Skills Prices, Occupations and Changes in the Wage Structure

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Abstract

This paper proposes and estimates a model of occupational choice with time-varying skills prices and heterogeneous human capital to understand the evolution of the wage structure since 1979. 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 role of technology. We document the relative role of demand-side factors and supply-side factors.

Very Preliminary and Incomplete -estimates are in progress not fully converged- Please do not circulate

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. There is wide agreement that technological changes have been a main driving force. Technological progress complements skilled labor raising the earnings of college graduate while technological progress substitutes unskilled labor lowering the demand for unskilled labor and their earnings. This hypothesis has proved empirically quite successful in accounting for the evolution of the skill premium in the United States throughout the twentieth century (See Goldin and Katz, 2009).

Yet, this is only part of the picture as the patterns differ substantially across decades and across measures of earnings inequality. For example rise in 90/10 quantiles of the earnings distribution rises throughout yet the 50/10 decline over the full period for low educated men. It suggests technological change has impact on the wage structure that is far more complicated than a workhorse model with two skill categories can possibly explain. Some have associated these evolutions with employment polarization (see Acemoglu and Autor, 2011 for a survey) with the simultaneous rise of employment in low-paid and high paid occupations. Yet, the effect of employment polarization on the wage structure needs further work. While wage polarization (Autor and Dorn, 2013) is part of the story, the patterns are much more complicated. The quantitative impact of employment polarization, and more generally occupational composition, on the wage structure is rather unexplored. If ones goal is to train workers in response to this change in the demand for skills, one needs to know which combination of skills are becoming more value. This is the main goal of our research.

This paper tries to understand the role of technology, multi-dimensional skills and occupational choice in explaining the evolution of the wage structure since 1979. Our approach can be summarized by the following log wage equation. An individual i at time t in occupations $j = 1, .., J$ is paid according to,

$$w_{ijt} = f_{tj}\left(h_{ijt}\right) \tag{1}$$

where w_{ijt} and h_{ijt} are the wage and occupation human capital for individual i in occupation j at time t. Key to our study is f_{tj}, the hedonic wage equation for human capital. It changes over-time with net shifts in technology. Different levels of human capital are not perfectly substitutable with each other so the relative price of that human capital can change over time with perhaps the relative wage of higher human capital increasing relative to lower levels.

In our structural model we assume further that

$$h_{ijt} = e^{\theta'_{it}\beta_j}.$$

The human capital index: $\theta'_{it}\beta_j$ is the product of a vector skills θ_{it} and a vector of intensity β_j. $\theta_{it} = (\theta^c_{it}, \theta^i_{it}, \theta^m_{it}) \in \mathbb{R}^3$ is a vector of general skills composed of cognitive θ^c_{it}, interpersonal θ^i_{it} and manual skills θ^m_{it} that are used at different rates in different occupations according to β_j. The simplest example, also widely used in the literature, is the specification

$$f_{tj}\left(e^{\theta'_{it}\beta_j}\right) = \delta_{tj} e^{\theta'_{it}\beta_j}$$

where δ_{tj} is the partial derivative of the aggregate production $F_t\left(H_{t1}, \ldots, H_{tJ}\right)$ and H_{tj} is the aggregate stock of human capital in occupation j at time t. Formally,

$$\delta_{jt} \equiv \left(\frac{\partial F_t(H_{1t}, ..., H_{Jt})}{\partial H_{jt}}\right)$$

Indeed, some technological shifts affect uniformly different parts of the earnings distribution within an occupation which corresponds to variations in δ_{jt}. We consider a richer specification that can account for the rise in within-occupation wage inequality and the convexification of the returns to skills. Are differences in talent translated to larger differences in earnings due to technological shifts such as globalization and capital-skill complementarities? One goal of this paper is to provide empirical evidence for this type of phenomena. While many of these ideas have been suggested in previous work, our contribution is to develop methodology to identify these technological shifts in the data.

One of the biggest challenges in this literature is separating wage changes within an occupation into the part due to changes in prices (f_{jt}) versus changes in composition (the distribution of θ_{it}). 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 θ_{it} that can reconcile any f_{jt}. This is, of course, a feature of any analysis that follows different cohorts over time not just a problem in our paper. We address this problem in two separate ways-hoping that they give similar answers.

First, we use the CPS and look at individuals in their “flat spot” (See Heckman et al., 1998 or Bowlus and Robinson, 2012). The flat-spot method assumes that after a certain number of years experience, age effects are unimportant. In other words, $h_{ijt} \approx h_{ij\tau}$ for some t and τ. Time-variation in earnings of individuals in their flat-spot will identify variations in the hedonic-pricing function f_{tj}. Simply put, it solves the age/cohort/time identification problem by assuming that age effects are zero in some range of the age distribution. A theoretical justification for this assumption comes from the model of human capital accumulation developed in Ben-Porath (1967). If skill investment are the result of endogenous investments, an individual will reduce his investment as he gets closer to retirement.

This approach has two drawbacks. First the flat spot method is somewhat arbitrary as one never knows for sure that human capital is flat in this range. Second, this method only allows us to estimate the one dimensional object h_{ijt} for each occupation. We can say nothing about how skills translate across occupations. We address these problems by putting more structure on the problem and estimating a full model. We use O'NET to estimate the skill intensity of each occupation measured by β. We then build and estimate a model combining the NSLY79 with the CPS to recover the evolution of the different stock of human capital over the life cycle $\{\theta_{i1}, \ldots, \theta_{iR}\}$. This part imposes a lot structure but the results of the reduced-form approach led to more questions that we could only answer by building structural model of skills accumulation and occupational choice.

The focus of this version paper is on Male's with a high school degree or less. We intend to expand to other groups in future drafts.

Section 2 very briefly discusses the related literature and Section 3 describes the data. In section 4 we present some motivating facts and then Section 5 uses the flat spot method to explain them. We present the structural model in Section 6.

2 Related Literature (very incomplete)

This paper is related to a large literature on skill-bias technological change and human capital (see the survey Goldin and Katz, 2009). Our contribution is to allow for heterogeneous effects of technological change on different parts of the distribution and to consider a richer definition of human capital consisting of a vector of general skills and some occupation-specific human capital.

Our paper is also related to the literature on tasks specific human capital (see the survey by Sanders and Taber, 2012). Most of this literature focusses does not allow for time-varying skills prices and the consequences for evolution of the wage structure.

A recent growing literature document the polarization of the U.S. labor market (see the survey by Acemoglu and Autor, 2011). Our contribution is to quantify its importance for wage inequality and more general how it affected the wage structure.

Our paper is also related to several important papers that estimate equilibrium models of the labor market to understand the skill premium (see Heckman et al., 1998), the growth of the service sector (see Lee and Wolpin, 2006) and the evolution of the wage structure (Johnson and Keane, 2013).

3 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. For each demographic group we aggregate occupations in different ways. For low education men we use the 8 occupations listed in Table 1.

Table 1

Occupation Categories Low Educated Men

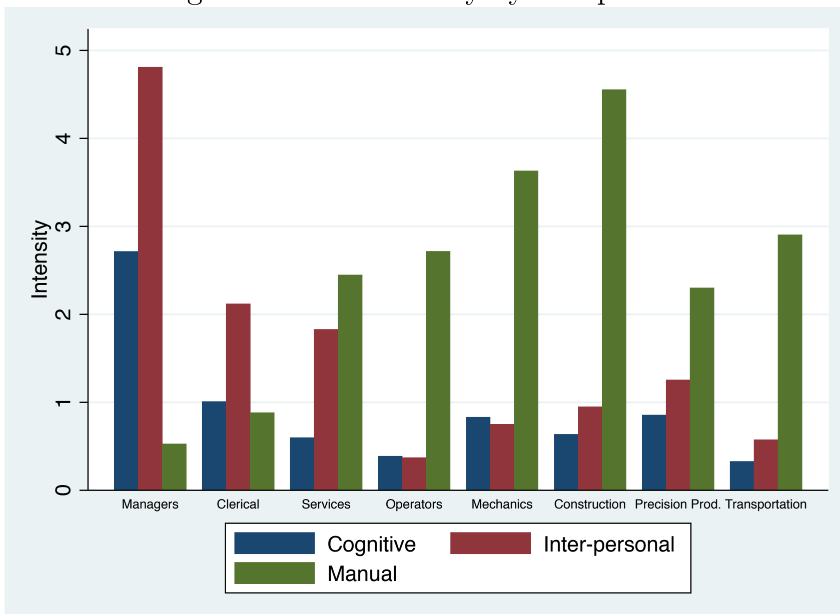
	Occupations	Label	Share 1983	Share 2012
1	Executive, Administrative, and Managerial Professional Specialty	Managers	6.1%	6.6%
2	Technicians Sales Administrative Support	Clerical	13.4%	16.4%
3	Housekeeping and Cleaning Protective Service Other Services	Services	12.2%	18.9%
4	Farming, Forestry, and Fishing 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%

ORG CPS Wages are calculated using ORG CPS data 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).

