The Impact of Body Weight on Occupational Mobility and Career Development

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Abstract

This paper examines the relationship between individuals' weight and their employment decisions over the life cycle. I estimate a dynamic stochastic model of individuals' annual joint decisions of occupation, hours worked, and schooling. The model allows body weight to affect non-monetary costs, switching costs, and distribution of wages for each occupation; and also allows individuals' employment decisions to affect body weight. I use conditional density estimation to formulate the distributions of wages and body weight evolution. I find that heavier individuals face higher switching costs when transitioning into white collar occupations, earn lower returns to experience in white-collar occupations, and earn lower wages in socially intensive jobs. Simulating the model with estimated parameters, decreased occupational mobility accounts for 10 percent of the obesity wage gap. While contemporaneous wage penalties for body weight are small, the cost over the life cycle is substantial. An exogenous increase in initial body mass by 20 percent leads to a 10 percent decrease in wages over the life course.

Keywords: Labor, occupational choice, obesity, dynamic discrete choice, productivity, switching costs

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1 Introduction

How does body weight affect employment behavior and wages over the life cycle? We know obesity yields high costs in the workplace.[1] In addition to the oft cited health care costs, estimates place annual workplace productivity costs of obesity between $12 and $30 billion. While obese workers miss 15 to 50 percent more work time than the healthy weight, two-thirds of these productivity costs are due to decreased at-work performance. Reduced productivity not only affects contemporaneous wages and employment decisions, but also decreases subsequent pay increases and employment opportunities (Holmstrom, 1999). Body weight today therefore affects expected future wages and labor market opportunities.

The workplace costs of high body weight are inherently dynamic and vary by occupation. Studies have shown obesity leads to difficulty managing professional interpersonal relationships and reduces stamina when performing physical tasks.[2] While lower productivity affects wages, difficulties with certain job requirements may yield additional non-monetary costs and therefore influence occupational choices. An individual's body weight may also provide a signal about that individual's self-discipline or work ethic, the value of which may differ between occupations. Such a negative signal would lead to decreased occupational mobility for individuals of higher body weight.[3] Occupational differences in the costs of high body weight provide additional motivation for modeling these costs as a part of forward-looking individuals' employment decisions. When an individual chooses an occupation, he accrues human capital that is not perfectly transferable to other occupations (Kambourov and Manovskii, 2009). Thus, contemporaneous occupational choice affects both expected future wages and future occupational decisions. Finally, an individual's body weight is itself dynamic, and maybe affected by one's choice of occupation and hours.

[1]See, for example Ricci and Chee (2005), and Andryeva (2014)

[2]See Pronk et al. (2004); Johar and Katayama (2012); Hamermesh and Biddle (1994); DeBeaumont (2009); Han et al. (2009)

[3]Anecdotally, a hospital in suburban Houston, Texas recently instituted an explicit ban on the hiring of employees who were at least moderately obese.

Despite the inherent dynamic relationship between body weight and employment outcomes, the existing literature on the subject has largely relied on static approaches and abstracted from either occupational choice or wages.[4] I formulate and estimate a dynamic discrete choice model where body weight affects both the distribution of wage offers and non-monetary costs of each employment alternative; and employment decisions subsequently affect weight.[5] Both the model and method follow in the dynamic discrete occupational choice literature (Keane and Wolpin, 1997; Altug and Miller, 1998; Lee, 2005; Lee and Wolpin, 2006; Flabbi, 2010; Sullivan, 2010; Gayle and Golan, 2012; Eckstein and Lifshitz, 2011; Yamaguchi, 2013; Baird, 2014). I construct indices of the intensity of mental, physical and social job requirements for each occupation to determine how the monetary and non-monetary costs of body weight in the workplace vary with these requirements.

I estimate the parameters governing the individuals' decision making process using data from the National Longitudinal Survey of Youth, 1979 cohort. The model is solved in a finite-horizon setting, using backwards recursion, value function interpolation and maximum likelihood estimation (Keane and Wolpin, 1994; Mroz and Weir, 2003). Consistent with earlier work, I do not find large, direct wage contemporaneous penalties for high body weight (Cawley, 2004). I do find that high body weight presents significant barriers to occupational mobility and inhibits career development over the life cycle. Results indicate that one weight class (35 pounds on a 6-foot male), leads to an additional \$6,500 in switching costs when transitioning into professional and managerial occupations. These switching costs account for 25 percent of the occupational attainment gap between obese and non-obese workers. By affecting early career occupational choices, these costs lead to differences in human capital and subsequent wages. High body weight impedes career development in other ways as well. Individuals of high body weight are also found to earn lower returns to experience in white

[4] Section 2 reviews papers that examine body weight and wages, or occupational choice and body weight, or occupational choice and wages.

[5] The purpose of this paper is not to investigate the effects of employment decisions on weight, but rather the opposite. The model permits employment decisions to affect body weight, but through a feedback mechanism rather than modeling change in body weight as a choice.

collar occupations, and face lower wages and higher non-monetary costs in socially intensive jobs. The non-monetary costs (including switching costs) of employment are not recoverable without modeling the individual's forward looking employment decision.

I use semi-parametric methods to estimate the full distribution of wages (conditional on body weight, experience, education, job requirements, etc.) inside the model. Individuals of high body weight are much less likely to be observed in the upper quantiles of the distribution of wages. All wage differentials for high body weight, including lower returns to white-collar experience, education, and lower wages in socially intensive jobs, stem from the reduced probability of receiving wage offers from the upper quartile of the wage distribution. The combination of these results indicates that body weight is a significant impediment to career progress in white collar occupations.

Using the estimated parameters of the model, I simulate the dynamic effects of a considerable (5 BMI points) exogenous weight reduction on a 35 year-old individual. While instantaneous effects are small (wages increase by 4 percent) the dynamic effects are substantial. Relative to the baseline, the 45 year old individual who experienced an exogenous shock at age 35 is nearly 5 percent more likely to be in a managerial occupation, 10 percent more likely to attain work in a sales or administrative occupation, and the individual's overall expected wage increases by 10 percent.

In summary, I find that while contemporaneous aggregate wage penalties for body weight are small, that high body weight nevertheless presents significant costs to workers. Over the life cycle, high body weight decreases occupational mobility, decreases wages, increases non-monetary costs in socially intensive jobs, and particularly decreases the probability of receiving wage offers in the upper quantiles of the distribution of wages.

This paper proceeds as follows. Section 2 provides a brief motivation and background on the relationships between body weight and employment outcomes. Section 3 describes the relevant data: the National Longitudinal Study of Youth, 1979 cohort, the Dictionary of Occupational Titles (DOT), O*NET and the ACCRA cost of living index. Section 4 details the dynamic model. Section 5 discusses identification and the empirical implementation of the theoretical model. Section 6 contains the parameter results and discusses how the model predicts the variation of interest in the data. Section 7 contains the counterfactual simulations using the estimated parameters of the model, and Section 8 concludes with a brief discussion.

2 Relevant Literature

This paper contributes to a few different subsets of the literature. Specifically, I contribute to the literature on dynamic models of forward looking individuals' occupational decisions as cited above. Within that literature, this is first paper to examine differences in earnings and occupational attainment on the basis of body weight in a dynamic discrete occupational choice framework. In so doing, this paper extends the literature on body weight and labor market outcomes. Most prior work in that literature has focused on the effects of individuals' weights on their wages, utilized static methods, and abstracted from modeling occupational choice (Cawley, 2004; Pagan and Davila, 1997; Johar and Katayama, 2012; Hamermesh and Biddle, 1994; Han et al., 2009).[6] Dynamic models of differences in occupational choice and wage differences have more often been utilized in examining the gender wage gap (e.g., Altug and Miller (1998); Gayle and Golan (2012); Eckstein and Lifshitz (2011); Flabbi (2010); Yamaguchi (2013)) and black-white wage gap (e.g., Keane and Wolpin (2000); Bowlus and Eckstein (2002); Lehmann (2013)).

This paper also contributes to a growing literature where job requirements are incorporated into dynamic models as a determinant of occupational choice (Sanders, 2010; Yamaguchi, 2012). In permitting contemporaneous employment decisions to affect future body weight, I also contribute to the literature on how one's employment behavior affects

[6]Notable exceptions to the lack of dynamic modeling include Gilleskie, Norton, and Han (2011) and Tosini (2008), but neither study models occupational choice.

one's health (King et al., 2001; Lakdawalla and Philipson, 2002; Kelly et al., 2011; Courtemanche, 2009; Ravesteijn et al., 2014).

Additionally, this paper incorporates prospective wage differentials into a single-agent occupational choice framework. Theoretically, the model seeks to merge Mincer (1958), Ben-Porath (1967), and Becker (1957). Prior dynamic models in this area have have typically used a general equilibrium approach and focused on search rather than occupational choice to better identify discrimination. The structure of this model closely resembles Keane and Wolpin (1997) and Sullivan (2010), focusing on how current and expected future monetary and non-monetary costs affects individuals' decisions over the life cycle. As Coate and Loury (1993) show, anticipated wage differentials can affect the formation of human capital, which affects subsequent wages. In this model, weight-related wage differentials are incorporated into the individual's dynamic optimization problem. Forward-looking agents choose occupations and amount of labor to supply mindful of expected future wages, returns to experience, and switching costs, all of which vary by body weight.

There is also a small methodological contribution to the literature on dynamic models of occupational choice regarding the distribution of unobserved wages. Often when integrating over missing prices or wages, parametric distributions are assumed as in Stinebrickner (2001). Here, I estimate the full distribution of wages inside the model using conditional density estimation (Gilleskie and Mroz, 2004). When integrating over missing wages, I can use the full estimated density of those unobserved wages when performing quadrature to calculate choice probabilities.

3 Data

The data come from three sources. The data on individuals' wages, employment decisions, body mass, environments, and family states are from the National Longitudinal

Survey of Youth, 1979 cohort (NLSY '79). Data on job requirements comes from the Dictionary of Occupational Titles (DOT) and its successor, the Occupational Information Network (O*NET). City level data on food prices come from the 4th quarter reports from ACCRA (formerly the Inter-City Cost of Living Index).

The NLSY '79, conducted by the Bureau of Labor Statistics, follows a nationally representative cohort of youths initially aged 14-22 annually from 1979 to 1994 and biennially to 2010.[7] Respondents were asked questions regarding family background, schooling, occupation, hours of work, wages, criminal activity, health, etc. Weight data are recorded for 1981, 1982, and in each wave since 1985. The NLSY '79 is the longest running nationally representative panel that contains data on weight, wages, and employment decisions. The estimation sample is restricted to white males. Individuals that missed an interview in the biennial phase were dropped. [8] Table 1 details the sample construction. The final sample consists of 29,693 person-year observations. Descriptive statistics for the full sample of white males and the estimation sample are available in Table 2.

Table 1: Sample Construction

N	Description
12,686	National Longitudinal Survey of Youth, 1979 cohort, full sample
3,720	Sample after restricting demographics to white males
2,566	Sample after dropping poor white and military oversample
1,291	Sample after dropping those individuals missing an interview in the biennial phase

1291 unique individuals yields 29,693 person/year observations

Source: National Longitudinal Survey of Youth, 1979 cohort

Individuals' reported occupations are classified as one of five major categories from the 1970 Census Occupational Classification System.[9] Table 3 lists the five occupation categories

[7] http:\\www.nlsinfo.org

[8] I restrict the sample to white males to keep an already heavily parameterized model computationally feasible. Including females and other races would involve cultural norms, require parameters for demographic shifters on all variables of interest. Similarly, keeping individuals who miss interviews during the biennial phase would involve integrating over missing histories, choices and state variables during those years, creating substantial additional computational difficulties.

[9] As the NLSY progressed, the occupation classification system was updated for the 1980 census (in 1983) and the 2000 census (in 2002). Where necessary, I used BLS-provided crosswalks to convert more recent occupation codes to the coarser 1970 SOC classification.

Table 2: Summary Statistics- Full v. Working Sample of 1979 NLSY

	Working Sample		Full Sample	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Age	17.36	2.25	17.89	2.31
Yrs. Ed.'79	10.41	2.83	10.33	2.71
Weight	144.50	29.69	145.50	29.70
Yrs. Ed '98	13.52	5.57	13.02	4.99
Income 79 ($1,000's)	17.81	13.18	14.78	12.50
Income 98 ($1,000's)	27.14	26.84	25.52	26.53
# of Kids	0.34	0.71	0.37	0.74

Occupation Class Percentages, 1981		
Variable	Working Sample	Full Sample
No Work	46.51	5.09
Professionals	5.70	5.31
Sales & Admin	16.44	14.76
Craftsmen	5.08	4.84
Laborers	13.15	11.60
Service	14.43	12.35
N	1,291	3,720

used in this research and displays the proportion of obese and non-obese individuals selecting into these occupations for three time periods.

3.1 Preliminary Evidence on Weight, Wages, and Employment Behavior

Preliminary examination of the data yields evidence of differences in optimal employment behavior and wages related to body mass. While this study treats body mass as a continuous variable both theoretically and empirically, the following statistical analyses use an indicator function for whether the individual is obese.[10] Table 4 contains the results of fixed effects regressions of log wages on a dummy variable for whether the individual is obese, years of experience in each of the five occupational categories, indicators for if the individual has graduated high school and college, family state, and a time trend. The results indicate

[10]The Centers for Disease Control define obesity as a Body Mass Index (kg/m^2) of 30+.

Table 3: Occupational Sorting - Proportions of Obese and Non-Obese Workers by Occupation Category

	Occupation 1: Professionals Technicals Managers		Occupation 2: Administrative Clerical and Sales		Occupation 3: Craftsmen (Skilled) Blue		Occupation 4: Operatives and Laborers		Occupation 5: Service Workers	
Ages	$B_t < 30$	$B_t \geq 30$	$B_t < 30$	$B_t \geq 30$	$B_t < 30$	$B_t \geq 30$	$B_t < 30$	$B_t \geq 30$	$B_t < 30$	$B_t \geq 30$
24-30	**24.80**	15.51	**11.96**	9.74	17.80	**22.07**	21.8	**28.83**	8.28	**10.93**
31-37	**36.33**	27.24	12.25	12.23	19.52	**24.59**	20.36	21.82	6.31	**9.71**
38-45	**40.51**	37.17	9.25	9.99	18.25	19.77	15.47	15.31	6.52	7.91

Table 4: Fixed Effect Regression of Log Wages on Experience, Obesity, and Family Variables

	Occupation 1: Professionals Technicals Managers		Occupation 2: Administrative Clerical and Sales		Occupation 3: Craftsmen (Skilled) Blue		Occupation 4: Operatives and Laborers		Occupation 5: Service Workers	
Variable	**Coef.**	**(S. E.)**	**Coef.**	**(S. E.)**	**Coef.**	**(S. E.)**	**Coef.**	**(S. E.)**	**Coef.**	**(S. E.)**
Obese	**-0.05	0.02	**-0.05	0.02	0.02	0.03	-0.03	0.03	-0.02	0.03
H.S.	0.17	0.24	***0.28	0.09	0.16	0.10	0.08	0.07	0.08	0.10
College	***0.14	0.04	***0.19	0.07	*0.16	0.10	**0.27	0.13	0.13	0.10
Experience (Occ. 1)	**0.01	0.01	***0.03	0.01	0.01	0.01	0.01	0.01	**0.02	0.01
Experience (Occ. 2)	**0.02	0.01	***0.03	0.01	0.01	0.01	0.00	0.01	*0.04	0.02
Experience (Occ. 3)	-0.01	0.01	0.02	0.02	*0.01	0.01	**0.01	0.01	0.02	0.01
Experience (Occ. 4)	**-0.02	0.01	0.02	0.01	0.00	0.01	0.01	0.05	0.01	0.01
Experience (Occ. 5)	0.01	0.01	-0.01	0.02	**0.03	0.02	-0.01	0.01	**0.02	0.01
Married	**0.02	0.01	0.01	0.01	***0.03	0.01	***0.03	0.01	0.01	0.01
No. of Kids	***0.06	0.01	***0.06	0.02	**0.03	0.01	***0.01	0.01	*0.04	0.02
t	***0.02	0.01	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01
Constant	***6.32	0.24	***6.23	0.10	***6.35	0.08	6.30	0.05	***6.19	0.09

that obese individuals face lower wages, but these differences are statistically significant only in 'white-collar' occupations. Additionally, returns to own and cross-occupational experience vary by occupation. Experience in the five categories is not rewarded equally.

The data also show that individuals of high body mass exhibit differences in occupational choice frequencies that create subsequent differences in human capital. Figure 2 shows that obese individuals are less likely to work in white collar occupations than the non-obese, particularly early in their careers. Note the white collar occupations are also the ones that exhibit negative wage differentials for body weight. It is unclear whether these differences induce the observed differences in employment behavior. Another implication of these preliminary results is that experience accrued in a given period may partially be determined by weight in earlier periods. Because experience affects future wages, understanding the relationship between body mass and wages requires understanding how body mass influences optimal employment behavior. From the regression and bar chart, note the obese sort into the occupations that yield less valuable experience. Experience in blue collar and service jobs is minimally valued in white collar occupations. The obese and non-obese also differ in their occupational transition patterns. Table 10 (see Section 6) summarizes these differences.

