important later and occupation specific skills seem to be most important overall. Fourth, occupational composition does little to explain both earnings inequality and median wages. Both of these trends are driven by skill prices that evolve within occupation. Fifth, the skill that grows most important over time is interpersonal which has little value at the beginning of the period but substantial returns later.

The next paragraph briefly discusses the related literature. Section 2 describes the data. In section 3 we present some motivating facts and then Section 4 presents a model to explain them. Section 5 describes the estimation strategy and Section 6 presents the results. Section 7 performs counterfactuals.

Related Literature (very incomplete in this draft-our apologies to authors of related work) This paper is related to a large literature on skill-bias technological change

and human capital (see the survey by Goldin and Katz, 2009). Closest to our objectives and methodology 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) and the evolution of the wage structure (Johnson and Keane, 2013). At the other side of the spectrum, a mainly empirical literature document the polarization of the U.S. labor market (see the survey by Acemoglu and Autor, 2011). 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.

Our emphasis on the multi-dimensionality of skills builds on the tasks specific human capital literature (see the survey by Sanders and Taber, 2012). Further, there has been a growing effort both theoretical and empirical, recently, to model sorting and mismatch in settings with multi-dimensional skills (see Lindenlaub (2017); Guvenen et al. (2016); Postel-Vinay and Lise (2016); Lindenlaub and Postel-Vinay (2016)). Our contribution is to quantify its importance for wage inequality and more generally how it affected the wage structure.

2 Data

We use three different datasets which we describe below. 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 8 occupations listed in Table 1.

ORG CPS Wages are calculated using Outgoing Rotation Group data from the Current Population Survey for earnings years 1979-2012 for all workers aged 16-64 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 (\$3.41/hour in 2008 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 (January 1994 to August 1995). We start from the cohort that left or graduated from high school no

Table 1: Occupation Categories Low Educated Men

	Occupations	Label	Share 1983	Share 2012
1	Executive, Administrative, and Managerial Professional Specialty	Managers	6.1%	6.6%
2	Technicians Sales Administrative Support	Clerical	13.4%	16.4%
3	Housekeeping and Cleaning Protective Service Other Services	Services	12.2%	18.9%
4	Farming, Forestry, and Fishing Machine Operators, Assemblers, Inspectors	Operators	19.1%	10.7%
5	Mechanics and Repairers	Mechanics	11.4%	8.4%
6	Construction Trades, Extractive	Construction	11.5%	10.5%
7	Precision Production	Production	7.5%	6.5%
8	Transportation and Material Moving	Transportation	20.4%	21.9%

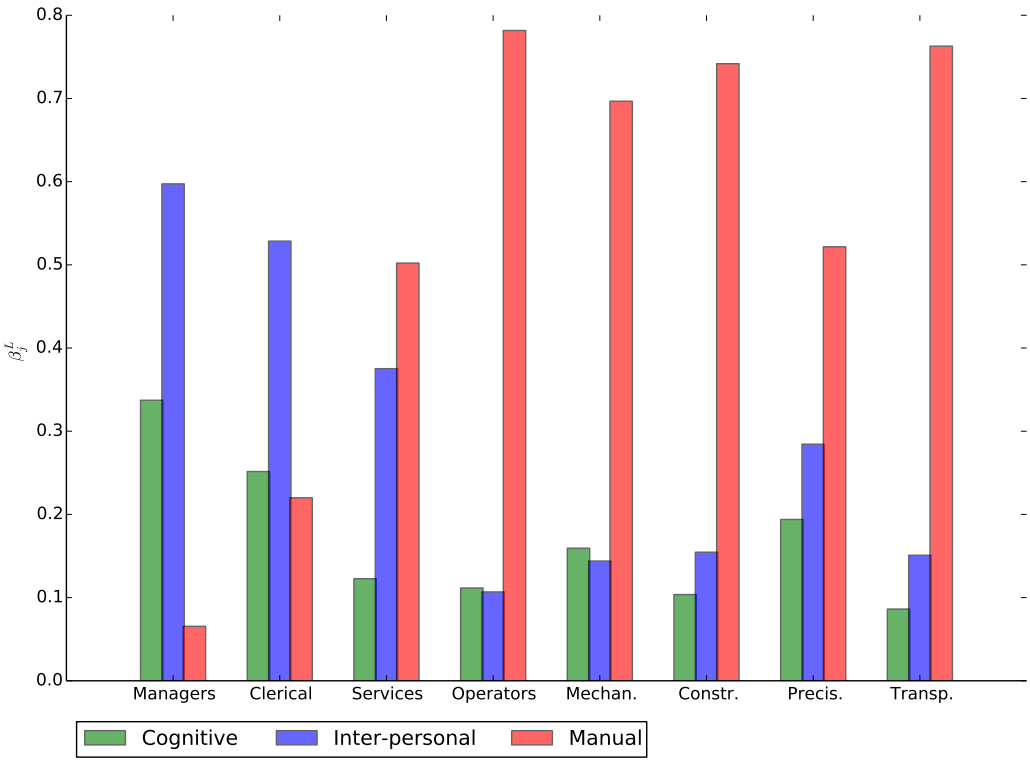
latter than 1915 and we end with cohorts that left or graduated from high school no earlier than 2012.

NLSY. We use the 1979–2012 survey years of the 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 focus on white males from the core 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.[1]

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. Individ-

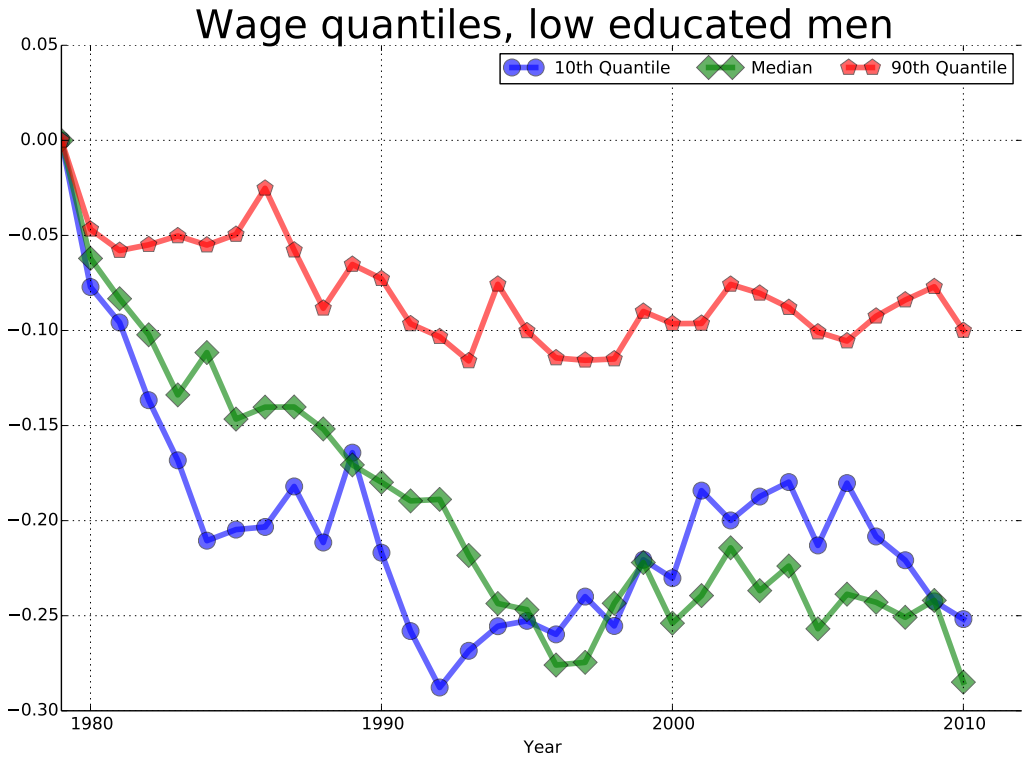
[1]This definition of occupation-specific tenure is different from its model counterpart presented below. However, it is less affected by misclassification errors.

Figure 1: Skill intensity by occupations



uals were asked to complete a survey asking about the tasks and activities workers perform in those occupations. We categorize skills into cognitive, interpersonal and manual. We use a factor analysis to reduce all these questions to a one dimensional factor for each combination of occupation and skill. Figure 1 reports the implied skill intensity of each occupation. Occupations can be characterized into three groups broadly defined. The first two occupations, which correspond to managerial and clerical occupations, 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 agriculture and blue-collar manufacturing jobs. Overall, there is a wide dispersion in the type of skills used by different occupations. Individuals switching to different occupations over-time will be particularly useful for identifying the extent to which skills are transferable across occupations.

Figure 2: Changes in Log Wage Quantiles over Time



Source: CPS. Schooling ≤ 12. Each quantile is normalized in 1979.

3 Motivating Facts

We start by presenting the raw data on changes in the distribution of log wages over time. 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, most of the increase in earnings inequality for this group during this period occurs at the top-there is a large change the the 90/50 gap over time. Over the full period the 50/10 gap has not changed much and even has slightly narrowed. The story on the lower end is different across decades-the 50/10 gap widened in the 1980s, but since 1992 or so the 10th quantile of log wages has increased relative to the median. Of course the most notable feature of this figure is the large decline in real wages throughout the wage distribution.

At the same time the occupation distribution has been changing considerably over time as can be seen in Figure 3. The most notable changes are the decline in operators and increase in services and clerical workers. What is the driving behind this reallocation? Have people moved away for manual occupations because of better opportunities?

Figure 3: Changes in Occupational Distribution over Time

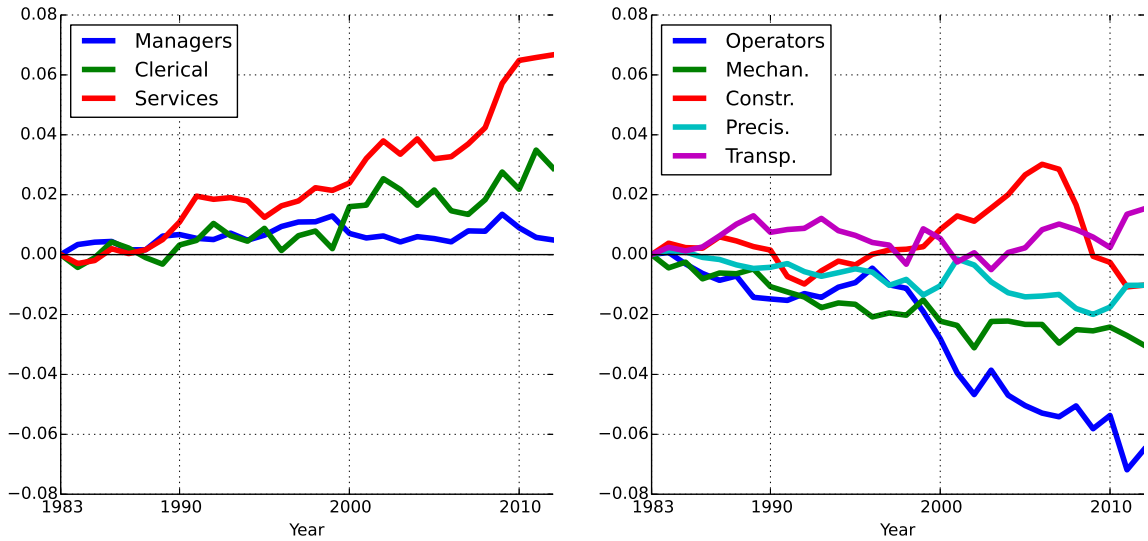


Figure 4 presents the changes in median wages across time for different occupations. Other than managers, we see that all occupations experience large decreases in wages. If one compares Figures 3 and 4 together, it is clear that wage patterns are not that closely related to the changes in occupation share. For example, both clerical and service workers see quite a large fall in their wages even though they are growing occupations. 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. We try to sort out these differences with our model.