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 male 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. Our measure of ability is the Armed Forces Qualification Test (AFQT), a composite score derived from the the Armed Forces Vocational Aptitude Battery (ASVAB). We adjust for differences in test-taking age following Altonji et al. (2012).

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. Individuals were asked to complete a survey asking about the tasks and activities workers perform in those occupations. We use a standard principal component analysis. We consider three skill categories: cognitive, manual and inter-personal. 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 1: Skill intensity by occupations



4 Motivating Facts

This Section documents changes in prices at different quantiles of the wage distributions since 1979 and its implications for occupational choice and changes in the wage structure. 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 the1980s, 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.

Figure 4 presents the changes in median wages across time for the different occupations. Other than managers, we see that all occupations experience large decreases in average wages. If one compares Figures 3 and 4 together, it is clear that wage patterns are not that closely

Figure 2: Changes in Log Wage Quantiles over Time

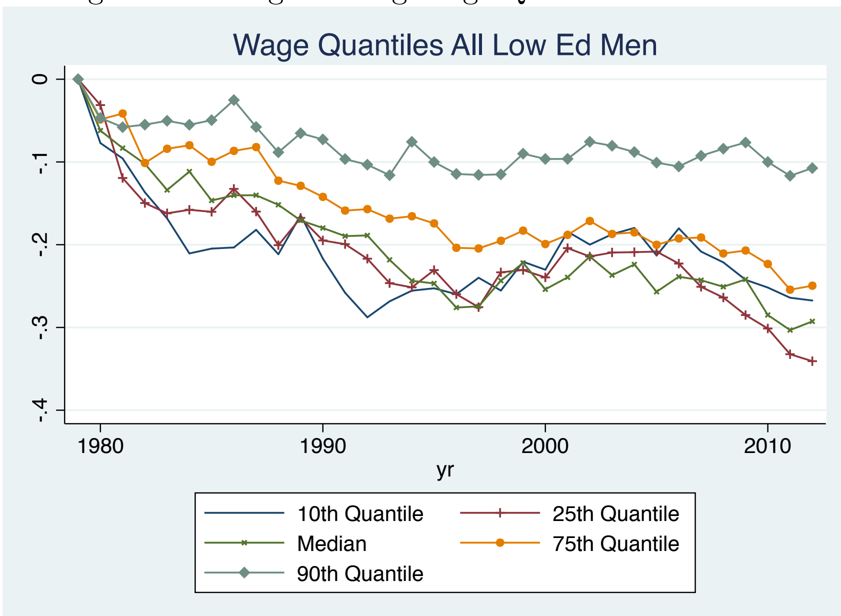


Figure 3: Changes in Occupational Distribution over Time

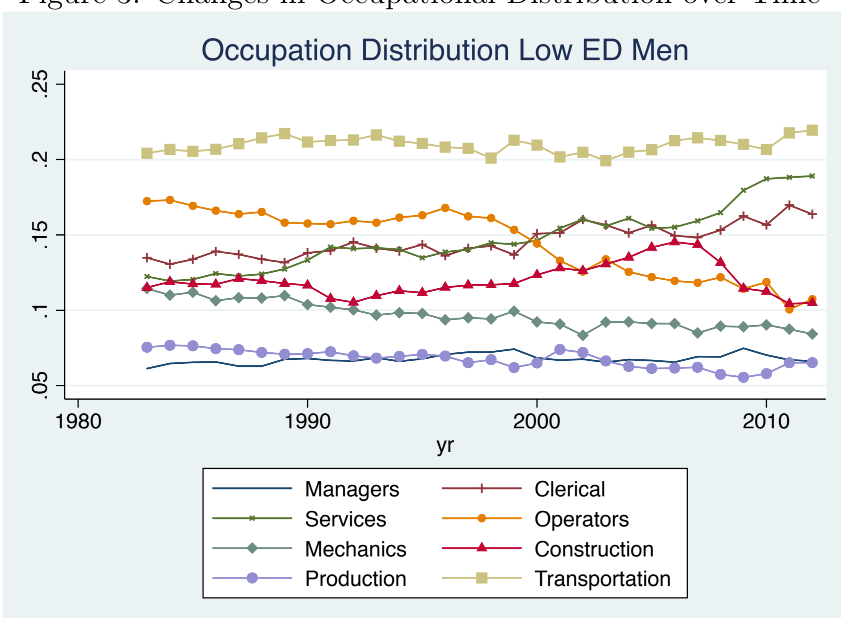
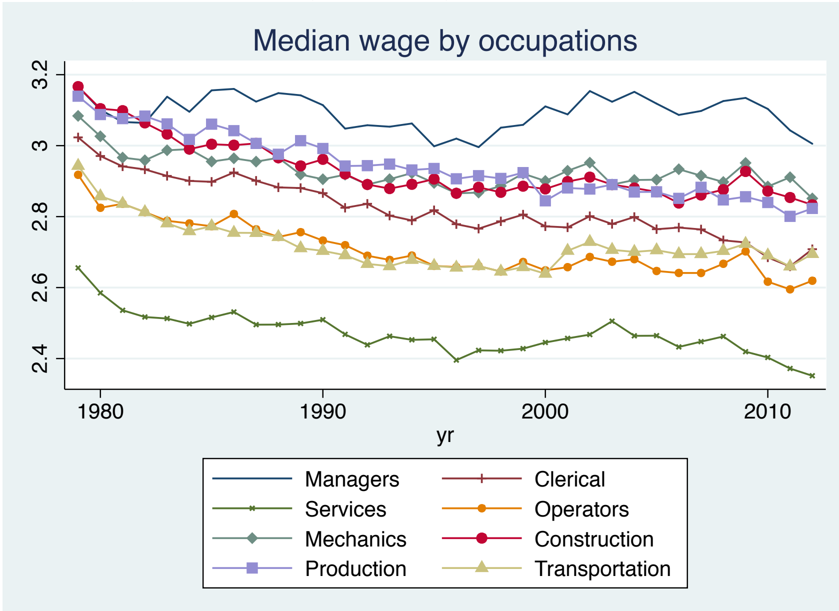


Figure 4: Changes in Wages across occupations



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. 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.

5 Flat Spot Method for Price Series

5.1 Price Series

We first approximate prices by assuming the "flat spot" for individuals who were aged between 40 and 55.[1] We will use the structural model to confirm the quality of the approximation. We approximate the hedonic pricing function f_{tj} defined in Equation 1 with a linear spline (in logs). Let j_i and t_i be the occupation and time period for which we observe person i. Formally, we consider the specification:

$$\log(w_i) = \begin{cases} \delta_{j_i t_i} + \alpha_{1 j_i t_i} \log(h_{i j_i t_i}) & \text{if } h_{i j_i t_i} > h^*_{j_i} \\ \delta_{j_i t_i} + \alpha_{1 j_i t_i} \log(h^*_{j_i}) + \alpha_{2 j t_i} \left(\log(h_{i j_i t_i}) - \log(h^*_{j_i})\right) & \text{otherwise} \end{cases} \tag{2}$$

[1] We explored using narrower age ranges within this range but basic results were similar.

where w_i is the wage of individual i working in occupation j_i at time time t_i. It depends on his skills index $h_{ij_it_i}$ which changes depending on the occupational choice of the individual. All individuals are affected equally by technology changes through the occupation specific constant δ. Yet, depending on the level of his human capital index $h_{ij_it_i}$, an individual sees his skills prices either by α_1 or α_2 depending on whether his index is below (or above) some threshold $h^*_{j_i}$. We set the threshold to the median wage in each occupation in 1979.

We use the ORG CPS to estimate this model by minimum distance to fit five quantiles of the wage distribution, $Q25, Q50, Q75, Q90$, by year, cohort and occupation. The key assumption is that for the age group we see the distribution of h_{ijt} and $h_{ij\tau}$ are the same conditional on a given occupation and a given cohort of workers. For example, we assume the distribution of human capital for 48 year old managers in 1991 is the same as the distribution of human capital for 50 year old managers in 1993.