Figure 3 depicts the difference in average real wages between obese and non-obese workers for each of the five occupational categories for each age in the sample period. The obese earn equal or lower wages than the non-obese in all categories. The differential in real wages for white collar occupations quadruples over the sample period: obese workers earn approximately one dollar per hour less than their non-obese counterparts at age 25, but four dollars less at age 49.[11]

3.2 Dictionary of Occupational Titles and Occupational Information Network

The data used to construct indices of job requirements come from the DOT and O*NET. The data on job requirements are taken from the 1977 edition, 1982 updates, 1986 updates, and 1991 revision. In the mid-1990s, the DOT was deemed obsolete and replaced with the O*NET, the first release of which was in 1998. In contrast to the DOT, the O*NET is aligned with the Census system of occupation classification and provides information on between 850-1000 'job families'. The O*NET focuses on white-collar occupations and on information and service jobs, and it contains much finer numerical ratings (on level and importance) for far more requirements per occupation. Appendix B contains additional details on forming the requirement indices.

[11] Real wages are calculated using 1983 as the base year.

3.3 ACCRA Data on Food Prices

Food price ratios were constructed using data from C2ER.[12] The data contain prices of commonly purchased items as reported by Chambers of Commerce in over 200 Metropolitan Statistical Areas, including: T-bone steaks, ground hamburger, iceberg lettuce, tomatoes, canned green beans, 2-piece fried chicken meals, McDonalds quarter-pounders, and Pizza Hut/Pizza Inn 12-inch pizzas. I utilize annual data from 1976 to 2008 to construct a fast-food-to-produce price index. These local indices are then linked to the Geocoded NLSY data. These indices proxy for the costs of consuming healthy food relative to unhealthy food over the sample period.[13] Additional data on construction of food price ratios and geographic matching is available in Appendix B.

4 Dynamic Stochastic Discrete Choice Model

I specify a dynamic stochastic model of employment behavior in which body weight and the requirements of the job affect both the distribution of wages and non-monetary costs of each alternative. Subsection 4.1 defines the set of alternatives. Subsections 4.2 and 4.3 define the components of contemporaneous utility from each alternative. Subsections 4.4 and 4.4.1 discusses the distribution of wages and growth of human capital. Subsection 4.5 discusses the weight transition equation and Subsection 4.6 assembles these components to formulate the individual's dynamic optimization problem in a value function framework.

4.1 Set of Alternatives

In this model agents jointly decide whether to work, how much to work, in which occupation to work, and whether to attend school. There are a total of 23 alternatives,

[12] Formerly ACCRA and The Inter-City Cost of Living Index

[13] Utilizing ratios rather than levels will mitigate the confounding factors of both regional variation in cost of living and food prices and changes in food price levels over time.

$hj \in HJ$, available to an individual in each discrete period. The employment alternatives, h, are:

$$\begin{array}{lcl} h=1 & : & \text{work part time: weekly hours} \in \{15,34\} \\ h=2 & : & \text{work full time: weekly hours} \in \{35,49\} \\ h=3 & : & \text{work more-than-full-time: weekly hours} \geq 50 \\ h=4 & : & \text{work part-time and attend school part-time} \\ h=5 & : & \text{not work and attend school full time} \\ h=6 & : & \text{not work and attend school part time} \\ h=7 & : & \text{neither work nor attend school} \end{array} \tag{1}$$

The occupational alternatives available to an agent each period are denoted by j:

$$\begin{array}{lcl} j=0 & : & \text{No occupation} \\ j=1 & : & \text{Professionals,Technicals, Managers} \\ j=2 & : & \text{Salesmen, Clerks, Administrative workers} \\ j=3 & : & \text{Craftsmen} \\ j=4 & : & \text{Operatives and Laborers} \\ j=5 & : & \text{Service workers} \end{array} \tag{2}$$

If an agent chooses an employment alternative that includes work, ($h \in \{1, \ldots, 4\}$), he also chooses an occupation($j \in \{1, \ldots, 5\}$) jointly with that employment alternative.[14] The combination of the four h alternatives that involve work times the 5 occupational categories plus $h = \{5, 6, 7\}$ comprises the set of 23 alternatives. The indicator d_t^{hj} equals one if employment alternative h and occupation j are chosen in period t, zero otherwise. I define the vector $\mathbf{d}_t = \big(d_t^{hj}, (\forall j \in \{1, \ldots, 5\} | h \in \{1, 2, 3, 4\}), j = 0 | h \in \{5, 6, 7\}\big)$.

Agents make their first decision at age 17. Education entering a period t is captured by accumulated years of school. Agents can either go to school full time, part time, or attend school part time in conjunction with working part time.[15] Degree attainment is determined by years of schooling only, rather than modeled as a separate decision.

[14]If an agent chooses an employment/school alternative which does not include working, ($h = \{5, 6, 7\}$), then $j = 0$ by definition.

[15]Details on special cases and construction of completed years of schooling can be found in Appendix B.1.

The information state vector $\mathbf{S_t}$ includes: age, marital status and spousal earnings, number of kids, years of schooling, body mass, years of experience in each of the five occupational categories, and the occupational alternative chosen in the previous period. Known to the agent, but not the econometrician, are time-invariant unobserved heterogeneity ϕ and alternative-specific, idiosyncratic component ϵ_t^{hj}. At the beginning of period t, the individual observes his wage offers, which are assumed to arrive with probability one for all alternatives. The chosen alternative in period t determines the evolution of the state variables at the end of the period (defined here as a year). The individual's state variables entering the subsequent period reflect the accumulated work experience or schooling. Body mass, marital status, and number of kids updated based on stochastic realizations and the period t decision.

4.2 Per-period Utility and Constraints

The contemporaneous utility of an alternative, hj, is a function of consumption, leisure, the annual fixed costs of participating in an occupation, variable costs of hours worked, and any transitional costs of changing occupational categories between periods. In the function below, c_t represents consumption, $h_t(\mathbf{d}_t)$ defines the number of hours worked and/or spent in school for the set of alternatives, and $M_j(\cdot)$ and $M_s(\cdot)$ are the annual fixed and switching costs of occupation j and schooling alternative s, respectively. $N(h_t(\cdot))$ represents the variable costs of working h_t hours. Information available to an individual at the start of period t, $\mathbf{S_t}$, influences the utility of each alternative. The preference error term in the utility function, ϵ_t^{hj}, are assumed to be i.i.d. Type 1 Extreme Value. Per-period utility for each alternative, conditional on both observed and unobserved information is:

$$u(\mathbf{d}_t, \mathbf{S_t}, \epsilon_t|\phi) = \frac{c_t^{1-\alpha} - 1}{1-\alpha} \tag{3}$$
$$- \left(\sum_j \big[M_j(\mathbf{S}_t|\phi)\big(\sum_{h=1}^{4} d_t^{hj}\big)\big] + M_s(\mathbf{S}_t|\phi)\big(\sum_{h=4}^{6} d_t^{hj}\big) + N(h_t(\mathbf{d}_t), \mathbf{S}_t|\phi) \right) + \epsilon_t^{hj}$$

Consumption is constrained by income, defined as earnings plus discretized unearned spousal income. Time is constrained by the time endowment per week Ω and is allocated between labor supply, h_t, and leisure, l_t. Time spent on education counts as "non-leisure" time in the model. An agent is assumed to spend 20 hours per week on school if attending part time and 40 hours per week if attending full time. [16] The budget and time constraints are:

$$\begin{aligned} c_t &\leq w_t(\mathbf{d}_t, \mathbf{S}_t)h_t(\mathbf{d}_t) + I(\mathbf{S}_t) \\ \Omega &= l_t + h_t(\mathbf{d}_t) \end{aligned} \tag{4}$$

where w_t and h_t are hourly wages and hours that depend on the observed state vector and the alternative chosen in period t. The I_t denotes unearned spousal income and Ω represents the individual's total amount of time in a given period.

4.3 Non-Monetary Costs: Fixed, Switching, and Variable

The model assumes that individuals receive wage offers from every occupational sector in each period. However, individuals in the data do not always select into occupations with the frequency one would expect if individuals solely maximized wealth and there were no labor demand frictions. To reconcile these differences, the model includes three types of costs for pursuing employment alternatives. First, the model includes per-period fixed costs of participating in each occupation that depend on one's human capital and body mass. These costs are incurred when an individual works in a given occupation, regardless of the

[16] If an agent pursues a part-time work, part-time school combination, his total non-leisure time is the sum of his hours spent working plus the 20 hours per week for part-time schooling.

number of hours worked. Second, the model includes variable costs of working additional hours. By allowing individuals to choose how much they work upon receiving a wage offer, the model captures how the marginal costs of working additional hours vary by weight and job requirement. Third, the model also includes costs of transitioning into occupation j from another occupation, j'. Switching costs vary by body mass and age, to capture that older or heavier workers may incur higher search costs or face additional frictions when transitioning into a particular occupation.

Fixed costs are a function of age and education, where the vector $\mathbf{E}_t$ contains three elements: an indicator for having accrued at least 12 years of school up to period t, an indicator for having accrued at least 16 years of school up to period t, and completed years of schooling up to period t. The fixed costs of occupational participation also depend on the physical, mental, and social requirements of that occupation: $\mathbf{J}_{jt} = [J^p_{jt}, J^m_{jt}, J^s_{jt}]$ respectively, and ϕ^k_j, an occupation specific match parameter. Because the levels of job requirements vary across occupations, the coefficients on the variables for job requirements are fixed across occupations. Body mass, B_t, captures an individual's distance from a "healthy weight".[17] The requirements of the occupation are interacted with age and B_t, to capture how body weight changes the per-period fixed costs of participating in an occupation. These fixed costs are expressed in the first line of equation 5.

Switching costs are detailed in the second line of equation 5. Switching costs vary by the occupation the individual worked in in the previous period, age, a_t, and body weight B_t. Age and occupation are correlated with body weight and may also affect switching costs. The variables for age and previous occupation are therefore included to isolate the body weight specific switching cost for each occupation. The per-period fixed cost, including any

[17] The Centers for Disease Control define "healthy weight" to be a body mass index that ranges from 18-25. There are only six individuals in my sample who fall into the "below healthy range" category at any point during the sample period.

switching costs, of participating in an occupation j are expressed as:

$$
\begin{aligned}
M_j(\mathbf{S_t}|\phi) &= \alpha \mathbf{J}_{jt} + \alpha \mathbf{J}_{jt} a_t + \alpha \mathbf{J}_{jt} B_t + \alpha_0^j + \alpha_1^j a_t + \alpha_2^j \mathbf{E}_t + \alpha_5^j B_t \\
&\quad + \sum_{j' \neq j} \alpha_{6+j'}^j \mathbf{1}(d_{t-1}^{hj'} = 1) + \alpha_{11}^j \mathbf{1}(d_{t-1}^{hj} \neq 1) B_t + \alpha_{12}^j \mathbf{1}(d_{t-1}^{hj} \neq 1) a_t + \rho_j^J \phi
\end{aligned} \tag{5}
$$

The utility costs of schooling depend on age (a_t), level of schooling, whether the individual was out of school in the preceding period, and the interaction of age and returning to school.

$$
M_s(\mathbf{S_t}|\phi) = \alpha_0^s \mathbf{E}_t + \alpha_1^s \big(\sum_{h=4}^{6} (d_{t-1}^{hj} \neq 1) \big) + \alpha_2^s a_t + \alpha_3^s a_t^2 + \alpha_4^s a_t \big(\sum_{h=4}^{6} (d_{t-1}^{hj} \neq 1) \big) + \rho^S \phi \tag{6}
$$

The individual also incurs variable costs of working more than the minimum threshold of 20 hours. The expression for the variable costs of labor supply, $N(h_t(\mathbf{d}_t))$ contains many of the same arguments as the expression for per-period fixed costs, adding interactions with h_t and a ϕ term to capture heterogeneity in preferences for working additional hours. In the model, hours pursuing education and work are treated the same, up to the differences in job requirements. In this expression, m_t is a variable for whether the individual is married, a_t is the individual's age at time t, and k_t is the number of children the individual has at time t. The occupational requirements $\mathbf{J}_{jt}$ and the interaction of those requirements with body weight also affect the cost of working more hours. The variable costs of working are expressed as: [18]

$$
\begin{aligned}
N(h_t(\mathbf{d}_t), \mathbf{S_t}|\phi) &= \psi_1 h_t + \psi_2 h_t m_t + \psi_3 h_t k_t + \psi_4 h_t B_t + \psi_5 h_t^2 B_t \\
&\quad + \psi_6 h_t \mathbf{J}_{jt} + \psi_7 h_t \mathbf{J}_{jt} B_t + \psi_8 h_t [a_t] + \psi_9 h_t [a_t^2] + \rho^N h_t \phi
\end{aligned} \tag{7}
$$

Body weight therefore affects both the per-period fixed and variable costs of each occupation via the requirements of the job. The parameters on these effects are assumed

[18] Although the variable for hours worked, h_t, is treated as continuous, the set of alternatives related to labor supply is polychotomous. If a specific value of hours is needed for calculation of the value function, I use 25 hours for part-time work, 40 hours for full-time work, and 50 hours for over-time work. For alternatives that are observed in the data, I use the observed value of h_t to calculate $N(h_t(\mathbf{d}_t), \mathbf{S_t})$.

common across the occupational categories. Body weight also has occupation-specific effects on per-period fixed and switching costs.

4.4 Distribution of Wages

The distribution of wages, not just the conditional mean, is meaningful in solution to the model and estimation of parameters. When an agent makes his employment decision, he considers how his decision this period affects the distribution from which future wage offers are drawn. These expectations over future outcomes thusly affect the agent's decision today. When estimating the model, calculating choice probabilities requires integration over the distributions of unobserved wage offers. It is often assumed that wages follow a continuous distribution (Keane and Wolpin, 1997; Stinebrickner, 2001). Rather than impose a parametric distribution on an error term and estimate a conditional mean, I estimate the full density of wages inside the model using Conditional Density Estimation (CDE). I define the density of wages:

$$f(w_{jt}|\phi) = f(j, \mathbf{S}_t, B_t, \mathbf{J}_{jt}, \phi) \tag{8}$$

where wage is determined by the state vector ($\mathbf{S_t}$), which includes work experience, education, body weight, occupational requirements, and unobserved occupation-specific "skill endowment", ϕ. The coefficients on the interaction of body mass and the vector of job requirements determine how much of the observed wage differences between individuals of different weights can be attributed to contemporaneous differences in effectiveness. I control explicitly for differences in occupational experience and education. Returns to education and experience are allowed to vary by body weight. The coefficients on body weight alone provide the best estimate for the contemporaneous "wage penalty" for body weight. Estimation of the distribution of wages by CDE is discussed in greater detail in Section 5.

4.4.1 Evolution of Human Capital State Variables

The model allows work experience to accumulate faster for agents who choose to work more hours. If an individual that works longer hours in a given occupation tends to gain weight faster than his less career-motivated peers, a failure to keep track of differences in accrued human capital will lead to bias in the estimation of the costs of body weight. The state variable x_t^j denotes "full-time-years of experience" in occupation j entering time t. The evolution of work experience in each occupation is:

$$x_{t+1}^j = \begin{cases} x_t^j & \text{if } (\sum_{h=1}^4 d_t^{hj}) = 0 & \text{(no employment in occupation } j) \\ x_t^j + \frac{1}{2} & \text{if } d_t^{1j} = 1 \text{ or } d_t^{4j} = 1 & \text{(part-time employment in occupation } j) \\ x_t^j + 1 & \text{if } d_t^{2j} = 1 & \text{(full-time employment in occupation } j) \\ x_t^j + \frac{3}{2} & \text{if } d_t^{3j} = 1 & \text{(over-time employment in occupation } j) \end{cases} \tag{9}$$

Years of schooling accrue as follows:

$$ed_{t+1} = \begin{cases} ed_t & \text{if } d_t^{hj} = 1, h = 1,2,3,7 & \text{(no schooling)} \\ ed_t + \frac{1}{2} & \text{if } d_t^{hj} = 1, h = 4,6 & \text{(part-time-schooling)} \\ ed_t + 1 & \text{if } d_t^{hj} = 1, h = 5 & \text{(full-time schooling)} \end{cases} \tag{10}$$

4.5 Weight Transition

The model permits employment decisions to affect body weight. Direct effects come through amount of on-job physical activity (or lack thereof) and number of hours worked. Food consumption and exercise behavior held constant, lower on-job activity levels equate to lower caloric expenditure. Due to limitations of the data and the focus of the research question, this model does not include an agent's control over food and exercise.[19] Nevertheless, it is still possible to conduct inference on the indirect effects of employment decisions on weight. In the model, body weight is conditioned on lagged body weight, food prices,

[19] Recent work suggests that the omitted variable of endogenous exercise is not that problematic. Colman and Dave (2011) use ATUS data and find that only 4 percent of total daily calorie expenditure is due to discretionary exercise, thereby reemphasizing the importance of on-job activity. However, the lack of insight into individuals' food choices remains an issue, albeit one which is addressable in part.

food supply factors, environmental factors, wages, and family states, the requirements of the occupation selected in that period, and hours worked. The state transition probabilities for body mass are estimated (and future expectations subsequently taken) using CDE. As with wages, estimation of the conditional density of body mass without imposing assumptions on the shape of the distribution. CDE also permits marginal effects to vary over the support of the distribution of the dependent variable.[20] Conditional on body mass B_t in period t, the density of B_{t+1} is:

$$f(B_{t+1}|\phi) = f(B_t, \mathbf{d}_t, \mathbf{S}_t, \mathbf{J}_{jt}, X_t^G, \phi) \tag{11}$$

where the X_t^G variables include local time-varying food price ratios and crime rates.