4 Model

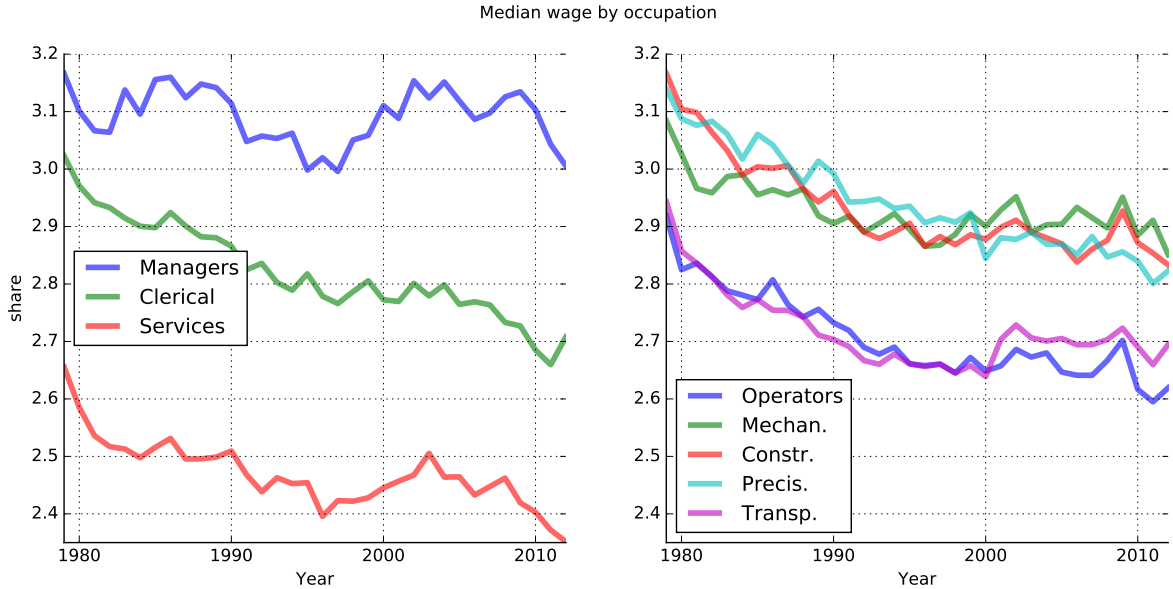
Overview The only decision people make in each period is their desired occupation. We will use the i subscript to denote an individual and t to index time. We let j_{it} denote the occupation in which individual i works at time t. Let $j = 1, .., J$ index occupations, $j = 0$ denotes not working.

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

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

where $\theta_{it} = (\theta^c_{it}, \theta^i_{it}, \theta^m_{it})$ is a vector of general skills composed of cognitive, interpersonal

Figure 4: Changes in Wages across occupations



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}. I_t summarizes the current and future values of aggregate variables. There is a discrete number of types indexed by $k \in \{1, \ldots, K\}$ that differ in skill endowments and preferences.

They 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 given the occupation choice

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

A complication of the model is that we restrict occupational choice with some frictions. Frictions may prevent some from working in their favored occupations. Each period an individual has three types of choices:

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 j.

If an individual chooses the third option, he will be able to find a job in that occupation

with probability λ_{jt}. If successful he moves to that occupation ($j_{it} = j$).[2] If unsuccessful, he must remain in his current occupation.

Utility We write the deterministic part of flow utilities for each occupation $u(j, \mathcal{S}_{it})$ as

$$u(j, \mathcal{S}_{it}) = w(j, \mathcal{S}_{it}) + c_{jk} + g_{jt} 1(j = j_{it-1}),$$

where w is the wage function described below. There will also be an idiosyncratic shock that we define below. Individuals permanently differ in their preferences for different occupations. Each type has distinct preferences for working in different occupations c_{jk} which decompose as

$$c_{jk} = \bar{c}_j + \sum_{l=1}^{L} \beta_j^l \tilde{c}_{lk}$$

The $\bar{c}_j$'s are the components common to each group while the $\tilde{c}'_{lk}$s measure the preference for using different skills.[3] We normalize $c_{0k} = 0, k \in \{1, \ldots, K\}$. Stayers get an additional utility g_{jt} that depends on age and occupation which is a reduced-form way of capturing many factors that affect occupational choice such as geographical location, marital status which are likely to be correlated with both age and current occupation.

Wages Wages are:

$$\begin{aligned} w(j, \mathcal{S}_{it}) &= f_{jt}(h(j, \mathcal{S}_{it})), \qquad j = 1, \ldots, J \\ h(j, \mathcal{S}_{it}) &= \theta'_{it}\beta_j + \sigma(j, \tau) 1(j = j_{it-1}) \\ w(0, \mathcal{S}_{it}) &= 0 \end{aligned}$$

where f_{jt} is an hedonic pricing equation. In practice, we simplify and approximate the hedonic pricing function f_{tj} with a linear spline (in logs). Let j_i and t_i be the occupation

[2] Search is costly and no new information is revealed so a worker will always choose to switch occupations after a successful search.

[3] Modeling heterogeneity in preferences for skills utilization instead of heterogeneity in preferences for different occupations reduces the number of parameters. Additional parameters are proportional to L instead of J.

and time period for which we observe person i. Formally, we consider the specification:

$$\log(w(j,\mathcal{S}_{it})) = \begin{cases} \delta_{jt} + \alpha_{1jt} h\left(j,\mathcal{S}_{it}\right) & \text{if } h\left(j,\mathcal{S}_{it}\right) > h_j^* \\ \delta_{jt} + \alpha_{1jt} h_j^* + \alpha_{2jt}\left(h\left(j,\mathcal{S}_{it}\right) - h_j^*\right) & \text{otherwise} \end{cases} \tag{1}$$

which is a linear spline 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. Yet, depending on the level of his human capital index $h\left(j,\mathcal{S}_{it}\right)$, an individual sees his skills prices multiplied by either α_1 or α_2 depending on whether his index is below (or above) some threshold $h_{j_i}^*$. We set this threshold to the median wage in each occupation in 1979. The wage value of non-employment is normalized to zero. α_1 is normalized to one in one occupation$\times$year cell.

A special case of Equation 1 is $\alpha_{1jt} = \alpha_{2jt} = 1, \forall j, t$. An individual wage level is the product of an occupation j price $e^{\delta_{jt}}$ in a given year t, and his human capital index h_{jt} in that occupation. This is a widely use formulation as it features aggregation, as discussed in the introduction. The main drawback of this formulation is that an increase in the within-variance can only be attributed to supply factor or occupational composition. Our more general formulation allows technological to have favored some level of human capital more than other. Finally, because of the different patterns of the different quantiles, we use a different α to model inequality between the top and the middle, vs the top and the bottom.

Evolution of State Variables Initial human capital $\widetilde{\theta}_i$ is drawn from a multivariate log-normal distribution.

$$\widetilde{\theta}_i \sim N\left(\mu_{ck}^{\theta}, \Sigma^{\theta}\right),$$

where Σ^{θ} is the variance, and μ_{ck}^{θ} is a type and cohort specific mean. It is the sum of two means,

$$\mu_{ck}^{\theta} = \mu_c^1 + \mu_k^2.$$

Cohort effects μ_c^1 account for selection on schooling before 1957. After 1957, we assume no cohort effects, since schooling has been roughly constant. And, different types differ in endowment μ_k^2 that may be correlated with non-pecuniary preferences.

The state variable transition $\mathcal{S}_{it+1} = F(j_{it}, \mathcal{S}_{it})$ takes the form

$$\begin{aligned}
a_{it+1} &= a_{it} + 1 \\
\theta^l_{it+1} &= \theta^l_{it}(1 - d_{4l}) + d_{0j_{it}} d_{1l} \left(\beta^l_{j_{it}}\right)^{\nu_l} \exp\left(-\left(d_{2l} + d_{3j_{it}}\right) e_{it}\right), \quad l = c, i, m. \\
\tau_{it+1} &= (\tau_{it} + 1) I(j_{it} = j_{it-1}) \\
I_{t+1} &= \Psi(I_t)
\end{aligned}$$

with $\text{tenure}_{j0} = 0$. Occupation tenure is reset to zero after a switch to keep the dimension of the state space tractable. General skill accumulation depends on potential experience $e_{it} = a_{it} - 18$. Wage growth depends on the evolution of the hedonic pricing function f_{jt} and the evolution of the human capital index. 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 according to $\exp\left(-\left(d_{2l} + d_{3j_{it}}\right) e_{it}\right)$. Skills depreciates at rate d_{4l}.

The intensity of skill' utilization and the relative weights of different skills both contributes to wage growth as individual switch occupations, due to changes in α and δ across occupations. For instance, wage grow as low skilled men move away from manual occupations as they get older. Finally, stayers get wage change as the slope of the wage function f' changes as individuals skill level changes.

We model occupation specific human capital as determined by

$$\sigma(j, \tau) = \begin{cases} 0 & \tau = 0 \\ \sigma(j, \tau - 1) + \gamma_{0j} e^{-\gamma_{1j}\tau} & \tau > 0 \end{cases}$$

which is deterministic function of τ. Stayers get additional occupation-specific tenure through $\gamma_{0j} e^{-\gamma_{1j}\tau}$ where $\gamma_{1j} > 0$ so the specific human capital profile is concave in τ.

Dynamic Programming Every period t, the agent chooses an occupation to maximize their discounted present value of utility. Since the terminal period is simpler than prior periods, we show this expression for periods prior to the terminal period. Every period t, the agent chooses an occupation according to the rule

$$\max_j \left\{ v_t(j, \mathcal{S}_{it}) + \nu_{it}(j) \right\},$$

where $v_t(j, \mathcal{S}_{it})$ is the deterministic part of the occupation-specific value function.

Define the expected value function $\bar{V}$ as

$$\bar{V}_t(\mathcal{S}) \equiv \int \max_j \{v_t(j, \mathcal{S}) + \nu(j)\} \, dG(\nu),$$

where G is the distribution of $(v_{it}(0), ..., v_{it}(J))$. Frictions may prevent some from working in their favored occupations. If an individual chooses to direct his search to a particular occupation in any given period, he will be able to find a job with probability λ_{jt}. If unsuccessful, he must remain in his current occupation for at least one period. Individuals who were successful (for at least one period), do not need to re-apply the following year. He can also choose to not work. These frictions, and more particularly their variations over time, will prove critical for fitting the evolution of occupational composition. Indeed, there is a weak link between employment and wage evolution in several occupations, which is difficult to rationalize without resorting to frictions.[4]

Formally, if an agent, previously holding occupation j_{it-1}, applies for work in a different occupation $j \notin \{0, j_{it-1}\}$, he receives an offer in that occupation with probability λ_{jt}. Otherwise, he stays in his current occupation for at least one more period. Job-seekers occur a cost ξ that is proportional to the probability of a failed search $(1 - \lambda_{jt})$.[5]

To derive the problem we first define the value function for occupation stayers or non-employed.

$$v_t(j, \mathcal{S}_{it}) \equiv u(j, \mathcal{S}_{it}) + \rho \bar{V}_{t+1}(F(j, \mathcal{S}_{it})), \text{ for } j \in \{j_{it-1}, 0\}.$$

For people who try so search for a new occupation

$$v_t(j, \mathcal{S}_{it}) = \lambda_{jt}\left[u(j, \mathcal{S}_{it}) + \rho \bar{V}_{t+1}(F(j, \mathcal{S}_{it}))\right] + (1 - \lambda_{jt})\left[v_t(j_{it-1}, \mathcal{S}_{it}) - \xi\right], \text{ for } j \notin \{j_{it-1}, 0\}.$$

[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 opposite sign.

[5] In a competitive labor market, f can be interpreted as an hedonic pricing function. Frictions complicate the interpretation of the function f. One micro foundation of the wage equation can be derived from the following assumptions. Firms differ in productivities and post wages. Posting a vacancy involves a fixed cost and its rewards is uncertain as a worker may leave a firm due to unobserved preference shocks. In equilibrium, firm pay a premium in order to keep workers.

and where $\bar{v}_{it+1}\left(F\left(j,\mathcal{S}_{it}\right)\right)$ is the expected continuation value if the agent chooses alternative j today.

We assume that $\nu_{it} = \{\nu_{it}(0), ..., \nu_{it}(J)\}$ is a vector of i.i.d extremely value distributed preference shocks with CDF $G_\nu = \exp\left\{-\exp\left(-\frac{\nu}{\sigma_\nu}\right)\right\}$. Each component has a mean equal to $\sigma_\nu\gamma$ where γ is Euler's constant and a variance equal to $\frac{\pi^2\sigma_\nu^2}{6}$. This means that we can write the continuation value in closed form

$$\bar{V}_t\left(\mathcal{S}_{it}\right) \equiv \sigma_\nu\left[\gamma + \left(\log\left(\sum_j \exp\left(\frac{v_{it}\left(j,\mathcal{S}_{it}\right)}{\sigma_\nu}\right)\right)\right)\right].$$

5 Estimation Method

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.[6] For an arbitrary value of the vector of parameters to be estimated Λ, we use the model to generate the target moments $\Psi\left(\Lambda\right)$. The parameter estimate $\hat{\Lambda}$ is then derived by searching over the parameter space to find the parameter vector that minimizes the criterion function,

$$\hat{\Lambda} = \arg\min_{\Lambda}\left(\hat{\Psi} - \Psi\left(\Lambda\right)\right)' W \left(\hat{\Psi} - \Psi\left(\Lambda\right)\right) \tag{2}$$

where W is a weighting matrix. This procedure generates a consistent estimate of Λ. We use bootstrap to estimate the variance-covariance matrix of the estimated parameters.

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

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

In principle that is $J\left(J-1\right))$ 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

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

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,

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

Pre-estimated parameters Some parameters are not estimated and are set outside the model $\left(\beta_j^l, r\right)$. We estimated β_j^l using O'NET in Section 2. The real interest rate is set to 5%.

Structural parameters Let Λ be the vector of structural parameters. We partition it into four components $\Lambda=(\Lambda_1,\Lambda_2,\Lambda_3,\Lambda_4)$ defined as follows.