In practice we normalize $\delta_{jt_0} = 0$ and $\alpha_{1jt_0} = \alpha_{2jt_0} = 1$ for the initial period (1979). To see how the parameters are identified, consider identification of the technology parameters in the second period. From t_0, we can identify that is q^{th} quantile of the human capital for the cohort born in; call this h^q_{j1930}. If we then look at the q^{th} quantile of wages in year t_0+1, it is

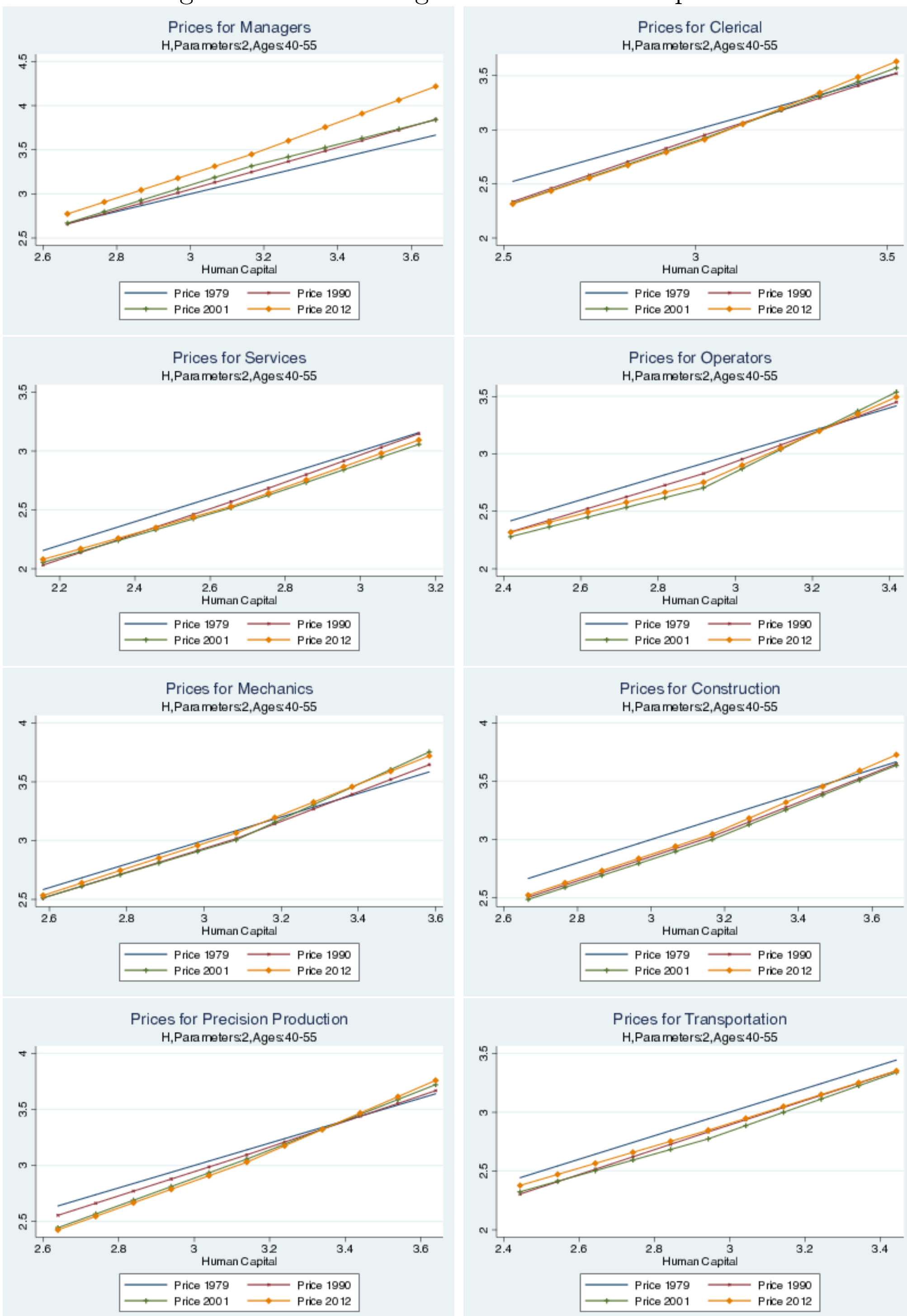
$$\begin{cases} \delta_{j(t_0+1)} + \alpha_{1j(t_0+1)} h^q_{j1930} & \text{if } h^q_{j1930} > h^*_j \\ \delta_{j(t_0+1)} + \alpha_{1j(t_0+1)} h^q_{j1930} + \alpha_{2j(t_0+1)} \left(h^q_{j1930} - h^*_{j_i}\right) & \text{otherwise} \end{cases}$$

With enough of these quantiles and cohorts we can identify the parameters of the pricing equation (as well as the quantiles of human capital for the different cohorts).

The resulting prices that are estimated in this procedure are presented in Figure 5. In each figure we graph the log price profile as a function of $\log(h)$ for four different periods of time. The heterogenous effects of technological changes are apparent. Only managers have been positively affected by technological change throughout their distribution. For them you see an increase in their price at both the median and the top and bottom quantiles.

A different picture emerges when looking a occupations that are intensive in manual skills (high β^m_j occupations). Most of these saw 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 numbers refers to the evolution of the manufacturing sector where

Figure 5: Price Changes in Different Occupations



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 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.

Given prices we can then use the CPS to estimate the distribution of h_{ijt} for all workers (not just those in the flat spot ages). We can do this by inverting Equation 1 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

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

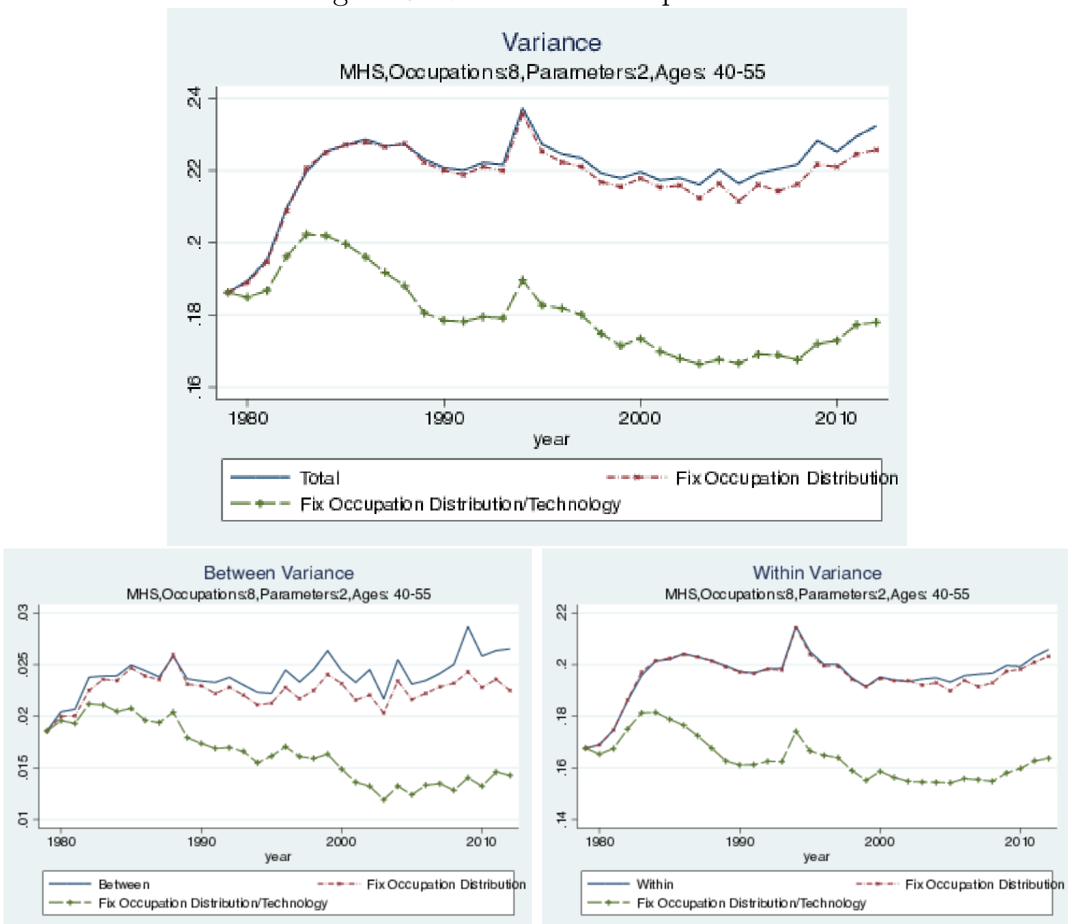
The first three terms are within components. First, individuals switches $[p_{jt} - p_{j\tau}]$ towards high (within) variance occupations $V_{jt}(f_{jt}(h_{ij_it_i}))$ contribute to the rise in the variance. For instance, managerial occupations grew in importance since the 1980s and it is an occupation characterized by a large within variance. Second, the hedonic pricing function has changed over-time within occupations as reflected by $V_{jt}(f_{jt}(h_{ij_it_i})) - V_{jt}(f_{j\tau}(h_{ij_it_i}))$. 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 $V_{jt}(f_{j\tau}(h_{ij_it_i})) - V_{j\tau}(f_{j\tau}(h_{ij_it_i}))$. 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.