4.6 Optimization Problem

The objective of the individual is to choose the alternative at time t to maximize expected lifetime utility. Lifetime utility at time t is represented by a value function using the Bellman formulation. The value function is comprised of current period utility and discounted expected future utility. The total current period utility is the sum of the deterministic utility from equation 3 and an alternative-specific i.i.d. preference shock:

$$U_{hj}(d_t^{hj} = 1, \mathbf{S}_t, \phi, \epsilon_t) = \overline{U}_{hj}(d_t^{hj} = 1, \mathbf{S}_t, \phi) + \epsilon_t^{hj} \tag{12}$$

In the empirical implementation, ϵ_t^{hj} is an additive econometric error (Rust, 1997). In the theoretical model, ϵ_t^{hj} is interpreted as an unobserved state variable (Aguirregabiria and Mira, 2010). The alternative specific lifetime value function in state $\mathbf{S}_t$, conditional on unobserved

[20]Details are discussed in the next section.

heterogeneity ϕ, is:

$$V_{hj}(\mathbf{S}_t, \epsilon_t^{hj}|\phi) = \overline{U}_{hj}(\mathbf{S}_t, \phi) + \epsilon_t^{hj} + \beta \int_B f(B_t, \mathbf{d}_t, \mathbf{S}_t, \phi) \\ \sum_{k=0}^{1} \sum_{m=0}^{3} P[M_{t+1} = m|\mathbf{S_t}, \mathbf{d_t}] P[K_{t+1} = k|\mathbf{S_t}, \mathbf{d_t}] E[V(\mathbf{S}_{t+1}|\phi)|d_t^{hj} = 1] dB \quad (13)$$

where $V(\mathbf{S}_{t+1}|\phi)$ is the maximal expected lifetime utility of being in state $\mathbf{S}_{t+1}$.[21] The value function is conditional on the unobserved heterogeneity component ϕ. The expectation operator is taken over the future wage and preference shocks. I use quadrature with the estimated conditional density of wages to evaluate the expectation within solution to the model.Let $\overline{V}_{hj}(\cdot) = V_{hj}(\cdot) - \epsilon_t^{hj}$. Assuming that ϵ_t^{hj} follows a Type 1 Extreme Value distribution, then maximal expected lifetime utility has the following closed form expression:

$$V(\mathbf{S}_{t+1}|\phi) = \lambda + ln(\sum_{hj} exp(\overline{V}_{hj}(\mathbf{S}_{t+1}|\phi)), \quad \forall t \quad (14)$$

where λ is Euler's constant. Furthermore, because the error term ϵ_t^{hj} is additively separable, the conditional choice probabilities take the following form:

$$p(d_t^{hj} = 1|\mathbf{S}_t, \phi) = \frac{exp(\overline{V}_{hj}(\mathbf{S}_t|\phi)}{\sum_{hj'} exp(\overline{V}_{hj'}(\mathbf{S}_t|\phi)} \quad (15)$$

The likelihood function consists of these choice probabilities, augmented to take expectations over unobserved wages as in Stinebrickner (2001), and transition probabilities for marriage, body mass, and number of children.

[21]The model includes marriage, spousal earnings, and number of children in the state vector. These variables are not treated as choices, but the individuals' employment decisions affect transition probabilities. Details on these state variables are available in Appendix A.

5 Empirical Implementation

Several features of the model are emphasized in the following discussion of the estimation of the theoretical model. This section concludes with a discussion of identification. Details on initial conditions and construction of the likelihood function are available in Appendix A.

5.1 Conditional Density Estimation

Rather than impose a parametric distribution on (log) wages and body mass, I semi-parametrically estimate the full conditional density of (level) wages and body mass inside the model. Estimating the conditional density utilizes a sequence of conditional probabilities to construct a discrete approximation to the density function of the outcome of interest, conditional on the explanatory variables. As in Gilleskie and Mroz (2004), these conditional probabilities used in the sequences are logistic.

Recent work using nonparametric methods (Kline and Tobias, 2008) and quantile methods (Johar and Katayama, 2012) has shown that the effects of weight on wages varies over the distribution of wages. CDE also permits explanatory variables to have different marginal effects at different points of support of the dependent variable. By employing CDE, we can examine how the marginal effect of interacted variables (e.g., the how body weight affects returns to experience) vary over the support of the distribution of wages. In the weight transition expression, we can similarly evaluate how the marginal effect of at work physical activity varies over the support of body weight. Gilleskie and Mroz (2004) show that expected wages can be approximated using the estimated density:

$$E[w_t|\mathbf{S_t}, \mathbf{J}_{jt}, \phi] = \sum_{k=1}^{K} \overline{w}_t(k|K) \cdot P[w_{k-1} \leq w_t < w_k|\mathbf{S}_t, \mathbf{J}_{jt}, \phi] \tag{16}$$

where $P[w_{k-1} \leq w_t < w_k|\mathbf{S}_t, \mathbf{J}_{jt}, \phi] = \lambda^W(k, \mathbf{S}_t, \mathbf{J}_{jt}, \phi) \prod_{j=1}^{k-1}[1 - \lambda^W(j, \mathbf{S}_t, \mathbf{J}_{jt}, \phi)]$, $\lambda(k, X)$ is a single logit hazard equation, and $\overline{w}(k|K)$ is the arithmetic mean of the wages observed in partition k. In solution to the model, expectations can be taken using this discrete estimated approximation rather than integrating over a continuously distributed error term. Similarly, the expectations and transition probabilities for body mass are:[22]

$$E[B_{t+1}|\mathbf{S_t}, \mathbf{d}_t, \phi] = \sum_{l=1}^{L} \overline{B_{t+1}}(l|L) \cdot P[B_{l-1} \leq B_{t+1} < B_l|\mathbf{S}_t, \mathbf{d}_t, p_t^F, X_t^G, \phi] \tag{17}$$

where $P[B_{l-1} \leq B_{t+1} < B_l|\mathbf{S}_t, \mathbf{d}_t, p_t^F, X_t^G, \phi] = \lambda(l, \mathbf{S}_t, \mathbf{d}_t, p_t^F, X_t^G, \phi) \prod_{j=1}^{l-1}[1-\lambda(j, \mathbf{S}_t, \mathbf{d}_t, p_t^F, X_t^G, \phi)]$

5.2 Indices of Job Requirements by Occupation

One contribution of this paper is the attribution of weight-based differences in employment costs and wages to the physical, mental, and social requirements for the occupations. The raw data for requirements for jobs come from the Dictionary of Occupational Titles and its present day counterpart, O*NET, the Occupational Information Network. The DOT contains information on over 12,000 jobs, many of which could be better characterized as tasks than positions for which an individual is solely hired. Aggregating these jobs up to five occupational classes is done in two steps. First, DOT jobs are crosswalked to Census Occupation Codes. The COC levels for job requirements are calculated by taking an unweighted average of the DOT ratings.[23] Second, CPS weights were used to aggregate the COC averages up to the Occupation-class-level values. Intrinsic variation in requirement values come from changes in the both from changes in reported values in DOT and O*NET revisions and from addition/subtraction of jobs between revisions. Extrinsic variation in requirement values comes from the variation in CPS weights as the distribution of jobs in a given occupation changes over time (e.g., computer systems analysts are much more heavily weighted in 2006 than 1980). Details on mapping the fine O*NET data into the coarser DOT are available in Appendix B.5. Conditional on the assumptions used for this crosswalk,

[22] K and L are the number of quantiles into which the data for wages and weight are divided. Here, 25 was used for both K and L.

[23] The O*NET reports at the COC level.

variation in predicted DOT ratings based on O*NET data can be interpreted as changes in job requirements. Graphs of the calculated job indices by occupation from 1977-2006 are also available in the appendix.

5.3 Permanent Unobserved Heterogeneity

The empirical model permits correlation in permanent unobserved heterogeneity in the error terms in the expressions for wages for each occupation, fixed costs for each occupation (including school), the weight transition, and taste for working additional hours. Permanent unobserved heterogeneity enters the model through the ϕ terms and associated factor loadings (ρ). The factor loadings allow for a different effect of the unobserved ϕ in each expression. Rather than impose a distribution on the unobserved heterogeneity, I approximate that joint distribution with a step function, estimating the factor loadings, mass points, and mixing weights, π (Heckman and Singer, 1984). The discrete factor random effects method performs well in approximating both normal and non-normal distributions (Mroz, 1999).

5.4 Weight Inference

The research question is not why people gain weight. The model includes stochastic weight transitions that might be directly and indirectly influenced by schooling, employment, occupation, and hours decisions to capture whether employment decisions affect body weight over the life cycle. Ignoring the possibility of this dynamic feedback mechanism (i.e. that occupations may affect body mass) would introduce bias to the estimates of how weight affects employment behavior. The data limitation is that the NLSY does not provide information on caloric intake and caloric expenditure. As such, the structural production of body mass (as a function of these inputs) cannot be modeled. Instead, the joint demands for caloric intake and expenditure are replaced by their theoretical arguments. The parameters in the weight transition expression (equations (11) and (17)) are therefore functions of structural parameters rather than structural parameters. By controlling for environmental factors such as food prices and crime rates, it is possible to control for factors that may magnify or reduce the unobservable indirect effects of employment behavior on weight via lifestyle choices. For example, supplying additional labor provides more money for (un)healthy food but leaves less time available for all forms of leisure, including exercise. Supplying additional labor may also encourage or necessitate agents to substitute towards restaurant meals or fast food (forsaking grocery/meal preparation time for leisure), both of which tend to be heavy in calories. During the sample period there has been a dramatic increase in the supply of "convenience food", habitual consumption of which leads to weight gain. Variation in these environmental factors and weight gain patterns informs us about how employment decisions probabilistically affect unobserved decisions regarding food and exercise.

5.5 Identification

For the identification of the model parameters, the contemporaneous utility of not working with no unearned spousal income is normalized to zero, as is the switching cost of transitioning to unemployment. The vector of job requirements when not working is normalized to zero. The identification of the parameters in the contemporaneous utility function are all identified through choice frequencies, conditional on observed wages. The identification of the parameters in the fixed-cost expression comes from the frequency with which individuals at various points in the state space (and their observed wage offers) choose various occupations relative to not working. The coefficients on the job characteristics $\mathbf{J}_{jt}$ are identified by the variation in frequency of occupational choice as job requirements evolve. Note these requirements vary over occupation and time. The parameters for variable cost of working additional hours are identified by the frequency that individuals choose alternatives with part, full, or overtime hours, conditional on observed wage offers and job requirements. The exponent in the utility function is identified through changes in the response of hours worked, h_t, to variation in wages as unearned spousal income changes. The pursuit of education early in the model also aids in the identification of the CRRA parameter as it will pick up inter-temporal elasticity of substitution with regards to consumption. If the CRRA coefficient is close to zero, the value of an additional year of education (and higher expected lifetime earnings) is greater than if the CRRA coefficient is larger.

6 Results

6.1 Wages

Tables 12 and 13 in Appendix A.4 contain parameter results from the conditional density estimation of wages and a discussion about how to interpret these hazard function parameters. Interpreting parameter results directly as marginal effects is infeasible. Marginal effects must be calculated by simulation. Calculated marginal effects for the variables of interest (B_t and B_t interacted with job requirements, education, and experience) are reported in tables 5 and 6.

Recall that B_t is the distance between an individual's BMI and the 'healthy weight' boundary of 25. The right column in table 5 shows that higher body weight leads to lower wages in mentally and socially intensive occupations. The relationship between body mass and wages in physically intensive occupations is positive. In all three requirements, however, the point estimates of the interaction effect of BMI and the requirement are greatest in the upper quartile of the distribution of wages. Because job requirements vary by occupation and time, the marginal effects of $B_t\mathbf{J}_{jt}$ do not vary by occupation.

Table 6 contains the occupation specific marginal effects of body weight on wages. Conditional on requirements, higher body weight is linked to lower wages in Sales and Administrative Occupations and Professional, Technical and Managerial occupations. The largest effects are again found in the upper quartile of the wage distribution. In all occupations, BMI has a negative effect in the upper quartile, although in the Blue collar and service occupations, observations in the upper quartile are far less common. Higher body mass is also linked to lower returns to 'white collar' experience in nearly all occupations.[24] Fourth, higher body mass reduces returns to education in white collar occupations. The greatest effects again occur in the top quartile.

While the marginal effects ofB_t and $B_t\mathbf{J}_{jt}$ on wages are meant to capture the weight-based wage penalty and wage differential attributed to productivity, respectively, they must be interpreted with caution. There may be productivity differences that these indices do not capture. Additionally, the possibility of factors such as persistence in statistical discrimination prevents me from attributing the lower returns to experience in white-collar occupations to productivity (Lehmann, 2013).

In summary, individuals of high body mass earn lower wages, lower returns to education and experience in white collar occupations, and lower wages in socially intensive jobs. All of these results are largest in the upper quartile of wages. While larger absolute values of wages will create larger absolute differences in wages between any two groups, the difference in wages on the basis of body weight is far greater at the mean than the median. Overall, the results indicate that heavier individuals are much less likely to be observed in the upper portions of the wage distribution in white collar occupations. This prediction fits the data. While our best estimates for contemporaneous weight-based wage penalties are relatively small, the lower returns to experience, education, negative marginal effects of social requirements and body weight jointly indicate that body weight is an impediment to career advancement.

6.2 Fixed, Variable, and Switching Costs

Tables 7 and 8 report the estimated cost parameters, including fixed costs of participating in each occupation and schooling, switching costs, and variable costs. The results suggest that heavier individuals face lower fixed costs of participating in occupations with greater physical and mental requirements, and higher fixed costs of participating in occupations

[24] "White Collar" occupations include Professional, Technical, and Managerial Occupations (category 1) and Sales and Administrative Occupations (category 2).

Table 5: Marginal Effects of Job Requirements on Wages
Occupation-Invariant Effects

Requirement	Quartile	Effect	Requirement *BMI	Quartile	Effect
Physical	Lower	46.52	Physical	Lower	1.09
	Inter	125.86		Inter	9.29
	Upper	153.84		Upper	18.85
Mental	Lower	-2.85	Mental	Lower	-0.46
	Inter	5.01		Inter	-2.31
	Upper	18.57		Upper	-1.75
Social	Lower	-16.26	Social	Lower	-1.15
	Inter	8.66		Inter	-2.05
	Upper	48.06		Upper	-5.86

Values are in 1983 cents

Table 6: Occupation-Specific Marginal Effects - BMI and Interactions

Variable	Quartile	Professional Estimate	Sales/Admin Estimate	Craftsmen Estimate	Laborers Estimate	Service Estimate
BMI	Lower	-8.56	-2.34	9.06	6.02	5.05
	Inter	-13.56	-6.78	0.44	-3.23	-8.27
	Upper	-14.07	-11.09	-12.03	-4.46	-15.05
BMI ×	Lower	-0.53	1.11	2.85	-1.40	4.36
Education	Inter	-0.60	-2.15	4.68	6.00	4.95
(Year)	Upper	-1.60	-3.52	3.68	5.12	3.38
BMI ×	Lower	-28.78	-4.84	0.9	14.50	-8.52
Bachelor's Degree	Inter	-21.92	-17.49	-15.07	13.56	-1.09
	Upper	-24.91	-22.4	-10.64	-18.48	2.36
BMI ×	Lower	-0.15	4.46	1.10	-1.54	-5.19
Experience Occ.1	Inter	-0.70	-1.64	-0.49	-5.36	-2.61
	Upper	-3.46	-6.15	-1.49	-6.36	2.39
BMI ×	Lower	0.56	3.19	2.48	-2.90	-4.06
Experience Occ.2	Inter	-1.59	-2.96	0.52	-1.81	-0.75
	Upper	-3.65	-5.32	-0.68	-0.81	-0.96
BMI ×	Lower	0.18	3.29	1.19	0.69	1.42
Experience Occ.3	Inter	-2.68	4.56	0.43	0.78	3.27
	Upper	-1.60	0.10	0.57	0.98	36.64
BMI ×	Lower	0.30	1.56	0.43	0.72	0.24
Experience Occ.4	Inter	1.80	-1.42	0.99	0.47	0.58
	Upper	-0.76	1.26	0.65	0.07	0.99
BMI ×	Lower	2.14	2.95	1.04	0.02	2.28
Experience Occ.5	Inter	2.75	-4.97	-3.03	-1.78	0.30
	Upper	1.94	-8.79	-2.00	-3.03	-1.70

Values are in 1983 cents

that have greater social requirements. Linking with the wage results, heavier individuals face lower wages and higher fixed costs in socially intensive jobs while the opposite is true for physically intensive jobs.

Conditional on the requirements of the job, heavier individuals are found to face higher fixed costs of working in Professional, Technical, and Manager (PTM); Sales, Clerical, and Administrative (SCA), and Craftsmen occupations. Heavier individuals face lower fixed costs of working in Laborer occupations. Since nearly all customer facing jobs are found in the Sales and Administrative category, this result is not inconsistent with a beauty effect (Hamermesh and Biddle, 1994). The results also suggest that greater body mass leads to higher switching costs when entering white collar jobs, which are also the most socially intensive. The effects are twice as strong for PTM occupations ($6,500 at the mean wage) as SCA jobs ($2,700). Results therefore suggest that body mass affects occupational attainment, which in turn affects future experience and future wage distributions. This relationship is further explored in Section 7.