$\Lambda_1=\left(\bar{c}_j,\tilde{c}_{lk},\mu_{lk},\Sigma,g_{jt},\delta_j^0,\alpha_j^{01},\alpha_j^{02},\lambda_j^0,\sigma_{\nu a},\sigma_w,E\right)$ contains the preferences and technology parameters with $\bar{c}_j$ non-pecuniary benefits, $\tilde{c}_{lk}$ unobserved preferences for skills, μ_{lk} and Σ unobserved endowment average and variance, f_{jt} utility of staying, δ_j^0,α_j^0 initial prices and λ_j^0 initial occupation offer, $\sigma_{\nu a}$ preference shock, σ_w measurement error in wages, E baseline classification rate. $\Lambda_2=(d_{0j},d_{1l},\nu_l,d_{2l},d_{3j},d_{4l},\gamma_{0j},\gamma_{1j})$ contains all the skill accumulation parameters with γ_{0j},γ_{1j} constant and slope occupation specific, $d_{0j},d_{1l},d_{2l},d_{3j}$ constant and slope general, d_{4l} depreciation and ν_l skill intensity. $\Lambda_3=\left(\delta_{jt},\alpha_{jt}^1,\alpha_{jt}^2,\mu_c\right)$ are the trend in prices and the cohort trend parameters. $\Lambda_4=(\lambda_{jt})$ contains the trend in frictions parameters. This leaves us with a total of 213 parameters divided into groups of 72, 42, 75 and 25.

Auxiliary Parameters Let m be the vector of auxiliary parameters. We partition it into four vectors $m=(m_1,m_2,m_3,m_4)$ defined as follows. m_1 contains all the moments that are used to identify the vector Λ_1. The data moments are

- (CPS) Quantiles of the wage distribution by occupation and by age
- (CPS) 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 $J+1$ 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 moments that are used to identify the vector Λ_2. Using NLSY79 data, the moments are

- (CPS) The median wage by occupation and age.
- (NLSY79) The median wage conditional on having below (or above) median occupation-specific tenure and conditional on having below (or above) average experience by occupation.
- (NLSY79) The auto-correlations of wages in level between t and $t+1$ separately for occupation stayers and occupation switchers.

m_3 contains all the moments used to identify movement in prices. These are quantiles of the wage distribution for each year and occupation calculated in the CPS. m_4 are the proportions of individuals choosing each of the $J+1$ occupations by year in the CPS.

Algorithm Details It is in principle possible to estimate the full vector of parameters Λ at once but we chose not to. Small variations in some parameters can lead some individuals to switch occupations creating discontinuities in the objective function. There may not exist any variations in the parameters that leads to small changes in the objective function. And given the large number of parameters, it is computationally prohibitive to resort to a global optimization procedure. Instead, we develop a sequential algorithm. 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 $m_4\left(\Lambda_1, \Lambda_2, \Lambda_3, \Lambda_4 \left| \mathcal{J}\left(\Lambda_1, \Lambda_2, \Lambda_3, \Lambda_4\right)\right.\right)$

We repeat these four steps until convergence. Step 1 estimates the life-cycle parameters Λ_1 using NLSY79 moments m_1. Step 2 estimates life-cycle wage growth parameters Λ_2, holding fixed individual choice, to fit m_2. The advantage t is that we only need to solve the model at the beginning of this step. We apply a similar procedure to estimate prices Λ_3 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 Λ_4. We use gradient-free minimization algorithms in Step 1 and Step 4, and gradient-based algorithms for Step 2 and Step 3. In practice, Step 2 and Step 3 are fast and Step1 and Step 4 are slow.

6 Results

6.1 Parameter Estimates

6.1.1 Occupations

Table 2 reports occupation specific parameters that are identified using the NLSY79. Some parameters are normalized. Non-pecuniary benefits of not-working are normalized to zero. The slope of the wage function below the median α_1 is normalized to one in clerical occupation until 1979. Finally, the utility of staying in the same occupation is restricted to be the same across all occupations but can take a different value when an individual is not working. There exists a wide dispersion in non-pecuniary tastes for jobs, the availability of jobs and the wage schedule across occupations. Managerial occupations have the lowest availability of jobs at labor market entry. Their offer probability then rises with age by 0.05 percentage point per year. Further, the intercept (δ) of their wage function is the most negative one implying the lowest wages for very low skilled workers. For these reasons, it is a small occupation that attracts the more talented individuals and late in their life-cycle. Applicants to become operators or in transport occupations have a high chance of being successful.[7] Construction has the highest constant in the wage equation δ and the lowest slope below the median

[7]Though, it became harder for operators over time as will be discussed below.

Table 2: Occupation Static Parameters

Occup.	non-pecu. utility($\bar{c}_j$)	Offer prob. (λ_{jt})	Wage Cons. (δ_{j0})	Slope 1 (α_{1j0})	Slope 2 (α_{2j0})
Managers	-38.46	0.22*	-3.84	1.50	0.59
Clerical	-34.72	0.43	-1.89	1.00*	0.17
Services	-38.72	0.45	-2.98	1.25	1.05
Operators	-66.89	0.95	-1.65	0.96	0.78
Mechanics	-61.37	0.27	-2.01	1.10	0.42
Construction	-84.67	0.40	-0.96	0.87	1.40
Production	-56.19	0.15	-1.32	0.98	0.54
Transportation	-67.53	0.97	-1.87	1.04	1.15
Non-employed	0.00*	1.00*	0.00*	0.00*	0.00*
Stayers Utility-workers (g_{jt})			346.31		
Stayers Utility-nonworkers (g_{jt})			337.96*		
Search Cost (ξ)			24.62		

Note: The asterisk (*) indicates normalized parameters. The star ($\star$) denotes average over the life-cycle

α_1 suggesting it will be picked by individuals with low skills. However, the slope of the wage function is high when the human capital is above the median which leads to lots of within-occupation wage inequality. It also has the lowest non-pecuniary benefits.

There are large costs of switching occupations, though they are weighted against the variance of idiosyncratic shocks which is also large.

6.1.2 Workers

Table 3 reports heterogeneity across individuals in terms of preferences, endowment and luck. We allow for four discrete types $K = 4$ with equal probability. Group 1 is the reference group. Group 2 has a higher endowment in manual skills and a higher than average preference for manual occupations. Individuals in Group 3 have higher inter-personal skills initially but strongly dislike working in all occupations, and more so if they are intense in either cognitive or inter-personal skills. Group 4 has a high endowment in all three skills and enjoys using these skills more than any other groups. We report unconditional standard deviations and correlations, i.e. after integrating out unobserved heterogeneity.

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. Physical skill and inter-personal skills are about equally unequally distributed at labor market entry.

Table 3: Heterogeneity

I. Non-pecuniary benefits ($\tilde{c}_{lk}$)					
Cognitive	-24.8116	-38.5510	5.6754		
Inter-pers.	-42.4402	-52.7443	6.9209		
Manual	3.4024	-5.3942	23.6948		
II. Skills Endowment: Cross-Sectional Dispersion (μ^{θ}_{ck} andΣ^{θ})					
	Group/Skill Specific Means			Std. deviation	Correlation
Cognitive	-0.0009	0.0006	0.0050	0.0059	-0.4313
Inter-pers.	-0.0014	0.0032	0.0117	0.0106	0.0098
Manual	0.0017	0.0004	0.0029	0.0102	-0.2914
III. Shocks					
σ_{ν}	σ_{w}	E			
329.15*	0.3152	0.8720			
IV. Skills Endowment: Cohorts Trend (trend in μ^{θ}_{ck})					
Cognitive	-0.0017				
Inter-pers.	0.0040				
Manual	-0.0015				

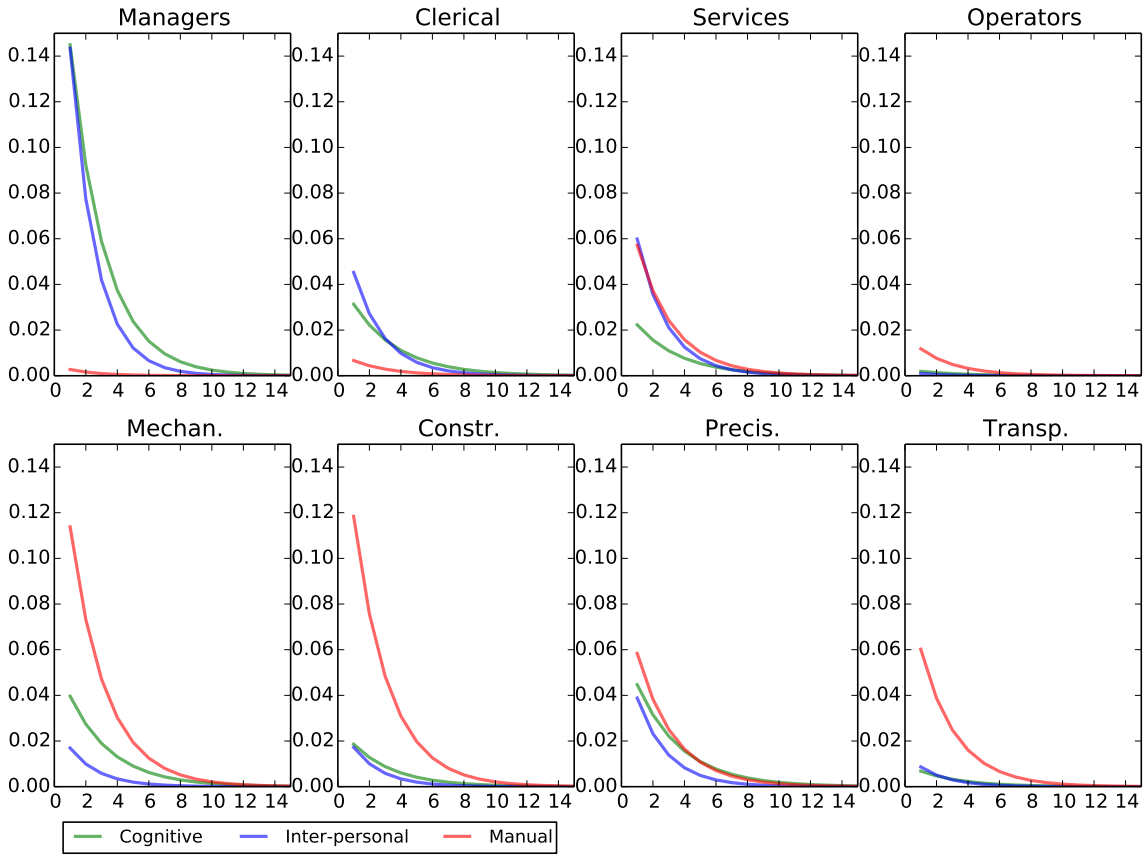
Note: The asterisk (*) indicates normalized parameters. The star ($\star$) denotes average over the life-cycle

Dispersion in cognitive skills is half as high. Correlation between cognitive and inter-personal is close to zero while it is strongly negative for the other two pairs of skills. There is a strong positive correlation between non-pecuniary preferences for using manual skills and manual skills' endowment, close to 0.9. It is plausible that the latter have been accumulated during the schooling period. These correlations are positive but weaker for the other two skills.

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 this metric.

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

Figure 5: Skills' growth: parameters



6.1.3 Sources of Wage Growth

Figure 5 displays parameters related to life-cycle skills' growth for stayers by general labor market experience. It shows skills' growth for counterfactual individuals who would stay in each occupation for a long period of time. We show how each of the three components of skills evolve in each occupation. Interpersonal and cognitive skills are accumulating at a faster path for managerial and clerical' occupations. In the remaining occupations, physical skills are accumulating at a faster rate. Interestingly, Individuals do not learn much skills that are useful in other occupations while working as operators. In other words, there is a large reallocation of labor away from occupations that provide relatively little general training. It makes occupational transitions costly for older individuals.

The patterns in Figure 5 on page 20 do not take into account occupation transitions and more generally people' choices. To understand the role of each skills in wage growth, it is

necessary to go a step further. It is possible to decompose additively log wage growth by simulating career decisions. In simulating this we ignore technological change and assume that the δ and α 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 $\alpha_j^1 = \alpha_j^2$ for each occupation. Letting w_{it} be the log wage of individual i at time t we can write

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

where we use the shorthand notation $h_{j_{it}t} = h\left(j_{it}, \mathcal{S}_{it}\right)$ and $\sigma_{it} = \sigma\left(j_{it}, \tau_{it}\right)$. Then

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

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 $(\alpha_{j_{it-1}} \sigma_{it-1})$.