Tables 2A-2D and Figure 6 report this decomposition for low education men for different time periods. The main lesson is apparent from Figure 6-most of the increase in the variance of earnings is due to changes in technology. This "Total" line graphs the full variance over

Figure 6: Variance Decomposition



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. Clearly, holding the occupational proportions constant does not substantially alter the pattern, but 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) 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.

Tables 2A-2D provide much more detail. Table 2A covers the full period, 2B 1979-1990, 2C 1990-2000 and 2D 2000-2012. 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. The results are quite different for the different periods. Table 2C is not particularly interesting because there was essentially no change in the variance of log wages for this group (it fell slightly). 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. 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.

Table 2A

Variance Decomposition

Years: 1979-2012

Variance Change: 0.186-0.232

	Occupational Composition		Prices		Skills	
	Within	Between	Within	Between	Within	Between
Total	0.144		1.035		-0.179	
Total	0.056	0.087	0.857	0.178	-0.086	-0.093
Managers	-0.029	-0.030	0.248	0.168	-0.132	-0.048
Clerical	0.069	-0.022	0.227	-0.003	-0.056	0.001
Services	-0.055	0.139	0.011	0.027	0.020	-0.009
Operators/Agricultur	0.034	0.011	0.110	0.018	0.012	-0.018
Mechanics	0.019	-0.004	0.087	0.021	-0.024	-0.001
Construction	-0.000	0.001	0.113	-0.025	-0.006	-0.011
Precision Production	0.021	-0.006	0.124	-0.032	-0.055	0.002
Transportation	-0.003	0.000	-0.063	0.005	0.155	-0.009

Table 2B

Variance Decomposition

Years: 1979-1990

Variance Change: 0.186-0.221

	Occupational Composition		Prices		Skills	
	Within	Between	Within	Between	Within	Between
Total	0.022		1.202		-0.224	
Total	0.008	0.014	1.041	0.162	-0.189	-0.035
Managers	-0.028	-0.029	0.181	0.142	-0.080	-0.016
Clerical	0.022	-0.018	0.193	-0.007	-0.082	0.004
Services	-0.005	0.058	0.107	0.005	-0.025	-0.026
Operators/Agricultur	0.008	0.009	0.184	-0.006	-0.012	0.006
Mechanics	0.002	0.001	0.082	0.013	0.033	-0.005
Construction	-0.004	0.002	0.112	-0.047	-0.047	0.015
Precision Production	0.014	-0.010	0.079	0.021	0.030	-0.011
Transportation	-0.001	0.000	0.103	0.041	-0.005	-0.002

Table 2C

Variance Decomposition

Years: 1990-2000

Variance Change: 0.221-0.220

	Occupational Composition		Prices		Skills	
	Within	Between	Within	Between	Within	Between
Total	-0.982		-2.391		4.374	
Total	-0.429	-0.553	0.532	-2.923	1.745	2.629
Managers	-0.023	-0.027	-0.590	-1.438	0.439	0.849
Clerical	-0.388	0.212	-2.381	-0.111	0.993	0.029
Services	0.236	-0.712	4.566	-0.931	-2.464	0.626
Operators/Agricultur	-0.100	-0.027	-0.603	-0.600	1.316	0.306
Mechanics	-0.007	0.070	-1.766	-0.720	0.442	-0.178
Construction	-0.014	-0.087	-0.032	0.044	-1.176	0.234
Precision Production	-0.092	0.018	-2.537	0.611	2.183	0.661
Transportation	-0.041	-0.000	3.876	0.222	0.012	0.102

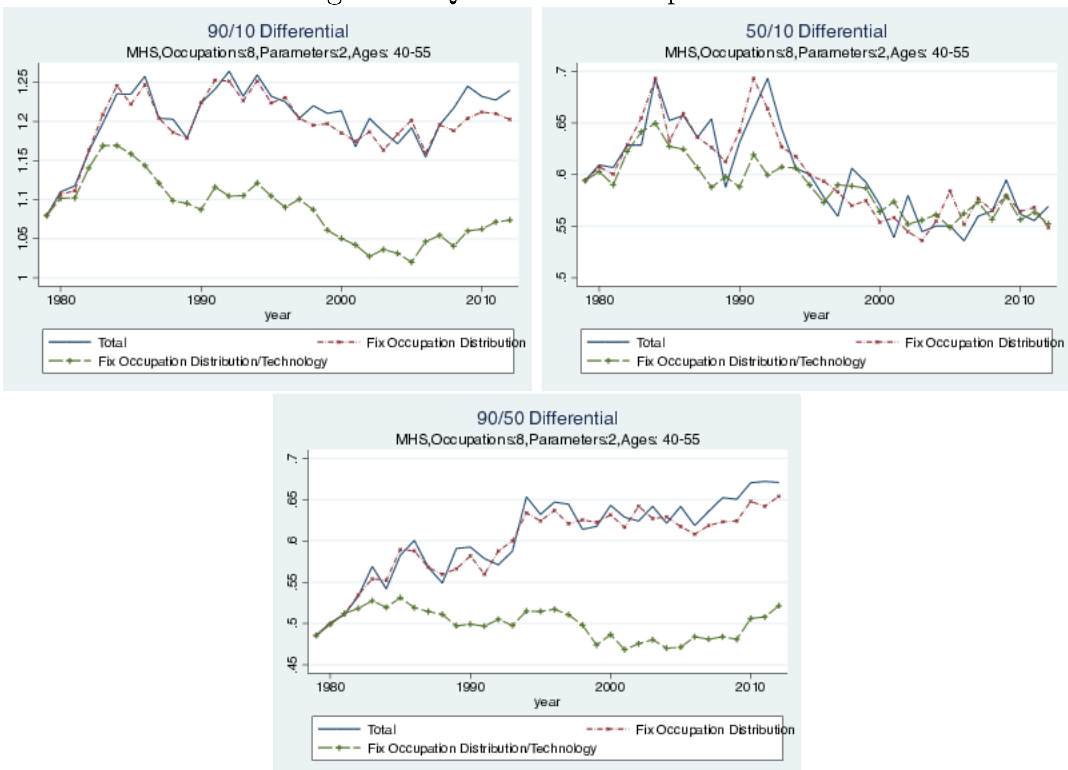
Table 2D
Variance Decomposition
Years: 2000-2012
Variance Change: 0.220-0.232

	Occupational Composition		Prices		Skills	
	Within	Between	Within	Between	Within	Between
Total	0.171		0.669		0.160	
Total	-0.001	0.172	0.365	0.304	0.469	-0.309
Managers	-0.014	-0.015	0.311	0.304	-0.202	-0.270
Clerical	0.053	-0.021	0.205	-0.011	0.118	-0.014
Services	-0.094	0.224	0.048	0.066	-0.001	0.063
Operators/Agricultur	0.046	0.014	-0.209	0.013	0.253	-0.041
Mechanics	0.023	-0.004	-0.002	-0.017	-0.178	-0.007
Construction	-0.007	-0.024	0.145	0.034	-0.017	-0.053
Precision Production	-0.001	-0.002	0.030	-0.069	-0.091	0.071
Transportation	-0.006	0.000	-0.162	-0.017	0.587	-0.059

We perform a similar analysis using quantiles. As is clear from Figure 1, the variance misses differences between what is happening at the top and at the bottom of the wage distribution. The disadvantage of quantiles is that the within and between distinction can not be easily made. We perform these simulations in the same was as for the variance-setting the occupational distribution to the base year and then setting both the occupational distribution and the prices to their initial levels. Figure 7 presents the analogue of Figure 6 for the quantile differences. The decomposition of the 90/10 ratio has a very similar interpretation than the variance decomposition-the dominant factor is the price change. Looking at the 90/50 and 50/10 gives a different picture. The 50/10 declines overall. The rise in the 80s is noisy but was primarily due to price changes and then not much is going on for any of the series afterward. The subsequent decline in the ratio seems primarily due to the composition. By contrast, the 90/50 shows a clear pattern-it rises quite steeply and the main driver is the price differences.