6.3 Weight Transition

The parameter estimates for the body mass transition equation are reported in Table 9. Similar to the results for wages, the marginal effects require additional interpretation.[25] Conditional on body mass entering the period, higher wages are associated with lower body mass in the following period for individuals with a BMI less than 28, but increasing body mass for those with a BMI greater than 28. The result for the relatively fit people is consistent with the notion that higher wages garner more resources for investment in health capital (Grossman, 1972). However, the interaction effect of body mass and wages is positive, implying that individuals of higher body mass may use those additional resources on less healthy goods. The estimates for hours exhibit a similar pattern. While an increase in hours worked leads to lower body mass in the ensuing period, the interaction effect of body mass

[25] See Appendix A.4 for notes on interpretation.

Table 7: Utility Function Parameters

Variable	Estimate	ASE			
α	0.5948	0.070			
Occupation-Invariant Variable Costs			Fixed Costs of Schooling		
Variable	**Estimate**	**ASE**	**Variable**	**Estimate**	**ASE**
Constant	***-0.823	0.007	Constant	***1.109	0.082
M_t	***-0.237	0.008	(Ed $\geq$ 12)	*** 0.373	0.010
K_t	***-0.018	0.002	(Ed $\geq$ 16)	**0.902	0.001
B_t	***0.018	0.001	t	***0.306	0.010
hours*B_t	***0.042	0.001	t^2	**-0.098	0.038
Physical	***-0.647	0.008	Working	***0.007	0.000
Mental	***-0.345	0.003	Returning	***0.166	0.003
Social	***0.005	0.001			
Physical*B_t	*** -0.007	0.001			
Mental*B_t	*** -0.009	0.001			
Social*B_t	**0.003	0.001			
t	- 0.002	0.001			
hours*t	0.002	0.001			
hours	***0.452	0.002			
Unobserved Heterogeneity					
Factor Loading	-0.533	0.009	Factor Loading	0.202	0.006

Table 8: Utility Function Parameters – Switching and Per-period Fixed Costs

Occupation Invariant Fixed Costs								
Requirement	**Estimate**	**ASE**	**Requirement* t**	**Estimate**	**ASE**	**Requirement* Body Mass**	**Estimate**	**ASE**
Physical	***1.378	0.030	Physical	-0.001	0.000	Physical	***-0.007	0.001
Mental	***0.203	0.028	Mental	***0.014	0.001	Mental	*-0.003	0.001
Social	***0.328	0.023	Social	***-0.004	0.001	Social	***0.005	0.001

Occupation Specific Per-Period Fixed Costs										
Occupation	Professional		Sales & Admin		Craftsmen		Laborers		Service	
Variable	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**
Constant	***3.115	0.104	***0.552	0.034	***0.712	0.043	***-0.205	0.008	***-0.283	0.026
Years of School	***-0.058	0.006	-0.002	0.000	-0.002	0.000	0.000	0.000	***-0.019	0.002
(Ed $\geq$ 12)	***-1.115	0.050	***-0.002	0.000	***-0.209	0.035	*** -0.499	0.031	***-0.312	0.032
(Ed $\geq$ 16)	***-2.707	0.033	***-1.924	0.048	***-0.988	0.056	***0.011	0.002	***-1.496	0.061
Body Mass	***0.010	0.001	***0.009	0.002	***0.035	0.002	***-0.004	0.000	***0.004	0.001
t	***0.033	0.003	***0.024	0.002	*-0.009	0.004	***0.007	0.000	***0.039	0.002

Occupation Specific Switching Costs										
Occupation	Professional		Sales & Admin		Craftsmen		Laborers		Service	
Variable	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**
$\mathbf{1}[j_{t-1} = 0]$	***1.934	0.051	***2.351	0.073	***2.391	0.060	***1.985	0.055	***1.649	0.071
$\mathbf{1}[j_{t-1} = 1]$	–	–	***0.009	0.001	***0.035	0.004	***0.132	0.015	***0.003	0.000
$\mathbf{1}[j_{t-1} = 2]$	***0.042	0.003	–	–	***0.859	0.082	***-0.016	0.003	0.000	0.000
$\mathbf{1}[j_{t-1} = 3]$	0.001	0.000	***0.899	0.084	–	–	***0.042	0.004	***1.130	0.075
$\mathbf{1}[j_{t-1} = 4]$	***0.122	0.012	***0.018	0.004	***-0.074	0.006	–	–	***0.011	0.001
$\mathbf{1}[j_{t-1} = 5]$	0.000	0.000	***0.010	0.001	***0.090	0.009	***0.010	0.001	–	–
$\mathbf{1}[j_{t-1} \neq j] * t$	***0.100	0.002	***0.149	0.003	***0.120	***0.003	***0.013	0.003	***0.198	0.004
$\mathbf{1}[j_{t-1} \neq j] * B_t$	***0.052	0.004	***0.024	0.001	***0.001	0.001	***-0.007	0.001	***0.002	0.000
Unobserved Heterogeneity										
Factor Loadings	-0.256	0.030	0.136	0.045	-0.090	0.027	0.111	0.021	0.008	0.003

Table 9: Parameter Estimates for Body Mass Density

Variable	Estimate	ASE	Variable	Estimate	ASE
Constant	***12.720	0.229	Physical	**0.138	0.051
γ	***-8.840	0.146	Physical*γ	***0.072	0.022
γ^2	***2.173	0.035	Mental	-0.013	0.141
γ^3	***0.9953	0.009	Mental*γ	-0.008	0.006
t	***0.023	0.007	K_t	0.016	0.028
t*γ	***0.029	0.003	K_t*γ	-0.002	0.012
$t^2/100$	**-0.043	0.021	Spouse Inc. (1000's)	-0.002	0.005
$(t^2/100)$*γ	***-0.076	0.009	Spouse Inc.*γ	0.001	0.002
Body mass	***-0.354	0.006	(hours/10)*B_t	***-0.167	0.031
Body mass*γ	***0.421	0.005	(hours/10)*B_t*γ	***0.059	0.009
(Ed $\geq$ 12)	0.103	0.091	wage	***1.035	0.045
(Ed $\geq$ 12)*γ	0.016	0.038	wage*γ	0.018	0.015
(Ed $\geq$ 16)	-0.070	0.055	wage*(hours/10)	***0.009	0.002
(Ed $\geq$ 16)*γ	***-0.075	0.022	wage*(hours/10)*γ	***0.004	0.001
Married	*0.099	0.055	wage*Body mass	***-0.324	0.014
Married*γ	**0.56	0.025	wage* Body mass*γ	***-0.036	0.005
hours/10	***0.621	0.103	FF Index	***-0.017	0.004
(hours/10)*γ	*-0.040	0.024	FF Index*γ	**-0.005	0.002
$\text{hours}^2/100$	-0.001	0.006	Crime Index	**-0.143	0.056
$(\text{hours}^2/100)$*γ	-0.002	0.003	Crime Index*γ	0.002	0.006
Unobserved Heterogeneity					
Factor Loading	0.202	0.045			

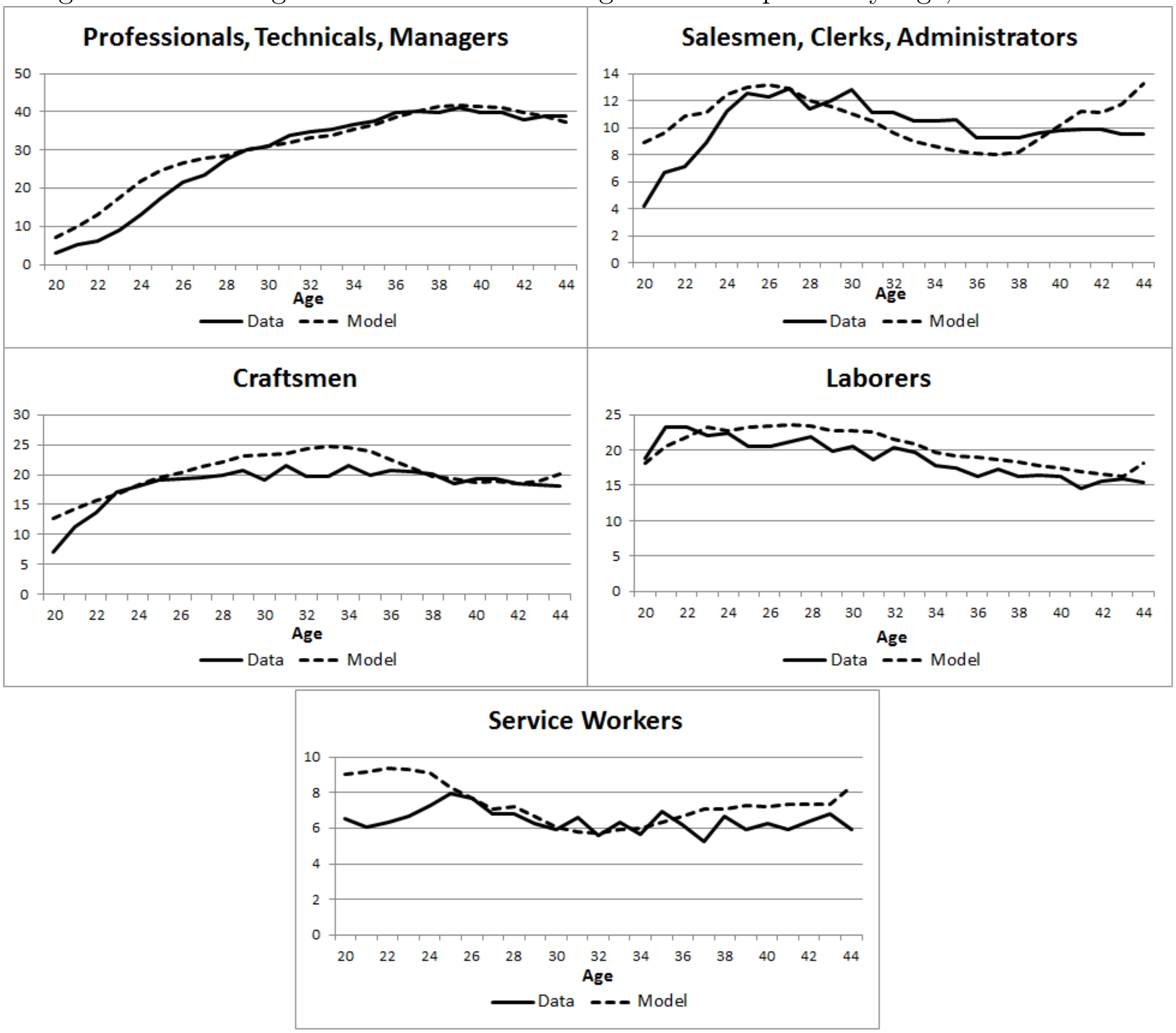
and hours is positive. The education dummies corresponding to high school and college graduation are associated with lower body mass.

Conditional on education, income, unobserved heterogeneity, and age; physically intensive jobs are shown to increase body mass at the low end of the distribution, but have a negative effect on body mass in the upper portion of the distribution. As the index for physical requirements is primarily based on strength, it is logical that slightly-built individuals might gain some muscle mass. It also follows that very heavy individuals will be most likely to experience weight loss in response to an increase in physical exertion. The parameters on mentally intensive work are not statistically significant.

6.4 Model Fit

To assess how well the model fits the observed data, I simulate employment decisions and wages using the model and the estimated parameters for 10,000 individuals. Initial conditions are randomly drawn using observed frequencies in the data and the estimated

Figure 1: Percentage of Individuals Choosing Each Occupation by Age, Model v. Data



parameters of the model. Details are available in Appendix A. An individual's "type" is also drawn randomly using proportions from the estimated distribution of unobserved heterogeneity. Figure 1 shows the predicted proportions of chosen occupations by age and the same proportions from the observed data.

Figure 2 plots the observed and predicted proportions of occupations chosen for the obese and non-obese by specific age groups. The model predicts the relative differences between the obese and non-obese well. In each age group in the data, obese workers are less likely to be found in professional occupations than non-obese workers. When workers are under the age of 30, obese workers are less likely to be found in sales and administrative occupations than non-obese workers. The opposite is true in later years. The model predicts both the levels of and differences between obese and non-obese workers sorting into craftsmen, laborer, and service occupations. The model mispredicts weight-based differences in occupational choice in three ways: the model over predicts selection into Craftsmen occupations, the model over predicts the selection of obese workers into Laborer jobs, and under predicts the selection of obese workers into service occupations.

Figure 3 plots the observed and predicted wages for the obese and non-obese by age for each occupational category. In the white collar occupations where growth in wage disparity on the basis of weight is common, the model captures the growth in wages for both weight groups. In the observed data from professional occupations, obese workers make \$0.84 per hour (in 1983 dollars) less than their non-obese counterparts at age 25, and \$4.27 less than non-obese workers at age 45. The model predicts these differences to be \$0.67 and \$4.42 at ages 25 and 45 respectively. The model also predicts the growth in the difference in mean wages as individuals age for Sales, Clerical, and Administrative Occupations. In the data, obese workers earn \$1.42 per hour less than their non-obese counterparts at age 25, and \$3.71 less at age 45. The model predicts these differences to be \$1.39 and \$4.10 respectively. As seen in Figure 3, the model not only predicts the end points fairly well, but also predicts the trends in between. The model also predicts wages by weight status for blue collar occupations, and predicts non-disparities in blue collar occupations, and stable disparity in service occupations. Note that the scaling is smaller in the bottom three panels of Figure 3 as mean wages in these occupations were lower in both initial values and growth rates over the sample period. In all occupations, the model over predicts wages for non-obese workers for the last 2-4 years.

Table 10 contains the observed and predicted transition matrices for obese and non-obese individuals. The model under predicts persistence in unemployment for obese workers, over predicts persistence in sales/administrative occupations, over predicts the transition of

Figure 2: Predicted and Observed Proportions of Occ's, Obese and Non-Obese

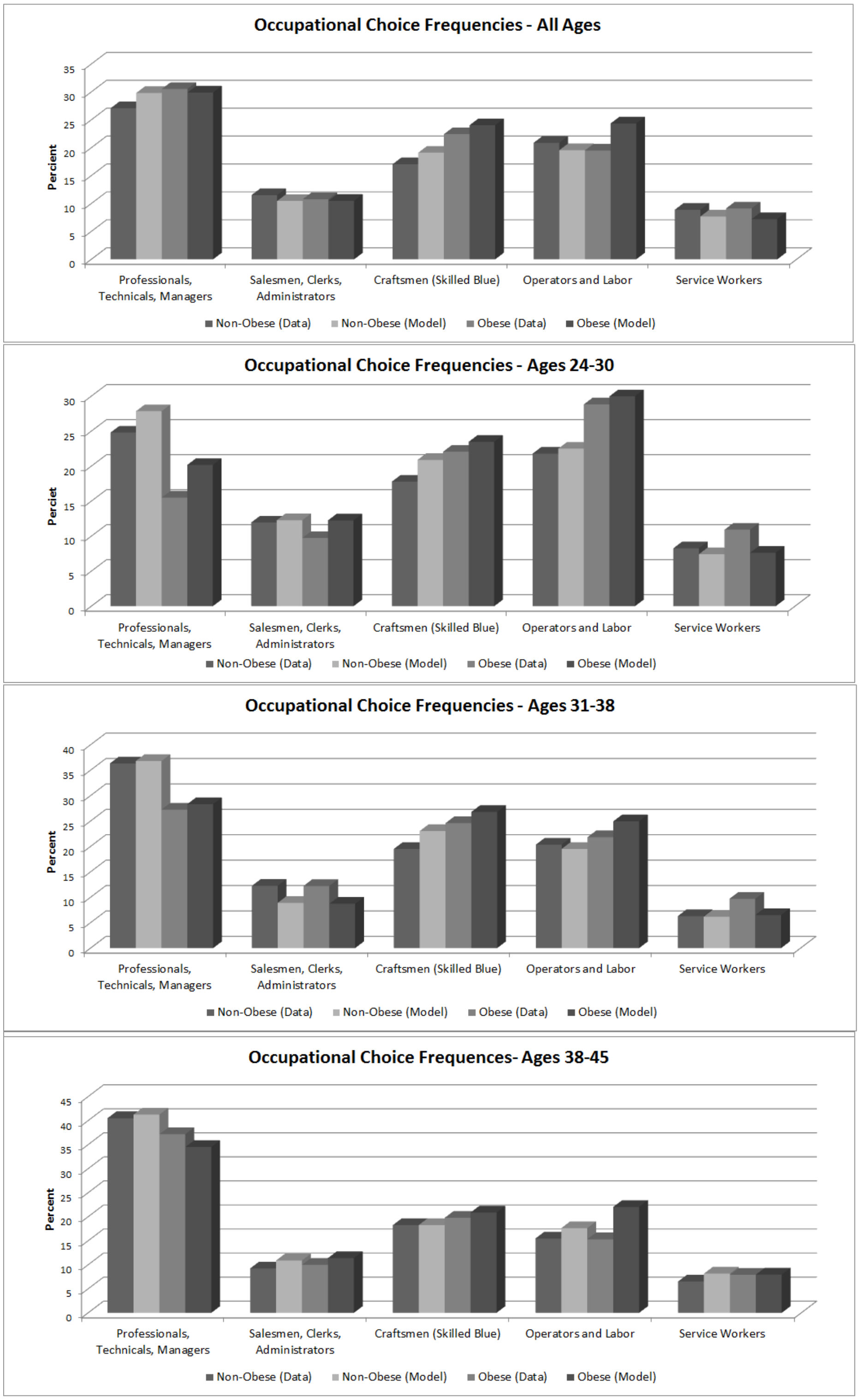
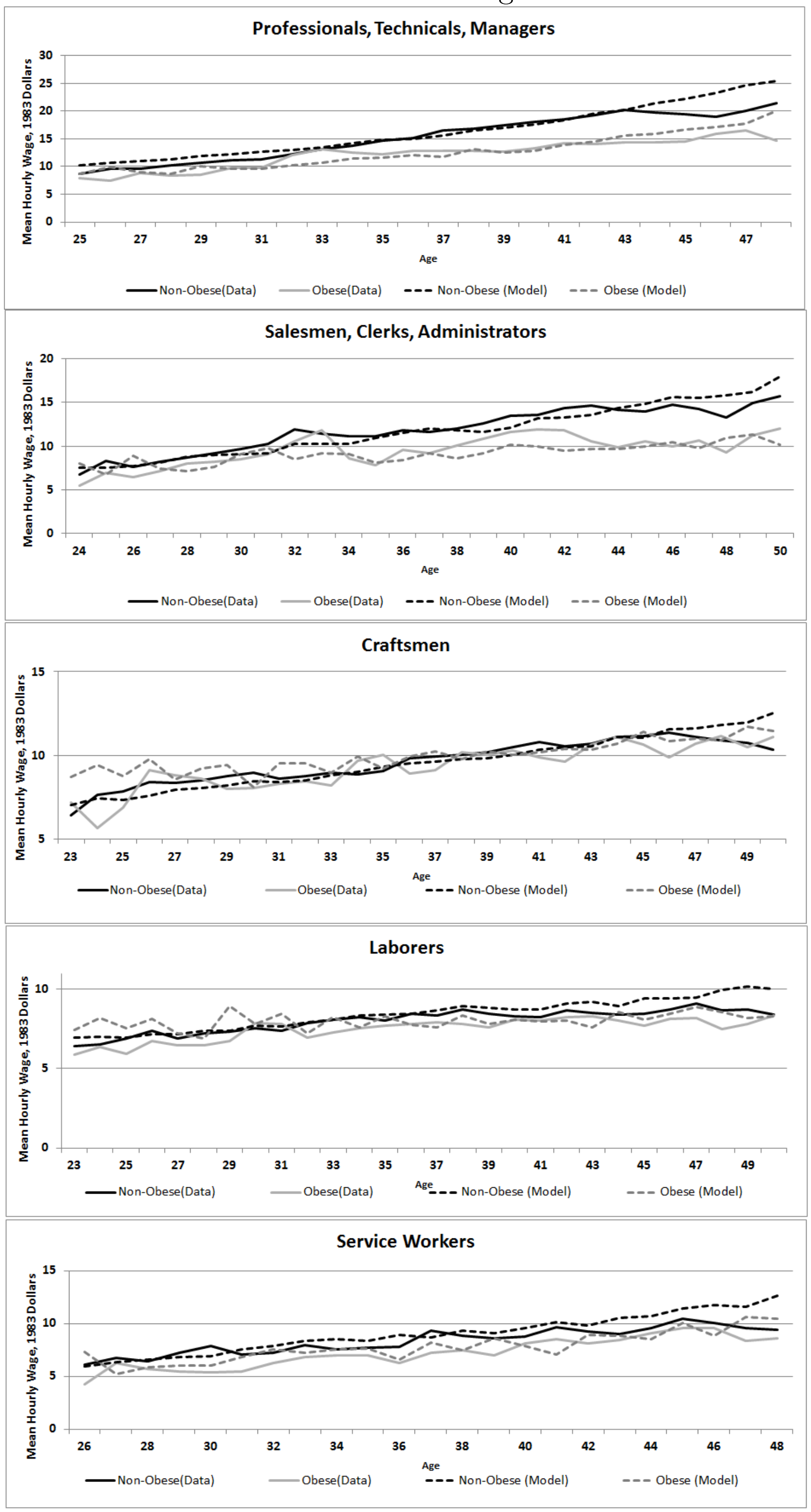