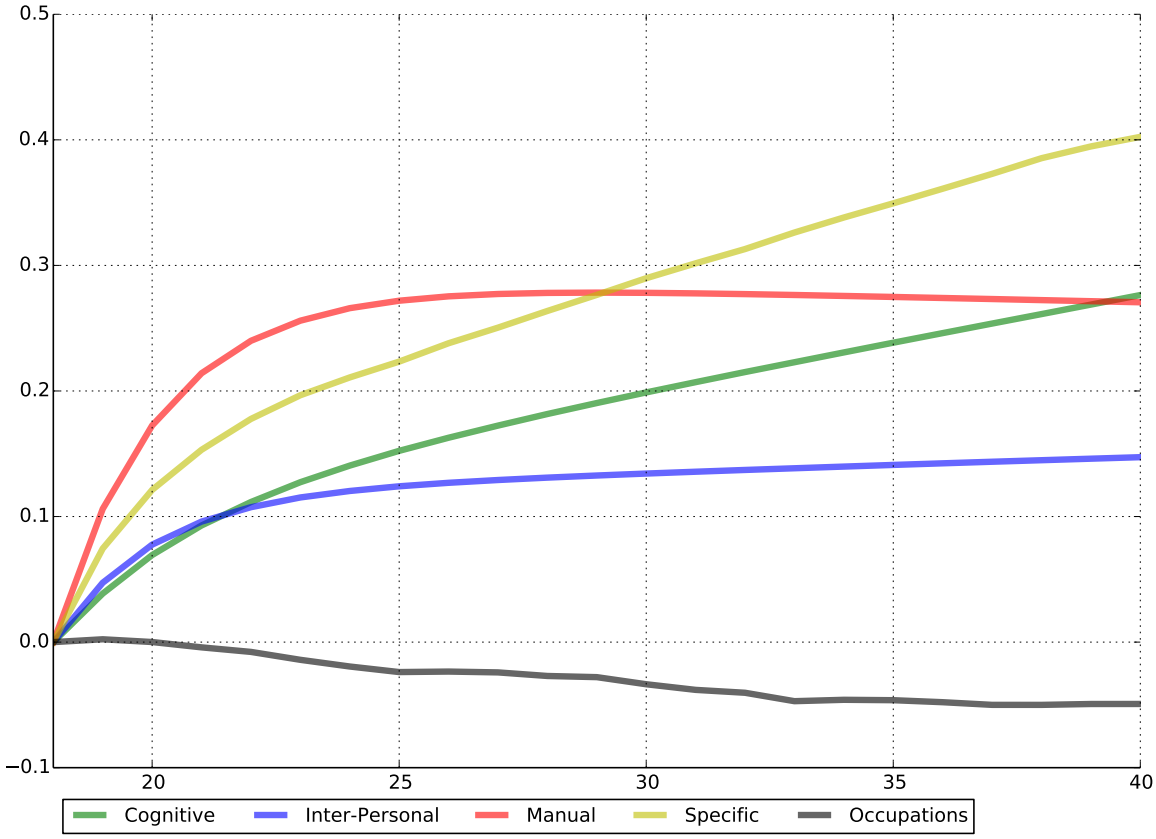
In practice we can not use the simple formula above because $\alpha_j^1 \neq \alpha_j^2$ but rather use a linear approximation to these equations.

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

where

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

Figure 6: Sources of wage growth: decomposition



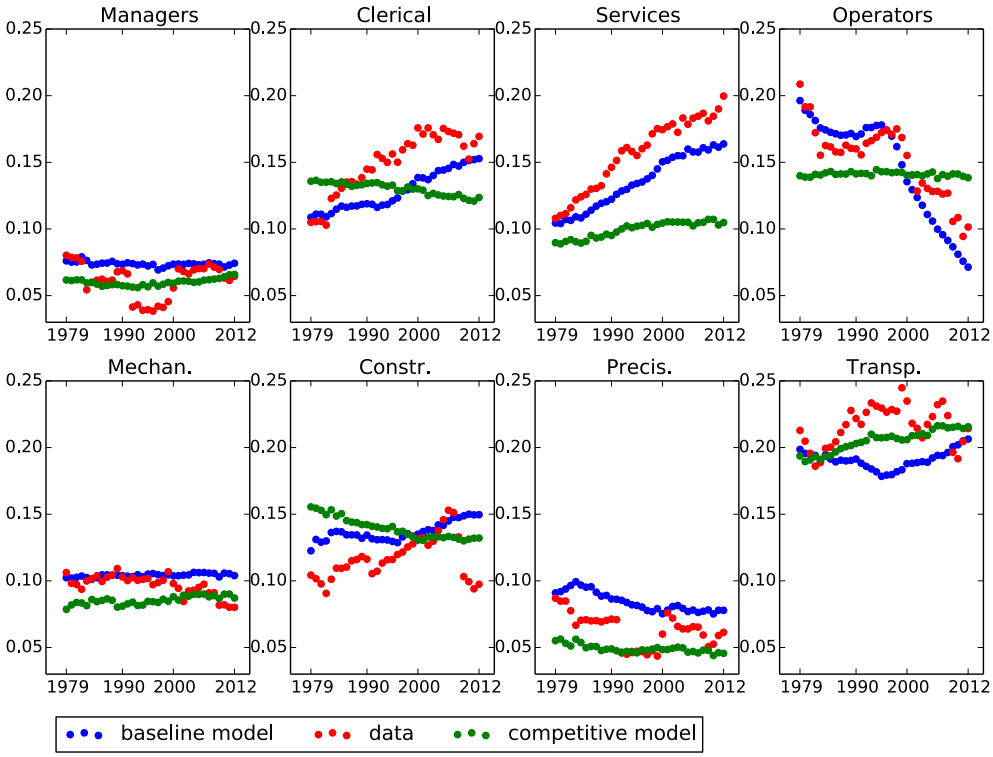
Details of this can be found in Appendix B. The results of the decomposition of the five terms above is presented in Figure 6.

Manual occupations and occupation-specific skills explain most wage growth early in life while cognitive skills' role grows in importance over the lifecycle. The contribution of manual skills to wage growth becomes slightly negative after individuals reach their late twenties. This happens as individuals move away from physical jobs when they get older $\Delta\beta_j^{\text{physical}} < 0$ and because manual skills depreciate faster than other skills.

6.2 Evolution of Occupational Composition

The model does a good (though not great) job at fitting the data. Some auxiliary parameters are reported in Appendix A. Fitting the evolution of employment share over time in the CPS is the main challenge. We saw in the descriptive part of the paper that employment and

Figure 7: Evolution of occupation share by year



wages evolutions are only weakly related. There are two reasons why it is 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.

Figure 7 reports the evolution of employment share by occupation. The blue dots are from the simulated model and the red dots are from the CPS data. The green dots represents the fit of a competitive model with $\lambda_{jt} = 1$ for all j and t.[8] Table 4 reports the estimates of the trend in frictions.

While the baseline model fits the evolution of employment share in each occupation well, the competitive model can not match the decline of operators nor the rise of services. Supply adjusts very little to price changes across occupations. We found in the previous section a large role for unobserved heterogeneity that shapes individuals choices and variations in prices are not enough to explain the reallocation of labor. Non-competitive forces drove indi-

[8]We estimated the competitive model using the full model parameters as starting values and imposing the absence of frictions.

Table 4: Frictions Trends

	Trend
Managers	-0.0029
Clerical	0.0358
Services	0.0323
Operators	-0.0047
Mechanics	0.0098
Construction	0.1169
Production	-0.0011
Transportation	0.0580

viduals away of manual occupations while keeping wages high. And, the service sector grew without significant improvement in its wage rate. Indeed, the estimated trend suggests it became harder to find jobs as operator over time. Unions and efficiency wages considerations are likely to play a role and further work is needed to investigate the precise mechanisms at play. By contrast, service occupations jobs became increasingly available.

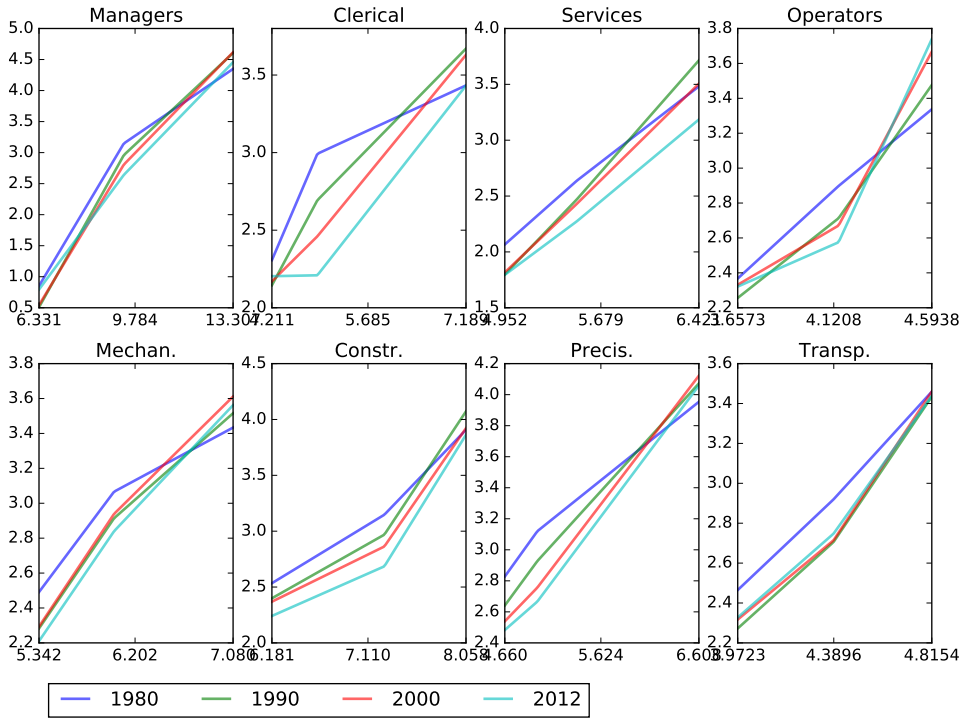
6.3 Skill: supply and demand

6.3.1 Occupations Price

Figure 8 reports the price series. Recall that this is just estimated off high school men-so some of these categories are quite different then what one might get for other groups. For each occupation, we graph the log price profile as a function of human capital h for four different periods of time. The heterogenous 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.

Most of the occupations that are intensive in manual skills (i.e. high β_j^m occupations) see a large decline in the price of human capital supplied by their individuals up to 2000. Yet, individuals at the top of the skill distributions in these overall declining occupations experienced an increase the valuation of their skills. A striking example are operators who saw price increase larger than 10% in the 90s 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.

Figure 8: Price Series by decades



This is an example that leads to a rise in within occupation wage inequality. The evolution of prices in the services occupations is particularly interesting. The 1980s led to a large a decline in the price for all but the best workers. This is precisely the period of acceleration of technological change documented by the literature dating back to at least Katz and Murphy (1992). In the 1990s the price for even the highest ability service workers fell with little action after that. Overall, most price changes occurs in the 1980s which coincide with the large rise in wage inequality.

We now link these occupation-specific prices to the returns to different skills.

6.3.2 Skills Price

We compare the median wage of different groups of individuals. For each skill, we calculate the difference in median earnings of individuals below or above the median for each skill separately. The median skill level is calculated year-by-year to account for changes in skill supplies. For example for cognitive skills let $\theta^c_{t,med}$ be the median level of θ^c_{it} at time t. We plot the evolution of

$$E\left(w_{it} \mid \theta^c_{it} \geq \theta^c_{t,med}\right) - E\left(w_{it} \mid \theta^c_{it} < \theta^c_{t,med}\right)$$

over time. Figure 9 presents the results. The returns to each type of skills increased in the 80s which was expected from the evolution of occupation-specific prices. Inter-personal skills see the highest increase, followed by cognitive. This trend kept on rising for inter-personal, with an acceleration in the 90s and deceleration since 2000. Since the 90s, the price of cognitive skills has been fairly stable. The trend has been negative for physical skills such that its level is about the same today as it was in 1980. The returns to interpersonal skills is now about as high as the returns to manual skills for low skilled men. Cognitive skills still have the highest premium, though the difference with inter-personal shrink from 0.5 to 0.1 log points.