Tables 3A-3L provide a lot more detail. We study 12 different cases: the three different quantile comparisons and the same four time periods we studied for the variance decomposition. We first decompose into the three channels and then provide the more detailed 24 part decomposition. The table is different than the variances as we do not normalize by the

Figure 7: Quantiles Decomposition



total difference, so the numbers add up to the total difference rather than one. In the 80s clearly changes in skill prices drive most of the changes. Occupational composition never seems particularly important, but the distribution of skills plays a more important role in the later periods.

Table 3A

90/10 Quantile Decomposition

Years: 1979-2012

Quantile Change: 1.080-1.240

	Occupational Composition	Prices	Skills
Total	0.037	0.129	-0.006
Managers	0.001	0.043	0.007
Clerical	0.005	0.037	0.012
Services	0.027	0.027	0.028
Operators	-0.002	0.008	0.037
Mechanics	0.003	0.009	-0.021
Construction	-0.001	-0.000	-0.037
Precision Production	0.004	0.021	-0.032
Transportation	0.000	-0.016	0.001

Table 3B

50/10 Quantile Decomposition

Years: 1979-2012

Quantile Change: 0.594-0.569

	Occupational Composition	Prices	Skills
Total	0.020	-0.004	-0.042
Managers	0.001	0.010	-0.011
Clerical	0.005	0.025	0.004
Services	-0.001	0.020	0.028
Operators	0.019	-0.031	-0.005
Mechanics	0.000	0.000	-0.023
Construction	0.000	-0.017	-0.018
Precision Production	-0.004	-0.005	-0.013
Transportation	0.000	-0.004	-0.005

Table 3C

90/50 Quantile Decomposition

Years: 1979-2012

Quantile Change: 0.485-0.671

	Occupational Composition	Prices	Skills
Total	0.017	0.132	0.036
Managers	0.000	0.033	0.017
Clerical	0.000	0.012	0.008
Services	0.028	0.007	0.000
Operators	-0.021	0.040	0.041
Mechanics	0.003	0.009	0.002
Construction	-0.001	0.017	-0.019
Precision Production	0.008	0.026	-0.019
Transportation	0.000	-0.011	0.005

Table 3D

90/10 Quantile Decomposition

Years: 1979-1990

Quantile Change: 1.080-1.224

	Occupational Composition	Prices	Skills
Total	0.000	0.137	0.007
Managers	0.000	0.014	-0.004
Clerical	0.000	0.027	-0.012
Services	-0.007	0.017	0.027
Operators	0.007	0.039	0.031
Mechanics	0.000	0.019	0.004
Construction	0.000	-0.009	-0.027
Precision Production	0.000	0.016	0.000
Transportation	0.000	0.013	-0.011

Table 3E
50/10 Quantile Decomposition
Years: 1979-1990
Quantile Change: 0.594-0.631

	Occupational Composition	Prices	Skills
Total	-0.011	0.054	-0.006
Managers	0.000	0.008	0.012
Clerical	0.000	0.008	-0.036
Services	-0.013	0.008	0.021
Operators	0.013	0.014	0.020
Mechanics	-0.001	0.019	0.004
Construction	0.001	0.002	-0.009
Precision Production	-0.011	0.014	0.002
Transportation	0.000	-0.019	-0.019

Table 3F
90/50 Quantile Decomposition
Years: 1979-1990
Quantile Change: 0.485-0.593

	Occupational Composition	Prices	Skills
Total	0.011	0.083	0.014
Managers	0.000	0.006	-0.015
Clerical	0.000	0.018	0.024
Services	0.006	0.010	0.006
Operators	-0.006	0.026	0.011
Mechanics	0.001	0.000	0.000
Construction	-0.001	-0.011	-0.018
Precision Production	0.011	0.002	-0.002
Transportation	0.000	0.032	0.008

Table 3G
90/10 Quantile Decomposition
Years: 1990-2000
Quantile Change: 1.224-1.214

	Occupational Composition	Prices	Skills
Total	0.012	0.029	-0.051
Managers	0.001	0.011	-0.016
Clerical	-0.002	0.006	-0.004
Services	0.010	-0.006	0.000
Operators	0.004	0.009	-0.003
Mechanics	-0.004	0.011	-0.004
Construction	0.005	-0.004	0.000
Precision Production	-0.001	0.015	-0.013
Transportation	0.000	-0.014	-0.011

Table 3H
50/10 Quantile Decomposition
Years: 1990-2000
Quantile Change: 0.631-0.571

	Occupational Composition	Prices	Skills
Total	0.010	-0.042	-0.029
Managers	-0.000	0.006	-0.003
Clerical	-0.003	-0.004	-0.006
Services	0.013	-0.009	-0.006
Operators	0.002	-0.014	0.007
Mechanics	-0.002	-0.000	0.000
Construction	0.002	-0.000	-0.004
Precision Production	-0.002	0.004	-0.006
Transportation	0.000	-0.024	-0.012

Table 3I

90/50 Quantile Decomposition

Years: 1990-2000

Quantile Change: 0.593-0.643

	Occupational Composition	Prices	Skills
Total	0.002	0.070	-0.022
Managers	0.001	0.005	-0.013
Clerical	0.000	0.010	0.002
Services	-0.004	0.003	0.006
Operators	0.003	0.023	-0.011
Mechanics	-0.002	0.011	-0.004
Construction	0.004	-0.004	0.004
Precision Production	0.001	0.012	-0.007
Transportation	0.000	0.011	0.001

Table 3J

90/10 Quantile Decomposition

Years: 2000-2012

Quantile Change: 1.214-1.240

	Occupational Composition	Prices	Skills
Total	0.018	0.003	0.005
Managers	0.000	0.010	-0.020
Clerical	0.000	0.006	-0.010
Services	0.018	-0.002	0.029
Operators	-0.005	-0.007	0.007
Mechanics	0.002	0.003	-0.020
Construction	0.003	0.009	0.001
Precision Production	0.000	0.000	-0.003
Transportation	0.000	-0.016	0.020

Table 3K

50/10 Quantile Decomposition

Years: 2000-2012

Quantile Change: 0.571-0.569

	Occupational Composition	Prices	Skills
Total	0.001	0.020	-0.023
Managers	0.000	0.004	-0.009
Clerical	0.000	0.000	-0.013
Services	-0.005	-0.007	0.017
Operators	0.006	-0.000	-0.011
Mechanics	0.000	0.002	-0.004
Construction	-0.001	0.014	-0.011
Precision Production	0.000	-0.001	0.004
Transportation	0.000	0.008	0.004

Table 3L

90/50 Quantile Decomposition

Years: 2000-2012

Quantile Change: 0.643-0.671

	Occupational Composition	Prices	Skills
Total	0.017	-0.017	0.028
Managers	0.000	0.006	-0.011
Clerical	0.000	0.006	0.004
Services	0.022	0.004	0.012
Operators	-0.011	-0.007	0.018
Mechanics	0.002	0.002	-0.016
Construction	0.004	-0.005	0.012
Precision Production	0.000	0.001	-0.008
Transportation	0.000	-0.025	0.016

6 A Structural Model

Notation We will use the i subscript to denote an individual and t to index time. We let j_{it} denote the occupation that individual i has 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 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 evolution of aggregate variables. Finally, we allow for discrete types indexed by $k \in \{1, \dots, K\}$ that differ in their initial skills endowment and their valuation of the non-pecuniary benefits of working in different occupations.

If an individual decides to move to a different occupation in any given period, we assume he manages to obtain an offer with probability λ_j. He can always choose to stay in his current occupation or choose to not-work.

Let Λ be the vector of structural parameters. To save on notation, the dependence on Λ is left implicit.

Utilities We write the flow utilities for each occupation as

$$U\left(j, \mathcal{S}_{it}, \nu_{it}\right) = w(j, \mathcal{S}_{it}) + c_{jk} + \left(f_{0j} + f_{aj} a_{it}\right) 1\left(j = j_{it-1}\right) + \nu_{it}(j),$$

where $w(j, \mathcal{S}_{it})$ is logged wages in occupation j, The $f_{0j} + f_{aj}a_{it}$ reflects occupational choice persistence. We allow the utility cost of switching to depend 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.