Figure 3: Predicted and Observed Differences in Wages Between the Obese and Non-Obese



obese workers from unemployment to laborer work, and under-predicts the transition from unemployment to professional work. However, as the model over predicts the selection of obese workers into sales/administrative occupations laborer occupations, this final result is not surprising.

7 Simulations

Having shown that the estimated model fits the key stylized facts of the observed data, I conduct a few simulations using the specified model and estimated parameters to illustrate the dynamic effects of body weight on employment decisions and wages over the life cycle. I first construct a simulated sample of 10,000 individuals that reflects the distribution of unobserved heterogeneity and initial conditions for years of schooling body mass. I then simulate wage offers, employment decisions and weight gain from age seventeen onward. While the previous section treated the effects of body weight on employment decisions as separate, they are interrelated. The non-monetary costs of employment affect employment decisions and subsequent wages. Wage differentials affect employment decision and outcomes. These simulations serve to show how these different costs and factors work in concert. As this is a partial equilibrium model, all of these effects should be interpreted in the context of the individual worker rather than the population.

The first simulation supposes individuals no longer incur any additional switching costs due to their body weight and evaluates how this increased occupational mobility will affect employment choices and wages. The results are displayed in Figure 4. Since the white collar occupations were the only ones estimated to have substantial entry frictions due to body mass, these occupations are the focus of this simulation. Figure 4 shows that in the absence of weight-specific switching costs, the probabilistic gap in choosing Professional, Technical, and Managerial occupations shrinks by approximately 20 percent. The top left panel shows the percent gap in attainment for non-obese and obese workers as predicted by the model

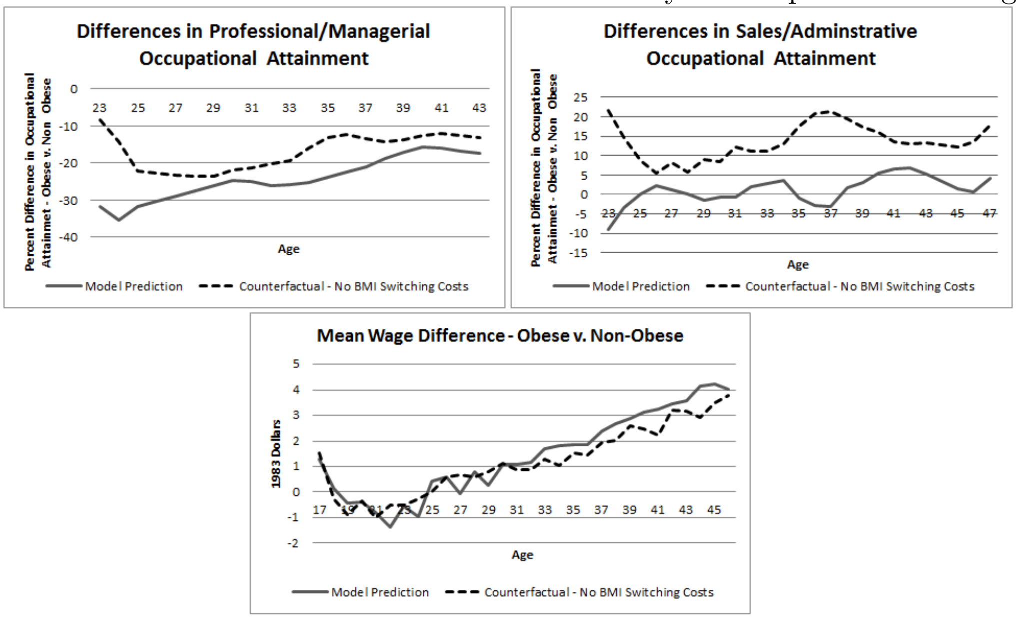
Table 10: Occupational Transitional Matrix

Non-Obese Individuals: $t-1$ in rows, t in columns							
	No Work	PTM	Sales/Admin	Craftsmen	Ops/Labor	Service	Total
No Work	69.55	8.81	4.11	5.22	8.58	3.72	100.00
(Model)	70.01	7.49	3.63	4.98	8.31	5.57	100.00
PTM	4.56	83.27	4.63	3.78	2.31	1.46	100.00
(Model)	2.68	84.15	3.95	4.18	3.73	1.32	100.00
Sales Admin	5.29	16.84	65.78	3.30	7.31	1.48	100.00
(Model)	5.17	12.59	67.03	3.40	8.17	3.65	100.00
Craftsmen	4.14	7.27	1.90	72.95	12.26	1.39	100.00
(Model)	4.95	6.72	2.22	76.29	8.69	1.13	100.00
Ops/Labor	6.14	4.42	4.49	12.75	68.90	3.29	100.00
(Model)	5.09	5.83	4.68	10.52	70.58	3.29	100.00
Service	8.66	7.59	2.83	5.61	10.69	64.62	100.00
(Model)	5.66	6.02	5.09	7.42	8.62	67.17	100.00
Total	20.40	28.89	9.58	17.09	18.07	5.98	100.00
(Model)	17.55	27.72	10.28	18.12	18.71	7.62	100.00

Obese Individuals: $t-1$ in rows, t in columns							
	No Work	PTM	Sales/Admin	Craftsmen	Ops/Labor	Service	Total
No Work	67.76	11.70	3.57	5.99	6.99	3.99	100.00
(Model)	60.31	8.64	3.88	8.18	13.48	5.51	100.00
PTM	3.84	86.84	3.50	3.61	1.41	0.79	100.00
(Model)	2.07	87.40	2.43	3.90	3.37	0.83	100.00
Sales Admin	4.56	11.50	70.99	4.56	6.20	2.19	100.00
(Model)	2.91	9.10	78.19	2.40	5.84	1.58	100.00
Craftsmen	2.28	5.59	1.97	80.24	8.35	1.57	100.00
(Model)	3.51	4.30	1.41	83.34	6.58	0.86	100.00
Ops/Labor	4.44	3.06	3.45	10.26	75.64	3.16	100.00
(Model)	3.29	3.80	3.10	6.81	81.17	1.83	100.00
Service	5.75	4.20	3.10	1.77	5.97	79.20	100.00
(Model)	3.19	3.40	2.70	4.99	6.10	79.62	100.00
Total	11.61	31.34	9.56	21.92	17.49	8.06	100.00
(Model)	7.34	27.23	11.85	22.68	23.93	7.29	100.00

Source: NLSY '79

Figure 4: Counterfactual Results - Elimination of Body Mass Specific Switching Costs



and the hypothetical simulation. The model predicts that an obese worker is 25 percent less likely than a non-obese worker to choose employment in a professional occupation in his early thirties. Without weight specific switching costs, an obese male is only 15 percent less likely to be employed in a professional occupation by age 35. The sharpest reduction in the attainment gap occurs between ages 30 and 35, when careers are advancing.

The upper panel on the right side shows the effects of the hypothetical policy on weight-based differences in attaining work in sales, clerical, and administrative occupations. Without weight-specific switching costs, an obese worker is 10 percent more likely than a non-obese worker to choose a sales and administrative occupation after age 30. These occupations are high paying relative to laborer and service occupations, and have lower social requirements than the professional occupations. The third panel in Figure 4 shows the growth of the difference in mean real wages between obese and non-obese workers as predicted by the baseline model and the counterfactual simulation. If an obese individual experienced no weight-specific barriers to occupational mobility, the expected wage gap between an obese worker and non-obese worker would decrease by an average of12 percent over the sample period.

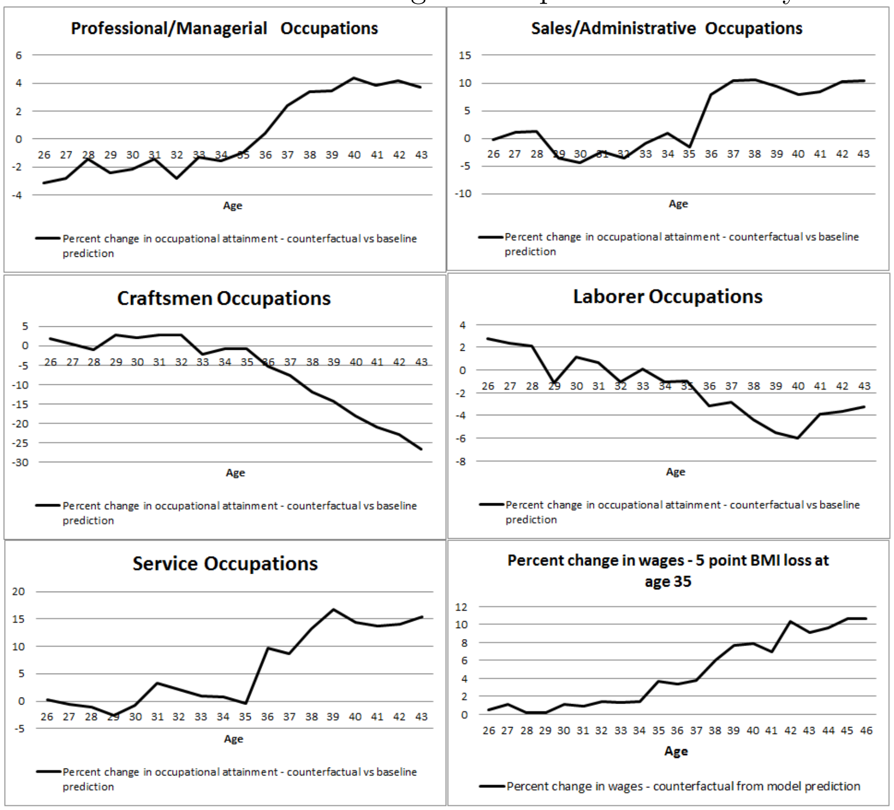
The second simulation examines the effects of a one-time exogenous mid-career shock to an individual's body weight. Baseline predictions were formed by simulating the model using the estimated parameters and the observed data. I again predicted occupational choices and wages using the estimated parameters of the model, but reduced the individual's Body Mass Index by one weight class (5 points) at age 35.[26] The results are displayed below in Figure 5. The initial change in wages is small ($<$ 4 percent), which is consistent with prior literature that has found no direct wage penalties' for body weight. However, by age 45, an individual who lost a weight class at age 35 is expected to earn 10 percent more than an individual who did not.

This increase is driven by both a predicted increase in the probability of attaining a white collar occupation after the shock (see top panels), and increases in expected wages in those occupations. The model predicts that such an exogenous shock would increase wages by approximately $1.54 in professional occupations and $.1.37 in sales and administrative occupations. The individual is 4 percent more likely to attain work in a professional occupation, and as much as 10 percent more likely to be employed in a sales or administrative job. Weight loss does not substantially affect the distribution of wage offers in either blue collar or service occupational category.

I also simulate the effects of an early career exogenous change in an individual's initial body weight on their life cycle occupational choices and wages. I decreased the individual's initial body mass by 20 percent (approximately one weight class) in one simulation, and increased the individual's initial body mass by 20 percent in the other. Figure 6 contains the results. When an individual's initial body weight was reduced, he was 5 percent more likely to gain employment in professional occupations in his 20's and 30's, relative to the original prediction. Raising initial body mass had a stronger effect. Simulating the model with a 20 percent increase in initial body mass, an individual is 15 percent less likely to choose PTM occupations and 10-15 percent more likely to select either blue collar occupation (Craftsmen

[26]For a five foot eight inch male, this is the equivalent of losing 25 pounds. For a 6 foot tall Male, this equates to losing 29 pounds.

Figure 5: Counterfactual Results - Exogenous 5-point Loss of Body Mass at Age 35



or Laborer).[27] The final panel in figure 6 shows that overall, a 20 percent increase/decrease in initial BMI leads to a 10 percent decrease/5 percent increase in real wages over the life course.

Finally, I conduct simulations with certain aspects of the wage distribution held fixed to ascertain what 'shares' of the observed growth in wage differences on the basis of weight are attributable to changes in job requirements, unobserved heterogeneity, and the compounding effects of lower wages earned individuals of higher body weight. Graphs of the expected difference in wages for an obese and non-obese worker as predicted under baseline and counterfactual conditions are exhibited in figure 7. Unobserved heterogeneity is shown to be important as the top right panel shows that the wage gap shrinks by approximately 40-50 percent when the model is simulated without heterogeneity. The top left panel shows

[27] The effects on occupational attainment for SCA jobs were not definitive.