6.3.3 Skills Supply

What has been the supply of skills response to these price changes? The left panel of Figure 10 reports the evolution of the (normalized) stock of skills since 1979. The units are differences in log wages in clerical occupations. The right panel reports the normalized evolution of the share of each skill in the human capital index h supplied to each occupation. The stock of cognitive skills declined since 1979 despite the increase in the cognitive skill

Figure 9: Prices of skills by year

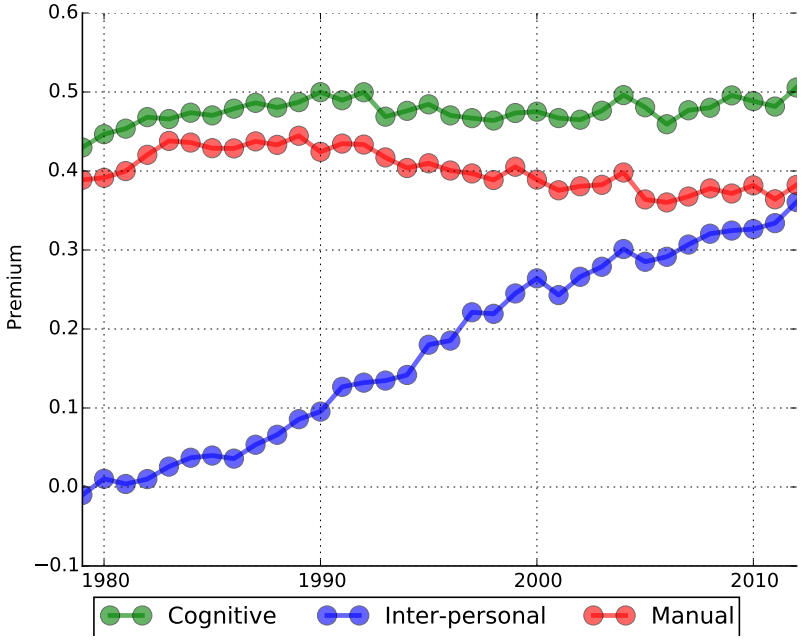
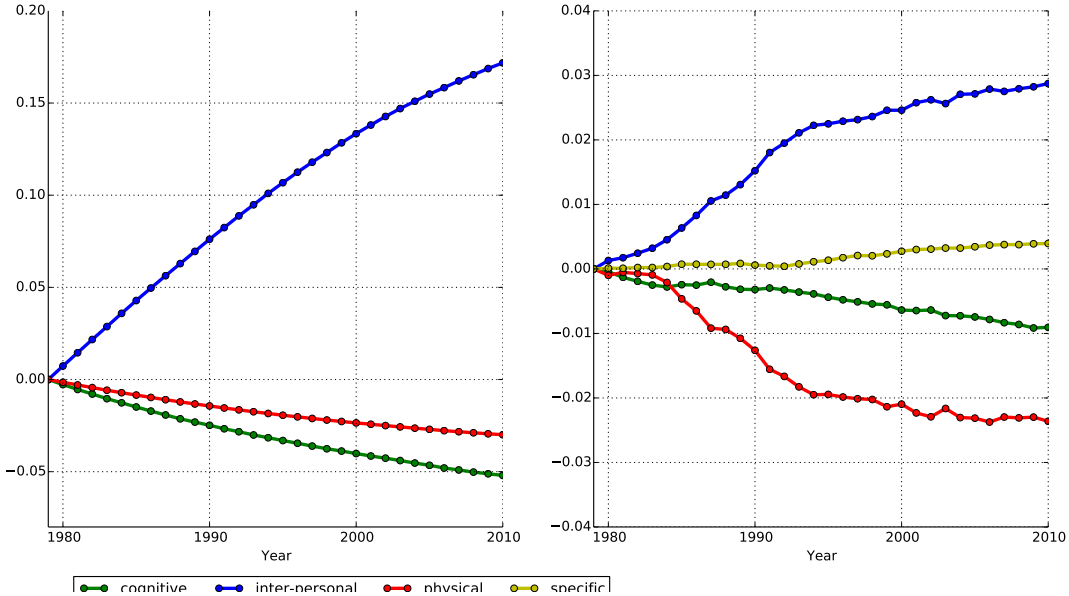


Figure 10: Supply of Skills since 1979



price premium in the 1980s. Most of it come of the decline in cognitive skills endowment of younger cohorts. It is characterized by declining cognitive skills and manual skills, while interpersonal skill rose. Indeed, with the rising price of cognitive skills, schooling attainment has been rising in the population up to the cohort born in the fifties. It is thus natural to observe individuals poorly endowed in cognitive skills that forgo the opportunity to go to school in our selected sample. We saw that while manual occupations are declining, there remain a number of jobs where manual skills are highly valued. These jobs are now performed by computer and individuals that operate these machines are highly trained in manual skills. The increased in the stock of personal skills is due to the rise of the service sector which is relatively intense in inter-personal skills as well as the rise of the clerical sector.

7 Changes in the Wage Structure

Given our estimates we can decompose the findings of our structural model into various components. We can do this by inverting Equation **??** for all individuals in the data set. We recover an estimate of the human capital supplied to the market.

$$h_{ijt} = f_{jt}^{-1}\left(w_{ijt}\right) \tag{3}$$

From this we can estimate the relative importance of changes in prices, changes in the distribution of h_{ijt}, and changes in the occupational composition.

Juhn et al. (1993) propose to decompose changes in earnings distribution into three components: a within and between-industry wage differences and a shift in industry composition. We extend this work by decomposing the rise in earnings inequality between a period t and a reference year τ into six terms. Let p_{jt} denote the population proportion in occupation j at time t and V_{jt} the variance in occupation j at time t. We use the decomposition

$$
\begin{aligned}
& Var_t\left(w_i\right) - Var_\tau\left(w_i\right) \\
= & \sum_j \left[p_{jt} - p_{j\tau}\right] V_{jt}\left(f_{jit}\left(h_{ij_it_i}\right)\right) && (W1) \\
& + \sum_j p_{j\tau}\left[V_{jt}\left(f_{jt}\left(h_{ij_it_i}\right)\right) - V_{jt}\left(f_{j\tau}\left(h_{ij_it_i}\right)\right)\right] && (W2) \\
& + \sum_j p_{j\tau}\left[V_{jt}\left(f_{j\tau}\left(h_{ij_it_i}\right)\right) - V_{j\tau}\left(f_{j\tau}\left(h_{ij_it_i}\right)\right)\right] && (W3) \\
& + \sum_j \left(p_{jt} - p_{j\tau}\right)\left[E_{jt}\left(f_{jt}\left(h_{ij_it_i}\right)\right) - E_t\left(f_{jt}\left(h_{ij_it_i}\right)\right)\right]^2 && (B1) \\
& + p_{j\tau}\sum_j \left(\left[E_{jt}\left(f_{jt}\left(h_{ij_it_i}\right)\right) - E_t\left(f_{jt}\left(h_{ij_it_i}\right)\right)\right]^2 - \left[E_{jt}\left(f_{j\tau}\left(h_{ij_it_i}\right)\right) - E_t\left(f_{j\tau}\left(h_{ij_it_i}\right)\right)\right]^2\right) && (B2) \\
& + p_{j\tau}\sum_j \left(\left[E_{jt}\left(f_{j\tau}\left(h_{ij_it_i}\right)\right) - E_t\left(f_{j\tau}\left(h_{ij_it_i}\right)\right)\right] - \left[E_{j\tau}\left(f_{j\tau}\left(h_{ij_it_i}\right)\right) - E_\tau\left(f_{j\tau}\left(h_{ij_it_i}\right)\right)\right]^2\right) && (B3)
\end{aligned}
$$

The first three terms are within components. First, individuals switches $[p_{jt} - p_{j\tau}]$ towards high (within) variance occupations $V_{jt}\left(f_{jt}\left(h_{ij_it_i}\right)\right)$ contribute to the rise in the variance. For instance, managerial occupations grew in importance since the 1980s and it is an occupation characterized by a large within variance. Second, the hedonic pricing function has changed over-time within occupations as reflected by $V_{jt}\left(f_{jt}\left(h_{ij_it_i}\right)\right) - V_{jt}\left(f_{j\tau}\left(h_{ij_it_i}\right)\right)$. It captures the fact that prices within occupations are evaluating differently over-time the same variations in the human capital index. This term captures, for instance, the convexification of the returns to skills within an occupation. Third, the dispersion in ability within occupation may change as reflected by $V_{jt}\left(f_{j\tau}\left(h_{ij_it_i}\right)\right) - V_{j\tau}\left(f_{j\tau}\left(h_{ij_it_i}\right)\right)$. This evaluates whether occupations became more selective over time in the sense that they attract individuals with similar skills indexes.

The remaining terms are between occupations factors. First, people are moving towards high and low occupations which leads to more inequality. This factor is precisely quantifying the effect of employment polarization (see Acemoglu and Autor, 2011) on the wage structure. The last two terms reflect the change in price differences and skill differences across occupations.

We can decompose further from 6 terms to 48 terms where we can look at the contribution of each of the 8 occupations to each of the 6 terms. Table 5 and Figure 11 report this decomposition for low education men for different time periods. The main lesson is apparent from Figure 11-most of the increase in the variance of earnings is due to changes in pricing. This "Total" line graphs the full variance over time. The "fix occupation" line

calculates the variance at each point in time fixing the occupation proportions (p_{jt}) to their 1979 levels. The "fix occupation/Technology" line fixes both the occupational distribution and the hedonic pricing function to the 1979 levels. Thus the difference between the "total" and "fix" occupation shows the contribution of the occupational distribution. Clearly, holding the occupational proportions constant does not substantially alter the pattern. The difference tween the "Fix Occupation..." and "fix occupation/Technology" lines shows the importance of prices. Again, clearly, holding the pricing function constant eliminates most of the variance. This is true overall and for both the within and between variance figures (especially the within variance). Finally the difference between a flat line at the origin and the "fix occupation/Technology" shows the importance of the skill composition. Once again this is not an important factor. Another interesting thing to note is that within variance accounts for the bulk of the level of the variance yet the between variance accounts for much of the change over time (the figures are not on the same scale).

Table 5 provides much more detail. Table 5a covers the full period and Table 5b covers 1979-1990. The first row of each table provides a 3 part decomposition, the second row gives the 6 part decomposition, and the remaining rows provide the full 48 piece decomposition. For the first period almost all of the action comes from the within occupation changes in prices-and primarily within occupation. Other than services and transportation, all of the occupations experienced large increases inequality from the increase in the within prices. Remaining decades are reported in Appendix C. The results are quite different for these periods. The period 1990-2000 is not particularly interesting because there was essentially no change in the variance of log wages for this group (it fell slightly). The 2000-2012 table shows a much more nuanced picture as almost all of the pieces contribute either positively or negatively. It shows an increase in the heterogeneity in skills within an occupation but a decrease in the heterogeneity across occupations. Both within and between price changes matter and the composition matters for the between variance.

While the results on variance are interesting we know that it misses an important part of the wage distribution. As we know from Figure 2 that the patterns at the high and low end are quite different-which the variance misses. In Figure 12 we show the analogous pattern for the 90/10 differential, the 50/10, the 90/50 and also for comparison the median level. While the patterns are different from the variance, one can see the same basic explanation-changes in the prices are the primary explanation of the patterns with composition of workers essentially flat and changes in the sorting patterns not very important.[9]

[9] As is clear from Figure 1, the variance misses differences between what is happening at the top and

Figure 11: Variance Decomposition

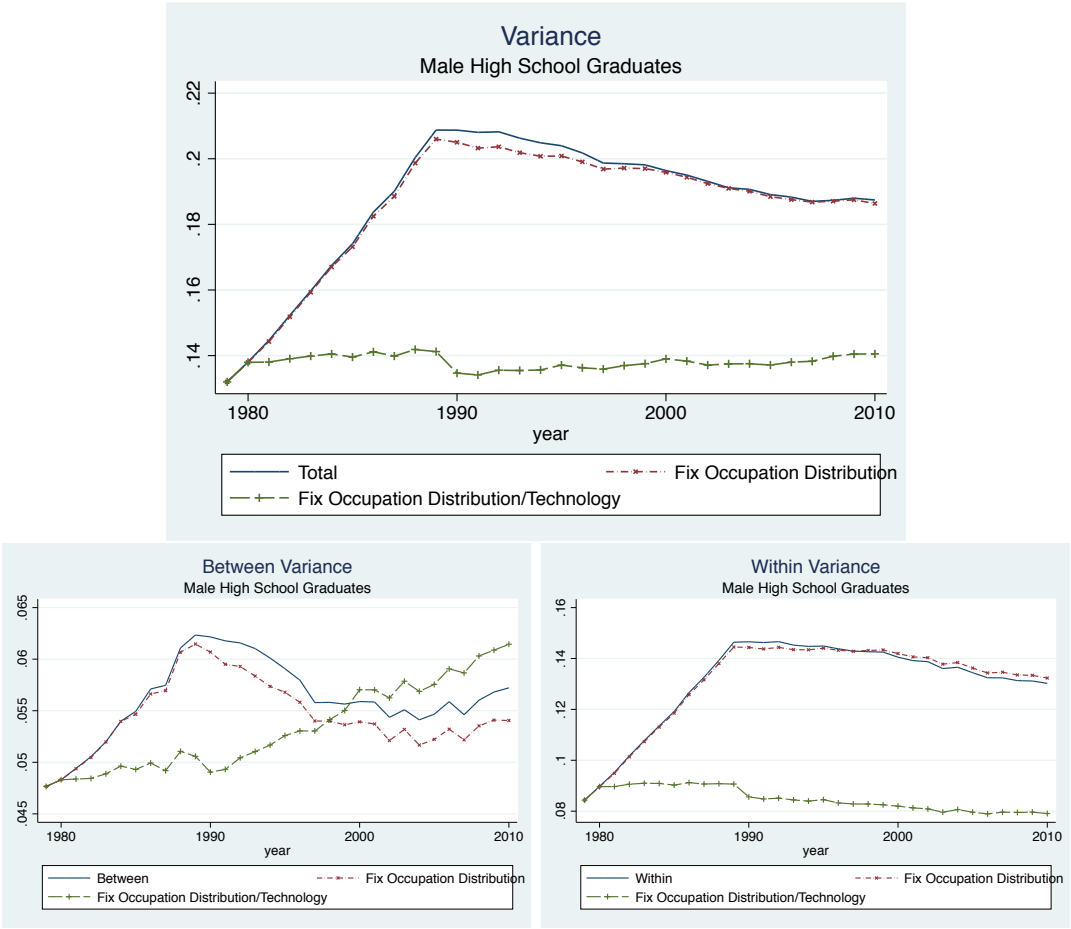


Table 5: Variance Decomposition.