Individuals permanently differ in their preferences for different occupations. Each type has distinct preferences for working in different occupations c_{jk} which decompose as

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

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.[2] We normalize $c_{0k} = 0, k \in \{1, \ldots, K\}$. Log wages are:

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

where f_{jt} is an hedonic pricing equation. In practice, we simplify by using a piecewise linear approximation to f_{jt}. The value of non-employment is normalized to zero. α_{j0} is normalized to one in the occupation $\tilde{j}$: $\alpha_{\tilde{j}0} = 1$.

$\nu_{it} = \{\nu_{it}(0), ..., \nu_{it}(J)\}$ is a vector of i.i.d extremely value distributed preference shocks with CDF G_ν,

$$G_\nu(\nu) = \exp\left\{-\exp\left(-\frac{\nu}{\sigma_\nu}\right)\right\}$$

Each component has a mean equal to $\sigma_\nu\gamma$ where γ is Euler's constant and a variance equal to $\frac{\pi^2\sigma_\nu^2}{6}$.

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

$$\tilde{\theta}_i \sim N\left(\mu^\theta_{ck}, \Sigma^\theta\right)$$

We allow for cohort effects, to account for selection on schooling before 1957. After 1957, we assume no cohort effects, since schooling has been roughly constant. Formally,

$$\mu^\theta_{ck} = \mu^1_c + \mu^2_k$$

State variables evolve according to,

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

[2] 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.

with $\text{tenure}_{j0} = 0$. Tenure is reset to zero $\tau_{it} = 0$ if you switch to a different occupation or if you are not-working. Potential experience is define as $e_{it} = a_{it} - 18$. We summarize the evolution of the vector of state variables as

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

Wage growth depends on the evolution of the hedonic pricing function f_{jt} and the evolution of the human capital index. For stayers, the latter is,

$$\left(d_{0j_{it}} \sum_{l=1}^{L} d_{1l} \left(\beta^l_{j_{it}}\right)^{\nu_l} \exp\left(-\left(d_{2l} + d_{3j_{it}}\right) e_{it}\right) + \gamma_{0j} \exp\left(-\gamma_{1j}\tau_{it}\right)\right) - \sum_{l=1}^{L} \beta^l_{j_{it}} d_{4l} \Delta\theta^l_{it}$$

It is the product of two different forces. First, 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 $\exp\left(-\left(d_{2l} + d_{3j_{it}}\right) e_{it}\right)$. We also allow for some skills depreciation $\sum_{l=1}^{L} \beta^l_{j_{it}} d_{4l} \Delta\theta^l_{it}$. Second, stayers get additional occupation-specific tenure through $\gamma_{0j} \exp\left(-\gamma_{1j} e_{it}\right)$ while switchers optimally decide to forgo this component by choosing $j_{it} \neq j_{it-1}$. These two forces are added into a human capital index whose level gets priced differently over time.

Dynamic Programming Every period t, the agent chooses an occupation according to the rule

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

where $v_{it}\left(j, \mathcal{S}_{it}\right)$ is the occupation-specific value function. If his optimal decision is $\tilde{j} \notin \left\{0, j_{it-1}\right\}$, he receives an offer from a firm in that occupation with probability $\lambda_{\tilde{j}}$. Otherwise, he has to stay in his current occupation for one more period (at least). Formally,

$$v_{it}\left(\tilde{j}, \mathcal{S}_{it}\right) = \lambda_{\tilde{j}} v^{\text{switch}}_{it}\left(\tilde{j}, \mathcal{S}_{it}\right) + \left(1 - \lambda_{\tilde{j}}\right) v^{\text{stay}}_{it}\left(\mathcal{S}_{it}\right)$$

with

$$\begin{aligned} v^{\text{stay}}_{it}\left(\mathcal{S}_{it}\right) &= w\left(j_{it-1}, \mathcal{S}_{it}\right) + \left(f_{0j} + f_{aj} a_{it}\right) + c_{jk} + \frac{1}{1+r} \bar{v}_{it+1}\left(F\left(j_{it-1}, \mathcal{S}_{it}\right)\right) \\ v^{\text{switch}}_{it}\left(j, \mathcal{S}_{it}\right) &= w\left(j, \mathcal{S}_{it}\right) + c_{jk} + \frac{1}{1+r} \bar{v}_{it+1}\left(F\left(j, \mathcal{S}_{it}\right)\right) \end{aligned}$$

and where $\bar{v}_{it+1}(F(j,\mathcal{S}_{it}))$ is the expected continuation value if the agent chooses alternative j today. Every period t, it can be written as

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

7 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.[3] 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,

$$\hat{\Lambda} = \arg\min_\beta \left(\hat{\Psi} - \Psi(\Lambda)\right)' W \left(\hat{\Psi} - \Psi(\Lambda)\right) \tag{4}$$

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.

Data The NLSY79 dataset can be summarized as $\left\{s_i, j^*_{it}, w^*_{it}, e^*_{it}, \tau^*_{it} : i = 1,\ldots,N; t = \tilde{t}_i,\ldots,T_i\right\}$, where s_i denotes reported education, j^*_{it} denotes reported occupation, w^*_{it} reported wages, and $\tilde{t}_i$ and T_i are years where each individual, respectively, enters and exit the dataset. Using the work history, we construct measures of work experience e^*_{it} and occupation-specific experience τ^*_{it}. We assume schooling is measured without error but both reported wages and occupations are contaminated by measurement errors.

Using the MORG CPS, we observe repeated cross-section of individuals wages and occupation on an annual basis from 1979 to 2012. We start from cohort that left or graduate from high school no latter than 1915 and we end with cohorts that left or graduate from high school no earlier than 2012.

Measurement Errors Measured logged wage w^*_{it} is the sum of true logged wages w_{it} and a measurement error term u_{it},

$$w^*_{it} = w_{it} + u_{it}$$

where u_{it} is classical and normal measurement error with standard deviation σ_u.

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

Let $\pi_t(j_0, j_1)$ be the probability that occupation j_0 is reported given that the true occupation is j_1 at time t.

$$\pi_t(j_0, j_1) = \Pr(j_{it}^* = j_0 \,|j_{it} = j_1), \qquad j_0, j_1 = 0, \ldots, J$$

In principle that is $T \times (J \times J - J)$ additional parameters to be estimated. We follow Keane and Wolpin (2001) and assume that classification errors are unbiased. The probability that a person is observed in an occupation is equal to the true probability that he/she chooses that occupation or

$$\Pr(j_{it}^* = j) = \Pr(j_{it} = j), \qquad j = 0, \ldots, J$$

The $\pi_t(j_0, j_0)$ are known up to one parameter E.

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

Pre-estimated parameters Some parameters are not estimated and are set outside the model $\left(\beta_j^l, E, r\right)$. We estimated β_j^l using O'NET as explained in Section 3. The real interest rate is set to 5%. E is set using "spurious" transitions in the NLSY following Neal (1999) and Kambourov and Manovskii (2009). 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. We estimate that about 10% of occupational shifts are "spurious" transitions.

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

$\Lambda_1 = \left(\bar{c}_j, \tilde{c}_{lk}, \mu_{lk}, \sigma_w, \sigma_{\nu a}, E, \Sigma, f_w, f_0, f_1, \delta_j^0, \alpha_j^{01}, \alpha_j^{02}, \lambda_j^0\right)$ contains the preferences and technology parameters with $\bar{c}_j$ compensating differentials, $\tilde{c}_{lk}$ unobserved preferences for skills, μ_{lk} unobserved endowment, σ_w measurement error in wages, $\sigma_{\nu a}$ preference shock, E baseline classification rate, Σ variance covariance matrix, f_w, f_0, f_1 utility of staying, δ_j^0, α_j^0 initial prices and λ_0 initial occupation offer J. $\Lambda_2 = (d_{0j}, d_{1l}, \nu_l, d_{2l}, d_{3j}, d_{4l}, \gamma_{0j}, \gamma_{1j})$ 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. Finally, $\Lambda_4 = (\lambda_{jt})$ 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.
- (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

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.

m_3 contains all the moments used to identify movement in prices. These are the moments we used when applying the Flat-Spot method. Finally, m_4 is based on the CPS. It is the proportion of individuals choosing each of the $J+1$ occupations by year.