Figure 6: Counterfactual - Exogenous 20 percent Decrease and 20 percent Increase in Initial BMI

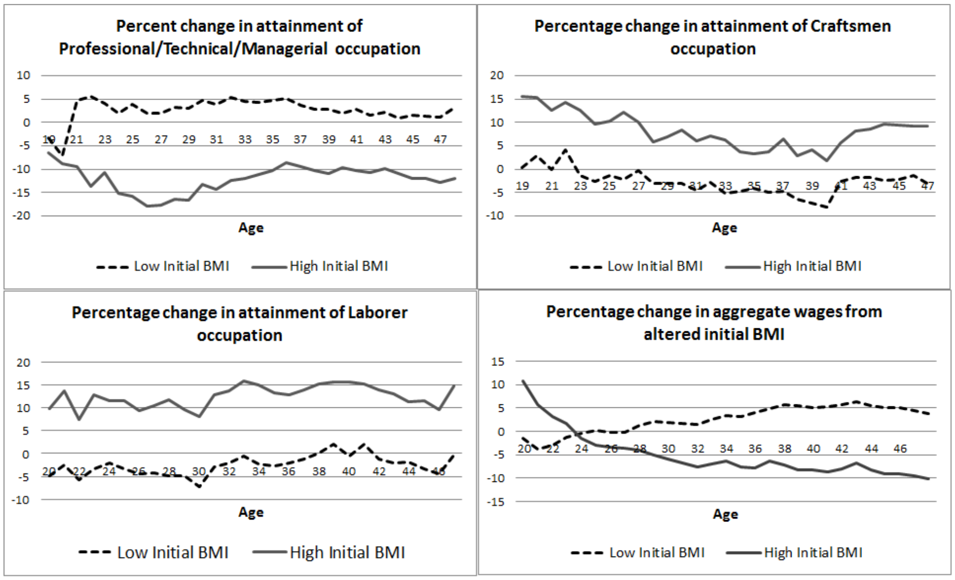
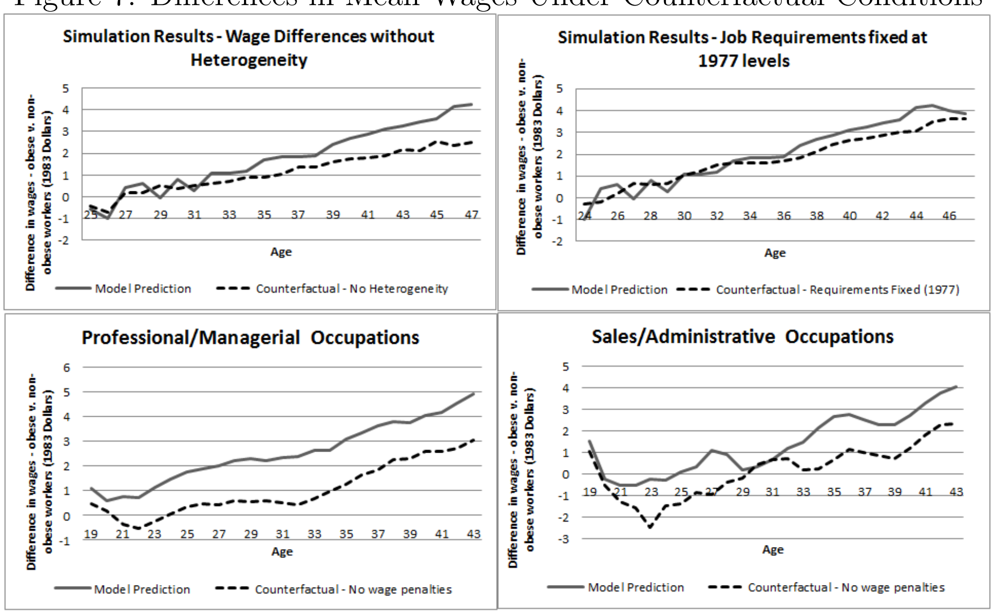


Figure 7: Differences in Mean Wages Under Counterfactual Conditions



that changes in job requirements account for 10-20 percent the observed growth in wage differences between obese and non-obese workers.

The bottom two panels contain simulated wage differences in the two white-collar occupational categories from the model under baseline conditions and with the parameters in the wage distribution on body weight and body weight interacted with education set to zero. While we have found that contemporaneous wage penalties for obesity are relatively small, the compounding effect of residual weight-based wage differentials and differences in returns to education are substantial. These "wage penalties" for obesity account for roughly 25 percent of the wage gap between obese and non-obese workers. To evaluate the impact of differences in experience between the weight classes, I used the estimates for the parameters of the wage distribution to evaluate the difference in wages between the obese and non-obese workers if the obese workers were arbitrarily assigned the experience profiles of non-obese workers. I found that this reduced the mean difference in wages between obese and non-obese workers by 9 percent and 6 percent for the professional and clerical occupations respectively.

8 Discussion

This study formulates and estimates a dynamic stochastic model of employment decisions and wages over the life cycle to determine the composite effect of body weight on labor market outcomes. Where previous work has focused on attributing weight-based differentials to discrimination, productivity, or other motivations; this paper focuses on the manifestation of monetary and non-monetary costs of body weight and how those costs can compound over the life cycle. Body weight is found to decrease occupational mobility, lower returns to white-collar occupational experience, and lower the returns to education in white collar occupations. Body weight leads to lower wages and higher non-monetary costs in jobs with greater social requirements, but the opposite is true in jobs with intense physical requirements.

Previous work in literature (e.g., Cawley (2004)) has found that wage penalties for obesity are small in white males. While our results are consistent with that finding, I also find that high body weight nevertheless presents significant costs to workers. The joint finding that body weight reduces returns to experience, reduces returns to education, reduces occupational mobility into professional and managerial jobs is consistent with higher body weight being an impediment to career development. This is especially true, given that the wage effects are particularly strong in upper quantiles of distribution of wages. While this study focused on occupational choice, a separate examination that linked body weight to the probability of receiving promotions could validate or debunk this mechanism.

From the results and simulations, two results are troubling. First, although contemporaneous wage penalties for body weight are small, higher body weight is shown to decrease earnings and occupational mobility over the life cycle. Second, as evidenced by the simulation where job requirements are held fixed at 1977 levels, the ongoing transition to a service-based economy is not good news for heavier people. Given that the generation entering the workforce in the U.S. is the heaviest yet, these results have negative implications for future average productivity of labor. Further, the number of blue collar jobs that favor heavier workers is shrinking. These results of this model imply that income inequality on the basis of body weight will likely continue to worsen. While this paper does not posit a policy-based solution, the findings certainly raise the stakes for prevention and remediation of adolescent obesity. While the adverse health effects of high body weight are well documented, rates of overweight and obesity continue to increase. Perhaps knowledge of how body weight affects career decisions can influence healthy behavior. If individuals do not respond to health incentives, maybe they will respond to monetary incentives.

References

Aguirregabiria, V. and P. Mira (2010). Dynamic discrete choice models: a survey. *Journal of Econometrics 156(1)*, 38–67.

Altonji, J. G. and C. R. Pierret (2001). Employer learning and statistical discrimination. *Quarterly Journal of Economics 116*, 313–350.

Altug, S. and R. A. Miller (1998). The effect of work experience on female wages and labor supply. *Review of Economic Studies 65*, 45–85.

Averett, S. and S. Korenman (1996). The economic reality of the beauty myth. *Journal of Human Resources 31*, 304–330.

Baird, M. (2014). Occupational transitions, wage and non-wage benefits: Estimation of a dynamic model. *Working Paper*.

Becker, G. S. (1957). *The Economics of Discrimination.* The University of Chicago Press.

Bowlus, A. J. and Z. Eckstein (2002). Discrimination and skill differences in an equilibrium search model. *International Economic Review 43(4)*, 1309–1345.

Cawley, J. (2004). The impact of obesity on wages. *The Journal of Human Resources 39(2)*, 451–474.

Coate, S. and G. C. Loury (1993). Will affirmative-action policies eliminate negative stereotypes. *American Economic Review 83(5)*, 1220–1240.

Colman, G. J. and D. M. Dave (2011). Exercise, physical activity and exertion over the business cycle. *NBER Working Papers Series 17406*, 1–38.

Courtemanche, C. (2009). Longer hours and larger waistlines? *Forum for Health Economics and Policy 67*, 543–564.

DeBeaumont, R. (2009). Occupational differences in the wage penalty for obese women. *Journal of Socio-Economics 38*, 344–349.

Eckstein, Z. and O. Lifshitz (2011). Dynamic female labor supply. *Econometrica 79(6)*, 1675–1726.

Flabbi, L. (2010). Gender discrimination estimation in a search model with mathcing and bargaining. *International Economic Review 51(3)*, 745–783.

Gayle, G.-L. and L. Golan (2012). Estimating a dynamic advere selection model: Labor force experience and the changing gender earnings gap 1968-97. *Review of Economic Studies 79(1)*, 227–267.

Gilleskie, D. B., E. Han, and E. C. Norton (2011). Untangling the direct and indirect effects of body mass dynamics on earnings. *Working Paper*.

Gilleskie, D. B. and T. A. Mroz (2004). A flexible approach for estimating the effects of covariates on health expenditures. *Journal of Health Economics 23*, 391–418.

Grossman, M. (1972). On the concept of health capital and the demand for health capital. *Journal of Political Economy 80*, 223–255.

Hamermesh, D. and J. Biddle (1994). Beauty and the labor market. *The American Economic Review 84*, 1174–1194.

Han, E. C., E. C. Norton, and S. C. Stearns (2009). Weight and wages: fat versus lean paychecks. *Health Economics 18*, 535–548.

Heckman, J. J. and B. Singer (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica 52(2)*, 271–320.

Holmstrom, B. (1999). Managerial incentive problems: A dynamic perspective. *Review of Economic Studies 66*, 169–182.

Johar, M. and H. Katayama (2012). Quantile regression analysis of body mass and wages. *Health Economics 21*, 597–611.

Kambourov, G. and I. Manovskii (2009). Occupational specificity of human capital. *International Economic Review 50(1)*, 63–115.

Keane, M. P. and K. I. Wolpin (1994). The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte carlo evidence. *The Review of Economics and Statistics 76(4)*, 648–672.

Keane, M. P. and K. I. Wolpin (1997). The career decisions of young men. *Journal of Political Economy 105*, 473–522.

Keane, M. P. and K. I. Wolpin (2000). Eliminating race differences in school attainment and labor market success. *Journal of Labor Economics 18(4)*, 614–652.

Kelly, I. R., D. M. Dave, J. L. Sindelar, and W. T. Gallo (2011). The impact of early occupational choice on health behaviors. *NBER Working Papers Series 16803*, 1–62.

Khwaja, A. (2010). A life cycle analysis of the effects of medicare on indiviual health incentives and health outcomes. *Journal of Econometrics 156*, 130–147.

King, G., E. Fitzhugh, D. B. Jr, S. S. JE McLaughlin, and DL Thomson, and A. Swartz (2001). Relationship of leisure-time physical activity and occupational activity to the prevalence of obesity. *International Journal of Obesity 25*, 606–612.

Kline, B. and J. Tobias (2008, September). The wages of bmi: Bayesian analysis of a skewed treatment-response model with nonparametric endogeneity. *Journal of Applied Econometrics 23*, 767–793–234.

Lakdawalla, D. and T. Philipson (2002). The growth of obesity and technological change: A theoretical and empirical examination. *NBER Working Paper Series 8946*, 1–42.

Lange, F. (2007). The speed of employer learning. *Journal of Labor Economics 25(1)*, 1–35.

Lee, D. (2005). An estimable dynamic general equilibrium model of work, schooling and occupational choice. *International Economic Review 46*, 1–34.

Lee, D. and K. I. Wolpin (2006). Intersectoral labor mobility and the growth of service sector. *Econometrica 47*, 1–46.

Lehmann, J.-Y. K. (2013). Job assignment and promotion under statistical discrimination: Evidence from the early careers of lawyers. *Working Paper*.

Lindeboom, M., P. Lundborg, , and B. van der Klaauw (2010). Assessing the impact of obesity on labor market outcomes. *Economics and Human Biology 8(3)*, 309–319.

Mroz, T. A. (1999). Discrete factor approximations in simultaneous equation models: Estimating the impact of a dummy endogenous variable on a continuous outcome. *Journal of Econometrics 92*, 233–274.

Mroz, T. A. and D. R. Weir (2003). Stochastic dynamic optimization models with random effects in parameters: An application to age at marriage and life-cycle fertility control in france under the old regime. In T. W. Guinnane, W. A. Sundstrom, and W. C. Whatley (Eds.), *History Matters: Essays on Economic Growth, Technology, and Demographic Change*, pp. 483–508. Stanford Press.

Pagan, J. A. and A. Davila (1997, September). Obesity, occupational attainment and earnings. *Social Science Quarterly 78*, 756–770.

Pronk, N. P., B. Marinson, R. C. Kessler, A. L. Beck, G. E. Simon, and P. Wang (2004). The association between work performance and physical activity, cardiorespiratory fitness, and obesity. *Journal of Occupational and Environmental Medicine 46(1)*, 19–25.

Ravesteijn, B., H. V. Kippersluis, and E. V. Doorslaer (2014). The wear and tear on health: What is the role of occupation. *Working Paper*.

Ricci, J. A. and E. Chee (2005). Lost productive time associated with excess weight in the u.s. workforce. *Journal of Occupational and Environmental Medicine 47(12)*, 1227–1235.

Rust, J. (1997). Using randomization to break the curse of dimensionality. *Econometrica 65*, 487–516.

Sanders, C. E. (2010). Skill undertainty, skill accumulation, and occupational choice. *Job Market Paper*.

Stinebrickner, T. R. (2001). A dynamic model of teacher labor supply? *Journal of Labor Economics 19*, 196–230.

Sullivan, P. (2010). A dynamic analysis of educational attainment, occupational choice, and job search. *International Economic Review 51*, 289–317.

Tosini, N. (2008). The socioeconomic determinants and consequences of women's body mass. UPenn working papers.

Yamaguchi, S. (2012). Tasks and heterogeneous human capital. *Journal of Labor Economics 30(1)*, 1–53.

Yamaguchi, S. (2013). Changes in returns to task-specific skills and the gender wage gap. *Working Paper*.

A Technical Appendix

A.1 Solution and the Likelihood Function

In a finite horizon maximization problem, at any given time t, I model an individual's decision making behavior as if he is maximizing his expected discounted utility over the balance of his lifetime, conditional on the current state. Three aspects of the data must be addressed in estimation. First, the lives of agents continue past the horizon of the data, and agents will continue to receive utility beyond the observed periods. To capture this unobserved continuation payoff, this model uses a closing function as in Mroz and Weir (2003) to approximate the unobserved future utility as a linear function of state variables including experience, body mass, and indicators for occupation in the final period. The parameters of this linear function $g(\cdot)$ are estimated jointly within the model. The final period closing function is

$$\widehat{V}(\mathbf{S}_T|\phi) = g(\mathbf{S}_T|\phi) \tag{18}$$

With this approximation for the closing function, the value of a specific alternative in time $T-1$, as in equation (15) conditional on type and observed wage offer ω^j_{T-1}, is

$$V^{hj}_{T-1}(\mathbf{S}_{T-1}|\phi, \omega^j_{T-1}) = U_{hj}(\mathbf{S}_{T-1}, \omega^j_{T-1}, \phi) + \beta E\widehat{V}(\mathbf{S}_T|\mathbf{S}_{T-1}, \mathbf{d}_{T-1}, \phi) \tag{19}$$

I proceed by backward recursion to solve for value functions in preceding periods.

Second, I must account for the fact that individuals' wage offers in each occupation are not observed when those occupations are not chosen. As in Stinebrickner (2001), I integrate over the distribution of unobserved wages when calculating the conditional choice probability in equation (17). Defining ω_{-j} as the vector of unobserved wage offers, the choice probability conditional on state $\mathbf{S}_t$ and wage offer ω_j is:

$$p(d_t^{hj} = 1|\mathbf{S}_t, \omega_t^j, \phi) = \int_{\omega_{-j}} \frac{exp(\overline{V}_{hj}(\mathbf{S}_t|\omega_j, \phi)}{\sum_{hj'} exp(\overline{V}_{hj'}(\mathbf{S}_t|\omega_{j'}, \phi)} P[w_{k-1} \leq \omega_t^j < w_k|\mathbf{S}_t] \quad d\omega_{-j} \tag{20}$$

which does not have a closed form solution. Integration is conducted by taking D Halton draws from the joint distribution of unobserved wages as estimated by CDE. Equation (22) can thus be rewritten as:[28]

$$P(d_t^{hj} = 1, \omega_t^j|\mathbf{S}_t, \phi) = \frac{1}{D}\sum_{d=1}^{D} \frac{exp(\overline{V}_{hj}(\mathbf{S}_t|\omega_t^j, \phi))}{\sum_{hj'} exp(\overline{V}_{hj'}(\mathbf{S}_t|\omega_t^{j'(d)}, \phi))} P[w_{k-1} \leq \omega_t^j < w_k|\mathbf{S}_t] \tag{21}$$

Finally, the likelihood function accounts for the switching of the NLSY '79 from an annual to a biennial survey in 1994. While data on employment behavior, wages, and family status for the missing years can be recovered from the retrospective questions, I integrate over body mass in the odd numbered years. Because body mass as a state variable enters the conditional choice probabilities and transition probabilities for marriage state and number of children, integration is required when calculating these probabilities. For exposition, I define the variable y_t as follows:

$$y_t = \begin{cases} 0 & \text{if year is during annual survey period (up to 1994)} \\ 1 & \text{if year is during biennial survey period and is a survey year} \\ 2 & \text{if year is during biennial survey period and is not a survey year} \end{cases} \tag{22}$$

Let $G_t^{y=0}|\phi$ be the individual's likelihood contribution in period t when $y_t = 0$ and conditional on unobserved heterogeneity term ϕ, suppressing notation for $\mathbf{S}_t, \mathbf{d}_t$, and ϕ as $(\cdot)$, where

[28] D=80

$$G_t^{y=0}|\phi = \prod_{hj=1}^{HJ} \Big[\tilde{P}(d_t^{hj} = 1, \omega_t^j|\cdot) * \prod_{l=1}^{L} (P_t^B|\cdot)^{\mathbf{1}[B_{t+1}=B_l]} * \prod_{m'=0}^{3} (P_t^M|\cdot)^{\mathbf{1}[M_{t+1}=m']} * \prod_{k=0}^{1} (P_t^k|\cdot)^{\mathbf{1}[K_{t+1}=K_t+k]}\Big]^{(d_{ti}^{hj})} \tag{23}$$