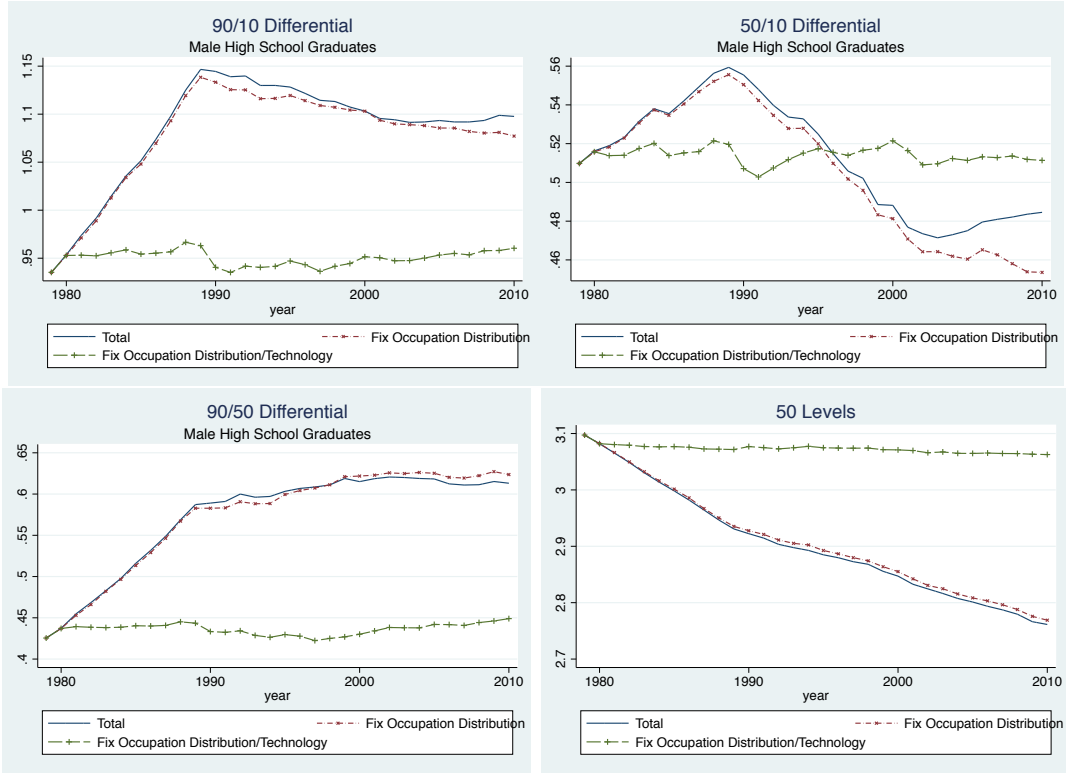
(a) Years: 1979-2010. Variance Change: 0.132-0.187.

	Occ. Composition		Skills		Prices	
	Within	Between	Within	Between	Within	Between
Total	0.019		0.827		0.154	
Total	-0.038	0.057	0.960	-0.133	-0.095	0.249
Managers	-0.023	-0.032	0.202	-0.065	-0.015	0.215
Clerical	0.002	-0.014	0.115	0.022	-0.007	-0.003
Services	-0.028	0.118	0.016	0.129	0.002	-0.057
Operators/Agriculture	0.028	0.010	0.172	-0.140	0.004	0.113
Mechanics	0.000	0.000	0.129	0.038	0.022	-0.017
Construction	0.007	0.001	0.134	-0.057	-0.026	-0.006
Precision Production	-0.002	-0.026	0.127	-0.036	0.007	-0.012
Transportation	-0.021	0.000	0.064	-0.024	-0.082	0.016

(b) Years: 1979-1990. Variance Change: 0.132-0.209

	Occ. Composition		Skills		Prices	
	Within	Between	Within	Between	Within	Between
Total	0.048		0.917		0.035	
Total	0.029	0.019	0.765	0.152	0.017	0.018
Managers	-0.006	-0.011	0.117	0.050	0.007	0.055
Clerical	-0.002	-0.012	0.083	0.002	-0.002	-0.003
Services	0.001	0.037	0.088	0.034	-0.000	0.010
Operators/Agriculture	0.018	0.007	0.115	-0.007	-0.006	-0.014
Mechanics	0.003	0.004	0.073	0.004	0.017	-0.010
Construction	0.015	0.000	0.139	0.023	0.010	-0.011
Precision Production	0.002	-0.005	0.056	0.018	0.010	-0.013
Transportation	-0.000	0.000	0.094	0.028	-0.019	0.005

Figure 12: Quantile Decomposition



8 Conclusion

We proposed and estimated a model to understand the evolution of the wage structure since 1979. We allow for a rich specification of technological change which has heterogenous effects on different occupations and different parts of the skill distribution. We documented the relative role of demand-side factors and supply-side factors.

We have five main findings from the estimates of the model. First, we are able to estimate the changes in the hedonic pricing equation over time. In general we see skill prices falling in all occupations but falling relatively less slowly (and sometimes rising) for relatively high skilled workers in those occupations. Second, we could not reconcile the data with a frictionless model. Many of the occupations that are expanding actually see relatively large declines in skill prices. While in theory, several features of our model could reconcile these patterns, in practice they could not. Third, all four skills are important in explaining wage growth over the lifecycle. Interpersonal skills are the least important. Manual skills are important at the very beginning. Cognitive skills are important later and occupation specific skills seem to be most important overall. Fourth, occupational composition does little to explain both earnings inequality and median wages. Both of these trends are driven by skill prices that evolve within occupation. Fifth, the skill that grows most important over time is interpersonal which has little value at the beginning of the period but substantial returns later.

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 as important as the others for this group, though if the goal is to increase interpersonal skills it is not completely clear how. 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.

at the bottom of the wage distribution. For this reason, we performed a similar analysis using quantiles. The disadvantage of quantiles is that the within and between distinction can not be easily made. The two important findings are unaffected, i.e.. (i) changes in skill prices drive most of the changes in the 80s and (b) Occupational composition never seems particularly important, but the distribution of skills plays a more important role in the later periods. More details are available upon request.

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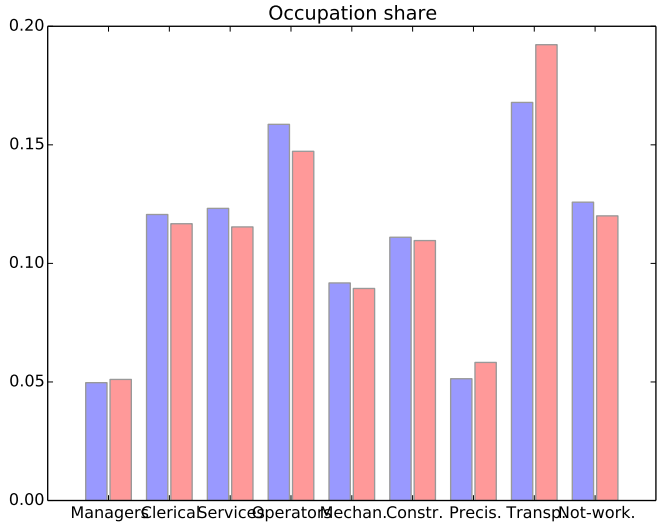


Figure 13: Occupation Share - CPS data, NLSY cohorts

A Additional 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 13 and Figure 14 report, respectively, occupation share in the population and occupation share by age. We use the CPS data but restricts to NLSY cohorts. Each occupation share by age are normalized to zero at age 18. We fit a linear spine in age with knots at age 25 and 34.

Figure 15report different quantiles of the wage distribution by occupation in the NLSY79 cohorts using CPS data. The upper-left panel reports all 3 quantiles, the upper-right reports the median. The lower panel represents the 90/50 50/10 ratios.

Figure 16 reports age-earning profile by occupation in the NLSY79 cohorts using CPS data. We then using the NSLY to classify depending on whether they are low or high in labor market experience and occupation-specific experience. For each occupation, we report the median in each four subgroups relative to the median wage in that occupation in Figure 17.

Figures 18, 19 and 20 report different quantiles of the wage distribution by year and occupation in the CPS. These auxiliary parameters identify prices once we control for selection

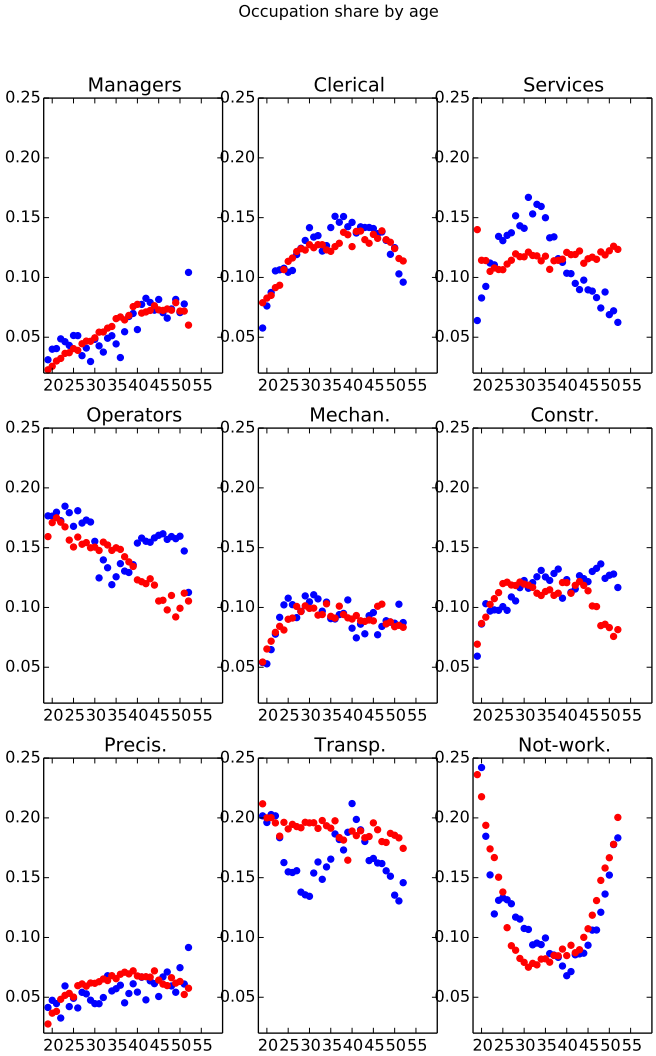


Figure 14: Occupation Share by Age - CPS data, NLSY cohorts

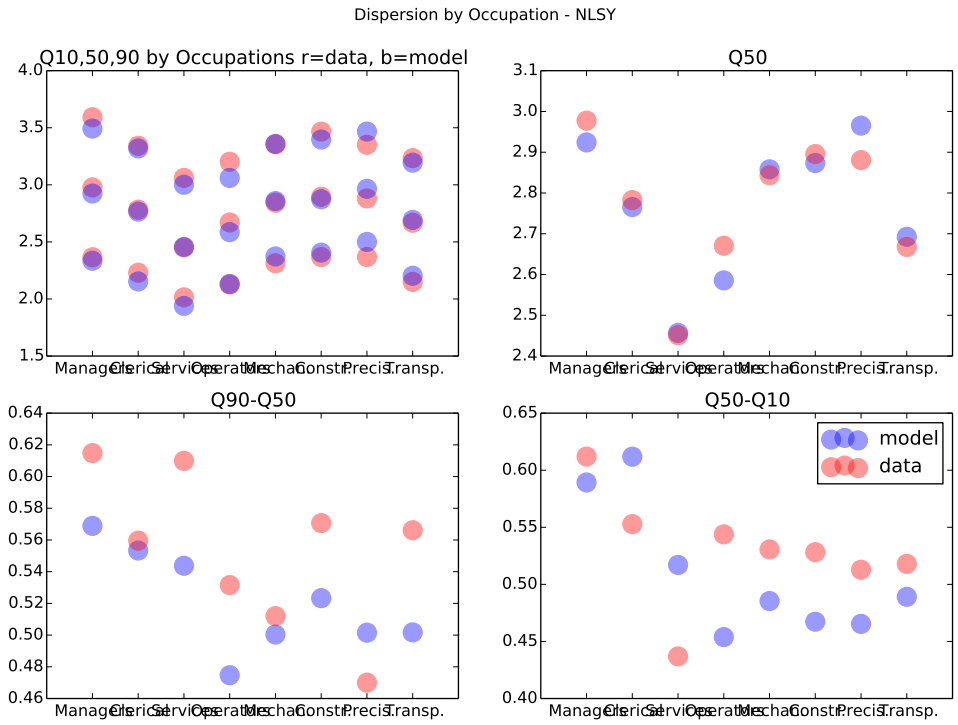


Figure 15: Quantiles of the Wage Distribution by Occupation - CPS data, NLSY cohorts