Algorithm Details It is in principle possible to estimate the full vector of parameters Λ at once. The objective function may be discontinuous. Small variations in the parameters may lead some individuals to switch occupations. Then there could not exist any variations in the parameters that leads to small changes in the objective function. We would need to use a global optimization procedure which is computationally prohibitive given the large number of parameters. We instead use a sequential algorithm where each steps selects a subset of 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 $m_1\left(\Lambda_1, \Lambda_2^{-1}, \Lambda_3^{-1}, \Lambda_4^{-1} \middle| \mathcal{J}\left(\Lambda_1, \Lambda_2^{-1}, \Lambda_3^{-1}, \Lambda_4^{-1}\right)\right)$
2. Choose Λ_2 to fit $m_2\left(\Lambda_1, \Lambda_2, \Lambda_3^{-1}, \Lambda_4^{-1} \middle| \mathcal{J}\left(\Lambda_1, \Lambda_2^{-1}, \Lambda_3^{-1}, \Lambda_4^{-1}\right)\right)$
3. Choose Λ_3 to fit $m_3\left(\Lambda_1, \Lambda_2, \Lambda_3^{-1}, \Lambda_4^{-1} \middle| \mathcal{J}\left(\Lambda_1, \Lambda_2, \Lambda_3^{-1}, \Lambda_4^{-1}\right)\right)$
4. Choose Λ_4 to fit $m_4\left(\Lambda_1, \Lambda_2, \Lambda_3, \Lambda_4 \middle| \mathcal{J}\left(\Lambda_1, \Lambda_2, \Lambda_3, \Lambda_4^{-1}\right)\right)$

We use Random-Search for Step 1 and Step 4 and we use Newton-Raphson for Step 2 and Step 3.

8 Results (preliminary)

8.1 Parameter Estimates

We present the parameters estimates at the current stage of the algorithm. Table 1, Table 2 and Figure 8.

Table 1 reports occupation specific parameters that are identified using the NLSY79. Some parameters are normalized. Compensating differentials are estimated relative to the option of not-working which is normalized to zero. The slope of the function in clerical occupation below the median is normalized to one. Finally, the utility of staying in the same occupation is restricted to be the same across all occupations but is different when an individual is not working. There exists a wide dispersion in compensating differentials, the availability of jobs and the wage schedule across each occupation. Managerial occupations both have the lowest compensating differential and the lowest availability of jobs. Further the constant of the wage function is the more negative. It explains why this is a small occupation that attracts only the more talented individuals late in their life-cycle. By contrast, services

Table 1: Occupation Static Parameters

Occupation	Comp. diff.	Offer prob.	Cons. wage	Slope1 wage	Slope2 wage	Stayer utility
1	-141.55	0.30	-4.35	0.81	0.71	49.27
2	-70.31	0.45	-1.78	1.00*	0.85	49.27*
3	-52.91	0.69	-2.46	0.92	1.13	49.27*
4	-50.21	0.28	-2.22	1.21	0.85	49.27*
5	-62.89	0.26	-1.85	0.77	0.76	49.27*
6	-58.24	0.35	-0.79	0.49	0.53	49.27*
7	-73.12	0.18	-0.33	0.64	0.58	49.27*
8	-43.42	0.70	-3.08	1.34	1.02	49.27*
9	0.00*	1.00*	0.00*	0.00*	0.00*	58.33

Note: The asterisk (*) indicates normalized parameters

Table 2: Heterogeneity

I. Comp. diff

	Group 1	Group 2	Group 3	Group 4
Cognitive	0.00*	-3.15	-16.95	-24.17
Inter-pers.	0.00*	12.95	-22.94	4.90
Manual	0.00*	-24.57	3.92	7.85

II. Skills Endowment

Average				
Cognitive	0.00*	-0.0023	-0.0054	-0.0031
Inter-pers.	0.00*	0.0019	-0.0078	-0.0027
Manual	0.00*	-0.0102	-0.0070	0.0011

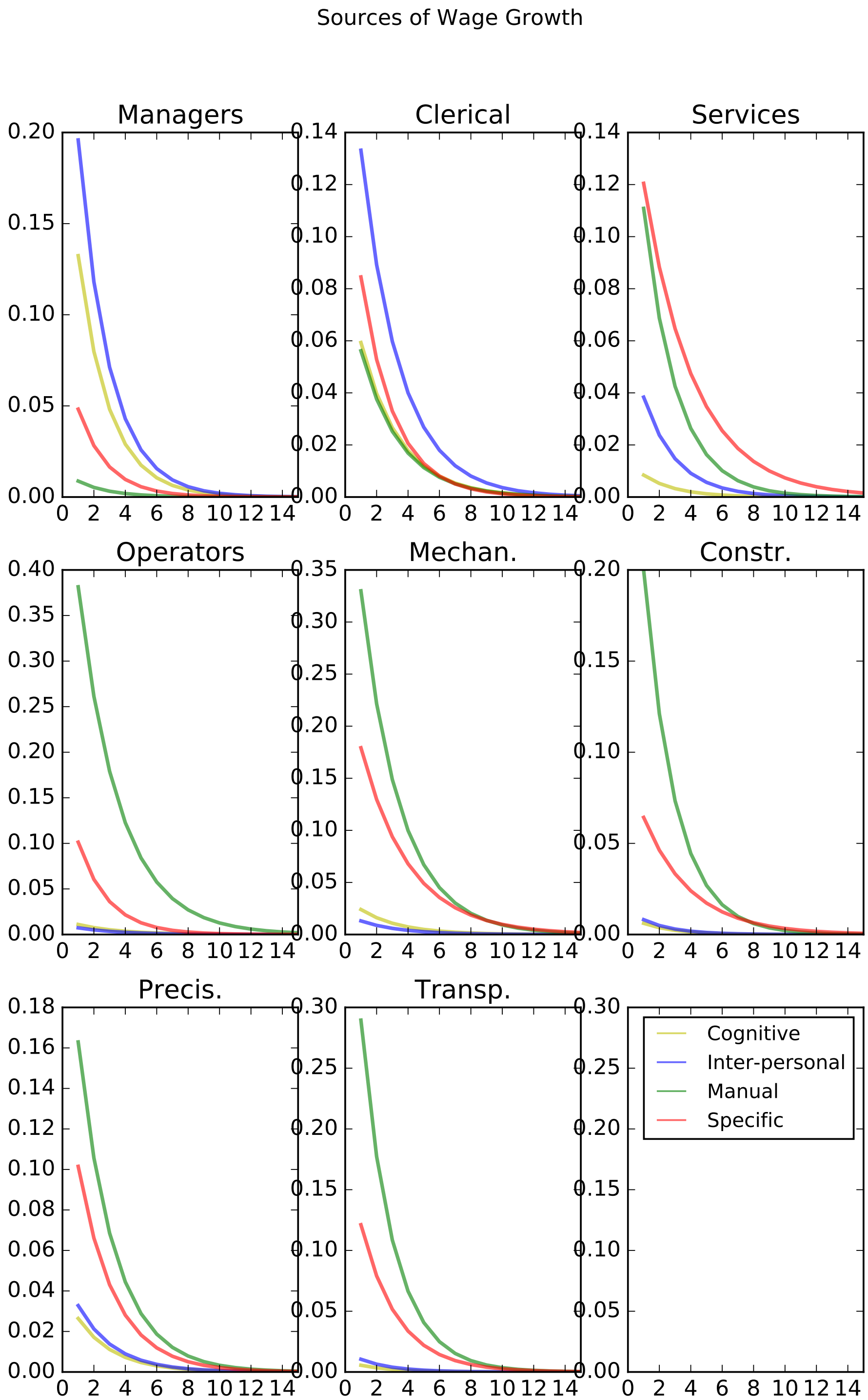
Std. deviation		Correlation		
Cognitive	0.0059	Cognitive	Inter-pers	-0.0236
Inter-pers.	0.0054	Cognitive	Manual	-0.0140
Manual	0.0049	Inter-pers	Manual	0.0751

III. Shocks

σ_ν	σ_w	E
194.26	0.12	0.79

Note: The asterisk (*) indicates normalized parameters

Figure 8: Sources of wage growth



and transportation have both a high availability of jobs with job offer over 2/3. Construction has the highest constant suggesting it will be picked by individuals with lower skills.

Table 2 reports heterogeneity across individuals in terms of preferences, skills endowment and luck. We allow for four discrete types $K = 4$ with equal probability. Group 1 is the reference group. Group 2 likes using his inter-personal skills and his endowment is a higher than average in personal skills but below average in manual. Group 3 values cognitive and inter-personal occupation less and has a lower endowment in all three skills. Group 4 is characterized by a higher endowment in manual skills and a higher than average preference for manual occupations. There exist about equal dispersion in each type of skills in the population. Further, cognitive skills endowment are negatively related to both inter-personal and manual skills. Manual skills and interpersonal skills are positively related.