The choice probability, conditional on observed wage, is defined as above, P_t^B is the CDE weight transition probability, P_t^M and P_t^K the transition probabilities for marriage and children from equations (11) and (12) respectively. In survey years during the biennial period, the individual's contribution is similar *except* body mass transition probabilities are not calculated as body mass will not be observed in the next period. Therefore when $y_t = 1$:

$$G_t^{y=1}|\phi = \prod_{hj=1}^{HJ} \Big[\tilde{P}(d_t^{hj} = 1, \omega_t^j|\cdot) * \prod_{m'=0}^{3} (P_t^M|\cdot)^{\mathbf{1}[M_{t+1}=m']} * \prod_{k=0}^{1} (P_t^k|\cdot)^{\mathbf{1}[K_{t+1}=K_t+k]}\Big]^{(d_{ti}^{hj})} \tag{24}$$

and when $y_t = 2$, I use the parameters of the model to integrate over the missing body mass state variable when calculating all four probabilities:

$$\begin{aligned} G_t^{y=2}|\phi = \sum_{b=1}^{B} P_{t-1}^B \Bigg(\prod_{hj=1}^{HJ} \Big[\tilde{P}(d_t^{hj} = 1, \omega_t^j|\cdot, B_t = b) * \prod_{l=1}^{L} (P_t^B|\cdot, B_t = b)^{\mathbf{1}[B_{t+1}=B_l]} \\ * \prod_{m'=0}^{3} (P_t^M|\cdot, B_t = b)^{\mathbf{1}[M_{t+1}=m']} * \prod_{k=0}^{1} (P_t^k|\cdot, B_t = b)^{\mathbf{1}[K_{t+1}=K_t+k]}\Big]^{(d_{ti}^{hj})} \Bigg) \end{aligned} \tag{25}$$

where the cell means from the body mass CDE are used for the discrete missing values of B_t. To complete the likelihood function I need initial conditions as discussed above. With initial condition probabilities in place, an individual's contribution to likelihood function to estimate the above, conditional on ϕ is:

$$L_i(\Theta|\phi^k) = \prod_{t=1}^{T_i} \Bigg[\prod_{y'=0}^{2} \Big(G_t^{y'}|\phi \Big)^{\mathbf{1}[y=y']} \Bigg] \tag{26}$$

The unconditional likelihood function for an individual can then be written as

$$L_i(\Theta) = \sum_k \pi_k L_i(\Theta|\phi^k) \tag{27}$$

The likelihood function is therefore:

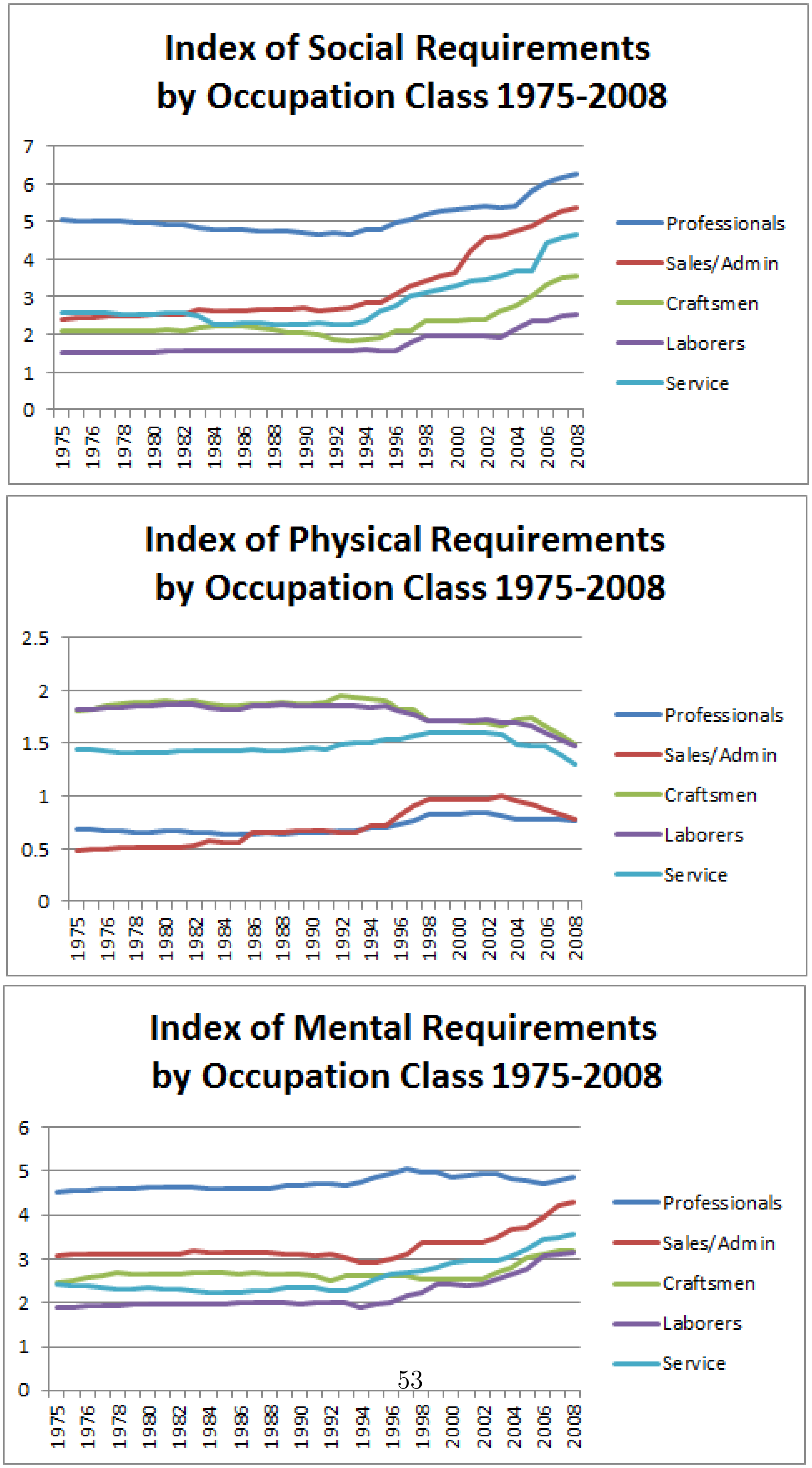
$$Li(\Theta) = \prod_{i=1}^{N} \sum_k \pi_k L_i(\Theta|\phi^k) \tag{28}$$

A.2 Initial Conditions

In the model, agents are assumed to make their first schooling/employment choice at age 17. At age 17, agents are assumed to have no accrued occupational experience.[29] The endogenous state variables of years of completed schooling and initial body mass require the modeling of initial conditions. The initial condition for completed years of schooling is modeled using an ordered probit regression with birth quarter and information about presence of newspapers, magazines, and library cards as exclusion restrictions. Initial conditions for body mass are modeled using regional dummies, information about parents' health, and the same time-varying environmental factors (linked with the geocoded data) from the weight equation. The NLSY began recording weight in 1981. For the significant portion of the sample who was older than 17 by 1981, I use the results of the 17 year olds whose weight I do observe in 1981 to estimate the conditional distribution of the age-17 weights of the individuals who were 17 prior to 1981. Using the model, I can simulate weights (probabilistically) for each period from age 17 until their weight is actually observed. Thus, I use the model to generate probabilities of an individual's weight when weights are first recorded in 1981 (Khwaja, 2010).

[29] Approximately 2 percent of the white males in the full NLSY79 sample are married by age 17, and less than 2 percent of the white males in the sample has a child by age 17. All individuals in the working subsample (discussed in the data section) are single and childless at age 17.

Figure 8:


Index of Social Requirements
by Occupation Class 1975-2008
7
6
5
4
3
2
1
0
1975 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008
Professionals
Sales/Admin
Craftsmen
Laborers
Service
Index of Physical Requirements
by Occupation Class 1975-2008
2.5
2
1.5
1
0.5
0
1975 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008
Professionals
Sales/Admin
Craftsmen
Laborers
Service
Index of Mental Requirements
by Occupation Class 1975-2008
6
5
4
3
2
1
0
1975 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008
Professionals
Sales/Admin
Craftsmen
Laborers
Service

A.3 Additional State transitions - Marriage and Children

There are four possible values for marriage (M_t), delineated by spousal earnings.An agent is single, married to a non/low earner, married to an average earner, or married to a high earner. This earnings distinction is necessary for two reasons. First, differences in spousal earnings are likely to create different incentives for labor force participation and labor supply. Ceteris paribus, the spouses of high earners should respond differently to wage shocks than spouses of low earners. I allow an individual's weight to stochastically influence his marriage and spousal income, as in Tosini (2008). As spousal earnings in turn subsequently affect the relative utility appeal of employment alternatives, these differences are worth capturing. The marriage state transitions stochastically, but exogenously. The marriage transition probabilities (in log odds) are specified as follows:[30]

$$ln \frac{P[M_{t+1} = m' | M_t = m, \mathbf{S_t}, \mathbf{d_t}]}{P[M_{t+1} = 0 | M_t = m, \mathbf{S_t}, \mathbf{d_t}]} = \delta^M_{m'} \otimes [1, M_t, Ed_t, B_t, B_t * M_t, a_t, Y_t], m' = 1, 2, 3 \quad (29)$$

Similarly, the probability transition for number of children,K_t, is specified (in log odds) as:

$$ln \frac{P[K_{t+1} = K_t + 1 | \mathbf{S_t}, \mathbf{d_t}]}{P[K_{t+1} = K_t | \mathbf{S_t}, \mathbf{d_t}]} = \delta^K \otimes [1, a_t, K_t, Ed_t, [M_t > 0], h_t] \quad (30)$$

A.4 Conditional Density Estimation - Parameter Results and Interpretation

Tables 12 and 13 contain the results from the conditional density estimation of wages, which utilizes a logit hazard equation. A positive parameter value indicates that an increase in the variable of interest increases the probability that wages will be observed in lower

[30]Marriage status and children themselves do not provide utility. Marriage is included as a stochastic state to capture variation in employment decisions resulting from variation in unearned spousal income, which enters the budget constraint. Due to the concavity of the utility function in consumption, this unearned spousal income would decrease the optimal number of hours worked. Children influence stochastic weight gain.

Table 11: Estimates for State Transitions - Marriage and No. of Children

Marriage State Transitions							Number of children		
Outcome	$M_{t+1}=1$		$M_{t+1}=2$		$M_{t+1}=3$			$K_{t+1}=K_t+1$	
Variable	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Variable**	**Estimate**	**ASE**
Constant	-2.824	0.064	-3.393	0.051	-4.108	0.612	Constant	-1.032	0.098
K_t	0.0112	0.002	0.064	0.002	-0.161	0.002	K_t	0.054	0.024
Body Mass	0.004	0.002	0.021	0.004	-0.003	0.001	Ed_t	-0.001	0.000
$(M_t = 1)$	5.653	0.349	3.859	0.198	2.835	0.108	hours	-0.001	0.001
$(M_t = 1) * B_t$	-0.001	0.000	0.002	0.003	-0.012	0.004	age	-0.071	0.008
$(M_t = 2)$	4.55	0.234	6.476	0.096	4.355	0.074	age^2	0.000	0.002
$(M_t = 2) * B_t$	-0.005	0.010	-0.002	0.005	0.005	0.001	$(M_t = 1)$	1.015	0.103
$(M_t = 3)$	4.049	0.211	4.734	0.128	6.737	0.142	$(M_t = 2)$	0.948	0.120
$(M_t = 3) * B_t$	0.001	0.002	-0.001	0.001	0.002	0.001	$(M_t = 3)$	1.043	0.156
Education	0.001	0.000	-0.023	0.002	0.001	0.001	B_t	-0.002	0.005
Hours	-0.003	0.001	0.000	0.001	0.000	0.002			
Wage	0.001	0.000	0.030	0.002	0.050	0.032			

quantiles of the support of wages. Conversely, a negative value indicates that an increase in the variable of interest will decrease the probability that wages will be observed in the low part of the distribution of wages. Negative parameter values therefore indicate that increases in the variable of interest lead to higher expected wages. Each variable is also interacted with γ, a term that enables the effect of the variable to differ over the support of wages. Specifically, letting K equal the number of quantiles used for CDE, $\gamma = (-1) * ln(K - k)$ for each cell k in constructing the logit hazard probabilities (Gilleskie and Mroz, 2004). Because for a positive variable x, the interaction term $x * \gamma$ is negative, a positive parameter value on $x * \gamma$ indicates a positive effect on expected wages, although that effect diminishes in the upper quantiles of the support of wages. Parameter estimates for a variable x and its interaction with γ must be interpreted jointly. For example, consider the effects of a bachelor's degree on wages in Professional occupations. The estimated parameter for a bachelor's degree is 0.162, indicating that having a bachelor's degree increases the probability that the individual's wages will fall in the lowest quantile of wages (and in the second lowest quantile, should the individual's wage not be observed in the lowest quantile, and so on). However, the estimated parameter on "bachelor's degree*γ" is 0.295. Since in the lowest quantile, $\gamma = (-1) * ln(25 - 1) = -3.17$, the combined sign on the effects of a bachelor's degree is negative (0.162 + 0.295*-3.17 = -.773) indicating that individuals with a bachelor's degree are less likely to be observed earning wages in the lowest quantile (and each successive quantile to the penultimate quantile, if calculated). This combined result indicates that the effect of the bachelor's degree on the probability that a wage is observed in a given quantile is most strongly negative in the lower parts of the distribution of wages.

B Details on Sample and Index Construction

This appendix contains details on the construction of the data set used to estimate the model, namely particulars related to determining the years of completed schooling, correcting for errors in reported wages, re-constructing missing years in the biennial portion of the survey, reconstructing years pre-1979 for individuals aged greater than 17 at the outset of the survey, and the regression specifics for connecting job requirement indices from the DOT and O*NET.

B.1 Constructing Years of Schooling

The NLSY '79 is contains notoriously messy data on years of completed schooling. Information on individuals' education decisions are available from the following questions:

- Since the last interview, had the individual been enrolled in school full-time, part-time, or not at all? At what grade level level (e.g. High School, College, or GED)?
- Had the individual completed an additional grade since the last interview ? If so, what was the previous highest completed grade? What was the new highest grade completed?
- Has the individual attained any degrees since the last interview? If so, what is the highest degree attained by the individual?

Table 12: Estimates of Wage Density Parameters

Occupation Invariant Parameters

Variable	**Estimate**	**ASE**	**Requirement**	**Estimate**	**ASE**	**Body Mass * Requirement**	**Estimate**	**ASE**
Constant	-1.009	0.006	Physical	-0.217	0.031	Physical	-0.026	0.003
γ	0.426	0.003	Physical*γ	-0.121	0.004	Physical*γ	-0.008	0.001
γ^2	0.707	0.012	Mental	-0.067	0.011	Mental	-0.002	0.002
γ^3	0.182	0.005	Mental*γ	-0.254	0.014	Mental*γ	-0.001	0.001
t	0.003	-0.000	Social	-0.257	0.024	Social	0.003	0.000
t*γ	-0.016	0.005	Social*γ	-0.116	0.001	Social*γ	0.001	0.000

Occupation Specific Parameters

Occupation	Professional		Sales & Admin		Craftsmen		Laborers		Service	
Variable	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**
Constant	4.465	0.012	3.108	0.017	2.733	0.018	1.245	0.018	–	–
γ	1.892	0.006	1.283	0.009	1.110	0.008	0.589	0.008	–	–
t	0.083	0.001	-0.013	0.001	0.028	0.002	0.010	0.000	–	–
t*γ	0.039	0.001	-0.028	0.001	0.013	0.001	-0.001	0.000	–	–
Education	-0.163	0.002	-0.259	0.004	0.012	0.001	0.233	0.006	0.331	0.006
Education*γ	-0.010	0.001	-0.004	0.001	0.058	0.001	0.111	0.002	0.200	0.003
Experience Occ.1	-1.289	0.010	-0.319	0.013	-0.375	0.018	-0.108	0.013	1.223	0.057
Experience Occ 1*γ	-0.124	0.004	0.227	0.004	-0.044	0.004	0.185	0.005	0.731	0.025
Experience Occ.2	-1.998	0.019	-0.062	0.007	0.728	0.034	0.896	0.034	-2.285	0.041
Experience Occ 2*γ	-0.585	0.007	0.659	0.009	0.213	0.018	0.443	0.014	-0.372	0.016
Experience Occ.3	-0.594	0.014	1.438	0.028	0.019	0.003	0.750	0.018	2.932	0.091
Experience Occ 3*γ	-0.069	0.005	1.045	0.021	0.380	0.006	0.514	0.009	1.475	0.033
Experience Occ.4	-0.814	0.013	1.898	0.038	0.737	0.021	0.841	0.016	1.539	0.052
Experience Occ 4*γ	-0.397	0.007	0.928	0.018	0.397	0.010	0.608	0.007	0.763	0.021
Experience Occ.5	-0.002	0.001	-1.928	0.083	0.102	0.009	-0.379	0.049	0.431	0.019
Experience Occ 5*γ	-0.251	0.007	-0.771	0.031	0.008	0.001	-0.327	0.016	0.837	0.013
Bachelor's Degree	0.162	0.006	1.819	0.033	0.597	0.024	-1.321	0.066	-0.014	0.002
Bachelor's *γ	0.295	0.004	0.739	0.012	0.217	0.014	-0.435	0.021	0.082	0.004
Body Mass	0.013	0.001	0.054	0.003	0.045	0.003	0.009	0.001	0.010	0.002
Body Mass*γ	0.001	0.001	0.001	0.003	0.027	0.001	0.015	0.001	0.000	0.001

Table 13: Estimates of Wage Density Parameters- BMI Interacted with Experience & Education

Occupation	Professional		Sales & Admin		Craftsmen		Laborers		Service	
Variable	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**
Education	0.003	0.001	0.016	0.001	-0.005	0.001	-0.009	0.001	-0.003	0.001
Education*γ	0.001	0.000	0.002	0.003	0.002	0.001	0.001	0.001	0.001	0.000
Experience Occ.1	0.251	0.015	1.967	0.006	-0.573	0.035	-0.070	0.008	-1.504	0.115
Experience Occ 1*γ	-0.005	0.001	-0.107	0.002	-0.311	0.016	-0.250	0.015	-1.239	0.059
Experience Occ.2	1.133	0.031	0.738	0.015	0.914	0.079	-0.313	0.032	8.2010	0.111
Experience Occ 2*γ	0.463	0.020	1.021	0.019	0.452	0.052	-0.124	0.020	2.389	0.048
Experience Occ.3	0.417	0.018	0.343	0.042	0.458	0.016	0.781	0.032	-3.131	0.108
Experience Occ 3*γ	0.131	0.009	-1.410	0.028	0.129	0.011	0.199	0.022	-1.001	0.056
Experience Occ.4	0.203	0.012	2.047	0.058	-0.615	0.032	-0.080	0.010	2.6802	0.092
Experience Occ 4*γ	0.084	0.005	0.752	0.040	-0.454	0.022	-0.124	0.008	0.954	0.045
Experience Occ.5	-0.917	0.028	2.898	0.125	2.934	0.129	1.018	0.086	1.785	0.045
Experience Occ 5*γ	-0.023	0.003	1.094	0.071	0.900	0.070	0.343	0.430	0.772	0.035
Bachelor's Degree	-0.104	0.002	-0.280	0.007	-0.175	0.001	0.207	0.018	0.027	0.004
Bachelor's *γ	-0.081	0.001	-0.107	0.002	-0.093	0.003	0.090	0.007	-0.002	0.000
Unobserved Heterogeneity										
Factor loadings	-0.154	0.009	0.025	0.005	-0.143	0.005	-0.165	0.005	-0.014	0.002

In some circumstances, the reported data contain outcomes beyond the scope of the model. Some of these instances are due to reporting error. Examples include individuals reporting reductions in grades completed, or oscillating between grade levels, advancing grades without being enrolled in school, advancing three or more years in a single year (outside of GED completion), or failing to report changes in educational attainment until some reconciliation round. Complications also arise from non-traditional education activities including GED's, accelerated degree-completion programs, very part-time enrollment in school (e.g. one college course per year), and other educational enrollments which do not result in traditional grade advancement (certificate programs, or cosmetology school).