Figure 16: Age earnings profile by occupation - CPS data, NLSY cohorts

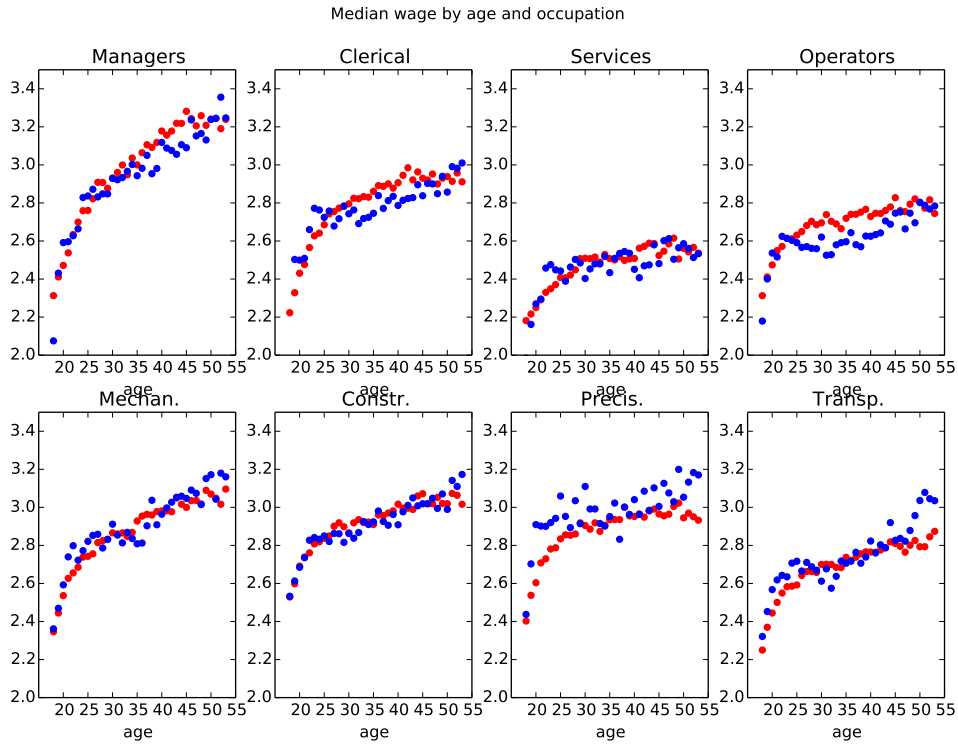


Figure 17: Median wage by labor market experience and occupation-specific experience. NLSY data

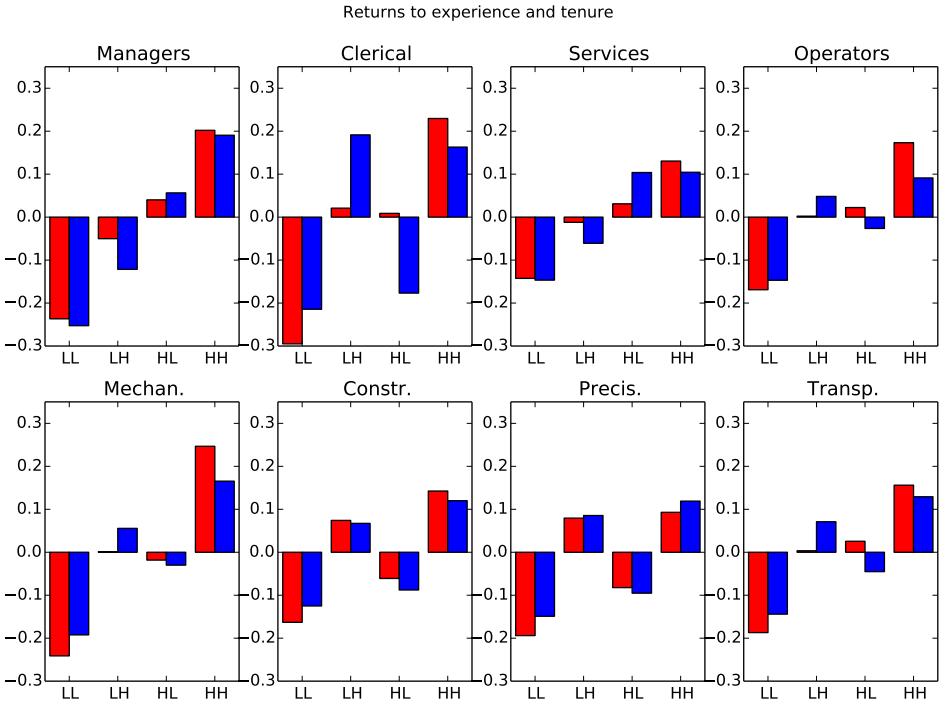
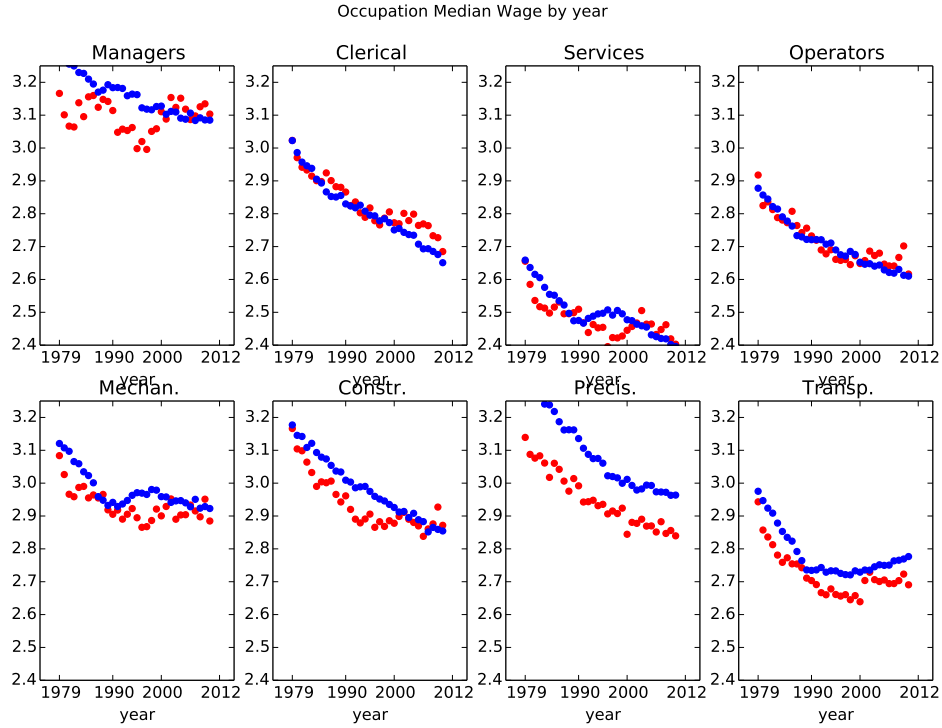


Figure 18: Median wage by year and by occupation. NLSY data



using the previous moments.

B Wage Growth Decomposition

This is quite messy as there are many terms.

We omit the i subscript. We use the steady-state delta's and alpha's of 1979 and earlier.

Wage function is:

$$w_t = \delta_t + \alpha_t^1 (h_t + \sigma_t) \times \left\{h_t \leq h^*_{j(t)}\right\} + \left(\alpha_t^2 \left[h_t + \sigma_t - h^*_{j(t)}\right] + \alpha_1^t h^*_{j(t)}\right) \times \left\{h_t > h^*_{j(t)}\right\}$$

Stayers We omit the j subscript. Different cases to consider:

1. $\{h_t + \sigma_t \leq h^*\} \times \{h_{t-1} + \sigma_{t-1} \leq h^*\} + \{h_t + \sigma_t > h^*\} \times \{h_{t-1} + \sigma_{t-1} > h^*\} > 0.$

$$\Delta w_t = \left(\alpha_t^1 \{h_t + \sigma_t \leq h^*\} \times \{h_{t-1} + \sigma_{t-1} \leq h^*\} + \alpha_t^2 \{h_t + \sigma_t > h^*\} \times \{h_{t-1} + \sigma_{t-1} > h^*\}\right) \times (\beta \Delta\theta_t + \Delta\sigma_t)$$

Figure 19: 90-50 ratio by year and by occupation. NLSY data

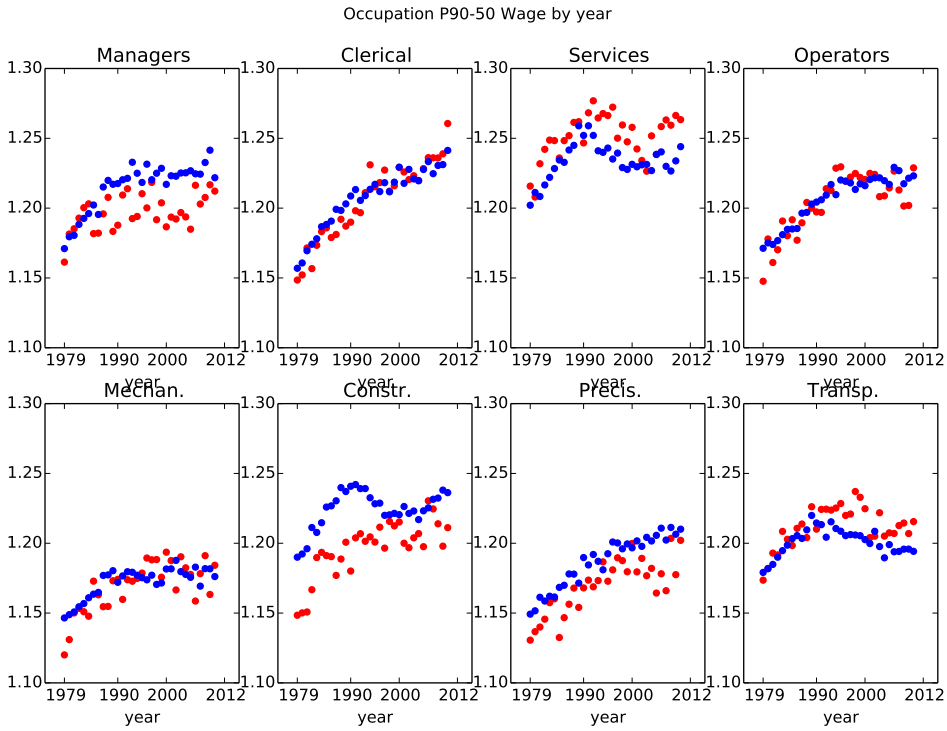
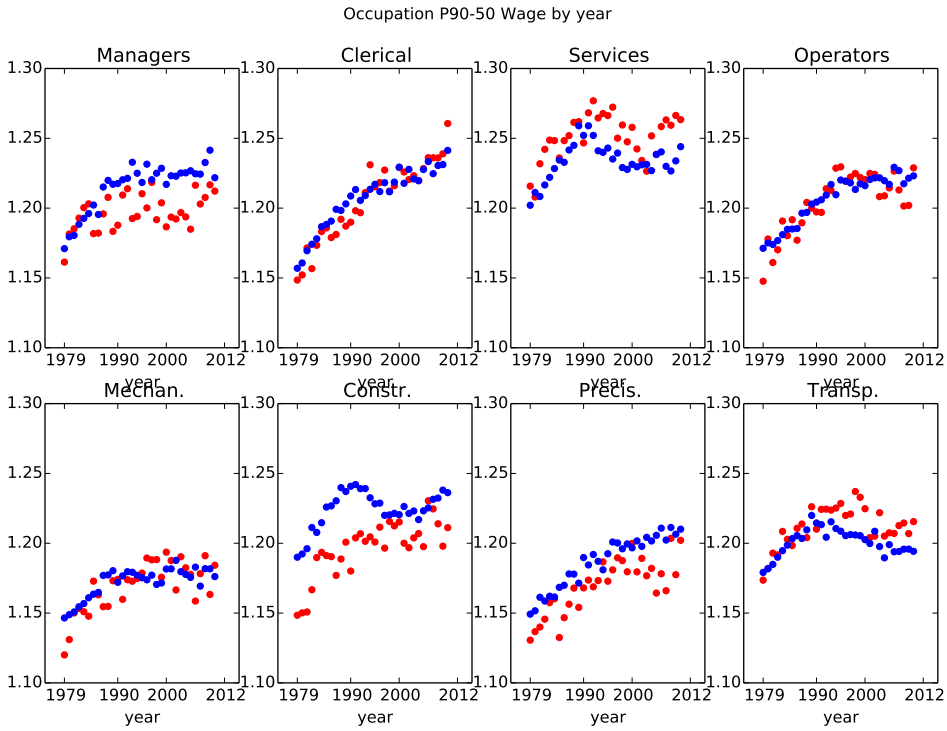


Figure 20: 50-10 ratio by year and by occupation. NLSY data



2. $\{h_t + \sigma_t > h^*\} \times \{h_{t-1} + \sigma_{t-1} \leq h^*\} = 1$.

$$\begin{aligned}
\Delta w_t &= \alpha^1 h^* + \alpha^2 (h_t + \sigma_t - h^*) - \alpha^1 (h_{t-1} + \sigma_{t-1}) \\
&= \alpha^2 (h_t + \sigma_t - h^*) + \alpha^1 (h^* - (h_{t-1} + \sigma_{t-1})) \\
&= \alpha^* (h_t + \sigma_t - (h_{t-1} + \sigma_{t-1}))
\end{aligned}$$

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

3. $\{h_t + \sigma_t \leq h^*\} \times \{h_{t-1} + \sigma_{t-1} > h^*\} = 1$.

$$\begin{aligned}
\Delta w_t &= \alpha^1 h_t - \alpha^1 h^* + \alpha^2 h^* - \alpha^2 h_{t-1} \\
&= \alpha^2 (h^* - (h_{t-1} + \sigma_{t-1})) + \alpha^1 (h_t + \sigma_t - h^*)
\end{aligned}$$

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

Switchers

$$\begin{aligned}
w_t =& \delta_{j(t)} + \alpha^1_{j(t)} h_{j(t)} \left\{h_t \leq h^*_{j(t)}\right\} \\
&+ \left[\alpha^2_{j(t)} \left(h_t - h^*_{j(t)}\right) + \alpha^1_{j(t)} h^*_{j(t)}\right] \left\{h_t > h^*_{j(t)}\right\} \\
w_{t-1} =& \delta_{j(t-1)} + \alpha^1_{j(t-1)} (h_{t-1} + \sigma_{t-1}) \left\{h_{t-1} \leq h^*_{j(t-1)}\right\} \\
&+ \left[\alpha^2_{j(t-1)} \left(h_{t-1} + \sigma_{t-1} - h^*_{j(t-1)}\right) + \alpha^1_{j(t-1)} h^*_{j(t-1)}\right] \left\{h_{t-1} > h^*_{j(t-1)}\right\} \\
\Delta \delta_t =& \delta_{j(t)} - \delta_{j(t-1)}
\end{aligned}$$

Different cases to consider.