Figure 8 displays wage growth for stayers by general labor market experience and occupation-specific tenure. Interpersonal and cognitive skills are the main source of wage growth for manager and clerical. They play a fairly minor for the other six occupations where individual wage growth depend on combination of manual skills and occupation-specific skills. Occupation specific skills plays a relatively more important role in the service occupations.

8.2 Model Fit

The model does a reasonable job at fitting moments in the NLSY79. We relegate the figures to the Appendix as both the economics and the data have been discussed since Keane and Wolpin (1997). The main challenge for our model is to fit the evolution of employment and wages share in the ORG CPS. We saw in the descriptive part of the paper that employment and wages are sometimes evolving in opposite direction in some occupation which is difficult to rationalize within a competitive model. Figure 9 and Figure 10 report respectively, the evolution of median wages by occupation and 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 lines are splines fitted decade by decade both in the model and the data.

Figure 9: Evolution of median wages by year

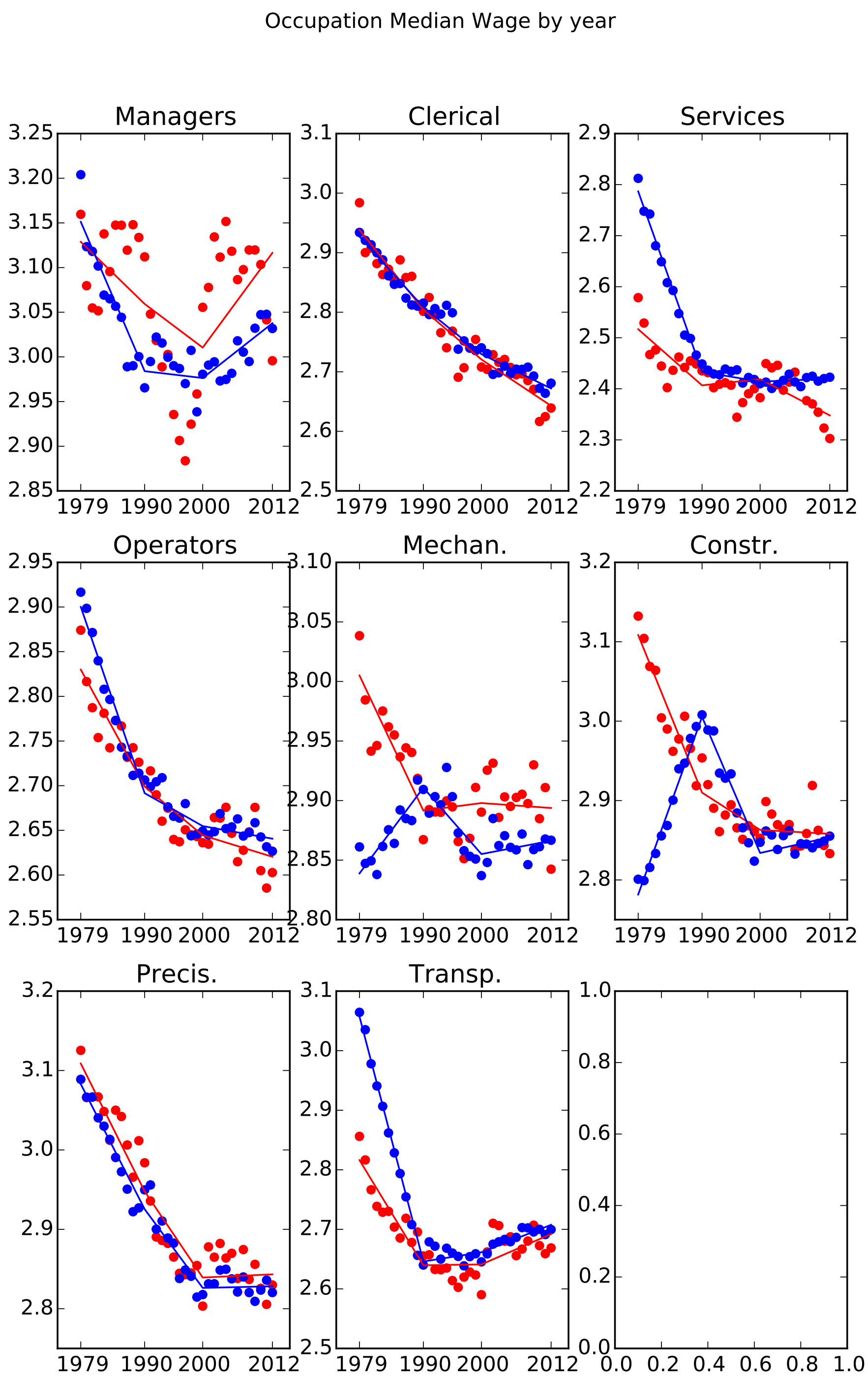
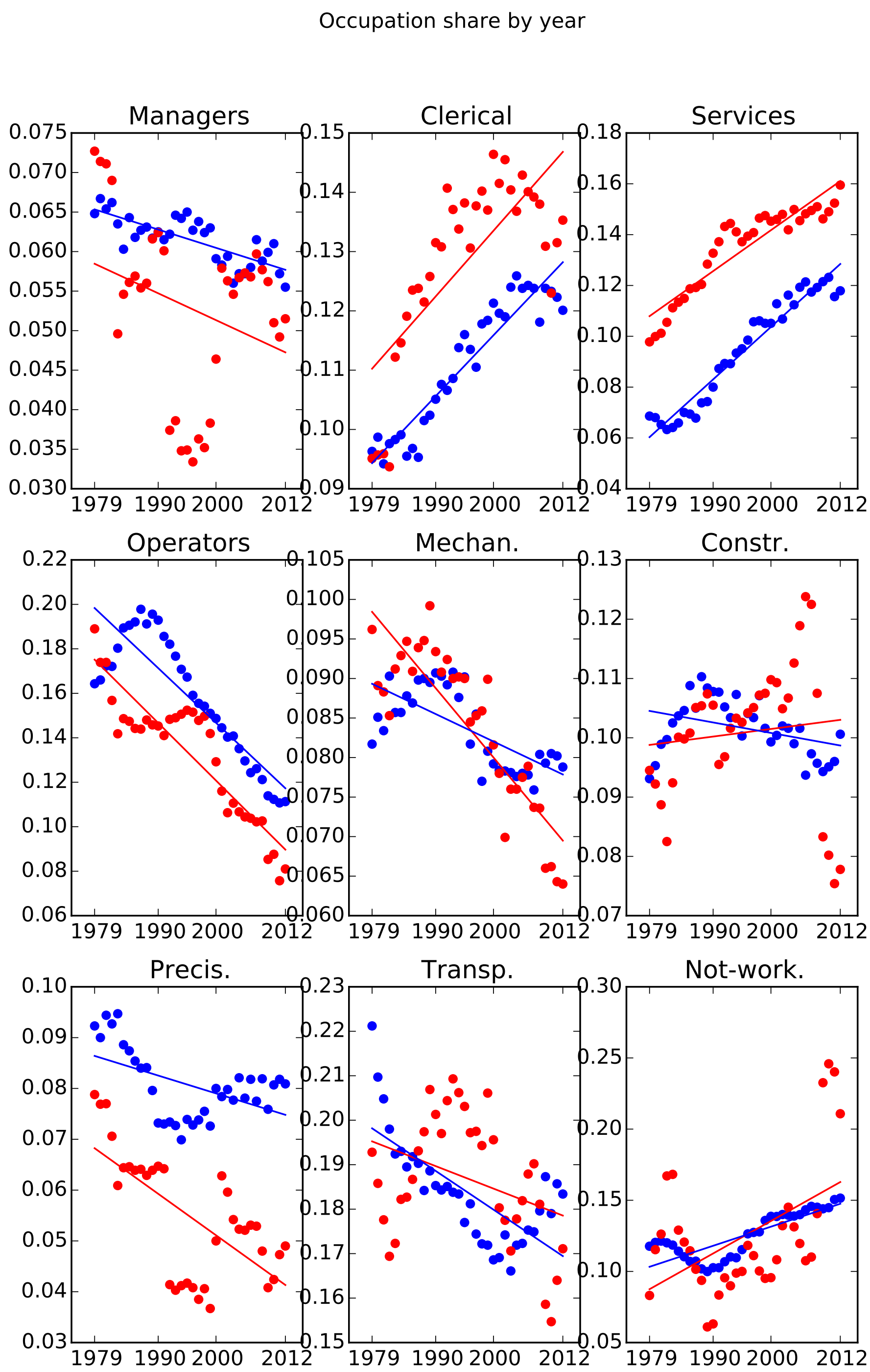


Figure 10: Evolution of occupation share by year



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