Because this model allows for non-linear effects of high school and bachelor's degrees on wages and non-monetary costs of employment, it is important that indicator functions in the constructed data for whether the individual has completed 12 or 16 years of schooling match whether the individual actually has earned their high school or college degree. I therefore used the following rules to determine whether an individual was enrolled in school, and if they were enrolled full or part time, conditional on being enrolled.

- If an individual was enrolled in school in two consecutive years, and reported advancing a grade in each year, I treated that as full time enrollment in school, regardless of employment status.

- If an individual was enrolled in school in two years (consecutive or non-consecutive) and reported advancing a total of one grade, I treated that circumstance as part-time enrollment in each year.

- I disregarded GED's. A person with a 9th grade education and a GED is treated as having a ninth-grade education.

- If a person reported being enrolled in school for K years, and during that time advanced one grade level, I treated the person as being enrolled part-time (jointly with whatever employment decision they reported) for each of the last two years.

- Suppose an individual reported having completed X years of school at time t. If at some reconciliation year after t, say 1998 or 2008, the individual reported having completed $X + j$ years of school, and the individual had reported enrollment, but not advancement in the years between t and $t + j$, then I treated that as valid enrollment in school. If the individual did not have sufficient enrollment years to reconcile the difference, I treated the report in the reconciliation year as false.

- If an individual appears to have enrolled in an accelerated degree program, I credited them with full-time enrollment in school for the years in school, but I cannot match four years of completed school in two years.

- The model does not permit individuals to attend school full time and work, nor work full time and attend school. In cases where the individual reported attending school full time, working, and advancing a grade every other year, I treated that as part-time work and part-time school. If the individual reports working in excess of 35 hours per week, I recoded their hours worked to be 34 hour per week, or the highest value of hours per week classified as 'part time'.

- All years of high school education are treated as full-time school.

- I assume that any work experience gained while attending high school does not impact post high school decisions. The model does not therefore differentiate between attending high school while working and attending high school and not working.

- If an agent is observed to advance a grade during high school range, they are classified as attending full time school. If an agent is observed going to college and working full time, they are recoded as working part time (albeit at the top of the hours range) and attending school part time.

With these adjustments in place, I was able to reduce the percentage of mismatched observations between the indicator functions for whether the individual's constructed 'state variable' for completed years of schooling was greater than 12 (or 16), and a similar function for the individuals' self-reported highest grade completed from approximately 5 percent to 0.9 percent.

B.2 Correcting for Errors in Reported Wages

In the NLSY '79, hourly wages are a constructed variable. Individuals are asked about their rate of pay and over what unit of time (hourly, daily, weekly, bi-weekly, monthly, annually, etc.). Respondents are also asked about how many hours they work per week, the numbers of weeks worked since the last interview. Reconciling this information with reported spells of unemployment (meaning time spent not working rather than the BLS definition), the NLSY estimates the total hours worked since the last interview. Estimates of hourly rates of pay are constructed from these variables. In order to minimize the impact of misreported/misrecorded wages, I used two criteria to determine if a reported wage required further verification. First, I flagged a reported wage for further examination if an individual's wage was greater than $25.00 in 1983 dollars or less than minimum wage. Second, I examined the reported wage if an individual's wages increased or decreased more than 15 percent in a single year.

I was able to correct or verify (or at least verify that the misreporting was internally consistent) over 90 percent of these flagged wages because the mistakes were obvious in the context provided by the primary variables. In most cases the fix was clear due to a decimal (wage was within a small margin of 10x times the expected amount) or a misreported pay interval (ratio of expected to reported wages was in the neighborhood of 2x, 4x, or 52/12x). In the case of some wages flagged for discontinuity (wages increased more than 15 percent) the change in wages was accompanied by a change in occupation. In the cases where I lacked the data to plausibly correct the reported wage, I treated the wage as missing when calculating the choice probability.

B.3 Imputing Data for Missing Years in the Biennial Phase of the NLSY '79

In 1994, the NLSY switched from interviewing respondents on an annual basis to conducting interviews biennially. However, the NLSY does contain sufficient information to re-construct the data from the non-interview years for all variables except body weight, as discussed in the section on empirical interpretation. More specifically, the NLSY asks respondents about their tenure (in weeks) at their current job; their start date at their current job; whether the respondent's current wages are the same as their initial wages; when was the current wage initiated; what was the preceding wage rate ; and start dates, ending dates, hours, wages, and tenure at up to 4 additional jobs.

I imputed occupation in the non-interview years with according to the following rules:

- If the respondent is currently employed, and has been at that job longer than 78 weeks, I assumed their occupation during the non-interview year was the same as the interview year.

- If the respondent is currently unemployed, they reported being at their last job longer than 52 weeks, and started that job within six months of the start of the calendar year of the non-interview year, I used their primary occupation for their occupation during the non-interview year.

- If the respondent has been at their current (primary) job less than 52 weeks, and started their second job within three months prior to (or six months after) of the start of the calendar year of the non-interview year, and they were at their second job for longer than 26 weeks, I used the occupation of the second job as the occupation for the non-interview year

- For any observations still missing occupations in the non-interview year, if the respondent held more than two jobs since the last interview, and their tenure at their current job is less than 78 weeks, I used the occupation with the most hours worked over the most weeks of the non-interview year as the primary occupation.

Occupation and hours were reported jointly for each 'job' held. Hours were not updated as were wages. I thusly used reported hours worked per week as paired with each occupation for each job.

I imputed wages in the non-interview years according to the following rules:

- If I coded the respondent as having any occupation other than the primary - the reported wage from that job was used.
- If the primary occupation was used, and the person reported no changes in wages since starting that job, I used the reported wage from the primary occupation.
- If the primary occupation was used, and the person reported a change in wages occurring in the last 12 months, I used the reported prior wage.

I used the age of the youngest child in the household to determine whether any child births occurred during interview or non-interview years. I also used variables on marital status, change in marital status since last interview, and date of change in marital status to impute missing information on marital status in the missing period. If there was no change in marital status over the two-year span between interviews, I used the difference in spousal income during previous-calendar-year and spousal income since-last-interview to estimate unearned (by respondent) spousal income during off years.

B.4 Imputing Data for Missing Years Pre-1979

I model individuals' joint annual choices of occupation, hours of work, and schooling from ages 17 on. However, the age of individuals in the NLSY '1979 ranges from 14-22 at the time of the initial interview. However, in that initial interview, respondents were asked about school and employment history as far back as 1974. There is sufficient information, therefore, to reconstruct employment, marriage, child acquisition, school enrollment, and wages back to age 17 for even the oldest individuals in the sample. However, as the historical data in the first round is quite messy, I used the following variables and rules to construct the individual's decision history and initial conditions.

- The initial interview contains a question "What was the last year you were in school?" All years prior to that year, I treat as years of being in school. The initial condition for years of completed schooling is then calculated by subtracting years of schooling since age 17 from reported years of completed schooling at the time of the first interview.

- If the individual reported exiting school in 1978 or earlier, and their tenure at their current job was greater than 78 weeks, I used reported occupation, hours, and wages from that job for the individual's employment decision in 1978.

- If the individual reported exiting school prior to 1978 and their tenure at the current job was less than 78 weeks, I used the longest tenured job during 1978 (the survey allowed individuals to report up to 5 jobs) for the occupation, hours, and wages data for that year.

- I followed a similar procedure for years 1974-1977.

- If any conflicting information was present about whether the individual was working or attending school, I assumed the individual was attending school.

- If at all unclear, I assumed the respondent attended school in the years they were ages 17-18.

Age of youngest child and dates of any current or previous marriage/divorces were also available in the initial round. I used these variables to construct family history back to age 17. Three people in my working sample had children at age 17. I did not model this as an initial condition, but rather imposed that the children were born in the first year of the model, between ages 17 and 18 of the respondent.

Table 14: DOT Requirement Values and Definitions

Value	Interpretation
	Physical Requirements
4	Very Heavy (Exerting 100+ lbs force occasionally, 50-100 lbs frequently)
3	Heavy (Exerting 50-100 lbs force occasionally, 20-50 lbs force frequently)
2	Medium (Exerting 20-50 lbs force occasionally, 10-25 lbs force frequently)
1	Light (Exerting 10-25 lbs force occasionally, up to 10 lbs frequently)
0	Sedentary (Exerting up to 10 lbs of force less than 1/3 of time)
	Mental Requirements
6	Advanced Calculus (Math)
5	Read & Write Journal level work (Language); Advanced Algebra (Math)
4	Read & Write Business level material (Language); Basic Algebra (Math)
3	Read Shop Manuals, Proper Grammar (Language); Formulaic Computational Skills (Math)
2	Literacy Rate of 190 words per minute (Language); Four-function Computation (Math)
1	Literacy Rate of 95 words per minute (Language); Addition & Subtraction (Math)
	Social Requirements
8	Mentoring
7	Negotiating
6	Instructing
5	Supervising
4	Diverting
3	Persuading
2	Speaking/Signalling
1	Serving
0	Taking Instructions/Helping

B.5 Connecting the Indices of Job Requirements Between DOT and O*NET

As discussed briefly in the sections on data and empirical implementation, forming the time varying indices of job requirements necessitated converting the rich scaling of O*NET back to the coarser DOT data. The Dictionary of Occupational titles uses a 6-point scale for two mental aspects of a job, mathematical and language abilities. For the mental requirement of each DOT occupation (of which there are over 13,000 task level categories), I used the max value of the Math and Language Ratings. I used the social rating as given in the occupation's DOT number and the physical rating as assigned. These values of these ratings and their definitions are listed in Table 14.

Table 15: Occupation categories assumed fixed

Requirement	**Occupation**
	Physical Requirements
Physical	Administrative & Secretarial Occupations, Personal Service Occupations Skilled Trades (SOC 43, 33, 35 49)
Mental	Managerial Occupations, Plant Operatives, Associate Professionals (SOC 51, 11, 21, 22)
Social	Professional Occupations, Secretarial Occupatons (SOC 13, 43, 17, 19, 25)

The O*NET, by contrast, contains continuous 0-5 scales, interpretable as cardinal numbers for both level and importance of over 100 aspects of each occupation. To convert the O*NET ratings for each occupation to the DOT ratings for each occupation, I first multiplied level and importance for each category for each occupation to get a single number for the 'intensity' of a job requirement for an occupation. I then aggregated DOT tasks and O*NET occupations (based on Census 2000) code to C70 occupation codes using BLS provided weights for the O*NET and an arithmetic mean for the DOT ratings. I then used a Welsh study from Felstead et al (2006) which studied the how occupations in the UK have changed from 1986-2006. The authors estimated percentage changes in coarse job requirements along such dimensions as literacy, mathematical skills, and physical requirements. In order to connect the two indices to form a single time varying index of job requirements (for each of physical, mental, and social), a conversion of O*NET measures to DOT measures is needed. From the Felstead study, I used the skills of influence, client communication, and horizontal communication as my measures for social skills, and the aforementioned categories of interest for the mental and physical skills. Occupations which the authors treated as having an percentage change of less than five percent in a given requirement, I treated as being constant.

Under the assumption that the specific requirements of these occupations were changing minimally, I used regression to convert the O*NET 1998 ratings to the DOT 1991 rating scale as the requirements of these occupations did not sufficiently change. More specifically, I regressed the DOT 1991 ratings for physical, mental, and social requirements (aggregated to the Census '70) occupation code level on a set of requirements from O*NET). The results of the specifications with the highest adjusted R^2 are in Table 16.

In addition to converting the rich O*NET data to single indexed values, the output of these regressions are useful in two ways. First, I can use the results from these regressions (under the assumption that the subsets of the occupations used were, in fact, unchanging in their requirements) to calculate 1998 values of requirements for all C70 occupations. I assumed that changes in job requirements are smooth and linear from 1991-1998 for the occupations not assumed unchanging for the purposes of calculation. Weighting C70 codes by their CPS weights, I calculate the requirement index values for each of the five occupational categories. Second, I can use the results from these regressions to calculate the intrinsic changes in job requirements for each Census 70 occupation after 1998. Graphs of these requirements are shown in Figure A.1.

Unfortunately, all of the lines in these graphs either have a hockey-stick shape, or display more variation after the conversion to the O*NET system of rating job requirements. The primary motivation for replacing the DOT was that is not adequately capturing changes in available jobs. The DOT was insufficiently agile to effectively track changes in the set of available jobs, changes in required skills for each occupation, and was a relic of a manufacturing based economy. I therefore believe if there is error in calculating changes in job requirements, it results from insufficient variation in the DOT ratings rather than excess variation in the O*NET system.

B.6 Supplementary Material on Food-Price Ratios

Per the data section, I construct a ratio of fast-food price to fresh-produce price for each city in the ACCRA data base. The summary statistics for four years spread over the

Table 16: Regression Results - DOT ratings on O*NET Ratings

Variable	**Estimate**	**Std. Err.**
Physical Rating R^2=0.67		
Speed of Limb Movement	-0.004	0.016
Static Strength	*** 0.099	0.011
Explosive Strength	*** 0.055	0.018
Dynamic Strength	0.007	0.018
Trunk Strength	***-0.053	0.014
Stamina	-0.001	0.022
Gross Body Coordination	** 0.040	0.019
Constant	*** 0.957	0.055
Mental Rating R^2=0.71		
Written Comprehension	0.004	0.017
Oral Comprehension	*** 0.039	0.012
Mathematical Reasoning	-0.012	0.017
Mathematics	*** 0.036	0.014
Writing	*** 0.038	0.013
Reading Comprehension	*** 0.079	0.019
Constant	*** 1.554	0.094
Social Requirements R^2=0.66		
Active Listening	* 0.036	0.020
Monitoring	-0.028	0.019
Social Perceptiveness	*** 0.131	0.022
Persuasion	-0.004	0.040
Negotiation	** 0.063	0.031
Instructing	0.021	0.019
Service Orientation	**-0.035	0.018
Mgmt of Personnel Resource	** 0.024	0.012
Constant	*** 1.928	0.198

sample are included listed in the table below. Unfortunately, the UNC library only has ACCRA data as far back as 1981. I used 1981 ratios for all prior years.[31].

The ACCRA data base contains data on prices of various goods in 300 cities and Metropolitan statistical areas. Approximately 71 percent of the working sample lives in an MSA about which ACCRA reports data. For individual/year observations where the respondent was living in a FIPS code not covered by ACCRA, I assigned them ACCRA prices from closest geographic city. An alternative strategy of imputing missing prices would be to match the missing geographic area to the closest reported geographic area of a similar size. However, as small towns are sparse in the ACCRA database, it is often infeasible to match small market or rural areas within a neighboring state area.

Table 17: Summary Statistics - Ratio of Food Prices from ACCRA

Year	**Mean**	**S. D.**	**Min**	**Max**
1982	2.54	0.28	2.03	3.89
1991	2.86	0.27	2.18	4.38
2001	4.38	0.49	2.58	5.78
2008	4.26	0.55	3.31	5.57

[31] Adjusting for inflation is irrelevant - the ratio would remain constant under global price adjustment