1. $\left\{h_t \leq h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} \leq h^*_{j(t-1)}\right\} = 1.$

$$\begin{aligned}
\Delta w_t =& \Delta\delta_t + \alpha^1_{j(t)}\beta'_{j(t)}\theta_t - \alpha^1_{j(t-1)}h_{j(t-1)} - \alpha^1_{j(t-1)}\sigma_{t-1} \\
=& \Delta\delta_t \\
& + \alpha^1_{j(t)}\beta'_{j(t)}\theta_t - \alpha^1_{j(t-1)}\beta'_{j(t-1)}\theta_t \\
& + \alpha^1_{j(t-1)}\beta'_{j(t-1)}\theta_t - \alpha^1_{j(t-1)}\beta'_{j(t-1)}\theta_{t-1} \\
& - \alpha^1_{j(t-1)}\sigma_{t-1} \\
=& \Delta\delta_t \\
& + \left(\alpha^1_{j(t)}\beta'_{j(t)} - \alpha^1_{j(t-1)}\beta'_{j(t-1)}\right)\theta_t \\
& + \alpha^1_{j(t-1)}\beta_{j(t-1)}\Delta\theta_t - \alpha^1_{j(t-1)}\sigma_{t-1}
\end{aligned}$$

2. $\left\{h_t > h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} > h^*_{j(t-1)}\right\} = 1.$

$$\begin{aligned}
\Delta w_t =& \Delta\delta_t + \left(\alpha^2_{j(t)}\left(h_{j(t)} - h^*_{j(t)}\right) + \alpha^1_{j(t)}h^*_{j(t)}\right) \\
& - \left(\alpha^2_{j(t-1)}(h_{j(t-1)} - h^*_{j(t-1)}) + \alpha^1_{j(t-1)}h^*_{j(t-1)}\right) \\
& - \alpha^2_{j(t-1)}\sigma_{t-1} \\
=& \Delta\delta_t + \left(\alpha^2_{j(t)}\left(\beta'_{j(t)}\theta_t - h^*_{j(t)}\right) + \alpha^1_{j(t)}h^*_{j(t)}\right) - \left(\alpha^2_{j(t-1)}\left(\beta'_{j(t-1)}\theta_{t-1} - h^*_{j(t-1)}\right) + \alpha^1_{j(t-1)}h^*_{j(t-1)}\right) \\
& + \alpha^2_{j(t-1)}\beta'_{j(t-1)}\theta_t - \alpha^2_{j(t-1)}\beta'_{j(t-1)}\theta_t \\
& - \alpha^2_{j(t-1)}\sigma_{t-1} \\
=& \Delta\delta_t + \left(\left(\alpha^1_{j(t)} - \alpha^2_{j(t)}\right)h^*_{j(t)} - \left(\alpha^1_{j(t-1)} - \alpha^2_{j(t-1)}\right)h^*_{j(t-1)}\right) \\
& + \left(\alpha^2_{j(t)}\beta'_{j(t)} - \alpha^2_{j(t-1)}\beta'_{j(t-1)}\right)\theta_t \\
& + \alpha^2_{j(t-1)}\beta'_{j(t-1)}\Delta\theta_t - \alpha^2_{j(t-1)}\sigma_{t-1}
\end{aligned}$$

3. $\left\{h_t > h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} \leq h^*_{j(t-1)}\right\} = 1.$

$$\begin{aligned}
\Delta w_t =& \Delta\delta_t + \left(\alpha^2_{j(t)}\left(h_{j(t)} - h^*_{j(t)}\right) + \alpha^1_{j(t)} h^*_{j(t)}\right) \\
& - \alpha^1_{j(t-1)} h_{j(t-1)} \\
& - \alpha^1_{j(t-1)} \sigma_{t-1} \\
=& \Delta\delta_t + \left(\alpha^2_{j(t)}\left(\beta'_{j(t)}\theta_t - h^*_{j(t)}\right) + \alpha^1_{j(t)} h^*_{j(t)}\right) - \alpha^1_{j(t-1)}\left(\beta'_{j(t-1)}\theta_{t-1}\right) \\
& + \alpha^1_{j(t-1)}\beta'_{j(t-1)}\theta_t - \alpha^1_{j(t-1)}\beta'_{j(t-1)}\theta_t \\
& - \alpha^1_{j(t-1)}\sigma_{t-1} \\
=& \Delta\delta_t + \left(\alpha^1_{j(t)} - \alpha^2_{j(t)}\right) h^*_{j(t)} \\
& + \left(\alpha^2_{j(t)}\beta'_{j(t)} - \alpha^1_{j(t-1)}\beta'_{j(t-1)}\right)\theta_t \\
& + \alpha^1_{j(t-1)}\beta'_{j(t-1)}\Delta\theta_t - \alpha^1_{j(t-1)}\sigma_{t-1}
\end{aligned}$$

4. $\left\{h_t \leq h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} > h^*_{j(t-1)}\right\} = 1.$

$$\begin{aligned}
\Delta w_t =& \Delta\delta_t + \alpha^1_{j(t)} h_{j(t)} \\
& - \left(\alpha^2_{j(t-1)}(h_{j(t-1)} - h^*_{j(t-1)}) + \alpha^1_{j(t-1)} h^*_{j(t-1)}\right) \\
& - \alpha^2_{j(t-1)}\sigma_{t-1} \\
=& \Delta\delta_t + \alpha^1_{j(t)}\beta'_{j(t)}\theta_t - \left(\alpha^2_{j(t-1)}\left(\beta'_{j(t-1)}\theta_{t-1} - h^*_{j(t-1)}\right) + \alpha^1_{j(t-1)} h^*_{j(t-1)}\right) \\
& + \alpha^2_{j(t-1)}\beta'_{j(t-1)}\theta_t - \alpha^2_{j(t-1)}\beta'_{j(t-1)}\theta_t \\
& - \alpha^2_{j(t-1)}\sigma_{t-1} \\
=& \Delta\delta_t - \left(\alpha^1_{j(t-1)} - \alpha^2_{j(t-1)}\right) h^*_{j(t-1)} \\
& + \left(\alpha^1_{j(t)}\beta'_{j(t)} - \alpha^2_{j(t-1)}\beta'_{j(t-1)}\right)\theta_t \\
& + \alpha^2_{j(t-1)}\beta'_{j(t-1)}\Delta\theta_t - \alpha^2_{j(t-1)}\sigma_{t-1}
\end{aligned}$$

Comparing stayers and switchers, there is the following additional term for switchers only

$$
\begin{aligned}
\Delta w_t &= \Delta\delta_t \\
&+ \left(\alpha^1_{j(t)}\beta'_{j(t)} - \alpha^1_{j(t-1)}\beta'_{j(t-1)}\right)\theta_t \left\{h_t \leq h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} \leq h^*_{j(t-1)}\right\} \\
&+ \left(\alpha^2_{j(t)}\beta'_{j(t)} - \alpha^2_{j(t-1)}\beta'_{j(t-1)}\right)\theta_t \left\{h_t > h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} > h^*_{j(t-1)}\right\} \\
&+ \left(\alpha^2_{j(t)}\beta'_{j(t)} - \alpha^1_{j(t-1)}\beta'_{j(t-1)}\right)\theta_t \left\{h_t > h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} \leq h^*_{j(t-1)}\right\} \\
&+ \left(\alpha^1_{j(t)}\beta'_{j(t)} - \alpha^2_{j(t-1)}\beta'_{j(t-1)}\right)\theta_t \left\{h_t \leq h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} > h^*_{j(t-1)}\right\} \\
&+ \left[\left(\alpha^1_{j(t)} - \alpha^2_{j(t)}\right)h^*_{j(t)} - \left(\alpha^1_{j(t-1)} - \alpha^2_{j(t-1)}\right)h^*_{j(t-1)}\right]\left\{h_t > h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} > h^*_{j(t-1)}\right\} \\
&\left(\alpha^1_{j(t)} - \alpha^2_{j(t)}\right)h^*_{j(t)}\left\{h_t > h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} \leq h^*_{j(t-1)}\right\} \\
&- \left(\alpha^1_{j(t-1)} - \alpha^2_{j(t-1)}\right)h^*_{j(t-1)}\left\{h_t \leq h^*_{j(t)}\right\} \times \left\{h_{t-1} + \sigma_{t-1} > h^*_{j(t-1)}\right\} \\
&= \Delta\delta_t \\
&+ \Bigg[\left(\alpha^1_{j(t)}\left\{h_t \leq h^*_{j(t)}\right\} + \alpha^2_{j(t)}\left\{h_t > h^*_{j(t)}\right\}\right)\beta'_{j(t)} \\
&- \left(\alpha^1_{j(t-1)}\left\{h_{t-1} + \sigma_{t-1} \leq h^*_{j(t-1)}\right\} + \alpha^2_{j(t-1)}\left\{h_{t-1} + \sigma_{t-1} > h^*_{j(t-1)}\right\}\right)\beta'_{j(t-1)}\Bigg] \\
&\times\theta_t \\
&+ \left(\alpha^1_{j(t)} - \alpha^2_{j(t)}\right)h^*_{j(t)}\left\{h_t > h^*_{j(t)}\right\} \\
&- \left(\alpha^1_{j(t-1)} - \alpha^2_{j(t-1)}\right)h^*_{j(t-1)}\left\{h_t + \sigma_{t-1} \leq h^*_{j(t)}\right\}
\end{aligned}
$$

C Variance Decomposition. Additional Tables.

Table 6: Variance Decomposition

Years: 1990-2000. Variance Change: 0.209-0.196

	Occupational Composition		Prices		Skills	
	Within	Between	Within	Between	Within	Between
Total	0.023		1.006		-0.028	
Total	0.095	-0.073	-0.296	1.302	0.692	-0.721
Managers	0.040	0.053	-0.259	0.425	0.054	-0.473
Clerical	0.003	0.032	-0.033	-0.031	0.046	0.008
Services	0.027	-0.164	0.271	-0.081	0.039	0.241
Operators/Agriculture	-0.031	-0.037	-0.272	0.407	-0.089	-0.356
Mechanics	0.011	0.000	-0.146	-0.185	0.015	0.023
Construction	-0.000	-0.002	0.309	0.294	0.200	-0.017
Precision Production	0.001	0.046	-0.221	0.264	0.087	-0.002
Transportation	0.045	-0.000	0.055	0.208	0.341	-0.145

Years: 2000-2010. Variance Change: 0.196-0.187

	Occupational Composition		Prices		Skills	
	Within	Between	Within	Between	Within	Between
Total	0.002		0.739		0.259	
Total	0.115	-0.113	0.499	0.240	0.534	-0.275
Managers	0.023	0.033	0.079	0.455	0.102	-0.429
Clerical	0.001	-0.013	0.317	-0.150	-0.303	0.051
Services	0.038	-0.142	0.463	-0.595	-0.098	0.281
Operators/Agriculture	-0.036	-0.008	-0.136	0.241	0.436	-0.296
Mechanics	-0.001	0.001	-0.067	-0.042	0.084	0.080
Construction	0.032	-0.013	-0.239	0.153	0.231	0.033
Precision Production	-0.008	0.028	-0.005	-0.070	-0.058	0.018
Transportation	0.066	-0.000	0.087	0.247	0.140	-0.013